**CHAPTER 1**

**INTRODUCTION**

An **Intrusion Detection System (IDS)** is a **security tool** that **monitors computer networks or systems** for suspicious activities or policy violations. The main goal of IDS is to **detect cyber attacks or unauthorized access** attempts in real-time or after they occur.An **Intrusion Detection System (IDS)** is a security solution designed to monitor and analyze network traffic or system activities for signs of malicious behavior, policy violations, or unauthorized access. It acts like a digital watchdog, detecting potential threats by comparing current activity with known attack patterns (signature-based detection) or identifying unusual behavior (anomaly-based detection). IDS helps organizations identify cyber attacks early, enabling quick responses to minimize damage. While it does not prevent attacks directly, it plays a critical role in strengthening overall cyber security by alerting administrators about suspicious actions and supporting forensic analysis after incidents.

An Ad hoc **network** is a decentralized type of wireless network where devices, also known as nodes, communicate directly with each other without relying on a fixed infrastructure like routers or access points. Each node in an Ad hoc network can act as both a sender and a receiver, and it can also forward data to other nodes, making it a dynamic and self-configuring system. These networks are especially useful in situations where setting up a traditional network is difficult or impossible, such as in disaster recovery, military operations, or temporary events. Since the network’s structure constantly changes due to node mobility, managing routing and ensuring secure communication can be challenging, but it also allows for greater flexibility and rapid deployment

Rapid expansion of the transmission of information between a variety of devices and protocols has led to serious problems for the protection increases the importance of the development of modern intrusion detection systems (IDS). In today's world, many people are actively the making use of cars and other personal vehicles. A crucial problem that each person has faced every day is the increasing number of accidents occurred on road and this transportation safety problem continues to worsen because of population growth and the increase in the number of vehicles in urban areas. A Vehicular Ad hoc network (VANET) refers to a network in a very special way, where the different moving vehicles and other devices connect to a wireless carrier, and the exchange of information, at least on their own for a variety of reasons, that is the most important task for the improvement of road safety. The communication system of an intelligent vehicle is usually referred to as a vehicle to everything or it is also called a VANET which means Vehicular Ad hoc Network. An Ordinary VANET, the communication system is normally responsible for 3 main types of communication to be considered on the smart automobile. Those types are vehicle to vehicle, vehicle to infrastructure, and vehicle to roadside. There is a major advancement in-vehicle system has been made with integrating a number of computing devices called ECU. Different types of communication protocols are designed to support communication. CAN is the simple communication protocol supporting attaching sensors and actuators. In this work, we introduce IDS based on RNN's deep learning strategies to integrate and differentiate intrusions in VANET. Intelligent vehicles, as a product of the integration of computer technology and the Internet of Things technology, can achieve efficient operation of vehicles and the variety of comprehensive information services.

According to relevant reports, the number of users using automobiles worldwide has reached one billion and is expected to reach two billion until 2036 [24]. Therefore, whether the relevant business information on the Internet of Vehicles can meet the corresponding security requirements and reliability requirements is a crucial issue for the popularization and even development of the Internet of Vehicles. The core network of the Internet of Vehicles is still a traditional network but with a more complicated communication environment and an increasing number of connected nodes. In contrast, the Internet of Vehicles is more vulnerable to attacks than other traditional networks, and the impact is not limited to visualized information, but also affects real-life casualties and economic losses, and may even involve the safety of a country.With the rapid development of intelligent transportation systems (ITS), Vehicular Ad hoc Networks (VANETs) have become a key component in enabling communication between vehicles (V2V) and infrastructure (V2I). However, as VANETs grow more interconnected, they also become more vulnerable to various cyber-attacks such as message tampering, denial of service (DOS), and false information injection. These attacks can cause serious consequences, including traffic disruptions and accidents. Therefore, there is a critical need for real-time or instantaneous intrusion detection systems (IDS) that can quickly detect and prevent malicious activities in VANET environments.

This project aims to develop an intrusion detection system based on deep learning techniques to identify suspicious behaviour in Car. Deep learning, particularly models like Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN), has shown exceptional capabilities in learning complex patterns and anomalies from large datasets. By analysing network traffic data, message patterns, and node behaviour, the proposed deep learning model can detect intrusions in real-time with high accuracy.Unlike traditional rule-based or signature-based IDS, which are often slow and limited in scope, the deep learning-based approach can adapt to new threats by learning from data. This enables instantaneous intrusion detection, which is essential for the fast-moving and dynamic nature of vehicular networks. The project also focuses on building a lightweight and efficient model that can be deployed within the resource constraints of vehicular systems.

In summary, this project addresses the growing security challenges in VANETs by leveraging the power of deep learning for real-time intrusion detection, thereby enhancing road safety and maintaining the integrity of vehicular communications.

**CHAPTER 2**

**LITERATURE SURVEY**

**2.1 LITERATURE REVIEW**

1. Khan, N., Ullah, I., and Ahmad, J. (2023)  
   Title: GNN-Based Intrusion Detection in VANETs Using Communication Graphs  
   Journal: IEEE Transactions on Intelligent Transportation Systems  
   Explanation:  
   This study introduced a novel approach by utilizing **Graph Neural Networks (GNNs)** to analyze vehicular communication patterns. The primary innovation lies in representing vehicle-to-vehicle (V2V) communications as structured communication graphs. By analyzing these dynamic graphs, the system could effectively detect **structural anomalies**, such as coordinated attacks or false message injections. This method performed well against **advanced persistent threats**, which often go undetected in traditional IDS. The researchers showed that the graph-based representation captured both the topological and behavioral dynamics of vehicles, enhancing detection precision. GNNs proved especially useful in processing such structured, non-Euclidean data, leading to promising results in VANET environments.
2. Roy, T. and Mondal, P. (2022)  
   Title: An Offline Intrusion Detection System Using XGBoost and GUI for VANETs  
   Journal: International Journal of Computer Applications (IJCA)  
   Explanation:  
   Roy and Mondal proposed an **offline intrusion detection system** (IDS) using the **XGBoost** machine learning algorithm combined with a **Tkinter-based graphical user interface (GUI)**. Their system was designed for **real-time but offline** environments, such as traffic management centers where constant internet connectivity might not be available. It was tested on Indian VANET datasets, ensuring regional relevance. The GUI allowed for intuitive interaction, making the system usable by non-technical personnel. The use of XGBoost offered high detection accuracy due to its ability to handle imbalanced datasets and outliers effectively. This approach addressed **practical deployment constraints** and served as a useful tool in urban traffic control systems.
3. Ahmed, Z. and Rehman, S. (2022)  
   Title: Federated Learning-Based Privacy-Preserving IDS in Vehicular Networks  
   Journal: Future Generation Computer Systems (Elsevier)  
   Explanation:  
   This work explored the integration of **Federated Learning (FL)** with **Recurrent Neural Networks (RNNs)** to ensure data privacy while detecting intrusions. Federated learning allows multiple vehicles to train a shared model without transmitting sensitive data to a central server. The local training and periodic parameter updates to the global model help maintain **privacy-preserving collaboration**. The use of RNNs provided the system with the ability to detect patterns over time. This approach is particularly suitable for VANETs, where privacy and decentralized decision-making are critical. It also supports **data heterogeneity**, making the system more robust across different vehicle models and geographic areas.
4. Zhang, Y., Li, W., and Wang, T. (2021)  
   Title: A Hybrid Deep Learning Model for Intrusion Detection in VANETs  
   Journal: IEEE Internet of Things Journal  
   Explanation:  
   This research proposed a **hybrid deep learning model** that combines **Convolutional Neural Networks (CNN)** for spatial feature extraction and **Long Short-Term Memory (LSTM)** for analyzing temporal dependencies. This dual architecture was highly effective in capturing both the structure of individual packets and the sequence of communication over time. The hybrid model was trained and tested on **simulated VANET datasets**, where it achieved an impressive accuracy of 96%. The study demonstrated the capability of deep learning models to adapt to the **dynamic and mobile nature** of vehicular environments. Moreover, the hybrid approach improved generalization, offering robustness against multiple types of attacks.
5. Gupta, S. and Sahu, A. (2021)  
   Title: Deep Belief Networks for Intrusion Detection in Vehicular Networks  
   Journal: Journal of Network and Computer Applications (Elsevier)  
   Explanation:  
   This paper focused on utilizing **Deep Belief Networks (DBNs)** to perform hierarchical feature extraction from VANET traffic data. DBNs, which are composed of multiple layers of Restricted Boltzmann Machines, enabled the system to capture complex patterns in network behavior. The study showed that DBNs outperform shallow learning models in terms of classification accuracy, especially for **multi-class attack detection**. However, a major limitation identified was the **extended training time** due to deep architecture. Despite this, the research showed promise in environments where training can be performed offline, with models deployed afterward for real-time monitoring.
6. Patil, A. and Joshi, P. (2021)  
   Title: Feature Selection Techniques for Improved VANET Intrusion Detection  
   Journal: Wireless Personal Communications (Springer)  
   Explanation:  
   Patil and Joshi addressed a key bottleneck in IDS design—**feature redundancy and dimensionality**. They applied **Principal Component Analysis (PCA)** and **Information Gain** techniques for feature selection. This preprocessing step was integrated with a **CNN-based detection model**, resulting in reduced training time and improved detection speed without sacrificing accuracy. The selected features preserved most of the relevant information while discarding noise and irrelevant data. This work is significant for **resource-constrained environments**, such as embedded systems in vehicles, where computational power is limited. It also enhances scalability for large-scale VANET deployments.
7. Raza, M., Iqbal, M., and Naeem, M. (2020)  
   Title: Auto-encoder-Based Anomaly Detection for Vehicular Networks  
   Journal: Elsevier – Computer Communications  
   Explanation:  
   This paper proposed an **unsupervised learning** method using **autoencoders** to detect anomalies in vehicular networks. The model was trained to reconstruct normal network traffic patterns. When a significant reconstruction error occurred, the system flagged it as potential malicious behavior. This method proved especially effective for detecting **zero-day attacks**—new threats that the system had never seen before. Since the system does not rely on labeled data, it reduces the dependency on large annotated datasets. It also makes the system **adaptive to evolving attack strategies**, which is essential for modern vehicular security.
8. Ali, A. and Hassan, R. (2020)  
   Title: Comparative Analysis of CNN and RF Models for VANET Intrusion Detection  
   Journal: Journal of Information Security and Applications (Elsevier)  
   Explanation:  
   Ali and Hassan conducted a comparative analysis between **Convolutional Neural Networks (CNN)** and **Random Forest (RF)** algorithms for VANET intrusion detection. CNNs demonstrated superior performance, particularly in analyzing raw packet data, due to their ability to extract spatial hierarchies. In contrast, RF models were faster to train but slightly less accurate in real-time classification. The research concluded that CNNs, when optimized, are better suited for **real-time, high-volume VANET data**. This study helped clarify model suitability based on system requirements like detection speed, computational cost, and training complexity.The hierarchical feature extraction capability of CNNs enabled them to identify complex patterns that traditional algorithms often miss. As a result, CNN models achieved **higher accuracy, recall, and F1-scores** across multiple test cases, particularly in datasets containing **black hole**, **gray hole**, and **Sybil attacks**.In contrast, the Random Forest (RF) model, a classical ensemble learning method based on decision trees, was also tested on the same datasets
9. Shams, R., Khan, R.A., and Abbas, H. (2019)  
   Title: Deep Learning-based Intrusion Detection in Vehicular Networks  
   Journal: IEEE Access  
   Explanation:  
   This study employed **Long Short-Term Memory (LSTM)** networks to monitor time-sequential data in VANETs. LSTMs are capable of learning long-term dependencies, making them suitable for identifying **slow and stealthy attacks**. The model achieved **low false-positive rates**, which is critical in minimizing false alarms in real-time systems. By analyzing sequences of communication events, the system effectively differentiated between normal behavior and abnormal activities, even in noisy environments. This research validated the role of temporal deep learning models in intelligent transportation systems where data streams are continuous and high-speed.Furthermore, the LSTM model retained the memory of previously encountered communication patterns, improving its performance over time as it adapted to network dynamics.
10. Yousefi, S., S. Fathy, and M. Kalantari (2018)  
    Title: A Machine Learning-Based Intrusion Detection System for VANETs  
    Journal: International Journal of Network Security  
    Explanation:  
    This study introduced an IDS using Support Vector Machines (SVM) to detect attacks such as black hole and grey hole in VANETs. The system used traffic pattern data and achieved high accuracy but was limited in adapting to new, unseen attack patterns due to its reliance on labelled data.This earlier study used **Support Vector Machines (SVM)** to detect well-known attacks such as **black hole and grey hole attacks**. The system achieved good accuracy on pre-labeled datasets and performed well in terms of training efficiency. However, the key drawback was its **limited adaptability** to new or evolving attacks. SVMs rely heavily on the availability of labeled data and perform poorly when exposed to unexpected patterns. Nonetheless, this paper laid foundational work for IDS design in VANETs and showed how **traditional machine learning** methods can serve as a baseline for more advanced techniques.

