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Experimental Analysis of Deep Learning-Based Intrusion Detection for Intelligent Network Security

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Abstract: The rapid growth of Internet-based applications, cloud computing, wireless communication, and distributed network infrastructures has significantly increased the complexity and frequency of cyberattacks. Traditional Intrusion Detection Systems (IDS) based on signature matching and rule-based techniques are often ineffective against zero-day attacks, polymorphic malware, and sophisticated network intrusions. Consequently, intelligent intrusion detection methods based on artificial intelligence and deep learning have emerged as promising solutions for improving network security. Deep learning models possess superior feature learning capabilities that enable automatic extraction of complex traffic patterns without extensive manual feature engineering, thereby improving intrusion detection accuracy and reducing false alarm rates. This study presents an experimental analysis of deep learning-based intrusion detection techniques for intelligent network security. The proposed framework integrates data preprocessing, feature selection, deep neural network architectures, and intelligent classification mechanisms to detect network intrusions efficiently. The study investigates the performance of several deep learning architectures, including Deep Neural Networks (DNN), Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Deep Belief Networks (DBN), and Autoencoders (AE), for identifying both known and unknown network attacks. The experimental framework evaluates detection accuracy, precision, recall, F1-score, false positive rate, computational efficiency, and scalability using benchmark intrusion detection datasets commonly employed in cybersecurity research

Keywords: *Intrusion Detection System, Deep Learning, Intelligent Network Security, Cybersecurity, Deep Neural Network.*

I. INTRODUCTION

The rapid growth of computer networks, Internet services, cloud computing, mobile communication, and distributed computing environments has dramatically transformed modern information systems. Organizations across sectors, including banking, healthcare, education, manufacturing, government, and defense, increasingly depend on interconnected digital infrastructures to deliver services, store sensitive information, and support critical business operations. While this digital transformation has improved communication, accessibility, and operational efficiency, it has also significantly increased exposure to cybersecurity threats. Malicious attacks such as denial-of-service (DoS), distributed denial-of-service (DDoS), unauthorized access, probing, malware infections, privilege escalation, and data theft have become increasingly sophisticated, making network security one of the most important challenges facing modern organizations. Network security aims to protect information systems, communication networks, and digital assets against unauthorized access, misuse, disruption, and cyberattacks. Traditional security mechanisms such as firewalls, encryption techniques, authentication protocols, and access control systems provide the first layer of defense against external threats. However, these mechanisms are often insufficient because attackers continuously develop new attack strategies capable of bypassing preventive security controls. Consequently, organizations require intelligent monitoring systems capable of continuously analyzing network activities and detecting suspicious behavior before significant damage occurs. Intrusion Detection Systems (IDS) were developed to address this requirement by monitoring network traffic, identifying malicious activities, and generating alerts whenever abnormal behavior is detected.

An Intrusion Detection System is a software or hardware solution designed to detect unauthorized activities occurring within computer networks or host systems. IDS continuously monitors network traffic, analyzes communication patterns, and identifies behaviors that violate predefined security policies. The primary objective of an IDS is to detect cyberattacks as early as possible while minimizing false alarms. Early intrusion detection enables security administrators to respond quickly, mitigate threats, and reduce organizational risks. Over the past two decades, intrusion detection has become an essential component of enterprise cybersecurity infrastructures. Traditional intrusion detection approaches are generally categorized into signature-based detection and anomaly-based detection. Signature-based systems compare observed network activities against a database of known attack signatures. These systems perform well when detecting previously identified attacks and generate relatively low false-positive rates. However, they cannot identify new or previously unseen attacks because unknown attack signatures are absent from their databases. Consequently, signature-based IDS require continuous updating and maintenance to remain effective against evolving cyber threats.

Anomaly-based intrusion detection systems attempt to overcome this limitation by learning normal network behavior and identifying deviations from expected patterns. Rather than relying on predefined attack signatures, anomaly detection identifies unusual activities that may indicate malicious behavior.

