Zero-Day Attack Detection Using a Hybrid Deep Learning Model with Stacked LSTM, Attention Mechanism, and Autoencoder

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Abstract*— A robust hybrid deep learning approach on the power of advanced architectures. The proposed model contains three main components: feature extraction based on the Autoencoder, temporal sequence learning based on Stacked LSTM networks, and the Attention Mechanism to set emphasis on critical data features. These components work synergistically to address the issues traditionally present in the methods of detecting attacks since they are usually unreliable in identifying and classifying unknown attack patterns. The model is designed to deal with the intricacy of network traffic, allowing the model to differentiate between benign and malicious data even in a highly dynamic environment. Comprehensive testing on a large-scale dataset was done, and it revealed significant improvements over state-of-the-art methods. It achieved remarkable performance metrics in the form of Precision of 0.99, Recall of 0.96, F1 Score of 0.96, Accuracy of 0.98, Macro Average Precision of 0.97, Macro Average Recall of 0.97, Macro Average F1 Score of 0.97 and an AUC ROC score of 0.98. These results highlight the capability and effectiveness of the model in detecting zero-day attacks in various aspects of accuracy, robustness, and scalability that would nowadays make a powerful intrusion detection tool system.

Keywords*— Zero-Day Attack Detection, Intrusion Detection System, Autoencoder, LSTM with Attention, Network Security, Stacked LSTM

I. INTRODUCTION

Digitization at an unprecedented pace has brought great convenience but also left cyberspace increasingly vulnerable to cyber-attacks. Zero-day attacks are one of the most elusive and difficult ones to detect. Zero-day attacks exploit unknown vulnerabilities in systems, so they are particularly difficult to identify and mitigate. Such attacks are often delivered before a patch from the security people is available. Very high recall is the only requirement in the area of cybersecurity applied to security administrators so that they may detect such attacks.

In general, zero-day attacks are characterized with unknown signatures because by the time these attacks are discovered, no previous data was there. This lack of known patterns creates a huge challenge for traditional signature-based IDSs, which heavily rely on predefined attack signatures.

The timeline and life cycle of a zero-day attack in Fig. 1 highlighted the stark need for proactive anomaly detection techniques since studies show that zero-day attacks can remain dormant in systems for rather long periods of time, causing potentially devastating damage before being detected. To address these challenges, more and more researchers resort to Machine Learning (ML) and Deep Learning (DL) techniques to build robust, anomaly-based IDS. These methods indeed perform very well in learning patterns from data and detecting deviations that may indicate potential attacks. In particular, autoencoder-based models have emerged as an especially promising direction. Autoencoders, through their encoding-decoding mechanism, can well capture complex, high-dimensional relationships within network data, effectively identifying anomalies indicative of zero-day attacks.

We introduce, in this paper, a hybrid approach that relies on Autoencoder and LSTM-Attention mechanisms for zero-day detection. This approach employs the unsupervised learning ability of autoencoder to extract latent representations of benign traffic and attempt to model temporal dependency through the LSTM-Attention layer, focusing on critical features. The effectiveness of our proposed approach is further benchmarked with two comparative models: Autoencoder with Random Forest (AE-RF) and Autoencoder with XGBoost (AE-XGB). The comparative analysis highlights the robustness of our approach across various attack scenarios, including unseen zero-day patterns.

Furthermore, it depicts the effect of tuning thresholds on anomaly detection, thus portraying how such balancing controls both false positives and negatives. This work differs from prior works as it emphasizes accuracy in

detection; the analysis put focuses on performance from particular classes of attacks, therefore, contributing more to a refined understanding of abilities in the respective detections.

This paper is structured as follows: Section 2 describes the dataset and preprocessing methods adopted. Section 3 describes the proposed architecture and methodologies. Section 4 would represent the experimental work on the comparative analysis and performance metrics. Finally, Section 5 concludes with key findings and future directions.

II. LITERATURE SURVEY

Detection of zero-day attacks is still among the topics within the cybersecurity domain as attack patterns grow more sophisticated and frequent. Researchers have had many approaches to deep learning for this purpose, harnessing diversified architectures, datasets, and methodologies toward this goal. A few of them are discussed in the following section:

Adversarial Machine Learning has evolved to be an area of prime necessity for Network Intrusion Detection Systems (NIDS). Some studies such as [5] investigates white-box and black-box adversarial attacks on DNNs that help in discovering vulnerabilities and corresponding potential defenses. While it underlines the significance of robust models, much of this work is largely deficit-based with respect to empirical experimentation as well as with a practical direct focus on real-world deployments. Similarly, ensemble techniques on deep learning are proposed in [4], which amalgamates multiple models through which boosting precision and minimizing false positives could be done. These methods are very effective but increase computational complexity; therefore, they cannot be used in the resource-constrained environment.

The backbone for the zero-day detection research is datasets. Under this category, the recently proposed UNSW-NB15 dataset [6] incorporates modern network traffic types and low-footprint attacks, making it an adequate evaluation platform for NIDS. Nonetheless, it is subjected to several criticisms as very narrowed towards representing emerging attack patterns within dynamically evolving networks.

