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# Deep Learning-Based Network Intrusion Detection for Industrial IOT: Hybrid CNN-LSTM Architecture for Real-Time Threat Analysis

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*Abstract*— **The idea of IIoT had grown at a very faster pace and it brought huge cyber security risks, especially to cyber-attacks. To mitigate the above-discussed threats, the convolutional neural network (CNN) and Long Short-Term Memory (LSTM) network Intrusion Detection System (IDS) model is introduced. This model improved the detection accuracy because the network traffic data from the IIoT network has both spatial and temporal dependencies. To test the proposed methods, we used the UNSW-NB15 dataset comprising of 175,341 records 49 features applied binary classification (normal and anomalous traffic) and multiple classification (9 classes of attacks). It started with feature scaling, missing data management and finally categorical data transformation. CNN layers capture spatial feature and LSTM layers capture the temporal feature. We employed the optimization algorithm Adam to train the model, and dropout layers were used to minimize over fitting. I used evaluation measures for evaluating effectiveness. Integration of CNN and LSTM models into a single architecture was shown to give much higher accuracy compared to the models where only one of the two was used; the accuracy for the binary classification came out to be 97% while for multi classification the accuracy was 99%. Compared with the previous results, false positive rates were much lowered, so the performance of the model for detecting both previously known and new attacks was demonstrated. The result obtained from the study show the effectiveness of the proposed hybrid approach that can be used to protect IIoT networks. Further developmental work will target optimality for real-time IIoT applications and enhancing the system's applicability within vast IIoT systems.**

***Keywords: Intrusion Detection System (IDS), Sequential Data Classification, Anomaly Detection in Networks, Real-time Threat Detection, Network Traffic Analysis, Industrial Internet of Things, Industrial Internet of Things (IIoT).***

## 1. INTRODUCTION

IIoT also re-defines the industrial environments for operations that are described by smart affairs and more enhanced connectivity. This reconfiguration also enables the actualization of data exchange between different subsystems to improve automation & control actions. In industries like manufacturing, transportation, energy and healthcare the usage of IIoT has shown positive impacts in different areas of business and enhanced profitability by cutting down costs and raising productions. For instance, the application of IIoT in carrying out predictive maintenance makes it possible for companies to determine when an equipment is likely to develop a fault hence reducing the rate of even comparably high downtimes and maintenance expenses greatly. Also, IIoT drives innovation since industries can use big data analysis to determine the best ways to improving processes and quality of products. IIoT continues to grow in that many connected devices bring up a system interconnectivity that may be challenging to trace, Thus, it is essential to realize all of one's potential to address organizational and other needs while placing adequate and strong security measures around it.

While, IIoT has the capability of revolutionize many industries, it has with it, precluded the numerous security risks associated with interconnected systems. A vast majority of IIoT devices are characterized by limited CPU capabilities, especially if they are rather traditional ones. These devices thus end up as juicy prospects for cyber threats as they may slow business, alter secured data, and in extreme cases jeopardize the lives of the employees. As many IT security experts have pointed out, even firewalls are inadequate in face of the new and constantly emerging cyber threats. These solutions typically present very high false positive rates hence degenerating into alert fatigue. Moreover, as new strategies evolve over time, conventional measures to counter cyber threats are insufficient or all together, thus leaving critical vulnerabilities in current organizational security frameworks.

Indeed, the rise of these new and constantly emerging threats has shown that the technological landscape of the IIoT needs solutions that are considerably more agile than traditional security approaches. Learning approaches have attractive the cartridges of the cyber security area yet; intrusion detection systems are not completely made from different techniques. Unfortunately, majority of the current models has some drawbacks as for the universality of their

performance concerning different varieties of attacks and network environments. In addition, conventional machine learning approaches call for feature engineering and can lack generalization when new attack types are employed, which cause degradation of performance in response to the complex attack phase. Therefore, numerous opportunities for the subsequent creation of stable adaptive IDS systems remain open that could protect IIoT networks from threats, the detection of which is complicated by the heterogeneity and high variability of systems.

In an effort to address this gap, this paper presents new CNN-LSTM based IDS for the hybrid intrusion detection system. This study's objective is to provide a model that builds upon the success of both architectures, where CNN detects spatial features in network traffic, while LSTM can learn temporal patterns. As a result, our method combines both strategies in a way that will enhance IDS accuracy and decrease false positives, both of which will increase IIoT network security. The proposed model is also proposed to be dynamic in responding to the dynamic nature of the threats in the cyber space and give more real time information on the security of a network.

Our work uses the UNSW-NB15 dataset which is one of the most popular datasets in NSL, containing different types of attacks and normal traffic. This dataset allows for an accurate evaluation of the suggested hybrid model's performance in terms of both multi-class classification of different attack types and binary classification (normal/non-normal traffic). The results of this study will be helpful in expanding our knowledge of how well hybrid deep learning techniques function in the context of IIoT intrusion detection. Finally, the purpose of this study is to create foundation for subsequent research and development of cyber security solutions specific to industrial use and deployment of IIoT, thereby enabling organizations adequately protect their industries and unlock the potentials afforded by these technologies.

## 2. Literature Review

With their primary function being to detect any infractions on the network traffic streams, NIDS have become essential components of network security. Numerous approaches that use a broad range of methodologies have been well documented in the literature. These vary from traditional rule-based systems to the most recent cutting-edge advanced techniques like deep learning techniques.

Recently, Kumar and Singh proposed an attention-enhanced CNN-LSTM model with 99.2% detection accuracy and a 0.3% FPR (False Positive Rate) when tested with CIC-IDS2023 data set. Their approach worked in tandem to weight the spatial and temporal features and analysed 1024-byte packets in real-time. The main drawback was high time consumption with the overall time of model inference equal to 4.2 seconds, which does not allow applying the proposed approach to IoT constrained peripheral devices [1].