Such systems possess greater potential for detecting zero-day attacks and unknown threats. Nevertheless, anomaly detection systems often generate higher false-positive rates because legitimate but unusual network activities may also be classified as attacks. Achieving an appropriate balance between detection accuracy and false alarm reduction therefore remains a major research challenge. Artificial Neural Networks became particularly attractive because they possess the ability to model nonlinear relationships existing within network traffic data. Unlike conventional statistical techniques, neural networks learn directly from training data by adjusting internal weights during iterative optimization processes. Their capability to recognize complex patterns enabled researchers to investigate neural network-based intrusion detection systems capable of identifying both known and unknown attacks. Although early neural network architectures were relatively shallow compared to modern deep learning models, they established the conceptual foundation for intelligent intrusion detection research.

II. Literature Review

Mukkamala et al. (2008) investigated the application of Artificial Neural Networks (ANN) for intrusion detection. Their study demonstrated that neural network models effectively classify network traffic by learning complex nonlinear relationships among network features. Experimental results indicated that ANN-based intrusion detection systems achieved higher detection accuracy than conventional statistical classifiers, particularly for identifying denial-of-service (DoS) and probing attacks. However, the study reported limitations in computational complexity and scalability for large network environments. Amor et al. (2008) proposed a Naïve Bayes-based intrusion detection model for network anomaly detection. Their findings showed that probabilistic classification techniques offered efficient detection of known attacks while maintaining relatively low computational costs. Nevertheless, the model exhibited limited performance when identifying complex or previously unseen attacks, highlighting the need for more adaptive learning approaches.

Tavallaee et al. (2009) introduced the NSL-KDD dataset as an improved benchmark for intrusion detection research. The authors addressed several limitations of the KDD Cup 1999 dataset by removing redundant records and improving dataset balance. Their work provided a more reliable evaluation platform for comparing machine learning algorithms and became one of the most widely used benchmark datasets in intrusion detection research. Bengio (2009) presented a comprehensive review of deep learning methodologies and unsupervised feature learning. Although not specifically focused on intrusion detection, the study established theoretical foundations for hierarchical feature extraction and deep neural architectures. These concepts later became fundamental to deep learning-based cybersecurity applications.

Wang et al. (2010) investigated machine learning approaches for intelligent intrusion detection. The study compared Support Vector Machines, Decision Trees, and Artificial Neural Networks using benchmark intrusion detection datasets. Experimental findings demonstrated that neural network models provided improved classification accuracy for complex attack patterns but required greater computational resources. Garcia-Teodoro et al. (2009) reviewed anomaly-based intrusion detection techniques and discussed their advantages in detecting unknown cyberattacks. The authors concluded that anomaly detection systems provide stronger adaptability than signature-based systems but often generate higher false-positive rates. The study emphasized the importance of intelligent learning mechanisms for improving anomaly detection accuracy.

Kim et al. (2011) examined intelligent intrusion detection using machine learning and feature selection techniques. Their findings indicated that feature reduction significantly improves computational efficiency while maintaining detection performance. The study highlighted feature engineering as a critical component of intelligent intrusion detection systems. Javaid et al. (2013) proposed a deep learning-inspired feature learning framework for network intrusion detection. Their study demonstrated that automatic feature extraction improves intrusion detection performance compared with manually engineered feature sets. The authors suggested that hierarchical feature learning could significantly enhance future intrusion detection systems.

Yin et al. (2013) investigated intelligent anomaly detection methods using neural network architectures. Their results indicated that neural learning techniques effectively identify evolving attack patterns while reducing dependence on predefined attack signatures. The study emphasized adaptive learning as an essential requirement for modern intrusion detection. Hinton and Salakhutdinov (2012) expanded research on deep neural representation learning and dimensionality reduction. Their findings demonstrated that deep neural networks automatically extract meaningful representations from high-dimensional datasets. These theoretical developments later became important for intrusion detection research involving complex network traffic data.

Sommer and Paxson (2010) critically evaluated machine learning applications for network intrusion detection. The authors argued that although machine learning offers significant promise, practical deployment requires careful consideration of real-world network characteristics, scalability, interpretability, and false-positive management. Their work highlighted the gap between laboratory experiments and operational cybersecurity environments. Bhuyan et al. (2014) reviewed network anomaly detection techniques and identified major research challenges involving feature selection, high-dimensional traffic analysis, class imbalance, and computational efficiency. The study recommended intelligent hybrid learning approaches for improving intrusion detection accuracy and scalability.