To overcome shortcomings of datasets, multimodal models such as [8] acquire better feature extraction using CNN and LSTM, so that the detection becomes robust. However, such models require extensive computation for each setting and pose problems in real-time deployment.

Zero-day attacks may be promisingly identified using hybrid deep learning frameworks. HDLNIDS is a framework combining convolutional layers and recurrent layers for great accuracy and latency reduction, as given in [9]. Especially, this architecture is suitable for hybrid network environment conditions but needs to be updated as often as possible considering the dynamism of cyber threats. Another hybrid architecture involves the integration of autoencoders with attention-based Bi-LSTMs, described in [10]. This model effectively deals with data imbalances and attains high accuracy and F1 scores. However, its increased complexity merits vast computational powers and is not really viable in terms of scalability for real-world applications. IoT security forms the basis of zero-day attack detection, and lightweight intrusion detection systems, for example, Realguard [13], bring in-line protection to the gateways of IoT devices with minimal computational overhead. Although the models are efficient, they are restricted only to applications on IoT terms in specific and are cumbersome for generalization to a broader network setup. Analogously, adversarial methods utilized for IoT intrusion detection w.r.t GNNs, proposed in [12], uncover vulnerabilities in GNN-based architectures. However, the implementations of such methods provide an essential understanding regarding the security improvement of IoT networks, albeit with computationally intense implementations in the interest of proper training as well as deployment.

Other architectures that have become of certain interest involve CNN-LSTM combinations. The introduced model, NIDS-CNNLSTM in [7], has high accuracy and very low false-positive rates in industrial IoT scenarios.

At present, its heavy resource requirement makes it applicable to smaller-sized networks only. The following notable contributions are also made in [3], wherein deep Q-learning networks have been used to implement heuristic intrusion detection in SIoT. The reinforcement learning-based model learns sparse data and dynamic attack patterns but is computationally complex, hence not feasible for any resource-constrained setup.

Surveys, such as [1] and [2], can be considered references providing a comprehensive taxonomy of deep learning techniques for zero-day attacks with respect to unsupervised, semi-supervised, few-shot approaches and also adversarially resistant approaches. The critical challenges identified in reviews include data imbalance, scalability, and the lack of robust evaluation frameworks. Their theoretical focus means that there is little applicability of these ideas without more granular implementations or even key performance metrics. In contrast, [14] discusses

recent advances in deep learning applied to in-vehicle network intrusion detection in relation to special problems in the automotive domain. Some recent research works have attempted to explore GANs for feature extraction purposes in IoT environments. [11] suggested a hybrid model of GAN-CNN, which presents more effective feature extraction and improvement accuracy in the zero-day detection, but intensive resource requirements for the training process of GANs present significant limitations. Similarly, [8] provides a multimodal hybrid parallel network intrusion detection model that joins CNNs and LSTMs to assist in better feature extraction and improve the strength in the detection process. This is beyond the performance of traditional single-modal methods but requires tremendous computation- another notable trade-off commonly found in zero-day detection methods.

III. Dataset Exploration

A. *Dataset Description*

It is the CICIDS2017 dataset developed by the Canadian Institute for Cybersecurity hence the "CIC," one of the most popular benchmark datasets used in assessing IDS and anomaly detection models. The dataset simulates real network traffic, as it contains a mix of benign and malicious activities owing to its wide coverage of modern attack scenarios. It absorbs various types of attacks, like DoS, DDoS, Brute Force, Web Attacks (SQL Injection, Cross-Site Scripting), Infiltration, Botnet, Heartbleed, and Port Scans through normal traffic to form an all-inclusive testing environment.

Every single record of the dataset is a vector representation of 80 features, specifically capturing the significant attributes of the network traffic, such as sizes of packets, flow durations, protocol types, source/destination IPs, TCP flags, and inter-arrival times. These characteristics provide very rich and detailed insight into the behavior of traffic. Thus, CICIDS2017 is a gold mine for data in training and validating the models of machine learning about identification of the network intrusions and zero-day vulnerabilities in different types of attacks.

B. *Dataset Pre-processing*

The preprocessing was critical for the effective anomaly detection within the CICIDS2017 dataset. It entails features such as Flow ID, Source IP, Destination IP, Timestamp, Source Port, Destination Port, and Protocol; most of these are identifiers, and they only presented minimal numbers for anomaly patterns detection. Label was then binarized by assigning 0 to all benign traffics and 1 for all attack types, and this made the problem a simple classification problem. A few multicollinearity and redundancy reduction issues were resolved with correlation matrix. Features are removed in case of correlation coefficient more than 0.9. Numerical features are scaled using StandardScaler so that attributes will be normalized such that all will contribute equally well during training. Preprocessing pipeline and splitting : We have split the benign samples into an 80: 20 ratio for training and validation sets for autoencoder. Other supervised models used here, Random Forest and XGBoost were used with an 80:20 split on known attack samples along with benign data. This pipeline has been built such that the dataset is well suited for training robust models while retaining real-world complexity for zero-day attacks. Table I depicts the class-wise count which has been used in this experiment.