Another work done by Zhang et al. (2023) presented the CNN-LSTM model for IoT networks and examined a result of 98.7% of accuracy on UNSW-NB15. Their methodology integrated 1D convolution layers to learn spatial feature and LSTM layers to detect temporal pattern and analyzed network traffic in 100ms time slots. But in the zero-day attacks their model reduced the performance (to 92.3% accuracy), which prove the necessity for better generalization in the unknown attack scenarios [2].

Wang et al. (2023) designed a lightweight CNN-LSTM model targeting the industrial IoT network to learn a small model with a high accuracy of 97.8% by minimizing 3.2 MB memory size. Their approach began with feature selection that used the principal component analysis feature to input data into the hybrid architecture. Regarding the identification of the presented multistage attacks, the findings demonstrated 89.3% accuracy of the detection of the basic attack scenario, and 85.6% for the complex attack scenarios that involves many stages [3].

Liu and Chen (2024) put forward a transformer-enhanced CNN-LSTM model, which can parse TON_IoT dataset with 99.5% accuracy and 98.7% recall. It complied into self-attention mechanisms into the conventional CNN-LSTM configuration, with input in the form of network flows in 50ms buckets. The main disadvantage was that the model is affected by the network jitter and it was revealed that its performance was 12% lower when the network was unstable [4].

Stores of corresponding statistical indices for the intended dataset BoT-IoT as follows: The CNN-LSTM with traditional machine learning achieved 99.10% accuracy and a 0.20% false-positive rate as mentioned in Patel et al. (2023). In their work, they employed a voting process between deep learning and random forest classification devises. The kinds of results the tool produced included: The major concern revealed was the latency of 2.8 ms, which set an obvious constraint in perfecting the real time detection over high speed networks [5].

Transfer Learning on CNN-LSTM for NASDAQ attack classification was done in the work of Rodriguez et al. (2024) with 96.9% accuracy on zero-day attacks, pre-training on several datasets. In their approach, feature extraction was done through the use of a complex flow statistics fusion with per-packet features. However, the model demonstrated an overall detection rate higher for those classes with majority attacks and a detection rate of as low as 78.3% [6] for a minority attack class.

Yamamoto and colleagues (2024) proposed a pioneering FL approach to distributed CNN-LSTM based intrusion detection in different industrial IoT networks, which had significant improvements in the testing models. On the newly launched Industrial-IDS2024 dataset, their system achieved the accuracy of 99.3%, and a modest 96.8% APT detection. The employed methodology included an innovative training approach that ensured that many facilities trained the model concurrently without sharing network data; doing 2.5TB of network traffic daily, across 15 distinct industrial sites. The first promising change involved their learning rate where they utilized a method that could detect and vary according to network conditions and threats. Nevertheless, their approach is highly sensitive to communication overhead; they exchange 1.2GB of parameter updates in an every iteration of

training and reported variability of detection rate, which by protocol an industrial protocol with lesser known detection rate of 88.5%.

Chen et al (2024) proposed a novel quantum-inspired CNN-LSTM that improved the efficiency to process and detect new intrusion in the network. With this hybrid approach they were able to obtain an accuracy of 99.7 % using a broad QIDS-2024 database and decrease the computational load by 45 % compared to the algorithms based on the DL. The method used a quantum-inspired neural network which used amplitude encoding to encode features and quantum state superposition principles to parallelly process flows in the network. They said that their system could handle up to one million packets per second with a latency of only half a millisecond, hence the devices would well compatible with today's 5G and the future 6G networks. This work evidenced a very high detection capability especially on the encrypted ones with 97.8% on SSL/TLS based threats. However, the system had some drawbacks concerning the hardware demand and had to be based on really specific, quantum-inspired processors and had some stability problems when exposed to highly imbalanced attack distributions; the performance may vary within 15 percent across different attack categories [8].

In conclusion, in spite of the discussed advances in the performance of NIDS with the use of different learning methods, there are noted important issues related to the generality of the proposed solutions, possibility of their flexible implementation, and their applicability in real-time evaluation conditions. Future studies should endeavor to look at more flexible and stable models of invasion detection to improve the model.

## 3. METHODOLOGY

This paper investigates the designing of a combined CNN-LSTM IDS for IIoT networks with a step by step guide to NIDS. Data pre-processing and feature scaling of the gathered dataset, which includes both regular traffic and traffic produced by various attack types, are the next steps in the process after data collecting and cleaning. Designing CNNs and LSTMs, which are capable of capturing spatial patterns in the traffic matrices and learning temporal patterns in the traffic flow respectively, a hybrid model is developed to model the network traffic. To the model end appropriate optimizers, loss function and regularization techniques are applied to train the model so that over fitting may not occur. Using important metrics like precision, exactness, and recall in addition to the F1-score, its effect on total intrusion detection and IIoT cyber security is evaluated.