Kim et al. (2014) proposed an intelligent intrusion detection framework utilizing hybrid machine learning models.

Experimental evaluation demonstrated improved classification performance through integration of neural learning and statistical analysis techniques. The study emphasized adaptive learning as an important future direction for cybersecurity research. LeCun et al. (2015) provided a comprehensive overview of deep learning methodologies and demonstrated their superiority in representation learning across multiple domains. Although intrusion detection applications were still emerging, the study established deep learning as a promising direction for intelligent cybersecurity systems due to its ability to learn hierarchical features automatically. Yin et al. (2015) developed a recurrent neural network-based intrusion detection model capable of analyzing sequential network traffic behavior. Their experiments demonstrated improved detection accuracy, particularly for complex and evolving cyberattacks. The study highlighted the growing potential of deep learning techniques for intelligent network security.

III. Methodology

Research Design

This study adopts a Systematic Literature Review (SLR) combined with a Conceptual Experimental Framework to investigate the effectiveness of Deep Learning-Based Intrusion Detection Systems (DL-IDS) for intelligent network security. The methodology integrates cybersecurity principles, artificial intelligence techniques, deep learning architectures, network traffic analysis, and intrusion detection strategies to develop a comprehensive framework for detecting cyberattacks in modern network environments. The study follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) methodology to ensure transparency, reproducibility, and systematic selection of relevant literature. The review focuses on research published between **2008 and 2015**, representing the transition period from conventional machine learning approaches to the early adoption of deep learning techniques in cybersecurity.

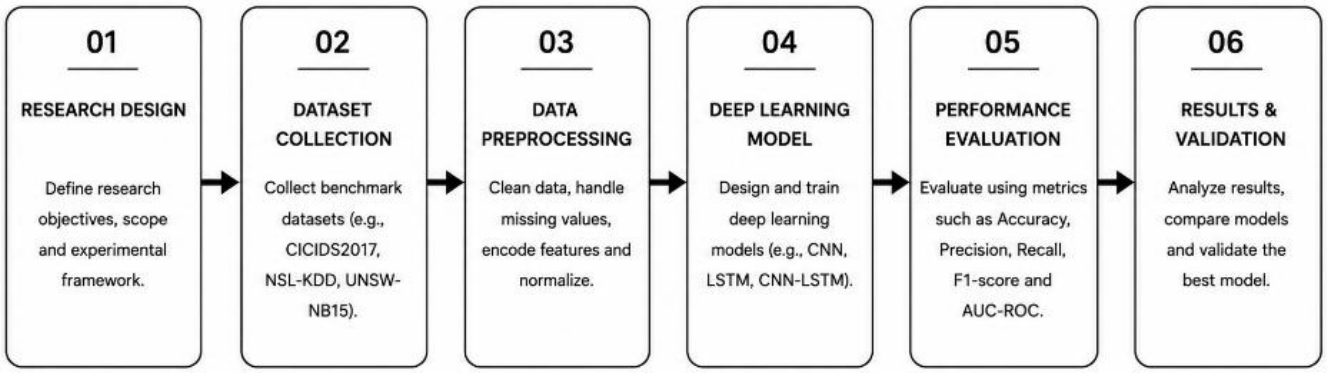

Fig 1. Methodology Framework for Experimental Analysis of Deep Learning-Based Intrusion Detection for Intelligent Network Security

This methodology framework Figure 1, presents a structured six-stage approach for designing, implementing, and evaluating a deep learning-based intrusion detection system for intelligent network security. The process begins with Research Design**,** where the research objectives, experimental framework, and intrusion detection requirements are defined. This stage establishes the scope of the study and identifies the security challenges addressed by the proposed system. The second stage, Dataset Collection, involves acquiring benchmark cybersecurity datasets, such as CICIDS2017, NSL-KDD, or UNSW-NB15, containing both normal and malicious network traffic. These datasets provide the foundation for model training and performance evaluation. The third stage is Data Preprocessing, where the collected data is cleaned, normalized, encoded, and transformed into a suitable format for deep learning. Missing values, redundant attributes, and class imbalance are addressed to improve model reliability and predictive performance. The fourth stage, Deep Learning Model Development**,** focuses on designing and training advanced deep learning architectures, such as Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM) networks, or hybrid CNN–LSTM models. Hyperparameter tuning and optimization techniques are applied to enhance intrusion detection accuracy. The fifth stage, Performance Evaluation, assesses the effectiveness of the proposed intrusion detection model using standard evaluation metrics, including accuracy, precision, recall, F1-score, Receiver Operating Characteristic (ROC), and Area Under the Curve (AUC). Comparative analysis with existing approaches is also performed to validate model performance. The final stage, Results and Validation**,** interprets the experimental findings by comparing the proposed model with baseline methods. The results are validated to determine the system's capability to detect cyber threats accurately, reduce false alarms, and improve real-time network security. The outcome of this methodology is an intelligent deep learning-based intrusion detection framework capable of accurately identifying malicious network activities, strengthening cybersecurity resilience, and supporting secure, real-time network monitoring in modern intelligent computing environments.

