

A NETWORK TRAFFIC ANOMALY CLASSIFICATION MODELBASEDON SELF ATTENTION MECHANISM AND CONVOLUTIONAL GATED RECURRENTUNIT

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Abstract: With the fast boom of web services, cloud computing, and IoT devices, cutting-edge networks generate big volumes of visitors data. Monitoring and examining this site visitors is fundamental for detecting cyber threats, malicious attacks, and ordinary behaviors that may additionally compromise community security. Traditional intrusion detection structures be counted on signature-based or rule-based mechanisms, which frequently fail to become aware of new or evolving assault patterns. Machine getting to know and deep gaining knowledge of tactics have these days been brought to enhance anomaly detection abilities by way of routinely studying complicated patterns in community site visitors data. However, many traditional fashions fighting to seize each spatial and temporal dependencies current in high-dimensional community site visitor's sequences.

This lookup proposes a Network Traffic Anomaly Classification Model based totally on Self-Attention Mechanism and Convolutional Gated Recurrent Unit (Conv-GRU) to enhance detection accuracy and classification performance. The convolutional layers are used to extract spatial facets from community site visitors data, whilst the GRU layers seize temporal dependencies in sequential site visitors patterns. The self-attention mechanism allows the mannequin to focal point on the most applicable aspects via assigning

significance weights to unique components of the enter data. By combining these techniques, the proposed mannequin efficiently identifies anomalies such as Distributed Denial of Service (DDoS) attacks, malware traffic, and unauthorized get admission to attempts. Experimental assessment demonstrates that the hybrid structure appreciably improves detection accuracy, reduces false positives, and enhances the universal effectivity of community safety monitoring structures.

Keywords: Network Traffic Anomaly Detection, Self-Attention Mechanism, Convolutional Gated Recurrent Unit (Conv-GRU), Deep Learning, Intrusion Detection System, Cybersecurity, Network Traffic Classification, Distributed Denial of Service (DDoS) Detection, IoT Network Security.

1. INTRODUCTION

Network site visitor's anomaly detection is an vital thing of contemporary cybersecurity systems. As community infrastructures come to be extra complicated due to the growing use of cloud services, cell devices, and Internet of Things (IoT) technologies, the quantity and variety of community visitors have grown significantly. This growth has created new possibilities for cyber attackers to take advantage of vulnerabilities inside community environments. Traditional safety mechanisms such as firewalls and rule-based intrusion detection structures frequently

fighting to discover unknown assaults or state-of-the-art threats that evolve rapidly. Therefore, smart detection mechanisms successful of inspecting large-scale visitors information are required to make certain strong community protection.

Deep getting to know strategies have proven wonderful success in examining complicated datasets and figuring out hidden patterns inside massive volumes of data. In the context of community security, deep studying fashions can routinely study significant representations of site visitors conduct besides relying on manually described features. Convolutional neural networks are in particular high-quality at shooting spatial patterns inside site visitors data, whilst recurrent neural networks such as GRU and LSTM are properly desirable for modeling sequential dependencies. Recently, interest mechanisms have been brought to in addition beautify deep mastering fashions by way of enabling them to center of attention on the most informative components of the enter data. The integration of convolutional layers, GRU networks, and self-attention mechanisms types a effective framework for precisely classifying community visitors anomalies.

The rapid advancement of digital technologies, including cloud computing, big data platforms, and Internet of Things (IoT) devices, has significantly increased the scale and complexity of modern communication networks. These technologies generate massive volumes of network traffic every second, making it increasingly difficult to monitor and manage network activities effectively. As networks continue to expand, they also become more vulnerable to various cyber threats such as Distributed Denial of Service (DDoS) attacks, malware propagation, data breaches, and unauthorized access attempts. Detecting such malicious activities in real time has therefore become a critical requirement for maintaining network security and reliability.

Traditional intrusion detection systems (IDS) primarily rely on signature-based or rule-based detection techniques. These methods identify attacks by comparing network traffic patterns against a predefined database of known attack signatures. While this approach can effectively detect previously identified threats, it often fails to recognize new or evolving attack patterns. Moreover, maintaining and updating large

signature databases is time-consuming and may lead to increased computational overhead. As a result, traditional methods struggle to keep pace with the rapidly changing landscape of cyber threats.