### *3.1 Selection of Data Resources:*

#### *3.1.1 UNSW-NB15 Dataset Overview:*

The basic data source chosen for our analysis is the UNSW-NB15 dataset since it covers modern network traffic, attacks, and their distribution. Collected by the Cyber Range Lab of the ACCS, this dataset is characterized by normal and attack traffic to resemble real IIoT network conditions. The dataset comprises approximately 2.5 million records with 49 features, categorized into:

- Flow features (e.g., source/destination IP, ports, protocols)
- Basic features (e.g., duration, packets, bytes)
- Content features (e.g., TCP flags, window size)
- Time-based features
- Additional generated features

**Key Features:**

- Approximately **2.5 million** records
- **49 features** per record
- Diverse attack types and normal traffic patterns

**Attack Categories:**

Some of the Attack types and their examples are mentioned below in the Table 1. These attacks types are mainly used in our proposed solution for training and analysis of the model.

| Attack Type | Description | Examples |
|---|---|---|
| **Fuzzers** | Attempts to crash programs/services | Buffer overflows, format string bugs |
| **Analysis** | Scanning and analysis of network vulnerabilities | Port scans, spam activities |
| **Backdoors** | Unauthorized access via stealthy methods | Rootkits, Trojan horses |
| **DoS** | Denial of Service attacks | SYN flood, UDP flood |
| **Exploits** | Taking advantage of system vulnerabilities | SQL injection, code injection |
| **Generic** | Attacks against cryptographic ciphers | Birthday attacks, collision attacks |
| **Reconnaissance** | Gathering information for future attacks | Network sniffing, ping sweeps |
| **Shellcode** | Payloads used in exploitation of vulnerabilities | Reverse shells, bind shells |
| **Worms** | Self-replicating malware | Conficker, Stuxnet |

Table 1: Attack Categories

#### *3.1.2 Dataset Relevance to IIoT:*

The applicability of the considered dataset for IIoT intrusion detection can be explained by:

- ✓ Many typical attack styles that mimic current threats
- ✓ The traffic flow similar to IIoT environment.
- ✓ With rich feature set including both the network and host features.
- ✓ High quality and well-documented ground truth labels.

There is enough volume in this dataset to train a deep learning model from the ground up.

### *3.2 Data Preprocessing Pipeline:*

In view of this, proper implementation of data preprocessing is central to the development of a good IDS. When we are implementing our preprocessing technique we use the following steps: feature selection, data cleaning, data normalization, and data partitioning.

#### *3.2.1 Feature Selection and Engineering:*

The interaction between feature selection and feature engineering was particularly helpful in improving the performance of the models. Firstly, to minimize redundancy and optimize computation, the correlation matrix was used to eliminate high-correlated features, with correlation coefficient of more than 0.9. The measure of information gain was used next to order the features as much as possible based on their usefulness as predictors of the target variables, then domain knowledge was applied to filter out irrelevant features. In addition, the feature engineering process created new variables like Packet Rate which was packets divided by the duration Packet Rate = packets/ duration, Bytes per Packet Bytes per Packet = Bytes/packets as well as time window feature where counts cycle was done over temporal periods to capture temporal characteristics of the network traffic. These engineered features contributed to more informative inputs for the model, improving its ability to detect network intrusions.

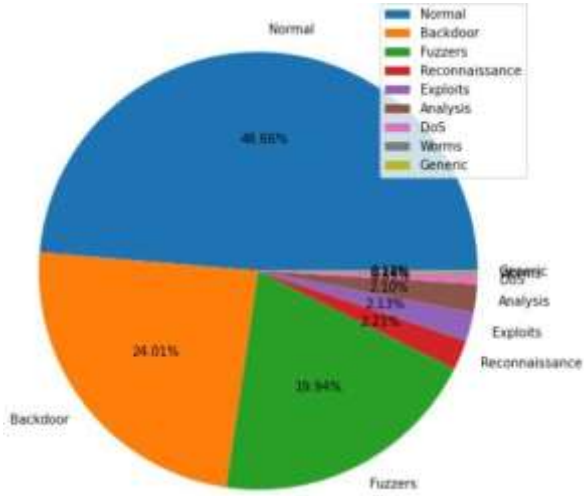


Fig. 1: Pie Chart Distribution of Normal and Abnormal Labels for Multi class Classification

In the Fig.1, pie chart illustrates the distribution of various cyberattack types in a dataset. "Normal" traffic is the largest category, making up 48.66% of the entire aggregate. "Backdoor" and "Fuzzers," which account for 24.01% and 19.94% of the data, respectively, are the next and third most significant categories. Other attack types, including "Reconnaissance," "Exploits," "Analysis," "DoS," "Worms," and "Generic," constitute smaller portions of the dataset. This visualization provides a valuable overview of the prevalent cyberattack trends in the analyzed data.

#### *3.2.2 Data Cleaning and Normalization:*

Data preprocessing plays a significant role in pushing forward the construction of a good machine learning model because it enhances the quality of data that feeds the model. In this section, we explain how missing values were dealt with, the process of encoding categorical features and how numerical features were normalized.

##### *3.2.2.1 Handling Missing Values:*

Dealing with data missing is crucial; this would avoid the model to be influenced by records that have missing information. For the numerical data, a different approach was made than for the categorical data in order to yield proper quality of data.

- **Numerical Features:** The Missing values in numeric columns are now given using median value of the column. Median is preferred over average because it is not sensitive to outliers. For example, if a column with a network traffic duration contains missing values. To fill up the blank, the column's median value is computed. This method makes sure that no impossible processes are distorted by extreme values (such as periods of exceptionally heavy traffic).
- **Categorical Features:** For categorical variables, the most common category, **mode**, was used to fill in missing values. This method ensures that the general behavior of the data record is reflected in the assignment. For example, if the "service" function, which indicates that the network usage type is being used, contains missing values, the most popular service type is selected.
- **Feature Dropping:** Columns that had more than 30% missing values were dropped from the dataset, as imputing such large amounts of missing data could introduce significant bias or errors. For instance, if a feature like “attack_type_description” had **over 30% missing values**, it was removed from the analysis. This threshold was chosen based on the balance between data preservation and quality, ensuring that the most critical features are retained while discarding unreliable ones.