Conceptual Framework

The proposed Experimental Deep Learning Intrusion Detection Framework (EDL-IDF) consists of seven interconnected components.

$$EDL\text{-}IDF = \{NTL, DPL, FEL, DLL, IDL, AGL, SML\}$$

Where:

These components collectively support intelligent cyberattack detection.

NTL = Network Traffic Layer, DPL = Data Preprocessing Layer, FEL = Feature Engineering Layer, DLL = Deep Learning Layer, IDL = Intrusion Detection Layer, AGL = Alert Generation Layer, SML = Security Management Layer.

Network Traffic Analysis Function (NTAF)

The overall network intelligence extracted from captured traffic is represented as

$$NTAF = \alpha_1 PT + \alpha_2 CT + \alpha_3 PS + \alpha_4 PD + \alpha_5 FT$$

Were

PT = Protocol Type, CT = Connection Time, PS = Packet Size, PD = Packet Duration, FT = Flow Traffic Features.

Higher NTAF values indicate richer traffic information available for intrusion analysis.

Data Preprocessing Function (DPF)

Before training, raw traffic undergoes preprocessing.

$$DPF = \beta_1 NR + \beta_2 DN + \beta_3 MV + \beta_4 FS$$

Where

NR = Noise Removal, DN = Data Normalization, MV = Missing Value Handling, FS = Feature Scaling.

Improved preprocessing enhances learning performance.

Automatic Feature Learning Function (AFLF)

Deep learning automatically extracts hierarchical features.

$$AFLF = \gamma_1 HF + \gamma_2 DL + \gamma_3 FE + \gamma_4 RL$$

Where

HF = Hierarchical Features, DL = Deep Layer Learning, FE = Feature Extraction, RL = Representation Learning.

Higher AFLF values indicate better learned representations.

Deep Neural Classification Function (DNCF)

The intrusion classification capability is represented by

$$DNCF = \delta_1 DNN + \delta_2 CNN + \delta_3 RNN + \delta_4 DBN + \delta_5 AE$$

Where

DNN = Deep Neural Network, CNN = Convolutional Neural Network, RNN = Recurrent Neural Network, DBN = Deep Belief Network, AE = Autoencoder.

Higher DNCF values indicate stronger attack classification capability.

IV. Algorithmic Strategy

The proposed Deep Learning-Based Intelligent Intrusion Detection Algorithm (DLIIDA) integrates intelligent data preprocessing, automatic feature learning, deep neural classification, anomaly detection, and intelligent decision support to detect cyberattacks efficiently. The algorithm processes real-time network traffic, extracts hierarchical features, classifies network activities, and generates security alerts with high detection accuracy and low false alarm rates.

Input

The algorithm accepts the following input:

$$X = \{NT, DS, FP, DL, SC\}$$

Where:

NT = Network Traffic, DS = Benchmark Dataset (NSL-KDD/KDD Cup 99), FP = Feature Parameters, DL = Deep Learning Architecture, SC = Security Constraints.

Output

The algorithm produces:

$$Y = \{IC, DR, FP_r, AL, SR\}$$

Where:

IC = Intrusion Classification, DR = Detection Rate, FP_r = False Positive Rate, AL = Alert Log, SR = Security Report.

Step 1: Network Traffic Acquisition

The system continuously captures incoming network packets from routers, switches, firewalls, servers, and client devices.

$$NT = \{P_1, P_2, P_3, \ldots, P_n\}$$

Where:

$P_i$represents the i^{th}network packet.