To address these limitations, machine learning and deep learning techniques have been widely adopted for network traffic analysis and anomaly detection. These approaches enable systems to automatically learn patterns and relationships from large volumes of network data without relying solely on predefined rules. Deep learning models such as Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Long Short-Term Memory (LSTM) networks have shown promising performance in detecting network anomalies. Convolutional networks are effective in extracting spatial features from traffic data, while recurrent architectures are designed to capture sequential and temporal patterns in network traffic flows.

However, existing models often face challenges in effectively capturing both spatial and temporal dependencies within complex and high-dimensional network traffic data. In addition, some models may struggle to focus on the most relevant features when dealing with large-scale datasets, which can reduce detection accuracy and increase false alarm rates. To overcome these challenges, attention mechanisms have been introduced in deep learning models to improve feature representation by allowing the model to focus on important information within the input data.

In this research, a network traffic anomaly classification model based on a Self-Attention Mechanism and Convolutional Gated Recurrent Unit (Conv-GRU) architecture is proposed. The convolutional layers are used to extract spatial patterns from network traffic features, while the GRU layers capture temporal dependencies in sequential traffic data. The self-attention mechanism further enhances the model's capability by identifying and emphasizing the most informative features during the classification process. By integrating these components, the proposed model aims to improve anomaly detection accuracy and reduce false positives in network traffic monitoring systems. The developed framework provides an efficient and scalable solution for identifying various types of

cyber attacks and abnormal network behaviors in modern network environments.

1.1 Problem Statement

The rapid expansion of internet technologies, cloud computing platforms, and Internet of Things (IoT) devices has led to a significant increase in the volume and complexity of network traffic. As modern networks continue to grow, they become more vulnerable to various cyber threats such as Distributed Denial of Service (DDoS) attacks, malware propagation, unauthorized access, and other malicious activities. Detecting these threats in real time has become a critical challenge for maintaining network security and ensuring reliable communication systems.

Traditional intrusion detection systems mainly rely on signature-based and rule-based techniques to identify malicious activities. Although these methods are effective for detecting known attacks, they often fail to identify new, unknown, or evolving threats. In addition, many conventional machine learning models struggle to effectively analyze high-dimensional and sequential network traffic data. These limitations lead to reduced detection accuracy, higher false alarm rates, and difficulty in handling large-scale network environments.

Another major challenge is the inability of existing models to simultaneously capture both spatial and temporal relationships present in network traffic data. Network traffic consists of complex patterns that evolve over time, and ignoring these dependencies can reduce the effectiveness of anomaly detection systems. Furthermore, many existing approaches lack mechanisms to focus on the most relevant features within large datasets, which may affect the overall performance of intrusion detection models.

Therefore, there is a need for an advanced and efficient network traffic anomaly detection system that can effectively analyze large volumes of traffic data, capture both spatial and temporal dependencies, and improve classification accuracy while reducing false positives. The proposed model addresses these challenges by integrating convolutional feature extraction, gated recurrent unit (GRU) based temporal learning, and a self-attention mechanism to enhance network traffic anomaly classification performance.

1.2 Objectives

The main objective of this research is to develop an efficient and intelligent network traffic anomaly classification model using advanced deep learning techniques. With the increasing complexity of modern network environments, there is a growing need for systems that can accurately detect malicious activities and abnormal traffic patterns. This study aims to design a hybrid deep learning framework that integrates convolutional neural networks, gated recurrent units, and a self-attention mechanism to effectively analyze both spatial and temporal characteristics of network traffic data. The proposed model focuses on improving anomaly detection accuracy while reducing false positive rates in intrusion detection systems.

Another objective of this work is to preprocess and analyze network traffic datasets in order to extract meaningful features that represent normal and malicious traffic behaviors. By applying feature analysis and data refinement techniques, the model can efficiently handle high-dimensional network data and improve classification performance. The research also aims to evaluate the effectiveness of the proposed model using standard datasets and performance metrics such as accuracy, precision, recall, and F1-score. Ultimately, the goal is to provide a reliable and scalable solution for detecting cyber threats in modern network infrastructures and enhancing the overall performance of network security monitoring systems..