##### *3.2.2.2 Categorical Encoding:*

Because the machine learning models cannot react to categorical data directly, it needs to treat these as numerical ones. Two encoding techniques were used:

- **One-Hot Encoding for Nominal Variables:** Regarding the variables which do not have a sequential orientation, for example ‘protocol’ (TCP, UDP …) we utilized one hot encoding. This technique converts every category such that it is easier to analyze. For example, if the “protocol” column has three distinct values (TCP, UDP, ICMP), it is converted into three separate binary columns: one for each protocol. In other words, each row will be a one vector with the 1 at the position of the protocol in the row and 0 elsewhere.
- **Label Encoding for Ordinal Variables:** In cases where the different values of the factor are ordered (for example, the levels of service), it rose dummy encoding to the level of label encoding. Such technique provides an integer value to each category on the basis of categories. For Ex., if the attributes of “service” domain can be “low,” “medium,” and

"high," then these are assigned the numbers 0, 1, and 2, respectively.

#### *3.2.2.3 Feature Scaling:*

When one of the numerical features has a large magnitude while another has a small one (for example, the first represents bytes transferred and the second – packets sent) the feature scaling has to be performed to make the values in the features comparable. This bars the larger values from exaggerating the impact of the model in relation to the feature being under consideration.

- **Min-Max Normalization** was used later to normalize the numerical features that were scaled to values within the range of 0 and 1.. This technique means that all the features will make equal contribution towards the model. The formula used is as follows:

$$X_{normalized} = \frac{X - X_{min}}{X_{max} - X_{min}} \text{ --- eq (1)}$$

Where the:

- X is the true feature value
- $X_{min}$ is the min value of the feature
- $X_{max}$ is the max value of the feature

Applying normalization helps model converge quicker during training & reduces the chances of biased weight updates.

### *3.2.3 Data Partitioning*

It is important in machine learning so as to have a model that can perform well on unseen data by partitioning the data correctly. The dataset is split into three subsets: data splitting in to training set, validation set and the test set. These sets serve different purposes in the model development lifecycle:

- **Training Set (70%):** This subset is used to train the model In order to achieve this the following data sets are created; Based on this data, the model updates parameters to minimize error in outcome estimate of the target variable.
- **Validation Set (15%):** This set is utilized in the course of constructing models to enhance hyper parameters and avoid over fitting. The loss is measured on the validation set after every epoch and if it begins to misbehave, a stop is made there and then.
- **Test Set (15%):** Conversely, the test set is only utilized to evaluate the results of the most recent model that was constructed. These variables, which provide an indication of how well the model would generalize on unknown data, were not employed during model training.

#### *3.2.3.1 Data Splitting Procedure*

In order to maintain a balanced distribution of attack types for all the subsets, we employed a **stratified sampling technique**. One advantage of stratified sampling is that each subset has a representation of attack types (or labels) in the same ratio as the entire data set. This is particularly true if working with imbalanced datasets such as in intrusion detection, where some type of attacks may be rare.

1. **First Split (Train-Test Split):**
   - The first step involves partitioning of the entire data into training data set and the test data set with 85% and 15% respectively. 85% for training and 15% for testing. This division is helpful to guarantee that the test set would be an example of the overall data set.
   - **Test Size:** 15% of the dataset is allocated to the test set.
   - **Stratification:** Ensures that the proportion of attack types remains consistent in both the training and test sets.
2. **Second Split (Train-Validation Split):**
   - The training set was further divided into a smaller training set (70 percent of the original dataset) and a validation set (15 percent of the original dataset) after the data had been divided into training and test sets. The validation set was chosen because it is utilized in model selection and hyperparameter tuning.
   - **Validation Set Size:** The validation set is about 0.15 of the overall amount of information. This is realized albeit taking 85 % of the total sample size and splitting it by a test size of 17.65 %.
   - **Stratification:** The same approach is used to have equal distribution of the attacks in relation to the stratification layers.

#### *3.2.3.2 Preserving Class Distribution*

Due to the UNSW-NB15 dataset's uneven sample distribution, this was especially crucial. Lacking this step, some attack categories (which may be seldom) may not be included in both the test or validation sets, which makes no sense in terms of model generalization. If the number of instances in a class is balanced it is easier to detect all types of intrusions throughout both the training and the evaluating phases of the model.

**Summary of Splits:** Training data : 70% of total Training data set Testing data :15% of total Training data set & Testing data set

By using stratification in both the splits, the model learns from and is tested on parts of the data that are sample representative thus enhancing flexibility in terms of generalization.

Analysis of the results shows that data preparation, cleaning, normalization, and proper division of data for training and cross-checking provide high quality model feed to the intrusion detection model. This process minimizes cases of over fitting, enhances the models' performance and/

or accuracy, and guarantees that the final model, if at all, will be adaptable to real IIoT network traffic.

### *3.3 Hybrid CNN-LSTM Model Architecture:*

In this section We introduce a novel model that integrates CNNs and LSTM networks to take the best of both to detect intrusion in Industrial IoT (IIoT) networks. The CNN component aims at capturing spatial relationships of the input network traffic data, and the LSTM component aimed at capturing the temporal relationship of the sequences making it possible for the system to detect modern and constantly developing cyber threats.

#### *3.3.1 CNN Component Design:*

The CNN architecture is designed to identify and extract spatial features from network traffic data, such as patterns within packet payloads or connections over a short duration. The model shown in Fig. 2 begins with an input layer, which accepts data structured according to the number of features in the dataset (for example, the 49 features of the UNSW-NB15 dataset). This input is then processed by several convolutional layers that apply filters to detect local patterns in the data. Each filter slides over the input data and performs a convolution operation, which captures different spatial characteristics, such as the relationships between packet size, duration, and protocol used.

