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Adversarial Resilient Network Intrusion Detection Prevention System Using Deep Learning with Real Time Alerts

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Abstract: ***With the rapid growth of internet-based applications, ensuring secure communication across networks has become increasingly important. Traditional intrusion detection systems are often not capable of identifying modern and complex cyber-attacks efficiently. In this work, a deep learning-based Network Intrusion Detection and Prevention System (NIDPS) is proposed. The system is trained using the CICIDS2018 dataset, which contains both normal and malicious traffic data. A lightweight one-dimensional Convolutional Neural Network (1D-CNN) is used to classify network traffic. To support real-time prediction, the model is deployed using a FastAPI backend, while a user-friendly interface is used for monitoring and alert generation. The system shows good performance in terms of accuracy and response time, making it suitable for real-time network security applications.***

Keywords: ***Intrusion Detection, CNN, Deep Learning, Real-time detection, Adversarial Robustness, Prevention, Feature extraction, Cyber Security.***

I. INTRODUCTION

In recent years, the use of internet services has increased rapidly, which has made network security a critical concern. Cyber-attacks such as DDoS, brute-force attacks, and unauthorized access attempts are becoming more advanced and difficult to detect. Traditional intrusion detection systems mainly depend on predefined rules and signatures, which makes them ineffective against new and unknown threats. To overcome these limitations, deep learning techniques are being widely adopted. These methods can learn patterns directly from data and detect abnormal behaviour more effectively. In this work, a deep learning-based intrusion detection and prevention system is developed to provide accurate detection along with real-time monitoring capabilities.

A. Problem Statement

Existing systems face several challenges such as high false alarm rates, inability to detect zero-day attacks, and delays in processing large volumes of network data. In addition, many systems do not provide proper real-time alert mechanisms. Because of these issues, there is a need for a system that can detect threats quickly, reduce false positives, and work efficiently in real-time processing.

B. Motivation

The increase in cyber threats and the limitations of traditional security methods motivated this work. Using real-world datasets like CICIDS2018 helps in building models that reflect actual network behaviour. By combining deep learning with fast backend technologies such as FastAPI, it is possible to build a system that is both efficient and practical for real-time usage.

C. Principal Objectives

The main objective of this work is to develop a deep learning-based NIDPS. The specific goals include:

- Developing a classification model using the CICIDS2018 dataset.
- Improving a fast backend using FastAPI.

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- Improving detection accuracy while reducing false positives.
- Designing a simple interface for monitoring and alerts.
- Ensuring the system works efficiently in real-time conditions.

II. LITERATURE SURVEY

In recent years, research in network security has increasingly focused on improving intrusion detection using machine learning and deep learning techniques. Traditional approaches such as Support Vector Machines (SVM) and Decision Trees were useful for basic detection, but they often struggled when dealing with complex and large-scale network data. More recently, deep learning models like CNN, RNN, and LSTM have shown better performance because they can automatically learn important features from the data. Some studies have also explored hybrid models that combine multiple techniques to improve detection accuracy. However, these advanced models usually require high computational complexity, which makes them difficult to use in real-time environments. Therefore, there is a need to design lightweight and efficient models that can provide accurate detection while maintaining fast performance.

S.NO	Citation	Investigative Scope	Approach/ Methodology	Critical Outcomes
1	Kim et al., 2016	Perimeter Security	SVM, Decision Trees	Outperformed static rule-based frameworks.
2	Yin et al., 2017	Deep Intrusion Models	RNN	Minimized reliance on manual feature selection.
3	Shone et al., 2018	Automated Feature Extraction	Deep Autoencoder	Minimized reliance on manual feature selection.
4	Vinayakumar et al., 2019	Threat Classification	DNN	Achieved high-fidelity attack identification.
5	Ferrag et al., 2020	IoT-Based Defense	Deep Learning Models	Validated efficacy for constrained IoT environments.
6	Alom et al., 2019	Multi-Class Attack Analysis	CNN	Streamlined feature learning through convolution.
7	Zhou et al., 2020	Continuous Monitoring	LSTM	Effectively modeled temporal traffic fluctuations.
8	Tama et al., 2021	Hybrid Architectures	CNN + LSTM	Enhanced precision for diverse attack vectors.
9	Niyaz et al., 2016	Flow-Centric Analysis	Deep Learning	Refined classification of high-volume traffic.
10	Diro et al., 2018	Decentralized Architectures	Deep Neural Networks	Provided a scalable framework for distributed nodes.