1.3 Existing System

Existing community site visitors anomaly detection structures specifically be counted on regular desktop gaining knowledge of algorithms such as Support Vector Machines (SVM), Decision Trees, Random Forest, and k-Nearest Neighbor classifiers. These strategies require guide characteristic engineering to extract applicable patterns from community site visitors data. Although these techniques can gain real looking overall performance on recognised assault types, they regularly hostilities to adapt to new or in the past unseen threats. Additionally, usual laptop studying fashions are restricted in their capacity to seize complicated relationships inside high-dimensional statistics generated by using modern-day community infrastructures. Deep gaining knowledge of fashions such as convolutional neural networks and recurrent

neural networks have been delivered to overcome these limitations. However, many present deep gaining knowledge of tactics nonetheless face challenges in shooting long-range dependencies and figuring out the most applicable facets inside giant site visitors datasets. Standard CNN fashions particularly focal point on spatial facets however might also neglect temporal relationships in site visitors sequences. Similarly, recurrent fashions may additionally go through from inefficient gaining knowledge of when dealing with lengthy community visitors sequences. Furthermore, many modern-day fashions deal with all points equally barring prioritizing the most necessary information, which can limit anomaly detection accuracy. These boundaries spotlight the want for superior architectures that combine interest mechanisms with deep getting to know fashions to enhance community visitors classification.

1.4 Disadvantages of Existing System

Despite the vast growth made in community intrusion detection and anomaly classification, current structures nonetheless face numerous obstacles that have an effect on their common overall performance and reliability. Many common strategies are based totally on signature-based detection techniques, which rely on predefined patterns of acknowledged attacks. These structures are positive solely for until now recognized threats and regularly fail to discover new or unknown assault types, making them much less appropriate for cutting-edge dynamic community environments.

Another important downside of present structures is their restrained functionality to analyze large-scale and high-dimensional community visitors data. With the speedy increase of web offerings and IoT devices, community site visitors has end up more and more complicated and voluminous. Conventional desktop mastering fashions regularly war to system such massive datasets efficiently, which can also end result in slower detection and decreased gadget performance.

Many present anomaly detection fashions additionally fail to seize both spatial and temporal relationships inside community visitors data. While some strategies center of attention solely on static characteristic extraction, others pay attention exceptionally on sequential patterns. This incomplete evaluation can lead to inaccurate classification of everyday and malicious site visitors patterns. As a result, the detection

accuracy may additionally limit when dealing with state-of-the-art cyber attacks.

In addition, typical and some computer learning-based structures regularly go through from excessive false tremendous and false bad rates. A excessive false high-quality fee can generate needless alerts, growing the workload for community directors and making it challenging to pick out true threats. Similarly, false negatives may also enable malicious things to do to stay undetected, posing serious dangers to community security.

Furthermore, many present fashions lack adaptive getting to know capabilities, which means they can't without problems alter to evolving community behaviors and rising cyber threats. This issue reduces their long-term effectiveness in real-world applications. Therefore, there is a want for greater superior tactics that can successfully analyze complicated community site visitors patterns, seize each spatial and temporal dependencies, and enhance the accuracy of anomaly detection in contemporary community environments..

2. RELATED WORKS

Network visitors anomaly detection has end up an vital lookup region in cybersecurity due to the growing range of cyber threats concentrated on cutting-edge conversation systems. Researchers have explored a number computing device gaining knowledge of and deep mastering strategies to enhance the accuracy and effectivity of intrusion detection systems. Traditional techniques specifically centered on statistical evaluation and rule-based approaches, whilst current research emphasize the use of smart gaining knowledge of fashions succesful of mechanically figuring out bizarre patterns in large-scale community site visitors data.

Early intrusion detection structures basically relied on signature-based detection methods, the place recognized assault patterns have been saved in databases and incoming community site visitors was once in contrast with these predefined signatures. Although these methods had been superb for detecting beforehand acknowledged threats, they have been unable to become aware of new or unknown attacks. To tackle this limitation, researchers added computer learning-based approaches, which include Support Vector Machines (SVM), Decision Trees, Random Forests, and K-Nearest Neighbor (KNN), which

analyze visitors conduct and classify it into regular or malicious classes based totally on realized patterns.

With the development of deep learning, quite a few research have proposed neural community fashions for community anomaly detection. Convolutional Neural Networks (CNNs) have been extensively used to extract spatial aspects from network site visitors information and enhance classification accuracy. CNN-based fashions are succesful of getting to know hierarchical characteristic representations, which makes them appropriate for inspecting complicated community patterns. However, CNN fashions by myself may additionally no longer efficaciously seize temporal dependencies existing in sequential community visitors flows.

