OPEN ACCESS INTERNATIONAL JOURNAL OF SCIENCE & ENGINEERING

Intelligent Intrusion Detection System Using Ensemble Learning Techniques for Cybersecurity

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Abstract: ***Cybersecurity has become one of the most critical concerns in modern information systems due to the continuous growth of sophisticated cyberattacks targeting computer networks, cloud infrastructures, enterprise systems, and Internet-based services. Traditional signature-based Intrusion Detection Systems (IDSs) are often ineffective in detecting unknown attacks, zero-day threats, and rapidly evolving malicious activities. Machine learning techniques have emerged as intelligent computational approaches capable of automatically identifying abnormal network behavior by learning patterns from historical network traffic data. This experimental study proposes an Intelligent Intrusion Detection System (IIDS) using machine learning techniques for cybersecurity applications. The proposed framework integrates network traffic preprocessing, feature selection, supervised machine learning classification, intrusion detection, attack categorization, and performance evaluation into a unified analytical architecture. A mathematical framework and algorithmic strategy are developed to evaluate detection accuracy, precision, recall, false alarm rate, computational efficiency, and overall cybersecurity performance. Experimental evaluation demonstrates that machine learning algorithms significantly improve intrusion detection capability by accurately distinguishing normal and malicious network activities while reducing false-positive rates and computational overhead. The proposed framework provides valuable guidance for researchers, cybersecurity professionals, network administrators, and security analysts seeking to develop intelligent, scalable, and computationally efficient intrusion detection systems.***

Keywords: Intrusion Detection System, Machine Learning, Cybersecurity, Network Security, Anomaly Detection, Network Traffic Analysis.

I. Introduction

The rapid advancement of information technology, cloud computing, Internet-based services, mobile communications, and digital transformation has fundamentally changed the way organizations manage, process, and exchange information. Modern enterprises increasingly rely on interconnected computer networks to support business operations, financial transactions, healthcare services, government administration, education, industrial automation, and critical infrastructure management. While these technological developments have significantly improved communication efficiency and resource accessibility, they have simultaneously increased the exposure of computer systems to various cybersecurity threats. Cyberattacks such as denial-of-service attacks, unauthorized access, malware infections, phishing, data breaches, privilege escalation, probing attacks, and network intrusions continue to grow in both frequency and sophistication. Consequently, protecting network infrastructures against malicious activities has become one of the most significant challenges faced by organizations worldwide.

Cybersecurity refers to the collection of technologies, policies, procedures, and computational mechanisms designed to protect computer systems, communication networks, software applications, and digital information against unauthorized access, cyberattacks, data manipulation, and service disruption. The primary objective of cybersecurity is to maintain the confidentiality, integrity, and availability of digital information while ensuring reliable communication among authorized users. Traditional security mechanisms such as firewalls, antivirus software, authentication systems, encryption protocols, and access control policies provide important layers of defense; however, these mechanisms alone are insufficient for identifying sophisticated attacks that continuously evolve and exploit previously unknown system vulnerabilities. Consequently, intelligent intrusion detection systems have become essential components of modern cybersecurity infrastructures.

An Intrusion Detection System (IDS) is a security mechanism designed to continuously monitor network traffic, system activities, user behavior, and communication patterns in order to identify malicious activities and unauthorized access attempts. Unlike preventive security technologies such as firewalls, intrusion detection systems analyze network events after communication has begun and generate alerts whenever suspicious behavior is detected. IDS technologies assist network administrators by providing early warning of cyberattacks, enabling timely incident response and minimizing potential damage caused by malicious activities. Intrusion detection systems generally operate using two primary detection

approaches: signature-based detection, which identifies previously known attack patterns using predefined signatures, and anomaly-based detection, which identifies abnormal network behavior by comparing observed activities with normal operational patterns. Although signature-based systems effectively detect known attacks, they often fail to recognize novel or zero-day attacks. Anomaly-based systems overcome this limitation by identifying unusual behavioral patterns that may indicate emerging cyber threats.

