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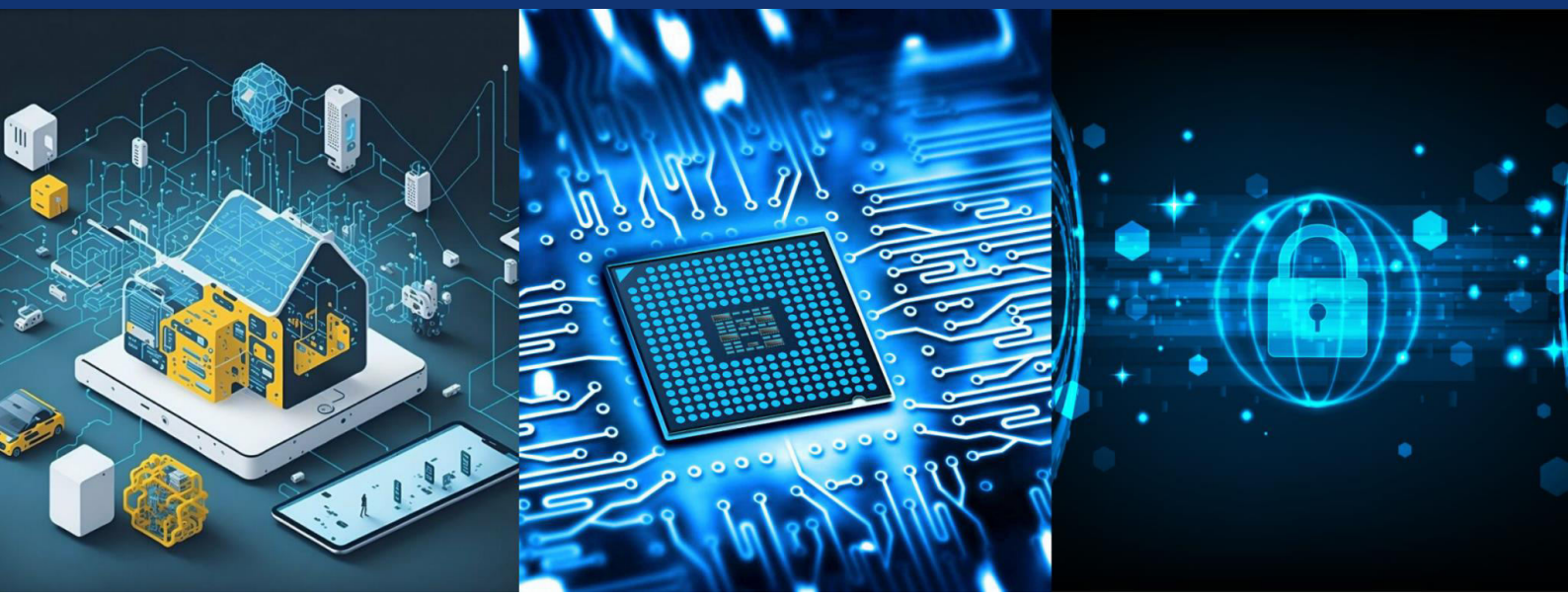