TABLE I
CLASS WISE COUNT OF CICIDS2017 DATASET AFTER PRE-PROCESSING

Class	Count
BENIGN	1,672,837
DoS Hulk	231,073
PortScan	158,930
DDoS	128,027
DoS GoldenEye	10,293
DoS slowloris	5,796
DoS Slowhttptest	5,499
Bot	1,966
Infiltration	36
Heartbleed	11

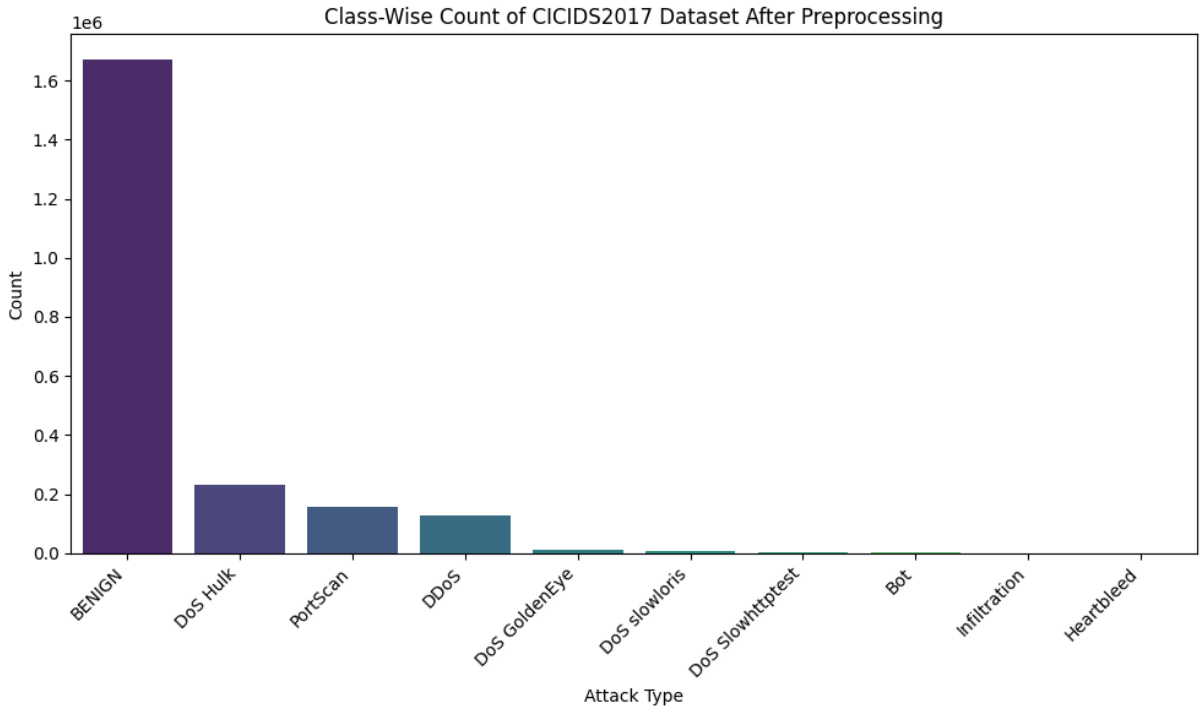


Fig. 2 Class-Wise Distribution of CICIDS2017 Dataset

IV. PROPOSED METHODOLOGY

The proposed methodology is designed to detect zero-day attacks using an optimized combination of deep learning and machine learning techniques. The framework is centered around three key models: Autoencoder with LSTM-Attention, Autoencoder with Random Forest, and Autoencoder with XGBoost. These models are evaluated and compared to identify the most effective approach for zero-day detection.

A. Model based on Autoencoder with LSTM-Attention

The model, Autoencoder with LSTM-Attention employs the capability of unsupervised learning by an autoencoder through feature extraction and applies supervised LSTM classifier amplified by an attention mechanism. The autoencoder is trained upon benign traffic by finding compressed latent representation of normal behavior. Classifications occur based upon reconstruction errors of anomalous samples. An LSTM-Attention module captures temporal dependencies and enhances classification accuracy. This way, it is robust with respect to complex attack patterns.