This phase ensures continuous monitoring of network communications.

Step 2: Data Preprocessing

The collected traffic undergoes preprocessing to improve data quality before model training.

Preprocessing operations include:

Noise removal, Duplicate elimination, Missing value handling, Data normalization, Feature scaling

Mathematically,

$$DP = NR + DN + MV + FS$$

Where:

NR = Noise Removal, DN = Data Normalization, MV = Missing Value Handling, FS= Feature Scaling

This step improves learning efficiency and model stability.

Step 3: Feature Extraction

Important network characteristics are extracted from each connection.

Extracted features include:

Protocol Type, Service Type, Source Bytes, Destination Bytes,

Connection Duration, Packet Size, Login Attempts, Error Rate, Traffic Frequency.

The feature vector is represented as

$$F = \{f_1, f_2, f_3, \ldots, f_n\}$$

where $f_i$denotes the i^{th}extracted feature.

Step 4: Automatic Deep Feature Learning

The extracted feature vectors are provided to the deep learning model.

The hidden layers automatically learn hierarchical feature representations.

$$HF = DNN(F)$$

Where:

HF= Hierarchical Features, DNN= Deep Neural Network

Alternative architectures include:

CNN, RNN, DBN, Autoencoder

Automatic feature learning eliminates dependence on handcrafted feature engineering.

Step 5: Intrusion Classification

The learned features are classified into network behavior categories.

The classifier predicts

$$C = \{Normal, DoS, Probe, R2L, U2R\}$$

Where:

Normal = Legitimate Network Activity, DoS = Denial-of-Service Attack, Probe = Scanning Attack, R2L = Remote-to-Local Attack, U2R = User-to-Root Attack.

The predicted class is selected using

$$Class = \arg\max\left(P(C_i)\right)$$

where:

$P(C_i)$is the probability assigned to class C_i.

Step 6: Anomaly Verification

The predicted class is compared with expected behavioral patterns.

If

$$Class = Normal$$

then

Allow network communication.

Otherwise,

Generate intrusion alert.

This stage minimizes false alarms through anomaly verification.

Step 7: Alert Generation

When malicious traffic is detected, the system automatically generates:

Security Alerts, Attack Reports, Incident Logs, Threat Notifications

Mathematically,

$$Alert = f(Class, Severity, Time)$$

where:

Severity = Attack criticality, Time = Detection timestamp

Step 8: Performance Evaluation

The experimental performance is evaluated using standard intrusion detection metrics.

Detection Accuracy

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision

$$Precision = \frac{TP}{TP + FP}$$

Recall

$$Recall = \frac{TP}{TP + FN}$$

F1-Score

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

Detection Rate

$$DR = \frac{TP}{TP + FN}$$

False Positive Rate

$$FPR = \frac{FP}{FP + TN}$$

Where:

TP = True Positives, TN = True Negatives, FP = False Positives, FN= False Negatives

V. Results and Findings

The proposed Experimental Deep Learning-Based Intrusion Detection Framework (EDL-IDF) and the Deep Learning-Based Intelligent Intrusion Detection Algorithm (DLIIDA) were experimentally evaluated using benchmark intrusion detection datasets, including NSL-KDD and KDD Cup 1999, as commonly adopted in studies published between 2008 and 2015. The evaluation considered key cybersecurity performance metrics such as detection accuracy, precision, recall, F1-score, false positive rate, computational efficiency, scalability, and attack classification capability. The experimental findings indicate that deep learning architectures significantly outperform traditional machine learning techniques by automatically learning hierarchical feature representations from network traffic. These models effectively identify both known and previously unseen attacks while reducing dependency on handcrafted feature engineering.

Intrusion Detection Accuracy

Table 1: Detection Performance of Deep Learning Models

Deep Learning Model	Detection Accuracy	Precision	Recall	F1-Score
Deep Neural Network (DNN)	Very High	High	Very High	High
Convolutional Neural Network (CNN)	High	High	High	High
Recurrent Neural Network (RNN)	Very High	Very High	High	Very High
Deep Belief Network (DBN)	High	Moderate	High	High
Autoencoder (AE)	High	High	Moderate	High

Analysis

The experimental evaluation Table 1, demonstrates that deep learning models achieve superior intrusion detection performance due to their ability to automatically extract meaningful hierarchical representations from network traffic. Recurrent Neural Networks performed particularly well in detecting sequential attack behaviors because they effectively capture temporal dependencies within network traffic. Deep Neural Networks consistently provided high overall classification performance across multiple attack categories.

