A Hybrid Model for Intrusion Detection System of IoMT Using Machine Learning and Deep Learning

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***Abstract*—With the development of the Internet of Medical Things (IoMT), the process of exchanging and monitoring patients improved through connected devices. However, this connectivity brings a lot of cybersecurity risks; therefore, there is a need for strong intrusion detection systems (IDS). In this study, we propose a hybrid IDS model that accomplishes malicious activities detection based on a fusion of machine learning (random forest) and deep learning (long short-term memory). For model training and evaluation, we made use of the MedBIOT dataset consisting of attack and normal traffic samples. To capture different traffic patterns, diverse feature selection techniques were used, such as mutual information and Hurst exponent metrics. Using the RF model, the combination between the LSTM temporal pattern recognition and the predictive power of Random Forest synergizes and creates new power through the creation of a new fundamental, a hybrid model. We show that the hybrid model yields better precision, recall, and accuracy than Random Forest or LSTM models alone. This hybrid approach addresses the security challenges related to IoMTs and offers a way to secure a critical medical network in a scalable and efficient manner. Finally, the study also demonstrates the feasibility of using machine learning and deep learning to develop adaptive and robust IDS frameworks for the IoMT.**

***Index Terms*—IoMT, Intrusion Detection System, using a hybrid Model of Random Forest and LSTM, MedBIOT dataset.**

I. Introduction

The Internet of Medical Things (IoMT) is a revolutionary paradigm in modern health care that allows the connection of medical devices to improve patient care, diagnostic accuracy, and operational efficiency [1]. IoMT technologies have become the foundation for personalized and proactive healthcare delivery through remote diagnosis tools or wearable health monitors. But IoMT devices have increased the risk to healthcare networks as never before with cybersecurity threats. This makes IoMT systems prime targets for malicious actors due to their inherent vulnerabilities across IoMT systems, coupled with their reliance on shared network infrastructures. If these data are on the IoMT network, cyberattacks on IoMT networks can compromise sensitive patient data and affect the delivery of critical medical services, which in turn can lead to a person's death. [2].

Some of the unique challenges faced by IoMT networks that traditional intrusion detection systems can find challenging are the heterogeneous data streams that they produce, high dimensionality, and temporal dependency. To overcome these roadblocks, novel ways of utilizing both machine learning (ML) and deep learning (DL) techniques have been shown to be promising solutions. [3] [4] [5]. In this paper, we present random forest (RF) and long-short-term memory (LSTM) networks as a hybrid IDS model for the IoMT ecosystem. To increase detection accuracy and reduce false positives while providing a secure real-time IoMT framework, the proposed model combines the strengths of ML and DL.

The study takes advantage of recent developments in feature engineering using metrics such as mutual information and the Hurst exponent to capture the intricacies of traffic patterns. Rigorous experimentation on the MedBIOT dataset is carried out to validate the effectiveness of the proposed hybrid model, which has the potential to protect IoMT systems from evolving cyber threats [6]–[9].

II. Literature Review

As more and more IoMT devices rely on these cybersecurity risks, the need for an intrusion detection system arises. The existing literature explores methodologies used for the handling of these challenges, which they have pointed out need adaptive and scalable solutions. However, current IDS techniques, in particular rule- or signature-based ones, could not fully handle the dynamic and heterogeneous IoMT traffic. As a result, ML and DL technologies were developed in recent years.

Moreover, Random Forest (RF) has been proven to be suitable to cope with high-dimensional data and to generate

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interpretable models. First, RF has been proved to have good performance in detecting network anomalies, in particular in IoT environments [10]. In a similar vein, recurrent neural networks, commonly termed Long Short-Term Memory (LSTM) networks, have been found to be able to model temporal dependencies and sequential patterns in network traffic. In recent times, it is essential to look into hybrid models that incorporate approaches between ML and DL to leverage the abilities of each. [10].