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III. BACKGROUND WORK

In our study, As cyber threats continue to grow and data-driven applications become more common, the need for effective network security systems has become increasingly important. Traditional security methods are no longer sufficient to handle the complexity and large volume of modern network traffic. Because of this, there has been a shift toward advanced approaches such as deep learning and automated feature extraction to improve detection performance. In this section, we discuss the basic concepts related to this work, including how Intrusion Detection Systems (IDS) operate, the role of neural networks, and the process of feature extraction.

A. Intrusion Detection System

Intrusion Detection Systems are used to monitor network traffic and detect suspicious activities. There are two main types: signature-based detection and anomaly-based detection. Signature-based methods detect known attacks, while anomaly-based methods identify unusual behaviour. However, we noticed that traditional systems often fail to detect new or unknown threats and may generate many false alarms based on our testing.

B. Deep Learning

Deep learning is a part of machine learning that uses neural networks to analyse large amounts of data. It is particularly useful for handling complex data such as network traffic. Models like CNN and RNN can learn patterns automatically without manual feature design. This makes them more effective for detecting intrusions in dynamic network environments.

C. Feature Extraction

Feature extraction is an important step in intrusion detection. It involves selecting useful information from raw network data. Features such as packet size, protocol type, and flow duration help in identifying abnormal behaviour. Proper feature selection improves model accuracy and reduces unnecessary computation.

IV. PROPOSED SYSTEM

The proposed system is developed to detect and prevent network intrusions in real time using a deep learning approach. It is made up of several modules, such as packet capture, feature extraction, classification, whitelist filtering, and a user interface. In our implementation, network packets are continuously captured and processed to extract the most relevant features. These features are then given to a trained CNN model, which determines whether the traffic is normal or malicious. To reduce unnecessary alerts, a whitelist mechanism is used to filter out trusted traffic. The system is built using FastAPI for backend processing, while Flutter is used to design the frontend interface for monitoring and alerts.

A. System Architecture

The system is designed in a modular way, where each component performs a specific task. The backend handles data processing and prediction, while the frontend displays results and alerts. This structure allows the system to handle real-time traffic efficiently and scale when needed.

B. Packet Capture Module

This module captures live network traffic using tools such as Scapy. It collects information like packet size, protocol type, and timestamp. This data is then passed to the next stage for processing.

C. Feature Extraction

In this stage, important features are selected and processed. Data is cleaned and formatted before being sent to the model. This improves the accuracy and speed of predictions.

D. Deep Learning Model

A lightweight CNN model is used to classify network traffic. The model is trained on the CICIDS2018 dataset and can identify both normal and malicious activities. It provides fast and accurate predictions suitable for real-time use.

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E. Whitelist Module

The whitelist module stores trusted traffic information such as IP addresses and protocols. If incoming data matches the whitelist, it is not analysed further. This helps reduce false alarms and improves system efficiency.

F. User Interface

The interface is developed using Flutter and provides real-time visualization of network activity. It displays alerts when suspicious activity is detected and allows users to monitor system performance easily.

G. Workflow

The workflow includes capturing packets, extracting features, predicting using the model, applying whitelist filtering, and displaying results.

