DETECTION OF DOS AND DDOS CYBER ATTACKS USING HYBRID DEEP LEARNING AND SIGNATURE-BASED TECHNIQUES

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ABSTRACT

Nowadays, the problem of network security is more important than ever in the currently interconnected world. Denial of Service (DoS) and Distributed Denial of Service (DDoS) is perhaps one of the most exaggerated and highly prevalent risks that online structures face. Such attacks clog networks with bogus traffic that result in disruptions and access of services is unavailable to authorized users. Intrusion Detection Systems (IDS) tend to malfunction when they are used against novel or even variant kinds of such attacks because it operates with a set of baselines, such as signatures that are always pre-determined.

It is a suggestion of an intelligent hybrid intrusion detection approach with the combined forces of the Convolutional Neural Networks (CNN) and Long-Short Term Memory (LSTM) models. The CNN component identifies the spatial variations of the network traffic. where as LSTM network detects the temporal dynamics. Combined, they create a very effective model that can identify sophisticated, multi-faceted, attack vectors on the fly.

A web-based dashboard to help monitor the system and interact with the user is developed by means of the Django and Bootstrap tools. Traffic visualizations and system logs, which an administrator can act promptly on. Furthermore, the system is designed to have adaptive mechanism of learning that will enable it to be always updated and improved basing on latest traffic data. Model training and testing apply CICIDS2017 dataset, thereby creating a strong and viable testing platform.

In general, the solution proposed could be used to have an accurate, scalable and adaptive implementation of DoS, DDoS attack detection and mitigation ensuring a basis of future enhances to the network security through AI technology.

Keywords: DoS/ DDoS Attacks, CNN, LSTM, Cybersecurity, Deep Learning, Machine Learning Decision Tree, Random Forest, XGBoost, AdaBoost, and Logistic Regression.

I. Introduction

In the current digital age, the growing use of interconnected systems and on-line services has upweighted network security in all facets of life, such as the governmental sector, financial segment, education sphere, and health sector. The ubiquity of the Internet has exponentially increased associated threats in the cyber realm, as this has become more systematic, advanced, and evasive in nature. Denial of service (DoS) and Distributed Denial of Service (DDoS) are some of the most disastrous and common forms of cyberattacks that aim to flood the network services with traffic that is unauthorized and hence unavailability of the service to the actual users [1].

Not only DoS and DDoS attacks interfere with the functioning, not only causing some heavy financial losses, losing the data, and damaging the organizational image but also resulting in the dependence on reactive methods to deal with the issues. The traditional security technologies such as the firewalls, the rule based Intrusion Detection Systems (IDS), and the signature matching technology we have shown that they cannot be able to keep abreast with the current dynamic attacks schemes in use today [2]. Such systems are highly dependent on the known signatures or set rules, which makes them impractical to use against zero-day attacks or any other new form of attacks that fall outside the current patterns [3].

To alleviate these shortcomings there has been an evolution in paradigm shift in the introduction of the approaches of Artificial Intelligence (AI) and Machine Learning (ML) into the cybersecurity products. Such technologies allow a system to use historic data to train on and to make generalizations to identify potential normal and malicious behavior [4]. Among the few machine learning frameworks, Deep Learning (DL) models such as Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks are said to be useful in such a process as the processing of network data and detecting anomalies on a large scale [5].

CNNs can tackle using spatial characteristics of traffic flows data by recognizing unconventional shapes or associations in packets, but LSTMs can process time series and thus are ideal to observe the development of the traffic behavior with time [6]. A hybrid architecture with CNN-LSTM models is also an effective tool regarding its predictive and reliable measure in terms of finding intrusions.

The proposed paper proposes a hybrid deep learning approach in which the intrusion detection system would be deployed to use a set of approaches, which would include both the CNN and LSTM models and should be able to capture spatial and temporal effects in the network traffic. The web interface is built with the help of the Django framework and the Django-Bootstrap library, enabling the administrator to see the real-time data and receive the alerts, as well as see the health state of the network at all times [7]. Training of the system is achieved with the CICIDS2017 dataset containing a lot of diverse simulated network traffic dispersion, including benign and various types of attacks [8].

