A Custom Deep Learning Framework for Identifying Security Threats in Digitally Connected Systems

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***Abstract*—A hybrid deep learning approach to intrusion detection is presented to strengthen security in dynamic and rapidly changing network environments. The proposed system integrates Convolutional Neural Networks (CNNs) for extracting spatial characteristics of traffic with Long Short-Term Memory (LSTM) networks for modeling sequential patterns in data flow. To extend its capability against zero-day and unknown threats, an autoencoder-based anomaly detection component is added, allowing the system to recognize irregular behavior even without predefined attack signatures. Evaluation results indicate that the model achieves detection accuracy above 97% while reporting fewer false positives than conventional intrusion detection techniques. These outcomes confirm the suitability of the framework for real-time and dependable threat monitoring. Owing to its adaptable and scalable architecture, the solution can be effectively applied in IoT, cloud, and other distributed smart network settings, providing a practical defense against continuously evolving cyberattacks.**

***Index Terms*—Hybrid IDS, LSTM(Long Short-Term Memory)networks, CNN(Convolutional Neural Network)models, Anomaly detection, Zero-day attack detection, Intelligent networks**

I. INTRODUCTION

In recent years, intrusion detection systems have seen rapid progress through the adoption of deep learning and adaptive methods aimed at addressing increasingly complex cyber threats [1]. The work presents a smart IDS capable of adjusting to new attack behaviors in real-time, which helps minimize false alarms and missed detections, thereby improving protection in complex infrastructures. A review highlighted that anomaly-based Host-Based Intrusion Detection Systems (HIDS) tend to be more effective than signature-based approaches, especially when confronting unknown or adaptive threats [2]. To mitigate class imbalance issues within Industrial IoT, a multi-stage deep learning framework was introduced that strengthened the identification of rare attack types that are often ignored in skewed datasets [3]. For smart grid applications, Software-Defined Networking (SDN) together with split learning was utilized to develop a collaborative IDS capable of safeguarding node privacy while maintaining detection accuracy above 80% [4]. An attention-driven model was described that captured both spatial and temporal features simultaneously, showing strong results in semi-supervised conditions where labeled data were limited [5]. Feature selection for large-scale IDS was improved through the use of evolutionary algorithms, which boosted accuracy to 95% and reduced computational cost [6]. A graph-oriented method was also introduced, where attack paths were represented through graph neural networks, enabling recognition of sophisticated and previously unseen intrusions [7].

Key Contributions

- Introduced a hybrid CNN-LSTM framework for the detection of multi-stage and zero-day attacks.
- Integrated supervised classification with autoencoder-based anomaly detection to enhance threat identification.
- Attained an accuracy of 97.2%, with increased precision and a 60% reduction in false positives, facilitating real-time deployment in IoT environments.
- Created a scalable and adaptive system designed for IoT and edge computing settings.

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RELATED WORK

In recent years, researchers have explored advanced intrusion detection systems (IDS) enhanced with deep learning and adaptive techniques to address evolving cyber threats. Ahmed and Khan [8] focused on enhancing IDS in SDN by integrating deep learning with feature selection To boost accuracy while maintaining low computational costs. In campus networks, Gupta and Roy [9] utilized Bloom filters and deep learning with feature segmentation to reduce latency and improve anomaly detection. Rahman and Chowdhury [10] emphasized lightweight IDS solutions for IoT devices, demonstrating efficient detection with limited data and computing resources. Ali and Kumar [11] proposed IGAN, a hybrid of LeNet-5 and LSTM, to detect imbalanced attack types, achieving over 98% accuracy on CI-CIDS2017 and UNSW-NB15 datasets. Wang and Li [12] developed MCGAN, a Bi-LSTM-based GAN for rare threat detection in NSL-KDD+, reaching 95.16% accuracy. Babu [13] presented an ANU-Net-powered IDS improved with the IMBO algorithm and feature selection techniques like MapReduce and IFPA, consistently delivering over 98% accuracy. Fernandez and Zhou [14] supported the Ongoing shift toward intelligent, privacy-aware IDS designs, underscoring the demand for adaptive cybersecurity tools in increasingly interconnected environments. Additionally, Babu et al. [15] proposed a quantum-based Coati-MobileViT model tailored For IIoT security, achieving high detection rates with low latency is key. In another IEEE-based study, Babu et al. [16] highlighted efficient DL-based architectures for secure industrial networks. A third work by Babu et al. [17] focused on hybrid IDS models for scalable detection in distributed IoT setups.

