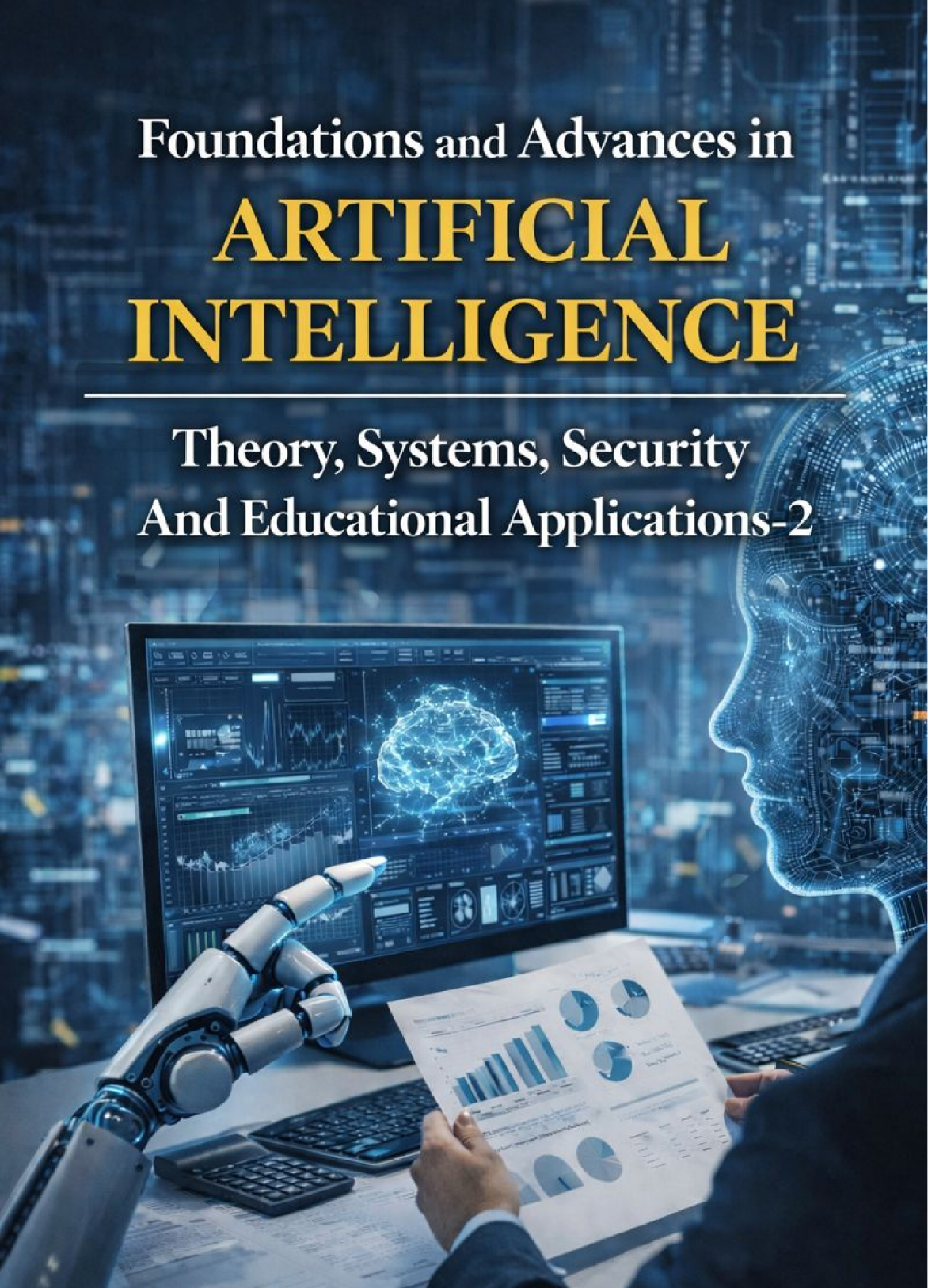
Foundations and Advances in ARTIFICIAL INTELLIGENCE

Theory, Systems, Security And Educational Applications-2



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www.bidgeyayinlari.com.tr - bidgeyayinlari@gmail.com
Krc Bilişim Ticaret ve Organizasyon Ltd. Şti.
Güzeltepe Mahallesi Abidin Daver Sokak Sefer Apartmanı No: 7/9 Çankaya / Ankara

PREFACE

The trajectory of Artificial Intelligence (AI) has shifted decisively from a niche theoretical pursuit to the very backbone of contemporary computing, cybersecurity, and algorithmic decision-making. We are currently witnessing a period where machine learning architectures and system-level refinements do not just process data—they redefine how we secure infrastructures and interpret complex information. This book emerged from a necessity to document these rapid shifts through a lens that balances technical rigor with practical interpretability.

Rather than offering a mere compilation of studies, this book orchestrates a dialogue between foundational theory and empirical validation. We begin by examining the subtle evolution of covert channel detection, moving progressively toward the systemic nuances that dictate AI model performance. A significant portion of our inquiry is dedicated to the "black box" of deep learning; by dissecting activation functions and word embedding methodologies, we aim to expose the mathematical constraints that often go unaddressed in standard literature.

Crucially, the rise of Explainable AI (XAI) is treated here not as a luxury, but as a prerequisite for security-sensitive deployments. Our focus on phishing detection underscores a vital argument: for AI to be truly effective in real-world security, it must be as transparent as it is powerful.

What perhaps distinguishes this work most is its forward-looking exploration of the academic landscape itself. The proposal of a fully AI-integrated university learning ecosystem—specifically tailored for graduate-level engineering and educational sciences—challenges the traditional boundaries of pedagogy. It positions AI not merely as a supportive tool, but as a catalyst for a systemic redesign of how knowledge is produced and shared.

This collection is designed for those navigating the intersection of research and application—be they graduate students, scholars, or practitioners. It is our hope that these pages do more than inform; we intend for them to provoke new questions and inspire the next wave of interdisciplinary innovation in the ever-evolving AI domain.

Dr.Eyyup GULBANDILAR

Editor

İÇİNDEKİLER

CHAPTER 1

AN EMPIRICAL STUDY ON FEATURE SELECTION TECHNIQUES FOR NETWORK INTRUSION DETECTION SYSTEMS

Elif Yıldırım[1]
Yasin Ortakçı[2]
İsa Avcı[3]

1. INTRODUCTION

With the integration of the internet and network-based technologies into daily life, threats to information systems have increased significantly. Institutions, companies, and individuals are exposed to various cyberattacks such as unauthorized access, data breaches, denial-of-service, and malware. These attacks threaten information security and can lead to significant financial and reputational losses. In this context, detecting suspicious and unusual behavior occurring on computer networks is of paramount importance.

Intrusion Detection Systems (IDS) are security mechanisms that aim to distinguish between normal and abnormal behavior by monitoring network traffic. Traditional signature-based IDSs are only able to detect known attacks because they rely on predefined attack patterns and are insufficient against new types of attacks [1]. To overcome these limitations, anomaly-based and machine learning-supported intrusion detection approaches have been developed.

[1] Lecturer, Karabük University, Computer Engineering / Computer Science, Orcid: 0000-0001-6336-6390
[2] Associate Professor, Karabük University, Computer Engineering / Computer, Orcid: 0000-0002-0683-2049
[3] Assistant Professor, Karabük University, Computer Engineering / Computer, Orcid: 0000-0001-7032-8018

Machine learning algorithms offer effective results in detecting both known and unknown attacks thanks to their ability to learn complex patterns in network traffic [2]. However, network traffic datasets used in such approaches are usually multidimensional and contain a large number of features. Inclusion of unnecessary or repetitive features in the model can lead to overlearning, high computational costs, and performance degradation. Therefore, feature selection is a critical preprocessing step in intrusion detection systems [3].

Feature selection aims to obtain a subset of fewer but more meaningful features while maintaining or improving classification performance. Many studies in the literature show that appropriate feature selection methods significantly improve the performance of machine learning-based intrusion detection systems [4], [5]. In this study, the effects of feature selection methods and different machine learning classifiers on intrusion detection performance were examined comparatively.

2. LITERATURE REVIEW

With the increase in attacks on computer networks, intrusion detection systems (IDS) have taken on a critical role in ensuring information security. Traditional signature-based intrusion detection approaches can only detect pre-defined attack types and are insufficient against new or previously unseen attacks. Therefore, interest in anomaly-based and machine learning-supported intrusion detection systems has been increasing in the literature [1].

In machine learning-based intrusion detection systems, one of the most important factors affecting classification performance is the feature set used. Network traffic datasets are often high-

[1] Lecturer, Karabük University, Computer Engineering / Computer Science, Orcid: 0000-0001-6336-6390
[2] Associate Professor, Karabük University, Computer Engineering / Computer, Orcid: 0000-0002-0683-2049
[3] Assistant Professor, Karabük University, Computer Engineering / Computer, Orcid: 0000-0001-7032-8018

dimensional and contain redundant or repetitive features. This can negatively affect the performance of classification algorithms and lead to overlearning. Therefore, feature selection methods are widely used in the literature [4], [11].

The effect of feature selection methods on classification performance has been examined in detail in many studies. Demir and Kılıç evaluated different feature selection techniques together with various classification algorithms and showed that appropriate feature selection provides significant gains in terms of accuracy and computational cost [7]. Similarly, in the study by Tiryaki and Uysal, it was reported that feature selection significantly increased the F1-score and sensitivity metrics in unbalanced datasets [5]. In particular, it has been shown in the literature that Random Forest-based feature selection approaches improve intrusion detection performance [14].

In studies conducted in the field of cybersecurity, it is a common approach to consider feature selection and classification algorithms together. In their study on the CICIDS2017 dataset, Ekici and Takcı used Recursive Feature Elimination and Forward Feature Selection methods; they showed that Random Forest and Extreme Gradient Boosting algorithms provided high attack detection performance [3]. This study clearly demonstrates the effectiveness of using feature selection and ensemble-based algorithms together. In studies where different classification algorithms are compared, ensemble-based methods have been reported to be more successful than single classifiers [15], [16].

The advantages provided by ensemble-based learning methods in intrusion detection systems are frequently emphasized in the literature. The Random Forest algorithm is widely preferred

[1] Lecturer, Karabük University, Computer Engineering / Computer Science, Orcid: 0000-0001-6336-6390
[2] Associate Professor, Karabük University, Computer Engineering / Computer, Orcid: 0000-0002-0683-2049
[3] Assistant Professor, Karabük University, Computer Engineering / Computer, Orcid: 0000-0001-7032-8018

in IDS studies due to its robust structure against overlearning and its ability to calculate feature importance levels [9]. Boosting-based algorithms, on the other hand, are based on the principle of sequentially training weak learners and offer successful results, especially in complex and unbalanced datasets [10].

Datasets used in machine learning-based intrusion detection systems also hold an important place in the literature. The KDD Cup 99 and NSL-KDD datasets have been criticized in detail in the literature for not adequately representing current attack scenarios [18]. The UNSW-NB15 dataset has been preferred in many studies due to its inclusion of modern attack types and its structure close to realistic network traffic scenarios. Studies carried out on this dataset reveal the importance of evaluating feature selection and classifier performance together [2]. The UNSW-NB15 dataset has been preferred in many studies due to its inclusion of modern attack types and its structure close to realistic network traffic [19], [20].

The literature also emphasizes that focusing solely on the accuracy metric in the evaluation of intrusion detection systems can be misleading. In particular, classifying intrusion samples as false negatives can lead to serious security vulnerabilities. Therefore, it has been stated that metrics such as sensitivity (Recall), F1-score and ROC-AUC should be given priority in intrusion detection studies [1], [11]. Similarly, the effectiveness of machine learning-based intrusion detection approaches is emphasized in thesis studies [17].

Recent studies highlight the importance of performing feature selection and classifier comparisons under the same experimental environment [21]. Evaluating different algorithms

[1] Lecturer, Karabük University, Computer Engineering / Computer Science, Orcid: 0000-0001-6336-6390
[2] Associate Professor, Karabük University, Computer Engineering / Computer, Orcid: 0000-0002-0683-2049
[3] Assistant Professor, Karabük University, Computer Engineering / Computer, Orcid: 0000-0001-7032-8018

under different datasets or different preprocessing steps makes it difficult to directly compare the results. This study aims to fill this gap in the literature by comparatively examining different machine learning algorithms under the same dataset, the same preprocessing steps and the same feature selection approaches.

3. MATERIALS AND METHODS

This study addresses the problem of network-based intrusion detection using classification and feature selection methods. Experimental studies were conducted on the UNSW-NB15 dataset due to its inclusion of realistic attack scenarios and its widespread use in the literature. The general methodology of the study consists of dataset preparation, data preprocessing, feature selection, classification, and performance evaluation steps. The general workflow followed in the study is presented in Figure 1.

Figure 1. Feature selection–based machine learning framework for network intrusion detection

[1] Lecturer, Karabük University, Computer Engineering / Computer Science, Orcid: 0000-0001-6336-6390
[2] Associate Professor, Karabük University, Computer Engineering / Computer, Orcid: 0000-0002-0683-2049
[3] Assistant Professor, Karabük University, Computer Engineering / Computer, Orcid: 0000-0001-7032-8018

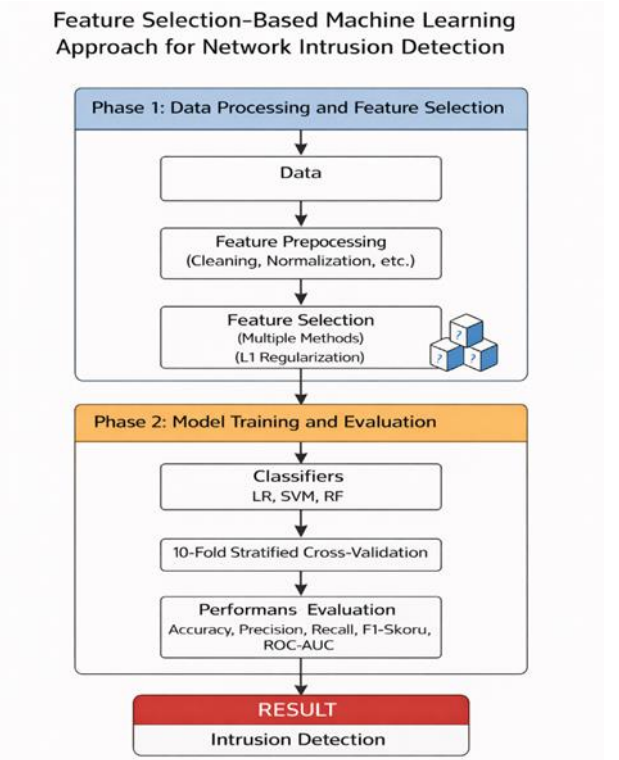

Figure 1 illustrates the general workflow of the proposed feature-selection-based machine learning approach for the network-based intrusion detection problem. In the first stage, data preprocessing steps were applied to the UNSW-NB15 dataset, and multiple feature selection methods such as L1 regularization, variance-based elimination, and statistical feature selection were used. In the second stage, Logistic Regression (LR), Support Vector Machines (SVM), and Random Forest classifiers were trained using the obtained feature subsets. The performance of the models was evaluated using a 10-fold stratified cross-validation method and

[1] Lecturer, Karabük University, Computer Engineering / Computer Science, Orcid: 0000-0001-6336-6390
[2] Associate Professor, Karabük University, Computer Engineering / Computer, Orcid: 0000-0002-0683-2049
[3] Assistant Professor, Karabük University, Computer Engineering / Computer, Orcid: 0000-0001-7032-8018

accuracy, precision, recall, F1-score, and ROC-AUC metrics, and the final intrusion detection results were obtained.

Data Set

In this study, the UNSW-NB15 dataset was used to solve the network-based intrusion detection problem. UNSW-NB15 is an up-to-date dataset created by the University of New South Wales in Australia, considering scenarios close to real network traffic and containing modern attack types. In the literature, it is frequently preferred because it offers realistic attack profiles and contains more up-to-date attack scenarios compared to classical datasets [3]. Many studies have reported that classification-based intrusion detection approaches provide effective results in network security [12], [13].

Table 1. Structural Characteristics of the UNSW-NB15 Dataset.

Feature	**Explanation**
Data Set	UNSW-NB15
Training Data Count	175,341 records
Number of Test Data	82,332 records
Total Number of Features	45
Data Type	Tabular network traffic data
Problem Type	Binary classification
Target Variable	label (0: Normal, 1: Attack)
Attack Type Information	attack_cat (for illustrative purposes only)
Protocol Information	proto (tcp, udp, arp etc.)

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[2] Associate Professor, Karabük University, Computer Engineering / Computer, Orcid: 0000-0002-0683-2049
[3] Assistant Professor, Karabük University, Computer Engineering / Computer, Orcid: 0000-0001-7032-8018

Service Information	service (http, dns, ftp etc.)
Status Information	state (FIN, INT, etc.)
Number of Packages	spkts, dpkts
Byte Information	sbytes, dbytes
Time-Based Features	stop, rate
Streaming / Session Features	ct_src_ltm, ct_srv_dst, ct_dst_src_ltm etc.
Content-Based Features	is_ftp_login, ct_ftp_cmd, ct_flw_http_mthd
Class Distribution	Balanced

In this study, as shown in Table 1, the training and test subsets of the UNSW-NB15 dataset were used. The dataset consists of a total of 45 features and includes attributes representing network traffic in terms of connection, time, packet, byte, and flow statistics. Within the scope of the binary classification problem, the label attribute was used as the target variable, while the attack_cat attribute, which shows the attack types, was evaluated only for descriptive purposes and was not included in the model. The UNSW-NB15 dataset includes different attack types such as DoS, Exploits, Fuzzers, Reconnaissance, Generic, Analysis, and Backdoor, in addition to normal network traffic. This diversity makes the dataset distinctive and challenging for intrusion detection systems. The dataset contains both numerical and categorical attributes; it consists of features that represent network traffic in detail, such as protocol type, service information, packet sizes, time-based measurements, and flow statistics.

[1] Lecturer, Karabük University, Computer Engineering / Computer Science, Orcid: 0000-0001-6336-6390
[2] Associate Professor, Karabük University, Computer Engineering / Computer, Orcid: 0000-0002-0683-2049
[3] Assistant Professor, Karabük University, Computer Engineering / Computer, Orcid: 0000-0001-7032-8018

In this study, the dataset was treated as a binary classification problem. Network traffic samples were divided into two classes: “normal” and “attack”. For this purpose, the label attribute in the dataset was used as the target variable. The attack_cat attribute, which represents attack types, only provides descriptive information and was not included in the feature set during the classification process. This choice was made to prevent indirect data leakage of the target variable into the model and to ensure a fair performance evaluation.

The UNSW-NB15 dataset exhibits class imbalance in the distribution of attack and normal traffic samples. This situation, reflecting real network environments, is a common problem in intrusion detection systems. Therefore, instead of focusing solely on the accuracy metric, this study prioritizes metrics such as sensitivity (recall) and F1-score as key evaluation criteria. This allows for a more thorough analysis of the impact of false negatives, which can lead to missed attacks.

The dataset contains pre-allocated subsets for use in the training and testing phases. In this study, this structure of the dataset was preserved, and particular attention was paid to preventing data leakage between the training and test data. All preprocessing, feature selection, and model training steps were performed only on the training data; the test data was used to measure the generalization ability of the models.

The multidimensional structure of UNSW-NB15 offers a significant advantage in examining the impact of feature selection methods. In this study, the dataset was evaluated under scenarios with and without feature selection, and the effect of the number of

[1] Lecturer, Karabük University, Computer Engineering / Computer Science, Orcid: 0000-0001-6336-6390
[2] Associate Professor, Karabük University, Computer Engineering / Computer, Orcid: 0000-0002-0683-2049
[3] Assistant Professor, Karabük University, Computer Engineering / Computer, Orcid: 0000-0001-7032-8018

features and the selected features on classification performance was analyzed in detail.

Data Preprocessing

During the data preprocessing phase, various operations were applied to enable classification algorithms to work more efficiently. First, missing values in the dataset were analyzed and corrected using appropriate statistical methods. Categorical features were digitized using appropriate coding techniques to convert them into a format that classification algorithms could process. The digitized features were then normalized to reduce negative effects that might arise from different scales.

In addition, the class imbalance problem frequently encountered in intrusion detection datasets has been considered, and metrics such as sensitivity and F1-score have been particularly focused on in performance evaluation [5].

Feature Selection

The high-dimensional nature of network traffic datasets can lead to the inclusion of redundant or repetitive features in the model. This increases computational costs and negatively impacts classification performance. Therefore, feature selection is considered a crucial preprocessing step in this study. Four different scenarios were evaluated: using all features without feature selection, embedded feature selection based on L1 regularization, variance-based feature elimination, and statistical (Chi-square) feature selection. All methods were applied to the same training and test sets to ensure fair comparison.

Without Feature Selection Applied (All Features):

In this approach, all features in the dataset are directly fed into the classification models without any filtering. This scenario

[1] Lecturer, Karabük University, Computer Engineering / Computer Science, Orcid: 0000-0001-6336-6390

[2] Associate Professor, Karabük University, Computer Engineering / Computer, Orcid: 0000-0002-0683-2049

[3] Assistant Professor, Karabük University, Computer Engineering / Computer, Orcid: 0000-0001-7032-8018

was used as a reference (baseline) to evaluate the impact of feature selection on classification performance.

L1 Feature Selection Based on Regularization:

Using an L1 regularized logistic regression model, features with low contribution to the classification process were automatically eliminated. This method provides an embedded feature selection mechanism by bringing the coefficients of ineffective features closer to zero during model training.

Variance-Based Feature Selection:

In this method, features with variance below a certain threshold in the dataset are eliminated. Based on the assumption that low-variance features do not carry distinctive information between classes, this approach specifically aims to remove features with values close to constant.

Chi-Square Based Feature Selection:

Using the Chi-square test, a statistical filtering method, the attributes with the highest correlation to the class label were selected. In this method, the contribution of each attribute to class information was statistically measured, and the most significant attributes were included in the model.

Both filter-based and embedded methods were used in the feature selection process. In filter-based methods, features were statistically evaluated according to their relationships with the target variable, and features with a high information carrying level were selected. These methods were preferred because of their low computational costs and ease of application to large datasets [4]. In embedded feature selection methods, feature weights obtained during the learning process of classification algorithms were used. By comparing scenarios with and without feature selection, the

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[2] Associate Professor, Karabük University, Computer Engineering / Computer, Orcid: 0000-0002-0683-2049

[3] Assistant Professor, Karabük University, Computer Engineering / Computer, Orcid: 0000-0001-7032-8018

effect of feature selection on classification performance was analyzed in detail.

Classification Algorithms

In this study, three different machine learning classifiers were used to evaluate the network-based intrusion detection problem with different learning approaches. The selected algorithms were chosen because of their ability to model both linear and nonlinear decision bounds and their widespread use in intrusion detection systems in the literature. Logistic Regression is a widely used method for binary classification problems, has a linear decision bound, and high interpretability. The fact that the model parameters directly reflect the feature-output relationship allows for the analysis of which features contribute to the decision process, especially in intrusion detection systems. Therefore, Logistic Regression was used as the baseline comparison model in this study [6].

Support Vector Machines (SVM) are a powerful classification method that aims to maximize the margin between classes, and performs effectively, especially in high-dimensional data spaces. Considering the high-dimensional and complex nature of network traffic data, SVM algorithms are frequently preferred in intrusion detection problems. In this study, the effect of feature selection methods on classification performance was analyzed more clearly using a linear kernel [7].

Random Forest The algorithm is an ensemble learning method created by combining a large number of decision trees []. Thanks to trees trained on random feature and sample subsets, it offers a structure robust against overlearning. It is widely used in intrusion detection systems, especially because of its ability to

[1] Lecturer, Karabük University, Computer Engineering / Computer Science, Orcid: 0000-0001-6336-6390
[2] Associate Professor, Karabük University, Computer Engineering / Computer, Orcid: 0000-0002-0683-2049
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model nonlinear relationships and produce stable results in the face of noisy data [8]. All classifiers were trained using the same training and test split; 10-fold cross-validation was applied during the training phase to increase the generalizability of the models and prevent overlearning. The performance of the models was evaluated using Accuracy, Precision, Recall, F1-Score and AUC metrics. In this way, the effects of different classification approaches and feature selection methods on intrusion detection performance were compared in a fair, consistent and statistically reliable manner.

Performance Evaluation

Accurate measurement of intrusion detection system performance requires evaluation of classification results using quantitative metrics. In this study, performance evaluation was carried out based on the confusion matrix. Using these values, the following performance metrics were calculated: The performance of the classification models was evaluated using accuracy, precision, recall, and F1-score.

Accuracy measures the ratio of correctly classified samples to the total number of samples and is defined as Accuracy = (TP + TN) / (TP + TN + FP + FN).

Precision indicates the proportion of correctly predicted positive samples among all predicted positives and is calculated as Precision = TP / (TP + FP).

Recall reflects the ability of the model to correctly identify actual positive samples and is computed as Recall = TP / (TP + FN).

F1-score is the harmonic mean of precision and recall, providing a balanced evaluation of model performance, particularly

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for imbalanced datasets. It is calculated as F1 = 2TP / (2TP + FP + FN). TP (True Positive), TN (True Negative), FP (False Positive), and FN (False Negative) represent correct intrusion detection, correct deteection of normal traffic, false intrusion alarm, and missed intrusion situations, respectively. TP (True Positive), TN (True Negative), FP (False Positive), and FN (False Negative) represent correct intrusion detection, correct detection of normal traffic, false intrusion alarm, and missed intrusion situations, respectively.

The Importance of Metrics from an IDS Perspective

False negatives (FNs) in intrusion detection systems pose serious security risks as they mean that attacks go undetected. Therefore, in this study, in addition to the accuracy metric, sensitivity (recall) and the F1 score were considered as primary evaluation criteria. Furthermore, the overall discrimination performance of the classifiers was compared using the ROC-AUC metric.

4. EXPERIMENTAL RESULTS

When the results are examined, it is seen that the scenario using a combination of feature selection based on L1 regularization and the Logistic Regression model provides the most balanced and highest overall performance among all experiments. In this scenario, the following values were obtained: Accuracy = 0.7332, Precision = 0.7416, Recall = 0.7910, F1-Score = 0.7655, and AUC = 0.8733. The particularly high Recall and F1-Score values indicate a significant improvement in the attack detection rate, which is critical for intrusion detection systems.

The Logistic Regression algorithm demonstrated stable performance in all feature selection scenarios; however, a

[1] Lecturer, Karabük University, Computer Engineering / Computer Science, Orcid: 0000-0001-6336-6390
[2] Associate Professor, Karabük University, Computer Engineering / Computer, Orcid: 0000-0002-0683-2049
[3] Assistant Professor, Karabük University, Computer Engineering / Computer, Orcid: 0000-0001-7032-8018

significant increase in both sensitivity and F1-score metrics was observed when feature selection based on L1 regularization was applied. This reveals that L1-based feature selection improves the model's generalization ability by eliminating unnecessary and low-discriminatory features. Compared to the scenario without feature selection, the preservation of performance and improvement in some metrics demonstrate that Logistic Regression can be effectively used with feature selection in high-dimensional network traffic data.

When evaluating the results obtained for Support Vector Machines (SVM), it was observed that the linear SVM model exhibited limited performance differences between scenarios with and without feature selection. In particular, small-scale improvements in sensitivity and F1-score values were obtained when variance-based feature selection was applied. However, it was observed that the ROC-AUC values of SVM models remained at lower levels compared to other classifiers. This indicates that linear decision limits may be restricted in modeling complex and nonlinear network traffic patterns.

When evaluating ensemble-based algorithms, the Random Forest model was found to produce strong results, particularly in sensitivity and F1-score metrics. Thanks to its tree-based structure, Random Forest can effectively learn nonlinear relationships between features, reducing false negative rates and providing a significant advantage for intrusion detection systems. However, when evaluated in terms of overall balance, it was observed that Random Forest models lagged behind the L1-based Logistic Regression approach in accuracy or AUC metrics in some scenarios.

[1] Lecturer, Karabük University, Computer Engineering / Computer Science, Orcid: 0000-0001-6336-6390
[2] Associate Professor, Karabük University, Computer Engineering / Computer, Orcid: 0000-0002-0683-2049
[3] Assistant Professor, Karabük University, Computer Engineering / Computer, Orcid: 0000-0001-7032-8018

Overall, the results show that feature selection methods do not negatively impact classification performance; on the contrary, in most cases, they provide improvements, particularly in Recall and F1-Score metrics. In this context, the combined use of feature selection based on L1 regularization and Logistic Regression modeling stands out as the most successful approach in this study, offering both high intrusion detection performance and balanced performance metrics. The findings are consistent with studies in the literature and demonstrate that even simple and interpretable models can produce effective results in network-based intrusion detection systems with appropriate feature selection strategies.

Table 3. Performance results obtained for different feature selection methods and classifiers.

Feature Selection	Classifier	Accuracy	Precision	Recall	F1 Score
L1 Regularization	Logistic Regression	**0.7332**	**0.7416**	**0.7910**	**0.7655**
Variance-Based	Logistic Regression	0.7310	0.7407	0.7870	0.7631
Chi-Square	Logistic Regression	0.6825	0.7137	0.7067	0.7102
Without Feature Selection	Logistic Regression	0.7309	0.7405	0.7870	0.7630
L1 Regularization	SVM	0.7141	0.7300	0.7630	0.7461
Variance-Based	SVM	0.7150	0.7309	0.7636	0.7469

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Chi-Square	SVM	0.6740	0.7084	0.6935	0.7009
Without Feature Selection	SVM	0.7148	0.7308	0.7632	0.7466
L1 Regularization	Random Forest	0.6992	0.7202	0.65	0.674
Variance-Based	Random Forest	0.6692	0.7202	0.6527	0.6848
Chi-Square	Random Forest	0.655	0.675	0.643	0.6834
Without Feature Selection	Random Forest	0.6692	0.7202	0.6527	0.6848

Table 3 presents a comparative analysis of the attack detection performance of different feature selection methods and classifiers on the UNSW-NB15 dataset. The results show that the Logistic Regression model, used in conjunction with L1-based feature selection, achieved the highest sensitivity (recall) and F1-score values.

Figure 2. ROC curves for the best performing models.