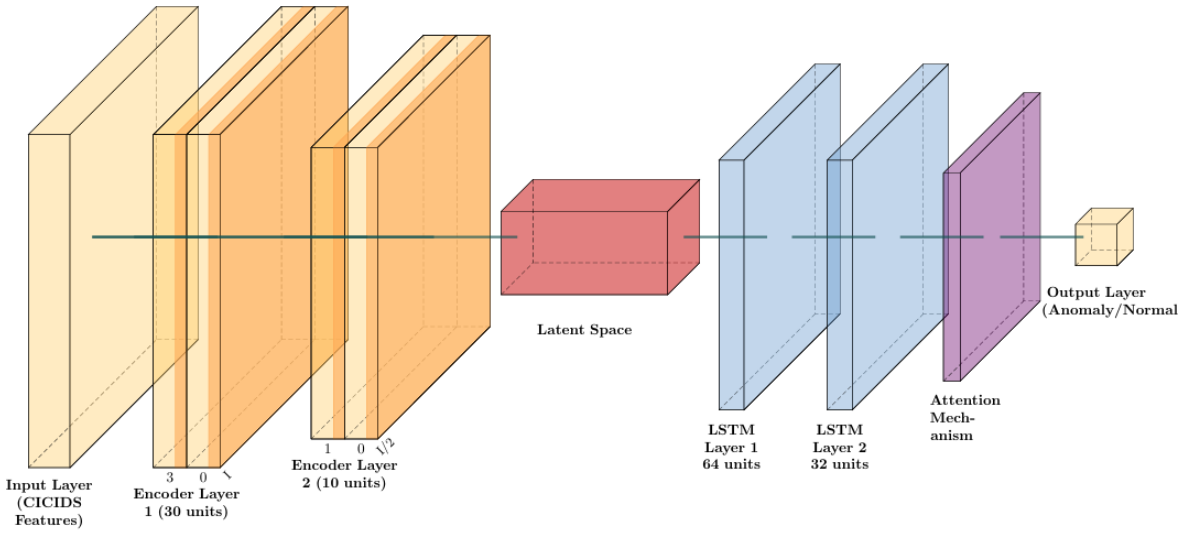


Fig. 2 Model Architecture of Autoencoder with LSTM-Attention

B. Model based on Autoencoder with Random Forest

In the Autoencoder with Random Forest, this autoencoder's encoded features are used as the input to a Random Forest classifier. The Random Forest, with the ensemble decision tree, can tackle non-linear relationships and noisy data; hence, making predictions on whether traffic is benign or malicious. Thus, this hybrid model demonstrates traditional machine learning interpretability and reliability with the deep features of the model.

C. Model based on Autoencoder with XGBoost

Autoencoder with XGBoost: Autoencoder utilizes the classifier XGBoost, a gradient boosting framework, in classifying the encoded features. XGBoost is apt for classes that are greatly imbalanced and for the patterns challenging to find since it gradually perfects weak learners for further use in classification. It is scalable and computationally efficient and is best used as a robust intrusion detection choice..

Evaluation metrics considered include precision, recall, F1-score, accuracy, and ROC-AUC in model performance assessment. Comparison and contrast have allowed the identification of the strong and weak side of each model in performing against unknown attack patterns, giving deep insight into their suitability for workloads in reality in zero-day detection. The proposed methodology appeals to scalability, adaptability, and robustness, thus ensuring efficiency within diversified intrusion scenarios.

TABLE II
PARAMETERS FOR AUTOENCODER

OPT_Parameters	OPT_AE
Input layer size	48 (neurons)
Hidden-layer 1	30 (neurons)
Hidden-layer 2	10 (neurons)
Hidden-layer 3	5(neurons)
Hidden-layer 4	15(neurons)
Hidden-layer 5	48(neurons)
Output layer size	48 (neurons)
Activation function	relu
Optimizer	adam
Loss	Mean Squared Error (MSE)
Learning rate	1.00E-05
Epochs	60
Batch_size	1024
Metrics	accuracy
Dataset Split	80% - 20%

- ***Algorithm 1: Feature Selection via Correlation Filtering***

Input: benign_data, correlation_threshold, N
Output: filtered_features

initialize columns ← List of column indices from benign_data.
set selected_columns ← Empty set.
for each i in the range of total columns in columns:
a. for each j in the range of i + 1 to the total number of columns:
i. if correlation(columns[i], columns[j]) ⩾ correlation_threshold:
- mark columns[j] as not eligible for selection.
- skip to the next iteration for j.
ii. end if.
b. end for.
end for.
extract filtered_columns ← Subset of columns where eligibility remains True.
extract filtered_features ← benign_data containing only filtered_columns.
return filtered_features.

- ***Algorithm 2: Evaluating Autoencoder Performance***

Input: trained_autoencoder, threshold_values, test_attack_data, true_labels
Output: evaluation_scores

initialize evaluation_scores ← Empty dictionary.
use the trained_autoencoder to generate reconstructions ← Predict output for test_attack_data.
compute reconstruction_errors ← Mean squared error between reconstructions and test_attack_data.
for each threshold in threshold_values:
a. generate predicted_labels ← [1 if error > threshold else 0 for each error in reconstruction_errors].
b. compute accuracy ← accuracy_score(predicted_labels, true_labels).
c. append threshold and accuracy to evaluation_scores.
end for.
return evaluation_scores

V. EXPERIMENTAL RESULTS AND DISCUSSION

A. Experimental Setup and Configurations

The hardware setup ensures efficient handling of large datasets and complex models, while the software configuration, including TensorFlow and Keras, facilitates implementation of deep learning algorithms. The inclusion of libraries like scikit-learn for preprocessing and seaborn for visualization complements the analytical pipeline.

