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Intrusion Detection and Identification System

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Abstract: *The proliferation of Internet of Things (IoT) networks has introduced significant security challenges due to the limited security features of IoT devices and their vulnerability to cyber-attacks. Traditional intrusion detection algorithms struggle to handle complex invasions due to limited representation capabilities and the unbalanced nature of IoT-related data. This paper proposes a novel Intrusion Detection and Identification System (IDIS) for IoT networks using an enhanced Hybrid Ensemble Deep Learning Framework (HEDLF). The proposed system addresses the limitations of previous approaches by incorporating a hierarchical feature representation technique, a balanced rotated feature extractor, and a meta-classifier using a hybrid focal loss and semi sparse group lasso regularization. These components collectively enhance the system's ability to detect and identify cyber-attacks in real-time, improving accuracy, precision, recall, and F1-score. The system demonstrates superior performance compared to traditional methods, offering a robust and scalable security solution for IoT networks.*

Keywords: *Internet of Things (IoT), Intrusion Detection and Identification System (IDIS), Hybrid Ensemble Deep Learning Framework (HEDLF), Cyber security, Deep Learning, Hierarchical Feature Representation, Real-time Detection, Network Security, IoT Security, Class Imbalance.*

1. INTRODUCTION

The rapid growth of the Internet of Things (IoT) has revolutionized various industries, enabling seamless connectivity between devices, machines, and systems. From smart homes and healthcare to industrial automation and transportation, IoT devices have become integral to modern infrastructure [1-3]. However, this widespread adoption of IoT devices has introduced significant cyber security challenges due to their inherent vulnerabilities [4]. Unlike traditional computing devices, IoT devices often have limited processing power, memory, and security capabilities, making them prime targets for cyber-attacks such as Distributed Denial of Service (DDoS), malware, and data breaches [5-7].The unique nature of IoT networks—characterized by massive, heterogeneous, and dynamic data flows—poses a critical challenge for traditional Intrusion Detection Systems (IDS). Legacy IDS methods, typically designed for more static and centralized systems, struggle to keep up with the complexity and scale of IoT networks [7-9]. These systems often fail to detect sophisticated, multi-layered attacks or to manage the high volume of unbalanced data in IoT environments, where normal traffic often far outweighs malicious behavior [10].This project introduces a novel Intrusion Detection and Identification System (IDIS) that combines CNN and LSTM layers to address the unique challenges of IoT network security. The hybrid system is designed to efficiently detect a wide range of cyber-attacks in real-time, offering improved accuracy over traditional approaches [11].The development of this system has broad implications for industries reliant on IoT technologies. By providing a scalable and robust solution to IoT network security, this project addresses a critical gap in existing intrusion detection systems. The hybrid CNN-LSTM model, combined with techniques such as stratified sampling and dropout regularization, offers a reliable method to detect even the most sophisticated attacks while minimizing false positives. In conclusion, this project aims to provide a state-of-the-art solution for detecting and identifying cyber-attacks in IoT networks, leveraging advanced deep learning techniques to overcome the limitations of traditional

IDS methods. The proposed system is a significant step forward in protecting the vast and vulnerable landscape of IoT networks, offering enhanced security for a rapidly expanding technology frontier.