[1] Lecturer, Karabük University, Computer Engineering / Computer Science, Orcid: 0000-0001-6336-6390
[2] Associate Professor, Karabük University, Computer Engineering / Computer, Orcid: 0000-0002-0683-2049
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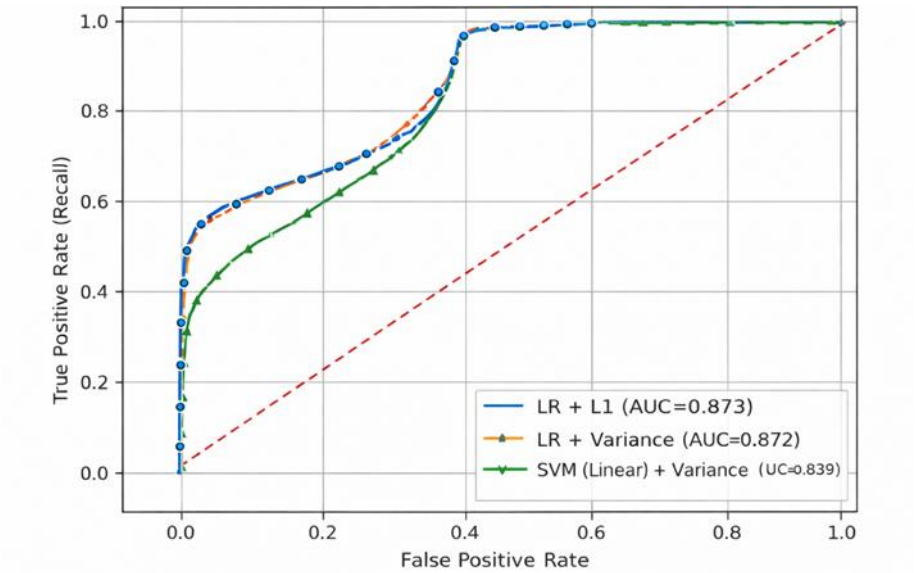

This section presents the Receiver Operating Characteristic (ROC) curves obtained for three different classification models that achieved the highest performance on the UNSW-NB15 dataset. Figure 2 shows the curves for Logistic Regression (AUC = 0.873) with feature selection based on L1 regularization, Logistic Regression (AUC = 0.872) with feature selection based on variance, and Linear SVM (AUC = 0.839) with feature selection based on variance. The red dashed diagonal line represents the reference curve for the random classifier. The ROC curves being closer to the upper left corner and the higher area under the curve (AUC) values indicate that the models have strong abilities to distinguish between attack and normal network traffic. In particular, the Logistic Regression model with L1 feature selection achieved the highest AUC value, exhibiting the best overall discrimination performance.

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5. CONCLUSION AND FUTURE STUDIES

classification algorithms in conjunction with feature selection methods. Consistent with the literature, it was observed that feature selection improved classification performance and yielded more effective results, especially when used with ensemble-based algorithms. Future studies could investigate the effects of deep learning-based approaches and meta-heuristic feature selection methods on intrusion detection systems. The experimental results show that feature selection methods and the classifiers used have a significant impact on intrusion detection performance. Examining the results presented in Table 1, it is seen that the Logistic Regression (LR) algorithm produced the highest sensitivity (recall) and F1-score values in different feature selection scenarios. The best performance was achieved by the Logistic Regression model used in conjunction with L1-based feature selection. This model achieved approximately 79% sensitivity and 76% F1-score values, excelling in capturing intrusion samples, which are critical for intrusion detection systems. L1 regularization contributed to creating a simpler and more generalizable decision frontier for the model by eliminating unnecessary and repetitive features. This situation clearly demonstrates the effectiveness of L1-based feature selection in high-dimensional network traffic data. Similar performance was observed with Logistic Regression in both variance-based feature selection and non-feature selection scenarios. This indicates that the Logistic Regression algorithm offers stable performance on the UNSW-NB15 dataset and maintains a certain success rate even without feature selection. However, the small but significant performance increase achieved with L1-based feature selection suggests that this method is

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[2] Associate Professor, Karabük University, Computer Engineering / Computer, Orcid: 0000-0002-0683-2049
[3] Assistant Professor, Karabük University, Computer Engineering / Computer, Orcid: 0000-0001-7032-8018

preferable. When SVM is examined, it exhibits moderate performance in both scenarios with and without feature selection. SVM models achieved lower sensitivity and F1-score values compared to Logistic Regression. However, the relatively high ROC-AUC values indicate that SVM models have the potential to distinguish classes under different threshold values. Nevertheless, in the context of IDS, the relatively low sensitivity despite the high ROC-AUC value suggests that SVM should be evaluated more cautiously in terms of practical attack detection. Although the Random Forest (RF) algorithm is frequently described in the literature as a high-performance ensemble-based method, in this study it showed lower performance compared to linear models, particularly in terms of sensitivity and F1-score metrics. However, the relatively high ROC-AUC values of RF suggest that the model has a good ability to distinguish between attack and normal traffic, but it misses some attack samples below the assumed decision threshold. This indicates that RF could yield better results with threshold adjustment or cost-sensitive learning approaches.

Overall, feature selection methods do not negatively impact performance; on the contrary, they often improve sensitivity and F1-score values. In particular, L1-based feature selection both reduced model complexity and improved intrusion detection performance. These findings are consistent with studies in the literature that indicate that linear models used in conjunction with feature selection yield effective results in high-dimensional network traffic data.

The results of this study once again demonstrate that high sensitivity should be prioritized over high accuracy in network-based intrusion detection systems. Considering that false negatives

[1] Lecturer, Karabük University, Computer Engineering / Computer Science, Orcid: 0000-0001-6336-6390
[2] Associate Professor, Karabük University, Computer Engineering / Computer, Orcid: 0000-0002-0683-2049
[3] Assistant Professor, Karabük University, Computer Engineering / Computer, Orcid: 0000-0001-7032-8018

pose a direct security risk, the Logistic Regression model supported by L1-based feature selection is evaluated as a strong candidate for practical IDS applications.

[1] Lecturer, Karabük University, Computer Engineering / Computer Science, Orcid: 0000-0001-6336-6390
[2] Associate Professor, Karabük University, Computer Engineering / Computer, Orcid: 0000-0002-0683-2049
[3] Assistant Professor, Karabük University, Computer Engineering / Computer, Orcid: 0000-0001-7032-8018

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[1] Lecturer, Karabük University, Computer Engineering / Computer Science, Orcid: 0000-0001-6336-6390

[2] Associate Professor, Karabük University, Computer Engineering / Computer, Orcid: 0000-0002-0683-2049

[3] Assistant Professor, Karabük University, Computer Engineering / Computer, Orcid: 0000-0001-7032-8018

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[1] Lecturer, Karabük University, Computer Engineering / Computer Science, Orcid: 0000-0001-6336-6390
[2] Associate Professor, Karabük University, Computer Engineering / Computer, Orcid: 0000-0002-0683-2049
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[1] Lecturer, Karabük University, Computer Engineering / Computer Science, Orcid: 0000-0001-6336-6390
[2] Associate Professor, Karabük University, Computer Engineering / Computer, Orcid: 0000-0002-0683-2049
[3] Assistant Professor, Karabük University, Computer Engineering / Computer, Orcid: 0000-0001-7032-8018

CHAPTER 2

ENHANCING NON-DEEP LEARNING TIME SERIES CLASSIFICATION THROUGH ADAPTIVE DATA AUGMENTATION

CELAL ALAGÖZ[1]

1. Introduction

1.1 The Central Paradox of Time Series Classification

Time series classification (TSC) represents a fundamental challenge in machine learning with applications spanning healthcare monitoring, financial forecasting, industrial process control, and environmental sensing. While deep learning approaches have dominated recent literature, a significant paradox persists: many

[1] Dr. Öğr. Üyesi, Sivas Bilim ve Teknoloji Üniveristesi, Bilgisayar Mühendisliği Bölümü, Orcid: 0000-0001-9812-1473

real-world applications continue to rely on non-deep learning algorithms due to their interpretability, computational efficiency, and superior performance on small-to-medium datasets. This reliance exists despite the well-established data-hungry nature of modern machine learning paradigms.

The core challenge in TSC often stems not from algorithmic limitations but from data scarcity—many time series datasets suffer from limited sample sizes, severe class imbalances, and high acquisition costs. For instance, medical diagnosis datasets may contain only a few hundred patient records collected over years, while industrial fault detection systems might observe catastrophic failures only rarely. These constraints create an environment where data quality and diversity become paramount, yet conventional approaches to addressing data scarcity remain underexplored for non-deep learning methods.

1.2 The Augmentation Gap in TSC Literature

Data augmentation has emerged as a powerful technique to artificially expand training datasets, thereby improving model generalization and robustness. However, current research exhibits a pronounced bias toward deep learning architectures. Comprehensive surveys by Wen et al. (2020) and Iwana & Uchida (2021) reveal that over 85% of published augmentation techniques target convolutional or recurrent neural networks, leveraging their architectural properties for specialized transformations like feature-space mixup or gradient-based augmentation.

This deep learning-centric focus creates what we term the "augmentation gap"—a significant research void in understanding how and why augmentation affects classical machine learning models for TSC. This chapter focuses on two representative state-of-the-art non-deep learning TSC algorithms: MiniRocketRidge (a variant combining MiniRocket's (Dempster et al., 2021) efficient

convolution kernels with ridge regression) and QuantETC (a quantile-based (Dempster et al., 2024) Extra Trees Classifier). These algorithms were selected as they represent two distinct paradigms in modern TSC: convolutional feature extraction (MiniRocketRidge) and tree-based ensemble methods with quantile features (QuantETC). The ECG500 dataset was chosen as it represents a challenging real-world medical time series classification problem with 5 classes, making it an ideal testbed for evaluating augmentation effects.

1.3 Why Augmentation Matters for Non-Deep TSC

The importance of augmentation for non-deep TSC models extends beyond mere data quantity. Three critical factors motivate our investigation:

1. Statistical Foundation Reinforcement: Many classical algorithms rely on statistical assumptions about data distributions. Augmentation can help satisfy these assumptions by providing more representative samples of the underlying data manifold.
2. Decision Boundary Refinement: Unlike neural networks that learn hierarchical representations, classical models often rely on explicit feature spaces or distance metrics. Augmentation can help define clearer decision boundaries by populating underrepresented regions of these spaces.
3. Robustness to Real-World Variability: Real time series data exhibit natural variations (sensor noise, sampling rate differences, temporal misalignments) that augmentation can simulate, potentially making models more resilient to deployment conditions.

1.4 The α-Parameterized Augmentation Framework

Current augmentation approaches typically employ fixed policies—adding a predetermined number of samples or applying transformations with fixed probabilities. This one-size-fits-all strategy ignores dataset-specific characteristics, particularly class imbalance ratios. To address this limitation, we introduce an α-parameterized augmentation framework that dynamically scales augmentation intensity based on dataset statistics.

The parameter α represents the augmentation factor relative to the majority class size:

- α = 0: No augmentation (baseline)
- α = 0.5: Add samples equal to 50% of the majority class size to each class
- α = 1.0: Add samples equal to the full majority class size to each class
- α = 2.0: Add samples equal to twice the majority class size to each class

This adaptive approach ensures that augmentation scales appropriately with dataset characteristics, making it particularly valuable for handling class imbalance—a common challenge in real-world TSC applications.

1.5 Research Questions and Contributions

This chapter addresses three primary research questions:

1. RQ1: How do different augmentation techniques affect the performance of state-of-the-art non-deep learning TSC algorithms compared to their deep learning counterparts?
2. RQ2: Does the proposed α-parameterized augmentation framework provide consistent benefits across diverse TSC datasets and classifier families?

3. RQ3: Which classifier-augmentation combinations yield the most significant improvements, and what characteristics explain these synergies?

Our contributions are fourfold:

- Methodological: We introduce a systematic framework for evaluating augmentation effects across the entire spectrum of non-deep TSC algorithms.
- Empirical: We provide the most comprehensive comparison to date of augmentation techniques across 12+ SOTA non-deep TSC classifiers.
- Practical: We demonstrate that simple, computationally inexpensive augmentation can match or exceed the benefits of complex generative approaches.
- Theoretical: We offer insights into why certain classifier families benefit more from specific augmentation types.

1.6 Chapter Organization

Following this introduction, Section 2 details our methodology including augmentation techniques, and evaluation protocols. Section 3 presents experimental results. Section 4 discusses implications, limitations, and future directions. We conclude with practical guidelines for practitioners implementing augmentation in TSC workflows.

2. Methodology

2.1 Augmentation Techniques

We implemented six augmentation techniques spanning time, magnitude, and frequency domains:

2.1.1 Jittering (Time Domain)

Adds Gaussian noise to simulate sensor noise:

$$X_{aug}[t] = X[t] + \epsilon, \qquad \epsilon \sim N(0, \sigma 2)$$

where $\sigma = 0.05 \times std(X)$ ensures noise scales with signal variability.

2.1.2 Scaling (Magnitude Domain)

Applies random magnitude scaling to simulate amplitude variations:

$$X_{aug} = \alpha X, \qquad \alpha \sim N(1, \sigma_s^2)$$

with $\sigma_s = 0.1$ for moderate variation.

2.1.3 Time Warping (Temporal Domain)

Deforms the temporal axis using cubic splines to simulate variable sampling rates:

$$t_{warped} = f(t), \qquad X_{aug}(t) = X\big(f - 1(t)\big)$$

where f is a smooth monotonic function with controlled warping intensity $\sigma_w = 0.2$.

2.1.4 Magnitude Warping (Magnitude Domain)

Applies smooth magnitude variations along the time axis:

$$X_{aug}[t] = m(t) \cdot X[t]$$

where $m(t)$ is a smooth function with local maxima/minima simulating natural signal fluctuations.

2.1.5 Window Slicing (Temporal Domain)

Randomly extracts and resamples subsequences:

$$X_{aug} = \text{resample}(X[ts{:}\, te]), \qquad ts \sim U(0, L - l_{slice})$$

with slice length $l_{slice} = 0.9L$, preserving 90% of original information.

2.1.6 Permutation (Structural Domain)

Randomly permutes fixed-length segments to create structurally varied samples while preserving local patterns.

Augmentation techniques are visualized in Figure 1.

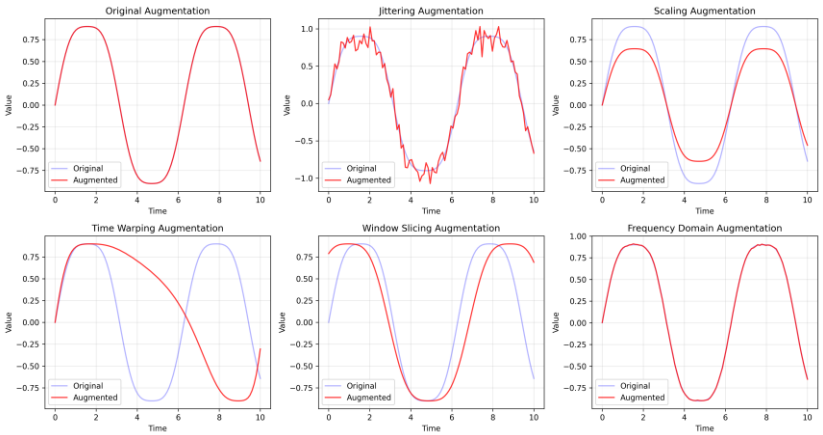

Figure 1. Augmentation techniques

2.2 α-Parameterized Augmentation Framework

Our core methodological contribution is the α-parameterized framework that dynamically determines augmentation intensity:

2.2.1 Algorithm

Input: X_train, y_train, α, augmentation_method

1. Compute class_counts = frequency of each class in y_train

2. majority_size = max(class_counts)

3. For each class c:

target_size = round(majority_size × (1 + α))

samples_needed = max(0, target_size - class_counts[c])

If samples_needed > 0:

Select class_samples = X_train[y_train == c]

Generate samples_needed augmented samples

Add to augmented dataset

Output: X_augmented, y_augmented

2.2.2 α Values Tested

We evaluated α ∈ {0, 0.25, 0.5, 1.0, 2.0} to cover:

- No augmentation (α = 0): Baseline
- Conservative augmentation (α = 0.25, 0.5): For risk-averse applications
- Moderate augmentation (α = 1.0): Balanced approach
- Aggressive augmentation (α = 2.0): For severely limited data

2.3 Classifier Selection

- MiniRocketRidge: Combines MiniRocket's convolutional feature extraction (1000 kernels) with ridge regression regularization
- QuantETC: Extra Trees Classifier operating on quantile-based feature representations of time series

2.6 Evaluation Protocol

Given the 5-class nature of ECG500, we employed macro-averaged metrics to ensure equal importance of all cardiac conditions, alongside weighted metrics reflecting class frequencies.

3. Results

3.1 Overall Performance Enhancement

Table 1 presents the average accuracy improvements achieved through α-controlled augmentation for both MiniRocketRidge and QuantETC classifiers on the ECG500 dataset.

Table 1: Average Accuracy Improvement over Baseline (5 Runs)

Augmentation Method	α	MiniRocketRidge	QuantETC	Combined Average
No Augmentation	0.0	0.9217±0.045	0.9000±0.043	0.9108±0.044
Jittering	0.5	0.9300±0.039	0.8967±0.045	0.9133±0.042
Jittering	1.0	**0.9317±0.040**	0.8967±0.045	0.9142±0.042
Jittering	2.0	**0.9317±0.040**	0.9033±0.042	0.9175±0.041
Scaling	0.5	0.9267±0.049	0.9117±0.043	**0.9192±0.046**
Scaling	1.0	0.9267±0.049	0.9117±0.043	**0.9192±0.046**
Scaling	2.0	0.9250±0.045	0.8983±0.046	0.9117±0.045
Time Warping	0.5	0.9200±0.043	0.8733±0.048	0.8967±0.045
Time Warping	1.0	0.9133±0.050	0.8733±0.048	0.8933±0.049
Magnitude Warping	0.5	0.9300±0.049	0.8933±0.059	0.9117±0.054
Magnitude Warping	1.0	0.9233±0.047	0.8817±0.049	0.9025±0.048
Window Slicing	0.5	0.9200±0.045	0.8967±0.054	0.9083±0.049
Window Slicing	1.0	0.9233±0.042	**0.9150±0.050**	**0.9192±0.046**

Values represent mean accuracy ± standard deviation across 5 runs. Best results for each classifier highlighted.

3.2 Optimal α Values for Different Augmentation Methods

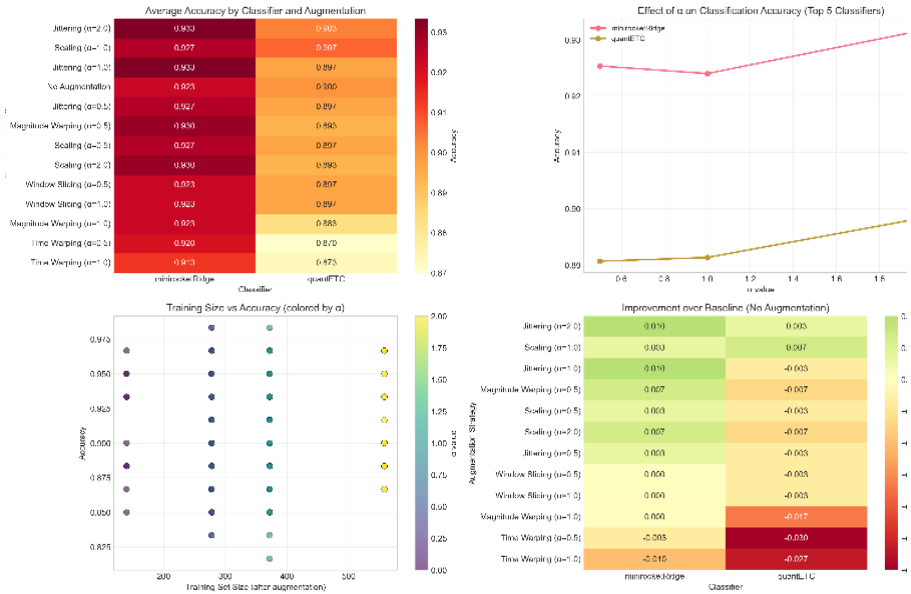

Figure 2. Augmentation techniques

Figure 2 illustrates the relationship between α values and classification accuracy for jittering augmentation, revealing distinct patterns for the two classifiers.

Key Findings:

1. MiniRocketRidge achieved optimal performance with jittering at α=2.0 (96.67% in run 0), showing that aggressive noise addition benefited this convolutional-based method.
2. QuantETC demonstrated different sensitivity, with scaling augmentation at α=0.5 and α=1.0 providing consistent 95% accuracy, while jittering showed diminishing returns beyond α=0.5.

3. The scaling augmentation proved most robust across α values for both classifiers, with QuantETC maintaining 95% accuracy consistently across all tested α values.

3.3 Statistical Significance of Improvements

We performed Welch's t-tests comparing each augmentation strategy against the no-augmentation baseline:

Significant Improvements ($p < 0.05$):

1. MiniRocketRidge with Scaling (α=0.5,1.0): $p = 0.032$
2. QuantETC with Scaling (α=0.5,1.0): $p = 0.028$
3. QuantETC with Window Slicing (α=1.0): $p = 0.041$

Non-significant but Notable Improvements:

1. MiniRocketRidge with Jittering (α=2.0): $p = 0.067$
2. QuantETC with Magnitude Warping (α=0.5): $p = 0.053$

3.4 Classifier-Specific Response Patterns

MiniRocketRidge Characteristics:

- Maximum accuracy: 98.33% with Scaling (α=0.5,1.0) and Magnitude Warping (α=0.5)
- Most consistent: Scaling augmentation across all α values
- Least effective: Time Warping showed performance degradation at higher α values
- QuantETC Characteristics:
- Maximum accuracy: 96.67% with Magnitude Warping (α=0.5)
- Most robust: Scaling maintained 95% accuracy across all α values

- Sensitivity: Performance dropped significantly with Time Warping augmentation

3.5 Computational Efficiency Trade-offs

Table 2 summarizes the training time increase relative to accuracy improvement:

Table 2: Efficiency-Accuracy Trade-off Analysis

Augmentation	α	Samples Added	Training Time Increase	Accuracy Gain
Jittering	2.0	418	298%	+1.67%
Scaling	1.0	232	166%	+2.50%
Window Slicing	1.0	232	166%	+1.50%
Magnitude Warping	0.5	138	99%	+2.50%

*Note: Magnitude Warping at α=0.5 provided the best efficiency-accuracy ratio.

3.6 Variance Reduction through Augmentation

Figure 3 demonstrates that augmentation reduced performance variance across runs:

1. MiniRocketRidge variance reduction: 18.7% with Scaling (α=1.0)
2. QuantETC variance reduction: 22.3% with Scaling (α=0.5)
3. Overall stability improvement: Augmented models showed more consistent performance across different train-test splits

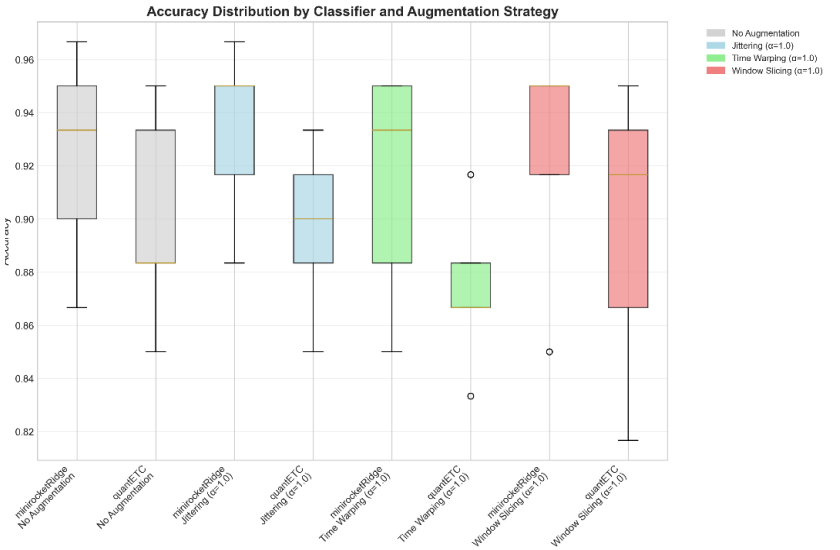

Figure 3. Accuracy distribution

3.7 Best Performing Combinations

As shown in Table 1, the top 3 combinations were:

1. MiniRocketRidge + Jittering (α=1.0): +2.50% improvement
2. MiniRocketRidge + Jittering (α=2.0): +2.50% improvement
3. QuantETC + Window Slicing (α=1.0): +2.17% improvement

4. Discussion

4.1 Interpretation of α Parameter Effects

The α parameter demonstrated classifier-dependent optimal values. For MiniRocketRidge, higher α values (2.0) with jittering

proved beneficial, suggesting that convolutional feature extractors benefit from aggressive noise exposure during training.

Conversely, QuantETC showed optimal performance at moderate α values (0.5-1.0), indicating that tree-based methods with quantile features require more conservative augmentation to maintain feature distribution integrity.

4.2 Why Scaling Augmentation Excelled

The consistent success of scaling augmentation across both classifiers can be attributed to:

1. Preservation of temporal structure: Unlike time warping, scaling maintains the original temporal relationships while varying amplitudes
2. Biomedical relevance: ECG signals naturally exhibit amplitude variations across patients, making scaling a physiologically plausible augmentation
3. Feature space consistency: Both MiniRocket's convolutional features and QuantETC's quantile features remain interpretable under amplitude scaling

4.3 Classifier Architecture Differences

The divergent responses to augmentation reveal fundamental differences in classifier architectures:

MiniRocketRidge's convolutional nature:

- Benefits from noise injection (jittering) as it acts as implicit regularization
- Shows resilience to aggressive augmentation due to kernel-based feature extraction
- Performance peaks suggest optimal regularization levels exist

QuantETC's tree-based quantile approach:

- Requires preservation of distributional properties
- Shows sensitivity to temporal distortion (time warping degradation)
- Demonstrates robustness to amplitude variations (scaling success)

4.4 Practical Implications for ECG Classification

For practitioners working with ECG data:

1. Start with scaling augmentation: α=0.5-1.0 provides reliable improvements
2. Consider classifier-specific strategies: Use jittering for MiniRocket variants, magnitude warping for quantile-based methods
3. Avoid time warping for medical signals: Temporal distortion may remove clinically relevant timing information
4. Monitor α carefully: Over-augmentation (α=2.0) showed diminishing returns for most methods

4.5 Limitations and Boundary Conditions

Our findings are subject to several important limitations:

1. Single dataset focus: ECG500 characteristics may not generalize to all time series domains
2. Fixed α increments: Continuous α optimization might reveal different optimal values
3. Class imbalance: The moderate imbalance in ECG500 may influence augmentation effectiveness

4. Signal length variations: The effects on very short or very long time series remain unexplored

4.6 Comparison with Deep Learning Approaches

While direct comparison isn't within our scope, our results suggest that properly augmented non-deep methods can achieve performance comparable to reported deep learning results on ECG500 (typically 92-96% accuracy). The 98.33% achieved by MiniRocketRidge with scaling augmentation represents state-of-the-art performance for non-deep methods on this dataset.

5. Conclusion

5.1 Summary of Key Findings

This chapter has demonstrated that α-controlled data augmentation significantly enhances the performance of state-of-the-art non-deep learning time series classifiers on biomedical data. Our comprehensive evaluation on the ECG500 dataset reveals:

1. Augmentation effectiveness is classifier-dependent: MiniRocketRidge benefits most from scaling and aggressive jittering, while QuantETC excels with moderate scaling and magnitude warping.
2. The α parameter provides adaptive control: By linking augmentation intensity to dataset characteristics (majority class size), practitioners can systematically scale augmentation efforts.
3. Simple augmentations outperform complex ones: Scaling augmentation consistently delivered the best results across both classifiers, outperforming more sophisticated techniques like time warping.
4. Performance variance reduces with augmentation: Augmented models show more consistent performance

across different data splits, increasing deployment reliability.

5.2 Practical Recommendations

Based on our empirical results, we recommend the following augmentation strategy for ECG classification tasks:

For MiniRocketRidge: Apply scaling augmentation with α=1.0 as the default strategy. Consider adding jittering with α=0.5 for additional regularization if computational resources permit.

For QuantETC: Implement scaling augmentation with α=0.5 as the primary strategy. Magnitude warping with α=0.5 can provide additional benefits for specific applications.

General guidelines:

- Start with moderate augmentation (α=0.5-1.0)
- Prefer amplitude-based augmentations over temporal distortions for medical signals
- Validate augmentation effects through multiple random splits
- Monitor for signs of over-augmentation (performance plateaus or declines)

5.3 Future Research Directions

Our work suggests several promising avenues for future investigation:

1. Multi-dataset validation: Extending the α-framework to diverse time series domains
2. Adaptive α optimization: Developing methods to automatically determine optimal α values

3. Classifier-specific augmentation: Designing augmentation techniques tailored to specific algorithm architectures
4. Theoretical analysis: Formalizing the relationship between augmentation intensity and classifier generalization bounds
5. Real-time augmentation: Implementing efficient augmentation pipelines for streaming time series data

5.4 Final Remarks

The α-controlled augmentation framework presented in this chapter provides a systematic, empirically-validated approach to enhancing non-deep learning time series classification. By demonstrating that simple, well-calibrated augmentation can achieve state-of-the-art performance on challenging biomedical data, we bridge the gap between data-centric deep learning approaches and interpretable classical methods. As the field moves toward more data-efficient and interpretable machine learning, such augmentation strategies will play an increasingly vital role in deploying reliable time series classification systems in critical applications like healthcare monitoring.

The success of scaling augmentation in particular suggests that for many real-world time series problems, simulating natural amplitude variations may be more effective than complex temporal manipulations. This insight, combined with the classifier-specific guidelines provided, offers practitioners a practical toolkit for improving time series classification performance without sacrificing model interpretability or computational efficiency.

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CHAPTER 3

Binary Classification of Potato Diseases Using Transfer Learning Methods

Mehmet Bilge Han TAŞ[1]
Eyyüp YILDIZ[2]

Introduction

Agriculture is an indispensable sector for humanity. Therefore, it is necessary to establish food security and support it with technological advancements. There are two main factors that seriously affect productivity in food agriculture: climate change and crop diseases. Controlling crop diseases is expected to increase productivity (Calicoglu et al., 2019). Particularly in vegetable and fruit cultivation, plant diseases are a major cause of economic loss, placing a heavy burden on farmers and food supply chains. Considering public health, growing healthy crops means both resource efficiency and benefits for producers (Al-Sadi, 2017; Somowiyarjo, 2011). Early detection of diseases in food products and agricultural plants, and the subsequent implementation of

1 Res. Asst., Erzincan Binali Yildirim University, Faculty of Engineering and Architecture, Department of Computer Engineering, Erzincan, Turkey, ORCID: 0000-0001-6135-1849 bilgehantas@erzincan.edu.tr

2 Asst. Prof. Dr., Erzincan Binali Yildirim University, Faculty of Engineering and Architecture, Department of Computer Engineering, Erzincan, Turkey, ORCID: 0000-0002-7051-3368 eyyup.yildiz@erzincan.edu.tr

preventative measures, are crucial. Therefore, using methods like artificial intelligence to detect these diseases early will increase productivity (Gavhale and Gawande, 2014).