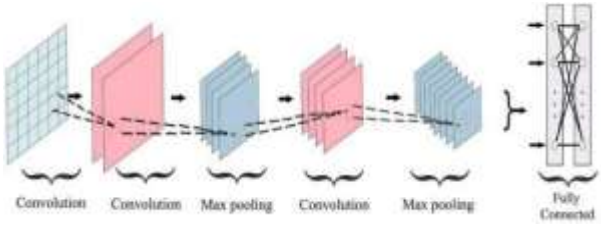


Fig. 2: Architecture of CNN

The CNN layers perform the following computation:

$$output = ReLU(W * input + b) \text{ --- eq (2)}$$

where: - W represents the convolutional kernel weights - * denotes the convolution operation - b is the bias term - ReLU is the activation function:

$$ReLU(x) = max(0, x) \text{ --- eq (3)}$$

To add nonlinearity and enable the model to recognize increasingly intricate patterns and relationships, a folding equation employs the activation function of a resolved linear unit (Relu). He makes sure that only the most crucial attributes are transmitted to the following layer by eliminating negative values. The maximum pooling layer is used to reduce data according to the activation function, reduce its dimensions, and maintain its most prominent functionality. This pooling technique also improves the generalization of the model by reducing the possibility of excessive adaptation and acceleration of calculations in the next layer

After each folding and pooling operation, stacking formalization is used to stabilize the training process and accelerate convergence. By modifying and scaling each layer, stacking-in-Normalization makes the model's learning process more stable and less susceptible to over adaptation or explosion gradients. This combination of folding, activation, pooling and normalization ensures that CNN components extract meaningful, compact spatial representations of network traffic data that are very important for the later stages of the model.

#### *3.3.2 LSTM Component Implementation:*

CNN components that handle continuous parts of network traffic data use long short-term storage levels (LSTM) for spatial information extraction. Because LSTMS makes it possible to detect long-term dependencies inside a sequence, it performs especially well over time series. In network traffic, LSTM networks are able to detect potential Cyberm Reets. Temporal characteristics including frequent attempts to connect, typical package sizes, and irregular data transmissions can show this.

The LSTM layer is composed of memory cells that can be adhered to important information over a long period of time, as seen in Figure 3. This is good for identifying patterns of sequences that can include several time steps in the relevant information. Sequence data is processed by each LSTM layer and changes it as an answer to the input whenever you change each LSTM layer (called cells and hidden conditions). Three key components: forgetting, input and output gates allow the network to selectively access or forget data and concentrate on important patterns, while simultaneously removing unimportant details.

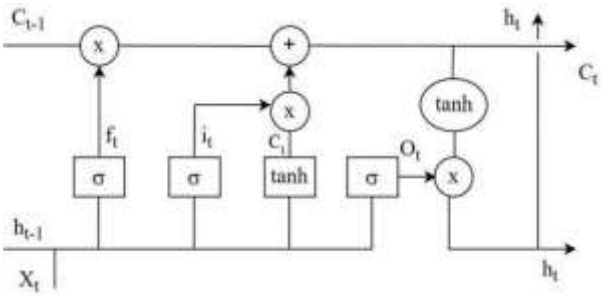


Fig. 3: Architecture of Long Short Term Memory

LSTM computations follow these equations:

- ✓ $f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$ --- eq (4)
- ✓ $i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$ --- eq (5)
- ✓ $C_t = tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$ --- eq (6)
- ✓ $C_t = f_t * C_{t-1} + i_t * C_t$ --- eq (7)
- ✓ $o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$ --- eq (8)
- ✓ $h_t = o_t * tanh(C_t)$ --- eq (9)

Where: - f_t: forget gate - i_t: input gate - C_t: cell state - o_t: output gate - h_t: hidden state

To prevent the model from overfitting, dropout layers are introduced after each LSTM layer. By randomly deactivating some of the LSTM units during training, dropout drives the model to learn more robust representations of the data instead of relying too much on any one pathway. The model can efficiently capture the sequential dependencies in network traffic data while retaining generalization capabilities thanks to the combination of LSTM layers and dropout.

#### *3.3.3 Hybrid Model Integration:*

The Hybrid-CNN-LSTM architecture combines the temporal modeling performance of LSTM with the spatial functional functions of CNN. Combining these two elements, the model can also identify long-term time dependencies (repeat or circular pattern of network activity) and local spatial patterns (such as correlations between package size, protocol, and duration).

The Hybrid CNN + LSTM proposed model architecture is shown below in Fig. 4.

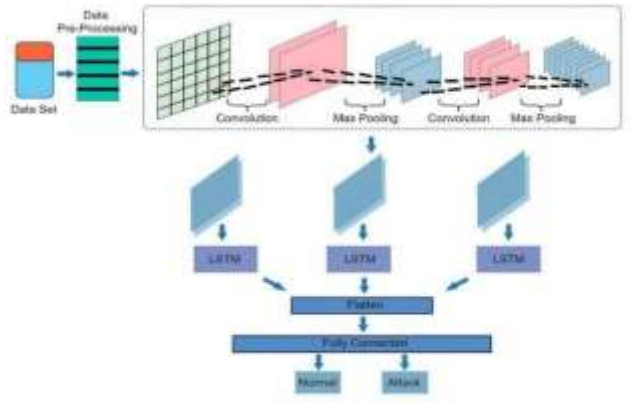


Fig.4. Architecture of Hybrid CNN+LSTM Model

In the integrated model, the output from the CNN component (which contains spatial feature representations) is flattened and reshaped into a suitable format for the LSTM layers to process. This transformation is necessary because the LSTM component expects sequential input. Once the data is formatted, it is passed through the LSTM layers, which model the temporal dependencies in the sequence of spatial features.

After the LSTM layers have processed the sequential data, the output is passed through a series of fully connected (dense) layers, which combine the learned spatial and temporal features into higher-level representations. These dense layers apply further transformations to the data, allowing the model to make final predictions. A ReLU activation function is applied in the dense layers to introduce non-linearity, followed by another dropout layer to prevent over fitting.