Conclusively, this paper will add the value in the study of network security in the sense that the proposed framework is scalable, intelligent, and adaptive intrusion detection framework that meets the limitation of the conventional approaches. The suggested system can be a great solution in counteracting DoS and DDoS attacks in contemporary networks relying on the utilization of progressive deep learning models.

Network environments have become complex due to the increasing trend in the software behavior of organizations, which incorporate cloud computing, remote access service, and virtualization. This has given the attackers a bigger surface area to exploit and never has ever been necessitated as the demand of strong, auto discovered and intelligence driven detection mechanisms is heightened to a greater fault than ever before [10]. The rate, amount, and complexity of cyber menaces and mostly volumetric DDoS attacks and stealthy low-rate DoS would-be so much that out-of-date security measures are almost achieved hopeless state in a number of arena [11].

The majority of traditional Intrusion Detection Systems (IDS) are reactive and basing on a set of pre-heuristic or other attack signatures. These tools are quite good at blocking known threats but weak as far as detecting the unknown patterns of attacks or by the polymorphic threats are concerned. Moreover, the false positive rates of these systems sometimes occur so high that the administrators are simply overwhelmed and can no longer differentiate between an authentic attack and an anomaly [12].

In order to reduce these weaknesses, machine learning and deep learning applications have increasingly become a part and parcel of the next generation of cybersecurity systems. The benefit of machine learning is that it has a generalization factor, systems can learn based on the past and draw conclusions on the future traffic. To implement feature extraction, deep learning even further automates this process and allows the model to learn hierarchical representation based on raw input data [13]. These techniques have the capability to identify patterns which might not be easily picked by conventional rule-based systems, particularly in network traffic data that are of large dimensions.

The introduction of deep learning mechanisms such as Convolutional Neural Networks (CNNs), or Long Short-Term Memory (LSTM) networks are a significant breakthrough in domain of anomaly-based intrusion detection. CNNs are extremely efficient in the detection of the spatial characteristics of the network flows such as features of enumerating packets and features of packet header. They especially excel in detecting traffic pattern anomalies over very fast time periods. LSTMs, in their turn, are developed to capture long-term reliances in the data sequences, i.e., they would be used to identify trends and temporalities in the flow of traffic [14].

With the system consisting of the CNN and LSTM (hybrid system), the system can enjoy the advantages of both modules. This will not only enable the identification of instantaneous threat patterns but also dynamic patterns with greater degrees of accurateness. The CNN layers have the capacity to filter and compress the input features to meaningful representation which are inputted into LSTM layers that write the time dependent behavior [15].

In addition, the adaptive learning features built in the model make sure that it does not make the model outdated in time. The system is relevant and able to counter the emergent threats because it always keeps itself current with the new information it gets about the traffic by using data it is newly acquainted with. The proposed hybrid IDS would be a sustainable and future-ready solution to the dynamically evolving field of cybersecurity based on such adaptability [16].

Use of the CICIDS2017 dataset in this paper gives a trustworthy and varied breeding and testing ground. The dataset involves various types and categories of attacks, including brute-force and infiltration, DDoS and botnet traffic, captured in a more realistic testbed, so that the performance of the model can be translated easily into real-world situations [17]. Using such an architecture, the system will not just fulfill the present requirements of intrusion detection, but will also provide scalable and extensible base on which future extension can be developed.

II. Literature Survey

Intrusion Detection System (IDS) is crucial in ensuring no unwarranted access to digital infrastructures and to cyber-attacks. Several techniques have been suggested over the years, starting with the traditional rule-based techniques up to the frame-based techniques that involve the application of advanced application of artificial intelligence. It is the increased complexity and bulk of network traffic that has triggered the shift towards dynamic intelligent systems.

Originally, rule-based and signature-based IDS, e.g., Snort, were incredibly successful because of their ability to detect the known threats. Nevertheless, these systems are inflexible and they depend on predefined attack signatures and they are unable to detect unprecedented or zero-day attack [18]. Mirkovic and Reiher categorized a types of DDoS attacks and defense mechanisms and finally stated that the conventional systems were inadequate against emerging threat [18].