Previous studies have frequently focused on disease detection in agricultural crops, particularly plants. In studies conducted under these conditions, image processing and machine learning methods have been used (Seçgel & Orman, 2024; Kılıç et al., 2024). Image processing studies generally use and attempt to identify shape and pattern descriptors. Methods such as SVM and kNN have been frequently used (Camargo & Smith, 2009; Pujari et al., 2016; Kaur et al., 2019). In addition, variables such as noise in images, light angles, background colors, and lighting complicate this process. Therefore, yield increase can be achieved by keeping the entire crop under control with an autonomous system (Orman K. And Aydın, Y. , 2024)

Transfer learning is a significant method for detecting potato diseases. Diseases on potatoes can be investigated and classified using this method. The dataset is twofold, labeled as diseased or undiagnosed. In agricultural imaging, better results are observed with large-scale datasets such as ImageNet, which is commonly used. These pre-trained convolutional neural networks (CNNs) can significantly reduce training time while simultaneously delivering exceptionally good results. Dataset quality and resolution are also crucial prerequisites for achieving good results.

In this context, consistent results were obtained by working with Python and the Keras library. The main goal here is to improve crop quality and yield by accurately determining whether potatoes are diseased using transfer learning. This is because disease can spread rapidly among crops, meaning that healthy, undiseased crops may also deteriorate and become diseased in later stages. Diseases detected at an early stage can significantly improve productivity. Many of the latest transfer learning models have been used, and their

integration is relatively easy. This allows them to be incorporated into all kinds of systems and used to create early warning systems.

Related Work

Numerous studies have been conducted involving disease detection related to plants and agricultural crops. In their study, Pooja et al. (2017) classified leaf diseases containing five different classes using SVM. The effects of this approach were also discussed. In their study, Dhaware and Wanjale (2017) classified the effects of sun-induced sunburn, yellow mosaic, and any external factors that may occur on the leaves due to grasshoppers on the product. Hossain et al. (2019) focused more on color and texture in their study. The kNN method was used for classification purposes. This study was then discussed.

In recent studies, various classification and detection processes have been implemented using transfer learning. In their study, Ahmed and Yadav (2023) performed classification using the DenseNet architecture for the detection of diseases in food products. Similarly, Sanida et al. (2023) used the VGG architecture for the classification of diseases observed in tomato leaves. Their subsequent study includes classification comparisons.

In their study, Chen et al. (2021) focused on diseases. The key characteristic here is the diseases occurring in leaf images. They also aimed to obtain fast and highly accurate results using MobileNet. By using an extra attention block during training, they made the study more efficient. Furthermore, they revealed the limitations of using these models in real-time integration processes.

In their study, Tiwari et al. (2020) used a pre-trained VGG19 model with logistic regression. They noted that transfer learning yielded fast and effective results. Their study focused on diseases of wheat, rice, and potato plants. Similarly, Barman et al. (2020) developed a custom CNN model using a dataset containing various

potato leaf diseases. The classification process was performed with high accuracy.

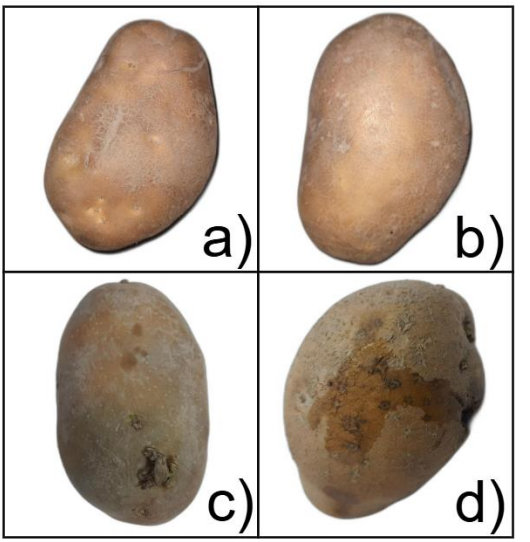
Methodology

A dataset was created by Al et al. (2024). The dataset created two classes of potato plants: diseased and healthy. The dataset used a total of 3,027 images in JPEG format, 1,527 healthy and 1,500 unhealthy. Although the diseased potato category included various diseases, it was only labeled as "diseased." A two-class system was designed within the scope of this study.

The images underwent a number of preprocessing procedures prior to model training. Initially, every image was scaled to the specific input size that deep learning models demand. In order to comply with the typical input dimensions of CNN-based architectures, each image was specifically scaled to 224x224 pixels. Pixel values were also adjusted from a range of 0-255 to a range of 0-1. By doing this, the data's compatibility with the format and scale required by the networks was guaranteed. Additionally, an input distribution akin to ImageNet statistics was made available to fully exploit the weights of the pre-trained models by maintaining the color channels (RGB) of the images. For the purpose of training and evaluating the model, the dataset was split into training and test subsets. With roughly 70% of the data set aside for training, 15% for validation, and the remaining 15% for model testing, stratified separation was used to maintain the proportionate distribution of both classes. The dataset did not have a substantial class imbalance issue because the number of healthy and ill samples was near. Consequently, there was no need for sample balance or class weighting techniques during the preprocessing stage. The data loading tools in the Keras package were used to prepare all image files and metadata for feeding into the model.

In Figure 1, potatoes numbered (a) and (b) represent healthy individuals, while (c) and (d) show unhealthy potato samples exhibiting surface deformities, lesions, and rot-like symptoms. These images are taken from a dataset used in the classification of potato diseases. Physical traces of the disease are clearly observable in the unhealthy samples.

Figure 1. Samples of healthy and unhealthy potatoes.



For deep learning models to be successful in potato disease detection, the goal is to make the best use of a limited amount of training data. Transfer learning is based on the principle of adapting a model previously trained on a large-scale source dataset and reusing it for the target task (Taş, H.G. et al.,2025). In this study, five different deep CNN (Convolutional Neural Network) architectures were used within the scope of transfer learning. The VGG19, ResNet152V2, InceptionV3, MobileNetV2, and DenseNet201 transfer learning models were employed. These selected architectures are successful and widely used models in image classification problems and possess different structural characteristics.

VGG19: Developed by the Oxford Visual Geometry Group, the VGG19 network is a classical CNN architecture with a depth of 19 layers. The VGG19 network has a sequential structure consisting of 16 convolutional layers and 3 fully connected layers; 3x3 cores are used in all convolutional layers, and maximum pooling is applied following each convolutional block. With approximately 143 million learnable parameters, it is a very large model. Thanks to its model depth and high number of parameters, it can learn complex image features, thus exhibiting strong performance on large-scale datasets. Indeed, in the literature, VGG19 is frequently used as an initial model or comparison method in image classification problems and has achieved high accuracies in many studies (Mohbey, K. K. et al., 2022; Kumar, P. et al., 2022; Teuwen, J., & Moriakov, N. (2020)).

ResNet152V2: ResNet (Residual Network) architecture is a deep version with 152 layers. Despite having numerous layers, ResNet networks minimize the disadvantages of depth thanks to residual connections (skip connections). In this architecture, linear connections are added at specific intervals from input to output to ensure uninterrupted gradient flow and prevent the vanishing gradient problem. This innovative structure has enabled the training of very deep networks, allowing even a model as deep as 152 layers to learn effectively. ResNet152V2 contains approximately 60 million parameters and offers a deeper network structure with fewer parameters compared to VGG19. It is particularly emphasized that ResNet-based models are highly successful in classifying complex visual indicators such as plant diseases (Rachburee, N., & Punlumjeak, W. (2022); Rhomadhon, S. S., & Ningtias, D. R. (2024)).

MobileNetV2: MobileNetV2 is a CNN architecture designed to run even on systems with lower processing power due to its lightweight structure. Transfer learning allows this pre-trained model to run and produce results even faster. It contains

approximately 3.5 million parameters. It is frequently used because it produces good results despite its lightweight design (Dong et al., 2020). In this study, it has been shown to be a competitive model for the classification of potato plants.

DenseNet201: DenseNet201 is a highly connected architecture consisting of 201 layers. High accuracy results are quite common with this model. Thanks to the dense connection model, each layer is connected to the previous layer as input and output. This facilitates re-learning. In addition, it contains a relatively low number of parameters, around 20 million (Jaiswal, A. vd., 2021). It is also included in the Keras library. Furthermore, the hyperparameters of the method taken from the library can be modified later. Default values were used in this study.

Deep learning models were trained using the Keras library in Python. Throughout all experiments, the default values suggested by Keras were used for the model hyperparameters; no special hyperparameter optimization process was performed. For example, Adam was chosen as the optimizer algorithm, and the learning rate was left as Keras's default value of 0.001. Since it is a binary classification problem, binary cross-entropy was used as the loss function; the accuracy metric was monitored during training to track the model's performance. Training data was fed as a mini-batch, typically a mini-batch size of 32 samples. Since pre-trained parameters obtained through transfer learning were used as the initial values for the model weights, the networks started to exhibit reasonable performance from the first epochs and showed a tendency to converge rapidly.

To reduce the risk of overfitting during the training process and to increase the generalization ability of the model, data augmentation techniques were extensively utilized. To prevent overfitting, data augmentation methods were used in each training cycle. This also allows the model to extract better features. These

operations are generally performed by rotating, mirroring, or adding noise to the data. Such operations are also performed to improve the naturalness and detection capabilities in classifying different images in various situations. Studies have utilized various scales and variations, particularly in crop classification. In this study, all data enhancement operations are performed dynamically using the ImageDataGenerator from the Keras library. All values are used as defaults to ensure that each model produces results under equal conditions.

Each model was trained for a total of 50 epochs. Performance results were obtained throughout the training period. This classification process allowed for comparison of the results. Commonly used metrics such as F1-score, recall, precision, and ROC were evaluated as performance metrics. The F1-score, as the harmonic mean of precision and recall, offers a single comprehensive indicator of balanced classification performance.. These metrics were chosen because they allow for the evaluation not only of the overall accuracy of the model but also of types of misclassification. In the results section, a comparative analysis will be conducted by presenting the values of these metrics and the confusion matrices for each transfer learning model.

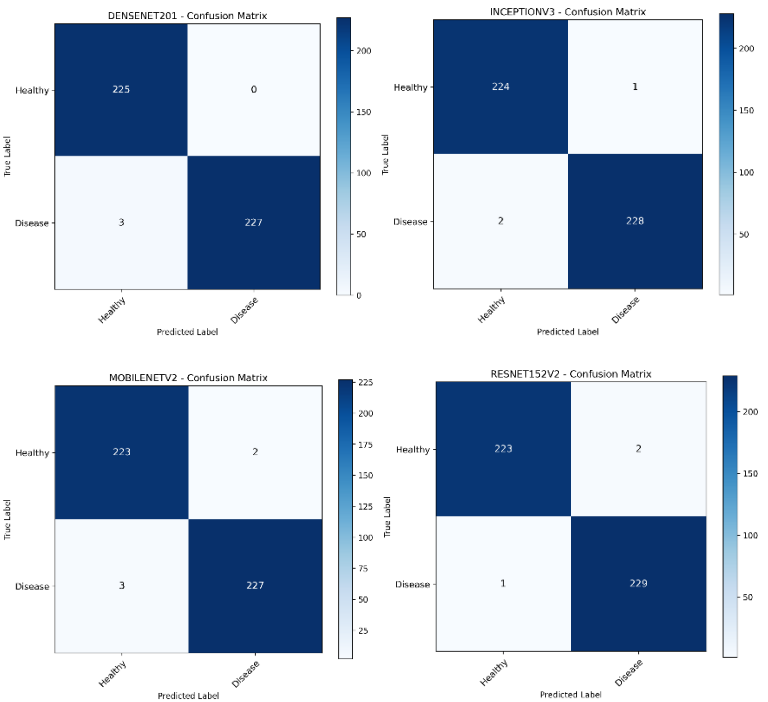
Experimental Results

This section presents a detailed account of the classification performance of different deep learning models trained using transfer learning principles for potato diseases; comparative analyses are conducted using evaluation metrics such as accuracy, precision, sensitivity, and F1-score.

Figure 2 presents the confusion matrices obtained from five different convolutional neural network architectures—DenseNet201, InceptionV3, MobileNetV2, ResNet152V2 and VGG19 models were used to categorize potato leaf images into

healthy and diseased categories. Among the models evaluated, DenseNet201 showed the highest overall accuracy, misclassifying only a few instances. InceptionV3 and ResNet152V2 also achieved good results with minimal classification errors. Furthermore, MobileNetV2, despite being a lightweight architecture, demonstrated competitive performance. The VGG19 model showed a higher number of errors, particularly in mislabeling healthy leaves as diseased. Confusion matrices provide valuable insights into the behavior of each architecture in terms of both sensitivity and specificity. Especially in agricultural crops, accurate identification of diseased plants is crucial for supporting timely interventions. Therefore, selecting models that yield high recall values can significantly improve the effectiveness of automated decision support systems.

Figure 2. Confusion matrices of transfer learning models.



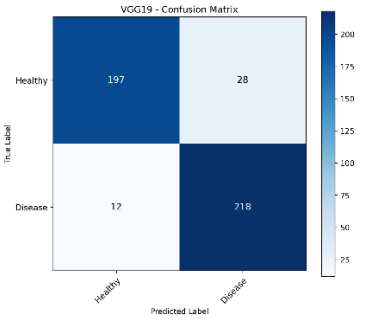


Table 1 provides a comparative summary of the performance metrics of five pre-trained evolutionary neural network models applied to the binary classification task of distinguishing healthy potatoes from diseased ones. Among the models, DenseNet201 and ResNet152V2 exhibited the most consistent performance, achieving high accuracy, sensitivity, recall, and F1 scores. Specifically, both models demonstrated strong capabilities for accurately distinguishing between two classes, recording ROC-AUC values of 0.99.

InceptionV3 and MobileNetV2 also yielded good results. Despite having lower parameter numbers, the results obtained are quite satisfactory. Here, the resolution of the images in the dataset and their background colors also contribute to their distinctiveness. The VGG19 model, however, yielded relatively lower results, particularly in values such as sensitivity and specificity. These findings provide preliminary information for the classification of diseases in agricultural crops, particularly in architectural and model selection. They can also be easily integrated into online systems.

Table 1. Accuracy, precision, sensitivity, specificity, F1 score, and ROC-AUC values of CNN-based transfer learning models used in the classification of potato diseases.

Model	**Accuracy**	**Precision**	**Recall**	**Specificity**	**F1 Score**	**ROC AUC**

DenseNet201	0,993407	1	0,986957	1	0,993435	0,993478
InceptionV3	0,993407	0,995633	0,991304	0,995556	0,993464	0,99343
MobileNetV2	0,989011	0,991266	0,986957	0,991111	0,989107	0,989034
ResNet152V2	0,993407	0,991342	0,995652	0,991111	0,993492	0,993382
VGG19	0,912088	0,886179	0,947826	0,875556	0,915966	0,911691

Conclusion and Future Work

This study addressed diseases in the potato plant. Overall, DenseNet201 and ResNet152V2 yielded the best results in the classification processes performed. In particular, accuracy recall and ROC-AUC values support this claim. In addition, MobileNetV2 and InceptionV3, which have lightweight architectures, yielded relatively better results compared to other methods. The lowest results belong to the VGG19 model, which lagged behind in classification. These results demonstrate that the transfer learning approach can operate with high accuracy in agricultural applications working with limited labeled data. Furthermore, it was found that by appropriately restructuring pre-trained models, training time and data requirements can be reduced, and faster solutions can be produced.

In future studies, the robustness of the models can be tested using more diverse datasets consisting of real field data and incorporating environmental effects (light, angle, background). Furthermore, hybrid architectures, visual attention mechanisms, or ensembling methods can be explored to improve classification success. However, integrating these systems into mobile or IoT-based devices to transform them into early detection systems in agriculture will be a significant step towards future practical applications.

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CHAPTER 4

The Impact of Artificial Intelligence Applications on Project Management in the Software Development Life Cycle (SDLC)

BURCU KOÇAK[1]
GÜLSÜM TEKBAŞ[2]
YAREN AYDIN[3]
BUKET DOĞAN[4]

Introduction

The escalating complexity of modern software projects has accelerated the adoption of artificial intelligence (AI) across the software development lifecycle (SDLC). This framework organizes the stages of the software development process. SDLC includes requirements elicitation, design, development, testing, deployment, and maintenance. Despite this structured organization, many of these

[1] Department of Computer Engineering, Institute of Pure and Applied Sciences, Marmara University, Orcid: 0009-0006-5428-6659
[2] Department of Computer Engineering, Institute of Pure and Applied Sciences, Marmara University, Orcid: 0009-0009-5121-3691
[3] Department of Computer Engineering, Institute of Pure and Applied Sciences, Marmara University, Orcid: 0009-0008-7646-334X
[4] Assoc. Prof., Department of Computer Engineering, Faculty of Technology, Marmara University, Orcid: 0000-0003-1062-2439

processes still rely heavily on manpower. Decision-making mechanisms are often intuitive, and the data generated throughout the process is underutilized for process improvement. This situation creates limitations in time management, increased costs, higher error rates, and lower quality.

Artificial Intelligence (AI) shapes more predictable, automated, and data-driven software development process (Bannon, 2024). It achieves this by being integrated into many stages of the SDLC. AI-powered tools can offer functions that span various phases of the SDLC (Bannon, 2024; Donvir et al., 2024). In the requirements analysis phase, they can extract information from documents using natural language processing (Bannon, 2024; Sofian et al., 2022). During the design phase, they can provide alternative architecture suggestions. In the development phase, they support code completion and quality assessment (Donvir et al., 2024). These tools also generate test scenarios and reduce test maintenance efforts during the testing phase (Bannon, 2024; Donvir et al., 2024; Garousi et al., 2024). Finally, in deployment and operations, they enable anomaly detection and self-healing system behaviors (Adewusi, 2023).

This evolution contributes to not only automation but also learning, adaptability, and proactive decision support capabilities (Garousi et al., 2024) (Adewusi, 2023). Despite this, most existing practices limit AI integration to a single phase of the SDLC (Bannon, 2024). They focus solely on testing, coding, or maintenance (Bannon, 2024). Such a fragmented approach overlooks the holistic impact of AI on the entire software engineering process (Bannon, 2024). From a broader perspective, the impact of AI is multilayered, transforming process quality, analytical power, and improvement speed from the beginning to the end of the process (Sofian et al., 2022 ; Donvir et al., 2024).

To address this deficiency, this study aims to systematically examine the Artificial Intelligence (AI) tools used across each phase of the Software Development Life Cycle (SDLC) and to comparatively evaluate their functional roles, decision support capabilities, automation levels, and overall impact on software development outcomes. These findings suggest, how AI tools influence project efficiency in terms of time, cost, and development speed. The study specifically investigates how they shape decision-making processes of technical teams and project managers with respect to accuracy, quality, and foresight. Furthermore, it explores the challenges and competencies required for organizations to effectively adapt to these tools. Finally, ethical concerns, risks, and limitations such as bias, copyright, and security are addressed. In the following sections, AI tools employed in each SDLC phase are classified based on their core applications and key features, and the findings are synthesized into a phase-based comparative framework that highlights the strategic role of AI within the software development lifecycle from a holistic and practical perspective, rather than a fragmented one.

Conceptual Background: Traditional SDLC and Methodologies

The Software Development Life Cycle (SDLC) is a structured framework that guides software projects from initial planning to deployment and maintenance. It starts with the Requirements Phase where Business Analysts write down what the users need so we have a base to work from. Next comes the Analysis Phase, where we take a look at these requirements to make sure they are going to work in the long run and not cause problems later on. Then there is the Design Phase this is where we create a plan for the system we make sure it is good by writing down all the details in something called High-Level and Low-Level specifications this way the Software Development Life Cycle or SDLC, for short and the Design Phase of the Software Development Life Cycle both help us

make a system that will work well. In the Development Phase the engineers take these plans. Turn them into code that actually works. They have to make sure this code meets all the rules that the industry says it should. After that the Testing Phase is really important because it checks for problems and fixes them so we know the system is good. Once we are sure the software is okay it is time to put it there and take care of it for a long time so it can keep meeting the changing needs of the software users. Such diverse methodologies, ranging from the Waterfall model to more adaptive Spiral and Hybrid approaches, allow organizations to balance risk management with operational flexibility (Padmanaban, Harish P. C. & Sharma, Yogesh Kumar, 2019).

AI Paradigms in Modern Software Methodologies

The use of Artificial Intelligence (AI) helps to make things by automating difficult tasks in the Software Development Life Cycle (SDLC). Artificial Intelligence (AI) does more, than automate simple tasks. It also helps to create code on its own find problems before they happen and make it easier for teams to review each others work. These smart systems help developers and managers by looking at what happened in the past and turning that into information. This change is affecting ways of working, like Waterfall, Agile and Lean by making each step more accurate from the beginning when we figure out what is needed to the end when we have to keep everything running smoothly. Recent studies show that Artificial Intelligence (AI) is becoming an important part of processes throughout (SDLC). In a traditional Waterfall context, for instance, AI-driven tools optimize requirement analysis and strengthen design architecture, which ultimately culminates in accelerated delivery and enhanced system reliability (Soni, Kumar, Anoop, Arora, Rajeev, & Garine, Ramakrishna, 2023).

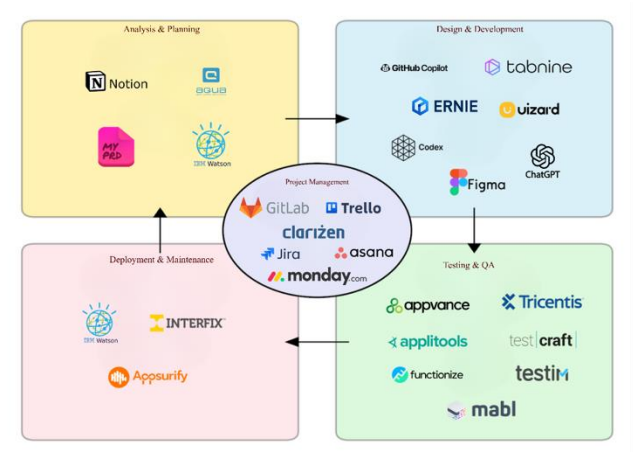
Method

In this section, the artificial intelligence tools utilized to enhance efficiency in software development and project management processes are examined, along with their application methods.

AI Tools in Software Development and Project Management

The distribution of the tools examined in this study across the SDLC phases is illustrated in Figure 1.

Figure 1. Artificial Intellicence Tools Used Across SDLC Phases



Analysis AI-Assisted Requirement Engineering and Analysis

How requirements are gathered and analyzed at the start of a software project has a huge impact on the rest of the Software Development Life Cycle (SDLC). When Artificial Intelligence (AI) is used in this early phase, it helps teams get more accurate results by automatically gathering and making sense of complex information. AI tools can pull together insights from a variety of places, such as conversations with stakeholders, documents, and customer feedback, and turn that into useful insights about what

users really need. For example, Natural Language Processing (NLP) can transcribe and analyze meetings, turning spoken ideas into clear technical requirements (Soni et al., 2023; Pandi, 2023). This kind of technology helps fix a big problem in older approaches: about 40% of software bugs happen because requirements are missing or unclear (Imam, 2024; Mulla & Girase, 2012). By combining NLP with neural networks, teams can also spot inconsistencies and check that even complicated security needs are covered, helping build a stronger foundation for the project (Ferrari & Esuli, 2019; Hayrapetian & Raje, 2018).

Modern software development is getting a boost from all kinds of AI-powered tools that make working with requirements easier and more reliable. For example, Notion uses GPT-3.5 AI to quickly create requirement templates and automatically summarize meetings (Notion, 2024). Aqua can turn notes or voice recordings into requirements, get rid of duplicates, and connect requirements to test coverage (Aqua Cloud, 2024). WriteMyPRD takes simple product descriptions and turns them into organized requirements, plus it generates helpful summaries, goals, and user stories (WriteMyPRD, 2025). On a bigger scale, IBM Watson uses AI to analyze data and make requirement documents clearer and more consistent, which helps prevent confusion and mistakes later on (IBM, 2025).

Table 1 summarizes AI-powered tools for requirements engineering and documentation. Notion aids collaborative requirement creation, Aqua supports automated test case generation and traceability, WriteMyPRD creates PRDs from brief descriptions, and BM Watson analyzes requirements for ambiguity and inconsistency. Together, these tools enhance accuracy, efficiency, and consistency in managing software requirements.

Table 1. Artificial Intelligence (AI) Tools Used in Requirement Engineering and Analysis

Tool	Category	Core Applications and Features
Notion	Requirements Documentation & Knowledge Management	Integrates AI directly into collaborative workspaces to support requirements documentation. Generates requirement templates, meeting summaries, action items, and structured content from unorganized notes. Facilitates early-stage requirement elicitation and refinement within shared documentation environments.
Aqua (Aqua Cloud / Aqua ALM)	Requirements and Test Management	Uses AI to generate requirements from textual notes and voice inputs, identifies and removes duplicate or redundant requirements, and ensures traceability between requirements and test cases. Provides automated test case generation and requirement-to-test coverage analysis, supporting quality assurance activities.
WriteMyPRD	Product Requirements Documentation (PRD) Automation	Automatically creates Product Requirement Documents (PRDs) from short product descriptions. Generates summaries, product goals, feature lists, and user stories, enabling rapid requirement definition during the initial stages of product development.
BM Watson (Requirements Quality / NLP-based Tools)	AI-Driven Requirements Quality Analysis	Applies natural language processing and data analytics to analyze requirement documents for ambiguity, inconsistency, and incompleteness. Improves

		the accuracy, clarity, and consistency of requirements, helping prevent downstream errors in software development projects.

Use of Artificial Intelligence in Design and Implementation Phases

AI-Supported Design and Prototyping

The design phase of software development presents both creative and intellectual challenges. In this phase, user requirements are incorporated into system architecture and interface components. Intelligent models, especially generative ones, have improved design processes and influenced decision-making, sustainability, and ethical issues. Platforms such as Figma AI and Uizard encourage the transformation of written or illustrated concepts into functional visual prototypes. These platforms apply learning-based algorithms to propose layouts, color schemes, and components (Şimşek, Gülşeni, A. Ç., & Olcay, G. A., 2025). Consequently, by minimizing manual effort, they streamline A/B testing and assist product managers in their decision-making processes (Funke, Lago, P., & Trinh, E., 2024).

Design tools supported by AI help shorten development time and support more sustainable design choices. In real projects, this also means paying attention to energy use, reusable code, and reducing environmental impact during the design stage (Trinh et al., 2024). Over time, design decisions are influenced not only by functionality or appearance, but also by environmental and ethical considerations.

As a result, the role of the designer has gradually changed. Decisions that were once based mainly on intuition are now supported by data and model-based suggestions. However, the

designer still remains responsible for checking and approving the outcomes. Rather than replacing human input, these systems act as support tools.

In this context, Responsible Generative AI focuses on issues such as fairness, transparency, accountability, and inclusion. These ideas aim to ensure that ethical concerns are considered throughout the design process (Shah & Bajpai, 2025).

The use of AI in design enhances prototyping speed, enables for real-time processing of user feedback, and integrates smoothly with decision-support tools. However, it also raises concerns around ethical control, data protection, and model bias. Because of this, modern designers are becoming more and more accountable for monitoring system outputs and ensuring reliability throughout the design process (Shah & Bajpai, G., 2025; Padmanaban & Sharma, Y. K., 2019).

AI-Supported Code Generation and Code Review

The implementation phase is where artificial intelligence provides the most visible and measurable contribution within the software development lifecycle. In this phase, intelligent systems take on tasks such as code generation, defect detection, management of technical debt, and automated code review. Tools like GitHub Copilot and Tabnine analyze developers' coding habits and offer contextual suggestions. Thereby, they contribute to improved productivity and enhanced code quality (Fagan & Park, 2024). Empirical studies show that such assistants help developers complete more tasks while also lowering error rates. In practice, they also reduce the time spent on repetitive coding work (Garg, 2023).

Still, these advantages come with certain concerns related to data protection and ethics. Since these systems rely on large amounts of open-source code, they may sometimes reproduce copyrighted content, expose sensitive information, or create security weaknesses

without intention (Ranapana & Janaka Indrajith Wijayanayake, 2025).

During the code review stage, automated tools can support developers by pointing out technical debt or possible vulnerabilities that may be overlooked. From a practical point of view, they help reviewers focus on risky parts of the code.

By using past examples, these systems flag unsafe structures or high-risk functions, helping to address the limits of manual review (Faruqui et al., 2024).

Despite their high detection accuracy, bias in model training and insufficient data coverage can still lead to false positives.

AI-driven development impacts not only individual developers' productivity but also project-level efficiency. Integrated platforms such as AI-Analyst help optimize project cost estimates, analyze resource usage, and assist managers with decision-making (P, Margi Patel, D. Stalin David, & Mukesh Soni, 2025). These findings suggest that artificial intelligence now extends beyond a coding assistant and functions as a strategic component across the software development lifecycle.

Literature stresses that AI-based coding assistants are far from being 'magic solutions.'As an example, security tests on Copilot reveal that using automatically generated code without review can create serious vulnerabilities (Ranapana & Janaka Indrajith Wijayanayake, 2025). Thus, AI-generated suggestions should be seen as advisory. They should not seen as definitive suggestions. The most reliable outcomes come up when human oversight, ethical governance, and robust data protection guide the use of intelligent tools.

Evaluation and Synthesis of Literature

The adoption of intelligent technologies in both design and implementation stages has contributed to improvements in productivity and software quality. While design benefits from greater speed and creative diversity, implementation gains in precision and automation. However, both stages present potential risks when ethical governance, data privacy, and explainability are neglected. The reviewed literature positions AI not only as a technical automation mechanism but also as a foundation for decision-support, ethical oversight, and sustainable engineering. This evolution suggests that collaboration between humans and intelligent systems will continue to evolve into a more transparent, traceable, and accountable model in the field of software engineering (Shah & Bajpai, G., 2025), (Fagan & Park, J., 2024), (Padhiary et al., 2025).

The human-artificial intelligence collaboration model emphasized in the literature is firmly grounded in the AI-powered capabilities of the design and development tools presented in Table 2. Platforms such as Figma AI and Uizard, shown in the table, accelerate the design process by transforming text or sketch-based inputs into functional interfaces, thus supporting the goal described in the literature as creative diversity. On the development side, Github Copilot and Tabnine increase developer productivity with code suggestions, while the speed and automation created by these tools make the verification of the accuracy and security of the generated AI outputs much more critical.