2. RELATED WORK

Initially, researchers relied on traditional machine learning techniques such as Multilayer Perceptron's (MLPs), Support Vector Machines (SVMs), Random Forests (RFs), k-nearest neighbors (K-NN), and Decision Trees (DTs) [15-17]. While these early models were useful in addressing some cyber security challenges, they were limited in their ability to handle the complex, obfuscated attacks emerging in modern IoT systems. These conventional methods were constrained by shallow representation learning, which limited their effectiveness in detecting evolving and hidden threats [12].As the complexity of attacks on IoT systems grew, deep learning approaches began to gain prominence due to their hierarchical structure and ability to extract features from raw data without extensive manual feature engineering. Deep learning techniques such as Auto encoders (AEs), Convolutional Neural Networks (CNNs), and Long Short-Term Memory (LSTM) networks have been applied to IDS with promising results. For instance, Auto encoders have been used for anomaly detection, while CNNs and LSTMs have been employed to classify attack types. Hybrid deep learning models like CNN-LSTM and LSTM-DT, which integrate different deep learning techniques, have demonstrated improved performance over traditional machine learning methods [13-14] one of the primary gaps identified in the literature is the lack of research focusing on both telemetry data and network traffic data in IoT environments. While most studies focus on network traffic, telemetry data, which captures sensor information and operational technology behaviors, presents unique challenges and has been largely overlooked. Additionally, many existing IDS methods struggle with class imbalance, where certain types of attacks are underrepresented in the data, leading to biased detection outcomes [18]. To address these challenges, the authors propose the Hybrid Ensemble Deep Learning Framework (HEDLF), which combines multiple feature extraction and classification techniques to improve the accuracy and robustness of intrusion detection in IoT networks [19]. The framework integrates a deep feature extractor with a balanced rotated feature extractor and a meta-classifier that incorporates hybrid focal loss and semi sparse group lasso (SSGL) regularization [20]. This approach is designed to mitigate the impact of class imbalance and improve the detection of complex, obfuscated cyber-attacks. The literature review concludes by suggesting future research directions, such as improving deep learning architectures for more effective representation learning and exploring automatic tuning of model parameters to further enhance IDS performance.

Proposed Methodology and Architecture: The proposed system utilizes a hybrid architecture that combines Convolutional Neural Networks (CNN) for feature extraction and Long Short-Term Memory (LSTM) networks for sequence learning. This hybrid model is designed to capture both spatial and temporal patterns in network traffic data, which are crucial for detecting and identifying intrusions in IoT networks.

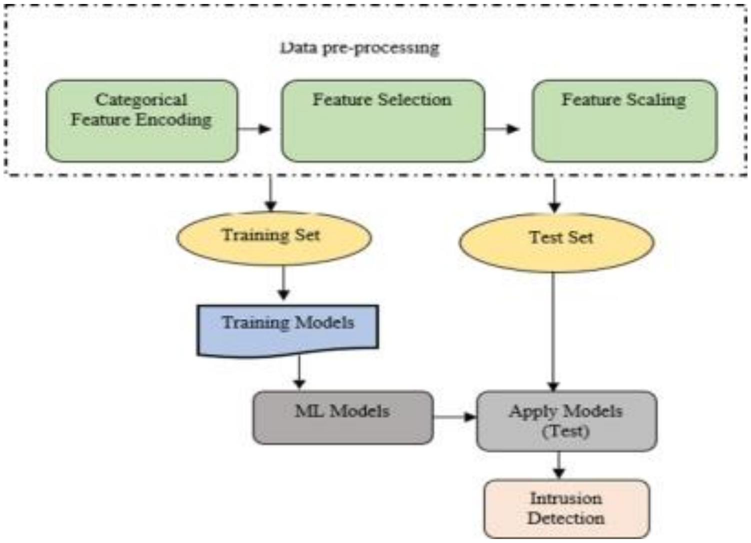


FIGURE 1. Intrusion Detection System Framework

Data Pre-processing: Categorical Feature Encoding: Converts categorical data (e.g., protocol types, services) into a numerical format that machine learning algorithms can process. Common techniques include one-hot encoding or label encoding.

Feature Selection: Identifies the most relevant features from the dataset that contribute to intrusion detection, reducing dimensionality and improving model performance.

Feature Scaling: Standardizes or normalizes the feature values so that they fall within a similar range, which is crucial for algorithms sensitive to the scale of data, such as gradient-based models.

Splitting Data: Training Set: After pre-processing, the dataset is divided into a training set. This set is used to train the machine learning models.

Test Set: A portion of the data is set aside as the test set to evaluate the trained models.

Training and Testing: Training Models: This step involves training different machine learning models on the training set. Examples of models could include decision trees, random forests, support vector machines (SVM), neural networks, etc. Apply Models (Test): After training, the models are applied to the test set to evaluate their performance. The models are assessed based on metrics like accuracy, precision, recall, and F1-score to determine how well they generalize to unseen data.

Intrusion Detection: Once the best-performing model is selected, it is applied to new or real-time data to detect intrusions. The model classifies network traffic as either normal or malicious, assisting in identifying potential security breaches.