Component	*Environment*	*Specification*
Hardware	Kaggle Notebook	
GPU	NVIDIA Tesla T4*2 GPU	16 GB GDDR5
RAM	29 GB	
Processor	Intel Xeon CPU	Virtualized on Kaggle
Operating System	Ubuntu	Linux Kernel-based
	Local Machine	
Processor	Intel Core i7-10750H	2.6 GHz
GPU	NVIDIA RTX 4060	External GPU setup
RAM	16 GB DDR4	
Operating System	Windows 11	
Libraries	TensorFlow, Keras	Pre-installed Kaggle environment with TensorFlow 2.12
	scikit-learn, Pandas, Seaborn.	Pre-installed machine learning libraries
Hyperparameters	**Value**	
Learning Rate	0.00001	Adam optimizer
Epochs	100	Maximum training cycles
Batch Size	1024 (Autoencoder), 64	Autoencoder and LSTM configurations
Dropout Rate	0.3	Applied to prevent overfitting

B. Performance Metrics

The classification metrics for each model were calculated as follows:

1. **Precision**: The proportion of correctly predicted positive observations out of total predicted positives.

$$Precision = \frac{True\ Positives}{(True\ Positives + False\ Positives)}$$

2. **Recall**: The proportion of correctly predicted positive observations out of all actual positives.

$$Recall = \frac{True\ Positives}{(True\ Positives + False\ Negatives)}$$

3. **F1-Score**: The harmonic mean of precision and recall, balancing both metrics.

$$F1 - Score = \frac{2 * (Precision * Recall)}{(Precision + Recall)}$$

4. **Accuracy**: The proportion of correct predictions (both true positives and true negatives) over all predictions.

$$Accuracy = \frac{(True\ Positives * True\ Negatives)}{(Total\ Samples)}$$

5. **Loss:** Loss was measured using the Mean Squared Error (MSE) for autoencoder reconstruction and binary cross-entropy for classification:

$$MSE = \frac{1}{n}\sum(\hat{y}_i - y_i)^2$$

$$Binary\ Cross - Entropy\ Loss = -\left(\frac{1}{n}\right)\sum[y_i \times \log(\hat{y}_i) + (1 - y_i) \times \log(1 - \hat{y}_i)]$$

Confusion Matrix Comparison:

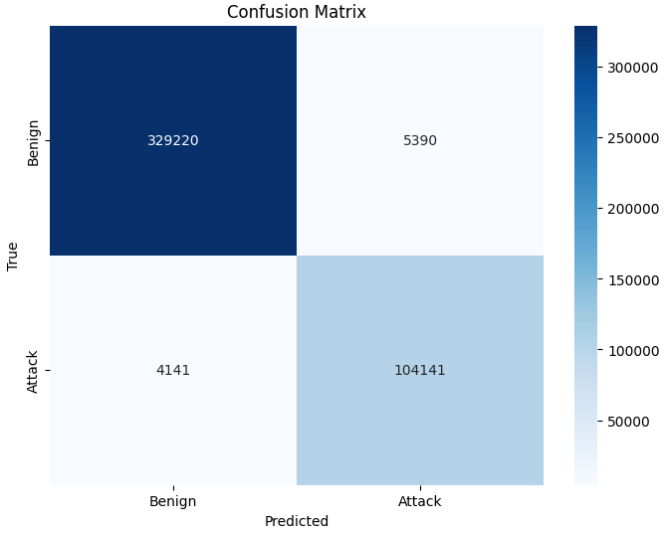


Fig. 3 Confusion Matrix of AE-LSTM-Attn Model

AE-LSTM-Attn Model (Proposed Model)