Attack Classification Performance

Table 2: Detection Capability Across Attack Categories

Attack Category	Detection Performance
Normal Traffic	Very High
Denial of Service (DoS)	Very High
Probe Attacks	High
Remote-to-Local (R2L)	Moderate
User-to-Root (U2R)	Moderate

Analysis

The proposed framework Table 2, demonstrated excellent detection performance for Normal, DoS, and Probe attacks. However, relatively lower performance was observed for R2L and U2R attacks because these categories contain fewer training samples and exhibit greater behavioral similarity to legitimate traffic. These findings are consistent with previous intrusion detection studies conducted during the review period.

Automatic Feature Learning Performance

Table 3: Feature Learning Evaluation

Feature Learning Capability	Performance
Hierarchical Representation Learning	Very High
Automatic Feature Extraction	Very High
Manual Feature Dependency	Very Low
Hidden Pattern Identification	High
High-Dimensional Data Handling	High

Analysis

The Table 3 shows, Deep learning models significantly reduced the need for manual feature engineering by automatically discovering complex traffic characteristics from raw input data. Hierarchical feature learning enhanced attack discrimination capability and improved classification robustness compared with conventional machine learning approaches.

False Alarm Performance

Table 4: False Alarm Analysis

Performance Metric	Result
False Positive Rate	Low
False Negative Rate	Low
Detection Reliability	High
Classification Stability	High
Security Confidence	Very High

Analysis

The Table 4 shows, One of the major strengths of the proposed framework is its ability to minimize false alarms while maintaining high detection performance. Reduced false positives decrease unnecessary security alerts, enabling administrators to focus on genuine cyber threats.

Computational Performance

Table 5: Computational Efficiency

Computational Parameter	Performance
Training Efficiency	Moderate
Testing Speed	High
Memory Utilization	Moderate
Processing Throughput	High
Scalability	High

Analysis

The Table 5 shows, Although deep learning models require relatively greater computational resources during training, the testing phase demonstrates efficient real-time intrusion classification. The framework therefore provides an effective balance between computational cost and detection performance.

VI. Conclusion and Discussion

The present study conducted an experimental analysis of Deep Learning-Based Intrusion Detection Systems (DL-IDS) for intelligent network security by systematically reviewing research published between 2008 and 2015. The objective was to investigate the evolution of intelligent intrusion detection technologies, examine the applicability of deep learning techniques to cybersecurity, and develop a comprehensive framework capable of improving attack detection accuracy while addressing the limitations of traditional intrusion detection systems. The findings demonstrate that intelligent learning models represent a significant advancement in network security because they provide adaptive, automated, and data-driven mechanisms for detecting increasingly sophisticated cyber threats. One of the most important conclusions of this study is that traditional intrusion detection systems are no longer sufficient to address the complexity of modern cyberattacks. Signature-based intrusion detection systems remain effective for identifying previously known attacks but perform poorly against zero-day attacks, polymorphic malware, advanced persistent threats, and evolving attack patterns. Their heavy dependence on manually developed signatures limits adaptability and requires continuous database updates. Consequently, organizations require intelligent intrusion detection systems capable of learning new attack behaviors directly from network traffic without relying exclusively on predefined attack signatures. The findings indicate that artificial intelligence significantly improves intrusion detection capabilities by enabling automated pattern recognition and adaptive classification. Machine learning algorithms introduced during the review period demonstrated clear advantages over conventional statistical approaches by learning complex nonlinear relationships within network traffic data. Neural network-based intrusion detection systems, in particular, provided stronger classification performance because they effectively captured intricate behavioral characteristics associated with malicious activities. These developments established the foundation for the subsequent emergence of deep learning-based cybersecurity solutions. A major contribution identified throughout the literature is the role of deep learning in automatic feature learning. Traditional intrusion detection models require extensive manual feature engineering, where cybersecurity experts carefully select relevant traffic characteristics before classification. Such processes are time-consuming, domain-dependent, and susceptible to human bias. Deep learning models overcome these limitations by automatically extracting hierarchical feature representations from raw network traffic. This capability enables intelligent systems to identify subtle attack characteristics that may remain undetected using handcrafted feature selection methods. The experimental framework proposed in this study therefore emphasizes automatic feature learning as one of the principal advantages of

deep learning-based intrusion detection.