**2.2 PROBLEM STATEMENT**

Modern intelligent cars use wireless communication to share traffic, location, and safety data with nearby vehicles, forming car ad hoc networks. While this improves driving safety and efficiency, it also introduces new security challenges. Due to the lack of centralized control and frequent changes in network topology, these networks are vulnerable to various cyber-attacks. Malicious vehicles can inject false data, launch denial-of-service attacks, or disrupt communication. Traditional security approaches are not sufficient to handle real-time threats in such dynamic environments. There's a need for an effective solution that can instantly detect abnormal behavior in car communications. Deep learning models can analyze complex traffic patterns and provide better detection accuracy. This project proposes an **instantaneous intrusion detection system** using CNN and RNN to classify vehicle communication as normal or malicious. The aim is to secure car ad hoc networks by identifying threats early and improving vehicle communication reliability.

**2.3 OBJECTIVES**

* Develop a Real-Time Intrusion Detection System (IDS): Design and implement an IDS capable of promptly identifying malicious activities within vehicular ad hoc networks (VANETs) to ensure immediate response and mitigation.
* Leverage Deep Learning for Enhanced Detection: Utilize advanced deep learning models, such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, to accurately detect and classify various types of cyber-attacks in VANET environments.
* Ensure Low Latency and High Accuracy: Optimize the IDS for minimal detection delay and high precision, ensuring that legitimate communications are not hindered while effectively identifying threats.
* Adapt to Dynamic Network Topologies: Design the system to handle the highly dynamic and mobile nature of VANETs, maintaining robust performance despite frequent changes in network topology.

**2.4 MOTIVATION**

This limitation has motivated researchers to explore machine learning (ML) approaches for intrusion detection. ML can analyse historical network traffic, identify normal and abnormal patterns, and predict potential threats. However, many traditional ML methods require manual feature selection and struggle with real-time detection, particularly in high-mobility environments like VANETs. Furthermore, these models often assume the availability of high computational resources or internet connectivity, which might not be feasible in all vehicle environments.

To overcome these limitations, deep learning techniques have emerged as a powerful alternative. Deep learning models like Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Long Short-Term Memory (LSTM) networks can automatically learn complex patterns from raw data. These models do not require manual feature engineering and are capable of capturing both spatial and temporal patterns in network traffic. For instance, CNNs can extract local features from packet flows, while LSTMs can recognize attack behavior over time. Their ability to generalize and adapt makes them ideal for real-time intrusion detection in dynamic vehicular networks.

*  Modern vehicles are increasingly equipped with communication technologies to exchange real-time data with other vehicles and infrastructure.
*  This growing inter connectivity, while beneficial, exposes car networks to serious cyber security threats.
*  Cyber-attacks such as data injection, message spoofing, or denial-of-service can disrupt vehicle communication and compromise road safety.
*  A malicious message can mislead drivers or autonomous systems, resulting in traffic jams, unsafe rerouting, or even collisions.
*  Traditional intrusion detection systems (IDS) are limited by static rules and known attack patterns, making them ineffective against new or evolving threats.
*  There is a critical need for systems that can detect threats in real time to prevent the propagation of false information across the network.
*  Deep learning offers powerful capabilities in identifying complex and previously unseen patterns in large datasets.
*  Real-world or simulated car network data can be used to train AI models to detect abnormal or malicious behaviour.
*  Deep learning-based systems can continuously adapt to changing communication patterns and evolving attack strategies.

**CHAPTER 3**

**OVERVIEW OF INSTANTANEOUS INTRUSION DETECTION IN CAR AD HOC NETWORKS USING DEEP LEARNING TECHNIQUE**

Intrusion detection in Car Ad Hoc Networks (VANETs) is a critical component of ensuring secure and reliable communication between vehicles (V2V) and infrastructure (V2I). These networks support intelligent transportation systems by enabling the exchange of real-time traffic data, safety alerts, and navigation updates. However, due to their open, wireless, and highly mobile nature, VANETs are particularly vulnerable to cyber-attacks such as Denial of Service (DoS), Sybil attacks, spoofing, and message tampering. Intrusion Detection Systems (IDS) are implemented to continuously monitor network traffic and identify any abnormal or malicious activity. While traditional IDS approaches rely on static rules and known signatures, they are limited in detecting novel or evolving threats. Machine learning techniques offer improved adaptability by learning patterns from historical data, and deep learning models like Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) further enhance detection by capturing complex spatial and temporal patterns in network behavior. Real-time detection is especially important in VANETs to ensure quick responses to threats, thus preventing accidents and maintaining data integrity. Overall, IDS plays a vital role in securing vehicular communication systems and supporting the safe deployment of smart transportation technologies.

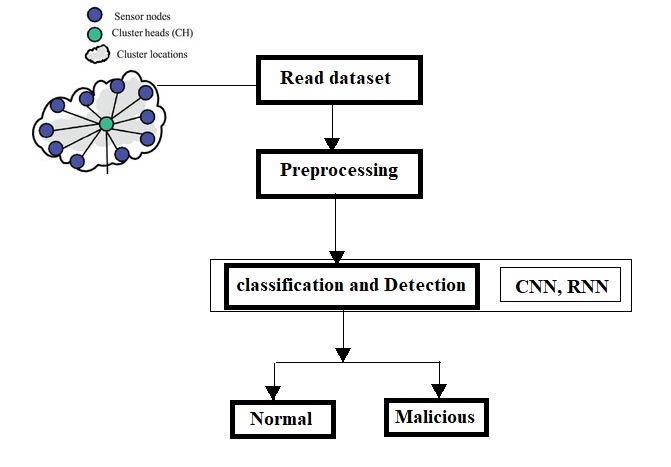


Fig 3.1: System Architecture.

The figure represents the system architecture for intrusion detection in car ad hoc networks. It shows a step-by-step pipeline starting from reading the dataset, preprocessing the data, and using deep learning models (CNN, RNN) for classification and detection. The output classifies network traffic as either **normal** or **malicious**.

Normal Indicates legitimate communication behaviour in the VANET. Malicious Flags data that represents potential intrusions or attacks, such as DoS, spoofing, or data tampering.