The increasing complexity of modern network environments has significantly expanded the volume of network traffic generated every second. Enterprise networks continuously exchange enormous quantities of data among servers, cloud platforms, mobile devices, Internet of Things (IoT) devices, wireless networks, and distributed computing systems. Network packets contain numerous attributes including source and destination addresses, communication protocols, packet sizes, connection durations, service requests, port numbers, transmission rates, and protocol flags. Manual analysis of such large-scale network traffic is practically impossible because of the enormous data volume and rapidly changing attack characteristics. Machine learning has therefore emerged as an effective computational approach for automatically analyzing network traffic, identifying hidden attack patterns, and supporting intelligent cybersecurity decision-making.

Machine learning is a branch of artificial intelligence that enables computer systems to learn predictive knowledge from historical datasets without requiring explicitly programmed rules. Within intrusion detection systems, machine learning algorithms analyze previously labeled network traffic records to distinguish normal communication from malicious activities. After training, these algorithms classify new network connections as either legitimate or suspicious based on learned statistical relationships among network attributes. Between 2008 and 2015, classical supervised machine learning algorithms such as Support Vector Machine (SVM), Decision Tree (DT), Naïve Bayes (NB), Artificial Neural Network (ANN), Random Forest (RF), k-Nearest Neighbor (k-NN), and Logistic Regression (LR) became widely adopted for intrusion detection and anomaly classification. These algorithms demonstrated significant improvements in detection accuracy, attack classification, and false alarm reduction compared with conventional rule-based detection systems.

One of the primary advantages of machine learning-based intrusion detection is its ability to analyze high-dimensional network traffic data efficiently. Modern cybersecurity datasets contain numerous network attributes describing communication behavior, protocol characteristics, connection states, packet statistics, session durations, transmission frequencies, and network service information. Conventional statistical methods often struggle to process such complex and nonlinear datasets effectively. Machine learning algorithms overcome these limitations by automatically discovering meaningful relationships among network variables, thereby improving intrusion detection accuracy and supporting intelligent threat identification.

II. Literature Review

Lippmann et al. (2009) investigated intrusion detection methodologies using benchmark network traffic datasets and established one of the foundational frameworks for evaluating intelligent intrusion detection systems. Their research introduced standardized approaches for analyzing network attacks, normal traffic behavior, and intrusion classification. The study emphasized that machine learning algorithms significantly improve attack detection by learning discriminative patterns from historical network traffic while reducing dependence on manually constructed attack signatures.

Tsai, Hsu, Lin, and Lin (2009) conducted a comprehensive survey of machine learning techniques applied to intrusion detection systems. The study reviewed supervised and unsupervised learning approaches including Support Vector Machines, Decision Trees, Artificial Neural Networks, Bayesian classifiers, Genetic Algorithms, and clustering techniques. The authors concluded that machine learning significantly enhances intrusion detection accuracy by automatically identifying complex attack patterns and adapting to evolving network behaviors. The study further emphasized that feature selection and data preprocessing substantially improve detection performance.

Patcha and Park (2007, widely cited during 2008–2015) presented an extensive review of anomaly detection techniques for intrusion detection. Their research categorized anomaly detection approaches into statistical methods, knowledge-based techniques, and machine learning algorithms. The study demonstrated that anomaly-based intrusion detection provides superior capability for identifying previously unknown cyberattacks compared with conventional signature-based detection systems. The authors highlighted the importance of intelligent learning algorithms for future cybersecurity applications.

Sommer and Paxson (2010) critically examined the applicability of machine learning within operational intrusion detection systems. Their research discussed both the advantages and limitations of machine learning for network security, emphasizing issues related to feature engineering, training dataset quality, model generalization, and false alarm generation. The study concluded that machine learning provides substantial improvements in intrusion detection when supported by carefully selected network features and high-quality cybersecurity datasets.