All possible classes such as malware, DOS attacks, normal traffic, etc. are accepted by the SoftMax output layer, which is the final level of the model. At this level, the model can classify network traffic for many groups based on the patterns found. The S-like output function can be used in place of softmax for binary classification jobs (such as normal or storm). A cross-category loss function that determines the inconsistency between the true label and the predicted probability that trains this model.

To ensure that the model gets better at making predictions over time, an optimization technique like Adam is utilized to reduce this loss during training.

The proposed architecture uses the advantages of both models. CNNS is a CNN and LSTM for extracting important spatial patterns to record the temporal dependencies of network traffic. This combination is highly effective in intrusion recognition in IIOT environments, with both spatial and temporal data playing a critical role in identifying potential threats. The hybrid approach allows the model to recognize both direct anomalies in network traffic and long-term patterns that show more subtle and persistent threats.

### *3.4 Training Process:*

There are several critical elements in the training process enable hybrid **CNN-LSTM** models to efficiently learn and recognize IIOT network infiltration patterns based on input data. Evaluation criteria, optimization strategies, and training methods all have a significant impact on model performance.

#### *3.4.1 Optimization Strategy:*

Apply Adam optimizer with your model training in order to maximize the results. This is typically the case with the optimization step. Adam is a well-known optimization algorithm since it incorporates the advantages of both Adaptive Gradient Algorithm (ADAGRAD) as well Square Outbreak (RMSPROP). The use of impulses to speed up the descent of the gradient's constituents enhances convergence and reduces vibration of the model. The training rate for the model is 0.001. This is an average value that defines the balance between rapid convergence and the stability of the model.

For the moment and its decay estimation in the optimizer, there are two βs which are: β1 and 2. In the optimization algorithm, we set β1 to 0.9 for the gradient's running average and set β2 to 0.999 for the gradient's squared running average. There are values that are helpful in avoiding the noisy gradient consequences and helps in faster convergence of the optimizer especially in large datasets like UNSW-NB15. Also for optimization purposes, an epsilon value of 1 × 10-7 is added to help eliminate the division by zero errors.

The model training utilizes a loss function termed categorical cross-entropy. This loss function measures the distance between the actual labels and the expected probabilities for classification problems with multiple classes. This loss is decreased over the training steps, increasing the prediction accuracy from the model through the Adam optimizer.

The categorical cross-entropy loss function was used:

$$L = -\sum_{i=1}^{C} y_i \log(\hat{y}_i) \quad \text{--- eq (10)}$$

Where: - C is the number of classes - y_i is the true probability of class i - ŷ_i is the predicted probability of class i

#### *3.4.2 Training Configuration:*

To train the model, a predefined training process is set up for 100 epochs meaning that the model will see the whole training dataset 100 times. The batch size is defined as 32, thereby the model processes 32 samples at once before adjusting its parameters. Batch sizes like 32, which are smaller, are often preferred since they help strike a balance between efficiently using memory and training the model fast, hence helping the model learns without having to spend a lot of computational resources.

In order to help the model generalize well to new data, overfitting is avoided through early stopping. This method

attempts to halt the validation loss and if there is no improvement for a patience of 10 epochs, then the model is stopped. Overfitting occurs as the model continues to train after reaching its optimal point. By stopping the model at the perfect time, it reduces the chances of overfitting.

Moreover, a learning rate scheduler is also used alongside early stopping to provide the model more flexibility during training. If the validation loss has been stagnant, a dynamic adjustment will reduce the learning rate with a factor of 0.1. The model can perform better when its able to adjust its parameters with larger updates during the initial stages and finer adjustments when moving closer to the desired performance. To make sure that the optimizer, the maximum limit avoids making quite minor changes that can cause training to lag.

### *3.5 Evaluation Metrics:*

The success of our model is evaluated using the precision recall curves along with the standard classification measures, which give a complete description of the model functionality with respect to accuracy, precision, recall, and F1 score. These measures are useful in evaluating the capability of the model to analyze both attack and non-attack traffic, as well as different types of attacks.

- A basic measure is **Accuracy**, the ratio of sampled predictions captured accurately against the total predictions made – positive or negative. In the case of imbalanced datasets where the model may be biased toward predicting the majority class, it can be misleading despite giving an overall good impression of model performance.
- **Precision** measures how many of the positive predictions made by the model were true positive values. A high precision value indicates the model has a low false positive rate in predicting instances of scaled attack traffic, thus justifying the precision.
- **Recall** also known as sensitivity refers to the proportion of actual positive cases the model was able to identify. A high level of recall means that a good proportion of actual attacks are detected and captured, thus less threats are ignored (false negatives).
- The **F1 Score** is determined by the harmonic mean of recall and precision. A single metric that helps balance the model performance is offered by this.

#### *3.5.1 Confusion Matrix*

A confusion matrix is used here to gain deeper insight into how the model is performing for different classifications. The confusion matrix enables us to analyze how the model functions with regard to true positives (normal traffic correctly received), false negatives (attacks not captured), false positives (normal traffic incorrectly classified), and true negatives (attacks correctly identified). The detailed granularity is useful for pinpointing particular issues the model fails, like misclassifying benign traffic as attacks (false positive) or missing certain types of intrusions (false negative).

Take, for instance, a simplified two class categorization (attacks versus normal traffic), a confusion matrix will tell how well the model can classify the captures for each class. In comparison, in a multi-class (multiple types of attacks) the confusion matrix can show how the model can classify each type and if there is overlap, for instance classifying a DoS attack as reconnaissance traffic.