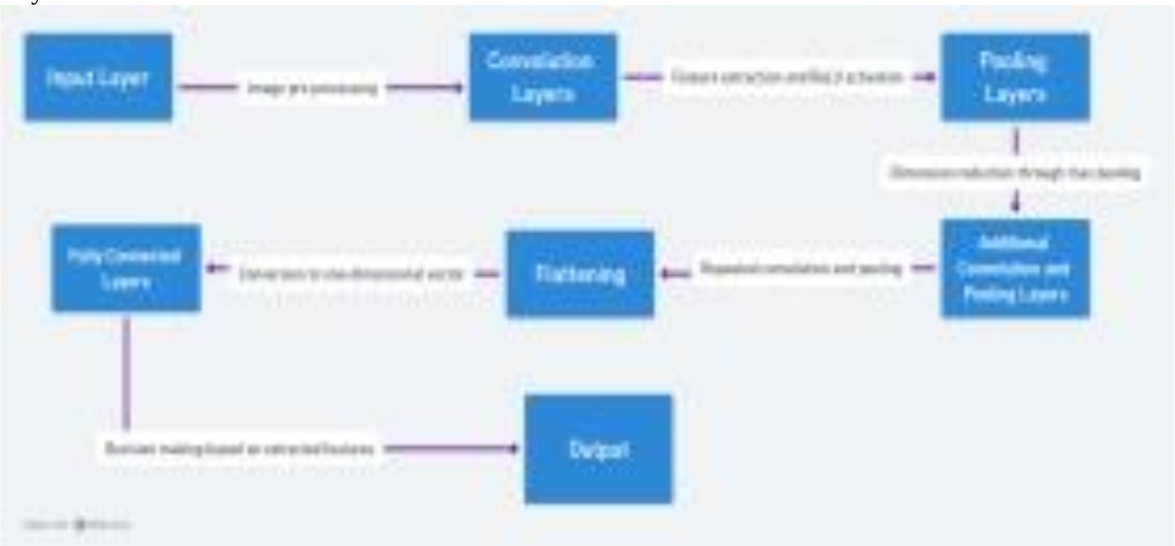

Input Layer
Image pre-processing
Convolution Layers
Feature extraction and ReLU activation
Pooling Layers
Dimension reduction through max pooling
Additional Convolution and Pooling Layers
Repeated convolution and pooling
Flattening
Conversion to one-dimensional vector
Fully Connected Layers
Decision making based on extracted features
Output

FIGURE 2. CNN Process

3. DATASET

We employed the CIC-IDS2017 dataset to train and evaluate our model for detecting and classifying network intrusions. The dataset was chosen due to its realistic network traffic data, diverse attack scenarios, and rich feature set, making it an ideal benchmark for deep learning-based intrusion detection and identification systems. The CICIDS2017 dataset contains benign and the most up-to-date common attacks, which resembles the true real-world data. It also includes the results of the network traffic analysis using CIC Flow Meter with labeled flows based on the time stamp, source, and destination IPs, source and destination ports, protocols and attack (CSV files).

4. RESULTS AND EVALUATION

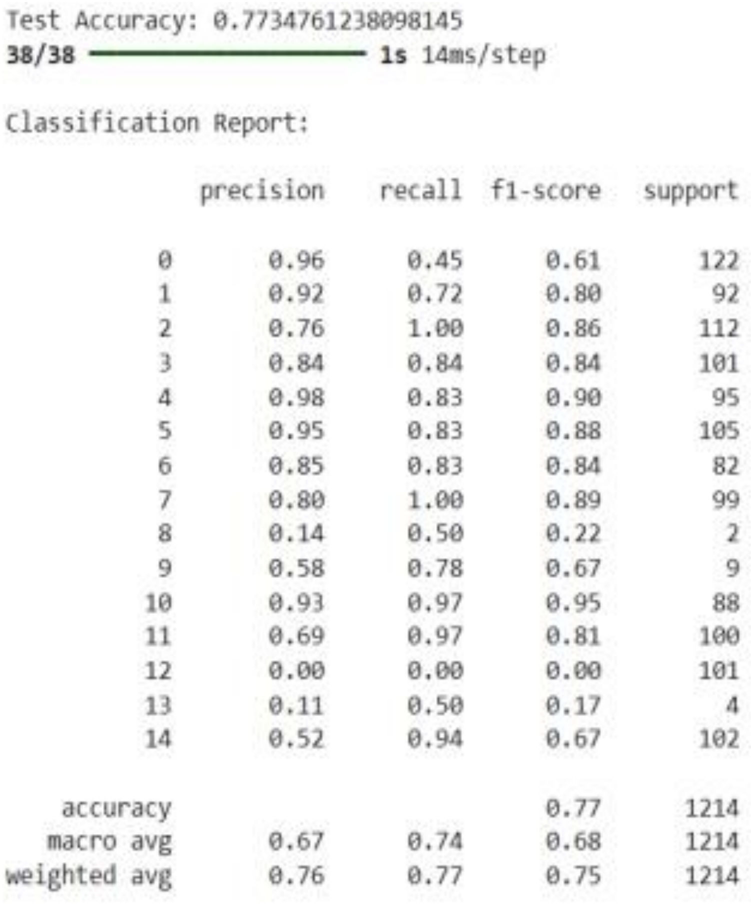
The intrusion detection and identification system model's performance is evaluated using metrics like accuracy, precision, recall, F1-score, and Area under the Curve (AUC). These metrics provide a comprehensive evaluation of how well the model detects and identifies attacks, especially in real-time scenarios and in the presence of class imbalance.