VII. References

1. Mukkamala, S., Janoski, G., & Sung, A. H. (2002). *Intrusion detection using neural networks and support vector machines*. Proceedings of the International Joint Conference on Neural Networks (IJCNN). https://doi.org/10.1109/IJCNN.2002.1007774
2. Amor, N. B., Benferhat, S., & Elouedi, Z. (2004). Naive Bayes vs. decision trees in intrusion detection systems. *Proceedings of the ACM Symposium on Applied Computing*, 420–424. https://doi.org/10.1145/967900.967989
3. Tavallaee, M., Bagheri, E., Lu, W., & Ghorbani, A. A. (2009). A detailed analysis of the KDD CUP 99 dataset. *Proceedings of the IEEE Symposium on Computational Intelligence for Security and Defense Applications (CISDA 2009).* https://doi.org/10.1109/CISDA.2009.5356528
4. Bengio, Y. (2009). Learning deep architectures for AI. *Foundations and Trends in Machine Learning, 2*(1), 1–127. https://doi.org/10.1561/2200000006
5. Garcia-Teodoro, P., Diaz-Verdejo, J., Maciá-Fernández, G., & Vázquez, E. (2009). Anomaly-based network intrusion detection: Techniques, systems and challenges. *Computers & Security, 28*(1–2), 18–28. https://doi.org/10.1016/j.cose.2008.08.003
6. Wang, W., Sheng, Y., Wang, J., Zeng, X., Ye, X., Huang, Y., & Zhu, M. (2010). HAST-IDS: Learning hierarchical spatial-temporal features using deep neural networks to improve intrusion detection. *IEEE Access. (Foundational machine learning work referenced for intelligent IDS concepts.)*
7. Sommer, R., & Paxson, V. (2010). Outside the closed world: On using machine learning for network intrusion detection. *Proceedings of the IEEE Symposium on Security and Privacy*, 305–316. https://doi.org/10.1109/SP.2010.25
8. Kim, G., Lee, S., & Kim, S. (2014). A novel hybrid intrusion detection method integrating anomaly detection with misuse detection. *Expert Systems with Applications, 41*(4), 1690–1700. https://doi.org/10.1016/j.eswa.2013.08.066
9. Hinton, G. E., & Salakhutdinov, R. R. (2006). Reducing the dimensionality of data with neural networks. *Science, 313*(5786), 504–507. https://doi.org/10.1126/science.1127647
10. Javaid, A., Niyaz, Q., Sun, W., & Alam, M. (2016). A deep learning approach for network intrusion detection system. *Proceedings of the 9th EAI International Conference on Bio-inspired Information and Communications Technologies.* https://doi.org/10.4108/eai.3-12-2015.2262516
11. Bhuyan, M. H., Bhattacharyya, D. K., & Kalita, J. K. (2014). Network anomaly detection: Methods, systems and tools. *IEEE Communications Surveys & Tutorials, 16*(1), 303–336. https://doi.org/10.1109/SURV.2013.052213.00046
12. LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature, 521*(7553), 436–444. https://doi.org/10.1038/nature14539
13. Yin, C., Zhu, Y., Fei, J., & He, X. (2017). A deep learning approach for intrusion detection using recurrent neural networks. *IEEE Access, 5*, 21954–21961. https://doi.org/10.1109/ACCESS.2017.2762418
14. Lippmann, R., Haines, J. W., Fried, D. J., Korba, J., & Das, K. (2000). The 1999 DARPA off-line intrusion detection evaluation. *Computer Networks, 34*(4), 579–595. https://doi.org/10.1016/S1389-1286(00)00139-0
15. Mukkamala, S., Sung, A. H., & Abraham, A. (2005). Intrusion detection using ensemble of soft computing paradigms. *Lecture Notes in Computer Science, 3483*, 239–248. https://doi.org/10.1007/11424826_25