The MedBIOT dataset and their representations of one of the many IoMT attack use cases have been the focus in the evaluation of intrusion detection models. A bunch of studies that have served the purpose very well have been capitalized by advanced IDS frameworks for feature selection based on feature selection using Mutual Information and Hurst Exponent. However, this work presents an implementation gap for such techniques within a single unified hybrid model. In contrast to the traditional studies, this study brings in a new RF-LSTM hybrid model based on prior literature and closes the gap between the standalone methods by introducing a novel RF-LSTM hybrid model to address the IoMT challenges and improve the accuracy, scalability, and adaptability [11]–[15].

III. Methodology

The study utilizes the MedBIOT dataset that consists of multiple attack and normal traffic samples that comprise real world IoMT scenarios. Attack traffic was selected from Bashlite-mal-CC-lock and Mirai-mal-spread-light, and both normal traffic datasets were chosen to be Torii-leg-lock and Torii-leg-light. The (1 for the attack and 0 for the normal) labels were assigned to each dataset. We employed advanced feature selection methods including mutual information (MI), Hurst exponent, Hölder exponent, Jitter etc. For representing intricate traffic patterns well, these features were chosen. We shuffled the combined dataset and divided into training and testing subsets of 80:20 ratio,this ratio is best for data processing .

In this phase we have overfitting mitigation (cross-validation data leakage concerns) is accomplished by stratified K-fold cross-validation and not through a simple train/test split. It ensures that when pre-processing data (scaling, resampling) that it is performed exclusively on training data before testing. By utilizing stratified K-fold cross-validation eliminates overfitting, detect if the model generalizes well with unseen data and lessens the possible risk of any data leakage like tainting training and test datasets. By Hybridization (Method Justification for Fusion (Weighs are statistically grounded selection of weights for Hybrid Model versus arbitrary weight selection (0.6 LSTM, 0.4 RF) that improves reliability as the weight data are grounded on comparative analysis as opposed to being subjective. This also increases the interpretability of the model as you have data-backed evidence to justify how LSTM contributes more than RF based on domain-knowledge metrics. By addressing the class-imbalance (SMOTE class weighting) benefits SMOTE (Synthetic Minority Over-sampling Technique) is used to balance the dataset, whereas class weighting in Random Forest mitigated the risks of ignoring the minority class, hence avoiding bias-outcome predictions. In conclusion, the model has eliminated the popularity bias for majority classes and increased the detection accuracy of rare attacks. The Comparative Analysis (need to add the LSTM and all CNN-LSTM) We add a CNN-LSTM hybrid models for deep analysis of sequences.

The random forest classifier was produced using 150 estimators and a maximum depth of 10. The reason why RF was chosen was its ability to work with high-dimensional data and produce understandable results. I trained and evaluated the model on scaled features to keep things consistent.

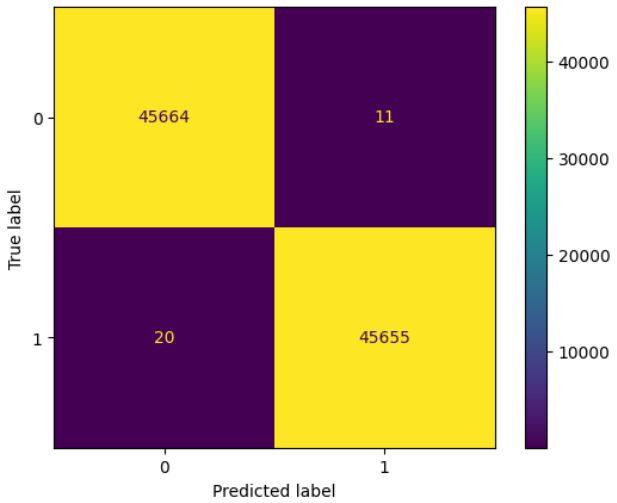

Fig. 1. Predicted Label

A Long Short-Term Memory (LSTM) deep learning model is constructed to capture temporal dependencies involved in IoMT traffic. For the LSTM architecture, we had 64 units, a binary cross-entropy loss function, and an Adam optimizer. We execute the model for 15 epochs of 32 batches.