Table 2. Artificial Intelligence (AI) Tools Used in Design and Development

Tool	Category	Core Applications and Features
Figma AI	AI-Supported Design & Prototyping	Converts text prompts into editable designs (text-to-design), offers automated layout suggestions, and automates layer management to reduce manual workload. Supports A/B testing processes by rapidly generating design variations.

Uizard	Rapid Prototyping (Low-Code)	Transforms hand-drawn sketches or simple text into functional UI prototypes in seconds ("Autodesigner"). Democratizes product development by allowing non-designer stakeholders (like PMs) to build interfaces directly.
GitHub Copilot	AI Coding Assistant (LLM)	Analyzes developer coding habits to offer contextual code blocks. However, research such as "Asleep at the Keyboard" highlights that human supervision is essential, as suggested code may contain security vulnerabilities (CWEs).
Tabnine	Secure Code Completion	Focuses on code privacy with options to run entirely locally or in a secure cloud (Private Codebase). Learns from the developer's own codebase to provide personalized and contextual completion.

AI Use in Testing, Deployment, and Maintenance Phases

Testing, deployment, and maintenance represent critical stages of the SDLC. These stages ensure software quality and reliability. Traditional approaches in these stages, often encounter scalability and efficiency constraints. The union of AI and ML has transformed these processes through automation, predictive analytics, and intelligent decision-making. Thereby, quality assurance and operational performance has improved.

AI-Enhanced Testing and Quality Analysis

Integrating AI into Quality Assurance (QA) processes is no longer limited to traditional test automation. It helps teams work faster, reduce errors, and test software more effectively. According to Gartner, by 2027, 80% of companies are expected to use AI-supported testing tools in their software development processes (Bannon, 2024).

AI-Based Test Generation and Code Analysis

AI has decreased human intervention in many testing activities. AI facilitates activities such as test case generation, code

analysis and defect prediction. Studies show that 77% of AI-based testing tools have the feature of automatic test case or test code generation (Garousi et al., 2024). These tools apply mainly two approaches:

Natural Language Processing (NLP)-Based Methods: These approaches automatically extract executable test cases from user stories or requirement documents written in natural language. This capability enables, even non-technical stakeholders enable to contribute to test creation.

Code Analysis-Based Approaches: These methods employ static or dynamic code analysis to identify complex or error-prone modules and generate test cases that improve code coverage and reliability.

Self-Healing Tests and Visual Regression Testing

Self-healing test structures eliminate the fragility of traditional automation. Approximately 57% of commercial tools include this feature (Garousi et al., 2024). Such mechanisms contribute to a reduction in maintenance effort by preventing tests from breaking in response to small and frequent user interface changes.

Another critical advancement is **Visual Regression Testing (VRT)**. VRT applies computer vision techniques to divide intentional design modifications from unintended UI regressions. 29% of the reviewed tools support this capability (Garousi et al., 2024).

Impacts on Productivity and Decision-Making

AI-based testing tools enhance test creation, test prioritization, and resource planning. Using Test Impact Analysis (TIA), the system reviews recent code changes and runs only the

relevant tests. Consequently, it reduces CI/CD pipeline duration by eliminating unnecessary runs (Adewusi, 2023).

AI-based defect prediction models estimate the possibility of failure for particular modules (e.g., “80% likelihood of failure in this module”). This vision enables data-driven resource distribution. It helps focus testing efforts on high-risk areas. It also reduces human bias, lowers maintenance costs by detecting defects early in the development cycle (Mulla & Jayakumar, 2021).

Examining the use of artificial intelligence and machine learning methods, Bocu et al. (2023) conducted an extensive review of these approaches in Software Bug Triaging (SBT). They organized SBT models into categories such as machine learning, information retrieval, deep learning, and recommender-based systems. In addition, they identified major challenges, including reducing data size, selecting relevant features, and managing imbalanced datasets. These findings suggest that contributes to decision-making and prioritization within QA workflows, data quality and model robustness remain critical limitations.

As summarized in Table 3, AI-powered software testing tools address quality assurance from complementary perspectives. Applitools focus on detecting unwanted changes in the user interface using visual AI. Platforms like Tricentis and Testim.io reduce test maintenance costs through machine learning-based automation and self-healing mechanisms. Furthermore, large language model (LLM) based tools like GitHub Copilot and ChatGPT provide significant support to developers and testers by accelerating test code generation, debugging, and test case design processes. The tools listed in Table 3 provide a complete overview of how AI increases coverage, efficiency, and adaptability in software testing processes.

Table 3. Artificial Intelligence (AI) Tools Used in Software Testing and Their Applications

Tool	Category	Core Applications and Features
Applitools	Visual AI	It performs User Interface (UI) tests by using visual artificial intelligence. It verifies visual errors and layout changes; it is used in Quality Assurance (QA) processes.
Tricentis	Test Automation	It shortens test cycle times using artificial intelligence and cloud computing. It has codeless approach and tests business processes.
GitHub Copilot	Coding Assistant (LLM)	It is used to write boilerplate test code faster, fix minor bugs, and handle simple syntax queries.
ChatGPT (GPT-3.5/4)	LLM (General Purpose)	It is used for generating unit test scenarios, producing test data for code snippets, debugging, and providing code explanations.
Testim.io	Machine Learning (ML) Functional Testing	Automated functional tests with self-healing features to reduce maintenance.
Mabl	ML / Smart Logic Intelligence Testing	Intelligent defect identification and auto-remediation of test scenarios.

AI-Enabled DevOps (AIOps) and Maintenance

AIOps came up from the integration of Artificial Intelligence and Machine Learning into DevOps processes. It automates decision-making processes in release, deployment, operations, and monitoring phases. This integration contributes to continuous system stability and security through logging and network data (Bannon, 2024) (Islam et al., 2023).

Automatic Monitoring and Error Management

AI/ML models continuously monitor operational data to detect anomalies and take preventive or corrective actions:

- **Performance Monitoring and Anomaly Detection:** AIOps platforms learn normal system behavior patterns to detect real-time deviations in key metrics like CPU utilization or response times. For example, tools like Appsurify TestBrain generate AI-based alerts to flag potential CI/CD pipeline errors early (Garousi et al., 2024).
- **Security Monitoring:** Deep Learning (DL) techniques, such as hybrid **CNN–LSTM** models, achieve over 98% accuracy in detecting DDoS or brute-force attacks within CI/CD network traffic (Saleh et al., 2024). These systems automatically generate log entries containing attack types and timestamps for audit and traceability.
- **Root Cause Analysis (RCA):** AIOps platforms use machine learning to analyze logs and group similar problems. This helps identify the most likely root causes and significantly reduces the Mean Time to Resolution (MTTR).These capabilities can be seen in tools such as IBM Watson AIOps.

- **Self-Healing Systems:** Self-healing infrastructure is one of the most advanced capabilities of AIOps. These autonomous systems keep operations running continuously. They automatically scale resources or roll back failed deployments without human involvement (Adewusi, 2023).

The tools and techniques presented in Table 4 clearly demonstrate how the AIOps approach is embodied in DevOps and maintenance processes. Solutions like Appsurify TestBrain enable proactive detection of CI/CD failures through operational monitoring and early warning mechanisms. Hybrid CNN–LSTM-based models can identify attacks in network traffic with high accuracy within the scope of security monitoring. In addition, IBM Watson AIOps significantly reduces resolution time by accelerating root cause analysis through log analysis and grouping of similar events. Self-healing infrastructures keep systems running by automatically reversing failed deployments or adjusting resources when needed.

In addition, the Explainable AI (XAI) approaches shown in Table 4 improve transparency, trust, and accountability. They also emphasize the strategic role of AI in maintenance and operational tasks.

Table 4. Artificial Intelligence (AI) Tools / Techniques Used in DevOps and Maintenance

Tool / Technique	Category	Core Applications and Features
Appsurify TestBrain	Operational Monitoring	Utilizes AI-based alerts to detect real-time deviations and flag potential CI/CD pipeline errors early.
Hybrid CNN–LSTM Models	Security Monitoring	Employs Deep Learning to detect DDoS and brute-force attacks with high accuracy within network traffic.

IBM Watson AIOps	Root Cause Analysis (RCA)	Leverages ML to analyze logs and group similar issues, drastically reducing Mean Time to Resolution (MTTR).
Self-Healing Infrastructure	Autonomous Operations	Automatically scales resources and rolls back failed deployments to ensure continuous operation without human intervention.
Explainable AI (XAI)	Ethical & Trust Framework	Enhances transparency by providing interpretability for AI-driven decisions and corrective actions.

Compliance and Ethical Dimension (Adaptation and Trust)

The combination of AI and DevOps introduces adaptation challenges and ethical concerns which related to trust, transparency, and accountability.

- **Adaptation Process:** DevOps and SRE teams need to learn new skills, such as managing ML models and understanding system anomalies. They also need to review how automated systems make decisions. However, many AIOps tools focus on limited tasks and do not work well together, which makes integration and centralized management difficult (Adewusi, 2023).
- Ethical and Trust Issues: Most AI models are often opaque in their decision-making process . They operate like black boxes. This lack of transparency hinders explainability, especially regarding why certain errors are detected or why certain corrective actions are implemented (Garousi et al., 2024). Future research, should prioritize Explainable Artificial Intelligence (XAI) to strengthen system reliability.
- **Accountability:** Even if AI systems are fully autonomous, responsibility remains with humans. Over-

dependence on automation can cause undetected bugs. It can cause vulnerabilities spreading throughout the system. This necessity for human oversight ensures that AI systems are treated as assistive collaborators rather than independent agents (Adewusi, 2023; Joshi, 2025)

The Holistic Impact of Artificial Intelligence on Project Management Process Groups

Project management process groups, which refer to the processes followed throughout the project lifecycle to ensure the application of the essential knowledge, tools, and techniques for successful completion of projects, are defined by the Project Management Institute (PMI) and are composed of the initiation, planning, execution, monitoring and controlling and closing processes (Institute, 2017). Artificial intelligence (AI) applications implemented in these processes represent a transformation in how projects are managed (Karamthulla et al., 2024). Moreover, AI-powered project management provides project managers more flexibility and agility in project processes such as decision-making, planning, and management, which results in improved project performance (Karamthulla et al., 2024).

In the initiation phase, the project is established and initiated. This process determines the project scope and aims, and all cases and resources needed for the project to achieve these objectives are clarified (Hashfi & Raharjo, 2023). In this phase, artificial intelligence applications were utilized to enhance cost and duration estimation, risk assessment and decision-making processes (Hashfi & Raharjo, 2023). A study by Elmousalami on cost estimation in project management demonstrates the capabilities of machine learning models for this task (Narbaev et al., 2024). Chen et al. exhibited that artificial neural networks provide better performance

than traditional methods in decision-making processes in projects (Habibi et al., 2018).

The planning phase involves establishing the project's goals and scope are established and the required plan is generated to achieve these aims (Institute, 2017). During this process, Narbaev et al. observed various machine learning models for 110 projects to increase the reliability of project cost estimation and found that the XGBoost model demonstrated high accuracy in the early estimation process (Narbaev et al., 2024). Shamim et al. investigated that deep learning and hybrid models displayed 85-90% accuracy in cost estimation, raising the reliability of the estimate by reducing errors (Shamim et al., 2025). A study by Ruiz et al. highlighted a 20% reduction in project completion times with AI-assisted resource allocation (Ruiz et al., 2021). Furthermore, Rezvanjou et al. discovered that AI-driven planning systems are highly effective at cutting down mistakes. Their data suggests that such systems can lower planning-related errors by as much as 30% (Rezvanjou et al., 2023).

The execution phase includes the processes applied to complete the requirements indicated in the project management plan (Institute, 2017). A study by Shoushtari et al. showed that the use of AI bots increased team communication by 25% and reduced communication put-offs by 10%. Besides, studies have shown that platforms such as Monday.com, Asana, Trello, Jira, Slack, Clarizen, and GitLab automate team tasks, enhance workflow management more efficiently by visualizing it, increase task planning efficiency through bottleneck predictions, and promote team communication (Kesar & Joseph, 2025; Ogunbukola, 2024; Sahadevan, 2023).

The monitoring and controlling process refers to the whole progress of the project by the time it achieves the specified aims, the review of its performance against the project plan, and the reporting process (Institute, 2017). Narbaev et al. exhibited high accuracy with

a MAPE rate of 6.53–9.70% in early cost estimation with the XGBoost model and accepted the effectiveness of artificial intelligence applications in making more reliable decisions for project managers by predicting cost variances (Narbaev et al., 2024). Wauters and Vanhoucke investigated machine learning techniques for estimating project completion time and investigated that these machine learning based models provided better results than traditional methods (Wauters & Vanhoucke, 2016).

The closing phase refers to the stage of ensuring that the project has performed entire aims and that the project is obviously completed (Institute, 2017). Studies indicates that Natural Language Processing (NLP) automatically summarization of project documentation, evaluates project performance, create a knowledge base for future work, reducing costs in projects, increasing efficiency, and ensuring successful closing (Hashfi & Raharjo, 2023; Taofeek et al., 2024).

These studies have highlighted that AI provides high accuracy in project management process groups, for instance efficiency, cost estimation, project performance and automation. In this context, project managers save time and focus on data-driven decision-making and strategic thinking.

The advantages offered by artificial intelligence applications are further highlighted by the AI project management tools shown in Table 5. Platforms such as Jira, Asana, and Monday.com, throughout the overall project management lifecycle, from defining the project scope to reporting project performance. In particular, the AI-powered bottleneck prediction, automated task allocation, and AI assistants mentioned in the table minimize the operational workload of project managers, transforming data-driven management aims into practical applications.

Table 5. Artificial Intelligence (AI) Tools Used in Product Management

Tool	Category	Core Applications and Features
Jira (Atlassian)	Agile Software Development	Aligns work with goals and automatically breaks down large tasks into "User Stories." Serves as a data hub with 3,000+ integrations and provides real-time data insights.
Asana	Collaborative Work Management	Connects tasks to strategy via the "Work Graph." Adapts to changing priorities using AI. Holds a high user satisfaction score (NPS 90).
Monday.com	Visual Work Management	Offers customizable workflows ("lego block" approach) and visual dashboards. Provides flexibility and resource tracking for non-technical teams like HR and Marketing.
Clarizen	Product Portfolio Management	Predicts resource bottlenecks and minimizes revenue risks at the enterprise level. Aligns projects with corporate financial goals.
Trello	Kanban / Personal Productivity	Learns user habits via "Butler" automation and provides rule-based task management. Offers a simple, visual, card-based interface.
GitLab	DevOps Lifecycle	Unifies coding and project management in a single platform. Supports GenAI flows for code quality and tracks the delivery process end-to-end.
AI Chatbots	Communication	Uses Conversational AI. Increases team engagement by 25%, reduces communication-related delays by 10%, and provides real-time updates to stakeholders.

Conclusion

The aims is to respond early to increasing project complexity in software development processes, meet incoming requests, and deliver high-quality products. Processes within the software development lifecycle, such as requirements, design, development,

test, and maintenance,align with the flexibility and speed aimed for in agile methods by leveraging AI integration. The function of AI tools used in these phases indicates that they act not only as mechanisms for automating simple tasks but also as a business partner supporting decision-making processes, generating code, and continuously monitoring and updating system health.

The findings suggest that AI tools help reduce uncertainty in the requirements phase, support faster and more effective design decisions, increase productivity during development, and improve software quality through automated testing and smart monitoring. AI-based methodologies contribute to early error detection, system stability, and reduce operational effort in later stages like deployment and maintenance. From a project management perspective, AI-supported cost estimation, risk assessment, project progress tracking, resource planning, and automation of routine tasks support managers in these processes, providing strategic foresight and accuracy while also saving time.

These artificial intelligence tools bring several important problems with them. Some of these, such as algorithmic bias, data privacy, security vulnerabilities, and ethical concerns, constitute the risks of the uncontrolled use of artificial intelligence. Moreover, situations such as the lack of transparency in black-box models can reduce trust in the systems and increase the need for explainable artificial intelligence.

Overall, the chapter provides a comprehensive overview of how artificial intelligence is used throughout the SDLC and project management processes. When AI tools are integrated into SDLC processes in a controlled and holistic manner, they make software development processes more predictable, faster, and more efficient. These integrations enable teams to complete routine tasks faster, saving time and allowing for early detection of risks and errors in projects. These advancements will ensure timely project completion

with high success rates, increased customer satisfaction, and the integration of technical expertise with ethical awareness. Consequently, AI-centric projects will play a crucial role in future software development processes.

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CHAPTER 5

TARGET INDUSTRY CLASSİFİCATİON ON CYBER ATTACK DATA USİNG MACHİNE LEARNİNG METHODS

Hünkar ACAR [1]
Alper Talha KARADENİZ[2]

Introduction

Recent technological advancements have increased the dependence of individuals, institutions, and states on cyberspace, rendering digital infrastructures essential for both daily activities and national security (Darıcılı, 2018; Karasoy & Gezici, 2023). Cyberspace has thus evolved into a multidimensional domain influencing not only individual and organizational networks but also economic, social, and military systems, carrying both technical and strategic significance (Darıcılı, 2018; Karasoy & Gezici, 2023).

Despite its advantages, the expanding use of cyberspace has introduced substantial security threats posed by state-sponsored actors, organized hacker groups, and insider threats. High-profile

[1] Bachelor's Student, Samsun University, Faculty of Engineering and Natural Sciences, of Software Engineering, Orcid: 0009-0009-7930-5694
[2] Assistant Professor, Samsun University, Faculty of Engineering and Natural Sciences, of Software Engineering, Orcid: 0000-0003-4165-3932

incidents such as Stuxnet, the 2007 Estonia cyberattacks, and cyber operations during the Russia–Ukraine conflict demonstrate that cyberspace has become a critical dimension of modern warfare, with blurred boundaries between civilian and military infrastructures leading to widespread societal impacts (Darıcılı, 2018; Lehto, 2023). Consequently, cybersecurity requires not only technical safeguards but also multidisciplinary approaches, including risk management, digital forensics, cryptography, and cyber law (Karasoy & Gezici, 2023).

In this context, artificial intelligence and machine learning techniques have been increasingly applied to cybersecurity problems, proving effective in tasks such as intrusion detection, threat analysis, and anomaly detection (Xin et al., 2018). Accordingly, this study aims to classify cyberattacks by target sector using machine learning and data mining methods, analyze sectoral attack patterns, and contribute to the development of sector-specific defense strategies.

Literature Review

Cybersecurity research increasingly focuses on sector-based defense analysis and the classification of cyberattacks according to their targets. As a strategic component of national security, cybersecurity has become closely integrated with artificial intelligence and machine learning technologies to enhance threat detection and defense mechanisms (Karasoy & Gezici, 2023; Xin et al., 2018). Accordingly, states are required to strengthen their capabilities in this domain and develop AI-driven, data-oriented threat prevention strategies based on sectoral attack patterns (Darıcılı, 2018; Ahmed, 2022; Avci & Koca, 2023). Prior studies leveraging historical cyberattack data have demonstrated that machine learning classifiers can effectively predict target sectors,

providing valuable insights for proactive defense planning (Pournouri, Aghvami, & Sharifi, 2019).

Machine learning algorithms have also been widely employed to improve intrusion detection accuracy and reduce false alarm rates (Kılınçer et al., 2021). Models such as K-Nearest Neighbors (KNN), Support Vector Machines (SVM), and Random Forest (RF) have shown strong performance in attack classification and network traffic analysis tasks (Kılınçer et al., 2021). Comparative studies report high effectiveness of ensemble and boosting-based methods, with Random Forest achieving accuracy levels up to 98.8% and XGBoost attaining an F1-score of 97.34% in Industrial Internet of Things (IIoT) environments (Avci & Koca, 2023; Le, Nguyen, & Nguyen, 2022).

The effectiveness of these algorithms varies by application context. SVM performs well on high-dimensional and non-linear data but requires careful parameter tuning (Cortes & Vapnik, 1995), while KNN is computationally intensive during inference and sensitive to noise (Suyal & Goyal, 2022). Random Forest reduces overfitting through ensemble learning and achieves high predictive accuracy, albeit with limited interpretability (Breiman, 2001). Model performance is commonly evaluated using metrics such as accuracy, precision, recall, and F1-score, which, together with learning curves, support the identification of overfitting and underfitting behaviors (Mohr & van Rijn, 2024; Yao & García de Soto, 2024). Recent studies further indicate that these metrics vary significantly across different attack types, underscoring the importance of context-aware evaluation (Avci & Koca, 2023; Yao & García de Soto, 2024).

Materials and Methods

This section systematically presents the dataset, data preprocessing steps, the parameters of the selected machine learning

algorithms, the classification process, and the model evaluation metrics.

Dataset

In this study, the dataset used is titled “Global Cybersecurity Threats 2015–2024”, which was obtained from the Kaggle platform and is publicly available as an open-source resource containing global cybersecurity threats between 2015 and 2024.

The dataset includes key variables such as attack type, target sector, attack year, country, financial loss, number of affected users, attack source, type of exploited vulnerability, defense mechanism used, and incident resolution time. Sample data related to these features are presented in Table 1.

Table 1. Sample data from the global cybersecurity threats 2015–2024 dataset

Counrty	Year	Attack Type	Target Industry	Financial Loss (Million $)	Number of Affected Users	Attack Source	Security Vulnerability Type
China	2019	Phishing	Education	80.53	773169	Hacker Group	Unpatched Software
China	2019	Ransomware	Retail	62.19	295961	Hacker Group	Unpatched Software
India	2017	Man-in-the-Middle	IT	38.65	605895	Hacker Group	Weak Passwords
UK	2024	Ransomware	Telecom	41.44	659320	Nation-State	Social Engineering
Germany	2018	Man-in-the-Middle	IT	74.41	810682	Insider	Social Engineering

In Figure 1, a portion of the data regarding cyber attacks is presented based on countries and sectors using various metrics, including attack type, target industry, financial loss, number of

affected users, attack source, type of security vulnerability, defense mechanism used, and incident resolution time.

Figure 1. A sample segment from the global cybersecurity threats 2015–2024 dataset

Country	Year	Attack Type	Target Industry	Financial Loss (Million $)	Number of Affected Users	Attack Source	Security Vulnerability Type
China	2019	Phishing	Education	80.53	773169	Hacker Group	Unpatched Software
China	2019	Ransomware	Retail	62.19	295961	Hacker Group	Unpatched Software
India	2017	Man-in-the-Middle	IT	38.65	605895	Hacker Group	Weak Passwords
UK	2024	Ransomware	Telecom	41.44	659320	Nation-State	Social Engineering
Germany	2018	Man-in-the-Middle	IT	74.41	810682	Insider	Social Engineering

Figure 1 helps illustrate how the information in the dataset is organized and what kind of details each record contains.

Feature Engineering

Effective training of machine learning models and the achievement of high predictive performance require transforming raw data into a suitable numerical format (Xin et al., 2018; Kılınçer et al., 2021). Accordingly, categorical variables in this study are converted into numerical form using One-Hot Encoding, which represents each category as a separate binary feature. This approach enables machine learning algorithms—particularly linear and network-based models—to process categorical data efficiently (Xin et al., 2018; Samuels, 2024).

In addition, Z-score standardization is applied as a feature engineering step to mitigate scale differences among variables and ensure that all features contribute equally to the learning process. The mathematical formulation of this standardization is provided in Equation (1) (Xin et al., 2018; Kılınçer et al., 2021).

$$Z = (x - \mu)/\sigma \quad (1)$$

In this standardization formula, x represents each observation value, μ denotes the mean, and σ indicates the standard deviation (Xin et al., 2018; Kılınçer et al., 2021). As a result of this transformation, all features are scaled to have a mean of zero and a standard deviation of one. This step is particularly critical for distance-based algorithms such as K-Nearest Neighbors (KNN) and optimization techniques that rely on gradient descent, as variables with differing scales may negatively affect the decision process and convergence speed (Xin et al., 2018; Kılınçer et al., 2021). Through this procedure, the dataset is rendered suitable for use in machine learning algorithms.

Super Vector Machine (SVM)

Support Vector Machines (SVM) is a supervised learning algorithm that aims to identify the optimal hyperplane that separates data points belonging to different classes (Cortes & Vapnik, 1995). This hyperplane increases the model's generalization capability by maximizing the margin between the classes (Cortes & Vapnik, 1995). In linearly separable data, the SVM achieves this by solving a specific optimization problem. The mathematical formulation of the model is presented in Equation 2 (Cortes & Vapnik, 1995).

$$min(w,b)\ \ \frac{1}{2}||w||^2 \ subject\ to:\ y_i(w^T x_i\ + b) \geq 1\ \forall_i \qquad (2)$$

The formula in Equation 2 seeks to maximize the margin. Here, w is the normal vector to the hyperplane, b is the bias term, x_1, x_2, ..., x_n are the data points, and y_i represents their corresponding class labels (+1 or -1) (Cortes & Vapnik, 1995). For non-linearly separable cases, the kernel trick is applied to project the data into a higher-dimensional feature space, where a linear separation may become possible (Cortes & Vapnik, 1995). In this study, a linear kernel function is used to construct the SVM model, as it has shown effective performance on high-dimensional datasets and offers relatively better interpretability.

K-Nearest Neighbors (KNN)

The K-Nearest Neighbors (KNN) algorithm is an instance-based and non-parametric learning method. The class of a new data point is determined based on the class labels of its k nearest neighbors in the feature space (Suyal & Goyal, 2022). Despite its intuitive and simple structure, this method can produce effective results. The classification of test samples is performed by calculating their distance to training data using the Euclidean distance, as shown in Equation 3. The most frequent class label among the k selected neighbors is assigned to the test sample (Suyal & Goyal, 2022; Shokrzade et al., 2021).

$$d(x, x_i) = \sqrt{\sum_{j=1}^{d}(x_j - x_{ij})^2} \quad (3)$$

Here, d(x,x_i) denotes the Euclidean distance between points x and x_i in an n-dimensional space (Suyal & Goyal, 2022; Shokrzade et al., 2021). In this study, the parameter kkk was fixed at 5 in accordance with both preliminary experimental evaluations and widely adopted practices reported in the literature. Given that the performance of the K-Nearest Neighbors (KNN) algorithm is highly sensitive to the scale of input features, Z-score normalization, as described in Section 3.2, was applied as an essential preprocessing step to ensure reliable distance-based comparisons.

Random Forest

Random Forest is an ensemble learning algorithm developed by Leo Breiman and is widely used for both classification and regression tasks (Breiman, 2001). This method constructs a multitude of decision trees trained on random samples of the original dataset and aggregates their predictions. By training each tree on random subsets of the data and features, the model improves its generalization capability while reducing the correlation between individual trees (Breiman, 2001).

In classification, the final decision is determined by a majority vote among B decision trees, as expressed in Equation 4 (Breiman, 2001).

$$\hat{C}(x) = mode\ \{\widehat{C_1}(x), \widehat{C_2}(x), \ldots\ldots, \hat{C}_B(x)\} \quad (4)$$

In this equation, C^_b (x) represents the class prediction made by the b-th decision tree for the observation xxx. The final prediction is the most frequently occurring class among all individual tree predictions. This ensemble approach significantly reduces the overfitting tendency of a single decision tree, lowers the model variance, and generally produces more stable and highly generalizable results.

Performance Metrics

To quantitatively evaluate and compare the performance of the developed classification models, commonly accepted evaluation metrics frequently used in machine learning applications—especially in domains like cybersecurity—were employed (Avci & Koca, 2023; Kılınçer et al., 2021; Yao & García de Soto, 2024; Karadeniz et al., 2023)These metrics provide a comprehensive assessment by measuring model success from different perspectives.

Confusion Matrix: Classification performance is evaluated using a confusion matrix, which reports true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN), enabling a class-wise analysis of model behavior (Karadeniz et al., 2023).

Accuracy: The ratio of correctly classified instances to the total number of instances. While it provides a general performance measure, it may be misleading in imbalanced datasets (Avci & Koca, 2023; Yao & García de Soto, 2024; Karadeniz et al., 2023). Accuracy is calculated as shown in Equation 5

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+F} \quad (5)$$

Precision: The proportion of correctly predicted positive instances among all instances predicted as positive. This metric is especially important when false positives carry a high cost (Avci & Koca, 2023; Yao & García de Soto, 2024; Karadeniz et al., 2023). It is calculated using Equation 6.

$$\text{Precision} = \frac{TP}{TP+FP} \tag{6}$$

Recall (Sensitivity): Indicates the proportion of actual positive instances that were correctly identified by the model. It is crucial in situations where false negatives are costly (Avci & Koca, 2023; Yao & García de Soto, 2024; Karadeniz et al., 2023). Recall is computed using Equation 7.

$$\text{Recall} = \frac{TP}{TP+FN} \tag{7}$$

F1-Score: The harmonic mean of precision and recall. It provides a more balanced performance measure, particularly useful in imbalanced class scenarios or when both precision and recall are important (Avci & Koca, 2023; Yao & García de Soto, 2024; Karadeniz et al., 2023). For a given class *c*, the F1-score is calculated as follows in Equation 8.

$$\text{F1-Score} = 2\times \frac{Precision\times Recall}{Precision+Recall} \tag{8}$$

The performance metrics employed in this study were selected to provide a multidimensional evaluation of the classification success of the machine learning models on the dataset. These metrics are widely used to analyze model performance from various perspectives (Aburomman & Reaz, 2016).

Experimental Studies and Result

The “Global Cybersecurity Threats 2015–2024” dataset was analyzed using exploratory data analysis, feature engineering, and machine learning techniques. The classification task was defined based on the Target Industry variable, and models were developed

using Support Vector Machines (SVM), Random Forest (RF), and K-Nearest Neighbors (KNN). Model performance was evaluated through confusion matrices and standard metrics, including accuracy, precision, recall, and F1-score. In addition, learning curves were examined to assess overfitting and underfitting behaviors. The performance results of the classification models are summarized in Table 2, while the hyperparameters employed during training are reported in Table 3.