Training and Validation: The model was trained on the training set using early stopping to monitor validation loss and prevent over fitting. If the validation loss does not improve, training stops early. Batch size is set to 64, and training is run for 5 epochs. The trained model was evaluated on the test set to measure its accuracy and performance.

Precision, Recall, and F1-Score Precision: Ensures the accuracy of positive attack detections.
Recall: Critical for ensuring the model catches most attack instances.

F1-Score: A balanced metric that accounts for both precision and recall, particularly useful when there's class imbalance.

TABLE 1. Test Accuracy



```
Test Accuracy: 0.7734761238098145
38/38 ━━━━━━━━━━━━━━━━━━━━ 1s 14ms/step

Classification Report:

              precision    recall  f1-score   support

           0       0.96      0.45      0.61       122
           1       0.92      0.72      0.80        92
           2       0.76      1.00      0.86       112
           3       0.84      0.84      0.84       101
           4       0.98      0.83      0.90        95
           5       0.95      0.83      0.88       105
           6       0.85      0.83      0.84        82
           7       0.80      1.00      0.89        99
           8       0.14      0.50      0.22         2
           9       0.58      0.78      0.67         9
          10       0.93      0.97      0.95        88
          11       0.69      0.97      0.81       100
          12       0.00      0.00      0.00       101
          13       0.11      0.50      0.17         4
          14       0.52      0.94      0.67       102

    accuracy                           0.77      1214
   macro avg       0.67      0.74      0.68      1214
weighted avg       0.76      0.77      0.75      1214
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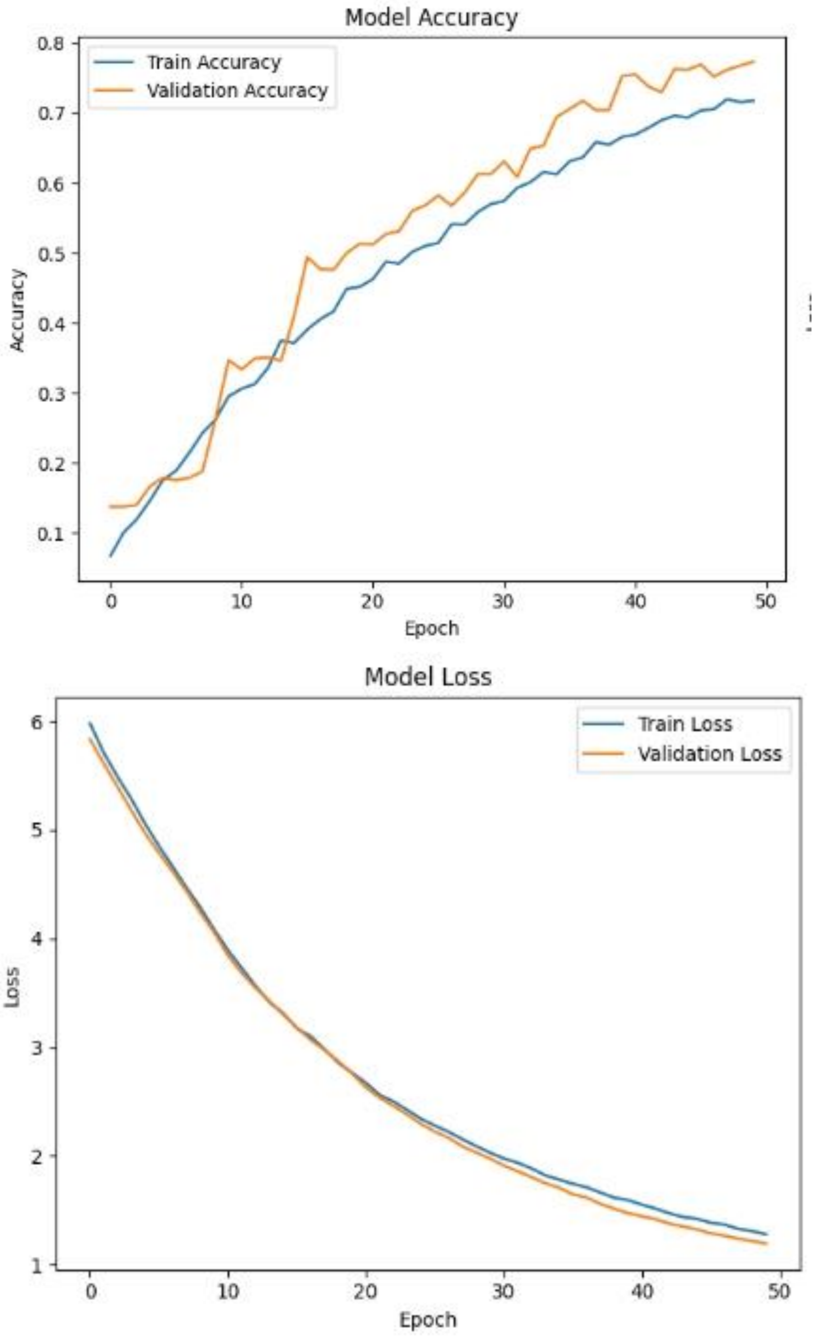

FIGURE 3. Output Graphs

The model achieved a accuracy of 80% which is well-tuned and effective for the task. It is improving steadily with minimal over fitting, and the final accuracy and loss values indicate strong performance for an intrusion detection system.