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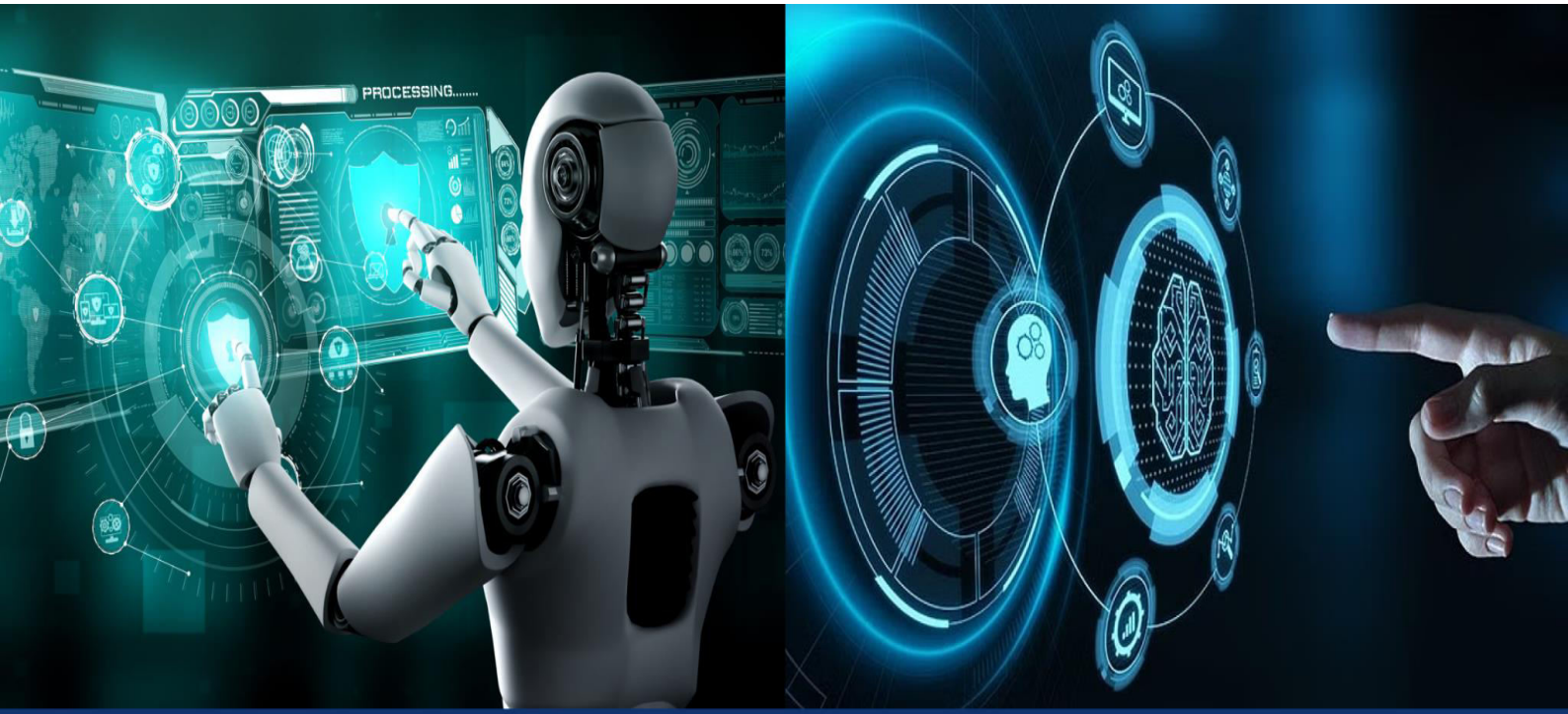

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Unified Network Intrusion Detection System Using Ensemble Machine Learning and Hybrid Feature Selection on AWID and NSL-KDD Datasets

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ABSTRACT: The exponential growth of network-connected devices has revolutionized daily life but has also attracted cybercriminals, leading to an increase in the frequency and sophistication of attacks targeting these devices. To address this, Network Intrusion Detection Systems (NIDS) have become essential for safeguarding network applications. However, the high-dimensional and complex nature of network data poses significant challenges for accurate attack detection and feature selection. This study proposes a novel machine learning-based NIDS framework that integrates Two-phased Hybrid Ensemble Learning and Automatic Feature Selection to enhance detection capabilities for both wired and wireless networks.

The framework employs a two-phased ensemble learning approach: the first phase utilizes classifiers adapted from the One-vs-One framework, while the second phase combines classifiers based on attack class combinations. Additionally, an advanced feature selection model is introduced, leveraging a multi-layer approach that includes filter methods (Information Gain, Chi-Square Test, Relief Algorithm, and Mutual Information), dimensionality reduction via PCA, and wrapper methods (Genetic Algorithms and Forward/Backward Feature Selection). Cross-dataset correlation analysis and variance thresholding further optimize feature subsets, validated through 10-fold cross-validation. The ensemble model combines diverse base classifiers, including Multilayer Perceptron (MLP), Self-Organizing Map (SOM), Boosted Decision Trees, Random Forest, and Support Vector Machines (SVM), whose probability outputs form meta-feature vectors for a meta-learner (e.g., Logistic Regression or XGBoost) to make final classification decisions. Evaluated on the NSL-KDD and AWID datasets, the proposed framework demonstrates superior attack detection accuracy, reduced false positives, and computational efficiency compared to existing methods. This study highlights the potential of scalable and adaptive intrusion detection systems capable of addressing the evolving landscape of cybersecurity threats.

KEYWORDS: Feature selection, feature engineering, classification, machine learning, ensemble learning, anomaly detection, intrusion detection system.