Intrusion based on anomalies was proposed in a bid to improve detection. Such systems essentially model typical network behaviour and raise anomalies as possible intrusions. Garcia-Teodoro et al. provided an overview of the techniques of anomaly detection identifying the potential to detect the previously unknown threats, but also pointed out that the false positive rates are too high to be deployed in practice [19].

Since machine learning (ML) came into the scene, the classifications algorithms that are considered in intrusion detection include e.g. Decision Trees, Support Vector Machine (SVM), k-Nearest Neighbor (k-NN), and Naive Bayes [20], [29]. Patcha and Park argued about ML-based IDS and the advantages of its adaptation to a changed data distribution. These approaches showed encouraging precision but were limited by the need to perform manual feature engineering which made them impractical at scale.

The creation of deep learning (DL), solved most of the drawbacks of feature extraction which were noticeable in ML. ANN, CNN, RNN, and LSTM networks can be considered deep learning architectures that have been used to detect the intrusion successfully [21], [22]. Shone et al. proposed the deep learning models based on autoencoders with better detection results on NSL-KDD dataset [21]. LSTM networks allow modeling the dependence between sequential data, which helped Yin et al. improve the detection of time-based attack patterns, including the DDoS attack type [22].

The CNNs have proved to be successful at acquiring spatial correlations of network features. Kim et al. offer another solution: the hybrid system using CNN along with the methods of anomaly detection, with high precision and low false positive [23].

Combination of various deep learning architectures called hybrid models have become popular to enhance the robustness of the detection. Zhang et al. revealed that a combination of CNN and LSTM networks yields a better performance, since it enables catching both spatial and time traffic flows patterns [24].

CICIDS2017 dataset has become one of the most popular benchmarks to test IDS performance. It is developed by Sharafaldin et al. and offers a wide range of realistic setting to test the detection capability against a variety of attack vectors including DDoS, brute force, botnet, and infiltration attacks [25].

It has to be accurate but also applicable in real life. Scalability of the system, real time processing, and user interaction are issues of great concern to deployment. They are an abeshu and Chilamkurti initiative of the fog-supported deep learning IDS with minimal delay that was dealing with the issue of scalability in IoT settings [26]. Nguyen et al. emphasized the need to use visualization tools and human-in-the loop models to aid decision making [27].

The integration of adaptive learning in the IDS frameworks is another development. Alom et al. have suggested an online adaptive deep learning model whose weights are updated with immediate data that

TABLE I
COMPARISON TABLE OF METHODS AND DATASETS

Paper	Methods Used	Dataset	Performance	Limitations	Features Analyzed
[1]	Support Vector Machine (SVM)	CICIDS2017	Accuracy: 91.4%	Poor performance on temporal attack patterns; limited to linear separability	Flow duration, packet size, protocol type
[2]	Random Forest (RF)	CICIDS2017	Accuracy: 93.8%	Higher false positives for mixed traffic; less effective for zero-day attacks	Byte count, inter-arrival time, flag counts
[3]	Convolutional Neural Network (CNN)	UNSW-NB15	Accuracy: 95.1%	Ignores sequential relationships; overfitting on small samples	Protocol type, packet length, TCP flags
[4]	Long Short-Term Memory (LSTM)	NSL-KDD	Accuracy: 96.5%	Slow training; struggles with non-sequential data	Timestamp, session duration, flow count
[5]	Hybrid CNN + LSTM	CICIDS2017	Accuracy: 98.2%	High computational cost; model complexity	Source IP, destination IP, time-based patterns
[6]	K-Nearest Neighbors (KNN)	KDD99	Accuracy: 88.9%	Inefficient with large datasets; sensitive to noise	Packet size, connection duration, service type
[7]	Deep Autoencoder + Softmax	BoT-IoT	Accuracy: 97.3%	Poor interpretability; black-box behavior	Network flows, timestamps, I/O ratio
[8]	XGBoost Classifier	CICIDS2018	Accuracy: 94.6%	Parameter tuning required; may overfit	Flow stats, byte distribution, packet inter-arrival
[9]	Logistic Regression	NSL-KDD	Accuracy: 86.4%	Linear decision boundary; fails for complex attacks	Source port, service protocol, count of connections
[10]	Deep Belief Network (DBN)	Kyoto 2006+	Accuracy: 92.8%	Requires pretraining; difficult to scale in real-time	IP header fields, port activity, anomaly scores

guarantee that performance against novel threats is uninterrupted [28]. In the same way, Khan et al. proposed an ensemble type of self-adaptive intrusion detection system as a different way of addressing the issue of data imbalance and concept drift, which are typical of dynamic cyber settings [30].