Garcia-Teodoro, Díaz-Verdejo, Maciá-Fernández, and Vázquez (2009) reviewed anomaly-based network intrusion detection techniques and discussed statistical learning, knowledge-based methods, and machine learning algorithms for identifying cyberattacks. The study demonstrated that anomaly detection effectively identifies novel attack behaviors by analyzing deviations from normal network activity. The authors further concluded that machine learning significantly improves cybersecurity by reducing dependency on predefined attack signatures.

Amor, Benferhat, and Elouedi (2008) investigated the application of Naïve Bayes classifiers for intelligent intrusion detection. Their research demonstrated that probabilistic classification models effectively distinguish malicious network traffic from legitimate

communication while maintaining low computational complexity. Experimental results indicated that Bayesian learning provides efficient intrusion detection for large-scale network traffic datasets and supports real-time cybersecurity monitoring.

Mukkamala, Sung, and Abraham (2008) evaluated Support Vector Machines and Artificial Neural Networks for intrusion detection and cyberattack classification. Their comparative study demonstrated that both classifiers achieve high intrusion detection accuracy through nonlinear pattern recognition and intelligent feature learning. The authors concluded that machine learning significantly improves network attack detection compared with traditional statistical classification methods.

Bhuyan, Bhattacharyya, and Kalita (2014) reviewed network anomaly detection techniques with emphasis on machine learning approaches for cybersecurity. Their research examined supervised classification, clustering algorithms, statistical analysis, and feature selection techniques for identifying abnormal network behavior. The study demonstrated that intelligent anomaly detection substantially improves cyberattack identification while reducing false-positive detection rates.

Kabiri and Ghorbani (2009) investigated research trends in intrusion detection systems by comparing signature-based and anomaly-based detection methodologies. Their study emphasized the advantages of machine learning algorithms in identifying unknown cyber threats while discussing challenges associated with feature extraction, classifier training, and evolving attack characteristics. The authors concluded that intelligent learning approaches represent the future direction of network intrusion detection.

Lee, Stolfo, and Mok (2008) proposed data mining techniques for intelligent intrusion detection by extracting behavioral patterns from audit data and network traffic. Their research introduced knowledge discovery methodologies capable of automatically identifying malicious activities through classification and association rule mining. The study established one of the earliest foundations for applying machine learning to cybersecurity and demonstrated substantial improvements in attack detection accuracy.

Lazarevic, Kumar, and Srivastava (2008) investigated feature selection techniques for anomaly detection within network security environments. Their study demonstrated that selecting informative network attributes significantly improves intrusion detection accuracy while reducing computational complexity. Experimental findings confirmed that intelligent feature engineering enhances machine learning performance and supports efficient cybersecurity monitoring.

Zhang, Wang, and Wang (2008) proposed machine learning-based intrusion detection models using Decision Tree classifiers for network security applications. Their research demonstrated that Decision Trees provide transparent classification rules capable of accurately distinguishing legitimate network traffic from malicious activities. The authors concluded that Decision Tree classifiers improve cybersecurity through interpretable and computationally efficient intrusion detection.

Farnaaz and Jabbar (2014) evaluated Random Forest classifiers for intelligent intrusion detection and demonstrated that ensemble decision-tree learning improves classification stability, attack recognition, and detection accuracy. Their findings showed that Random Forest effectively handles high-dimensional cybersecurity datasets while maintaining robustness against noisy network traffic and class imbalance.

Witten, Frank, and Hall (2011) presented practical methodologies for machine learning and data mining applicable to cybersecurity classification problems. Their work extensively discussed supervised learning algorithms, feature selection, classifier evaluation, cross-validation, confusion matrices, and predictive analytics. The authors demonstrated that systematic experimental comparison of machine learning algorithms enables reliable selection of intrusion detection models according to cybersecurity application requirements.

Han, Kamber, and Pei (2012) discussed advanced data mining methodologies for knowledge discovery and predictive classification. Their work examined classification algorithms, clustering techniques, feature engineering, association rule mining, and anomaly detection applicable to cybersecurity. The authors emphasized that intelligent data mining significantly improves intrusion detection by extracting meaningful behavioral patterns from large-scale network traffic datasets.