To overcome this issue, researchers have included Recurrent Neural Networks (RNNs) and their editions such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks. These fashions are designed to seize temporal relationships and sequential patterns in time-series data, making them appropriate for community visitors analysis. GRU-based models, in particular, have received interest due to their less complicated structure and decrease computational complexity in contrast to LSTM whilst preserving aggressive overall performance in sequence modeling tasks.

More recently, interest mechanisms have been delivered in deep getting to know fashions to decorate characteristic studying and enhance classification performance. The interest mechanism approves the model to focal point on the most applicable components of the enter information by way of assigning significance weights to special features. This strategy helps in enhancing mannequin interpretability and detection accuracy, in particular when dealing with massive and complicated datasets. Self-attention strategies have been effectively utilized in various community protection applications, together with intrusion detection and anomaly classification.

Several hybrid architectures combining CNN, RNN, and interest mechanisms have been proposed to enhance anomaly detection performance. These fashions strive to leverage the strengths of exceptional neural community buildings to seize each spatial and temporal dependencies in community site visitors data. However, many current fashions nevertheless face

challenges such as excessive computational cost, confined scalability, and subject in coping with large-scale real-time community traffic. Therefore, creating extra environment friendly and correct hybrid fashions stays an necessary lookup course in the area of community visitors anomaly detection..

3. PROPOSED METHODOLOGY

The proposed machine introduces a hybrid deep getting to know structure that combines Self-Attention Mechanism with Convolutional Gated Recurrent Unit (Conv-GRU) for environment friendly community site visitors anomaly classification. The convolutional layers first extract spatial aspects from community visitors datasets by means of inspecting packet-level or flow-level traits such as protocol type, packet size, supply and vacation spot addresses, and time intervals. These elements are then surpassed to GRU layers that seize temporal dependencies inside sequential community site visitors patterns. GRU networks are computationally environment friendly in contrast to normal LSTM fashions whilst nevertheless retaining sturdy sequence gaining knowledge of capabilities.

To in addition beautify the model's capacity to pick out integral features, a self-attention mechanism is built-in into the architecture. The interest module assigns special weights to aspects primarily based on their significance in figuring out peculiar community behavior. This permits the mannequin to focal point extra on suspicious visitors patterns whilst lowering the have an impact on of beside the point information. The aggregate of convolutional function extraction, sequential sample learning, and attention-based function prioritization appreciably improves anomaly detection performance. The proposed machine can precisely classify one-of-a-kind kinds of community anomalies and can be deployed in real-time community monitoring structures to give a boost to cybersecurity defenses.

3.1 System Architecture

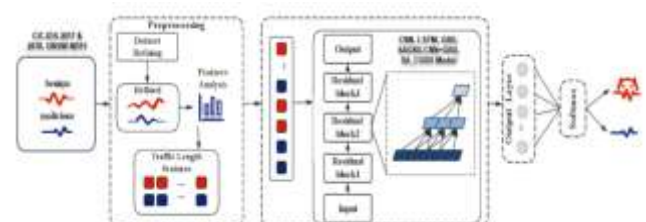


Figure 1 System Architecture

The proposed architecture for network traffic anomaly classification consists of several stages designed to process and analyze network data efficiently. Initially, network traffic datasets such as CIC-IDS 2017, CIC-IDS 2018, and UNSW-NB15 are collected as input, containing both benign and malicious traffic records. In the preprocessing stage, the raw data undergoes dataset refining where missing values, redundant attributes, and noise are removed to improve data quality. Feature analysis is then performed to identify relevant traffic characteristics such as packet size, flow duration, protocol type, and source–destination information. These processed features are converted into structured feature vectors representing the statistical properties of network traffic flows.

After preprocessing, the refined feature vectors are passed to the deep learning module, which combines convolutional neural networks (CNN) and recurrent neural network structures. The CNN layers are responsible for extracting spatial features from the traffic data, allowing the model to learn important patterns and correlations among different network attributes. The architecture also incorporates residual blocks to enhance feature learning and overcome issues such as gradient vanishing during deep network training. These residual connections allow the model to preserve important information while learning deeper representations of network traffic patterns.