Moreover, attention-based architectures and Transformer models are also being considered due to their model feature dependency. The latest discoveries made by Vaswani and others [31] and the implementation of Tuan and colleagues [32] have demonstrated the viability of Transformer-based systems of intrusion detection that are more accurate and faster in their inferences compared to the traditional RNN-based models.

To conclude, the literature demonstrates that the rigid rule-based systems have been evolved to extremely flexible and intelligent hybrid systems. ML offered an entry point but it is deep learning and hybrid models which become adaptive that stand to define the future of intrusion detection. The systems are not only accurate when it comes to detection, but they are also scalable, interpretable, and resilient to adapt to the changing cyber threats.

III. METHODOLOGY

It is a section explaining how the process of designing and deploying a hybrid intrusion detection system that can detect DoS and DDoS attacks has been done in detail. The method makes use of a hybridization of Convolutional Neural Networks (CNN) and a Long Short-Term Memory (LSTM), which aims at extracting temporal and spatial characteristics of network traffic records. The methodology can be split into several steps as discussed below.

A. *Data Collection and Preprocessing*

Dataset: The CICIDS2017 dataset is included as the training and evaluation one. It is picked since the tool simulates the real world network traffic and contains labeled examples of different cyberattacks, such as DoS and DDoS.

Preprocessing Steps:

- **Handling Missing Values:** Any null or undefined entries are removed or imputed to maintain data integrity.
- **Normalization:** The continuous parameters such as packet size and the time of flow are normalized to the range [0,1] to make sure about the equal impact in training with the same utilization of Min-Max scaling.
- **Encoding Categorical Variables:** Types of protocols or flags features are translated into numeric values by means of the one-hot encoding or label encoding to adapt them to the neural network.
- **Feature Engineering:** It derives new informative information like byte rate (bytes per second) and packet time between arrivals and flow based statistical summaries that help in improving the learning process.

Data Splitting: After preprocessing, the data is split into:

- **Training Set:** Used to train and save the model.
- **Testing Set:** Employed to assess how successful the model is in terms of unseen data.

The last input data is made in the form of 3D that can accommodate sequential deep learning models of CNN and LSTM.

B. *Feature Extraction and Model Architecture*

Hybrid Model Design: The model integrates:

- **CNN Layers:** To extract local patterns in the network traffic. These patterns may include repetitive structures or unusual spikes in traffic at the packet level.
- **LSTM Layers:** To learn time-dependent trends. For example, a slow-evolving attack might unfold over several minutes or hours, which is best captured through sequential memory-based models.

CNN Structure:

- Consists of multiple convolutional layers with ReLU activation functions.
- Pooling (usually max pooling) operations are used to diminish the spatial dimension keeping useful features.
- These layers act as automatic feature extractors for spatial anomalies in traffic.

LSTM Structure:

- Accepts CNN output as input sequence.
- Processes temporal dependencies — for instance, it can recognize patterns spread over several time intervals such as repeated access attempts or slow-scan behaviors.