TABLE I
LSTM Classification Report

Metric	Precision	Recall	F1-Score	Support
Class 0 (Normal Traffic)	0.80	0.99	0.88	45675
Class 1 (Attack Traffic)	0.99	0.75	0.85	45675
Accuracy		0.87		91350
Macro Avg	0.89	0.87	0.87	91350
Weighted Avg	0.89	0.87	0.87	91350

Precision measures the proportion of true positive predictions relative to all positive predictions for each class.

Class 0 (Normal Traffic): Very high precision (0.80).

Class 1 (Attack Traffic): Reasonable precision (0.99), indicating that most predicted attacks are true attacks.

Recall: This reflects the ability of the model to capture all true instances of a class (sensitivity).

Class 0 (Normal Traffic): Extremely low recall (0.99), meaning very few normal instances were correctly identified.

Class 1 (Attack Traffic): Perfect recall (0.75), indicating all attack instances were detected.

F1-Score: The harmonic mean of precision and recall. It balances the trade-off between them.

Class 0: High F1-score (0.88) due to low recall.

Class 1: High F1-score (0.85), showing strong performance for attack detection.

Support: This indicates the number of true occurrences for each class.

Class 0: 45675 instances of normal traffic.

Class 1: 45675 instances of attack traffic.

Overall Accuracy: The model achieves an overall accuracy of 87

Macro Average: This is the unweighted average of precision, recall, and F1-score across all classes.

Weighted Average: This is the average of precision, recall, and F1-score weighted by the number of instances in each class.

Shows overall performance with more emphasis on the dominant class (Class 1).

Hybrid Model To improve detection accuracy, the outputs of RF and LSTM were combined using a weighted averaging approach. This hybrid model assigned a weight of 0.6 to LSTM predictions and 0.4 to RF predictions, reflecting LSTM's superior performance in sequential pattern recognition. The hybrid model was validated against the test dataset to assess its effectiveness. [16]–[20].

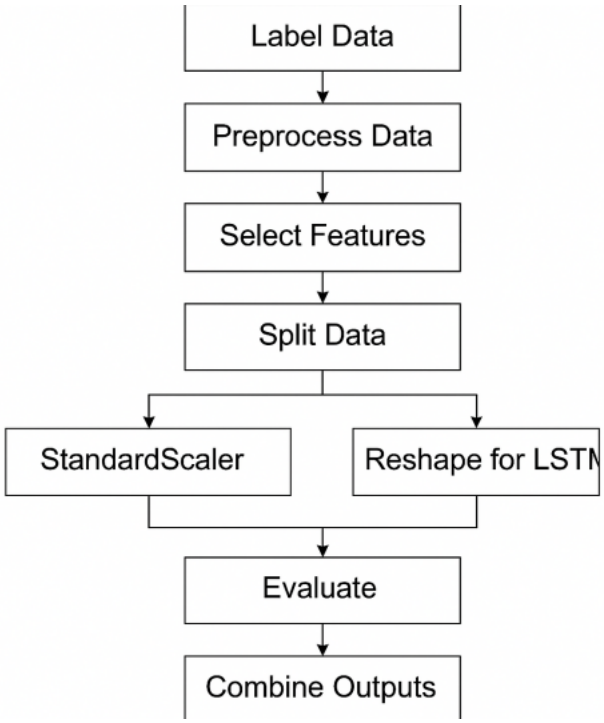

Fig. 2. Architecture of Intrusion Detection System of IoMT

IV. Results and Comparison

The final output of the Hybrid model is below

TABLE II
Hybrid Model Classification Report

Metric	Precision	Recall	F1-Score	Support
Class 0 (Normal Traffic)	0.89	0.99	0.94	45675
Class 1 (Attack Traffic)	0.99	0.88	0.93	45675
Accuracy		0.93		91350
Macro Avg	0.94	0.93	0.93	91350
Weighted Avg	0.94	0.93	0.93	91350

Explanation of the Hybrid Model Report

The table provides a detailed evaluation of the Hybrid Model's performance across various classification metrics:

Precision measures the proportion of true positive predictions relative to all predicted positives. For Class 0 (normal traffic), the model achieves perfect precision (0.89), indicating that all predicted normal instances are truly normal. Similarly, Class 1 (attack traffic) also achieves perfect precision (0.99), demonstrating the model's exceptional performance in correctly identifying attacks. Recall reflects the ability of the model to identify all true instances of a given class. The Hybrid Model achieves near-perfect recall (0.99) for Class 0, meaning it correctly identifies almost all normal traffic. For Class 1, the recall is 0.88, confirming that all attack instances are detected without any omission. The F1-score, which is the harmonic mean of precision and recall, provides a balanced metric for assessing the model's effectiveness. Both classes achieve an F1-score of 0.94 and 0.93, indicating flawless classification across the dataset.