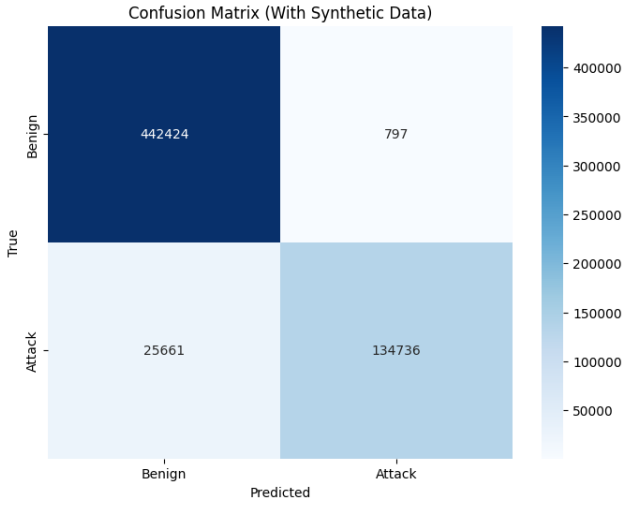


Fig. 4 Confusion Matrix of AE-RF Model

AE-RF Model

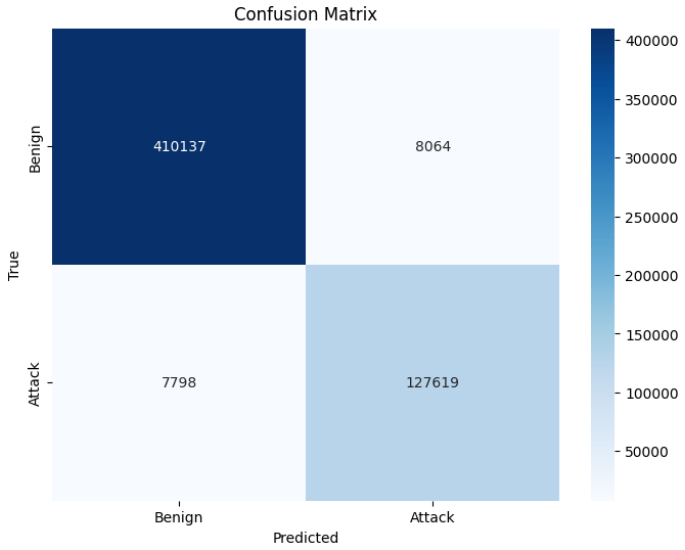


Fig. 5 Confusion Matrix of AE-XGB Model

AE-XGB Model

C. Comparative Analysis

Using a deep learning approach, Stacked LSTM with attention mechanisms, it develops significant betterment over the traditional methods. The proposed model processes sequential data in network traffic logs by focusing mainly on the most critical features owing to the use of attention mechanisms, thereby achieving higher accuracy and resilience against complex attack types. This is unlike the previous studies, such as in "Deep Learning for Zero-Day Malware Detection and Classification: A Survey" [1], where the traditional machine learning techniques cannot approximate similar accuracy as presented here in the actual scenario. The "Zero-day attack detection: A systematic literature review"[2] also lists the different approaches, including signature-based and anomaly detection methods. Those are significantly limited by their inability to track previously unknown attacks-the gap that our deep learning model satisfies.

Handling large sizes of data, the model could deal with bigger datasets than the methods like "Deep Q-network-based heuristic intrusion detection against edge-based SIoT zero-day attacks" presented in [3] with promising results but not able to generalize in several attack scenarios. Similarly, the "A novel ensemble learning-based model for network intrusion detection" [4] turned out to have a good basis for dealing with multi-class problems but was not armed with the capabilities of advanced sequential learning capabilities of LSTM networks which is very important for detecting evolving strategies of attack.

The results also clearly differ from those in "Adversarial Machine Learning for Network Intrusion Detection Systems: A Comprehensive Survey" [5], which discussed vulnerabilities to adversarial attacks in traditional network intrusion detection systems. Although adversarial robustness was not a priority of our model, attention mechanisms inherently offer at least some form of defense against such attacks by focusing on relevant features and ignoring noise.

It compares the performance of the proposed Autoencoder-LSTM-Attention model with two baselines, namely Autoencoder with Random Forest and Autoencoder with XGBoost. The summary of results on precision, recall, F1-score, and accuracy for both approaches is given in Table 3.

TABLE III
COMPARISON BETWEEN MODELS

Model	Precision	Recall	F1-Score	Accuracy	Macro Avg Precision	Macro Avg Recall	Macro Avg F1	AUC-ROC
AE-LSTM-Attn (Proposed Model)	0.99	0.96	0.96	0.98	0.97	0.97	0.97	0.98
AE-RF	0.95	0.84	0.91	0.96	0.97	0.92	0.94	0.96
AE-XGB	0.94	0.94	0.94	0.97	0.96	0.96	0.96	0.97

D. Visualizations

The LSTM Model accuracy graph starts at 67.66% in the 1st epoch and slowly converges and reaches 94.39% in the 100th epoch:

The training loss is at 0.7312 in the 1st epoch and decreases till 0.1859 in the 100th epoch