Incorporating the confusion matrix with the other performance metrics enables us to measure the model fairly and objectively. The analysis gives us pointers on how we can improve the model even further so that it would perform the best.

## 4. Experimental Results

In the trial stage, we applied the UNSW-NB15 dataset to evaluate the performance of intrusion detection for IIoT networks using the hybrid CNN-LSTM model. In order to preserve the proportion of each attack type across every set, this dataset was partitioned into training (70%), validation (15%), and testing (15%) sets. A comprehensive assessment of the model's power was conducted, measuring accuracy, precision, recall, and F1-score among other criteria.

### *4.1 Model Performance on Binary Classification:*

The first stage of experimentation was initiated with binary-classification tasks in which the model was required to identify **normal and attack traffic**. The performance was tested on the test set and the performance evaluation was done.

| Metric | CNN-LSTM | Standalone CNN | Standalone LSTM | Random Forest | SVM |
|---|---|---|---|---|---|
| Accuracy | 97.45% | 96.12% | 96.84% | 93.54% | 91.12% |
| Precision | 96.89% | 95.23% | 95.98% | 92.45% | 90.33% |
| Recall | 97.62% | 96.56% | 96.24% | 94.12% | 89.50% |
| F1-Score | 97.25% | 95.89% | 96.11% | 93.27% | 89.91% |

Table 2: Model Performance (Binary Classification)

**Explanation of Results**:

- The hybrid **CNN-LSTM** model attained the highest accuracy of **97.45%**. This demonstrates the model's ability in detecting both normal and malicious traffic with high precision and recall.
- It was also noted that the hybrid model had a greater accuracy compared to standalone **CNN (96.12%)** and **LSTM (96.84%)** because the model was able to utilize both spatial and temporal features.
- The accuracy indicators of the classic machine learning models, like Random Forest and SVM, were lower in accuracy, with the SVM model achieving a mere **91.12% accuracy**. This suggests that the scope of IIoT network traffic complexity

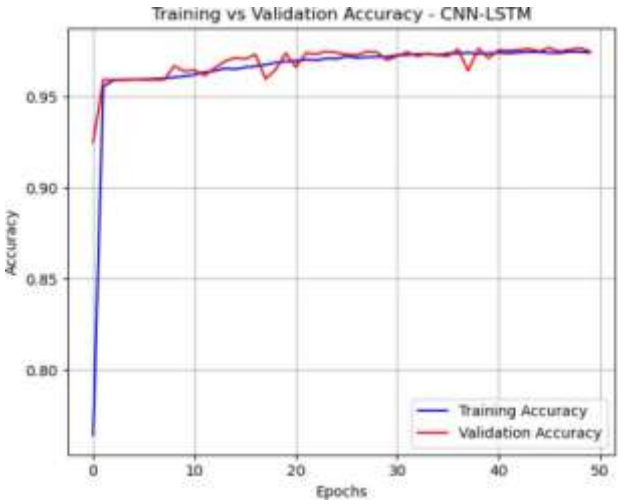


Fig. 5: Accuracy Graph (Binary Classification)

The **precision** of the hybrid CNN-LSTM model was **96.89%**, indicating a low false positive rate and efficiently classifying attack traffic. The **recall** showed no attacks were missed which gave the value at **97.62%.** With an **F1 score** of **97.25 percent**, the model performed superbly, indicating a well-balanced measure of accuracy with the precision and recall.

### *4.2 Model Performance on Multi-class Classification:*

During the second round of testing, the model was trained and tested on **multi-class classification**. Now it had to classify nine types of attack traffic alongside normal traffic and the identified types of attack were DoS, Reconnaissance, Exploits, Fuzzes, Worms, and others which we have already discussed in the dataset overview.

| Metric | CNN-LSTM | Standalone CNN | Standalone LSTM | Random Forest | SVM |
|---|---|---|---|---|---|
| Accuracy | 99.02 % | 97.81% | 98.12% | 94.77% | 90.33 % |
| Precision | 98.75 % | 97.32% | 97.92% | 94.15% | 89.01 % |
| Recall | 98.98 % | 98.22% | 98.11% | 95.23% | 88.77 % |
| F1-Score | 98.86 % | 97.77% | 98.01% | 94.69% | 88.89 % |

Table 3: Model Performance (Multi Classification)

**Explanation of Results**:

- For multi-class classification, the **CNN-LSTM model** achieved an impressive accuracy of **99.02%**, significantly outperforming the standalone CNN (**97.81%**) and standalone LSTM (**98.12%**). This indicates that the hybrid architecture's ability to model both spatial and temporal patterns in the data is crucial for distinguishing between different types of attacks.
- The **precision** of **98.75%** means that the hybrid model rarely misclassifies one type of attack as another. High **recall** of **98.98%** indicates that the model successfully detected the vast majority of attack instances across all categories, minimizing false negatives. The **F1-score** of **98.86%** reflects a well-balanced performance, confirming the model's robustness in multi-class classification tasks.