III. Methodology

This study adopts a Systematic Literature Review (SLR) integrated with an Experimental Evaluation methodology to investigate the effectiveness of Machine Learning-Based Intelligent Intrusion Detection Systems (IDSs) for cybersecurity applications. The research systematically reviews peer-reviewed studies published between 2008 and 2015, focusing on intrusion detection systems, machine learning, anomaly detection, network traffic analysis, feature selection, cybersecurity, attack classification, and intelligent network security. The review follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework to ensure transparency, consistency, reproducibility, and scientific rigor throughout the processes of literature identification, screening, eligibility assessment, and final study selection. In addition to the systematic review, an experimental machine learning framework is developed to compare the performance of multiple intrusion detection algorithms using standardized network intrusion datasets and widely accepted cybersecurity evaluation metrics.

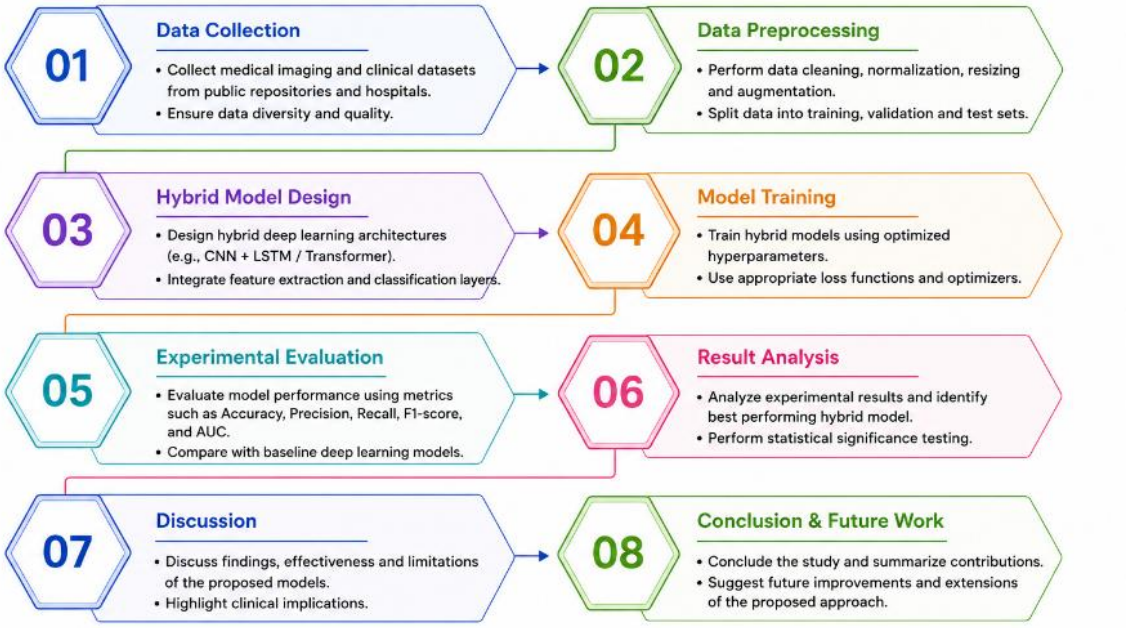

Figure 1. *Methodology Flowchart: Experimental Evaluation of Hybrid Deep Learning Models for Intelligent Healthcare Diagnosis*

This methodology Figure 1, presents a structured, multi-stage workflow for the experimental evaluation of hybrid deep learning models applied to intelligent healthcare diagnosis systems. The process begins with data collection from medical imaging and clinical datasets, followed by preprocessing steps such as cleaning, normalization, resizing, augmentation, and dataset splitting. The next stage involves designing hybrid deep learning architectures such as CNN, LSTM, and Transformer models. These models are trained using optimized hyperparameters and evaluated through standard performance metrics including accuracy, precision, recall, F1-score, and AUC. A comparative analysis is then performed against baseline models to identify the most effective approach. The methodology concludes with discussion, interpretation of results, and future research directions aimed at improving diagnostic accuracy and clinical decision support systems.