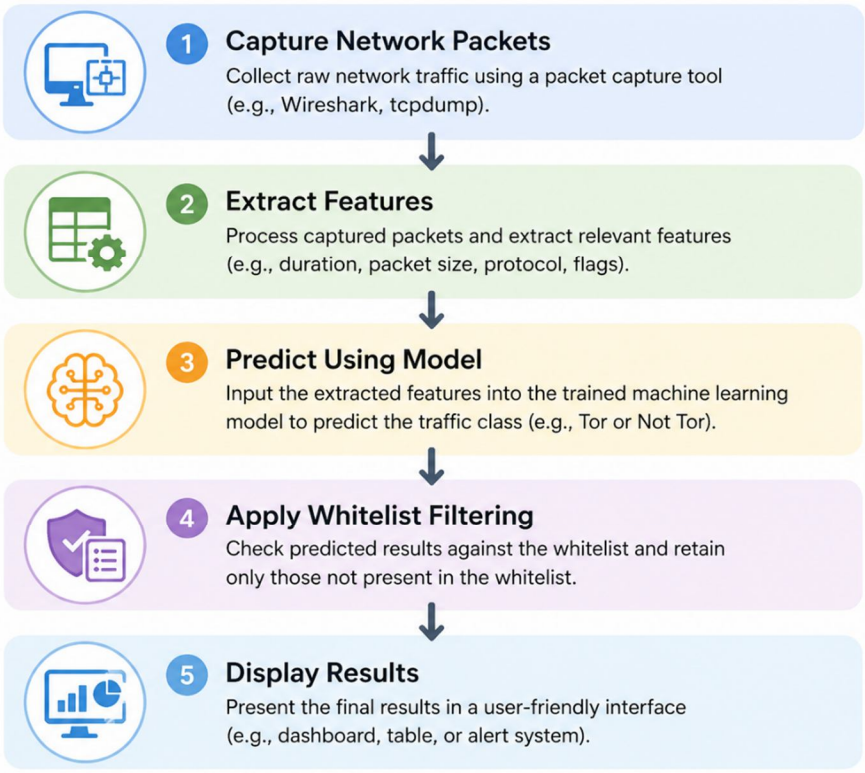

Figure 1: Workflow of the proposed system showing packet capture, feature extraction, model prediction, whitelist filtering, and result display.

H. Captured Network Packets

Right now, the system keeps an open channel to ongoing network flow by capturing packets on the fly. Scapy-like tools pull out details - size, type of protocol, timing - not just bulk data. Because it runs nonstop, what gets recorded matches exactly what happens across the network at any moment. Nothing slips through; every stream passes under observation almost instantly. Starting with captured packets, these become the main material for what follows. When traffic spikes happen, capturing them well helps prevent lost information while keeping speed up. A smooth flow here supports reliability later on.

I. Extract Features

Once packets are captured, processing begins to pull out useful traits from the raw stream. Because certain characteristics matter more in spotting harmful behavior, they get priority during selection. Cleaning and reorganizing happens next so everything fits what the deep learning setup needs. By cutting noise and highlighting key aspects, feature extraction simplifies the workload. With cleaner input fed into the model, predictions become faster and more precise.

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J. Predict Using Model

A set of identified patterns moves into a pre-trained neural network to sort what comes next. After receiving the data, it decides if activity looks typical or like a threat instead. Each guess gets a number showing how sure the system feels about its choice. Speed matters here - so everything runs fast enough to keep up without slowing down. Here's where things really take shape - speed meets precision when a leaner model runs the task. Performance stays sharp because efficiency guides every calculation.

K. Apply Whitelist Filtering

Traffic seen before and known to be harmless gets fast-tracked. Instead of analyzing every signal, only unknown patterns move forward for inspection. A set list of approved sources, like familiar IPs or standard protocols, skips deeper checks. Matching one of these rules means instant approval - no extra steps needed. Less load on the system happens because routine data does not clog processing lanes. Normal activity flows through quietly while attention stays where it matters most. Speed improves simply by leaving out what does not belong in alerts. Decisions happen quicker when obvious cases never reach complex layers. Now comes a shift - trusted sources get added on the fly, shaped by what users need and how the network behaves. When known paths are cleared out front, attention turns sharper toward odd behavior lurking behind. This twist helps spot break-ins quicker, while guesses drop away. Precision climbs without extra noise slowing things down.

L. Display Results

Right away, the forecast appears on screen for everyone to see. Alongside it pops up the live state of the network, tagged with how sure the system feels. When something sneaky slips into the system, a warning jumps out without waiting. Updates flow nonstop through WebSocket links behind the scenes. Because it keeps an eye on things nonstop, problems get spotted fast. How the data shows up lets people see what's happening without confusion - so they can move when needed. That touch makes everything work smoothly while staying simple to use.