To capture temporal dependencies within sequential traffic data, recurrent models such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) are used. These models analyze time-based traffic patterns and help detect abnormal behavior that evolves over time. Additionally, a self-attention mechanism is integrated into the architecture to assign importance weights to different features, enabling the model to focus on the most relevant information for anomaly detection. Finally, the processed features are passed to a classification layer that categorizes the traffic into normal or malicious classes. This hybrid architecture effectively combines spatial, temporal, and attention-based learning techniques to improve the accuracy and reliability of network traffic anomaly detection systems.

3.2 Module Description

3.2.1. Network Traffic Dataset Collection Module

The Network Traffic Dataset Collection Module gathers network traffic data required for training and evaluating the anomaly classification model. The dataset may include publicly available network intrusion datasets such as NSL-KDD, CICIDS, or UNSW-NB15, which contain labeled examples of normal and malicious network traffic. These datasets typically include features such as packet statistics, protocol information, connection duration, and traffic flow characteristics.

In addition to collecting datasets, the module organizes the data into training, validation, and testing subsets. Proper dataset organization ensures that the deep learning model can be trained effectively while maintaining reliable evaluation results. The module also maintains metadata describing traffic features and attack categories, which helps in understanding the distribution of normal and anomalous network traffic patterns.

3.2.2. Data Preprocessing Module

The Data Preprocessing Module prepares the collected network traffic data for deep learning training. Raw network traffic datasets often contain missing values, inconsistent feature formats, and irrelevant attributes that can negatively impact model performance. This module performs data cleaning operations such as handling missing values, removing duplicate records, and correcting inconsistent feature representations.

Furthermore, numerical features are normalized or standardized to ensure that all input variables fall within a consistent range. Categorical features such as protocol types or service identifiers may be encoded using techniques such as one-hot encoding. These preprocessing steps improve the efficiency of the training process and ensure that the model can effectively learn patterns from the dataset.

3.2.3 Feature Extraction using Convolutional Layers Module

The Feature Extraction Module utilizes convolutional neural network layers to identify meaningful spatial patterns within network traffic data. Convolutional layers apply filters that detect local feature patterns across different dimensions of the input data. These filters help identify

relationships between various traffic features, such as packet timing patterns or abnormal packet sizes associated with malicious activities.

The convolutional layers generate feature maps that highlight important patterns within the dataset. Pooling layers may also be applied to reduce dimensionality and improve computational efficiency. By extracting hierarchical representations of network traffic features, the convolutional module provides a strong foundation for further temporal analysis in the subsequent stages of the model.

3.2.4 Temporal Pattern Learning using GRU Module

The GRU module is responsible for capturing temporal dependencies within sequential network traffic data. Network attacks often occur in patterns over time, and analyzing traffic sequences can reveal abnormal behaviors that may not be visible in individual packets. GRU networks process sequences of feature vectors and learn how traffic behavior evolves over time.

Compared to traditional recurrent neural networks, GRU models are more computationally efficient while still retaining the ability to capture long-term dependencies. The GRU cells update their internal memory based on previous states and current inputs, allowing the model to detect sequential attack patterns such as slow port scans or gradual traffic flooding. This module plays a critical role in identifying time-based anomalies in network traffic.

3.2.5. Self-Attention Mechanism Module

The Self-Attention Mechanism Module enhances the model's ability to focus on the most relevant features within the network traffic data. Instead of treating all features equally, the attention mechanism calculates attention weights that indicate the importance of each feature or time step in the input sequence. Features with higher attention weights contribute more significantly to the final classification decision.

This mechanism improves the interpretability and effectiveness of the model by highlighting which parts of the traffic data are most indicative of anomalous behavior. For example, sudden spikes in packet transmission rates or unusual protocol usage may receive higher attention scores. By emphasizing important patterns and suppressing irrelevant information, the attention module significantly improves anomaly detection accuracy.

3.2.6 Anomaly Classification Module

The Anomaly Classification Module uses the extracted features and learned representations to classify network traffic into normal or abnormal categories. A fully connected neural network layer is typically used to combine the outputs from the convolutional, GRU, and attention modules. The final classification is performed using a softmax or sigmoid activation function depending on whether the task involves multi-class or binary classification.