I. INTRODUCTION

The rapid proliferation of network-connected devices has revolutionized communication and information exchange, becoming an integral part of daily life. However, this exponential growth has also introduced significant security challenges, particularly in safeguarding wired and wireless networks from increasingly sophisticated cyberattacks. Network Intrusion Detection Systems (NIDS) have emerged as a critical component in addressing these challenges by monitoring network traffic to detect and mitigate malicious activities. Despite extensive research in this domain, developing an effective NIDS capable of handling the high-dimensional, complex nature of network data and detecting both known and unknown attacks remains a formidable challenge.

Traditional NIDS approaches, such as specification-based and signature-based systems, have limitations in scalability, adaptability, and detection of zero-day attacks. Anomaly-based NIDS, which leverage machine learning, offer a more robust solution by automating attack detection and adapting to evolving threats. However, the high dimensionality of network data, coupled with the dynamic nature of cyberattacks, poses significant hurdles in designing an efficient and

accurate NIDS. Key challenges include automatic feature selection to reduce redundancy, multiclass classification for diverse attack types, and the ability to generalize across both wired and wireless network environments.

This study proposes a Unified Network Intrusion Detection System (UNIDS) that integrates advanced feature selection techniques with a Two-phased Hybrid Ensemble Learning (THE-AFS) framework to address these challenges. The proposed system employs a multi-layer feature selection process, combining filter methods (Information Gain, Chi-Square Test, Relief Algorithm, Mutual Information), dimensionality reduction techniques (Principal Component Analysis), and wrapper methods (Genetic Algorithms, Forward/Backward Selection) to optimize feature subsets. This approach reduces redundancy and enhances model performance, ensuring compatibility with diverse network scenarios.

The ensemble learning framework consists of two phases: the first phase utilizes an adaptation of the One-vs-One multiclass ensemble framework to generate attack candidates, while the second phase employs multiclass classifiers trained on combinations of attack classes to refine detection. This hybrid approach leverages diverse base classifiers, including Multilayer Perceptron (MLP), Support Vector Machines (SVM), Boosted Decision Trees (DT), Random Forest (RF), and Self-Organizing Maps (SOM), with a meta-learner (e.g., Logistic Regression or XGBoost) for final classification. The framework is validated on benchmark datasets, NSL-KDD for wired networks and AWID for wireless networks, demonstrating superior detection accuracy, low false positive rates, and computational efficiency compared to existing methods.

The primary contributions of this research are:

1. A Unified Framework for Intrusion Detection: A generalized NIDS capable of handling both wired and wireless network traffic, validated on widely-used datasets.
2. Advanced Feature Selection Techniques: A hybrid feature selection process that combines filter methods, dimensionality reduction, and wrapper techniques to optimize feature subsets and improve model performance.
3. Two-phased Hybrid Ensemble Learning: A novel ensemble framework that enhances multiclass attack detection by combining One-vs-One and multiclass classification approaches, achieving high detection rates and low false alarms.

By addressing the limitations of traditional NIDS and leveraging machine learning advancements, this research aims to contribute to the development of scalable, efficient, and accurate intrusion detection systems capable of securing modern networks against evolving cybersecurity threats. The proposed framework not only improves detection accuracy but also ensures adaptability to dynamic network environments, making it a promising solution for real-world deployment.

II. RELATED WORK

The rapid evolution of network-connected devices has necessitated the development of robust Network Intrusion Detection Systems (NIDS) to safeguard both wired and wireless networks from increasingly sophisticated cyberattacks. Traditional NIDS approaches, such as specification-based and signature-based systems, have shown limitations in scalability, adaptability, and detection of zero-day attacks. In contrast, anomaly-based NIDS, which leverage machine learning techniques, have gained prominence due to their ability to detect unknown attacks and adapt to evolving threats. However, challenges such as high-dimensional data, multiclass classification, and the need for efficient feature selection remain critical areas of research [1], [2].

Ensemble learning has emerged as a powerful approach for improving the accuracy and robustness of NIDS. Aburomman and Reaz [3] highlighted the advantages of ensemble methods, emphasizing that combining multiple learners trained on diverse attack types can enhance detection likelihood. Ensemble methods are broadly categorized into homogeneous (using the same learning technique) and heterogeneous (using diverse techniques) approaches. Heterogeneous ensembles, particularly stacking and voting methods, have shown significant promise. Stacking ensembles, which combine base models with a meta-model, and voting ensembles, which aggregate predictions through a voting mechanism, have been widely adopted in recent studies [4], [5].