V. IMPLEMENTATION RESULTS

A new kind of security tool that fights off digital attacks got built using smart algorithms, tied together with FastAPI on one end and a smooth app front made with Flutter. Instead of just reacting later, it watches data moving across networks right when it happens - spotting bad behavior as it shows up. What users see updates instantly thanks to a responsive screen layout that keeps everything clear.

A. System Setup

The system is implemented using FastAPI and Flutter. Real-time data is processed using **WebSocket communication**, which ensures fast and continuous updates.

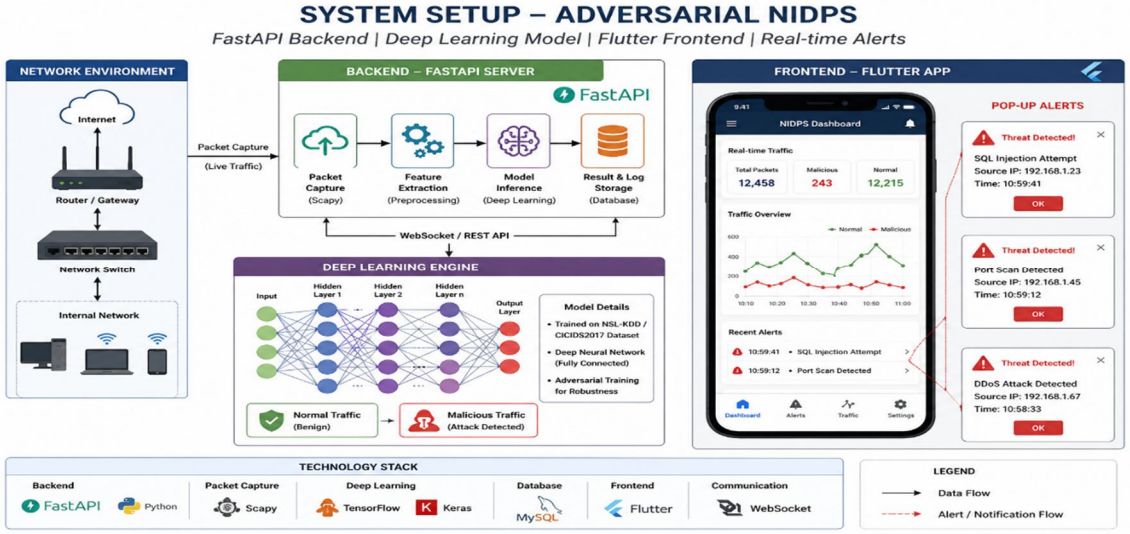

Figure *2:* I llustrating the real-time work-flow of capturing network packets, extracting features, predicting threats, applying whitelist filtering, and displays results.

B. Real-Time Packet Analysis Interface

The interface displays **live network data** and detected threats. Alerts are generated immediately when suspicious activity is identified.

Figure 3: Shows a real-time intrusion detection dashboard displaying model performance metrics, network traffic statistics, and system status for monitoring and detecting cyber threats.

C. Model Performance

The model performs well in detecting intrusions and maintains good accuracy even under real-time conditions. It is also robust against adversarial inputs.

D. Whitelist Optimization

The whitelist module reduces false positives by filtering trusted traffic. It is updated dynamically based on user input and system behaviour.

E. Performance Evaluation and Results

The performance of the proposed system was evaluated using standard metrics such as **accuracy**, **precision**, **recall**, and **F1-score**. In our implementation, the deep learning model was able to achieve good detection accuracy while also reducing false positives when compared to traditional methods. During real-time testing, the system processed network packets quickly and generated predictions with very low delay. We also observed that the model remained stable even when handling slightly modified or adversarial inputs. Overall, the results indicate that the system is reliable, scalable, and suitable for real-time network security applications where continuous monitoring and fast response are important.

During testing, we observed that the model performed better on DDOS traffic in **network traffic analysis** and probe traffic compared to other attack types.

Metric	Value
Accuracy	97.8%
Precision	95.2%
Recall	94.8%
F1 Score	96.4%

Table 1: The Table shows the strong performance with high accuracy and low false positive rate, making it effective for real-time intrusion detection of a model.