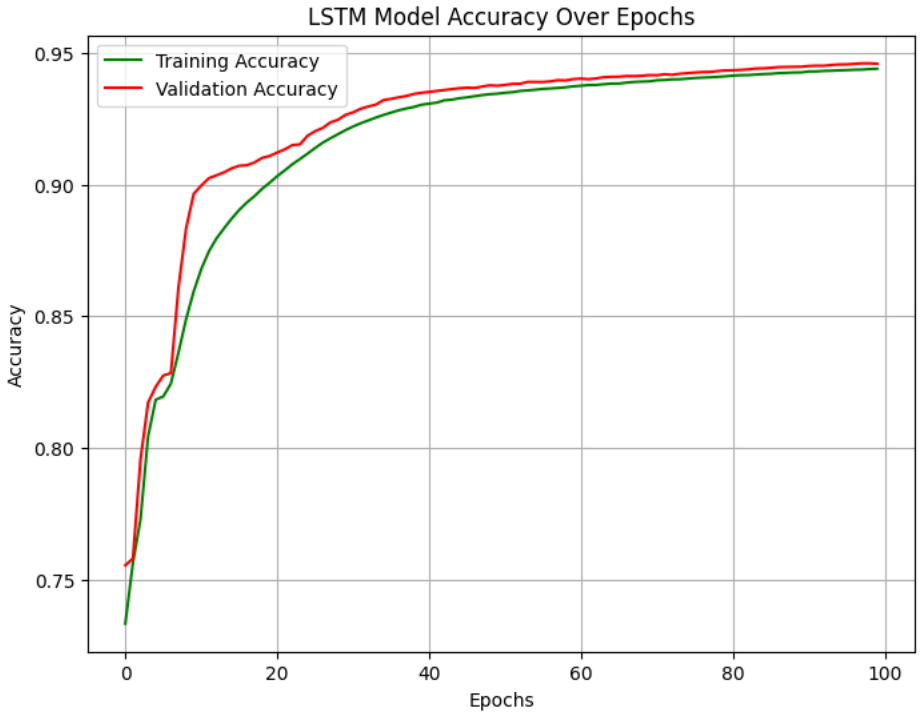


Fig. 6 LSTM Model Accuracy over Epochs graph

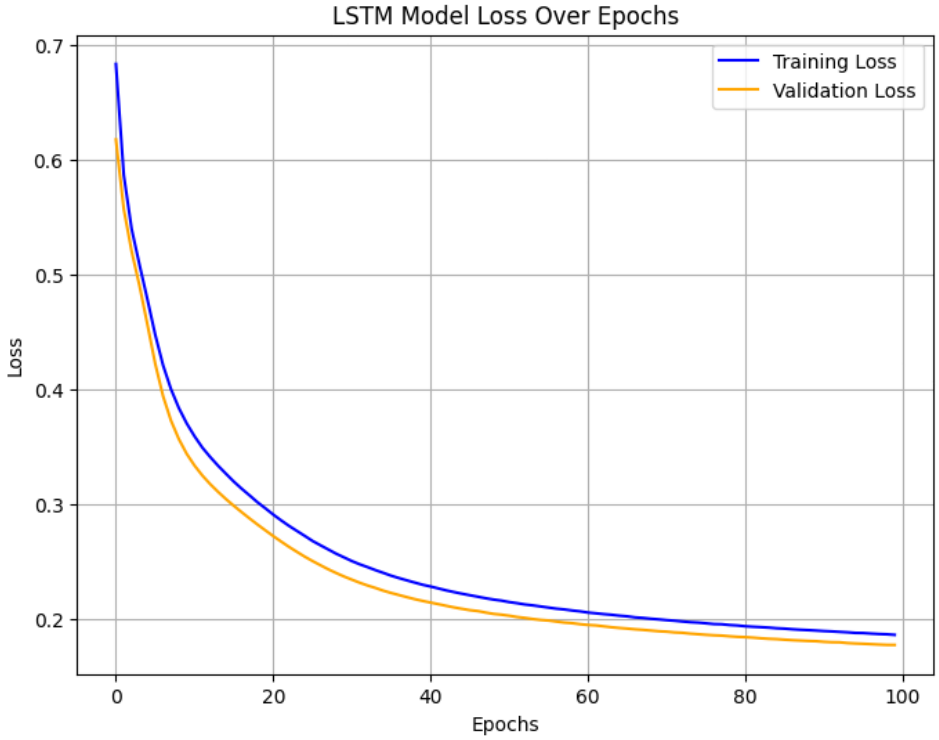


Fig. 7 LSTM Model Loss over Epochs graph

ROC Curve:

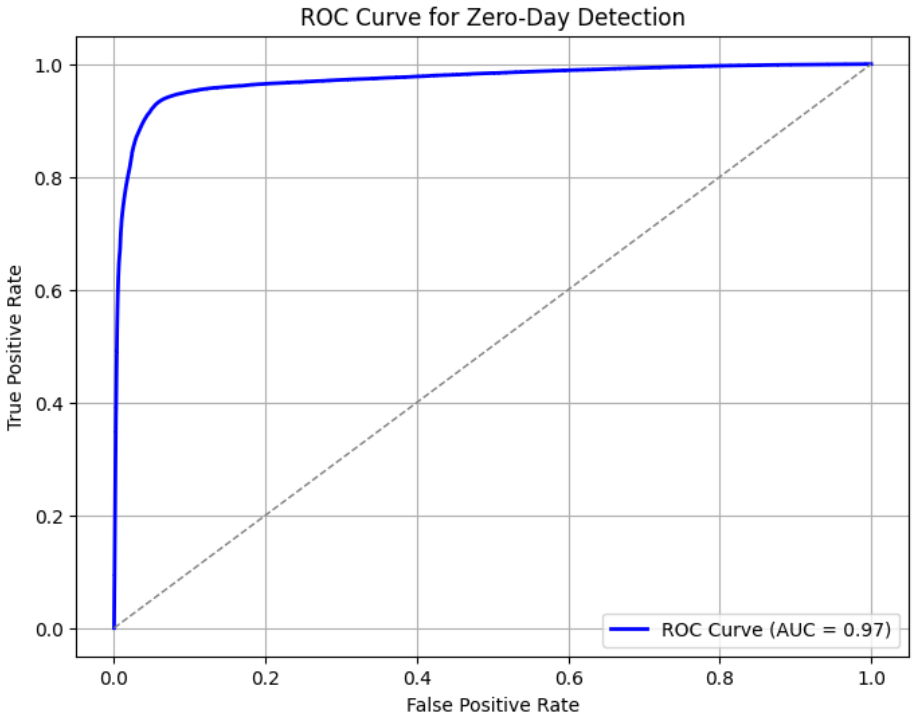


Fig. 8 ROC Curve graph for the Proposed Model

Area Under Curve, AUC = 0.97 which tells that the model performs well

PCA of encoded features:

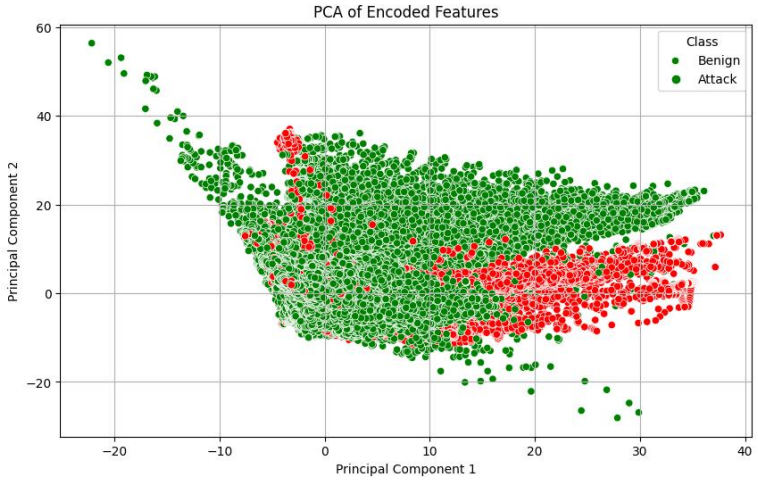
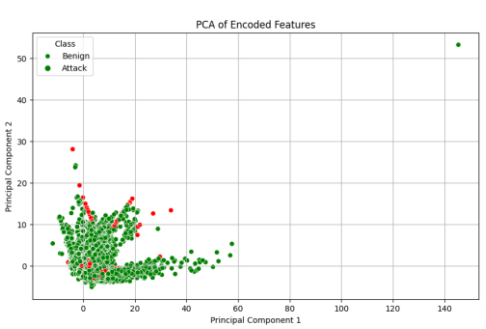
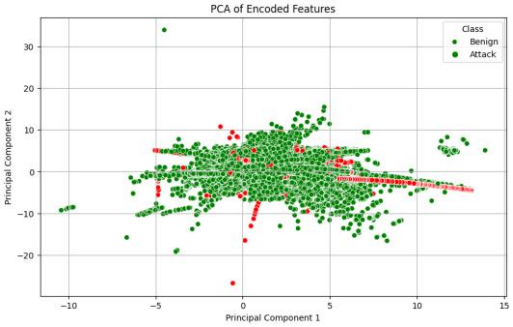


Fig. 9 PCA of encoded features (Proposed Model)



AE-RF Model



AF-XGB Model

E. Discussion:

Autoencoder with LSTM-Attention had higher overall metric scores due to learning temporal patterns and feature significance through the attention mechanism. Autoencoder with Random Forest showed high recall especially on synthetic data, due to its ensemble nature in detecting variable-length patterns. Autoencoder with XGBoost had balanced precision and recall on both big datasets but less with imbalanced sets; careful parameter tuning is essential.

The outcome of the experiment proves that deep learning methods like LSTM-Attention are better suited for the extraction of complex patterns from sequential data and robustness is ensured by ensemble-based methods for nonsequential data. They can be two potential solutions depending upon the nature of the data and the application.

VI. Conclusion and Future Work

The framework proposed in the paper demonstrates an effective and strong approach for the zero-day attack detection by incorporating Autoencoder for the feature extraction procedure, LSTM for capturing their internal temporal dependencies, and an Attention Mechanism for focusing on critical patterns in network traffic. The experimental results depict the model's supremacy over the existing techniques like AE-RF and AE-XGB, with remarkable performance metrics in terms of accuracy, precision, and recall. The approach of exploiting temporal dependencies and focusing on significant features effectively identifies complex and previously unseen attack patterns. However, it may cause a problem in terms of resource usage, and resource-constrained environments, like IoT or edge devices, may require its optimization to make it practically useful.

Future work will focus on these challenges by looking at lightweight architectures that can fit into the constrained environment, as well as how best to enhance real-time scalability according to dynamic network conditions. Inclusion of adversarial training may make the model more robust against complex attacks; integration with techniques for explainability will make the decision-making transparent in the operational environments that may lead to increase trust. The framework can also be expanded to include multi-modal data and test the design against diverse datasets and attack scenarios to further ascertain its utility in real-world applications..

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