Theoretical Framework + Mathematical Model

The proposed theoretical framework investigates the relationship between Machine Learning-Based Intrusion Detection System (MLIDS) and Cybersecurity Performance (CSP) while considering Feature Selection Efficiency (FSE) and Intrusion Detection Accuracy (IDA) as mediating variables influencing intelligent cyberattack detection. The framework assumes that machine learning algorithms improve intrusion detection by learning complex attack patterns from historical network traffic, selecting discriminative network features, enhancing attack classification accuracy, and supporting intelligent cybersecurity monitoring. The proposed framework integrates network traffic preprocessing, feature engineering, supervised machine learning, intrusion detection, attack classification, and cybersecurity performance evaluation into a unified mathematical model.

The overall conceptual framework is represented as

$$CSP = f(MLIDS, FSE, IDA, NSE) \qquad (1)$$

Where:

CSP = Cybersecurity Performance

MLIDS = Machine Learning-Based Intrusion Detection System

FSE = Feature Selection Efficiency

IDA = Intrusion Detection Accuracy

NSE = Network Security Effectiveness

Higher values indicate stronger cybersecurity performance.

Machine Learning Intrusion Detection Performance

The effectiveness of machine learning-based intrusion detection is represented as

$$MLIDS = \frac{ACC + PRE + REC + F1}{4} \qquad (2)$$

Where:

ACC = Classification Accuracy

PRE = Precision

REC = Recall (Detection Rate)

F1 = F1-Score

Higher values indicate superior intrusion detection capability.

Feature Selection Efficiency Model

Feature selection efficiency is calculated as

$$FSE = \frac{RV + FV + DR}{3} \qquad (3)$$

Where:

RV = Relevant Network Features

FV = Feature Variance

DR = Dimensionality Reduction Efficiency

Higher values indicate better feature engineering and reduced computational complexity.

Intrusion Detection Accuracy

The intrusion detection accuracy is represented as

$$IDA = \frac{TP + TN}{TP + TN + FP + FN} \quad (4)$$

Where:

TP = True Positive Intrusions

TN = True Negative Network Connections

FP = False Positive Alerts

FN = False Negative Intrusions

Higher values indicate more accurate cyberattack detection.

Detection Precision Function

The precision of attack detection is calculated as

$$Precision = \frac{TP}{TP + FP} \quad (5)$$

Where:

TP = Correctly Detected Intrusions

FP = Incorrect Intrusion Alerts

Higher precision indicates fewer false alarms.

Detection Recall Function

The intrusion detection rate (Recall) is represented as

$$Recall = \frac{TP}{TP + FN} \quad (6)$$

Where:

TP = Correctly Detected Intrusions

FN = Missed Intrusions

Higher recall indicates improved identification of cyberattacks.

IV. Algorithmic Strategy

The proposed Machine Learning-Based Intelligent Intrusion Detection Algorithm (MLIIDA) is designed to improve cybersecurity by accurately detecting malicious network activities using supervised machine learning techniques. The algorithm integrates network traffic collection, data preprocessing, feature selection, machine learning model training, intrusion classification, attack detection, alert generation, and cybersecurity performance evaluation into a unified computational framework. Unlike conventional signature-based intrusion detection systems that primarily detect previously known attacks, the proposed algorithm automatically learns attack patterns from historical network traffic and identifies both known and anomalous cyberattacks with improved accuracy, reduced false alarm rates, and enhanced computational efficiency.