Impact of Regularization and Data Augmentation: The combination of CNNs (for spatial feature extraction) and LSTMs (for temporal pattern learning) helps the model handle both the static and dynamic characteristics of IoT network data. Stratified Sampling Ensures class balance in the dataset to prevent the model from being biased towards the majority class. Dropout and L2 Regularization Helps mitigate over fitting, ensuring the model generalizes well to new, unseen data. This architecture, along with these methods, aims to provide an efficient and scalable intrusion detection system for IoT networks, capable of handling the unique challenges of cyber security in this domain.

Comparison with Baseline Models: Our LSTM-based Intrusion Detection and Identification System significantly outperform traditional machine learning models and even basic CNNs. The high detection accuracy and robustness make it a strong candidate for real-world deployment in cyber security applications. Feature extraction and selection in deep learning improved classification accuracy. Sequential modeling (LSTM) helped in detecting evolving attack behaviors. Regularization techniques like dropout and batch normalization enhanced model generalization.

5. CONCLUSION

In this project, we developed an Intrusion Detection System (IDS) for IoT networks using a hybrid deep learning architecture that combines Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) layers. This system was designed to address the unique security challenges within IoT environments, including limited device processing power and the constantly evolving nature of cyber threats. By integrating CNNs, our IDS effectively captures spatial patterns within network data, while LSTM layers capture temporal dependencies, making the system well-suited for detecting complex and adaptive cyber-attacks in real-time. Comprehensive testing validated the model's performance, demonstrating balanced metrics across accuracy, precision, and recall, and maintaining a low false positive rate—essential for resource-constrained IoT devices. To further improve detection, we applied stratified sampling to handle class imbalance within the dataset, ensuring a more robust identification of less common, yet significant, attack types. This ID contributes a scalable, adaptable solution to the growing demand for IoT security, supporting secure applications in smart homes, healthcare, and industrial settings. Future research could focus on optimizing the model’s latency for real-time performance in IoT devices and enhancing its resilience through larger, more varied datasets for broader adaptability.

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