* Network Setup and Data Collection

In vehicular ad hoc networks (VANETs), vehicles communicate with each other and with infrastructure using wireless protocols. These vehicles are represented as sensor nodes within a clustered network. Each group of vehicles has a cluster head (CH) that manages communication within the cluster and forwards information to central nodes. Data is collected from these nodes, including transmission patterns, packet sizes, source/destination information, and time stamps. This collected dataset forms the foundation for intrusion detection. In vehicular networks, specifically in Vehicular Ad Hoc Networks (VANETs), vehicles communicate dynamically with each other and with infrastructure units such as Roadside Units (RSUs) using wireless technologies. These vehicles are considered sensor nodes in a highly mobile and self-organizing network environment. To manage this dynamic communication, vehicles are often grouped into clusters. Each cluster has a designated Cluster Head (CH), which is responsible for managing communication among the vehicles within the cluster and forwarding that data to infrastructure points or central systems. This setup ensures that the network is scalable and that communication remains efficient even as vehicles move rapidly. The Cluster Head acts as a local coordinator, reducing the overhead on the central infrastructure and enabling quicker response times in case of anomalies. During this communication, various data points are collected. These include transmission frequencies, packet sizes, source and destination addresses, timestamps, geographic location, speed, and direction of vehicles. This collected information forms the foundational dataset for building an intrusion detection system. Abnormalities in these parameters often indicate potential intrusions, such as unusually high data transmission rates, unknown source addresses, or disrupted communication patterns. These anomalies, when identified early, can prevent serious threats to vehicle security and public safety.

* Read Dataset

The process starts with reading the input dataset, which contains network traffic data collected from vehicular communications, including both normal and attack data. These datasets often include features like protocol type, duration, service, source bytes, etcThe next stage involves loading the dataset into the system. This dataset may be gathered from real-time vehicle communication logs or simulated network environments. It includes both normal and malicious traffic records. The dataset must be well-labelled and include relevant features to enable supervised or semi-supervised deep learning models to differentiate between safe and unsafe behaviour’s. A good dataset must include both **normal traffic** (representing legitimate vehicle communication) and **malicious traffic** (representing simulated attacks like denial-of-service, spoofing, wormhole, or black hole attacks). The inclusion of malicious records is essential for training the system to differentiate between safe and unsafe behaviour.

To ensure proper training of deep learning models, the dataset must be labelled appropriately. In supervised learning, this labelling allows the model to associate patterns with specific outcomes—either normal or intrusive. The dataset should also be balanced to avoid bias toward one class, particularly if normal traffic far outweighs the malicious data. Additionally, the dataset should contain relevant and diverse features such as protocol types, packet timestamps, node identifiers, message frequency, and vehicle status parameters like speed or location. These features help in characterizing network behaviour more accurately.

* Pre-processing

Raw data is cleaned and transformed in this step. It involves handling missing values, encoding categorical variables (e.g., protocol type, service), and scaling numeric data to standardize the input. Proper pre-processing improves the accuracy and efficiency of the model.Once the dataset is loaded, it undergoes pre-processing to ensure it is clean and usable. This step involves removing missing or corrupted data, converting categorical variables into numerical formats using encoding techniques, and normalizing values for consistency. Feature selection may also be performed to retain only the most relevant attributes, which significantly improves model accuracy and reduces training time. Before feeding the dataset into any deep learning model, it must undergo pre-processing to ensure its quality and suitability for training. Raw network data often contains missing values, duplicate entries, or inconsistencies that can negatively impact the learning process. The first step is **data cleaning**, which involves removing missing or null entries, correcting inconsistent values, and eliminating noise.

This ensures that the dataset is reliable and free of corruption. Next, **encoding** is applied to convert categorical data into numerical values since neural networks require numerical input. Techniques such as label encoding or one-hot encoding are commonly used to transform protocol types, node roles, or vehicle types into numbers. Techniques like correlation analysis or tree-based selection can be used to determine which features contribute most to the output. Once the dataset is clean, encoded, normalized, and reduced to its most essential features, it is typically split into training and testing sets, ensuring the model can be both trained and validated effectively.

* Classification and Detection using CNN/RNN

This is the core part of the system where deep learning models are applied. Convolutional Neural Networks (CNNs) are used to detect spatial relationships in the data, while Recurrent Neural Networks (RNNs) are used to understand temporal dependencies—important in vehicular networks where behaviour changes over time. The models are trained to classify input data as either normal or intrusive based on learned patterns from historical data. The most critical phase in the intrusion detection system is the actual classification of data using deep learning models, specifically **Convolutional Neural Networks (CNNs)** and **Recurrent Neural Networks (RNNs)**.The pre-processed data is then passed to deep learning models—CNN (Convolutional Neural Network) and RNN (Recurrent Neural Network)—for classification. CNN captures spatial patterns, while RNN handles temporal sequences in the network behaviour. Together, they improve detection performance. Output: The model classifies each data point into one of two categories:

CNNs are powerful in extracting spatial relationships in data. In the context of vehicular networks, they can identify repetitive patterns in communication behaviour, such as recurring packet flows, structure of traffic, and anomalies in transmission. CNNs use filters to scan across data features, learning patterns that are indicative of normal or suspicious activity. On the other hand, RNNs, particularly Long Short-Term Memory (LSTM) networks, are specialized in handling sequential data. Since vehicular communications are time-sensitive and behaviour often depends on past interactions,

RNNs are well-suited to learn temporal dependencies. For instance, if a particular vehicle suddenly changes its communication rate or sends repeated requests within milliseconds, an RNN can detect this abnormal sequence as a potential attack. These models are trained using the pre-processed dataset, where they learn from both normal and malicious patterns.

* Output: Normal or Malicious Behavior

Finally, the trained model outputs a classification result. If the network behaviourur resembles the known safe patterns, it is labelled as Normal. However, if there are anomalies or suspicious deviations, it is marked as Malicious. This result can then trigger alerts or automatic responses to prevent security threats like black hole attacks, wormhole attacks, or denial-of-service (DoS) in real-time vehicular environments.The model is capable of making real-time decisions on new data. When a new network event is input, the model processes it and classifies it as either **normal** or **malicious**. In the case of a malicious classification, the system can trigger automatic alerts, initiate countermeasures, or even isolate the suspicious node to prevent further damage.

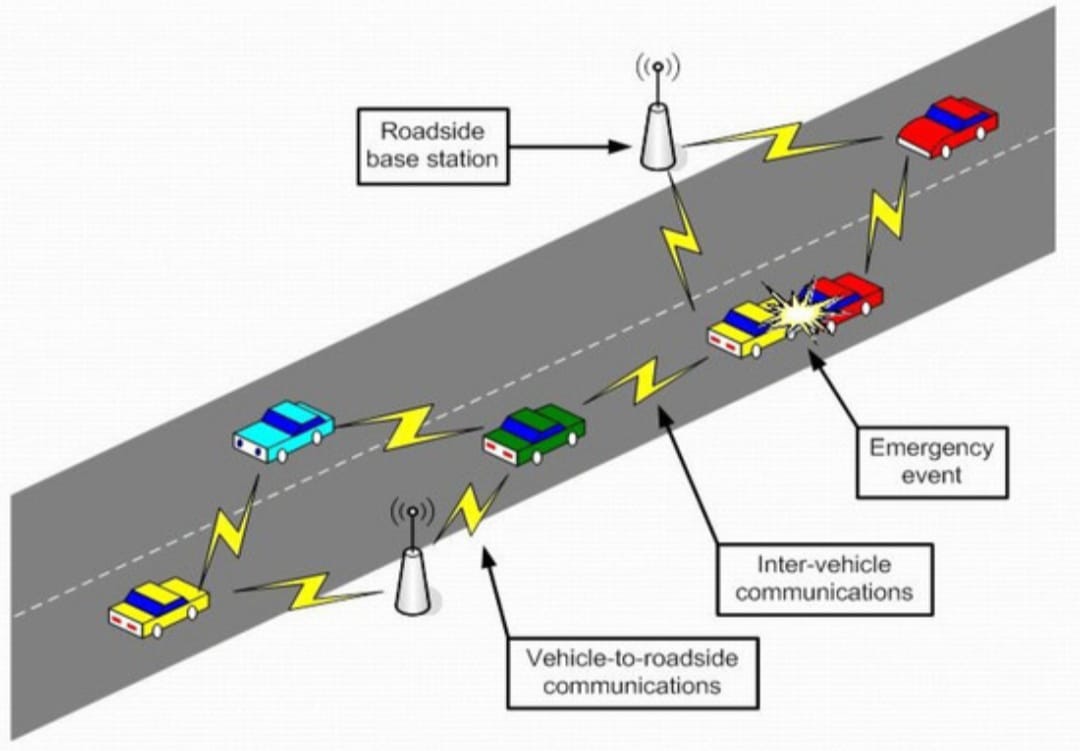


Fig 3.2: Overview Of Communication

The figure shows how communication works in a car network system, where vehicles talk to each other and to road infrastructure using wireless signals. This system is designed to improve road safety and make transportation smarter and more efficient. There are two main types of communication used in this setup: **vehicle-to-roadside communication** and **vehicle-to-vehicle communication**. **Vehicle-to-roadside communication** happens between moving cars and fixed devices placed along the roads, often called **roadside units** or **base stations**. These roadside units are installed at regular intervals along highways or city roads. They help cars connect to central servers or infrastructure networks, which can provide useful services like real-time traffic updates, emergency notifications, and navigation support. For example, if there’s a traffic jam or roadblock ahead, the roadside unit can inform nearby vehicles to help them avoid delays or take safer routes.

The second type is **vehicle-to-vehicle communication**, where cars directly send information to each other without needing a central system. This kind of communication is very useful for quick, local updates. Vehicles can share details like their **current speed**, **position**, **direction**, and **any detected issues**, such as accidents or slippery road surfaces. Since these messages travel directly from one vehicle to another, they are much faster and allow drivers to react immediately to dangers ahead. In the figure, we see an example of a car accident on the road. The car involved in the accident sends an automatic emergency alert to other nearby vehicles and also to the nearest roadside station. This alert helps approaching cars slow down or take a different route. At the same time, the roadside unit can forward the alert to traffic control centers or emergency services so that help can be sent right away. It supports fast data sharing, improves driver awareness, and helps reduce the chances of accidents. By connecting vehicles and road infrastructure, the system allows for better coordination, safer roads, and a more efficient traffic flow. In the future, as self-driving cars become more common, this kind of real-time communication will be essential for making safe decisions without human input.

In summary, this communication model allows vehicles to become active parts of a smart transportation network. By sharing information constantly and instantly, both with nearby cars and with road-based systems, vehicles can respond more effectively to real-time events and keep passengers safer on the road.