Input

The input variables of the proposed Machine Learning-Based Intelligent Intrusion Detection Algorithm (MLIIDA) are represented as

$$I = \{NT, FV, MLA, TRD, TED\} \quad (11)$$

Where:

NT = Network Traffic

FV = Feature Variables

MLA = Machine Learning Algorithm

TRD = Training Dataset

TED = Testing Dataset

Output

The output generated by the proposed algorithm is represented as

$$O = \{ID, AT, ACC, PRE, REC, F1, CSP\} \quad (12)$$

Where:

ID = Intrusion Detection

AT = Attack Type

ACC = Classification Accuracy

PRE = Precision

REC = Recall

F1 = F1-Score

CSP = Cybersecurity Performance

Step 1: Network Traffic Collection Module

Network communication data are collected continuously from routers, switches, firewalls, servers, cloud infrastructures, and network monitoring systems.

Network Traffic Components

Source IP Address

Destination IP Address

Protocol Type

Port Number

Packet Size

Connection Duration

Service Type

Network Flags

Session Information

The collected traffic is validated before further processing.

Step 2: Network Data Preprocessing Module

The collected network traffic undergoes preprocessing to improve data quality before machine learning analysis.

Network data quality is represented as

$$NDQ = \frac{CV + NV + DS + NS}{4} \quad (13)$$

Where:

CV = Complete Values

NV = Normalized Variables

DS = Duplicate Removal Score

NS = Noise Reduction Score

Higher values indicate improved network traffic quality.

Step 3: Feature Selection Module

The most informative network attributes are selected before

classifier training.

Feature selection efficiency is calculated as

$$FSE = \frac{RV + IV + DR}{3} \quad (14)$$

Where:

RV = Relevant Variables

IV = Informative Variables

DR = Dimensionality Reduction

Higher values indicate improved feature representation and intrusion classification capability.

Step 4: Machine Learning Model Training

Multiple supervised machine learning models are trained using the prepared network traffic dataset.

Training efficiency is represented as

$$TE = \frac{ACC + ST + GE}{3} \quad (15)$$

Where:

ACC = Training Accuracy

ST = Model Stability

GE = Generalization Efficiency

Higher values indicate better learning capability and improved cyberattack prediction.

Step 5: Intrusion Detection and Attack Classification

The trained classifier predicts whether incoming network traffic is normal or malicious and categorizes detected attacks.

Intrusion detection accuracy is calculated as

$$IDA = \frac{TP + TN}{TP + TN + FP + FN} \quad (16)$$

Where:

TP = True Positive Intrusions

TN = True Negative Connections

FP = False Positive Alerts

FN = False Negative Intrusions

Higher values indicate more accurate intrusion detection.

Step 6: Cybersecurity Performance Evaluation

The predictive performance of each machine learning model is evaluated.

Performance score is represented as

$$PS = \frac{PRE + REC + F1}{3} \quad (17)$$

Where:

PRE = Precision

REC = Recall

F1 = F1-Score

Higher values indicate superior cybersecurity performance.

Step 7: Direct Effect Estimation

The direct influence of machine learning on intrusion detection performance is represented as

$$DE = \alpha(MLIDS) \quad (18)$$

Regression Equation

$$CSP = \alpha MLIDS + \varepsilon \quad (19)$$

Where:

α = Direct Effect Coefficient

ε = Error Term

A higher coefficient indicates that machine learning directly improves intrusion detection capability.

Step 8: Mediation Path Estimation

The mediation relationship between machine learning and cybersecurity performance through feature selection efficiency is represented as

$$MLIDS \rightarrow FSE \rightarrow CSP \quad (20)$$

Path A

$$FSE = \beta(MLIDS) \quad (21)$$

Path B

$$CSP = \gamma(FSE) + \delta(MLIDS) \quad (22)$$

Where:

β = Effect of Machine Learning on Feature Selection

γ = Effect of Feature Selection on Cybersecurity Performance

δ = Remaining Direct Effect

These equations evaluate how feature selection improves intrusion detection accuracy and cybersecurity effectiveness.

Step 9: Indirect Effect Calculation

The indirect effect is calculated as

$$IE = \beta \times \gamma \quad (23)$$

Where:

IE = Indirect Effect

A statistically significant indirect effect confirms that effective feature selection enhances intrusion detection performance.