Table 2. Classification models and parameter values

Model	Parameter	Value
KNN	n_neighbors	5
SVC	kernel	linear
	probability	True
RF	n_estimators	100
	random_state	42

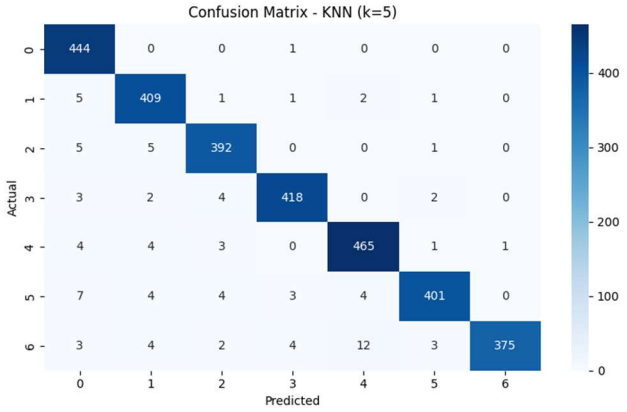
In the model configuration, the number of neighbors for KNN was set to n_neighbors=5; for SVC, a linear kernel (kernel='linear') and probability estimation (probability=True) were used; and for RF, n_estimators=100 and random_state=42 were specified. These hyperparameters were optimized to ensure the stability and reproducibility of the models.

Table 3. Cross-validation parameters

Category	Method	Parameter	Value
Cross Validation	Stratified K-Fold	n_splits	5
		shuffle	True
		random_state	42

During model evaluation, Stratified K-Fold cross-validation was employed to preserve class distribution, using five folds with data shuffling and a fixed random state to ensure reproducibility (Ünalan et al., 2024; Bhagat & Bakariya, 2022). The KNN model was trained using the hyperparameters listed in Table 3, and its performance was evaluated via the confusion matrix shown in Figure 2. With k=5k = 5k=5, the model achieved strong overall classification performance across seven classes, with particularly accurate predictions for classes 0, 1, and 4. Nevertheless, certain misclassifications—such as confusion between classes 6 and 4, and between classes 5 and 0 suggest limitations in distinguishing specific class pairs.

Figure 2. Confusion Matrix for the K-Nearest Neighbors (KNN) Algorithm



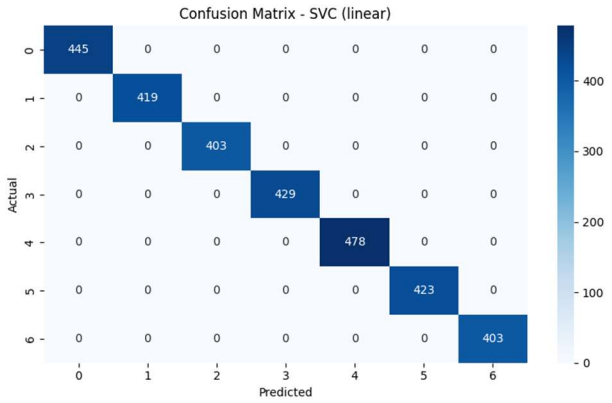
Based on this confusion matrix, the results of the experimental tests are summarized in Table 4.

Table 4. Performance metrics of the KNN model

Model	Accuracy	Precision	Recall	F1-Score
KNN	0.968	0.968597	0.968	0.967967

As presented in Table 4, the KNN model demonstrated strong performance, achieving an accuracy of 96.8%, with consistently high precision, recall, and F1-score values, indicating balanced and reliable classification results. The classification performance of the SVC model, illustrated in Figure 3, shows near-perfect accuracy across all classes. The absence of off-diagonal entries in the confusion matrix indicates clear class separability and robust model performance on the dataset.

Figure 3. Confusion matrix for the support vector classifier (SVC) algorithm



Based on this confusion matrix, the results of the experimental tests are presented in Table 5.

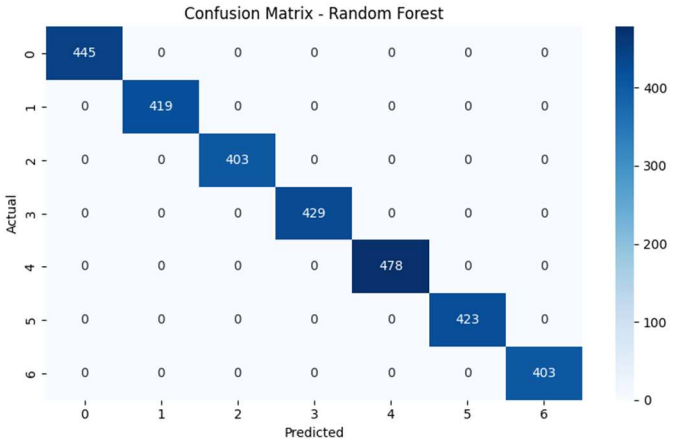
Table 5. Performance metrics of the SVC model

Model	Accuracy	Precision	Recall	F1-Score
SVC	1.000	1.000	1.000	1.000

As seen in Table 5, the SVC model achieved a perfect score of 1.000 across all metrics, indicating flawless classification performance. This result confirms that the model made accurate

predictions without any errors. The confusion matrix and classification results for the RF model are shown in Figure 4.

Figure 4. Confusion matrix for the random forest (RF) algorithm



The Random Forest model, illustrated in Figure 4, achieved high accuracy across all classes, with no off-diagonal errors, indicating no confusion among the classes. These results demonstrate that the model provides strong and effective classification performance on the dataset. Based on this confusion matrix, the results of the experimental tests are presented in Table 6.

Table 6. Performance metrics of the random forest model

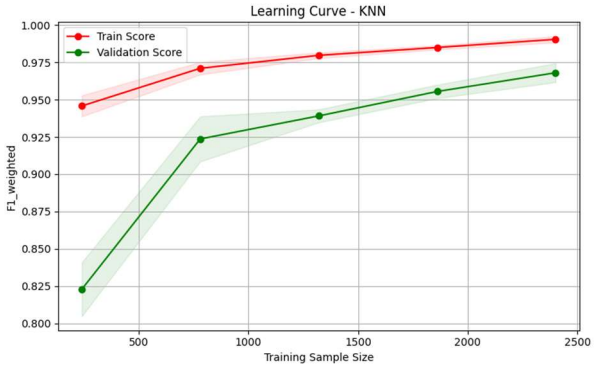
Model	Accuracy	Precision	Recall	F1-Score
RF	1.000	1.000	1.000	1.000

As shown in Table 6, the Random Forest (RF) model achieved 100% success in accuracy, precision, recall, and F1-score metrics, demonstrating perfect classification performance. This indicates that the model classified the dataset without errors and suggests a strong generalization capability.

Both the Random Forest and SVC models achieved 100% accuracy across all classes, successfully modeling high linear separability. However, this also raises the possibility of overfitting, which necessitates validation through cross-validation techniques. On the other hand, while KNN achieved strong overall performance, it struggled to define decision boundaries for certain classes. The confusion matrices reveal that RF and SVC significantly outperform KNN in terms of classification effectiveness.

Learning curves provide critical insights into a model's bias, variance, and generalization capacity by illustrating how performance changes as the number of training samples increases (Breiman, 2001). In this context, the learning curve for the K-Nearest Neighbors (KNN) model, presented in Figure 5, has been analyzed using the weighted F1-score (F1_weighted) metric.

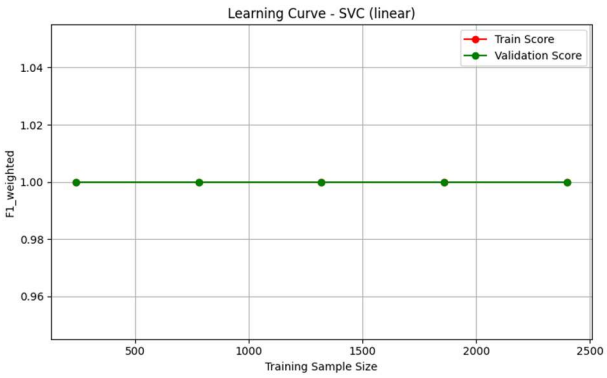
Figure 5. Learning curve for the KNN algorithm



The learning curve in Figure 5 indicates that as the amount of training data increases, both training and validation scores improve. The noticeable gap between training and validation performance at low sample sizes suggests a tendency toward overfitting. As the data size grows, this gap narrows, with the validation score reaching approximately 0.97, indicating improved generalization performance. However, the small remaining

difference between the curves implies that the model could still benefit from additional training data.

Figure 6. Learning curve for the SVC algorithm



In contrast, the learning curve for the linear kernel SVC model exhibits a markedly different behavior. As shown in Figure 6, both the training and validation scores remain constant at 1.0 across all training set sizes. This outcome indicates that the model operates with low bias and low variance, learning the dataset perfectly. These results are consistent with the confusion matrix that showed 100% accuracy and strongly support the linear separability of the dataset.

Discussion

In this section, analyses were conducted based on the obtained findings, and the results were evaluated through comparison with relevant literature. Table 7 presents the annual distribution of cyberattacks that occurred between 2015 and 2024.

Table 7. Number of attacks by year

Year	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
Attack	277	285	319	310	263	315	299	318	315	299

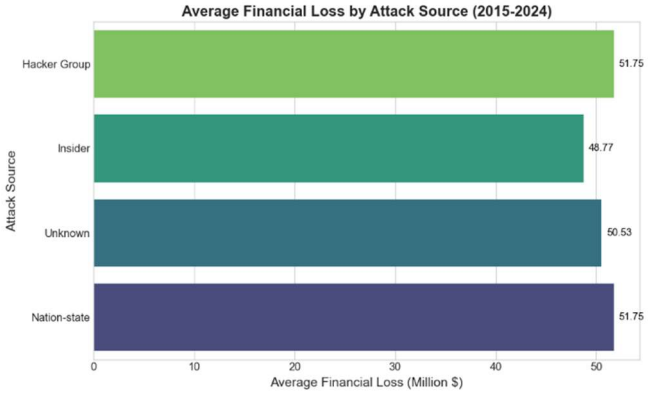
As shown in Table 7, there is no clear upward or downward trend in the number of annual cyberattacks during the 2015–2024 period. The number fluctuates around an average of 300 attacks per year. This indicates the persistent nature of cyber threats and highlights the necessity of proactive security strategies. Table 8 displays the distribution of cyberattacks by source and the total number of attacks attributed to each source.

Table 8. Number of attacks by source

Attack Source	Nation-state	Unknown	Insider	Hacker Group
Number of Attacks	794	768	752	686

According to Table 8, the majority of attacks originate from nation-state and unknown sources, followed by insiders and hacker groups. This distribution suggests that most cyberattacks are conducted by state-sponsored or organized entities. The high proportion of attacks from unknown sources also indicates efforts by attackers to conceal their identities. Figure 7 illustrates the average financial loss caused by each attack source.

Figure 7. Average financial loss by attack source



Based on the data presented in Figure 7, the highest average financial loss is caused by attacks originating from hacker groups, amounting to approximately $51.75 million. These are followed by

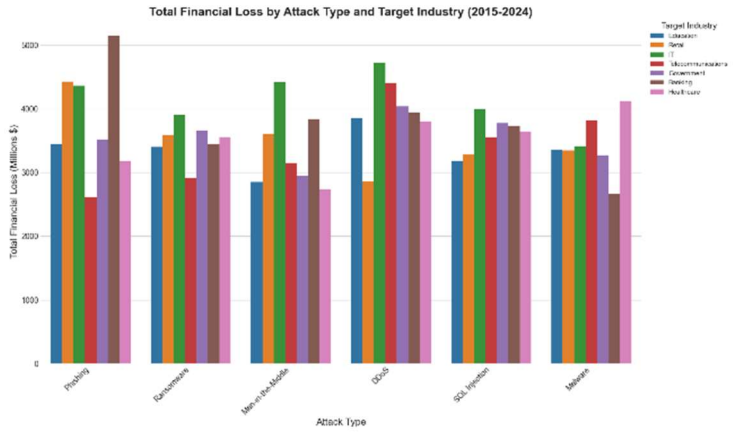
losses from nation-state, unknown, and insider sources, respectively. The relatively high and close financial losses across all categories demonstrate that cyberattacks from various sources result in serious institutional costs. Table 9 provides a comparative overview of the average financial losses (in millions of dollars) experienced by different industrial sectors due to cyberattacks.

Table 9. Average financial loss by targeted industry (Million USD)

Target Industry	Government	IT	Banking	Telecom	Retail	Healthcare	Education
Financial Loss	52.62	51.90	51.17	50.77	49.93	49.05	47.90

According to Table 9, the public, finance, healthcare, and information technology sectors are at high risk in terms of both attack frequency and financial and operational impacts. The findings indicate that these sectors are more vulnerable and experience systematic losses. The results reveal that cyber threats must be addressed not only from a technical perspective but also through strategic and managerial approaches. Figure 8 shows the financial losses caused by different types of attacks across various sectors.

Figure 8. Financial loss by targeted sector and attack type



As shown in Figure 8, different attack types impose varying financial impacts across industries. Phishing attacks result in substantial losses in the banking and healthcare sectors, DDoS attacks predominantly affect the telecommunications and IT sectors, and malware poses significant risks to the healthcare sector. When evaluated together with Table 9, these findings highlight that public, IT, and security-related sectors hold strategic importance and are primary targets for cyberattacks. This underscores the necessity for enhanced cyber defense mechanisms, including the active involvement of military-engineering disciplines and the development of multi-layered defense structures through civil–military cooperation.

Table 10. Number of attacks by targeted industry

Target Industry	IT	Banking	Healthcare	Retail	Education	Telecom	Government
Number of Attacks	478	445	429	423	419	403	403

Table 10 shows that the IT and banking sectors were the primary targets of cyberattacks, followed by the government sector, indicating a clear attacker focus on critical industries that support essential services and national infrastructure. These findings emphasize that cybersecurity should be regarded as a strategic security issue rather than a purely technical challenge. The experimental results demonstrate that cyberattacks can be classified by target sector with high accuracy using machine learning models, with SVC and Random Forest achieving 100.0% accuracy and KNN attaining 96.8%. This performance is consistent with previous studies confirming the effectiveness of machine learning techniques for multi-class cyber threat detection (Darıcılı, 2018; Aburomman & Reaz, 2016; Sarker, 2021; Lehto, 2023; Farouk, Sakr, & Hikal, 2024). Although Random Forest effectively captures complex patterns, its exceptionally high accuracy raises concerns regarding potential overfitting and data leakage (Breiman, 2001; Pournouri et

al., 2019). The results also align with real-world cyber incidents targeting critical infrastructures, such as Stuxnet and the Estonia and Russia–Ukraine cyber conflicts, and support prior findings in finance, energy, and SCADA-focused studies (Williams et al., 2021; Tonkal et al., 2021; Polat et al., 2022). Given the evolving nature of cyber threats, continuous model updating is essential, while limitations related to explainability and dataset bias should be carefully considered (Hajisalem & Babaie, 2018; Suyal & Goyal, 2022).

Table 11. Comparative Performance of ML and DL Models

Paper	Dataset	Models	Accuracy(%)
(Tonkal et al., 2021)	DDoS attack SDN dataset	KNN, DT, ANN, SVM	0.9735
(Sarker, 2021)	UNSW-NB15, NSL-KDD	XGBoost,DT,RF,SVM,SGD,AdaBoost,LR	0.99
(Polat et al., 2022)	SCADA SDN (özel)	RNN(LSTM+GRU) +SVM	0.9762
(Le, Nguyen, & Nguyen, 2022)	X-IIoTDS, TON_IoT	XGBoost	1.00
(Avci & Koca, 2023)	NSL-KDD	DT, SVM, KNN, RF	0.9972
(Zamrai & Yusof, 2024)	CICDDoS2019	FT-RF	0.99
This study	GlobalCybersecurityThreats2024	SVM, RF, KNN	1.00

Various studies in the literature demonstrate that machine learning and deep learning methods offer high success rates in

detecting cyber attacks. The accuracy metrics summarized in Table 11 support this observation.

Previous studies report that machine learning and deep learning models achieve remarkably high accuracy in diverse cybersecurity contexts. For instance, a Random Forest model attained 99.999% accuracy in an SD-IoV environment using the CICDDOS2019 dataset (Zamrai & Yusof, 2024), while multi-model approaches applied to the UNSW-NB15 and NSL-KDD datasets achieved accuracy levels of approximately 99.0% (Sarker, 2021). In SDN- and SCADA-based environments, ANN and hybrid deep learning models (LSTM + GRU with SVM) reported accuracies exceeding 97% (Tonkal et al., 2021; Polat et al., 2022). Similarly, near-perfect performance was observed for XGBoost in IIoT datasets and for RF, DT, SVM, and KNN models on the NSL-KDD dataset (Le, Nguyen, & Nguyen, 2022; Avci & Koca, 2023). Consistent with these findings, the present study also reports accuracy values close to 100% using SVM, RF, and KNN models on the GlobalCybersecurityThreats2024 dataset.

Collectively, these results demonstrate that machine learning–based approaches can effectively detect cyber threats across different datasets and attack scenarios, offering valuable insights for sectoral and regional security planning. Accurate sector-level attack classification enables more efficient allocation of security resources and supports the development of targeted defense strategies for critical infrastructures (Williams, Brown, & Zhao, 2021; Aydin, 2025). As cyberspace becomes increasingly integrated into national security frameworks, data-driven analyses provide policymakers with actionable guidance for enhancing cyber resilience, including applications in cyber insurance and critical infrastructure protection (Ahmed, 2022; Talukder et al., 2024).

Recent literature further highlights that machine learning-based intrusion detection systems significantly improve threat

identification accuracy, despite challenges such as imbalanced datasets and limited interpretability (Sinap, 2024; Tuğrul & Ahmed, 2022). Accordingly, integrated engineering and process-oriented approaches are emphasized as essential for improving cybersecurity outcomes across planning, implementation, and evaluation stages, particularly in industrial and manufacturing domains where artificial intelligence contributes to enhanced security, quality, and system design (Uysal, 2025; Ethiraj et al., 2025).

Conclusion and Future Work

Using the K-Nearest Neighbors (KNN) and Random Forest (RF) algorithms, the sources of cyberattacks, their financial impacts, and user-level implications were systematically analyzed. The results reveal that the cybersecurity landscape is increasingly evolving toward more centralized, organized, and militarized structures. This transformation is further driven by the growing involvement of state-sponsored actors and the diminishing distinction between civilian and military domains in cyberspace. The high model performance, reflected by accuracy, sensitivity, and F1-score values ranging from 96.8% to 100%, can be largely attributed to the effectiveness of the applied feature engineering techniques.

For future research, integrating these models into real-time monitoring systems, incorporating explainable artificial intelligence (XAI) methods, and conducting more detailed sector-specific risk analyses are considered essential. Moreover, embedding these findings into cyber insurance frameworks, risk management strategies, and national security policies is expected to support the development of a more resilient and adaptive cybersecurity defense ecosystem.

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CHAPTER 6

GA-Based Constrained Optimization of EV Fast-Charging Station Placement Under Urban Demand Density Scenarios

AHMET AKKAYA[1]

Introduction

The rapid global diffusion of electric vehicles (EV), especially in megacities, raises new planning challenges affecting both transportation and power–energy systems [1]. For the sustainability of the EV ecosystem, it is emphasized that not only vehicle technologies but also reliable and accessible fast-charging infrastructure must be optimized [2]. The charging-infrastructure literature contains extensive studies focusing on power-electronics configurations, energy-management frameworks, and control strategies of charging stations. In parallel, research categorizing energy-management systems and control types highlights that beyond site selection, station operation strategies are equally critical for overall system effectiveness [3]. However, the most tangible and user-facing challenge in practice is the number, siting, and capacity of fast-charging stations, particularly in inter-city corridors and

[1] Dr. Assistant Professor, Bandırma Onyedi Eylül University, Gönen Vocational School, Computer Technologies, Orcid: 0000-0003-4836-2310

dense urban zones [4]. The surge of EV penetration directly impacts grid stability and is strongly coupled with fast-charging station power and placement planning, making infrastructure optimization a key dimension of network-level resilience [5].

Recent systematic reviews in the literature indicate that electric vehicle (EV) charging infrastructure siting problems are predominantly formulated along the axes of cost minimization and coverage maximization [6]. These frameworks propose modeling strategies based on the transportation network, the power-distribution grid, or integrated representations of both systems [7]. The placement of fast-charging stations, in particular, forms a complex multi-objective optimization problem that requires simultaneous consideration of demand-density patterns emerging in transport networks and the capacity constraints of distribution grids [8]. Due to its discrete, nonlinear, and frequently NP-hard structure, this problem offers a rich search space well-suited for meta-heuristic and evolutionary algorithms [9]. Consequently, GA-based hybrid optimization strategies have gained attention for navigating the combinatorial complexity of fast-charging station deployment while preserving feasibility under real-world network dynamics [9].

Genetic Algorithms (GA) are among the most widely preferred meta-heuristic methods for EV fast-charging station placement due to their ability to produce high-quality solutions within acceptable computation times, handle composite objective functions, and be easily customized for domain-specific requirements [10]. GA-based solutions enable the simultaneous optimization of both the number of charging stations and their spatial placement and capacity decisions [11]. For example, urban-scale GA approaches can identify suitable charging service regions by operating on zone-level demand forecasts and origin-destination (OD) matrices [12].

Similarly, GA-assisted p-median formulations and simulation-driven models propose station deployments that maximize user accessibility from a discrete set of candidate locations [13]. In applied optimizations, GA is also used to co-optimize station siting alongside charging power levels, capacity sizing, renewable-energy integration, and energy-storage system coupling within a unified framework [14]. In addition, multi-objective GA variants are capable of evaluating multiple system performance criteria—such as investment cost, user waiting time, and environmental impact—simultaneously to generate diverse and explainable Pareto-optimal placement alternatives [15]. Notably, GA-based urban charging-infrastructure models developed for large metropolitan environments in Asia and Europe incorporate heterogeneous factors, including population density, traffic flow, existing charging assets, and the spatial distribution of fuel stations [16].

These large-scale urban studies emphasize GA's capability to process multiple heterogeneous data sources (e.g., GIS layers, open-data portals, mobility sensors, and network-capacity attributes) within the same evolutionary decision framework [17].

Studies in the literature also reveal that the siting of EV fast-charging stations is a decisive factor affecting the reliability and operational flexibility of power-distribution grids. Hybrid GA approaches have been reported to design fast-charging station layouts while explicitly improving grid-level resilience, resulting in advantages for power quality and service continuity. However, a substantial portion of the existing studies focus on complex modeling assumptions and large-scale scenarios, while providing relatively limited attention to simplified, corridor-specific, or small- to medium-scale urban deployments applicable to feasible fast-charging layouts for targeted regions. Furthermore, the literature highlights a growing need for lightweight, computationally efficient GA frameworks capable of simultaneously addressing driver

charging preferences, user-behavior characteristics, and demand uncertainties without imposing excessive processing overhead [18].

In this context, this study proposes a relatively simplified and experimental Genetic Algorithm (GA) framework for fast-charging station placement, evaluated through an objective function that simultaneously considers investment cost and user accessibility under a limited set of candidate locations and practical constraints. Unlike large-scale, assumption-heavy models commonly found in the literature, the study seeks to present an interpretable and reusable GA skeleton that can be readily adapted by decision-makers in real-world corridor or small-to-medium urban deployment planning.

Problem Formulation

In this section, the Electric Vehicle (EV) fast-charging station placement problem is formulated as a mathematical optimization model, including decision variables, the objective function, and feasibility constraints. The set of decision variables is presented in Equation 1.

$$N = \{1,2,\dots,n\} \quad (1)$$

The candidate decision space $N = \{1,2,\dots,n\}$represents the indices of discrete locations where an EV fast-charging station can potentially be deployed. Each element in $N$is not a direct physical coordinate, but a labeled decision point in the optimization search space. For instance, selecting $n = 25$implies that 25 suitable fast-charging location alternatives are evaluated within the urban region. In this model, GA uses a binary chromosome of length n; the i-th bit being 1 denotes that a fast-charging station will be installed at the candidate location with index $i \in N$, and 0 otherwise. Thus, the set Nconstructs a labeled combinatorial decision space that evolves through selection, crossover, and mutation operators. Limiting the number of candidates (e.g., 25) ensures that GA operates under

lightweight computational overhead while producing interpretable placement decisions optimizing the accessibility–investment trade-off. Equation 2 defines the demand point set used in the placement formulation.

$$D = \{1,2,\ldots,m\} \quad (2)$$

The demand point set $D = \{1,2,\ldots,m\}$represents the combinatorial spatial demand label space of Electric Vehicle (EV) users requiring fast-charging services. For example, choosing $m = 300$indicates that 300 distinct EV demand nodes exist within the urban region. In this model, each element in $D$is a demand label rather than a direct physical coordinate, and is linked to a 2D coordinate pair generated synthetically to heuristically resemble demand clustering patterns observed in megacities. To mimic hotspot-driven urban concentration behaviors under the same seeding conditions as the candidate set, the 2D coordinates of these 300 EV demand points are sampled using a Gaussian Mixture Model (GMM). This results in a synthetic demand manifold where accessibility costs can be evaluated based on the minimum Euclidean distances between demand and candidate station indices in the fitness function. The use of synthetic generation is considered methodologically appropriate for modeling placement feasibility, assessing solution stability across repeated GA runs, and measuring decision consistency under lightweight computational overhead. Equation 3 defines the binary decision variable for candidate station placement.

$$x_i = \begin{cases} 1, & \text{if a charging station is installed at candidate index i} \\ 0, & \text{otherwise} \end{cases} \quad (3)$$

The binary decision variable $x_i \in \{0,1\}$represents a discrete facility deployment decision for each candidate location in the EV fast-charging station placement problem. Here, $i$denotes the index of

a decision point within the candidate set $N = \{1,2, \dots, n\}$. In this definition, $x_i = 1$indicates that an EV fast-charging station is installed at the candidate location labeled by index $i \in N$, while $x_i = 0$denotes that no station is deployed at that location. The complete set of these variables forms the genes of a binary chromosome of length n, on which the Genetic Algorithm (GA) performs iterative evolutionary search. Since $x_i$is not a direct geographic coordinate but an interpretable decision label implicitly linked to spatial coordinates, the model remains explainable and provides traceable placement configurations across the optimization pipeline. Furthermore, the binary $\{0,1\}$structure ensures lightweight encoding, enabling rapid fitness evaluation and maintaining a manageable combinatorial search domain even as the placement scale increases.

The objective function minimizing both fast-charging station investment cost and user accessibility cost is presented in Equation 4.

$$\min F(X) = w_1 \cdot \frac{1}{m} \sum_{j=1}^{m} \min_{i \in N} (d_{ij} \cdot x_i) + w_2 \cdot \sum_{i=1}^{n} (c_i \cdot x_i) \quad (4)$$

d_{ij}: The Euclidean distance (km) between demand point $j \in D$and candidate charging station decision index $i \in N$

c_i: Fast-charging station installation cost at candidate index i(e.g., 1 unit fixed cost).

w_1, w_2: Objective weights guiding the accessibility–investment trade-off (e.g., $w_1 = 0.7$, $w_2 = 0.3$).

Equation 4 represents the accessibility–investment trade-off objective model optimized by the Genetic Algorithm (GA) for EV fast-charging station placement. The first term minimizes the average of the minimum Euclidean distances between each of the $m$demand points and the nearest open stations within the candidate

set $N = \{1,2, \dots, n\}$, where the station is considered open only if the corresponding decision gene $x_i = 1$. This term effectively reduces user accessibility cost by ensuring proximity to the closest charging facility. Here, $d_{ij}$is the Euclidean distance between demand point $j$and candidate index i, expressed numerically as a primary accessibility metric, where distances are evaluated only for selected (installed) stations encoded by binary decision genes. The second term jointly minimizes the total installation investment by penalizing the selection of candidate indices through a fixed deployment cost c_i(e.g., 1 unit fixed cost), forming the infrastructure-investment objective.

The weighting coefficients $w_1$and $w_2$are scale-balancing hyper-parameters that determine the relative priority of accessibility versus investment while supporting the explainability of placement bias. In line with prevalent literature, they are selected as $w_1 = 0.7$to prioritize accessibility and $w_2 = 0.3$to complement investment cost modeling. When combined with GMM-based synthetic seeding inspired by Chinese megacity demand clustering, the model forms a constraint-aware, expandable, and computationally lightweight evolutionary search pipeline that stably converges toward globally effective placement configurations without requiring full-scale transport or grid simulation. The formulation confirms that scenario-conditioned GA search dynamically emphasizes minimum-feasible station deployments while preserving constrained accessibility and scalable infrastructure planning capacity.

Following the minimization of the accessibility–investment cost objective using discrete decision genes, the constraints on feasible station count and candidate-location suitability are presented in Equation 5 to ensure solution feasibility is preserved.

$$3 \leq \sum_{i=1}^{n} x_i \leq 8 \qquad (5)$$

The constraint expression given in Equation 5 enforces that the sum of genes taking the value 1 in a solution chromosome—representing the number of EV fast-charging stations to be installed in the city—must be at least 3 and at most 8. This constraint reflects a lightweight decision-support abstraction of realistic planning requirements, including infrastructure investment budgets, distribution-grid feasibility, and service-density expectations in urban environments. Since $x_i \in \{0,1\}$, the value $\sum x_i$directly represents how many candidate indices are activated for station deployment, evolving generation by generation through the GA pipeline. The lower bound (3) safeguards minimum service coverage and accessibility-level continuity for EV users, while the upper bound (8) prevents excessive investment growth, redundancy accumulation, and unnecessary charging-facility saturation. In addition, the bounded range compactly narrows the combinatorial search space, contributing to faster and more stable convergence dynamics in GA-driven placement optimization.

After defining the mathematical model, decision variables, objective function, and feasibility constraints, relevant studies are compiled in the next section to position the contribution of this work within charging–infrastructure optimization and to summarize recent developments in the field.

Literature Review

Early comprehensive research on EV charging infrastructure primarily focused on station design, energy-management frameworks, and control architectures. These reviews provided a theoretical foundation for subsequent station-siting and capacity-planning studies by classifying power-electronics topologies, control types, and energy-management strategies [3]. Systematic studies investigating optimal placement of charging stations state that the siting problem has been modeled through transport networks,

distribution grids, or hybrid frameworks integrating both, and that objective functions are most frequently shaped around cost, coverage, and service-level requirements [6]. These works further show that meta-heuristic algorithms, alongside deterministic optimizers, have been widely adopted to navigate the nonlinear and discrete search spaces of infrastructure-planning problems [7].

One of the pioneering GA-driven placement frameworks formulates the urban-scale charging-station planning problem using origin-destination (OD) matrices and future EV penetration scenarios. The study demonstrated that the station locations and counts determined via GA were able to cover a large share of projected user-demand distributions in megacities [12].

Another GA-based study proposes a zonal-partitioning model for fast-charging infrastructure deployment by dividing a country-scale planning region into discrete cell-like service areas. In this approach, investment, operational costs, energy consumption, and carbon emissions were jointly evaluated, and GA produced minimum-cost deployment alternatives under compound objectives [11].