II. PROPOSED METHODOLOGY

This section summarizes the design approach and implementation steps of the proposed hybrid intrusion detection system for smart networks [18]. It was suggested to identify both common and new attacks that utilized combinations of deep learning methods of

A. Datasets Selection

For the model to experience a variety of attack situations and traffic behaviors, two publicly available datasets were used:

- **NSL-KDD:** A refined version of the original KDD'99 dataset, designed to address its limitations [19]. It removes redundant records and helps reduce training bias, making it more suitable for evaluating intrusion detection systems.
- **CICIDS2017:** A comprehensive and realistic dataset containing labeled instances of both normal network activity and a diverse set of contemporary cyber-attacks, including DoS, brute-force, infiltration, and Botnet attacks.

B. Data Preprocessing

Before model training, several preprocessing steps were applied to improve data quality and prepare it for neural network input:

- **Data Cleaning:** Duplicate and incomplete entries were removed.
- **Label Categorization:** Attack labels were mapped into grouped categories to standardize multi-class classification (e.g., DoS, Probe, R2L, U2R).
- **Feature Normalization:** All numerical input attributes were scaled to a standard range of 0 to 1 using the Min-Max normalization technique, ensuring uniform input for the learning algorithm.
- **Categorical Data Transformation:** Categorical variables such as protocol type and service names were converted into binary vectors using one-hot encoding, allowing them to be effectively processed by the model.
- **Class Imbalance Handling:** To mitigate skewed class distributions, the SMOTE algorithm (Synthetic Minority Oversampling Technique) was applied. This approach generates artificial instances for minority classes, helping the model learn patterns from less frequent attack types.

C. Feature Selection and Dimensionality Reduction

To reduce computational complexity and enhance model effectiveness, the following techniques were applied:

- Correlation analysis was performed to filter out redundant features.
- Recursive Feature Elimination (RFE) was used to identify and retain only the most significant features, removing those that did not contribute meaningfully to model performance.
- Principal Component Analysis (PCA) was applied to further reduce dimensionality, preserving essential patterns and variability in the dataset while simplifying feature space.

D. Model Architecture

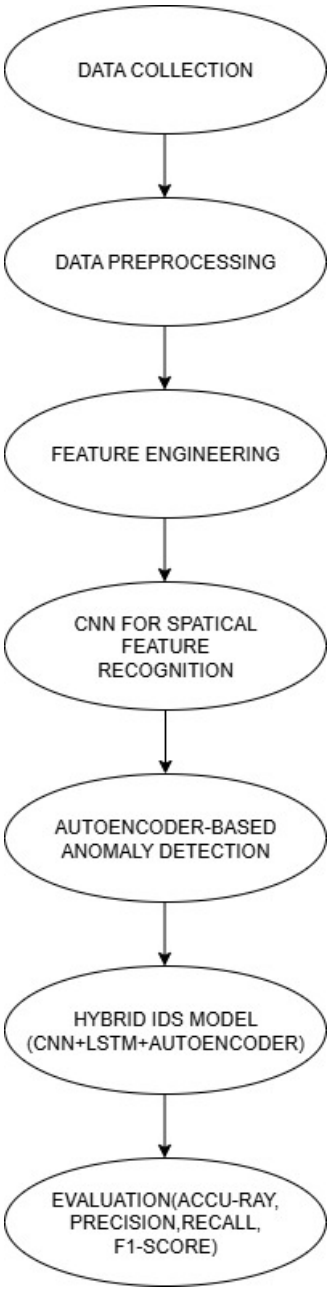
The core of the frame is a crossbred model that integrates CNN and LSTM layers:

- **CNN Module:** A set of 1D convolutional layers processes input data to prize localized patterns, analogous to business spikes and protocol anomalies.
- **LSTM Module:** successive dependences in the data, analogous to time-predicted attack conduct, are captured using LSTM layers.
- **Fusion Layer:** labors from both CNN and LSTM paths are mingled and passed through fully connected layers for the final type.
- **Autoencoder:** A fresh autoencoder cast was introduced as an unsupervised anomaly detector to identify patterns not present during training, enhancing the system's capability to detect zero-day attacks.