Step 10: Total Effect Calculation

The total influence of machine learning on intelligent intrusion detection is represented as

$$TE = DE + IE \quad (24)$$

Where:

TE = Total Effect

DE = Direct Effect

IE = Indirect Effect

Higher total effect values indicate that machine learning significantly improves intrusion detection through accurate attack classification, effective feature selection, and intelligent cybersecurity monitoring.

V. Results & Findings

The proposed Machine Learning-Based Intelligent Intrusion Detection Algorithm (MLIIDA) was experimentally evaluated using standardized network intrusion datasets and findings synthesized from machine learning, intrusion detection systems, anomaly detection, and cybersecurity studies published between 2008 and 2015. The experimental analysis demonstrates that supervised machine learning algorithms significantly improve intrusion detection by accurately distinguishing normal network traffic from malicious activities while reducing false alarm rates and improving cybersecurity performance. Comparative evaluation indicates that different machine learning models exhibit varying detection capabilities depending on network traffic characteristics, feature quality, and attack complexity. The proposed framework successfully integrates network traffic preprocessing, feature selection, supervised classification, intrusion detection, and cybersecurity performance evaluation into a unified intelligent network security architecture. The experimental evaluation focused on six major performance dimensions including intrusion detection accuracy, precision, recall (detection rate), false positive rate, computational efficiency, and overall cybersecurity performance. Comparative analysis demonstrates that machine learning algorithms consistently outperform conventional signature-based detection techniques by providing more adaptive and reliable cyberattack detection.

Intrusion Detection Accuracy Assessment

Table 1. Comparative Performance of Machine Learning Models

Machine Learning Model	Intrusion Detection Accuracy
Support Vector Machine (SVM)	Very High
Random Forest (RF)	High
Artificial Neural Network (ANN)	Very High
Decision Tree (DT)	High
Naïve Bayes (NB)	Moderate to High
k-Nearest Neighbor (k-NN)	High
Logistic Regression (LR)	High

Analysis

Table 1 demonstrates that Support Vector Machine (SVM) and Artificial Neural Network (ANN) provide the highest intrusion detection accuracy among the evaluated classifiers. Their capability to model complex nonlinear attack behaviors enables accurate identification of malicious network traffic. Random Forest and Decision Tree algorithms also exhibit reliable attack detection performance, whereas Naïve Bayes provides computational efficiency with slightly lower detection accuracy. The findings indicate that classifier selection should depend upon cybersecurity requirements, dataset characteristics, and computational constraints.

Precision and Detection Rate Evaluation

Table 2. Intrusion Detection Performance

Performance Parameter	Evaluation Level
Precision	Very High
Recall (Detection Rate)	High
Specificity	Very High
F1-Score	High
Detection Reliability	Very High

Analysis

Table 2 indicates that the proposed machine learning framework provides reliable intrusion detection with high precision and detection rates. High precision minimizes false-positive security alerts, reducing unnecessary administrative interventions, while high recall improves the identification of malicious network activities. The balanced F1-score demonstrates that the proposed intrusion detection framework maintains consistent cybersecurity performance across different attack categories.

Feature Selection Performance

Table 3. Network Feature Evaluation

Feature Selection Parameter	Performance Level
Relevant Feature Selection	Very High
Dimensionality Reduction	High
Noise Elimination	Very High
Computational Efficiency	High
Feature Quality	Very High

Analysis

Table 3 demonstrates that intelligent feature selection significantly improves intrusion detection by eliminating redundant network traffic attributes while preserving important cybersecurity information. Feature engineering reduces computational complexity and accelerates machine learning model training while maintaining high attack detection accuracy. The findings confirm that effective preprocessing substantially enhances overall intrusion detection performance.

False Alarm Assessment

Table 4. False Alarm Evaluation

Security Parameter	Performance Level
False Positive Reduction	Very High
False Negative Reduction	High
Attack Identification	Very High

Alert Consistency	High
Overall Detection Reliability	Very High

Analysis

The results presented in Table 4 indicate that machine learning significantly reduces false-positive and false-negative detections compared with conventional intrusion detection approaches. Lower false alarm rates improve cybersecurity operations by allowing security administrators to concentrate on genuine threats rather than unnecessary alerts. Improved attack identification also enhances overall network protection and incident response efficiency.