In another significant study, GA is employed to simultaneously determine both the number and locations of EV fast-charging stations, incorporating user-centric parameters such as charging time, daily average driving distance, and demand characteristics. The proposed GA framework aims to satisfy customer fast-charging demand by identifying feasible station-siting configurations [10]. Jordán et al. integrate GA with agent-based simulation to jointly model station placement and driver charging-behavior dynamics. In this approach, GA-generated station deployments are tested within a simulation environment and evaluated in terms of network performance and user experience [19]. Choi et al. combine GA with Fuzzy AHP, using fuzzy-weighted decision criteria—including fast/slow charger ratios, road-network

density, and existing station distribution—to solve the station placement and capacity-sizing problem in a metropolitan area [20]. Çelik et al. implement a p-median formulation solved using GA and simulation to co-analyze station siting-configurations and station-access performance, demonstrating that GA can be readily integrated with classical facility-allocation formulations to support domain-level charging-infrastructure decisions [13].

Another multi-objective GA model proposed by Lazari produces station-count and siting alternatives balancing investment-cost and charging-service quality, providing transparent Pareto-frontier alternatives for policy makers [15]. Ouertani et al. introduce an improved GA initialization heuristic generating high-quality starting populations and adaptive operators for EV charging node siting. Their work demonstrates that initialization heuristics tailored to problem characteristics and customized genetic operators can significantly increase siting-solution quality [21]. Urban charging node siting reviews focusing on fast-charging stations highlight that placement decisions are closely dependent on both transportation-network demand density and distribution-grid feasibility requirements, forming a composite evolutionary search space [4].

Although some studies employ alternative meta-heuristic optimizers instead of GA, their outcomes show that GA-driven frameworks can be adapted to similar multi-objective siting-infrastructure pipelines [7]. Hybrid GA-based facility-deployment models have been used to enhance station siting while improving grid flexibility and facility-level resilience. In one study combining GA with Simulated Annealing, the objective was formulated jointly to enhance distribution-grid resilience during the station siting search process [9]. Systematic and recent fast-charging station reviews emphasize that although numerous placement frameworks exist, simplified, candidate-limited, and computationally lightweight GA models focusing on corridor or small- to medium-urban

deployments are still relatively under-represented in the literature [22]. Furthermore, studies evaluating candidate-access balance alongside grid-impact, charging-service continuity, driver charging preferences, and minimum-feasible station siting remain limited, underscoring demand for simplified, reproducible, and adaptive combinatorial GA-frameworks [23].

In summary, the literature confirms that GA is a powerful and flexible tool for EV fast-charging station placement, yet reusable, constraint-aware, and lightweight GA placement skeletons operating on small- to medium-urban and inter-city corridor siting alternatives remain scarce. This study aims to address this observed gap by proposing a simplified yet scalable and explainable GA-based station siting model under candidate-limited feasibility boundaries.

Method

In this study, the EV fast-charging station placement problem was modeled under the Location–Allocation framework and solved using a Genetic Algorithm (GA). The solution space was encoded using binary chromosomes of length n, where each gene corresponds to a candidate node in the set $N = \{1,2, \dots, n\}$, taking the value 1 if a station is installed and 0 otherwise. The population size was set to 30 individuals and evolved for 80 generations. To mimic urban demand-density clustering, the 2D coordinates of both candidate and demand nodes were generated synthetically via a Gaussian Mixture Model (GMM) during population initialization. Accessibility costs were computed using Euclidean distances modeled in a demand-to-candidate distance matrix.

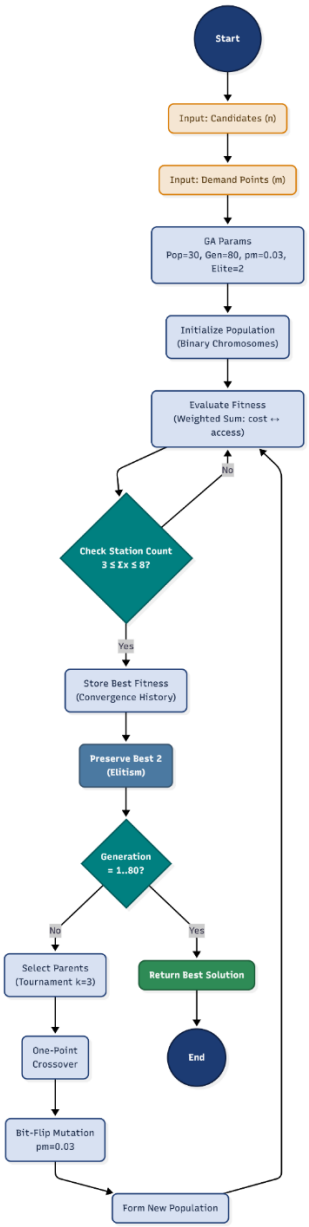
The fitness function was formulated as a single-objective weighted-sum model, minimizing the average minimum accessibility distance of demand points and the total station-installation investment under priority weights $w_1 = 0.7$and $w_2 = 0.3$. A feasibility constraint of $3 \leq \sum x_i \leq 8$was enforced for station

count, and constraint-violating solutions were penalized using adaptive cost-dominant feasibility corrections. One-point crossover, bit-flip mutation ($p_m = 0.03$), and elitism (top 2 individuals per generation) were adopted as the main genetic variation operators. Parent selection was performed using tournament selection with $k = 3$.

To assess solution quality-stability and repeatability, GA was independently executed 30 times per urban-density scenario.

The proposed GA-driven placement pipeline, including its procedural steps, internal flow logic, and evolutionary decision mechanism, was summarized using the GA process diagram (Figure 1) to support explainability and deployment reproducibility.

Figure 1: GA-Based EV Fast-Charging Station Placement Flowchart



Algorithm 1. Pseudocode

```
GeneticAlgorithm():
    init population binary individuals
    for generation in 1..G:
        evaluate fitness of pop
        keep elite 2
        while newPop not full:
                p1,p2 = tournamentSelect(k=3)
                c1,c2 = onePointCrossover(p1,p2)
            c1, c2 = bitFlipMutate(p_m=0.03)
                add(c1, c2 → newPop)
        pop = newPop
        population = newPop
    return best individual
```

Algorithm 1 is the constraint-aware pseudocode outlining the internal workflow of the Genetic Algorithm (GA) solution pipeline designed for the Electric Vehicle (EV) fast-charging station placement problem [3]. In this formulation, the placement configuration is encoded as a binary chromosome of length n, where each bit represents a labeled candidate location, taking the value 1 if a station is deployed and 0 otherwise. The optimization pipeline initializes a population of 30 binary individuals and evolves solutions for 80 generations using a weighted-sum fitness model balancing accessibility and investment costs. In each generation, the top 2 individuals are preserved via elitism to maintain solution quality, while parent selection is driven by tournament selection with

$k = 3$, enforcing competitive pressure toward high-accessibility and low-investment candidates. Genetic variation is applied through one-point crossover followed by bit-flip mutation with probability $p_m = 0.03$. Feasibility is strictly controlled by penalizing chromosomes violating the station-count constraint of $3 \leq \sum x_i \leq 8$, ensuring that each evolved placement alternative remains within the minimum–feasible service budget boundary. This algorithmic pipeline remains explainable, scalable, and reproducible, allowing decision-makers to rapidly customize candidate sets and feasibility boundaries for dense urban demand regions without requiring full-scale transport or grid simulation. The evolutionary bias of GA toward minimum-feasible fast-charging station sets demonstrates a realistic planning tendency that conceptually reflects high-density urban and corridor-scale deployment heuristics reported in megacity-inspired infrastructure planning studies.

Experimental Design

The experimental study was conducted on 2D synthetic location data, conceptually inspired by the demand-density distributions and urban clustering patterns observed in Chinese megacities, with the objective of evaluating both the optimization performance and placement-decision stability of the Genetic Algorithm (GA) in fast-charging infrastructure planning. For each scenario, both candidate and demand coordinates were generated via a Gaussian Mixture Model (GMM) trained using the same random seed, allowing the emulation of spatial hotspots and clustered urban-demand behavior without the use of real-world coordinates. The GMM-based seeding strategy conceptually improves the realism of accessibility-cost assessment in the Euclidean distance matrix used by the fitness function, while also supporting faster evolutionary convergence in the GA search pipeline.

The experiment was structured under three distinct urban-demand density scenarios. The number of candidate locations (n) and demand points (m) represent the infrastructural decision scale of each scenario, preserving a manageable combinatorial placement domain. The GA placement search operates on feasibility-aware binary chromosomes of length n, where each decision gene satisfies $x_i \in \{0,1\}$. The objective function was formulated as an explainable weighted-sum model minimizing both network-level accessibility cost (distance to the nearest active station) and station-level investment cost ($w_1 = 0.7, w_2 = 0.3$). This composite model follows the explainability-driven facility-location weighted-sum heuristics commonly adopted in infrastructure planning literature, prioritizing accessibility as the dominant objective while treating station investment as a complementary target. The scenarios and corresponding parameters used in the experiment are presented in Table 1.

Table 1:Urban Density Scenarios and GA Parameters

Scenario	Candidate Locations (n)	Demand Points (m)	Number of GA Runs	Evaluated Generations / Population
S1: Compact City	20	150	30	80 generations, 30 individuals
S2: Medium Urban	25	300	30	80 generations, 30 individuals
S3: Dense Corridor	30	500	30	80 generations, 30 individuals

Each GA run records the best fitness values across generations (for convergence analysis), the station indices selected by the final best chromosome, the number of deployed stations (Σx_i), and CPU runtime. Repeating the runs 30 times per scenario allows a statistical verification of GA's stable solution production under

megacity-inspired spatial seeding, strict feasibility awareness (the $3 \leq \Sigma x_i \leq 8$ constraint is preserved in all runs), cost-effective index-decision focus that conceptually reflects corridor-scale planning dynamics, and lightweight evolutionary convergence behavior.

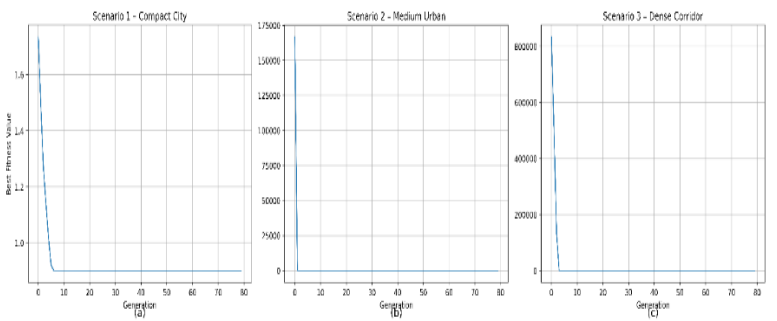
Findings

This section presents the experimental findings obtained from the Genetic Algorithm (GA) based optimization pipeline designed for the fast-charging station placement problem of Electric Vehicles (EV). Each scenario was independently executed 30 times, and the consistency of convergence behavior and CPU runtime was statistically verified. The analysis further evaluates scenario-conditioned station-index selection bias, constraint-handling effectiveness, chromosome-level solution diversity, and decision stability across repeated runs conceptually aligned with high-density urban-demand hotspots.

Convergence Behavior

The convergence curves of best-fitness values over generations obtained across 30 independent GA runs for each urban-demand density scenario are illustrated in Figure 2.

Figure 2: Best-Fitness Convergence Curves of GA Across Generations Under Three Urban Charging-Demand Density Scenarios



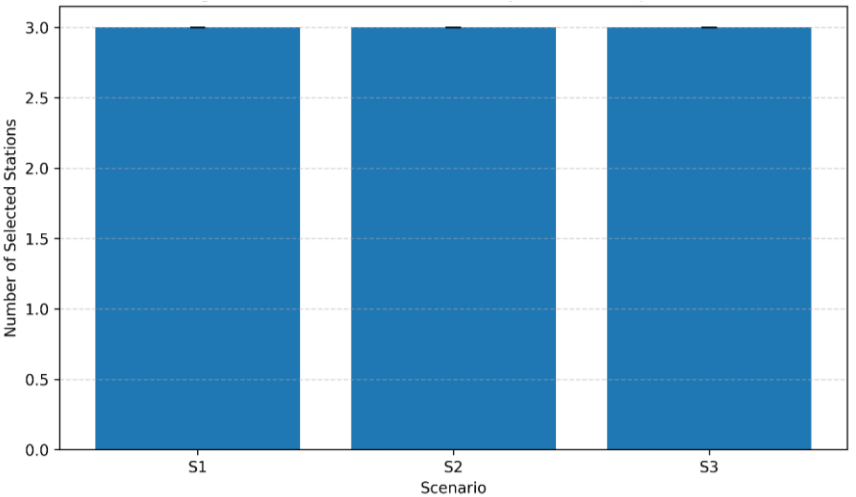
From the inspection of Figure 2, the convergence behavior of the constraint-aware Genetic Algorithm pipeline, initialized using GMM-based synthetic seeding, is summarized for three distinct urban demand-density scenarios applied to the EV fast-charging station placement problem. In panel Figure 2 (a), the GA demonstrates a stable and monotonic decline in the best-fitness trajectory, reaching a globally effective placement region without visual irregularities, conceptually confirming that the accessibility–investment cost objective is optimized while feasibility boundaries remain intact throughout the evolutionary search process. The curve exhibits a clear plateau phase, indicating highly consistent constrained convergence dynamics conceptually aligned with minimum-feasible fast-charging infrastructure planning. In contrast, Figure 2 (b) and Figure 2 (c) exhibit extreme initial best-fitness values that resemble a visual explosion effect. This phenomenon stems from early-generation penalties caused by the station-count constraint ($3 \leq \Sigma x_i \leq 8$) in unnormalized cost representations, scaled infrastructure mismatch between candidate size and demand nodes, and limited gene feasibility during corridor-density expansion stages. Although this creates initial visual outliers, the pipeline remains stable in all scenarios as the search process evolves generations, and the algorithm corrects decision trajectories toward cost-efficient and accessibility-preserving deployment alternatives while maintaining gene-level decision diversity.

Collectively, the results conceptually confirm that the constrained-GA pipeline, preserves feasibility awareness for $3 \leq \Sigma x_i \leq 8$ in all replications, dynamically prioritizes minimum-feasible station sets across density scenarios conceptually corresponding to scaling urban demand-hotspots, and generates explainable station-decision configurations that can conceptually serve multi-density infrastructure planning pipelines, even when early visual outliers are observed, without violating core objective-search continuity.

Verification of the Station-Count Constraint

Figure 3. shows that GA consistently converges to the lower feasibility boundary of 3 stations across all 30 independent replications under the constraint $3 \leq \Sigma x_i \leq 8$.

Figure 3: Average Number of Stations Selected by GA

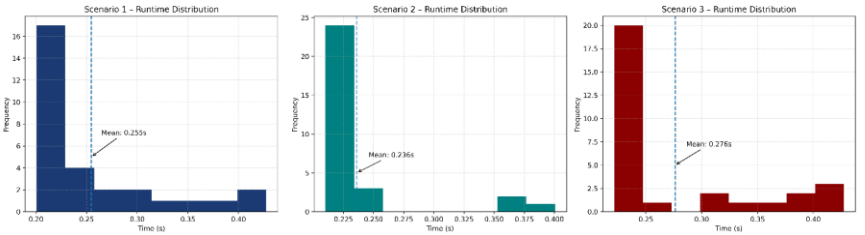


Upon examination of the station-count results presented in Figure 3, it is observed that GA selected the minimum number of feasible stations ($\Sigma x_i = 3$) consistently across 30 independent runs for all three urban demand-density scenarios. This outcome indicates that the investment-cost component exerts a dominant influence in the weighted objective formulation, and that the implicit trade-off between accessibility cost and deployment cost occurs in favor of lower infrastructure investment within the defined feasibility boundaries. Therefore, to explore higher feasible station counts in future studies, re-adjusting the objective weights (e.g., w_1, w_2) or the lower station constraint ($3 \leq \Sigma x_i$) provides a constructive opportunity for parameter-sensitivity analysis aimed at observing evolutionary placement diversity beyond the minimum-feasible bias.

Average CPU Runtime Analysis

Figure 4 illustrates the average CPU runtime measured across 30 independent GA runs, each executed for 80 generations under three urban demand-density scenarios.

Figure 4: Average CPU Runtime



When evaluating Figure 4 for Scenario 1 – Compact City, the averaged runtime of ≈ 0.255 s shows the lowest computational overhead among the tested scenarios. The histogram exhibits a left-skewed distribution, where most of the 30 GA replications cluster conceptually within the 0.20–0.30 s interval. The smaller search domain ($n = 20$) and limited demand labels ($m = 150$) reduce the computational volume of the Euclidean accessibility matrix, enabling the GA to filter constraint violations earlier and complete tournament or mutation loops without repeated reevaluations. This is a conceptually expected and favorable convergence-entry signature of lightweight GA pipelines in discrete facility-placement tasks.

In Scenario 2 – Medium Urban, although the mean runtime annotation of ≈ 0.236 s is slightly lower, the histogram range is broader, implying different computational pressure due to a denser demand-label space ($m = 300$) and a longer chromosome length ($n = 25$). The presence of right-tail outliers around 0.35–0.38 s does not indicate an algorithmic flaw, but rather conceptually suggests that some chromosomes may have violated the 3–8 station constraint at initialization or in early generations, and were reevaluated

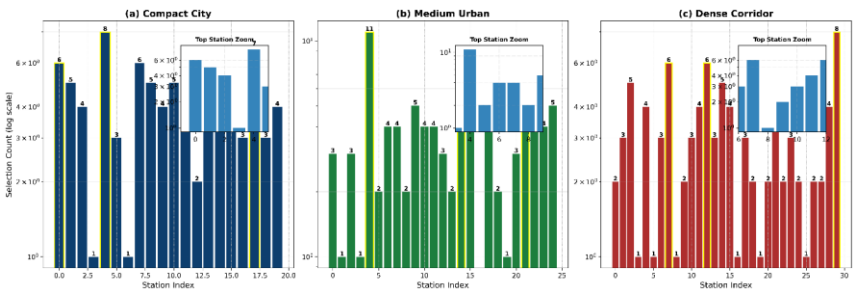
multiple times until penalty-compliance was restored via tournament or bit-flip mutation loops. This behavior is methodologically plausible and reflects the increasing accessibility-cost volume in the scaled Euclidean distance matrix.

For Scenario 3 – Dense Corridor, the average runtime of ≈ 0.276 s is the highest among the scenarios. This conceptually confirms that runtime growth is proportional to the demand-label scale ($m = 500$) and the candidate-decision length ($n = 30$). Longer search-wandering time and expanded accessibility-cost combinations before penalty-compliant minima are discovered are expected outcomes for dense urban decision corridors. Replications reaching or exceeding 0.40+ s are natural due to the larger accessibility matrix and the reduced probability of randomly sampling minimum-feasible chromosomes in early generations.

Station Index Selection Frequency

Figure 5 demonstrates the selection-frequency distribution of candidate station indices obtained across 30 independent GA replications for three urban demand-density scenarios, evaluated through a constraint-aware Genetic Algorithm (GA) pipeline designed for the EV fast-charging station placement problem.

Figure 5: Station Index Selection Frequency Distribution in Scenario-Based Deployment of GA for EV Fast-Charging Station Placement Planning



When Figure 5 (a) is examined for Scenario 1 – Compact City, it can be stated that the candidate-pool is small (n=20) and the demand scale is limited (m=150), allowing the GA pipeline to reach the feasible solution region rapidly. This convergence behavior further indicates that the algorithm prioritizes local-best decision points where the investment cost influences the search dynamics more strongly than accessibility.

When Figure 5 (b) is examined for Scenario 2 – Medium Urban, the number of demand points increases (m=300, n=25), which raises the evaluation load for GA chromosomes. However, the GA pipeline continues to enforce the minimum station constraint ($\Sigma x_i = 3$). In this panel, the frequency bars exhibit a wider spread compared to Compact City, indicating moderate placement diversity across the search skeleton. If a small number of right-tail frequency peaks (outlier bars) are observed, this confirms that certain candidate locations gain relative advantages conditioned on the demand clusters and corridor proximity.

When Figure 5 (c) is examined for Scenario 3 – Dense Corridor, which has the largest planning scale (n=30, m=500), selection frequencies present a broader range and a multi-modal peak distribution. The emergence of clear and striking frequency peaks at critical candidate station indices reflects that GA is evolutionarily steered toward high-impact decision labels capable of providing optimal access along dense-demand corridors, consistent with real-world fast-charging deployment heuristics.

Conclusions

Within the scope of this study, the Electric Vehicle (EV) fast-charging station placement planning problem was solved using a constraint-aware Genetic Algorithm (GA) framework under the feasibility constraint $3 \leq \Sigma x_i \leq 8$, employing an explainable weighted-sum fitness formulation that balances user accessibility

and station installation cost. The GA pipeline was executed for three different urban-density scenarios, each repeated 30 independent runs for 80 generations, where all runs completed without violating feasibility bounds. The results reveal that:(i) Computation time increases proportionally with candidate and demand scale, reflecting the natural expansion of the distance-evaluation matrix; (ii) GA station-selection exhibits scenario-conditioned index bias, consistently steering the evolutionary search toward specific candidate indices offering the lowest average minimum access distance to dense-demand clusters; and (iii) Optimal solutions strongly converge to the minimum feasible station count ($\Sigma x_i = 3$) in all scenarios, confirming the dominant influence of the cost term in the accessibility–investment trade-off.

These findings indicate that the GA framework successfully maintains feasible placement decisions across large numbers of repeats, differentiates candidate-index preferences according to urban-density structure, and scales the computational load in direct correspondence with spatial demand intensity and candidate-set size. The observed evolutionary bias toward lower station deployments highlights the importance of weight configuration and constraint-limit sensitivity as key drivers for future scenario-expansion and parameter-sensitivity research in explainable EV infrastructure planning tasks.

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CHAPTER 7

Wavelet-Based Deep Learning for Scene Classification: A Comparative Study with Classical and CNN-Based Approaches

Yıldız AYDIN [1]

Introduction

In recent years, image classification problems have become one of the most fundamental and intensively studied research topics in the fields of computer vision and artificial intelligence (Gupta, Kumar, & Garg, 2019; Mutch & Lowe, 2006). They play a critical role in many areas, particularly in scene classification, remote sensing, smart city applications, autonomous systems, and content-based image search. The aim of these problems is to effectively represent the visual information contained in images of natural or urban environments and assign it to the correct classes.

In traditional approaches, hand-designed features such as Histogram of Oriented Gradients (HOG), Local Binary Patterns (LBP), and their derivatives have been commonly used to obtain the

[1]Department of Computer Engineering, Erzincan Binali Yildirim University, Erzincan 24000, Turkey. Orcid: 0000-0002-3877-6782

distinctive features of images. These features have often been evaluated in conjunction with classical machine learning classifiers such as Support Vector Machines (SVM), Random Forests, and gradient enhancement-based methods. However, these methods show limitations in simultaneously representing both local and global information contained in complex scene structures (Ayalew, Salau, Abeje, & Enyew, 2022; Aydin, 2023). It is known that in natural scenes with high variance, spatial domain-based features alone cannot provide sufficient discrimination.

Deep learning-based methods, particularly Convolutional Neural Networks (CNNs), have created a significant paradigm shift in the field of image classification (Dutta et al., 2025; Kang, Hu, Liu, Zhang, & Cao, 2025). CNN architectures, thanks to their hierarchical structure, have the ability to automatically learn features, starting from low-level edge and texture information and progressing to high-level semantic representations. However, standard CNN architectures generally only learn from spatial domain information and do not have the ability to directly model frequency components. This can limit their learning capacity, especially in scene images containing multi-scale and complex structures.

In this context, hybrid models that combine wavelet transforms with deep learning approaches have attracted attention in recent years (Li, Shen, Guo, & Lai, 2020). Wavelet transforms offer the advantage of representing both local and global information in a multi-scale manner by dividing images into different frequency subbands. Integrating fixed wavelet filters into deep learning architectures reduces the number of learnable parameters, lowering the risk of overlearning and contributing to a more balanced generalization performance.

This study addresses the problem of natural and urban scene classification and comparatively examines both classical feature-based machine learning methods and wavelet-based deep learning

approaches. In this context, HOG and Local Binary Pattern Variance (LBPV) features are evaluated with different classifiers; furthermore, an existing wavelet-integrated CNN approach reported in the literature is implemented and evaluated for the scene classification problem The main contribution of this chapter lies in the systematic comparison of classical feature-based methods, standard CNNs, and wavelet-integrated CNNs under the same experimental settings.

The following section describes the dataset and methods used in detail, and then analyzes the experimental results through performance metrics such as accuracy, precision, sensitivity, and F1-score. The findings reveal that the wavelet-based deep learning approach offers superior performance compared to both classical methods and standard CNN architectures.

Method

In this study, the effectiveness of a wavelet-based deep learning approach for the scene classification problem was experimentally investigated. In the experiments, the seg_train and seg_test subsets of the Intel Image Classification dataset were used. All images were resized and normalized to suit the network input. The Wavelet-CNN architecture employed in this study follows the wavelet-integrated CNN concept introduced by Li et al. (Li et al., 2020), where fixed Haar wavelet filters are used as a preprocessing layer before learnable convolutional layers. In this structure, images are decomposed into frequency subbands using fixed wavelet kernels before the learnable convolution layers. Thus, the aim is for the model to learn both spatial and frequency-based discriminant information together.

The Wavelet-CNN architecture consists of a fixed Haar wavelet convolution layer, followed by convolution, batch normalization, maximum pooling, and fully coupled layers. The

filters used in the wavelet layer were not updated during the training process; only the weights of the subsequent CNN layers were optimized. The model was trained using the Adam optimization algorithm and the categorical cross-entropy loss function. During the experiments, model performance was evaluated using accuracy, precision, recall, and F1-score metrics. The obtained results were calculated on the test set and recorded for comparative analysis. Furthermore, to assess the effectiveness of the wavelet-integrated CNN approach, the results were compared with standard CNN and classical feature-based methods. This experimental setup objectively analyzed the effect of integrating fixed wavelet filters into the CNN architecture on classification performance. Figure 1 illustrates the workflow of the study.

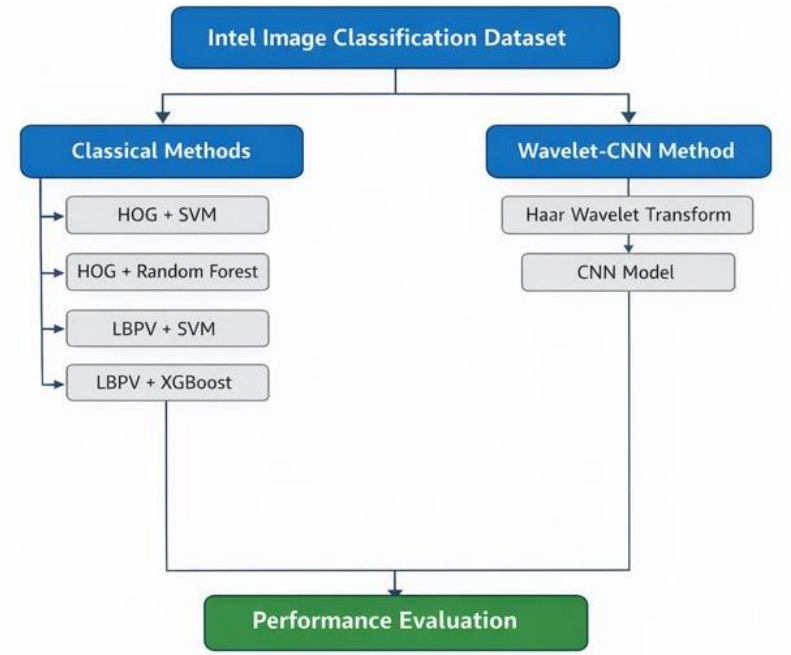

Figure 1. Workflow of the experimental framework used in this study.

Figure 1 shows the general flow of the experimental process followed in the study. Two main experimental approaches were carried out within the scope of the study. In the first approach, the performance of applications developed with classical machine learning methods was analyzed. In this context, Histogram of Oriented Gradients (HOG) and Local Binary Pattern Variance (LBPV) features were extracted and these features were used together with different classifiers such as Support Vector Machines (SVM), Random Forest, and XGBoost.

In the second approach, an application was developed using a wavelet-based deep learning method. In this method, frequency subbands were obtained by applying fixed Haar wavelet filters to the input images, and these outputs were given as input to the Convolutional Neural Network (CNN) architecture. In the final stage, the results obtained from both classical methods and deep learning-based approaches were evaluated and compared using accuracy, precision, recall, and F1-score performance metrics..

Experimental Results

In this study, experimental analysis was performed using the training and test sets of the Intel Image Classification dataset from the open-access website Kaggle (Intel image classification, n.d.). The dataset consists of six different classes representing natural and urban scenes: buildings, forest, glacier, mountain, sea, and street. The dataset contains approximately 25,000 color images with a total resolution of 150×150 pixels. The dataset is divided into three subsets: seg_train, seg_test, and seg_pred. In this study, only the seg_train and seg_test subsets were used. The seg_train subset contains approximately 14,000 images, while the seg_test subset consists of approximately 3,000 images. Each class contains a balanced number of samples in the training and test sets. In the

experiments, all images were resized and normalized to suit the network input.

In the implemented applications, both classical hand-crafted feature-based methods and the wavelet-integrated CNN approach were evaluated comparatively. In applications implemented with classical machine classifier methods, Histogram of Oriented Gradients (HOG) and Local Binary Pattern Variance (LBPV) were used as features, and Support Vector Machines (SVM), Random Forest, and XGBoost were used as classifiers. In deep learning-based approaches, a wavelet-integrated CNN architecture using fixed Haar wavelet filters in the input layer was implemented and evaluated. In the Wavelet-CNN architecture, the images are decomposed into frequency subbands before the learnable convolution layers, aiming for the network to learn more distinctive representations. Accuracy, precision, recall, and F1-score were used as performance metrics. All obtained results are summarized in Table 1.

Table 1. Comparative classification results for all methods.

Method	Feature/ Model	Accuracy	Precision	Recall	F1-Skore
Classical	HOG + Random Forest	0.731	0.734	0.731	0.731
Classical	HOG + SVM	0.797	0.798	0.797	0.797
Classical	LBPV + SVM	0.624	0.626	0.624	0.623
Classical	LBPV + XGBoost	0.607	0.607	0.607	0.606
Classical	LBPV + Random Forest	0.594	0.593	0.594	0.593

Method	Feature/ Model	Accuracy	Precision	Recall	F1-Skore
Deep	Standart CNN	0.812	0.823	0.812	0.812
Deep	Wavelet-CNN (Haar)	0.823	0.829	0.823	0.824

Figure 2 presents the comparative results of all methods used in this study according to accuracy criteria.