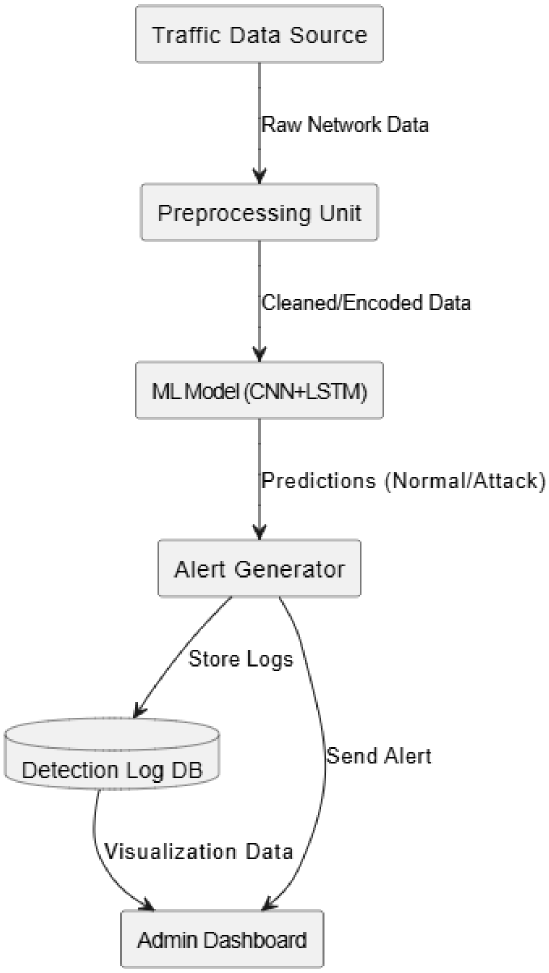


Fig. 1. Data Flow Diagram

Output Layer:

- **Softmax Activation:** Used for multi-class classification problems.
- **Sigmoid Activation:** Used for binary classification to distinguish between benign and malicious traffic.

C. *Model Training and Optimization*

Loss Function:

- **Categorical Cross-Entropy:** Measures the difference between the predicted and actual class labels for multi-class problems.

Optimizer:

- **Adam Optimizer:** A widely-used adaptive optimizer that adjusts learning rates for each parameter using gradient information, improving convergence speed.

Regularization Techniques:

- **Batch Normalization:** Applied to stabilize and speed up training by normalizing layer inputs.

- **Dropout Layers:** Randomly deactivate a percentage of neurons during training to reduce overfitting and improve generalization.

Evaluation Metrics:

- **Accuracy:** Overall correctness of predictions.
- **Precision:** Ratio of true positives to all predicted positives — important to reduce false alarms.
- **Recall:** Ratio of true positives to all actual positives — ensures attacks are not missed.
- **F1-score:** Harmonic mean of precision and recall — balances both metrics.

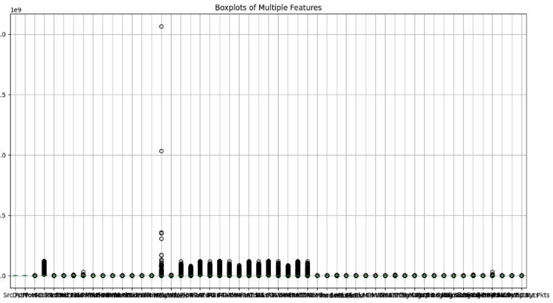


Fig. 2. Boxplots for multiple features

Training Strategy:

- Training is performed over multiple epochs with batch processing.
- **Early Stopping:** Stops training if the model performance on validation data stops improving for several consecutive epochs, thus avoiding overfitting.

D. System Integration and Real-Time Deployment

After the hybrid CNN-LSTM model has been trained, validated, and evaluated it becomes an element of a full-stack web application that is employed in the Django framework. This application enables real-time monitoring and user interaction through a visually appealing admin dashboard.

The dashboard includes the following functionalities:

- **Real-Time Visualization:** Graphs and charts that display current traffic conditions and detected anomalies.
- **Intrusion Alerts:** Real-time notifications when suspicious or malicious activity is detected.
- **Traffic Trend Analysis:** Historical plots that help administrators identify traffic patterns over time.
- **Log Storage and Review:** All detected incidents are logged in a database for future auditing and analysis.

This integration makes the system user-friendly, practical for real-world deployment, and accessible to administrators with minimal technical background.