Zhou et al. [6] proposed a multilevel ensemble using the AdaBoost-A algorithm, extending it for multiclass classification with a one-vs-rest strategy. Their architecture, composed of expert learners and sub-learners, demonstrated improved performance. Similarly, Li et al. [7] introduced a sustainable ensemble model with a weighting mechanism for different attack types and a retraining mechanism to incorporate new data while retaining historical knowledge. Louk

and Tama [8] proposed a dual ensemble model, combining Gradient Boosting Decision Trees (GBDT) with bagging techniques, achieving superior accuracy across multiple datasets.

Feature selection is a critical step in NIDS design, as high-dimensional data can lead to overfitting and increased computational complexity. Recent studies have explored advanced feature selection techniques to optimize model performance. For instance, Aminanto et al. [9] combined Stacked Auto Encoders (SAE) with weighted feature selection to achieve a 99.92% detection rate for impersonation attacks. Liu and Chung [10] extended this approach to multiclass classification, incorporating Principal Component Analysis (PCA) and clustering to further reduce feature redundancy, achieving a 79% detection rate.

Mikhail et al. [11] proposed a semi-boosted ensemble framework, combining standard and boosted learners with a weight matrix to improve multiclass detection rates, achieving an 86% detection rate. Lopez-Martin et al. [12] streamlined the Radial Basis Function Neural Network (RBFNN) architecture, achieving 95.5% accuracy using reinforcement learning. Lei et al. [13] introduced a deep neural network architecture based on Triangle Area Maps (TAM), combining Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks to extract spatial and temporal features, achieving high accuracy on a subset of the AWID dataset.

The Aegean Wi-Fi Intrusion Detection Dataset (AWID) has become a benchmark for wireless NIDS research, providing packet captures of well-known wireless attacks. Kolias et al. [14] highlighted the challenges of detecting impersonation attacks, motivating several studies to improve detection rates. For example, Aminanto and Kim [15] used unsupervised feature extraction with Stacked Auto Encoders (SAE) and Artificial Neural Networks (ANN) to achieve an 85% detection rate for impersonation attacks. Their follow-up study [16] improved this rate to 92% using SAE and K-means clustering.

Recent studies have also explored hybrid approaches, combining feature selection with ensemble learning. For instance, Shieh et al. [17] proposed a framework combining Correlation-Based Feature Selection with a Bat Algorithm (CFS-BA) and an ensemble of C4.5, Random Forest (RF), and Forest PA algorithms, achieving high accuracy on NSL-KDD, AWID, and CIC-IDS2017 datasets. Similarly, an ensemble-based multi-filter feature selection method using Decision Trees achieved high detection rates on the NSL-KDD dataset by reducing features from 41 to 13 [18].

Despite significant advancements, challenges remain in developing NIDS that can generalize across diverse network environments and detect unknown attacks. Many studies rely on datasets like NSL-KDD and AWID, which may not fully represent real-world traffic patterns [19]. Additionally, the computational efficiency of NIDS in real-time scenarios and their robustness against adversarial attacks are critical areas for future research [20]. The integration of advanced feature selection techniques, ensemble learning, and deep learning models presents a promising direction for enhancing the accuracy, scalability, and adaptability of NIDS in dynamic network environments [21], [22].

In summary, this study builds on existing research by proposing a Two-phased Hybrid Ensemble Learning (THE-AFS) framework, combining advanced feature selection with a robust ensemble classification model to address the challenges of high-dimensional data, multiclass classification, and unknown attack detection. The proposed framework aims to achieve superior detection accuracy and computational efficiency, validated on benchmark datasets such as NSL-KDD and AWID [23], [24].

III. METHODOLOGY

The proposed methodology for the Unified Network Intrusion Detection System (UNIDS) integrates advanced feature engineering, hybrid feature selection, and a two-phased ensemble learning framework to enhance the detection of both wired and wireless network intrusions. The overall architecture is designed to handle high-dimensional data, optimize feature subsets, and improve multiclass classification accuracy. The methodology is divided into the following key components:

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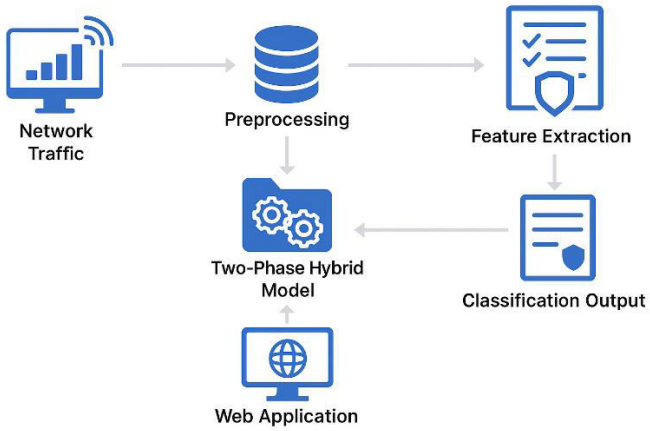