This module identifies various types of network anomalies such as denial-of-service attacks, intrusion attempts, malware communication, or unauthorized access activities. The classification results can be integrated into network monitoring systems to trigger alerts and initiate security responses when suspicious traffic patterns are detected.

3.2.7 Model Training and Optimization Module

The Model Training Module handles the process of training the deep learning model using labeled network traffic datasets. During training, the model learns to minimize a loss function that measures the difference between predicted labels and actual labels. Optimization algorithms such as Adam or stochastic gradient descent are used to update model parameters and improve prediction accuracy.

This module also monitors important training metrics such as accuracy, loss, precision, recall, and F1-score. Techniques such as dropout, batch normalization, and learning rate scheduling may be applied to improve model stability and prevent overfitting. Proper training ensures that the anomaly detection model generalizes well to new network traffic data.

3.2.8 Performance Evaluation and Visualization Module

The Performance Evaluation Module measures the effectiveness of the trained anomaly classification model using various evaluation metrics. Metrics such as accuracy, precision, recall, F1-score, and confusion matrix analysis are used to assess the model's ability to correctly identify normal and anomalous traffic patterns. These metrics provide insights into how well the model performs across different attack categories. Visualization techniques are also used to present evaluation results in an interpretable format.

Graphs such as ROC curves, training accuracy plots, and confusion matrices help researchers understand the model's performance and identify areas for improvement. This module plays a crucial role in validating the effectiveness of the proposed deep learning framework for network traffic anomaly detection..

FLOW DIAGRAM

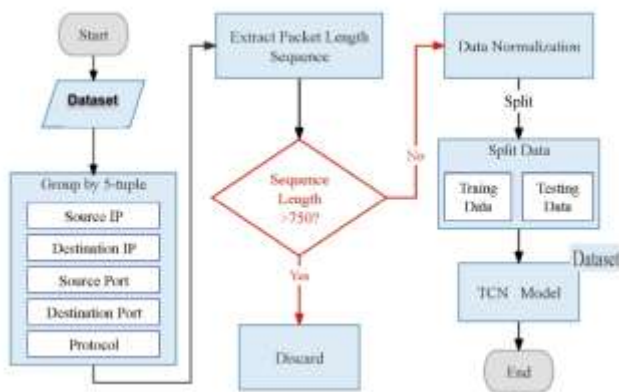


Figure 2 flow diagram

4.RESULTS AND DISCUSSION

The proposed Network Traffic Anomaly Classification Model based on the Self-Attention Mechanism and Convolutional Gated Recurrent Unit (Conv-GRU) was evaluated using benchmark network intrusion datasets to measure its effectiveness in detecting abnormal network activities. The datasets used for experimentation include CIC-IDS 2017, CIC-IDS 2018, and UNSW-NB15, which contain a variety of network traffic patterns including both benign and malicious activities. These datasets provide multiple attack scenarios such as Distributed Denial of Service (DDoS), botnet activity, brute-force attacks, and infiltration attempts. The performance of the proposed model was assessed using standard evaluation metrics including accuracy, precision, recall, and F1-score.

During the training process, the hybrid architecture effectively learned complex patterns in network traffic data by combining spatial feature extraction through convolutional layers and temporal pattern learning through GRU layers. The integration of the self-attention mechanism further improved the model's ability to focus on the most relevant features within the traffic dataset. As a result, the proposed model demonstrated improved classification performance compared with traditional machine

learning methods and basic deep learning models that rely solely on CNN or recurrent networks.

The experimental results indicate that the proposed model achieved high detection accuracy and significantly reduced false positive rates. The convolutional layers helped identify important feature relationships within the traffic data, while the GRU layers captured sequential dependencies that are essential for recognizing evolving attack patterns. The self-attention mechanism enhanced the model's capability by assigning higher importance to critical traffic features, thereby improving the overall classification performance.

Furthermore, the hybrid model demonstrated strong generalization capability across different network traffic datasets. The architecture was able to maintain consistent performance in detecting multiple types of cyber attacks while effectively distinguishing them from normal network activities. This makes the proposed system suitable for real-time network security monitoring environments where large volumes of traffic data must be analyzed continuously.

Overall, the experimental findings confirm that integrating convolutional feature extraction, recurrent temporal modeling, and self-attention mechanisms significantly improves anomaly detection performance in network traffic analysis. The proposed approach provides a reliable and efficient solution for detecting modern cyber threats in complex network infrastructures, thereby enhancing the effectiveness of intrusion detection systems in real-world applications.