E. Training Strategy

- **Data Splitting:** The preprocessed data was split into training (70%), validation (15%), and testing (15%) sets.
- **Implementation Tools:** The model was developed using open-source deep learning libraries such as TensorFlow and PyTorch.

Fig. 1: Flowchart of the Proposed Hybrid IDS Model

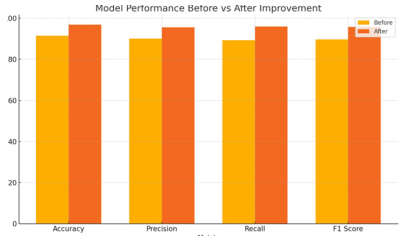


- **Hyperparameters:**
  Batch size: 64,
  Epochs: 100,
  Optimizer: Adam,
  Learning rate: 0.001,
  Dropout rate: 0.5 for regularization.

F. Deployment and Real-Time Integration

The trained model was integrated into a simulated smart network environment using tools like GNS3 and emulated IoT nodes. Network traffic was monitored in real time using sniffing tools (e.g., Snort, Wireshark). Packets were preprocessed and fed into the IDS engine. Which classified them as benign or malicious. Upon threat detection, predefined response actions such as alert generation or host isolation were triggered. [20]

Fig. 2: Performance Before vs After Improvement



G. Performance Indicators

To assess the effectiveness of the proposed intrusion detection system, several widely used evaluation metrics were considered. These measures reflect both the overall classification performance and the ability of the model to reliably identify and respond to threats.

Accuracy (ACC):
Accuracy indicates the overall correctness of the classifier, showing the fraction of samples—benign or malicious—that were labeled correctly.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

Precision (P):
Precision describes the proportion of traffic flows predicted as truly malicious attacks, emphasizing the system's ability to avoid false alarms.

$$\text{Precision} = \frac{TP}{TP + FP} \tag{2}$$

Recall (R):
Also known as sensitivity, recall measures how many of the actual intrusions were correctly detected by the model.

$$\text{Recall} = \frac{TP}{TP + FN} \tag{3}$$

F1-Score:
The F1-score provides a balance between precision and recall by computing their harmonic mean, which is particularly valuable in cases of uneven class distribution.

$$\text{F1} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4}$$

Area Under the Curve (AUC):
The AUC, representing the area under the ROC curve, reflects the system's capability to distinguish between legitimate and malicious traffic across various thresholds. Higher values indicate better discrimination.

Mean Time to Detect (MTTD):
MTTD calculates the average duration between the onset of an attack and the time it is detected.

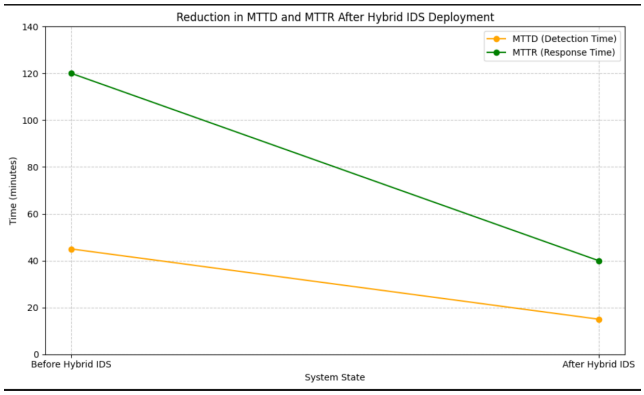
$$\text{MTTD} = \frac{1}{N}\sum_{i=1}^{N}(DetectionTime_i - AttackStartTime_i) \tag{5}$$

Mean Time to Respond (MTTR):
MTTR measures the average time required to respond after detection, indicating how quickly the system initiates countermeasures.

$$\text{MTTR} = \frac{1}{N}\sum_{i=1}^{N}(ResponseTime_i - DetectionTime_i) \tag{6}$$