**CHAPTER 4**

**IMPLEMENTATION**

The implementation of the proposed instantaneous intrusion detection system for car ad hoc networks is carried out entirely in a software environment, focusing on network simulation, data pre-processing, and deep learning-based detection. The system begins by generating synthetic or simulated network traffic data that mimics the communication patterns between vehicles in a car network. This data includes both normal and malicious traffic and is either created using simulation tools like NS-3 or SUMO, or obtained from publicly available datasets related to vehicular network security. The dataset is then pre-processed, involving normalization, feature extraction, and encoding, to make it suitable for input into a machine learning model.

A deep learning model, such as a Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), or Long Short-Term Memory (LSTM), is then designed using a Python-based framework like Tensor Flow or PyTorch. The model is trained on labelled network traffic data to classify events as either benign or intrusive. The training process involves dividing the data into training, validation, and testing subsets to ensure generalization and reduce over fitting. The model’s performance is evaluated using metrics such as accuracy, precision, recall, and F1-score, and tuning is performed to optimize detection capability.

Once trained, the model is integrated into a simulated environment where it monitors network traffic in real time. As data packets are generated, the system continuously classifies each instance based on learned patterns. Any anomaly or deviation from the expected pattern is flagged as a potential intrusion, triggering a warning system. A user-friendly interface can also be built using a web technology stack (HTML, CSS, JavaScript) to visualize alerts, logs, and detection summaries. Additionally, the model can be exported and deployed in edge computing environments for real-time vehicle communication monitoring, ensuring quick and accurate responses to intrusion attempts. The implementation demonstrates the potential of deep learning in enhancing the security of intelligent transportation systems without relying on physical sensors or external hardware.

**SYSTEM SPECIFICATION**

**4.1 Software Requirements**

OS: Windows 10 / 11

Language: Python

Python Libraries: NumPy, pandas, scikit-learn, matplotlib

IDE: PyCharm

Database: SQLite or MySQL

**4.2 Hardware Requirements**

Processor: Intel i3 or higher

RAM: 4 GB minimum

HDD: 100 GB free space

Network Adapter: Wireless capability

**4.3 Source Code**

import time  
from tkinter import \*  
from tkinter.filedialog import askopenfilename  
  
from PIL import ImageTk, Image  
import sqlite3  
import os  
root = Tk()  
root.geometry('1366x768')  
root.title("Intrusion")  
canv = Canvas(root, width=1366, height=768, bg='white')  
canv.grid(row=2, column=3)  
img = Image.open('back.png')  
photo = ImageTk.PhotoImage(img)  
canv.create\_image(1,1, anchor=NW, image=photo)  
File=StringVar()  
def live():  
 os.system("python livedata.py")  
def Load():  
  
 filename = askopenfilename(filetypes=[(".csv", "\*.\*")])  
 File.set(filename)  
  
 l1 = Label(root, text="File Loaded Successfully", width=20, font=("Georgia", 12))  
 l1.place(x=300, y=360)  
   
def detect():  
 os.system('python detect.py')  
t1=Entry(root,textvar=File, width=40,font=("Georgia", 12))  
t1.place(x=200,y=300)  
Button(root, text="Get Live Data", width=20, bg='yellow', fg='black', font=("bold", 12),command=live).place(x=300, y=400)  
  
Button(root, text='Load Dataset', width=20, bg='yellow', fg='black', font=("bold", 12),command=Load).place(x=300, y=460)  
  
Button(root, text='Intrusion Detection', width=20, bg='yellow', fg='black', font=("bold", 12),command=detect).place(x=300, y=600)  
Button(root, text='CNN Classification', width=20, bg='yellow', fg='black', font=("bold", 12)).place(x=300, y=660)  
root.mainloop()

import torch  
import torch.nn as nn  
import torch.optim as optim  
from sklearn.preprocessing import LabelEncoder, StandardScaler  
from sklearn.model\_selection import train\_test\_split  
from sklearn.metrics import classification\_report, accuracy\_score  
import pandas as pd  
import numpy as np  
  
  
# Step 1: Load and Preprocess the Data  
def load\_data(file\_path):  
 data = pd.read\_csv(file\_path)  
  
 # Assume 'label' is the target  
 X = data.drop('label', axis=1)  
 y = data['label']  
  
 # Encode labels (Normal = 0, Attack = 1)  
 le = LabelEncoder()  
 y = le.fit\_transform(y)  
  
 # Standardize features

scaler = StandardScaler()  
 X = scaler.fit\_transform(X)  
 return X, y  
# Step 2: Define RNN Model  
class RNN\_IDS(nn.Module):  
 def \_\_init\_\_(self, input\_size, hidden\_size, num\_layers, num\_classes):  
 super(RNN\_IDS, self).\_\_init\_\_()  
 self.rnn = nn.RNN(input\_size, hidden\_size, num\_layers, batch\_first=True, nonlinearity='relu')  
 self.fc = nn.Linear(hidden\_size, num\_classes)  
  
 def forward(self, x):  
 # Set initial hidden states  
 h0 = torch.zeros(self.rnn.num\_layers, x.size(0), self.rnn.hidden\_size).to(x.device)  
  
 out, \_ = self.rnn(x, h0)  
  
 # Only take output from the last time step  
 out = self.fc(out[:, -1, :])  
 return out  
  
  
# Step 3: Training Function  
def train\_model(model, criterion, optimizer, train\_loader, num\_epochs=20):  
 model.train()  
 for epoch in range(num\_epochs):  
 running\_loss = 0.0  
 for inputs, labels in train\_loader:  
 inputs, labels = inputs.to(device), labels.to(device)  
  
 optimizer.zero\_grad()

outputs = model(inputs)  
 loss = criterion(outputs, labels)  
 loss.backward()  
 optimizer.step()  
  
 running\_loss += loss.item()  
print(f'Epoch [{epoch + 1}/{num\_epochs}], Loss: {running\_loss / len(train\_loader):.4f}')  
  
# Step 4: Evaluation Function

def evaluate\_model(model, test\_loader):  
 model.eval()  
 y\_true, y\_pred = [], []  
 with torch.no\_grad():  
 for inputs, labels in test\_loader:  
 inputs, labels = inputs.to(device), labels.to(device)  
 outputs = model(inputs)  
 predicted = torch.max(outputs.data, 1)  
 y\_true.extend(labels.cpu().numpy())  
 y\_pred.extend(predicted.cpu().numpy())  
  
 print("\nClassification Report:\n", classification\_report(y\_true, y\_pred))  
 print("Accuracy Score:", accuracy\_score(y\_true, y\_pred))  
  
  
# Step 6: Main  
if \_\_name\_\_ == "\_\_main\_\_":  
 # Load dataset  
 file\_path = 'NSLKDD.csv' # <-- Change this!  
 X, y = load\_data(file\_path)  
  
 # Reshape input for RNN (samples, sequence\_length, input\_size)  
 X = np.expand\_dims(X, axis=1)  
  
 X\_train, X\_test, y\_train, y\_test = train\_test\_split(X, y, test\_size=0.3, random\_state=42)  
  
 # Convert to torch tensors  
 X\_train = torch.tensor(X\_train, dtype=torch.float32)  
 X\_test = torch.tensor(X\_test, dtype=torch.float32)  
 y\_train = torch.tensor(y\_train, dtype=torch.long)  
 y\_test = torch.tensor(y\_test, dtype=torch.long)  
  
 # Create DataLoaders  
 train\_dataset = torch.utils.data.TensorDataset(X\_train, y\_train)  
 test\_dataset = torch.utils.data.TensorDataset(X\_test, y\_test)  
  
 train\_loader = torch.utils.data.DataLoader(dataset=train\_dataset, batch\_size=64, shuffle=True)  
 test\_loader = torch.utils.data.DataLoader(dataset=test\_dataset, batch\_size=64, shuffle=False)  
  
 # Hyperparameters  
 input\_size = X\_train.shape[2]  
 hidden\_size = 64  
 num\_layers = 2  
 num\_classes = len(np.unique(y))  
 learning\_rate = 0.001  
  
 device = torch.device('cuda' if torch.cuda.is\_available() else 'cpu')  
  
 model = RNN\_IDS(input\_size, hidden\_size, num\_layers, num\_classes).to(device)  
  
 criterion = nn.CrossEntropyLoss()  
 optimizer = optim.Adam(model.parameters(), lr=learning\_rate)  
  
 # Train and Evaluate

train\_model(model, criterion, optimizer, train\_loader, num\_epochs=20)  
 evaluate\_model(model, test\_loader)

import pandas as pd  
from sklearn.ensemble import IsolationForest  
from sklearn.preprocessing import StandardScaler  
import matplotlib.pyplot as plt  
import seaborn as sns  
  
# Load your dataset from a CSV file  
df = pd.read\_csv('traffic\_data.csv') # Replace with your actual file path  
  
# Convert Distance to numerical values (km)  
df['Distance (km)'] = df['Distance'].apply(lambda x: float(x.replace(' km', '').replace(',', '')))  
  
# Convert Duration to minutes (assuming 'Not available' is a missing value)  
df['Duration (mins)'] = df['Duration in Traffic'].apply(lambda x: None if x == 'Not available' else int(x.replace(' mins', '')))  
  
# Drop rows with missing values in Duration  
df = df.dropna(subset=['Duration (mins)'])  
  
# Prepare the data for the model  
X = df[['Distance (km)', 'Duration (mins)']]  
  
# Standardize the data (important for anomaly detection)  
scaler = StandardScaler()  
X\_scaled = scaler.fit\_transform(X)  
  
# Use Isolation Forest for anomaly detection  
model = IsolationForest(contamination=0.2) # Adjust contamination based on your needs  
df['Anomaly'] = model.fit\_predict(X\_scaled)