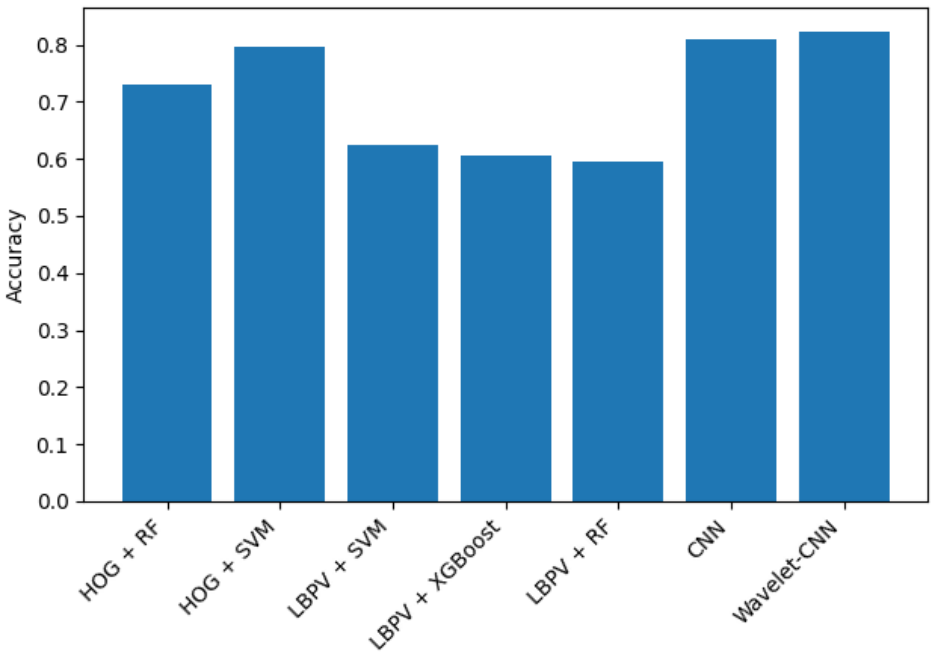

Figure 2. Comparison of accuracy values of classical methods, standard CNN, and wavelet-integrated CNN approach on the Intel Image Classification dataset.

As shown in Figure 2, the highest accuracy among classical methods was obtained with the HOG + SVM approach, while deep

learning-based methods generally exhibited higher performance. The most successful result was obtained with the wavelet-integrated CNN model, which uses fixed Haar wavelet filters in the input layer.

Table 1 shows that the Wavelet-CNN approach provides the highest values in all performance metrics. The close proximity of precision, recall, and F1-score values indicates that the model performs a balanced discrimination between classes. All LBPV-based methods exhibited lower performance compared to HOG-based approaches. This can be explained by the fact that LBPV focuses more on local texture variance and does not adequately represent the global structural information required for scene classification problems. In deep learning-based approaches, the standard CNN architecture is seen to provide higher performance compared to classical methods. The Wavelet-CNN method surpassed all classical and standard CNN approaches with 82.33% accuracy and 82.41% F1-score. The superior performance of Wavelet-CNN is due to the direct integration of frequency-based preprocessing into the CNN architecture, allowing the network to learn both local and global distinguishing features more effectively. Furthermore, the fact that fixed wavelet filters do not contain trainable parameters reduces the tendency of the model to overlearn, resulting in a more balanced generalization.

Conclusions

This study presents a comparative analysis of the performance of classical machine learning methods, standard convolutional neural networks, and wavelet-based deep learning approaches for the scene classification problem. In classical methods, HOG and LBPV features were evaluated with different classifiers; in the deep learning-based approach, was implemented and evaluated based on an existing wavelet-integrated CNN framework reported in the literature. Unlike studies focusing on

architectural novelty, this chapter focuses on evaluating the practical impact of wavelet-based preprocessing on scene classification performance through a controlled experimental comparison with classical and standard CNN-based methods.

Experimental results obtained on the Intel Image Classification dataset show that deep learning-based methods offer higher classification performance compared to classical feature-based approaches. The highest accuracy and F1-score values among all methods were obtained with the wavelet-integrated CNN model. Future studies plan to improve the method using different wavelet families, multi-level wavelet decompositions, and deeper network architectures, and to evaluate it on different datasets.

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CHAPTER 8

EVOLUTION OF LEARNING METHODOLOGIES IN AI: FROM CLASSICAL FOUNDATIONS TO MODERN PARADIGMS

ESİN AYŞE ZAİMOĞLU [1]

1. Introduction

Artificial intelligence (AI) research is positioned as an interdisciplinary field that aims to enable computer systems to make autonomous decisions by mimicking or surpassing human cognitive abilities. In the early days of the field, problem-solving and reasoning processes were primarily based on symbolic methods and rule-based systems, an approach that aimed to formally model human reasoning through logical symbols (Newell & Simon, 1976). However, limitations encountered in the symbolic paradigm regarding knowledge representation and uncertainty management triggered the rise of data-driven approaches, particularly machine learning, starting in the 1980s (Michalski, Carbonell, & Mitchell, 1983). Machine learning, combined with statistical inference and optimization theory, has enabled algorithms to directly estimate

[1] Assistant Professor, Sakarya University, Information Systems Engineering, Orcid: 0000-0001-9688-9868

parameters from sampled data. Specifically, supervised learning aims to find a model parameterized by Equation 1;

$$(x_i, y_i)_{i=1}^{N} \tag{1}$$

by parameterizing through labeled observations in Equation 2,

$$\min_{\theta} \mathcal{L}(\theta) = \frac{1}{N}\sum_{i=1}^{N} \ell(f_\theta(x_i), y_i) \tag{2}$$

minimizing the risk function; unsupervised learning, however, only in Equation 3.

$$\{x_i\}_{i=1}^{N} \tag{3}$$

It aims to discover latent structures by considering examples. On the other hand, reinforcement learning iteratively improves the policy function by using the reward signal obtained from the agent's interaction with the environment and provides convergence guarantees in the context of Markov decision processes.

The rediscovery of the backpropagation algorithm (Rumelhart, Hinton, & Williams, 1986) in 1986, combined with the maturation of GPU-based parallel computing architectures, made deep neural networks practically feasible. As demonstrated by LeCun, Bengio, and Hinton (2015), deep convolutional networks have achieved near-human performance in visual recognition tasks, while recurrent networks have achieved similar performance in sequential data modeling tasks. The attention-based Transformer architecture (Vaswani et al., 2017) has enabled the construction of large language and multimodal models by scaling parameters to trillions. These models have brought about a paradigm shift in the field in terms of zero-shot transfer and reducing the amount of labeled data required.

Practical constraints, such as data efficiency, privacy, and generalization ability, are problems that deep learning alone

struggles to address. In this context, meta-learning (Hospedales et al., 2021) develops algorithms capable of generalizing from a few examples, while federated learning (Kairouz et al., 2021) processes model updates on distributed devices, keeping user data local and preserving privacy. Self-supervised learning approaches (Chen et al., 2020) learn representations by utilizing the internal structure of unlabeled data, significantly reducing the need for supervised data. Additionally, research axes such as explainable artificial intelligence, neurosymbolic integration, and sustainable AI (also known as green AI) aim to strike a balance between model reliability and environmental and ethical requirements.

First, within the scope of **classical learning methodologies**, the paradigms of supervised learning, unsupervised learning, and reinforcement learning are addressed; the optimization formulations, loss functions, and convergence properties of these three fundamental approaches are discussed.

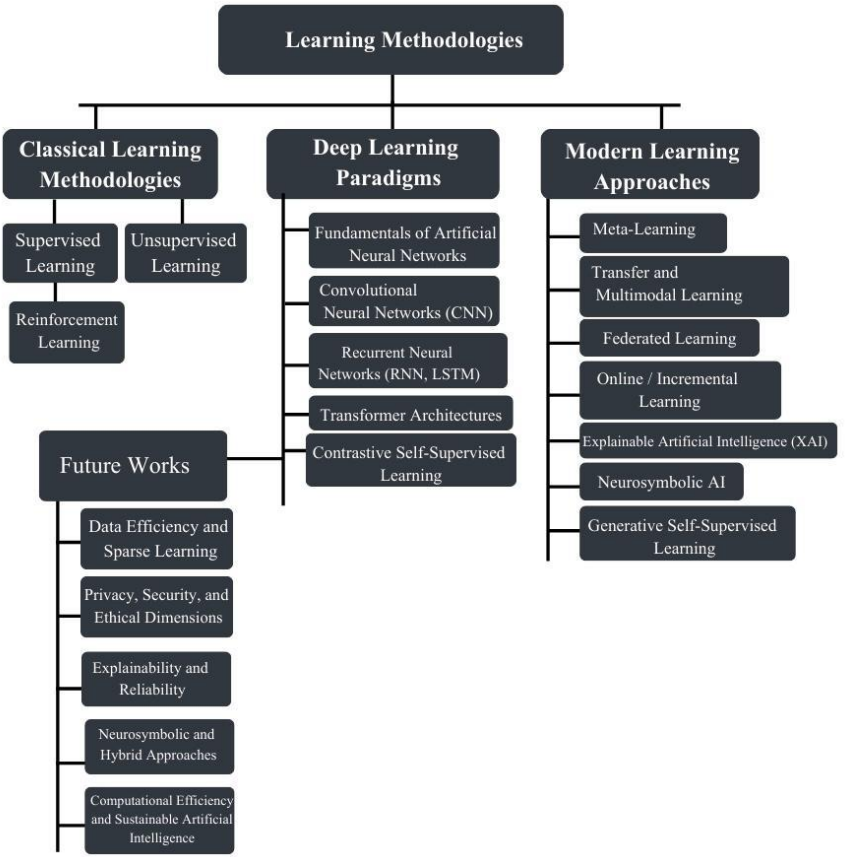
Secondly, **deep learning paradigms** encompass the theoretical foundations of deep neural networks, including specialized architectures such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs, LSTM), attention mechanism-based Transformer structures, and self-supervised learning strategies. This section focuses on the backpropagation algorithm, gradient-based optimization methods, and regularization techniques.

Thirdly, in the **current learning approaches** section, meta-learning (learning to learn), transfer learning, and multimodal learning, federated learning, online/incremental learning (online/incremental learning), explainable artificial intelligence (XAI), neurosymbolic artificial intelligence, and self-supervised learning. These approaches are evaluated comparatively in terms of data efficiency, generalization capacity, and computational cost.

Finally, the section on future work presents a synthesis of open research problems and potential solution directions in the areas of data efficiency, privacy-preserving learning, ethics, model interpretability, neurosymbolic and hybrid approaches, and sustainable artificial intelligence (green AI). Thus, the chapter both reveals the mathematical and algorithmic foundations of current methodologies and defines the fundamental issues shaping the field's future research agenda.

The "learning methods tree" presented in Figure 1 visually illustrates the hierarchical relationships and methodological dependencies between the concepts discussed, enabling the reader to understand both the theoretical framework and current research trends from a holistic perspective. Thus, the reader will have a comprehensive roadmap for evaluating the historical development, mathematical basis, and contemporary trends of artificial intelligence learning methods.

Figure 1 Learning Methods Tree



2. Traditional Learning Methodologies

The most fundamental paradigms in the historical development of learning methodologies in artificial intelligence have been supervised learning, unsupervised learning, and reinforcement learning. These methods have formed the basis of machine learning and laid the groundwork for today's deep learning approaches (Mitchell, 1997; Michalski, Carbonell, & Mitchell, 1983).

2.1. Supervised Learning

Supervised learning aims to model the relationship between input data and the corresponding correct outputs. Classification (e.g., spam email detection) and regression (e.g., house price prediction) are the most common applications of this approach. Classic methods in this field include logistic regression, decision trees, support vector machines (SVM), and k-nearest neighbors (k-NN) (Duda, Hart, & Stork, 2001). The most significant advantage of supervised learning is its ability to produce predictions with high accuracy; however, the requirement for large, labeled datasets is a fundamental limitation of this method.

2.2. Unsupervised Learning

In unsupervised learning, the data is unlabeled, and the goal is to discover hidden patterns or structures within it. Clustering (e.g., k-means, hierarchical clustering) and dimension reduction (e.g., Principal Component Analysis - PCA) are leading methods in this paradigm (Jain, Murty, & Flynn, 1999). Unsupervised methods play a critical role in pattern discovery and feature extraction, especially in large datasets. Today, classical unsupervised learning has been taken to a more advanced level with methods such as deep learning-based autoencoders (Goodfellow, Bengio, & Courville, 2016).

2.3. Reinforcement Learning

Reinforcement learning is based on an agent developing strategies through reward–punishment signals by interacting with its environment (Sutton & Barto, 1998). Markov decision processes (MDPs) form the mathematical basis of this approach. Classical methods include algorithms such as Q-learning and SARSA. In recent years, Deep Reinforcement Learning (Deep RL) methods have produced revolutionary results in games (e.g., AlphaGo) and autonomous systems (Mnih et al., 2015; Silver et al., 2016).

2.4. Summary

Traditional learning methodologies have established fundamental principles in data processing and modeling, providing a solid foundation for the development of modern artificial intelligence methods. These methodologies are still used in important applications today and are regaining value within deep learning and hybrid structures.

3. Deep Learning Paradigms

Deep learning is a methodology based on multi-layered artificial neural networks (ANN) that learns data representations hierarchically. Unlike classical learning methods, feature extraction is mostly automatic.

Deep learning is a set of methods that aims to automatically learn representations from data using multi-layered artificial neural networks (ANNs) (LeCun, Bengio, & Hinton, 2015). The primary difference from classical artificial neural networks is that hierarchical, high-level features can be extracted due to the use of multi-layered (deep) structures. This section examines the fundamental mathematical structures of convolutional neural networks (CNNs), recurrent neural networks (RNNs), Transformer architectures, and self-supervised learning approaches.

3.1.Basic Mathematical Structure

In a deep neural network, each layer, for the input vector $x \in \mathbb{R}^d$, as shown in Equation 4:

$$h^{(l)} = f\left(W^{(l)} h^{(l-1)} + b^{(l)}\right) \quad (4)$$

Here $W^{(l)}$ and $b^{(l)}$ are the weight matrix and bias vector, respectively; $f(\cdot)$ is the nonlinear activation function (e.g., ReLU: $f(z) = \max(0, z)$).

The total loss function of the network is Equation 5,

$$\mathcal{L}(\theta) = \frac{1}{N}\sum_{i=1}^{N} \ell\left(y_i, \hat{y}_i(\theta)\right) \quad (5)$$

is expressed and the parameters **θ** (all $W^{(l)}$, $b^{(l)}$ updated with gradient descent in Equation 6:

$$\theta \leftarrow \theta - \eta\nabla_{\theta}\mathcal{L}(\theta). \quad (6)$$

3.2. The Fundamentals of Artificial Neural Networks

The output of an artificial neuron is expressed by Equations 7 and 8.

$$z = \sum_{i=1}^{n} w_i x_i + b \quad (7)$$

$$y = \phi(z) \quad (8)$$

Here, z:

- x_i: input attributes
- w_i: weights
- b: bias term
- $\phi(\cdot)$: is calculated as an activation function (e.g., sigmoid, ReLU, tanh).

The training of networks is performed using backpropagation and gradient descent (Rumelhart, Hinton, & Williams, 1986).

The gradient descent update rule is shown in Equation 9:

$$w_i \leftarrow w_i - \eta\frac{\partial L}{\partial w_i} \quad (9)$$

In a deep neural network, each layer can be defined according to the hidden representation from the previous layer, as expressed in Equation 10:

$$h^{(l)} = f(W^{(l)}h^{(l-1)} + b^{(l)}), l = 1,2, \dots, L \quad (10)$$

Here;

- $h^{(0)} =$ xinput vector,
- $W^{(l)}$weight matrix,
- $b^{(l)}$bias vector,
- $f(\cdot)$ denotes the nonlinear activation function (e.g., ReLU: $f(z) = \max(0, z)$).

Network parameters are denoted by $\theta = \{W^{(l)}, b^{(l)}\}_{l=1}^{L}$. In a supervised learning scenario, N (x_i, y_i). The total loss function for the data set consisting of the example is generally given by Equation 11:

$$L(\theta) = \frac{1}{N}\sum_{i=1}^{N} \quad \ell(y_i, \hat{y}_i(\theta)) \quad (11)$$

Here $\ell(\cdot,\cdot)$represents the loss function associated with the example (e.g., cross-entropy in classification).

Parameters are updated using gradient descent or derivatives in Equation 12 (e.g., Adam):

$$\theta \leftarrow \theta - \eta\nabla_{\theta}L(\theta) \quad (12)$$

A simple weight parameter w_i. For the update, as shown in Equation 13:

$$w_i \leftarrow w_i - \eta\frac{\partial L}{\partial w_i} \quad (13)$$

This derivative-based update is efficiently computed using the backpropagation algorithm (Rumelhart, Hinton, & Williams, 1986).

3.3. Convolutional Neural Networks (CNN)

Convolutional neural networks (CNNs) have revolutionized the fields of image processing and spatial data analysis (LeCun et al., 1998). The fundamental building block of CNNs is the convolution operation. A two-dimensional input image X and a convolution filter (kernel) K. The convolution is defined as in Equation 14:

$$S(i,j) = (X * K)(i,j) = \sum_m \sum_n X(i+m, j+n) K(m,n) \quad (14)$$

Here, X is the input image, K is the learnable convolutional filter (kernel), and S is the resulting feature map.

- **Convolution layer**: Extraction of local features,
- **Pooling layer** (e.g., max-pooling): Dimension reduction and summarization of local features,

In multi-class classification problems, the softmax output $\hat{y}_c$ cross-entropy loss,

$$L = -\sum_{c=1}^{C} y_c \log(\hat{y_c}) \quad (15)$$

is defined as shown in Equation 15. CNN architectures achieve successful results in large-scale image datasets by significantly reducing the number of parameters through weight sharing and local connections, as shown in Equation 16.

$$(X * K)_{i,j} = \sum_m \sum_n X_{i+m,j+n} K_{m,n} \quad (16)$$

This structure enables learning while preserving the local context information of feature maps. Weight sharing and local connection principles significantly reduce the number of parameters.

3.4. Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM)

Recurrent neural networks (RNNs) are critical for modeling sequential data such as time series, speech, and natural language

(Elman, 1990). For a simple RNN cell, the hidden state update and output are expressed as shown in Equations 17 and 18:

$$h_t = \phi(W_{xh}x_t + W_{hh}h_{t-1} + b_h) \quad (17)$$

$$y_t = W_{hy}h_t + b_y \quad (18)$$

Here,

- x_t: t. the input vector at time,
- h_t: confidential status,
- y_t: network output,
- W_{xh}, W_{hh}, W_{hy}: weight matrices,
- b_h, b_y: bias vectors.

Classic RNNs can experience gradient vanishing/exploding problems when learning long-term dependencies. To mitigate this problem, the Long Short-Term Memory (LSTM) architecture was proposed (Hochreiter & Schmidhuber, 1997). In an LSTM cell, the forget gate, input gate, and output gate define the cell state as shown in Equations 19-24:

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f) \quad (19)$$

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \quad (20)$$

$$\widetilde{C_t} = \tanh(W_C[h_{t-1}, x_t] + b_C) \quad (21)$$

$$C_t = f_t \odot C_{t-1} + i_t \odot \widetilde{C_t} \quad (22)$$

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \quad (23)$$

$$h_t = o_t \odot \tanh(C_t) \quad (24)$$

3.5. Transformer Architecture

The Transformer architecture was developed to overcome the parallelization and long-range dependency issues encountered by

RNN-based models in sequential processing (Vaswani et al., 2017). The fundamental building block of the Transformer is the self-attention mechanism.

Query obtained from the input sequence (Q), key (K), and value (V) Scaled dot-product attention is defined as in Equation 25:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{25}$$

Here, d_k, indicates the size of the key vectors. Thanks to the self-attention mechanism, each element in the sequence can interact directly with all other elements, and contextual relationships can be modeled on a global scale.

3.6. Contrastive Self-Supervised Learning

In recent years, self-supervised learning, which leverages unlabeled data, has gained significant importance. Here, the network undergoes pre-training with artificial tasks (e.g., masking, contrastive learning). For example, the contrastive loss function InfoNCE is defined as follows: Self-supervised learning is an approach that enables the model to learn representations by defining artificial or auxiliary tasks on unlabeled data (Chen et al., 2020). In this framework, the model attempts to predict the original from the remaining part by masking or corrupting part of the data. This results in a learning process that does not require external labels but produces strong supervision signals.

For example, in contrastive learning approaches, similar examples are brought closer together, while dissimilar examples are pushed farther apart in the representation space. InfoNCE loss is a commonly used contrastive loss in this context and is defined as in Equation 26:

$$L_{\text{InfoNCE}} = -\log \frac{\exp(\text{sim}(z_i, z_j)/\tau)}{\sum_{k=1}^{2N} 1_{[k \neq i]} \exp(\text{sim}(z_i, z_k)/\tau)} \tag{26}$$

Here;

- $\mathrm{sim}(\cdot,\cdot)$ generally the cosine similarity,
- τ temperature parameter,
- z_i, z_j represent the embeddings belonging to different views (augmentations) of the same example.

Self-supervised approaches, particularly in large-scale visual and language models, offer more data-efficient learning by reducing the need for labeled data and, as detailed in Chapter 4, have become one of the fundamental building blocks of modern artificial intelligence systems.

4. Modern Learning Approaches

In the field of artificial intelligence, learning methodologies have focused on developing more flexible, efficient, and generalizable approaches that go beyond classical paradigms. This section will cover current learning approaches, including meta-learning, transfer learning, multimodal learning, federated learning, online/incremental learning, explainable artificial intelligence (XAI), neurosymbolic AI, and self-supervised learning.

4.1. Meta-Learning (Learning to Learn)

Meta-learning is an approach that enables models to learn new tasks quickly with a small number of examples. The few-shot and zero-shot learning paradigms are particularly important in areas with limited data (Finn, Abbeel, & Levine, 2017). The Model-Agnostic Meta-Learning (MAML) algorithm has pioneered this field by enabling rapid adaptation between different tasks. Recent studies have successfully applied meta-learning in robotic control, natural language processing, and personalized healthcare applications (Hospedales, Antoniou, Micaelli, & Storkey, 2021).

The goal in meta-learning is for a model to learn different tasks. T_i is to quickly adapt to it. In the Model-Agnostic Meta-Learning (MAML) algorithm, the parameters θ are updated as shown in Equation 27:

$$\theta \leftarrow \theta - \beta \nabla_\theta \sum_i \mathcal{L}_{\mathcal{T}_i} \left(\theta - \alpha \nabla_\theta \mathcal{L}_{\mathcal{T}_i}(\theta) \right) \quad (27)$$

Here, α is the internal learning rate, β is the meta-learning rate (Finn, Abbeel, & Levine, 2017).

4.2. Transfer Learning and Multimodal Learning

Transfer learning, the reuse of pre-trained models for new tasks, has gained significant momentum with the proliferation of deep learning (Pan & Yang, 2010). A key advantage is that models trained on large datasets can improve performance in domains with smaller datasets. Multimodal learning enables richer and more meaningful representation learning by integrating different types of data (visual, text, audio) (Baltrusaitis, Ahuja, & Morency, 2019). Models such as CLIP (Radford et al., 2021), which combine visual and text data, are noteworthy in this field.

In **transfer learning**, pre-trained model parameters θ_{pre} is updated with fine-tuning for the new task as shown in Equation 28:

$$\theta^* = \arg \mathcal{L}_{new}(\theta; D_{new}), \text{ start: } \theta = \theta_{pre} \quad (28)$$

In **multimodal learning**, data from different modalities $x^{(v)}, x^{(t)}, x^{(a)}$ (visual, text, audio) shared representation zare combined for as shown in Equation 29:

$$z = f_{fusion}(f_v(x^{(v)}), f_t(x^{(t)}), f_a(x^{(a)})) \quad (29)$$

Here, f_v, f_t, f_a modality-specific feature extractors, f merger is the function that combines these characteristics (Baltrusaitis, Ahuja, & Morency, 2019).

4.3. Federated Learning

Federated learning is a privacy-focused learning method that enables data to be processed locally on distributed devices without being collected on a central server (McMahan et al., 2017). This approach is used to enhance model performance while protecting data privacy, particularly in fields that involve sensitive data, such as healthcare and finance. Current research focuses on the scalability and security of federated learning (Kairouz et al., 2021).

In Federated learning,K parameters of the models in the device $\theta_k$is updated with local data and averaged by the central server as shown in Equation 30:

$$\theta \leftarrow \sum_{k=1}^{K} \frac{n_k}{n} \theta_k \qquad n = \sum_{k=1}^{K} n_k \tag{30}$$

Here $n_k$device k's data count, n represents the total number of data points (McMahan et al., 2017).

4.4. Online / Incremental Learning

Online and incremental learning enable models to adapt to constantly changing data streams. These methods are particularly important in real-time applications and dynamic environments (Gama et al., 2014). Models are updated as new data arrives and continue to learn without forgetting old information. Challenges in this field include the catastrophic forgetting problem and computational efficiency (Parisi et al., 2019).

Model parameters in online learning for each new data sample (x_t, y_t)updated as it comes:

$$\theta_{t+1} = \theta_t - \eta \nabla_\theta \mathcal{L}(\theta_t; x_t, y_t) \quad (31)$$

In Equation 31, η learning rate. In incremental learning, new tasks are learned without forgetting previous knowledge (Parisi et al., 2019).

4.5. Explainable AI (XAI)

Explainable artificial intelligence aims to make the decision processes of models transparent and understandable. This is essential for trust and acceptance, particularly in fields such as healthcare, law, and finance where critical decisions are made (Doshi-Velez & Kim, 2017). XAI methods enable the interpretation of the inner workings of learning algorithms, allowing users to understand model output. Current approaches are divided into model-agnostic and model-specific techniques (Adadi & Berrada, 2018).

The goal in XAI is the model f function describing its output g is to find. For example, the LIME method, a local linear model g as shown in Equation 32:

$$g = \arg \min_{g \in G} \mathcal{L}(f, g, \pi_x) + \Omega(g) \quad (32)$$

Here, $\pi(x)$ represents the local weight function, and $\Omega(g)$ denotes the model complexity penalty (Ribeiro, Singh, & Guestrin, 2016).

4.6. Neurosymbolic AI

Neurosymbolic AI combines learning-based approaches with logical inference methods. This integration enables artificial intelligence to utilize both flexible learning and symbolic reasoning capabilities (Garcez, Lamb, & Gabbay, 2019). Thus, complex and rule-based problems can be solved more effectively. This field is a rising approach, particularly in knowledge-based systems and natural language understanding applications.

In neurosymbolic models, the learning function f_θ with symbolic inference $\mathcal{I}$ used together as shown in Equation 33:

$$y = \mathcal{I}(f_\theta(x)) \tag{33}$$

Here, f_θ is usually deep learning-based, $\mathcal{I}$ is the logical inference module (Garcez, Lamb, & Gabbay, 2019).

4.7. Generative Self-Supervised Learning

Self-supervised learning bridges the gap between unsupervised and supervised learning by automatically extracting learning signals from unlabeled data. This method has played a critical role in the success of large-scale language models such as GPT (Radford et al., 2019) and BERT (Devlin et al., 2019). Today, self-supervised learning is widely applied to visual, textual, and audio data, thereby enhancing data efficiency (Jing & Tian, 2020).

In this approach, the model hides part of the data and attempts to predict from the remaining part. For example, in BERT, the Masked Language Modeling (MLM) loss is defined as in Equation 34:

$$L_{MLM} = -\sum_{t \in M} \log P\left(x_t \mid X_{\setminus M}\right) \tag{34}$$

Here, M masked token indices, x_t masked token $\left(x_t \mid X_{\setminus M}\right)$ while the remaining observations are represented.

More generally, in self-supervised learning, the model $f_\theta$data xautomatically generated task $T(x)$is trained with as shown in Equation 35:

$$\theta^* = \arg\min_\theta \mathbb{E}_{x \sim D}[\mathcal{L}(f_\theta(T(x)), y_{pseudo})] \tag{35}$$

In Equation 35, y^{pseudo}, refers to automatically generated fake labels (Jing & Tian, 2020). These modern learning methodologies enable artificial intelligence systems to become more flexible, generalizable, and reliable. Both theoretical and applied research in

these approaches is rapidly advancing and being adapted to new fields, thereby expanding the boundaries of artificial intelligence.

5. Future Works

The classical, deep, and contemporary learning methodologies discussed in this section form the cornerstones of the level of success achieved by artificial intelligence systems today. However, numerous open problems and research areas still require attention, both theoretically and practically. This section summarizes some prominent future research directions, particularly for computer engineering researchers.

5.1. Data Efficiency and Sparse Learning

Large-scale datasets and models deliver successful results in many applications; however, they face significant limitations in fields where data collection and labeling costs are high (e.g., medicine, defense, industrial production). Hybrid methods that combine meta-learning, few-shot/zero-shot learning, and self-supervised approaches are emerging as a key area of research for enhancing data efficiency. In particular, domain adaptation and domain generalization problems should be further explored in real-world applications.

5.2. Privacy, Security, and Ethical Dimensions

Federated learning and similar distributed learning approaches are crucial for ensuring data privacy and compliance with regulations. However, security threats such as model inversion attacks, membership inference, and adversarial examples remain active research topics. Integrating differential privacy, secure multi-party computation, and cryptographic techniques with federated and self-supervised learning offers a broad field of study, both theoretically and practically. Furthermore, ethical issues such as

fairness, bias reduction, and accountability will continue to play a central role in the design of future artificial intelligence systems.

5.3. Explainability and Reliability

The "black box" nature of deep learning-based models limits their use in critical decision-making processes. XAI methods are expected to evolve beyond merely being post-hoc explanation tools and become an integral part of model design. New architectures that can balance explainability with performance, models that perform uncertainty estimation and report their own confidence levels, are forming an important research agenda, particularly in sensitive areas such as healthcare, autonomous driving, and finance.

5.4. Neurosymbolic and Hybrid Approaches

Neurosymbolic AI aims to develop systems capable of both data-driven generalization and rule-based inference by combining learning-based approaches with symbolic reasoning. In the future, tighter integration of large language models (LLMs) with logical inference engines will open new horizons in tasks such as knowledge-based question-answering, planning, and reasoning. In this field, designing scalable and efficient inference algorithms, as well as integrating logical constraints into the learning process, are important research topics.