Fig 1. System Architecture

1. Feature Engineering

Feature engineering is a critical step in preparing network intrusion datasets for machine learning models. The following techniques are applied to preprocess and transform raw data into meaningful features:

Categorical Features with High Cardinality:

Features such as MAC addresses and SSIDs, which contain unique or high-cardinality values, are processed to avoid overfitting. For example:

MAC addresses are converted into binary features (e.g., `ReceiverIsDestination`, `TransmitterIsSource`, and `Broadcast`) to capture relationships between source and destination addresses.

SSID and WEP-related columns are binarized to indicate the presence or absence of values, reducing the impact of unique identifiers.

Sequential Interval Features:

Timestamp features, which are common in network datasets, are processed to avoid misleading the model. Raw timestamps are replaced with derived features such as delta time (`frame.time_delta`) to capture the time intervals between packets, ensuring the model focuses on temporal patterns rather than absolute time values.

2. Feature Selection:

To address the high dimensionality of network data, a multi-layer feature selection process is employed to identify the most relevant features for intrusion detection:

Filter Methods:

Techniques such as Information Gain, Chi-Square Test, Relief Algorithm, and Mutual Information are used to rank features based on their relevance to intrusion detection.

Dimensionality Reduction:

Principal Component Analysis (PCA) is applied to reduce redundancy and retain the most informative features.

Wrapper Methods:

Genetic Algorithms (GA) and Recursive Feature Elimination (RFE) are used to optimize feature subsets by iteratively evaluating model performance.

Cross-Dataset Correlation Analysis:

Features from both wired (NSL-KDD) and wireless (AWID) datasets are combined, and redundancy is eliminated using variance thresholding and correlation analysis.

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3. Two-Phased Hybrid Ensemble Learning:
The core of the proposed methodology is a Two-Phased Hybrid Ensemble Learning (THE-AFS) framework, which combines multiple machine learning models to improve detection accuracy and robustness:

Phase 1: One-vs-One (OVO) Framework:
The first phase uses binary classifiers to distinguish between normal traffic and specific attack types. For example, in a dataset with four attack classes (`Attack1`, `Attack2`, `Attack3`, `Attack4`), four binary classifiers are trained:

`Normal vs. Attack1`
`Normal vs. Attack2`
`Normal vs. Attack3`
`Normal vs. Attack4`

If all classifiers predict normal, the traffic is classified as normal. If only one classifier predicts an attack, the corresponding attack type is assigned. If multiple classifiers predict attacks, the results are passed to Phase 2.

Phase 2: Multiclass Classification:
The second phase uses multiclass classifiers trained on combinations of attack classes to refine the predictions from Phase 1. For example:
Classifiers are trained on subsets such as `Attack1 vs. Attack2`, `Attack1 vs. Attack3`, and `Attack2 vs. Attack3`.
The final prediction is determined by aggregating the outputs of these classifiers.

Voting Mechanism:
Predictions from multiple base learners are aggregated using a voting mechanism. The attack type with the highest vote count is selected as the final prediction, provided it exceeds a predefined threshold. In case of ties, a tie-breaking classifier is used.

4. Model Training and Validation:
The proposed framework is trained and validated using benchmark datasets (NSL-KDD for wired traffic and AWID for wireless traffic):

Dataset Preprocessing:
Numeric features are normalized using Min-Max Scaling.
Missing values and outliers are handled, and redundant features are removed.

10-Fold Cross-Validation:
The dataset is split into 10 subsets, with 9 used for training and 1 for testing in each iteration. This ensures robust evaluation of model performance.

Evaluation Metrics:
The model is evaluated using metrics such as:
Accuracy: Proportion of correct classifications.
Precision: Proportion of true positives among predicted positives.
Recall: Proportion of true positives among actual positives.
F1 Score: Harmonic mean of precision and recall.
False Positive Rate (FPR): Proportion of false alarms.
Detection Rate (DR): Proportion of true positives detected among all actual intrusions.