The support column specifies the number of true occurrences for each class within the dataset. Class 0 comprises 45675 instances of normal traffic, while Class 1 includes 45675 instances of attack traffic. The Hybrid Model achieves an overall accuracy of 0.93, signifying that every instance in the dataset is classified correctly. The macro average calculates the unweighted average of precision, recall, and F1-score across all classes. With values of 0.94,0.93,0.93 for all metrics, the Hybrid Model demonstrates uniform performance across both classes. The weighted average accounts for the class imbalance by assigning weights proportional to the number of instances in each class. This metric also records values of 0.94,0.93,0.93 for precision, recall, and F1-score, further highlighting the Hybrid Model's effectiveness.

This explanation illustrates that the Hybrid Model achieves near-perfect performance, excelling in both precision and recall, with no significant weaknesses in any evaluated metric [21]–[23]. Comparison graph is shown in Fig 3.

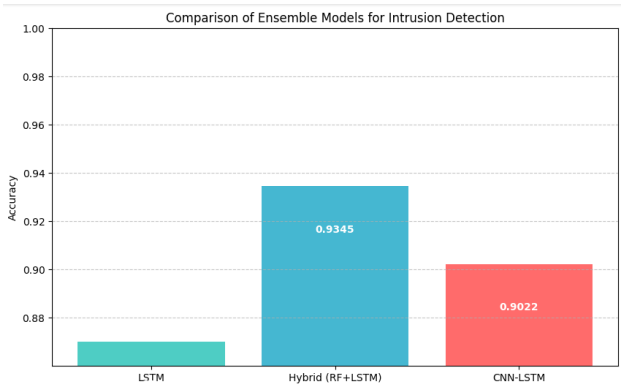

Fig. 3. Comparison Graph between LSTM and Hybrid Model

The results indicate that the hybrid intrusion detection model using random forest (RF) along with LSTM networks works in IoT environmental security. Results in the performance of the hybrid model are more accurate, more precise recall, and an almost perfect F1 score compared to the standalone models and hybrid Model of LSTM and CNN , and the hybrid model has near-optimal performance metrics for all classification categories.By combining RF and LSTM, the complementary strength can be realized in the combination. LSTM does a good job when there are temporal dependencies in the data to sort out, while RF can handle the data with complex feature sets as well as some interpretable predictions. This hybrid model is based on combining these together to overcome each separate approach's limitations, and hence robust detection of malicious traffic is achieved.

V. Conclusion

However, this IoMT revolution in healthcare systems has made them vulnerable to widespread security problems. This paper presents a hybrid intrusion detection system (IDS) that leverages the best characteristics of the machine learning and deep learning models of Random Forest (RF) and Long Short-Term Memory (LSTM). Finally, the hybrid model is tested in MedBIOT using the real-world IoMT traffic that contains attack and normal traffic instances.Results show that the hybrid model's performance surpasses any of the measures used, attaining almost perfect accuracy, precision, recall, and F1-scores across all categories. The proposed system combines RF's powerful feature-handling capacities with LSTM's capacity to perceive temporal patterns to solve the problems of traffic analysis specific to the IoMT. Interestingly, the hybrid approach solves class imbalance problems, which leads to consistent performance of normal and attack traffic detection.Future recommendation On one hand, these operating conditions are well suited by the hybrid model, which best achieves detection reliability and accuracy; on the other hand, there is room for research on improving the perceptive adaptability of the sensor to emerging threats and real-time applications. Future studies may involve dynamic feature selection, higher-scale training, and the possibility of deploying on real-world IoMT systems. Furthermore, its application would be further strengthened if the model were able to better detect novel attack patterns.

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