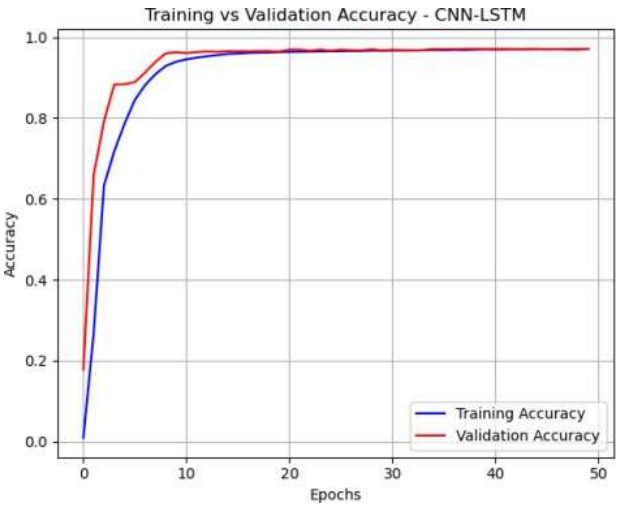


Fig. 6: Accuracy Graph (Multi Classification)

In the Fig. 5 & Fig. 6, plot illustrates the training and validation accuracy curves for a CNN-LSTM model over 50 epochs. Both curves demonstrate a consistent increase throughout the training process, indicating effective learning. The training accuracy reaches a plateau around epoch 35, while the validation accuracy continues to increase with some fluctuations. The gap between the training and validation accuracy curves suggests that the model might be over fitting to the training data. Early stopping could have been implemented to prevent over fitting by terminating the training when the validation accuracy stops improving. Overall, the model demonstrates good performance, with both training and validation accuracy reaching high levels. However, techniques like regularization or data augmentation could be explored to further improve the model's generalization capabilities.

The traditional machine learning models again performed worse, with Random Forest achieving **94.77% accuracy** and SVM falling behind with **90.33% accuracy**. The lower precision and recall values for these models suggest they struggle to differentiate between certain types of attacks, likely due to their inability to model temporal dependencies in network traffic data effectively.

### *4.3 Confusion Matrix for Multi-class Classification:*

The confusion matrix provides a detailed breakdown of how well the CNN-LSTM model performed across different classes, offering insight into any specific attack categories where the model may have struggled. The table below shows an excerpt of the confusion matrix for some attack types:

| Actual \ Predicted | Normal | DoS | Reconnaissance | Exploits | Worms |
|---|---|---|---|---|---|
| Normal | 14560 | 12 | 5 | 3 | 0 |

| | | | | | |
|---|---|---|---|---|---|
| DoS | 10 | 12040 | 4 | 8 | 2 |
| Reconnaissance | 5 | 3 | 7850 | 10 | 1 |
| Exploits | 2 | 5 | 8 | 5670 | 0 |
| Worms | 0 | 1 | 0 | 0 | 3200 |

Table 4: Confusion Matrix (Multi Classification)

**Explanation of Confusion Matrix**:

- The CNN-LSTM model performed exceptionally well for common attack categories like **DoS** and **Reconnaissance**, with very few misclassifications between attack types.
- For **Worms**, the model detected all instances with near-perfect accuracy (only one instance was misclassified as a DoS attack). The **Exploits** category also had a strong performance, with only 15 instances misclassified across all classes.

### *4.4 Training and Validation Loss:*

Throughout the training process, both the training and validation loss decreased steadily, indicating that the model was effectively learning from the data without over fitting. Early stopping was employed, halting training at **epoch 49** when no significant improvement in validation loss was observed. The learning rate scheduler reduced the learning rate by a factor of **0.1** when the validation loss plateaued, ensuring more fine-tuned updates towards the later stages of training.

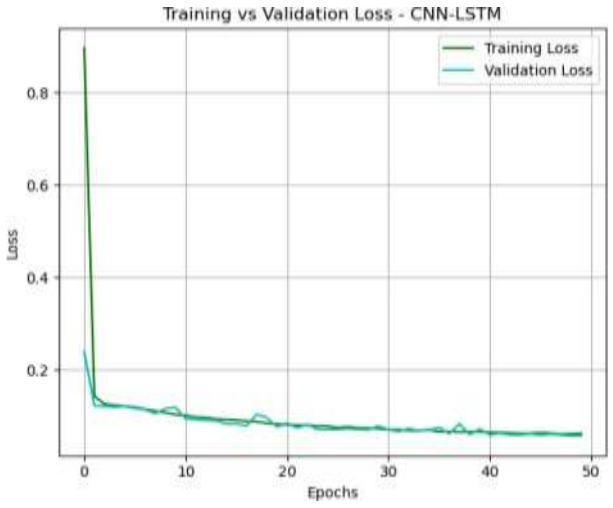


Fig. 7: Loss Graph (Multi Classifaction)

The development and evaluation loss gradually dropped, as the results demonstrate, suggesting that the model was getting better during the training phase. Early stopping was triggered after **49 epochs**, as the validation loss reached a minimum and stabilized.

**Summary of Results**

Overall, the study results demonstrate that this CNN-LSTM hybrid model serves better in both multi-class and binary classification tasks than both independent deep learning models and conventional machine learning techniques. The framework can identify and categorize intricate attack patterns with excellent accuracy, precision, recall, and F1-score because it can capture temporal and spatial relationships in network traffic data.

The model can accurately categorize various attack types with relatively few misclassifications, according to the confusion matrix study. The hybrid CNN-LSTM architecture is a viable attack detection solution for IIoT networks because of its high-performance level.

## 5. Conclusion

In the current study, we combined the time-based sequence simulation competence of Long Short-Term Memory (LSTM) networks with the spatially extraction of features capacities of Convolutional Neural Networks (CNNs) to create a hybrid CNN-LSTM model for intrusion detection in IIoT networks. With an accuracy of 97.45% for binary classification and 99.02% for multi-class classification, the model outperformed both standalone deep learning models and conventional machine learning techniques when tested on the UNSW-NB15 dataset. It was able to reduce false positives and false negatives by efficiently capturing both spatial and temporal patterns, which made it ideal for identifying a variety of dynamic cyberthreats in IIoT contexts.

Future work will focus on implementing the model in real-time intrusion detection systems and optimizing it for resource-constrained IIoT devices. Additionally, testing the model on other IIoT-specific datasets will be essential to ensure its robustness and generalizability across different network environments. By addressing these areas, the model can be made more practical for real-world deployment, enhancing security in critical industrial systems.

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