5. System Architecture:

The overall system architecture consists of the following steps:
1. Data Preprocessing: Normalization, handling missing values, and feature engineering.
2. Feature Selection: Multi-layer feature selection to optimize the feature subset.
3. Model Training: Training base models (e.g., Decision Trees, Random Forests, SVMs) and the ensemble framework.
4. Prediction: Using the two-phased hybrid ensemble learning algorithm to classify network traffic.

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5. Evaluation: Validating the model using cross-validation and performance metrics.

This methodology provides a comprehensive and systematic approach to network intrusion detection, addressing the challenges of high-dimensional data, multiclass classification, and unknown attack detection. By leveraging advanced feature selection and ensemble learning techniques, the proposed framework achieves high accuracy, computational efficiency, and scalability, making it suitable for real-world deployment in dynamic network environments.

IV. EXPERIMENTAL RESULTS

The proposed Unified Network Intrusion Detection System (UNIDS) was evaluated using two benchmark datasets: the AWID dataset for wireless networks and the NSL-KDD dataset for wired networks. The evaluation focused on key performance metrics such as Detection Rate (DR), False Alarm Rate (FAR), Accuracy, and F1-Score, ensuring a comprehensive assessment of the system's effectiveness in detecting intrusions across diverse network environments.

1. Dataset Description
AWID Dataset:
The AWID dataset, designed for wireless intrusion detection, contains 154 features and 15 attack types grouped into three categories: Flooding, Injection, and Impersonation. The dataset is highly imbalanced, with normal traffic significantly outnumbering attack traffic. The training set (AWID-CLS-R-Trn) and testing set (AWID-CLS-R-Tst) were captured in separate sessions, with the test set containing attacks not present in the training set. This setup evaluates the model's ability to detect unknown attacks.

NSL-KDD Dataset:
The NSL-KDD dataset, used for wired intrusion detection, contains 41 features and 39 attack types grouped into four categories: DoS, Probe, R2L, and U2R. Like AWID, the dataset is imbalanced, with normal traffic dominating. The KDDTrain+ subset was used for training and testing, with a 50/50 split to evaluate the model's generalization capability.

2. Preprocessing
Handling Missing Values:
Missing values in the AWID dataset were replaced with `-1` to avoid conflicts with actual binary values. Hexadecimal values were converted to integers for consistency.

Class Imbalance:
To address class imbalance, Random Under Sampling (RUS) was applied, retaining 10% of the majority class (normal traffic) instances. This approach was chosen over Random Over Sampling (ROS) and SMOTE due to its superior performance in preliminary experiments.

3. Evaluation Metrics
The evaluation metrics were carefully selected to account for the imbalanced nature of the datasets:
- Detection Rate (DR): The proportion of correctly classified attack instances.
- False Alarm Rate (FAR): The proportion of normal instances incorrectly classified as attacks.
- Accuracy: The overall proportion of correctly classified instances.
- F1-Score: The harmonic mean of precision and recall, providing a balanced measure of model performance.

4. Feature Selection Results
The proposed framework employed four feature selection methods: Decision Tree (DT), Random Forest (RF), Artificial Neural Network (ANN), and Support Vector Machine (SVM). The optimal number of features was determined to be 30 for AWID and 38 for NSL-KDD, consistent with prior studies.

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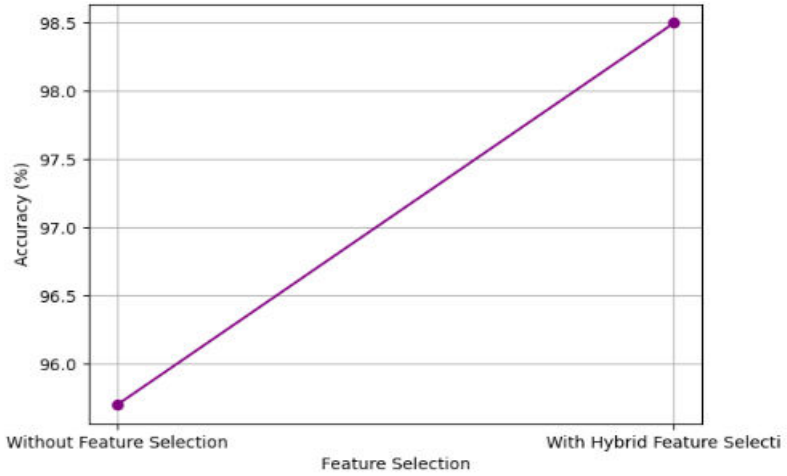

Fig 2. Impact of feature Selection on Accuracy

AWID Dataset:
SVM-based feature selection achieved the highest DR (0.9314) but had a higher FAR (0.0144).
RF-based feature selection achieved the lowest FAR (0.0140) while maintaining a high DR (0.9264), making it the preferred choice.