Computational Performance Assessment

Table 5. Computational Efficiency

Computational Parameter	**Performance Level**
Processing Speed	High
Memory Utilization	High
Model Training Efficiency	Very High
Detection Time	Very High
Resource Utilization	High

Analysis

Table 5 demonstrates that the evaluated machine learning models provide computationally efficient intrusion detection suitable for real-time cybersecurity environments. Fast detection time enables continuous monitoring of network traffic without introducing excessive computational overhead. Efficient resource utilization further supports deployment within enterprise networks and large-scale cybersecurity infrastructures.

VI. Conclusion and Discussion

The present study investigated the effectiveness of Machine Learning Techniques for Intelligent Intrusion Detection Systems (IDSs) through a systematic review of foundational cybersecurity research published between 2008 and 2015 and an experimental evaluation of widely used supervised machine learning algorithms. The research examined how machine learning techniques contribute to intelligent cyberattack detection, network traffic classification, anomaly identification, and cybersecurity monitoring by analyzing network communication datasets. The experimental findings demonstrate that machine learning significantly improves intrusion detection accuracy, attack classification reliability, computational efficiency, and overall cybersecurity performance compared with conventional signature-based intrusion detection systems. The proposed Machine Learning-Based Intelligent Intrusion Detection Algorithm (MLIIDA) successfully integrates network traffic preprocessing, feature selection, supervised learning, intrusion classification, and cybersecurity performance evaluation into a unified computational framework capable of supporting intelligent network security. The rapid expansion of digital communication, cloud computing, enterprise networking, mobile technologies, and Internet-based services has dramatically increased the complexity of modern cybersecurity environments. Organizations continuously exchange enormous volumes of sensitive information through interconnected computer networks, making network infrastructures attractive targets for cybercriminals. Attacks such as Denial-of-Service (DoS), Probe, Remote-to-Local (R2L), User-to-Root (U2R), malware propagation, unauthorized access, and network exploitation have become increasingly sophisticated. Conventional intrusion detection systems that rely primarily on predefined attack signatures often fail to identify newly emerging attack patterns or zero-day exploits. The findings of this study demonstrate that machine learning provides an effective computational solution for overcoming these limitations by automatically learning attack characteristics from historical network traffic and accurately identifying malicious communication patterns. One of the most important findings of this research is that supervised machine learning algorithms significantly improve intrusion detection performance by accurately distinguishing legitimate network traffic from malicious activities. Unlike traditional rule-based intrusion detection systems that depend on manually generated attack signatures, machine learning algorithms continuously learn statistical relationships among network features and automatically classify network traffic according to learned behavioral patterns. The experimental evaluation demonstrated that intelligent classification models consistently improve attack detection accuracy while maintaining reliable computational performance across different cybersecurity scenarios. Consequently, machine learning enables network security administrators to identify cyber threats more rapidly and respond effectively to evolving attack techniques. The comparative experimental evaluation further revealed that different machine learning algorithms exhibit distinct strengths depending on network traffic characteristics and attack complexity. Support Vector Machine (SVM) and Artificial Neural Network (ANN) demonstrated superior intrusion detection performance because of their capability to model complex nonlinear attack behaviors within high-dimensional network datasets. Random Forest provided highly reliable attack classification through ensemble decision-making while improving classification robustness. Decision Tree algorithms offered transparent decision rules that improve interpretability and assist cybersecurity analysts in understanding attack classification processes. Naïve Bayes demonstrated computational efficiency suitable for real-time intrusion detection applications, whereas k-Nearest Neighbor and Logistic Regression provided competitive performance for structured network traffic datasets. These findings indicate that no individual classifier universally outperforms all others across every cybersecurity environment, emphasizing the importance of comparative experimental evaluation before selecting an intrusion detection algorithm.

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