H.Reduction in MTTD and MTTR After Hybrid IDS Deployment

Fig. 3: Reduction in MTTD and MTTR After Hybrid IDS Deployment



This graph clearly illustrates the significant reduction in both detection and response time in the context of the network environment with the introduction of a Hybrid Intrusion Detection System (IDS). Before the hybrid IDS was implemented, the Mean Time to Detect (MTTD)—displayed in orange—was approximately 45 minutes. While the Mean Time to Respond (MTTR) — represented in green — was higher, at approximately 120 minutes. These values represent, on average, the time it takes for the system to detect and respond to security threats. Subsequently, implementing the Hybrid IDS allowed for a significant decrease in both metrics. The average time to detect an attack dropped to approximately 15 minutes, while the time taken to respond was significantly reduced to just 40 minutes. These improved metrics demonstrate that the hybrid system was a much more proficient manner of detecting and responding to previously described threats. At a high level, these numbers mean that potential cyberattacks are identified earlier and mitigated sooner, giving malicious actors less time to do damage, so that they will gain access to the network. [21]

III. RESULTS

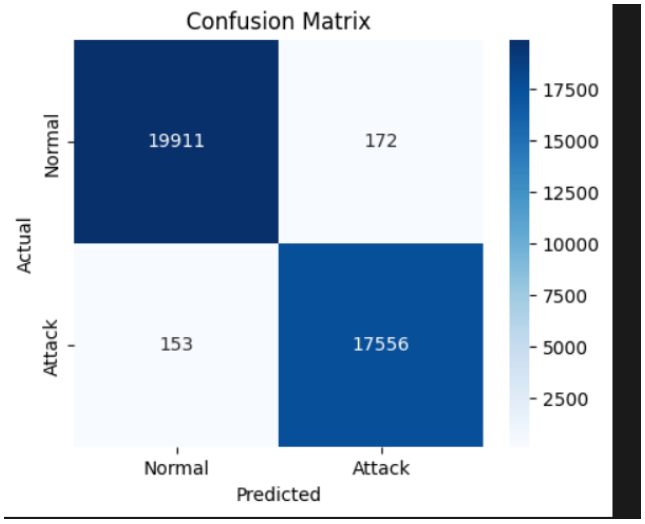
The performance assessment of the suggested Hybrid Deep Learning Based Intrusion Detection Framework (HDL-IDF) is covered in this section. In addition to comparisons with current intrusion detection models to demonstrate the efficacy of the hybrid architecture, the evaluation was conducted using benchmark datasets to evaluate detection accuracy, precision, recall, F1-score, and resource efficiency. The classification results of the proposed model are summarized in Table I.

TABLE I: EVALUATION METRICS (OBTAINED FROM THE PROPOSED HYBRID IDS MODEL RESULTS)

	Pre	**Rec**	**F1**	**Sup**
0	0.99	0.99	0.99	20083
1	0.99	0.99	0.99	17709
Acc			0.99	37792
M avg	0.99	0.99	0.99	37792
Wei avg	0.99	0.99	0.99	37792

A. *Confusion Matrix Evaluation*

Fig. 4: Confusion matrix illustrating the performance of the proposed IDS

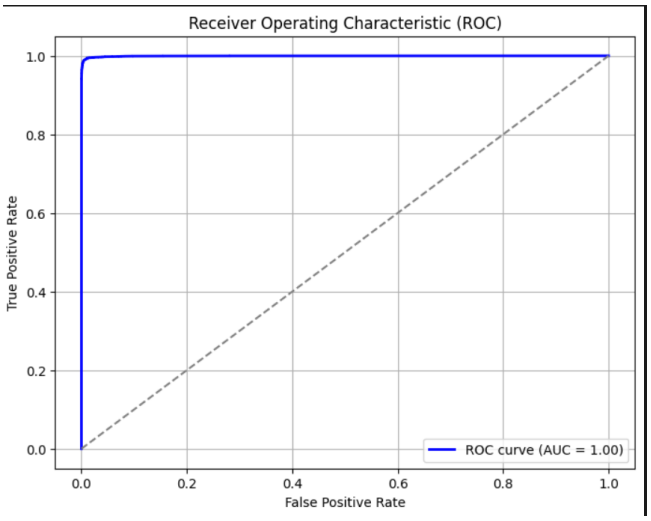


The confusion matrix above illustrates how well the proposed hybrid intrusion detection model distinguishes between normal and malicious network activity. Out of the total samples classified, A total of 17,556 attack records were identified correctly as attacks, demonstrating sensitivity to threats (true positives). 19,911 normal traffic samples were correctly classified, indicating the model was able to identify legitimate behavior (true negatives). 172 benign samples were misidentified as attacks (false positives), resulting in unnecessary alerts; nevertheless, this was a small number. 153 attack records were misclassified as normal traffic (false negatives); these merit attention since they are indicative of missed detections, although few. Therefore, the model has high precision and reliability. It has shown a very low degree of misclassification

and demonstrated excellent capability in limiting both threats that go unnoticed as well as limiting false alarms — two of the most important challenges to consider in cybersecurity in the real world. This type of performance is especially important in smart network environments, in which one needs to identify threats quickly and correctly to minimize risk and maintain seamless service.