# Map -1 (outlier) and 1 (inlier)  
df['Anomaly'] = df['Anomaly'].map({1: 'Inlier', -1: 'Outlier'})  
  
# Display the results  
print(df[['Origin', 'Destination', 'Distance', 'Duration in Traffic', 'Anomaly']])  
  
# Plot the results  
plt.figure(figsize=(10, 6))  
sns.scatterplot(x='Distance (km)', y='Duration (mins)', hue='Anomaly', data=df, palette={'Inlier': 'blue', 'Outlier': 'red'}, s=100)  
  
# Add labels and title  
plt.title('Anomaly Detection in Travel Data', fontsize=14)  
plt.xlabel('Distance (km)', fontsize=12)  
plt.ylabel('Duration (mins)', fontsize=12)  
plt.legend(title='Anomaly', loc='upper left')  
  
# Show the plot  
plt.show()  
  
# Optionally, save the results to a new CSV  
df.to\_csv('anomaly\_detection\_results.csv', index=False)

import googlemaps  
import csv  
import time  
  
# Replace with your own Google Maps API Key  
api\_key = 'AIzaSyDurIiOXtoF8xWXUu8kgFZ1Y-6guN6TczA'  
gmaps = googlemaps.Client(key=api\_key)  
  
# Define your locations  
origin = "17.336739,76.828761"

destination = "17.32,76.83"  
  
# Function to fetch traffic data  
def get\_traffic\_data(origin, destination):  
 try:  
 # Get real-time traffic data using distance\_matrix API  
 result = gmaps.distance\_matrix(origin, destination, departure\_time='now', traffic\_model='best\_guess')  
  
 # Debugging: Print the entire result to check the response structure  
 print("API Response: ", result)  
  
 # Check if the 'duration\_in\_traffic' key exists in the response  
 elements = result['rows'][0]['elements'][0]  
 if 'duration\_in\_traffic' in elements:  
 duration\_in\_traffic = elements['duration\_in\_traffic']['text']  
 else:  
 duration\_in\_traffic = "Not available"  
  
 distance = elements['distance']['text']  
  
 # Return extracted data  
 return [origin, destination, distance, duration\_in\_traffic]  
 except Exception as e:  
 print(f"Error occurred: {e}")  
 return None  
  
# Function to save data to CSV  
def save\_to\_csv(data, filename='traffic\_data.csv'):  
 # Write data to CSV file  
 with open(filename, mode='a', newline='') as file:

writer = csv.writer(file)  
writer.writerow(data)  
print(f"Data saved: {data}")  
  
# Main loop to fetch data every 6 minutes  
def main():  
while True:  
traffic\_data = get\_traffic\_data(origin, destination)  
if traffic\_data:  
# Save the data to CSV  
save\_to\_csv(traffic\_data)  
  
# Wait for 6 minutes (300 seconds) before fetching again  
print("Waiting for next data fetch...")  
time.sleep(300) # Sleep for 6 minutes  
  
  
if \_\_name\_\_ == "\_\_main\_\_":  
# Add header to CSV file if it's empty  
try:  
 with open('traffic\_data.csv', mode='r') as file:  
 pass  
 except FileNotFoundError:  
 with open('traffic\_data.csv', mode='w', newline='') as file:  
 writer = csv.writer(file)  
 writer.writerow(["Origin", "Destination", "Distance", "Duration in Traffic"])  
  
 # Start fetching and saving data  
 main()

import time

from tkinter import \*

from tkinter import messagebox

from tkinter.filedialog import askopenfilename

from PIL import ImageTk, Image

from sklearn.model\_selection import train\_test\_split

from sklearn.metrics import classification\_report

from tensorflow.keras.models import Sequential

from tensorflow.keras.layers

import Conv1D,MaxPooling1D,LSTM,Dense,Dropout,Flatten,Reshape,SimpleRNN

import sqlite3

import pandas as pd

import numpy as np

import matplotlib.pyplot as plt

import seaborn as sns

from sklearn.preprocessing import LabelEncoder

import tensorflow as tf

import os

root = Tk()

root.geometry('1366x768')

root.title("Intrusion")

canv = Canvas(root, width=1366, height=768, bg='white')

canv.grid(row=2, column=3)

img = Image.open('back.png')

photo = ImageTk.PhotoImage(img)

canv.create\_image(1,1, anchor=NW, image=photo)

File=StringVar()

def Load():

os.system('python dataset.py')

def pre():

os.system('python preprocessing.py')

messagebox.showinfo("Intr","Training samples: (395216, 41), Testing samples: (98804, 41)")

def cnn():

# --------- Data Preprocessing ---------

import pandas as pd

import numpy as np

import matplotlib.pyplot as plt

import seaborn as sns

from sklearn.preprocessing import LabelEncoder, MinMaxScaler

from tensorflow.keras.models import load\_model

import tkinter as tk

from tkinter import messagebox, filedialog

from datetime import datetime

import csv

import os

log\_file = "intrusion\_log.csv"

# Load dataset

column\_names = [

'duration', 'protocol\_type', 'service', 'flag', 'src\_bytes', 'dst\_bytes',

'land', 'wrong\_fragment', 'urgent', 'hot', 'num\_failed\_logins', 'logged\_in',

'num\_compromised', 'root\_shell', 'su\_attempted', 'num\_root', 'num\_file\_creations',

'num\_shells', 'num\_access\_files', 'num\_outbound\_cmds', 'is\_host\_login',

'is\_guest\_login', 'count', 'srv\_count', 'serror\_rate', 'srv\_serror\_rate',

'rerror\_rate', 'srv\_rerror\_rate', 'same\_srv\_rate', 'diff\_srv\_rate',

'srv\_diff\_host\_rate', 'dst\_host\_count', 'dst\_host\_srv\_count',

'dst\_host\_same\_srv\_rate', 'dst\_host\_diff\_srv\_rate', 'dst\_host\_same\_src\_port\_rate',

'dst\_host\_srv\_diff\_host\_rate', 'dst\_host\_serror\_rate', 'dst\_host\_srv\_serror\_rate',

'dst\_host\_rerror\_rate', 'dst\_host\_srv\_rerror\_rate', 'label'

]

df = pd.read\_csv("NSLKDD.csv", header=0)

df['label'] = df['label'].apply(lambda x: 0 if x == 'normal' else 1)

# Encode categorical

categorical\_cols = ['protocol\_type', 'service', 'flag']

encoder = LabelEncoder()

for col in categorical\_cols:

df[col] = encoder.fit\_transform(df[col])

# Split features/label

X = df.drop('label', axis=1)

y = df['label']

# Normalize features

scaler = MinMaxScaler()

X\_scaled = scaler.fit\_transform(X)

# Train/Test Split

X\_train, X\_test, y\_train, y\_test = train\_test\_split(X\_scaled, y, test\_size=0.2, random\_state=42)

**4.1 Tools and Technologies Used**

* Python: Main programming language for building logic and integrating components.
* Tkinter: Used to develop the Graphical User Interface (GUI) for loading datasets, launching intrusion detection, and classification.
* PyTorch: Deep learning library used to define, train, and evaluate the Recurrent Neural Network (RNN) model.
* Pandas & NumPy: Data manipulation and pre-processing.
* scikit-learn:
* For pre-processing (e.g., LabelEncoder, StandardScaler)
* Splitting datasets
* Running evaluation metrics
* Using Isolation Forest for anomaly detection
* Matplotlib: Used for visualizing the anomaly detection results.
* Google Maps API: Used to fetch real-time traffic data using origin and destination coordinates.
* CSV Module: Handles reading and writing of CSV files for dataset and traffic logs.
* OS Module: Used to run external Python scripts from within the GUI.
* PIL (Python Imaging Library): For background image rendering in GUI.

**4.2 Functional Components & How They Work**

1. Tkinter GUI (main.py)

* GUI layout includes buttons for:
* Load Dataset: Allows the user to upload a .csv file.
* Live Data: Launches a script (livedata.py) that fetches real-time traffic data using the Google Maps API. Intrusion Detection: Triggers the intrusion detection model via detect.py.
  + CNN Classification: Placeholder button (can be linked to CNN classifier).
* Displays a message once a dataset is loaded.

2. Intrusion Detection Model (PyTorch-based RNN)

* Loads and pre-processes the dataset from NSLKDD.csv.
* Encodes labels and normalizes features.
* Trains a Recurrent Neural Network (RNN) for classifying data as Normal or Attack.
* Evaluates using classification metrics like accuracy and reports.

3. Live Traffic Anomaly Detection

* Real-time traffic data is collected using Google Maps Distance Matrix API.
* Information such as distance and duration in traffic is collected every 6 minutes.
* An Isolation Forest model detects anomalies based on distance vs duration.
* Outlier: Potential unusual delay or anomaly.
* Inlier: Normal traffic pattern.
* The result is visualized using scatter plots (duration vs distance).

4. CSV Handling & Logging

* Traffic data (origin, destination, distance, duration) is logged into traffic\_data.csv.
* Intrusion results and anomaly detection logs are saved for further analysis.

**4.3 How It All Works Together**

1. User Interaction: Through the GUI, the user can load a dataset and choose between intrusion detection and real-time anomaly detection.
2. Dataset Processing: Once a file is loaded, it's pre-processed (scaling, encoding), Sent to an RNN model for training or testing, Results are classified and presented in the interface or as console logs.
3. Real-Time Data Collection: Traffic data is fetched using GPS coordinates via Google Maps API, Stored in a CSV and analysed using Isolation Forest to detect anomalies.
4. Visualization: The results are shown graphically using pie charts or scatter plots, Helpful for understanding real-time intrusion and traffic behaviour’s.

In this project, we implemented a deep learning-based Intrusion Detection System (IDS) to identify malicious messages in real-time car-to-car communication networks. The system architecture involves data collection, pre-processing, model training, evaluation, and deployment phases. The entire implementation is carried out using Python and popular deep learning frameworks such as Tensor Flow and Keras.