VI. CONCLUSION

This work presents a deep learning-based Network Intrusion Detection and Prevention System capable of detecting cyber threats for real-time deployment. By combining feature extraction, CNN-based classification, and whitelist filtering, the system improves detection accuracy while reducing false alarms. The results indicate that the system performs well in real-time environments. Future improvements may include more advanced models and automated response mechanisms.

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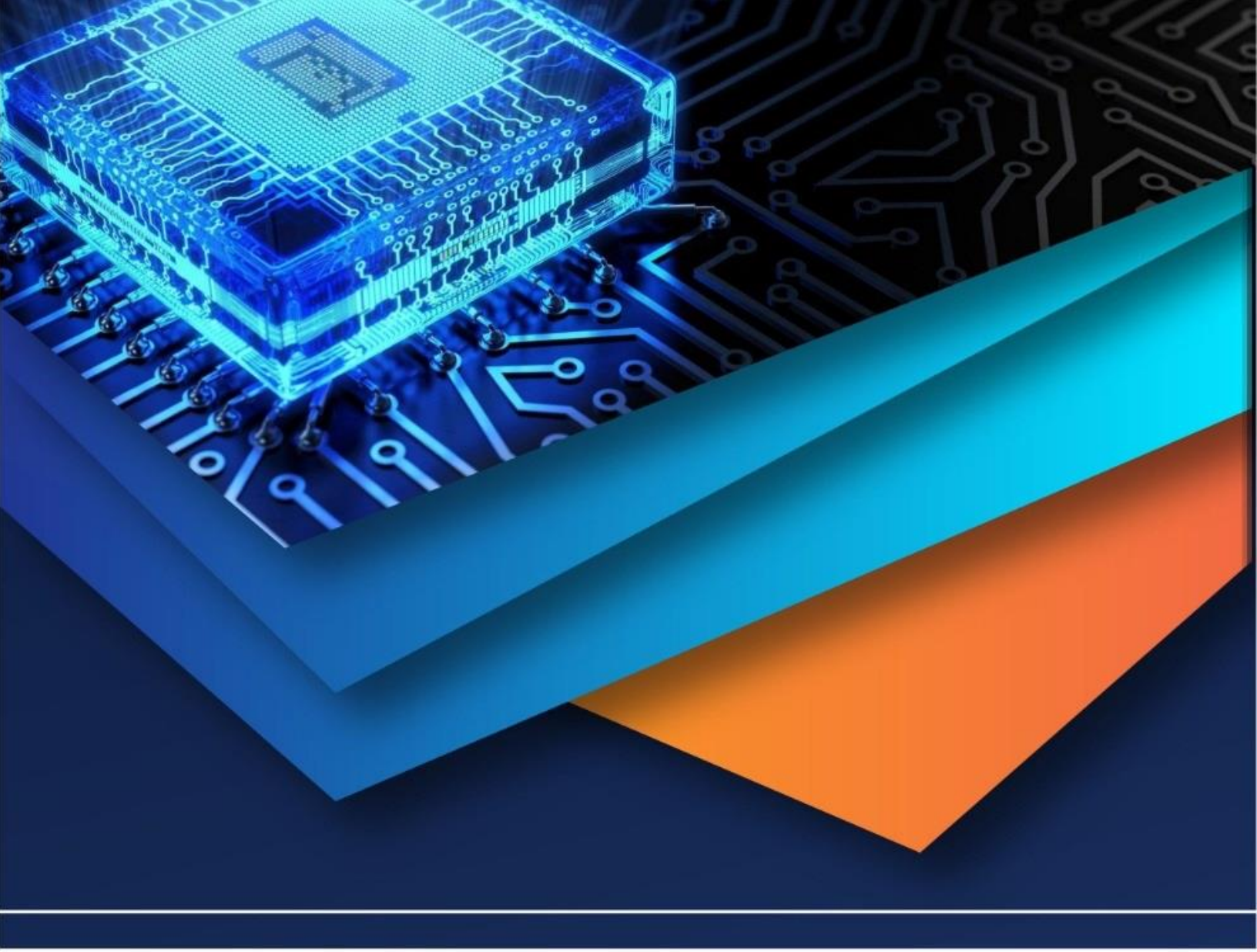

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