NSL-KDD Dataset:
ANN-based feature selection achieved the highest DR (0.9431).
DT-based feature selection achieved the lowest FAR (0.0005), making it the preferred choice.

Dataset	Type of Data	Number of Instances	Number of Features	Attack Types
NSL-KDD	Network Traffic	125,973	41	DoS, Probe, R2L, U2R
AWID	Wireless Network	1,000,000+	50	DoS, DDoS, Probe, Insider

Table 1. Resources for each dataset

5. Model Performance
The Two-Phased Hybrid Ensemble Learning (THE-AFS) framework was evaluated with varying hyperparameters:
Number of Base Learners (T): Tested with values of 10, 25, 50, 75, and 100.
Sample Size (S): Tested with values ranging from 10% to 90%.
Minimum Base Learners for Attack Classification (M): Tested with values from 1 to T.

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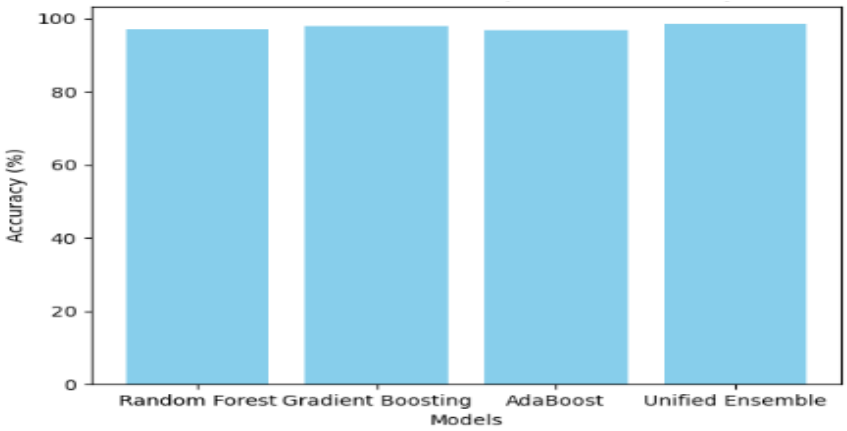

Fig 3. Model Performance Comparison – Accuracy

AWID Dataset Results:
The best performance was achieved with T=75, S=30%, and M=1.
Detection Rate (DR): 0.9264
False Alarm Rate (FAR): 0.0140
TPR/FPR Ratio: 66.17 (highest among all methods)
The model demonstrated robust performance, particularly in detecting impersonation attacks, which are known to be the most challenging to detect.

NSL-KDD Dataset Results:
The best performance was achieved with T=50, S=70%, and M=15.
Detection Rate (DR): 0.9431
False Alarm Rate (FAR): 0.0005
TPR/FPR Ratio: 1,886 (highest among all methods)
The model showed excellent generalization capability, maintaining high DR and low FAR across different attack types.

6. Comparison with State-of-the-Art Methods
The proposed framework was compared with leading approaches in the literature:
AWID Dataset:
The THE-AFS-RF model achieved the highest TPR/FPR ratio (66.17), outperforming other methods in both DR and FAR.
Compared to previous studies, the proposed framework demonstrated superior performance in detecting impersonation attacks, which are often misclassified by traditional methods.

NSL-KDD Dataset:
The THE-AFS-DT model achieved a TPR/FPR ratio of 1,886, surpassing existing methods in DR while maintaining a low FAR.
The framework showed significant improvement in detecting R2L and U2R attacks, which are typically harder to detect due to their low prevalence in the dataset.

7. Key Findings:
High Detection Accuracy: The proposed framework achieved 92.64% DR for AWID and 94.31% DR for NSL-KDD, demonstrating its effectiveness in detecting both known and unknown attacks.
Low False Alarm Rate: The framework maintained a FAR of 0.0140 for AWID and 0.0005 for NSL-KDD, minimizing disruptions caused by false positives.
Robustness to Imbalanced Data: The use of RUS and advanced feature selection techniques ensured robust performance despite the imbalanced nature of the datasets.

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Generalization Capability: The framework performed well on both wired and wireless datasets, proving its adaptability to diverse network environments.