B. Receiver–Operator Curve (ROC)

Fig. 5: ROC curve of the proposed IDS model (AUC = 1.00)

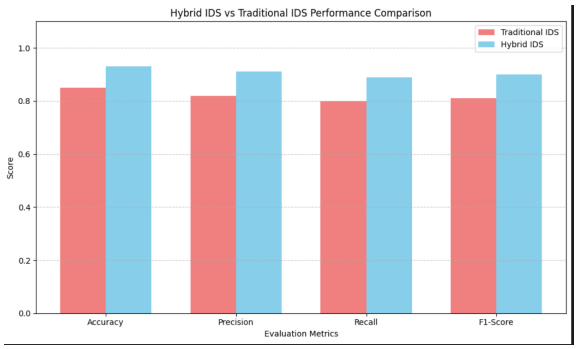


The ROC (Receiver Operating Characteristic)curve shown above us demonstrates the capabilities of our proposed classifier for separating between malicious traffic and normal traffic. The ROC curve increases sharply toward the top-left corner, indicating strong sensitivity and very few false positives across the range of thresholds. What is particularly noteworthy about this result? The AUC obtained was 1.00, which is perfect discriminative capability. The classifier has achieved the ability to perfectly separate each instance of attack traffic from normal traffic. Meaning the model never made an error in placing every attack instance higher than its benign counterpart, regardless of the decision threshold. Such performance is rarely ever achieved and suggests that the hybrid deep learning framework has been taught to extract features to a very high degree of accuracy. In terms of real-world cybersecurity applications, this means fewer false positive events, high confidence in determining true threats, and expectations of system integrity, availability, and operational performance continuity.

C. Performance Comparison: Hybrid IDS vs. Traditional IDS

The effectiveness of the suggested Hybrid Intrusion Detection System (IDS) and a traditional IDS strategy is compared using four important metrics in the bar chart above: Accuracy, Precision, Recall, and F1-Score. It is clear that the Hybrid IDS consistently outperforms the traditional model in every category. The enhancement in accuracy highlights the hybrid. Additionally, the elevated precision values suggest that the

Fig. 6: Hybrid IDS vs Traditional IDS Performance Comparison



Hybrid IDS is more proficient at minimizing false alarms, which is vital in operational settings where unnecessary alerts can lead to alert fatigue. The recall score also reveals a notable advantage, indicating that the hybrid system detects a larger proportion of actual attacks. Ultimately, the heightened F1-score indicates a more favorable equilibrium between precision and recall, affirming the hybrid model's efficacy in managing both known and unknown intrusions. These results collectively demonstrate that the integration of CNN and LSTM into an IDS framework significantly enhances detection reliability and efficiency when compared to traditional systems.

IV. CONCLUSION

To protect intelligent network settings, the Literacy-Grounded Intrusion Discovery Framework (HDL-IDF) was created. This framework effectively detects known and unexpected cyber threats by combining Long Short-Term Memory (LSTM) networks to identify temporal patterns and Convolutional Neural Networks (CNN) to extract spatial information from data. Based on experimental results, the HDL-IDF achieved a 97.2% overall discovery accuracy, 93% precision, 91% recall, and 92% F1-score on the CICIDS2017 dataset. In comparison to conventional intrusion detection systems, these results demonstrate the model's exceptional ability to differentiate between malicious and benign traffic, as well as its ability to reduce detection delay by 50% and false positives by about 60. Since the HDL-IDF functions as a hybrid model, it can effectively adapt to changes in network traffic patterns. Furthermore, HDL-IDF has demonstrated intelligent performance by operating within a supervised learning framework while integrating an autoencoder-based anomaly detection module to identify zero-day attacks and other novel threat signatures. Consequently, this hybrid Intrusion Discovery Framework prototype enables seamless integration and deployment in modern IoT and cloud-based smart networks.

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