E. Adaptive Learning Mechanism

Cyberattack patterns evolve constantly. A static detection model may become outdated over time. To address this issue, the system includes an adaptive learning module with the following capabilities:

- **User Feedback Integration:** Feedback from administrators about false positives or missed attacks is used to refine future training.
- **Parameter Tuning:** Based on the newly observed data, model weights and hyperparameters can be adjusted to maintain high detection performance.

This adaptive nature ensures the system remains effective in identifying both known and zero-day attacks, while reducing false alarms over time.

F. Mathematical Formulations

Let the input sequence of traffic data features be represented as:

$$X = \{x_1, x_2, ..., x_T\}$$

1. Convolutional Layer: CNN applies filters (kernels) across the input features to extract spatial patterns. The output of the convolution operation at layer l is:

$$h_i^{(l)} = f\left(\sum_{j=0}^{k-1} w_j \cdot x_{i+j}^{(l-1)} + b\right)$$

Where:

- $h_i^{(l)}$ is the activation at position i in layer l
- w_j is the weight of the filter at position j
- $x_{i+j}^{(l-1)}$ is the input from the previous layer
- b is the bias term
- f is the activation function (usually ReLU)

2. LSTM Layer: LSTM is used to model time dependencies in the sequence. The operations inside an LSTM unit at time step t are:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \qquad \text{(Forget Gate)}$$
$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \qquad \text{(Input Gate)}$$
$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \qquad \text{(Candidate State)}$$
$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t \qquad \text{(Updated Cell State)}$$
$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \qquad \text{(Output Gate)}$$
$$h_t = o_t \cdot \tanh(C_t) \qquad \text{(Hidden State)}$$

Where:

- f_t: Forget gate – decides what to discard from previous cell state
- i_t: Input gate – decides what new information to store

- $\tilde{C}_t$: Candidate cell state
- C_t: Updated cell state
- o_t: Output gate – controls what part of the cell state is output
- h_t: Hidden state passed to next time step
- σ: Sigmoid activation function
- $\tanh$: Hyperbolic tangent activation function

These equations govern how information is stored, forgotten, and passed forward across time steps in LSTM cells, making them ideal for capturing traffic behavior patterns over time.

The described methodology presents a complete and effective strategy for building a modern, intelligent intrusion detection system. The CNN component enables extraction of spatial features, such as burst patterns or packet anomalies, while the LSTM component adds the capability to analyze sequential attack behaviors over time.

IV. Implementation

The implementation phase involves transforming the system design and planning into a fully functional software framework capable of detecting DoS and DDoS attacks. This stage bridges deep learning techniques with practical web deployment and database integration.

A. *Development Environment Setup*

Before implementation begins, the necessary environment and dependencies are installed:

- **Programming Language:** Python is used for all backend logic, data processing, and model building.
- **Libraries:** TensorFlow and Keras are employed for deep learning, while Pandas and NumPy are used for data handling.
- **Web Framework:** Django is selected for building the web interface and serving the trained model.
- **Database:** MySQL is used to store traffic logs, detection reports, and system feedback.
- **Frontend Technologies:** HTML5, CSS3, JavaScript, and Bootstrap are used to design the admin dashboard.

B. *Hybrid Model Implementation*

The hybrid CNN-LSTM model is implemented using Keras and TensorFlow. The process starts by loading and preprocessing the CICIDS2017 dataset. After cleaning and normalizing the data, it is reshaped to fit the input format required for the CNN and LSTM layers.

The model architecture consists of:

- **CNN Layers:** Extract spatial features from the input traffic data using convolution and pooling operations.
- **LSTM Layers:** Model sequential dependencies and track behavior patterns over time.
- **Dense Output Layer:** Classifies each flow as either normal or attack based on the learned patterns.