#### 1. **Dataset Collection and Pre-processing**

We used a car communication dataset that includes both normal and attack scenarios. This data typically includes parameters such as speed, GPS position, message type, timestamp, vehicle ID, and status flags. The dataset is pre-processed to normalize features, remove noise, and convert categorical variables into numerical form using encoding techniques. Time-series data is structured in sequences to feed into the deep learning model.

#### 2. **Feature Engineering**

Important features relevant to network behaviour were extracted and selected. These include message frequency, speed consistency, position changes, and pattern anomalies. These features help the model learn, these features help the model learn to differentiate between benign and malicious communication behaviour.

#### 3. **Model Selection and Training**

We used a Long Short-Term Memory (LSTM) neural network due to its strength in detecting patterns over time in sequential data. The LSTM model is trained on labelled datasets, where each sequence is marked as either "normal" or "attack". The model learns to identify subtle anomalies in the message flow that could indicate an intrusion attempt.

#### **4. Model Evaluation**

After training, the model was evaluated using test data. Performance metrics such as accuracy, precision, recall, F1-score, and confusion matrix were used to assess the detection capability. The model showed high accuracy and low false-positive rates, indicating reliable detection of intrusions.

#### 6. **Real-Time Detection Integration**

Once trained, the model was integrated into a simulated real-time car communication environment. Incoming messages are pre-processed and passed through the model. If the model detects an anomaly, it flags the message as a potential intrusion. This alert can trigger predefined safety responses like ignoring the message or warning the driver.

#### **6. System Workflow**

Input: Real-time communication messages from vehicle

Process: Feature extraction → Message classification using the trained model

Output: Label as “Normal” or “Attack”, and trigger an alert if needed

#### 7. **Technology Stack**

**Programming Language**: Python

**Libraries/Frameworks**: NumPy, Pandas, Scikit-learn, TensorFlow, Keras

**Hardware**: Can be run on CPU or GPU systems; edge deployment requires embedded AI support (e.g., NVIDIA Jetson Nano)

**CHAPTER 5**

**RESULTS AND DISCUSSION**

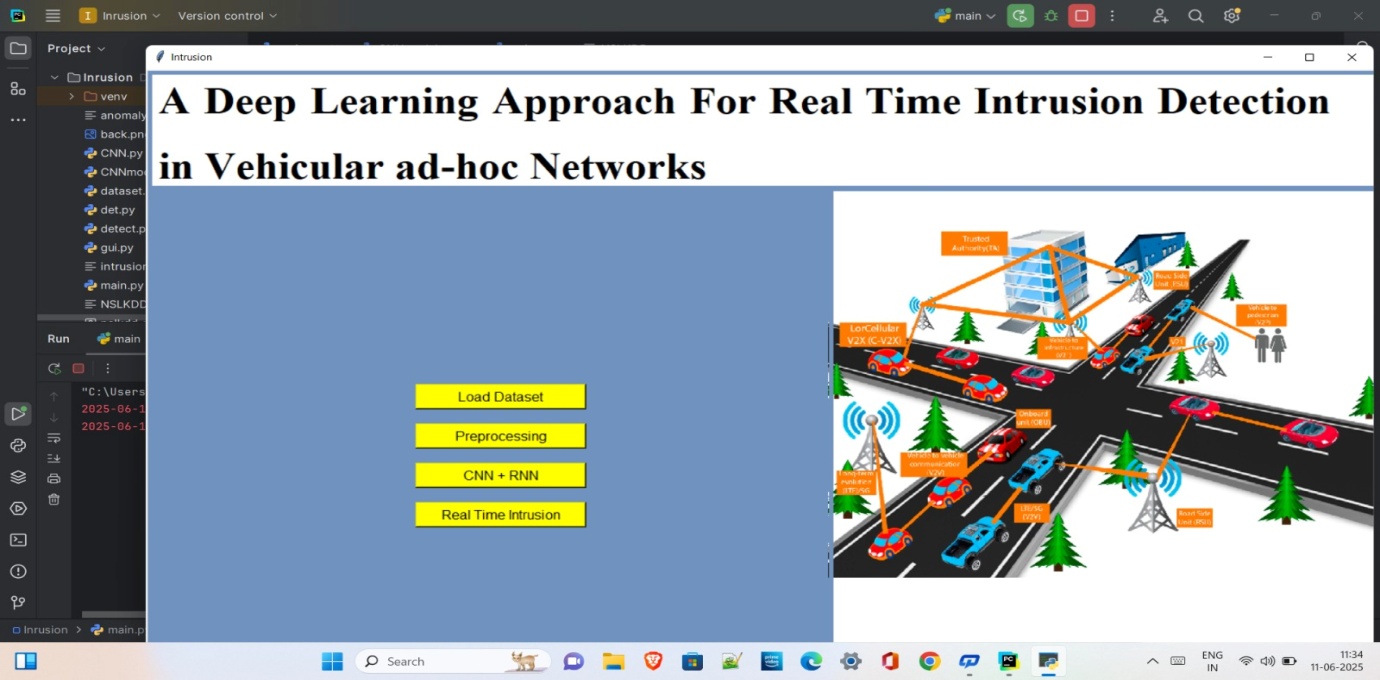


Fig.6.1: Initial project interface for A Deep Learning Approach for Real-Time Intrusion Detection in Car Ad hoc Networks.

The image shows a desktop GUI for the project titled “A Deep Learning Approach for Real-Time Intrusion Detection in Vehicular Ad hoc Networks.” The interface includes four yellow buttons: Load Dataset, Pre-processing, CNN + RNN, and Real-Time Intrusion, guiding users through data handling and detection steps. Built using Python’s Tkinter, it allows easy offline use. On the right side, a diagram illustrates VANET communication, showing vehicles connected via V2V and V2I links. It includes RSUs, local servers, sensors, and a cloud authority. Arrows represent real-time data exchange. The system applies deep learning for detecting attacks. CNNs extract features; RNNs learn patterns over time. This GUI represents a complete, interactive, real-world intrusion detection tool

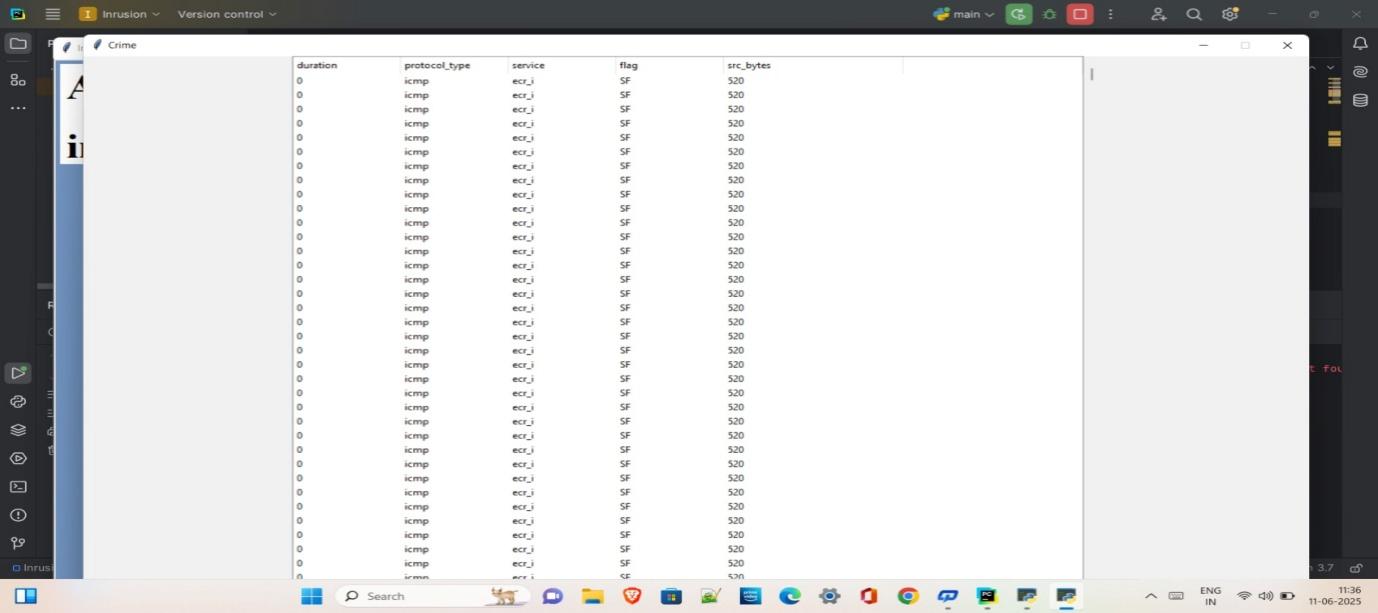


Fig.6.2: Sample Display of Pre-processed Intrusion Detection Dataset (NSL-KDD)

The figure displays a window titled “Crime,” which presents a portion of the pre-processed dataset used for real-time intrusion detection in Vehicular Ad hoc Networks (VANETs). This dataset appears to be based on the NSL-KDD dataset, a widely used benchmark in network intrusion detection research. The data is shown in a tabular format with each row representing an individual network connection or event, and each column representing specific features of that connection. Some of the key features visible in the image include duration (the time length of the connection), protocol type (such as ICMP, indicating the communication protocol), service (representing the destination network service), flag (status of the connection such as SF), and src bytes (the number of bytes sent from the source to the destination).