Performance Metric:

Classification Report:

	precision	recall	f1-score	support
analysis	0.00	0.00	0.00	2000
backdoor	0.00	0.00	0.00	1746
dos	0.00	0.00	0.00	12264
exploits	0.59	0.79	0.67	33393
fuzzers	0.05	0.00	0.01	18184
generic	0.99	0.98	0.99	40000
normal	0.65	0.99	0.78	56000
reconnaissance	0.71	0.28	0.40	10491
shellcode	0.00	0.00	0.00	1133
worms	0.00	0.00	0.00	130
accuracy			0.71	175341
macro avg	0.30	0.30	0.28	175341
weighted avg	0.59	0.71	0.63	175341

Figure 3 matrix

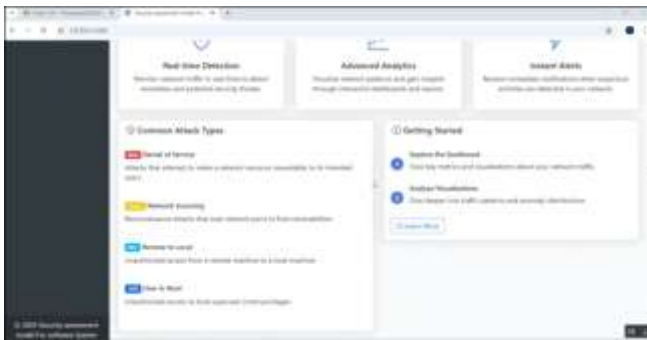


Figure 4 main page



Figure 5 Dashboard



Figure 6 Prediction

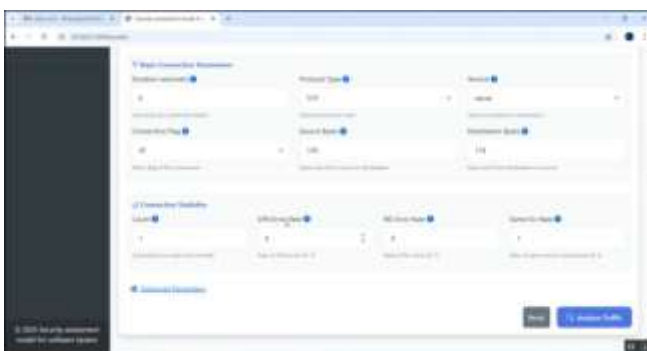


Figure 7Evaluation



Figure 8 Detection

5.CONCLUSION AND FUTURE SCOPE

In this research, a network traffic anomaly classification model based on a Self-Attention Mechanism and Convolutional Gated Recurrent Unit (Conv-GRU) was proposed to improve the detection of malicious network activities. The rapid growth of internet services, cloud computing, and IoT devices has increased the complexity of network traffic, making traditional intrusion detection techniques less effective in identifying modern cyber threats. To address these challenges, the proposed model integrates convolutional neural networks for spatial feature extraction, GRU layers for capturing temporal dependencies in network traffic sequences, and a self-attention mechanism to focus on the most relevant traffic features. This hybrid architecture enables the system to effectively analyze complex network traffic patterns and improve anomaly classification performance.

The experimental evaluation using benchmark datasets demonstrates that the proposed model achieves higher detection accuracy and reduced false positive rates compared with conventional machine learning and basic deep learning approaches. The combination of CNN, GRU, and attention mechanisms allows the system to learn both spatial and temporal characteristics of network traffic data, thereby enhancing its ability to detect various cyber attacks such as DDoS, malware traffic, and unauthorized access attempts. These results indicate that the proposed approach can serve as an efficient and reliable solution for modern intrusion detection systems and network security monitoring applications.

Although the proposed model provides promising results, there are still opportunities for further improvement. In future work, the model can be extended to support real-time intrusion detection in large-scale network environments with higher data throughput. Additional optimization techniques may be applied to reduce computational complexity and improve processing speed. Furthermore, integrating advanced deep learning models such as transformer-based architectures or federated learning techniques could enhance detection performance and enable distributed security monitoring across multiple network nodes. Expanding the model to analyze encrypted traffic and incorporating adaptive

learning mechanisms will also help improve its ability to respond to evolving cyber threats in dynamic network environments.

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