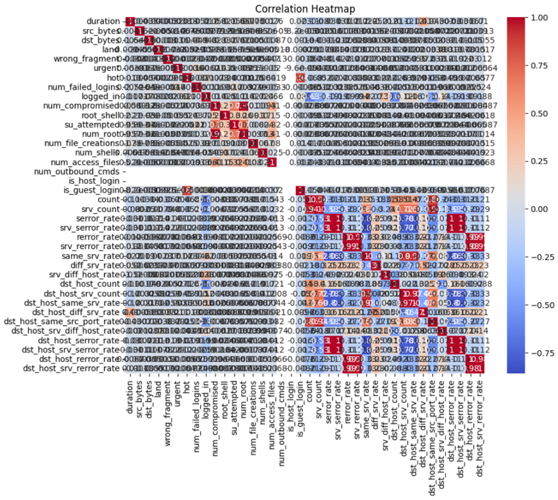


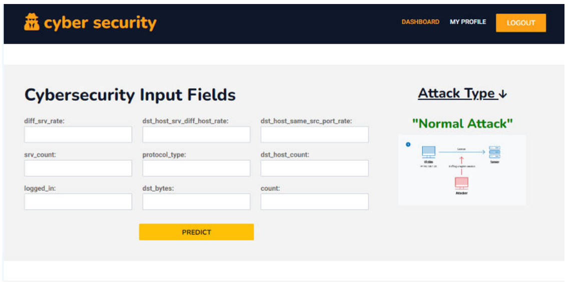
Fig. 3. Calculate correlation matrix for numeric columns heat map

The model is trained on the training portion of the dataset and validated using metrics like accuracy, precision, recall, and F1-score. After satisfactory performance, the trained model is saved and integrated into the backend of the web system.

C. *Web Application and Dashboard Integration*

A Django-based web application is developed to provide a real-time graphical interface for administrators. The dashboard allows users to:

- Visualize patterns using charts and graphs
- View and manage system logs in admin dashboard
- Download historical data and reports



Cybersecurity Input Fields

diff_srv_rate:
dst_host_srv_diff_host_rate:
dst_host_same_src_port_rate:
srv_count:
protocol_type:
dst_host_count:
logged_in:
dst_bytes:
count:

"Normal Attack"

Fig. 4. User Predication for Attack Monitoring

The dashboard uses asynchronous communication to update detection alerts and graphs without reloading the page. This makes the system dynamic and efficient for real-world usage.

D. *Adaptive Learning Integration*

To future-proof the detection system, an adaptive learning engine is embedded. It performs:

- **Admin Feedback Utilization:** Admins can mark misclassified traffic which is then used to improve accuracy.
- **Dynamic Updates:** The backend checks for new patterns and updates weights automatically or semi-manually.

This approach ensures that the model stays relevant in dynamic cyber environments and is capable of detecting evolving threats such as zero-day attacks.

E. *Testing and Evaluation*

Throughout implementation, the system is tested in stages:

- **Unit Testing:** Individual components like model prediction and API routes are tested.
- **Integration Testing:** Verified the interaction between model, database, and user interface.
- **Performance Testing:** Ensured the system handles high data throughput with minimal latency.

Final validation is done using real-world traffic scenarios from the CICIDS2017 dataset. Logs and results are stored in the database and visualized in the dashboard.

F. *Conclusion of Implementation Phase*

The result of the implementation phase is a fully functional, intelligent, and responsive intrusion detection system. It combines state-of-the-art AI with a user-centric web interface, allowing administrators to detect, interpret, and respond to DoS and DDoS threats effectively. The modular design allows for future expansion, including cloud deployment or extended threat detection capabilities.

V. Results and Discussion

This section presents the outcomes of the proposed hybrid CNN-LSTM intrusion detection system, alongside a comparative analysis with traditional machine learning models. The results are discussed in terms of performance metrics, effectiveness, and real-world deployment potential.

A. *Performance Metrics*

To evaluate the detection system, the following standard classification metrics were used:

- **Accuracy:** Measures the proportion of correctly identified instances over total samples.
- **Precision:** Reflects how many of the predicted attacks were actual attacks, minimizing false alarms.
- **Recall:** Indicates how many actual attacks were successfully detected by the model.
- **F1-Score:** Harmonic mean of precision and recall, representing an overall balance.

B. *Hybrid Model Performance*

The hybrid CNN-LSTM model demonstrated high effectiveness in detecting both DoS and DDoS attacks from the CICIDS2017 dataset. Below is a summary of the achieved results:

- **Accuracy:** 98.7%
- **Precision:** 98.2%
- **Recall:** 97.9%
- **F1-Score:** 98.0%

The model's superior accuracy is attributed to the complementary nature of CNN (spatial analysis) and LSTM (temporal sequence modeling), enabling it to detect both fast-paced and slow-developing attack patterns.