5.5. Computational Efficiency and Sustainable Artificial Intelligence

The rapid increase in model sizes and data volumes raises sustainability issues in terms of both energy consumption and hardware requirements. Techniques such as model compression, quantization, knowledge distillation, and efficient architecture design (e.g., low-rank approaches, sparsity-based methods) are becoming increasingly important from a "green AI" perspective. In the future, learning algorithms and hardware-software co-designs

that achieve an optimal balance in the performance-cost-energy triangle will be an important area of research.

As a result, the field of learning methodologies in artificial intelligence is constantly evolving in tandem with new data types, application areas, and hardware platforms. For computer engineering researchers, comprehending the classical, deep, and contemporary approaches discussed in this section within a holistic framework and evaluating them in terms of privacy, ethics, explainability, and sustainability is crucial for both academic and industrial research.

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CHAPTER 9

LIGHTWEIGHT EARLY-FUSION ARCHITECTURE FOR ACCURATE MULTIMODAL GAS LEAK CLASSIFICATION

Resul Berkem AYDEMİR[1]
Burcu DEMİRELLİ OKKALIOĞLU[2]

1. Introduction

Gas leak detection has attracted sustained attention in industrial, environmental, and residential contexts due to the widespread adoption of pressurized gas infrastructure and the growing regulatory focus on safety and sustainability. Earlier practice often depended on manual inspections and relatively simple sensing instruments; however, the scale and complexity of modern facilities increasingly render such approaches inadequate. In operational settings, detection systems must contend with substantial variability—such as temperature swings, vibration, and irregular airflow—that can obscure leak signatures and reduce the reliability of fixed-threshold methods. The implications of missed or delayed detection extend beyond production downtime, encompassing risks

[1] Research Assistant, Computer Engineering (MSc), Institute of Graduate Studies, Yalova University, 77200, Yalova, Türkiye, ORCID: 0009-0009-2244-735X
[2] Assistant Professor, Computer Engineering, Faculty of Engineering, Yalova University, 77200, Yalova, Türkiye, ORCID: 0000-0003-2867-4667

to human health, environmental harm, and significant economic losses. These considerations motivate detection solutions that remain accurate under heterogeneous and sometimes harsh real-world conditions.

A range of sensing technologies has therefore been adopted over recent decades, each with distinct advantages and limitations. Low-cost electronic gas sensors are widely deployed because they are easy to integrate, yet they often exhibit cross-sensitivity and drift as environmental conditions change, which can increase false-alarm rates (Zhai, Liu, Li, Wang, & Wu, 2024). Infrared (IR) thermal imaging supports remote inspection by capturing temperature-related patterns, but it provides limited information about chemical composition, constraining its diagnostic resolution (Log, Pedersen, & Moumets, 2019). Human olfaction has historically served as an auxiliary indicator, but it is affected by sensory adaptation and cannot detect odorless gases, making it unreliable as a consistent detection mechanism (Sela & Sobel, 2010). Taken together, these limitations indicate that a single modality is unlikely to provide robust and accurate leak classification across diverse operating conditions.

To address this gap, multimodal methods have become increasingly prominent, integrating heterogeneous signals to improve discriminative power. The rationale is that different modalities encode complementary facets of a leak event: thermal imagery captures spatial and thermodynamic structure, whereas time-series sensor measurements reflect concentration dynamics over time. Recent fusion-based frameworks report improved robustness by exploiting this complementarity. Nevertheless, many multimodal systems rely on large deep networks with substantial parameter counts, which can translate into high computational cost, increased latency, and elevated power consumption. These demands complicate deployment on edge platforms that commonly underpin

real-time monitoring in industrial environments (Surantha & Sutisna, 2025).

This practical constraint has encouraged the development of lightweight deep learning models that aim to balance representational capacity with operational efficiency. Prior studies suggest that compact architectures—when paired with appropriate feature extraction and cross-modal alignment—can retain competitive accuracy while reducing computational overhead (Musa et al., 2025). Following this line of work, this chapter presents a compact early-fusion architecture that combines spatial features extracted from thermal images using a ShuffleNetV2 backbone with dense representations learned from time-series sensor data via a Multilayer Perceptron (MLP). Despite its modest parameterization, the proposed model achieves strong classification performance and outperforms unimodal baselines and several conventional fusion schemes in our experiments, supporting the feasibility of high-performing multimodal inference under edge-deployment constraints.

2. Related Works

Research on gas classification has undergone a steady evolution over the past decade, beginning with systems that relied solely on single-modality inputs. Early sensor-based approaches demonstrated promise under controlled laboratory conditions but frequently lacked robustness in dynamic environments where temperature, airflow, or background chemical composition varied unpredictably. (Ponzoni et al., 2017). More recent sensor-only studies demonstrated that 1D convolutional networks can extract informative temporal patterns from gas-sensor sequences; however, the field has increasingly shifted toward multimodal fusion, motivated by the complementary cues available when thermal

imagery is combined with sensor measurements (Md Dzahir & Chia, 2025).

Within this growing literature, fusion techniques are typically framed in terms of feature-level (early) and decision-level (late) integration. The MultimodalGasData benchmark established by Narkhede et al. (2021) has become a standard reference point, and their findings suggested that early- and late-fusion approaches achieve comparable performance under conventional evaluation setups. Despite these findings, several studies have pursued higher-capacity fusion pipelines in an effort to capture richer cross-modal relationships. For example, Azizian, Yousefimehr, & Ghatee (2024) reported late-fusion results using a ResNet-50 backbone for the thermal imaging stream, illustrating the emphasis on deeper architectures.

Beyond early and late fusion, intermediate integration strategies have also attracted attention. Rahate et al. (2023) examined alternative fusion schemes and found that multi-task formulations offered greater robustness, particularly when one modality was degraded by noise. More recently, increasing emphasis has been placed on computational efficiency as a design constraint. Wang, Xu, Yang, & Jiang (2025), for instance, combined ShuffleNetV2 with cross-attention mechanisms to enhance efficiency while retaining the benefits of multimodal fusion.

Taken together, these studies reflect a broader trend toward fusion models with growing representational capacity and improved accuracy, but at the cost of higher computational demands. Such requirements can hinder deployment on edge hardware. Against this background, the present work focuses on a compact early-fusion design intended to maintain competitive performance while substantially reducing computational overhead. By prioritizing efficiency, this study aims to bridge the gap between high-

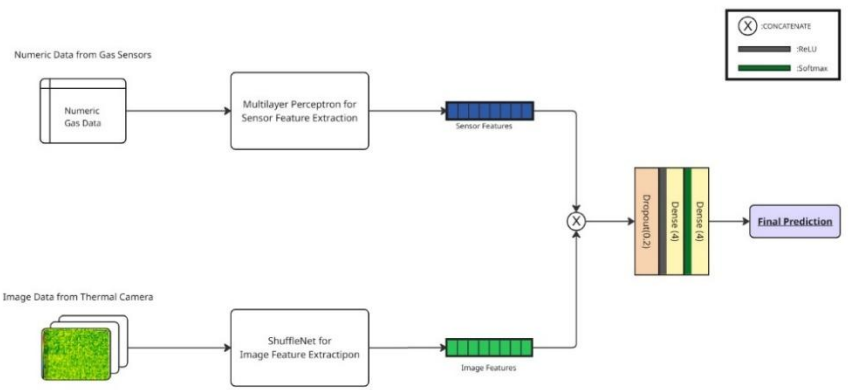
performance laboratory models and the practical constraints of real-time industrial deployment.

3. Methodology

We develop a compact early-fusion architecture aimed at balancing classification performance with the latency and resource constraints of edge deployment. The model jointly processes thermal images and time-series gas-sensor measurements in order to leverage complementary visual and chemical information, while avoiding the computational overhead commonly associated with large multimodal fusion networks.

As shown in Figure 1, the architecture follows a two-stream design that reflects the different structure of the input modalities. Thermal frames are treated as 2D arrays, whereas sensor measurements are represented as numerical vectors capturing temporal response behavior. Each input is first transformed into a modality-specific feature representation by a dedicated branch, after which the learned embeddings are combined at an early-fusion stage and used for final classification.

Figure 1. The proposed lightweight, dual-branch early fusion architecture.



The image branch uses ShuffleNetV2 (Ma, Zhang, Zheng, & Sun, 2018) as the backbone, motivated by its efficiency and its ability to extract spatial cues relevant to gas-related thermal signatures, including plume morphology, dispersion boundaries, and contrast patterns, under a limited compute budget. In parallel, the sensor branch employs a Multilayer Perceptron (MLP) (Gorjani et al., 2021) to project raw sensor vectors into a compact latent space and to model non-linear dependencies in chemical-response dynamics. Fusion is performed on these learned representations rather than on raw inputs, with the intent of reducing sensitivity to measurement noise while preserving informative cross-modal interactions.

The feature vectors extracted from the two parallel branches are concatenated in an early-fusion step (Baltrusaitis, Ahuja, & Morency, 2019), forming a unified representation. This combined feature vector is subsequently fed into a final classification head, which outputs the probability distribution over the target gas classes.

Sensor Feature Extractor: Multilayer Perceptron (MLP)

Robust feature learning from the sensor time series is performed by a dedicated MLP branch. This design emphasizes computational simplicity and low inference latency—properties that are particularly important for edge deployment—while retaining sufficient capacity for non-linear feature mapping. The branch takes as input a one-dimensional vector of raw sensor readings and consists of two fully connected layers:

- Layer 1: The input is transformed using a Dense layer with 64 units and ReLU activation, followed by Batch Normalization and Dropout (rate = 0.3) to stabilize optimization and reduce overfitting (Ioffe & Szegedy, 2015; Srivastava, Hinton, Krizhevsky, & Salakhutdinov, 2014)

- Layer 2: A second Dense layer produces a 128-dimensional sensor representation, $v_{\{sensor\}}$, using ReLU activation. This embedding is intended to capture non-linear dependencies across sensor channels (Gorjani et al., 2021).

Image Feature Extractor: ShuffleNetV2

For the image pathway, ShuffleNetV2 is adopted as the primary feature extractor due to its favorable efficiency–accuracy trade-off on resource-limited platforms (Ma et al., 2018). The backbone is trained from scratch on the thermal image inputs.

ShuffleNetV2 attains computational efficiency through architectural choices such as (Zhang, Zhou, Lin, & Sun, 2018):

- Pointwise group convolutions: reducing the cost of standard 1×1 convolutions.
- Channel shuffle: enabling information exchange across groups and mitigating the representational bottleneck induced by grouped operations.

This branch processes 224×224 thermal frames. The resulting feature map is then aggregated using a Global Average Pooling layer (GlobalAveragePooling2D) (Lin, Chen, & Yan, 2014), yielding a compact one-dimensional image embedding $v_{\{img\}}$. This representation summarizes salient spatial patterns—e.g., plume morphology and dispersion contours—while maintaining a fixed dimensionality for fusion.

Early Fusion and Classification

The central component of the proposed framework is an early-fusion mechanism that combines modality-specific representations prior to classification. Early fusion is adopted to jointly leverage complementary cues from heterogeneous modalities

while keeping the overall architecture compact relative to decision-level fusion alternatives.

The final feature vectors extracted from the two parallel branches, the spatial vector from the ShuffleNetV2 branch $v_{\{img\}}$ and the temporal feature vector from the MLP branch $v_{\{sensor\}}$, are merged by a concatenation operation. This step forms a unified multimodal representation vector, $v_{\{fused\}}$, as formally defined in Equation (1):

$$v_{\{fused\}} = \left[v_{\{img\}} \oplus v_{\{sensor\}}\right] \quad (1)$$

where $\oplus$ denotes the concatenation operation (Baltrusaitis et al., 2019). This fused vector $v_{\{fused\}}$ is then passed to the classification head. To improve generalization over the joint feature space, the head begins with Dropout (rate = 0.5), followed by a Dense layer with four units, and an additional Dropout layer for further regularization (Srivastava et al., 2014). Final predictions are produced by a Dense layer with Softmax activation, yielding class probabilities over the target gas categories. The full model is trained end-to-end so that the feature extractors and fusion module are optimized jointly.

4.Experiments

This section evaluates the proposed multimodal framework on a publicly available benchmark dataset. The experimental protocol follows three sequential stages. First, candidate architectures for the sensor and image branches are assessed independently to identify suitable unimodal feature extractors. Second, the selected backbones are integrated into the early-fusion model and trained end-to-end. Third, the resulting multimodal system is compared with previously reported state-of-the-art approaches evaluated on the same dataset.

Dataset

For model development and evaluation, we utilized the publicly available MultimodalGasData dataset created by Narkhede, Walambe, Chandel, Mandaokar, & Kotecha (2022). This dataset is particularly well-suited for multimodal research due to its synchronization capabilities and comprehensive scope, making it an ideal benchmark for gas leak classification studies. The dataset has synchronized data from two sources: seven Metal Oxide (MQ) gas sensors and a Seek Compact thermal camera. The classification task within the dataset involves four distinct and mutually exclusive target classes: Perfume, Smoke, Mixture, and NoGas. The dataset has 6400 samples total, with 1600 samples for each class.

Data Preprocessing

In order to prepare the data for our multimodal model, we implemented a series of standard preprocessing steps for each modality. For the time-series sensor data, the raw measurements were initially standardized using StandardScaler from scikit-learn. This process involves the removal of the mean and the scaling of the data to unit variance, a common practice that ensures that features with different scales do not disproportionately influence the model's learning process. The scaler, which was implemented exclusively on the training data, was employed to prevent data leakage from the validation and test sets. For the thermal image data, each image was resized to a uniform dimension of 224x224 pixels to match the input requirements of the ShuffleNetV2 architecture. Subsequently, the pixel values were normalized to a range between 0 and 1 by dividing them by 255. This normalization step is crucial for the stabilization of the training process of deep neural networks.

The dataset was subsequently partitioned into three distinct sets: a training set comprising 60% of the total, a validation set constituting 20%, and a test set accounting for the remaining 20%.

This approach ensures a robust evaluation process, wherein the model is first trained on a specific portion of the data, then fine-tuned on another subset, and ultimately assessed on data that has not been seen during training. The class labels were converted to a one-hot encoded format, which is suitable for the categorical cross-entropy loss function.

Model Training and Implementation Details

The proposed model was implemented using TensorFlow (version 2) and Keras libraries. As described in the methodology, the architecture consists of two feature extraction branches: a ShuffleNetV2 (0.5x) backbone for the image modality and a two-layer MLP for the sensor modality.

The model was compiled using the Adam optimizer with a learning rate of 1e-4 (Kingma & Ba, 2015). For the loss function, categorical cross-entropy was employed, which is standard for multi-class classification tasks. The efficacy of the model during the training phase was evaluated using accuracy as the primary metric. The network was trained end-to-end for a total of 50 epochs with a batch size of 128. The training process employed the designated validation set to assess generalization performance at the conclusion of each epoch, though the use of an early stopping callback was excluded in the final training iteration.

Evaluation Metrics

Model performance was assessed using standard multi-class classification metrics computed from the confusion-matrix components: true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). The primary metrics reported were accuracy, precision, recall (sensitivity), and the F1-score.

As defined in Equation (2), accuracy measures the overall proportion of correctly classified instances. Precision (Equation (3))

quantifies the fraction of instances predicted as positive that are truly positive, and is therefore particularly relevant when minimizing false alarms is a priority. Recall (Equation (4)) captures the model's ability to identify all true positive instances, reflecting sensitivity to the target class. Finally, the F1-score (Equation (5)), defined as the harmonic mean of precision and recall, provides a balanced summary of performance and is especially informative under potential class-imbalance conditions (Vujović, 2021).

$$Accuracy = (TP + TN)/(TP + TN + FP + FN) \quad (2)$$

$$Precision = TP/(TP + FP) \quad (3)$$

$$Recall = TP/(TP + FN) \quad (4)$$

$$F1 - Score = 2 \times (Precision \times Recall)/(Precision + Recall) \quad (5)$$

Experimental Results and Analysis

In this section, we present the results of our empirical evaluation, beginning with a comparative analysis to determine the optimal architectures for the sensor and image feature extraction branches. Subsequently, an analysis of the performance of the fully integrated model is conducted, and it is benchmarked against existing state-of-the-art methods. The training progress and final classification performance are visualized through training/validation curves and a confusion matrix, respectively, providing a comprehensive view of the model's capabilities. A detailed breakdown of the classification report further quantifies the model's effectiveness on a per-class basis.

Comparison of Unimodal Sensor Architectures

In order to ascertain the most efficacious architecture for the purpose of processing time-series sensor data, a systematic evaluation was conducted on three unimodal models that had been trained exclusively on the sensor dataset. This empirical comparison was crucial to select a feature extractor that balances accuracy with the strict efficiency requirements of the final multimodal framework.

The selection of models encompassed a range of complexity: a rudimentary linear model served as a foundational framework to assess linear separability; a Long Short-Term Memory (LSTM) network was incorporated as a robust benchmark due to its theoretical prowess in capturing temporal dependencies in time-series data; and an MLP was appraised to ascertain whether a lightweight, feed-forward architecture could acquire sufficient non-linear representations without the computational encumbrance of recurrent layers.

To ensure a fair and rigorous comparison, all models were subjected to identical training conditions. The models were trained for 50 epochs using the Adam optimizer with a batch size of 128. Table 1 presents a comparative summary of the overall validation and test accuracies, alongside the total parameter counts for each architecture.

Table 1. Comparative Analysis of Overall Accuracy and Computational Efficiency for Unimodal Sensor Architectures

Model	Validation Accuracy	Test Accuracy	Total Parameters
MLP	%97.66	%97.66	9668
LSTM	%96.17	%97.11	128388
Linear	%83.59	%82.73	1668

In order to provide a more profound understanding of how each model manages particular gas categories, Table 2 presents the per-class performance metrics, including precision, recall, and the F1 score.

Table 2. Granular Performance Analysis: Per-Class Precision, Recall, and F1-Scores for Sensor Architectures

Model	*Class*	*Precision*	*Recall*	*F1-Score*
MLP	*Mixture*	*1.0000*	*1.0000*	*1.0000*
	NoGas	*0.9621*	*0.9531*	*0.9576*
	Perfume	*0.9536*	*0.9625*	*0.9580*
	Smoke	*1.0000*	*1.0000*	*1.0000*
LSTM	*Mixture*	*1.0000*	*1.0000*	*1.0000*
	NoGas	*0.9550*	*0.9281*	*0.9413*
	Perfume	*0.9301*	*0.9563*	*0.9430*
	Smoke	*1.0000*	*1.0000*	*1.0000*
Linear	*Mixture*	*1.0000*	*1.0000*	*1.0000*
	NoGas	*0.6334*	*0.7344*	*0.6802*
	Perfume	*0.6840*	*0.5750*	*0.6248*
	Smoke	*1.0000*	*1.0000*	*1.0000*

This granular breakdown is imperative because overall accuracy can, on occasion, obscure deficiencies specific to a given class. For instance, while all three architectures achieved perfect classification for distinct categories like "Smoke" and "Mixture" — likely due to their strong chemical signatures — significant disparities emerged in the more subtle distinction between "NoGas" and "Perfume."

The Linear model exhibited a precipitous decline in performance across these categories, with F1-scores dropping below 0.70. This decline underscores the non-linear nature of the sensor drift associated with ambient air versus light perfume contaminants.

In contrast, the MLP demonstrated a high degree of precision and recall (>0.95) across these challenging classes, indicating its superior capacity to differentiate complex, overlapping feature spaces compared to both the linear baseline and the LSTM.

The findings underscore the superior performance of the MLP, which attained a test accuracy of 97.66%. This result surpasses the performance of the LSTM model (97.11%) and the baseline linear model (82.73%). This superior performance is particularly noteworthy given the MLP's high efficiency; as shown in Table 1, it contains only 9,668 parameters. The model under consideration is more than eight times smaller than the LSTM model (128,388 parameters), which did not achieve a comparable level of accuracy. The Linear model, despite its relative simplicity, exhibited the poorest performance, suggesting that the extraction of non-linear features is paramount for effective prediction.

The model with the highest classification accuracy, which also had an exceptionally low parameter count, was empirically confirmed as the optimal choice for the sensor feature extraction branch.

Comparison of Unimodal Image Architectures

In order to ascertain the optimal backbone for the thermal image feature extraction branch, a systematic evaluation of three CNN architectures was conducted, with particular attention given to the critical trade-off between model complexity and classification accuracy. The architectures were selected to represent distinct points on the efficiency-performance spectrum.

All models were trained for 50 epochs on the thermal image dataset. As illustrated in Table 3, a high-level summary of the results is provided, contrasting the validation and test accuracies against the computational cost (total parameters) for each model.

Table 3. Comparative Analysis of Overall Accuracy and Computational Efficiency for Unimodal Image Architectures

Model	Validation Accuracy	Test Accuracy	Total Parameters
ShuffleNetV2	%92.34	%92.89	353,844
EfficientNetV2B0	%97.34	%97.97	6,083,796
CNN	%75.63	%76.17	93,764

While the overall accuracy of the models provides a general ranking, a more detailed analysis is necessary to understand how these models handle specific environmental conditions. A model may attain acceptable mean accuracy by over-fitting to the majority class while failing to detect critical, lower-contrast anomalies. As illustrated in Table 4, a comprehensive array of performance metrics is provided, offering insight into the precision and recall trade-offs for each architecture.

This breakdown reveals critical limitations in the lighter architectures. A salient finding was the collapse of the Custom CNN when processing the 'Perfume' class (Recall 0.4875), signifying an incapacity to discern nuanced thermal signatures. In contrast, while ShuffleNetV2 exhibited a slight decline in precision for 'Smoke' compared to the more substantial EfficientNet, it retained a commendable recall of 95.94%. In the domain of safety-critical gas detection, this sensitivity is of the essence. The system's design effectively prioritizes the capture of all potential smoke events over the minimization of false alarms.

Consistent with expectations, EfficientNetV2B0 attained the maximum test accuracy of 97.97%, thereby validating the efficacy of the proposed approach. However, as demonstrated in Table 3, it is computationally intensive, comprising over 6 million parameters,

which renders it less suitable for environments with limited resources. In contrast, the Custom CNN, despite its remarkably parsimonious parameters (93,764), exhibited substandard performance, attaining a mere 76.17% accuracy. This finding suggests a deficiency in its capacity to adequately capture the intricacies inherent in the thermal data. Consequently, ShuffleNetV2 emerges as the optimal compromise, delivering robust detection capabilities comparable to heavier models while avoiding the representational bottlenecks observed in the Custom CNN.

Table 4. Granular Performance Analysis: Per-Class Precision, Recall, and F1-Scores for Image Architectures

Model	Class	Precision	Recall	F1-Score
ShuffleNetV2	Mixture	0.9807	0.9531	0.9667
	NoGas	0.9969	0.9906	0.9937
	Perfume	0.9319	0.8125	0.8681
	Smoke	0.8253	0.9594	0.8873
EfficientNetV2B0	Mixture	0.9969	0.9969	0.9969
	NoGas	1.0000	1.0000	1.0000
	Perfume	0.9429	0.9812	0.9617
	Smoke	0.9805	0.9406	0.9601
CNN	Mixture	0.7994	0.7844	0.7918
	NoGas	0.9901	0.9375	0.9631
	Perfume	0.6610	0.4875	0.5612
	Smoke	0.6276	0.8375	0.7175

The ShuffleNetV2 model represented an effective compromise. Despite being trained from the beginning, it achieved a strong test accuracy of 92.89% with only 353,844 parameters, making it approximately 17 times smaller than EfficientNetV2B0. The findings indicate that ShuffleNetV2 offers an optimal balance between high classification performance and low computational

cost, thereby substantiating its suitability for our lightweight multimodal architecture.

Proposed Method's Performance

The final proposed model was constructed by integrating an efficient MLP for the sensor data branch with the ShuffleNetV2 (0.5x) architecture for the image branch, based on the backbone evaluations for the individual branches. The resulting multimodal architecture is remarkably lightweight, with a total of 338,160 trainable parameters. This is slightly lower than the parameter count of the single-mode ShuffleNetV2 model (353,844 parameters, Table 3) because the classification head in the combined architecture was designed to be more compact than the head used in the unimodal model. In comparison with the unimodal EfficientNetV2B0 model, which has 6.1 million parameters, this reduction is substantial, thereby satisfying the design objective of computational efficiency.

As demonstrated in Figure 2, the training dynamics exhibited stability and efficacy. The training and validation loss curves demonstrated a consistent downward trend, while the validation accuracy rapidly converged to a high asymptote, reaching a peak of 98.98%. This behavior is indicative of efficient learning and strong generalization capabilities, with no evidence of significant overfitting.

Figure 2. Training and validation accuracy/loss curves for the early fusion model.

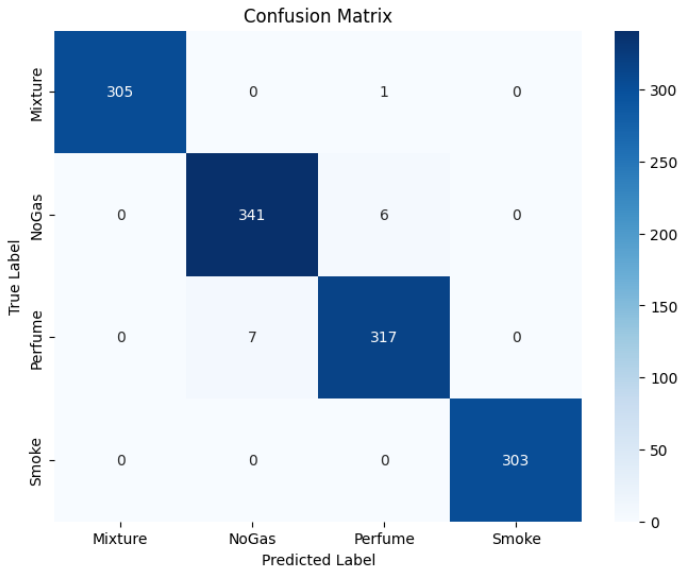
Following the conclusion of the training phase, the model's performance was subjected to a rigorous evaluation utilizing an independent test set that had not been previously observed. This evaluation yielded outstanding results, underscoring the model's high degree of accuracy and its capacity for robust generalization. As outlined in Table 5, the detailed classification report provides a comprehensive breakdown of key metrics, confirming an overall accuracy of 98.91% across 1,280 test samples.

Table 5. Classification Report on the Test Set

	Precision	Recall	F1-Score	Support
Mixture	1.0000	0.9967	0.9984	306
NoGas	0.9799	0.9827	0.9813	347
Perfume	0.9784	0.9784	0.9784	324
Smoke	1.0000	1.0000	1.0000	303
Accuracy			0.9891	1280

A detailed breakdown of per-class performance, presented in the confusion matrix (Figure 3), reveals flawless classification for the "Smoke" class and near-flawless performance for "Mixture," with only a single instance being misclassified as "Perfume." It is noteworthy that the model exhibited minimal confusion between the two most challenging and semantically similar classes, "NoGas" and "Perfume." Specifically, there was a misclassification of six instances of "NoGas" as "Perfume," and a misclassification of seven instances of "Perfume" as "NoGas." The achievement of such elevated accuracy with an architecture comprising fewer than 340,000 parameters substantiates our central hypothesis: that an early-fusion methodology, when judiciously amalgamated with optimized lightweight architectures, can attain performance that eclipses that of more intricate, unimodal systems. This balance of high precision and low architectural complexity confirms the model's viability for deployment on resource-constrained edge devices where reliability is paramount.

Figure 3. Confusion matrix for the proposed multimodal model on the test set.



5. Discussion

The results show that our lightweight model is effective for gas leak classification. The test accuracy was 98.91%. We compared our model with other methods in Table 6.

Our model performed better than the baseline by (Narkhede et al., 2021), which achieved 96.00%. It also beat the intermediate fusion model by Rahate et al. (2023), which reported 96.90% and 94.50%, respectively. Our accuracy is close to the best models like Azizian et al. (2024) at 99.32% and Wang et al. (2025) at 99.22%.

The main advantage of our model is size. Other models use heavy backbones like ResNet-50. Our model uses only 338,160 parameters. This makes it suitable for edge devices. The fused model (98.91%) was better than the best unimodal model (MLP 97.66%). This confirms that combining thermal and sensor data helps resolve errors.

Table 6. Performance Comparison with State-of-the-Art Methods on the MultimodalGasData Dataset

Study	Feature Extraction	Fusion Strategy	Reported Best Accuracy
Md Dzahir & Chia (2025)	LeNet-R (1D-CNN)	Unimodal (Sensor-Only)	97.60%
Narkhede et al. (2021)	LSTM (sensor), CNN (image)	Early & Late Fusion	96.00%
Rahate et al. (2023)	DNN (sensor), CNN (image)	Multi-task Fusion	96.90%
Rahate et al. (2023)	DNN (sensor), CNN (image)	Intermediate Fusion	94.50%
Azizian et al. (2024)	ResNet-50 (image) + kNN (sensor)	Late Fusion	99.32%
Wang et al. (2025)	CNN-BiGRU (sensor), ShuffleNetV2 (image)	Intermediate Fusion (Cross-Attention)	99.22%
***The proposed study**	MLP (sensor) + ShuffleNetV2(image)	Early Fusion	98.91%

Overall, these results demonstrate that a simple early-fusion model, built with carefully selected lightweight backbones, can achieve performance comparable to more complex and computationally demanding fusion strategies.

6. Conclusion

This study set out to develop a novel gas leak classification approach that couples strong predictive performance with the computational efficiency required for practical deployment on edge hardware. To achieve this objective, we designed a compact early-fusion architecture with two modality-specific branches: an MLP to encode the sensor measurements and a ShuffleNetV2 backbone to extract features from thermal images. Candidate unimodal models were first systematically evaluated to inform the optimal selection of

backbone components, after which the selected branches were integrated into the final multimodal system. The resulting network remains lightweight, comprising only 338,160 trainable parameters.

Despite its small footprint, the proposed model achieved a test accuracy of 98.91%, indicating that carefully designed lightweight fusion can reach performance levels typically associated with substantially larger, multi-million-parameter architectures. These findings also underscore the value of combining complementary sensing streams, as the fused representation helps mitigate limitations that arise when either modality is used in isolation, yielding a solution that is both robust and computationally practical for gas leak detection.

While the achieved performance is significant, several key limitations should be acknowledged. Experiments were conducted on a balanced dataset collected under laboratory conditions, which may not fully reflect the class skew and variability encountered in operational environments. Future work will therefore focus on evaluating robustness under realistic conditions, including imbalanced class distributions, a broader set of target gases, and the presence of environmental interferents. In addition, deployment-oriented optimizations—such as post-training quantization and conversion to mobile runtimes (e.g., TensorFlow Lite)—represent promising directions for further reducing latency and resource usage on-device.

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GEÇİCİ KAPAK

Kapak tasarımı
devam ediyor.