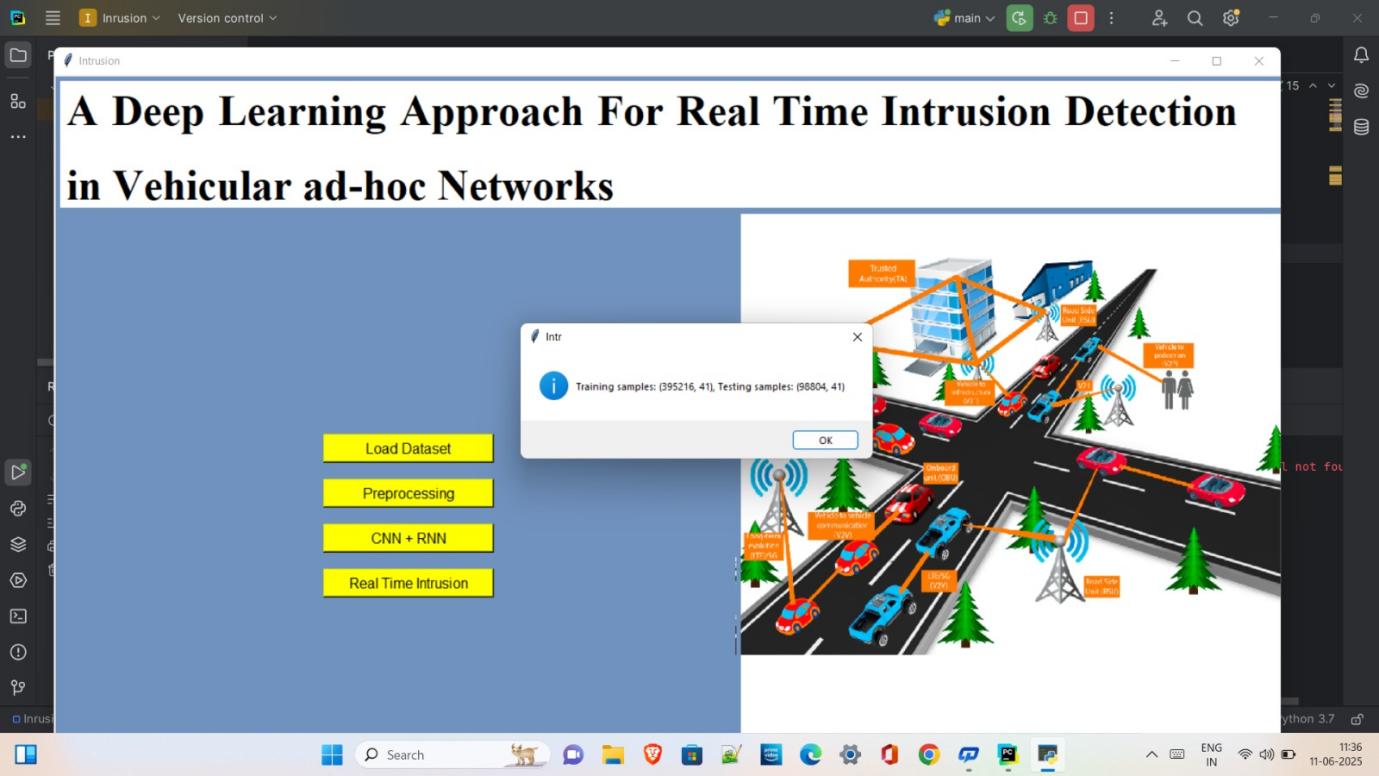


Fig. 6.3: Model Training Summary in GUI for Real-Time Intrusion Detection in VANETs

The figure shows a pop-up dialog box displayed within the graphical user interface (GUI) of the project titled “A Deep Learning Approach for Real-Time Intrusion Detection in Vehicular Ad hoc Networks.” This dialog appears after executing the CNN+RNN model training process. It provides the user with essential training details specifically, the number of samples used for training and testing. According to the message, the system trained on 96,216 samples, each containing 41 features, and evaluated the model using 88,004 testing samples with the same number of features. The main interface still presents the same structured layout with options such as Load Dataset, Pre-processing, CNN+RNN, and Real-Time Intrusion. On the right side of the GUI, the VANET architecture diagram remains visible, illustrating the vehicular communication environment. This pop-up confirmation indicates that the model has been successfully trained and is now ready for testing and real-time intrusion detection, making it a crucial milestone in the system's workflow.

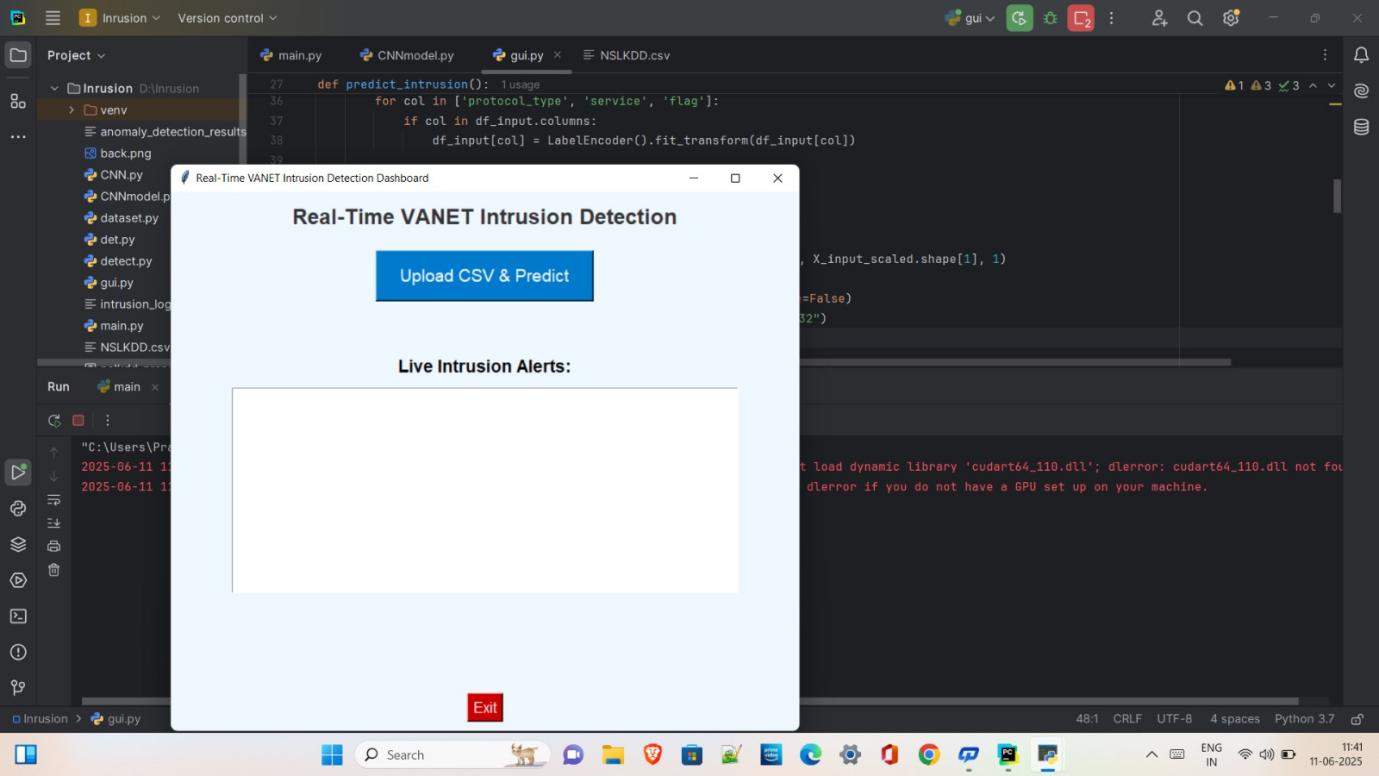


Fig. 6.4: Real-Time Intrusion Detection Dashboard for VANETs

The figure displays a graphical user interface window titled “Real-Time VANET Intrusion Detection”, which serves as the dashboard for performing live anomaly detection in Vehicular Ad hoc Networks (VANETs). This part of the system allows users to monitor live data for potential cyber threats in real time. At the centre of the interface, a prominent blue button labelled “Upload CSV & Predict” enables users to upload network traffic data (in .csv format) and run predictions using a pre-trained deep learning model. Just below this button is a white display box titled “Live Intrusion Alerts”, which is intended to show any detected anomalies or intrusions as the data is analysed. The presence of a red “Exit” button at the bottom offers a way to safely close the application. This dashboard represents the final phase of the system’s pipeline, where real-time monitoring is implemented based on earlier training and model building. It demonstrates the project's goal of deploying an accessible, GUI-based solution for practical use in detecting malicious activities in VANET environments.