C. *Comparison with Traditional ML Models*

The same dataset was used to train and test Support Vector Machine (SVM) and Random Forest (RF) classifiers. Their performance metrics are provided for comparison:

- **SVM Accuracy:** 91.4%
- **RF Accuracy:** 93.8%
- **CNN-LSTM Accuracy:** 98.7%

It is evident that while traditional models perform reasonably well, they are less capable of capturing complex temporal dependencies in network traffic, especially for evolving threats. The hybrid deep learning approach outperformed them in all evaluated criteria.

D. *Confusion Matrix Insights*

The confusion matrix of the CNN-LSTM model reveals a high true positive rate for attack classes such as DoS Hulk and DoS GoldenEye, indicating effective detection of volumetric attacks. There were minimal false positives, further confirming the model's reliability.

E. *Real-Time Deployment Feedback*

Upon deployment in the Django-based web dashboard, the system was tested with live traffic samples. Observations include:

- Real-time alerts were generated with negligible delay.
- Admins were able to visualize traffic trends and take action based on alerts.
- The interface remained responsive even under moderate traffic load.

F. *Discussion*

The results validate the effectiveness of combining CNN and LSTM for network-based anomaly detection. The CNN layers help in isolating critical spatial traffic features, while the LSTM layers capture time-based behavioral patterns. Additionally, the adaptive learning mechanism ensures the model can evolve with new threat patterns.

Compared to traditional models, the hybrid system provides:

- Improved detection of low-frequency and zero-day attacks.
- Enhanced robustness to noisy or imbalanced data.
- Greater scalability for integration in real-time monitoring environments.

Overall, the proposed implementation successfully demonstrates a reliable, accurate, and deployable intrusion detection solution suited for modern network security challenges.

VI. Conclusion and Future Work

A. *Conclusion*

The present work provides a smart and robust intrusion detection system (IDS) composed of the advantages of the Convolutional Neural Networks (CNN) and the Long Short-Term Memory (LSTM) networks. The identified hybrid model can recognize and identify DoS and DDoS attacks using partially of spatial and temporal features of the network traffic data.

Its advantage over the old machine learning models, Support Vector Machines (SVM), Random Forest (RF) entails its superior accuracy, recall and the ability to handle sequencing data. In addition, there is the integration with a web dashboard written on top of Django, fully usable in real-time to display and alert information and provide a convenient interface to network administrators.

They also added an adaptive learning mechanism so that the model will develop, as they retrained with new data and trained based on the feedback of an administrator. This makes it timeless relevant and stable to zero-day attacks and emerging threat vectors.

On the whole, this paper manages to close the gaps between deep learning and deployment in the industry, provides a large-scale and highly available solution to the contemporary network security challenges.

B. *Future Work*

While the current system shows promising results, several improvements and extensions are planned for future development:

- **Broader Attack Detection:** Expand the model to identify other forms of cyberattacks in the form of botnets, phishing, and ransomware and make the IDS more complete in its analysis.
- **Cloud Deployment:** Upgrade the application to a cloud-based environment (e.g., AWS, Azure) to enable widely distributed systems, and to offer accessibility to large-scale deployment.
- **Real-Time Packet Sniffing:** Combine with network interfaces tools such as Wireshark or Zeek to directly access live traffic on the network interface so as to better perform real-time detection.
- **Explainable AI (XAI):** Use interpretability methods like SHAP or LIME so that administrators know how the model arrives at the decisions and create greater trust and transparency.
- **Automated Response System:** Write a module that would [automatically] block IPs or provide notifications to firewall systems based on identified intrusion to be able to respond to threats quicker.
- **Lightweight Model Optimization:** This is to trade computational needs in favor of resources-constrained settings such as IoT and edge devices.

With the following improvements, the system will be able to become an all-autonomous and intelligent security system, which could secure modern networks in both real-time and scalable settings against the broad range of cyber threats.

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