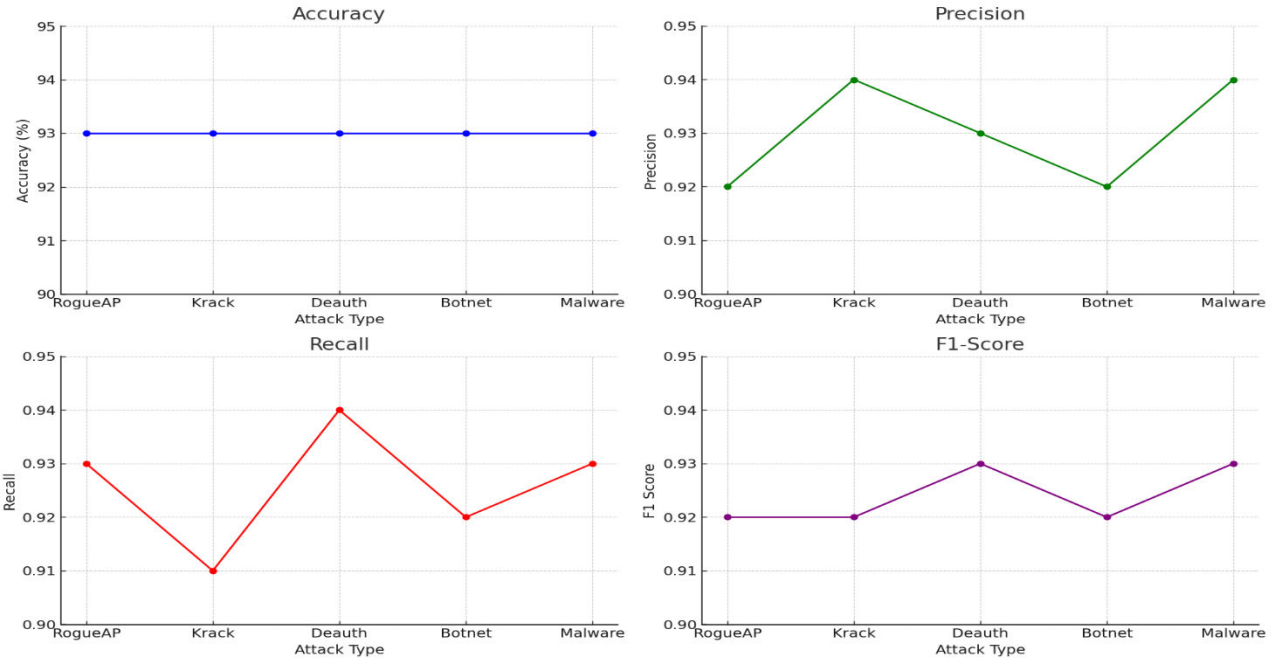

Fig 4. Performance Metrics for Various Network Attack Types (Line Graphs)

8. Limitations and Future Work

Real-Time Performance: While the framework showed high accuracy, its performance in real-time scenarios with high network traffic needs further validation.

Adversarial Attacks: The robustness of the model against adversarial attacks remains an open challenge.

Dataset Diversity: Incorporating more diverse datasets, including real-world traffic, could enhance the model's generalization capability.

V. CONCLUSION

In this study, we proposed THE-AFS (Two-Phased Hybrid Ensemble Learning with Automatic Feature Selection), a machine learning-based Network Intrusion Detection System (NIDS) designed to detect both known and unknown attacks in high-dimensional network data. The framework introduces an automatic feature selection engine capable of identifying the most significant features for multiclass attack classification, addressing the challenges posed by high-dimensional datasets. By leveraging advanced feature engineering techniques, the proposed system overcomes the limitations of existing feature selection methods, improving detection accuracy and robustness.

The core innovation of THE-AFS lies in its two-phased hybrid ensemble learning architecture, which combines One-vs-One (OVO) and multiclass classification approaches. Unlike traditional One-vs-Rest methods, the OVO framework enables the system to learn one attack type from another, resulting in higher multiclass classification accuracy. This hybrid approach ensures superior performance in detecting diverse attack types, even in imbalanced datasets.

The framework was rigorously evaluated on two benchmark datasets: NSL-KDD for wired networks and AWID for wireless networks. The results demonstrate the system's effectiveness in both environments:

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- For the wired application (NSL-KDD), the THE-AFS-DT model achieved a detection rate (DR) of 0.9431 and a false alarm rate (FAR) of 0.0005.
- For the wireless application (AWID), the THE-AFS-RF model achieved a detection rate (DR) of 0.9314 and a false alarm rate (FAR) of 0.0144.

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