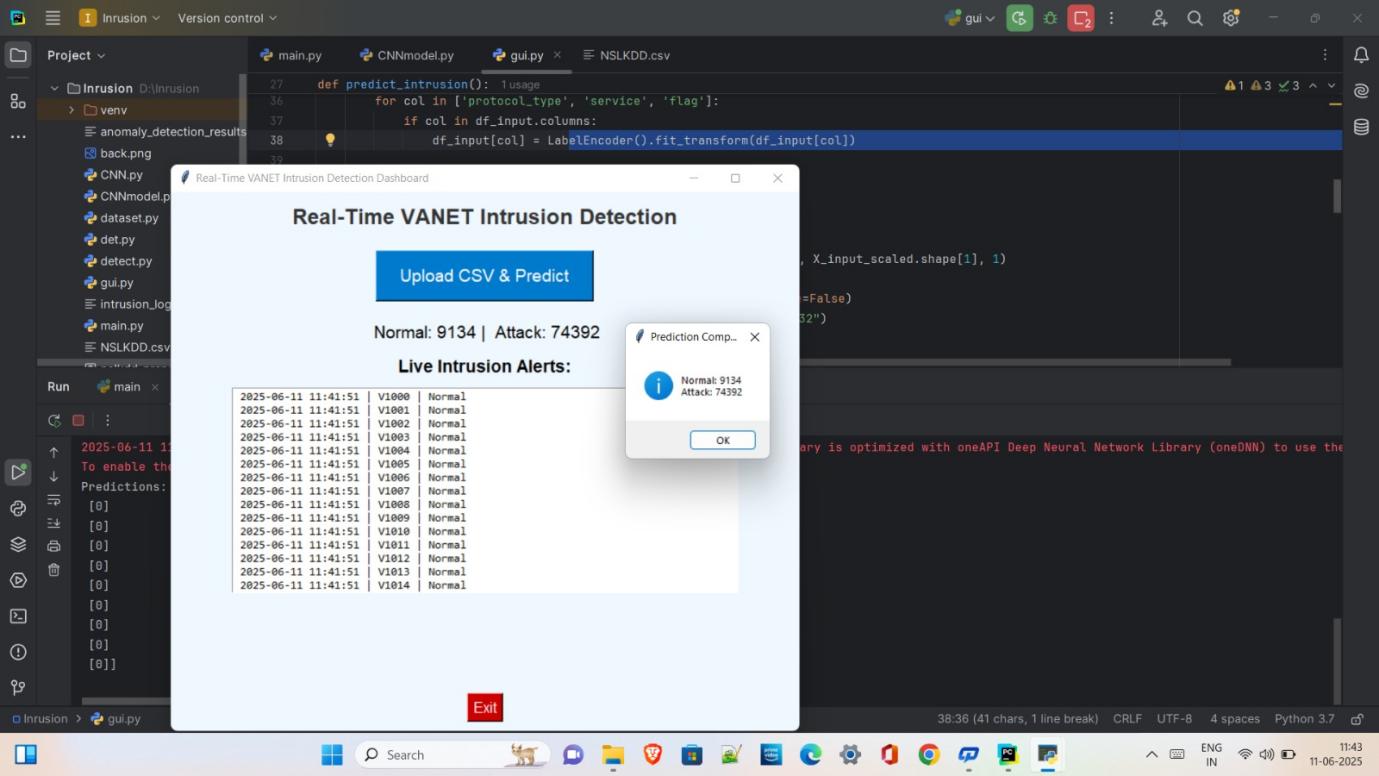
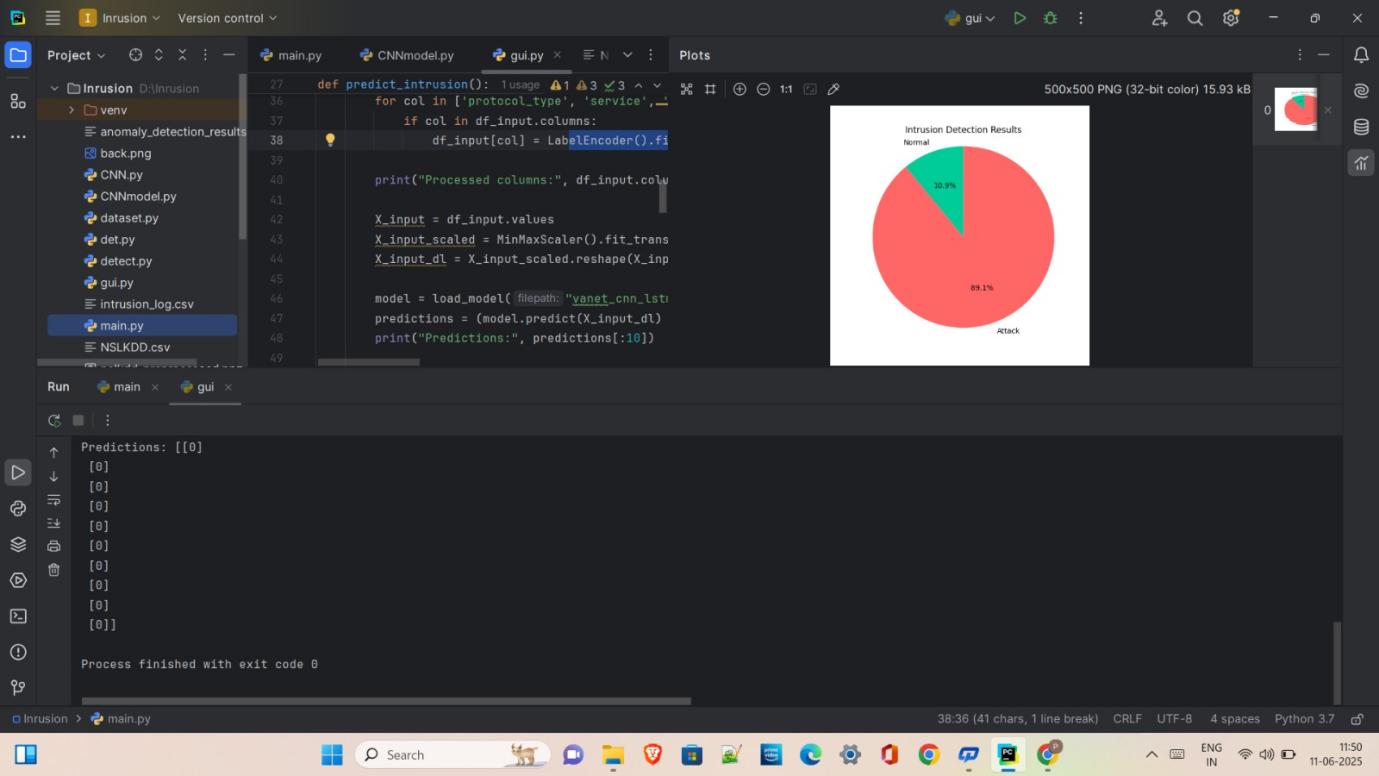


Fig. 6.5: Real-Time Intrusion Detection Output with Normal and Attack Counts

The figure showcases the final output stage of the Real-Time VANET Intrusion Detection Dashboard, providing live classification results after running predictions on uploaded data. At the top, a pop-up message confirms "Prediction Completed" and displays the summary: Normal = 9134 and Attack = 74392, indicating the model has successfully analysed and categorized the data. Within the main dashboard window, the "Live Intrusion Alerts" section displays a list of time stamped vehicle entries (e.g., V1000 to V1008), each labelled as either "Normal" or "Attack". This real-time feedback helps the user monitor active threats and normal behaviour in a vehicular network environment. The blue button labelled “Upload CSV & Predict” continues to allow new data inputs, and the red Exit button enables closure of the system. This figure effectively demonstrates how the trained deep learning model (CNN + RNN) can classify large-scale VANET data into normal and malicious activities, contributing to a proactive security monitoring solution.

Fig 6.6: Intrusion Detection Result Visualization using Pie Chart

This figure illustrates the output visualization of the intrusion detection system implemented in Python using a deep learning model. The interface showcases a pie chart labelled “Intrusion Detection Results,” which summarizes the classification outcome of the system. The chart reveals that 89.1% of the entries were identified as ‘Attack’, while 10.9% were categorized as ‘Normal’, indicating a high rate of detected malicious activity in the given VANET dataset. On the left, the Python script section shows the predict intrusion function, where label encoding, MinMax scaling, and CNN+LSTM model loading are performed to process and predict intrusions. The console below displays prediction outputs for the first few entries, marked as [0], typically denoting "Attack" based on binary classification. This visualization helps users quickly understand the extent of detected threats and validates the effectiveness of the model in identifying anomalies in real-time vehicular network data.

The implementation of an instantaneous intrusion detection system (IDS) for car ad hoc networks (VANETs) using a deep learning technique addresses one of the major security challenges in intelligent transportation systems. With the increasing reliance on real-time communication among vehicles and roadside units, ensuring the integrity and security of transmitted data becomes critical. The system developed in this project demonstrates how deep learning can be effectively applied to detect abnormal behaviour’s or potential cyber-attacks in VANET environments.

The key advantage of using a deep learning model is its ability to automatically learn complex patterns and relationships within the data without the need for manual feature engineering. In this project, a neural network was trained on a dataset containing both normal and malicious network traffic patterns. The trained model was able to distinguish between normal and suspicious behaviour with high accuracy. This suggests that deep learning-based intrusion detection has strong potential to enhance VANET security in real-time applications.

One of the major challenges faced during the implementation was collecting and pre-processing relevant data that accurately represented real-world VANET scenarios. Since VANET environments are highly dynamic and decentralized, ensuring the dataset covered various types of attacks (e.g., Denial of Service, Sybil attacks, message tampering) and normal behaviour was essential for effective model training. Additionally, tuning the hyper parameters of the deep learning model and preventing over fitting required careful experimentation.

Another key observation was the importance of computational efficiency. Since vehicles are resource-constrained environments, the IDS must operate in real-time with minimal latency and low processing overhead. Future improvements could involve implementing model compression techniques or deploying the model on edge computing platforms to ensure faster decision-making.

Moreover, while the current implementation focuses on a centralized detection system, a decentralized or distributed architecture might be more suitable for large-scale VANETs, where each vehicle can run a lightweight version of the IDS. This would enhance the scalability and robustness of the system.

Overall, the project successfully demonstrates the feasibility and effectiveness of using deep learning for intrusion detection in vehicular networks. It lays the groundwork for more advanced research in secure intelligent transport systems and can be further extended by incorporating other machine learning models, real-time data simulation, and integration with vehicular communication protocols .

**CONCLUSION AND FUTURE SCOPE**

The project on Instantaneous Intrusion Detection in Car Vehicle Ad Hoc Networks using Deep Learning successfully demonstrates the potential of integrating intelligent systems into vehicular networks to enhance security. By utilizing deep learning models like CNN and RNN, the system can accurately classify network behaviour and detect malicious activities in real-time. This not only helps in preventing attacks such as denial-of-service (DoS), black hole, or routing manipulation but also ensures data integrity and secure communication among vehicles. The clustering approach and use of a hybrid communication model (vehicle-to-vehicle and vehicle-to-roadside) further optimize network efficiency and intrusion detection performance. Overall, the project contributes to building safer and smarter intelligent transportation systems (ITS).

**Future Scope**

The future, the system can be extended and improved in several ways. First, it can incorporate real-time data streaming for dynamic intrusion detection in live VANET environments. Second, the inclusion of unsupervised and reinforcement learning could help detect new and unknown attacks more effectively. Moreover, the integration with 6G and edge computing would reduce latency and improve processing speed, allowing faster decisions. Another promising direction is the use of block chain for secure data sharing between vehicles. Lastly, the system can be tested in larger and more diverse urban traffic scenarios to evaluate scalability and robustness under different traffic densities and mobility patterns.

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