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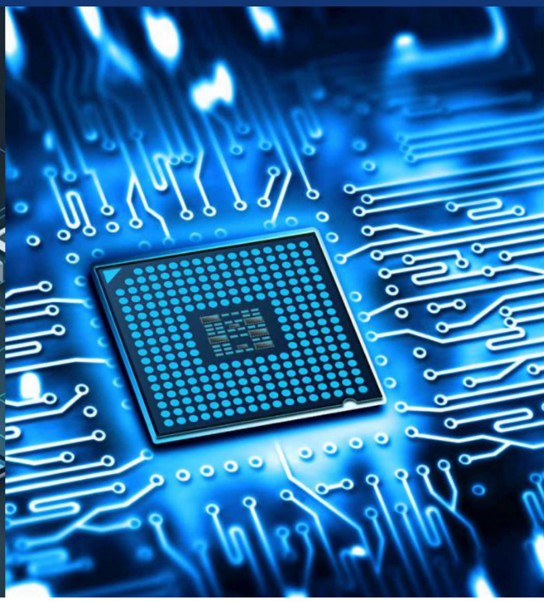

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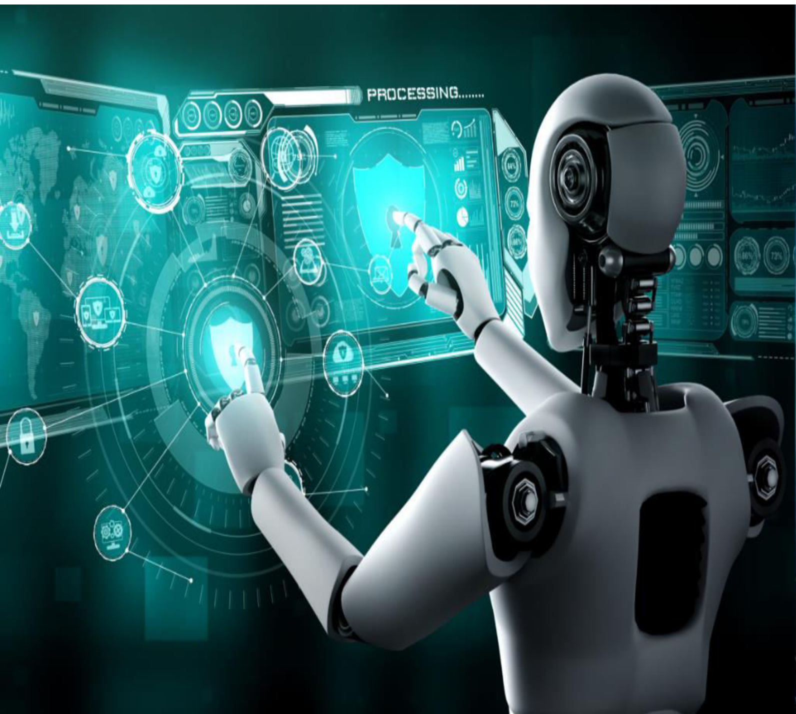

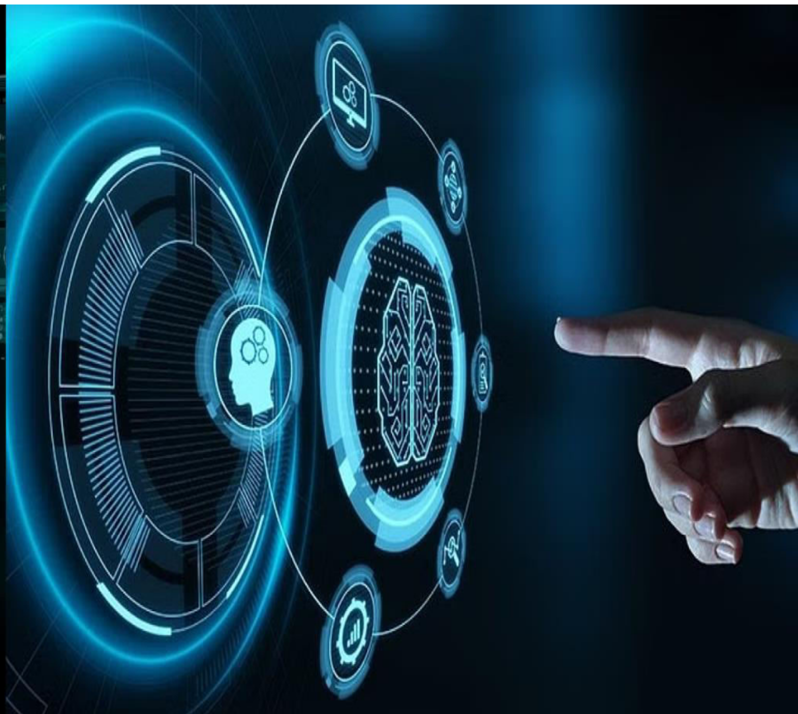

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Cellular Traffic Prediction Using Graph Neural Network

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ABSTRACT: In this work, going present an advanced Graph Neural Network – based approach for Long Term Evolution cellular traffic prediction, addressing the limitations of traditional machine learning. Convolutional Neural Networks are optimized for grid-like data such as images, and struggle with the irregular, graph-based Long-Term. Evolution networks with dynamic spatial relationships between cell towers. To overcome these challenges, we leverage Graph Convolutional Networks to model the inherent graph structure of Long -Term Evolution networks, capturing both spatial and temporal relationships between cell. Used a cleaned towers and pre-processed Long Term Evolution Network Dataset that includes multiple real-world mobility scenarios such as static, pedestrian, car, and bus environments. The model treats Long Term Evolution signals as a graph structure, with cell towers as nodes and inter-cell connectivity as edges based on geographical distance. The suggested Graph Neural Network model dramatically enhances prediction performance and generalization over traditional machine approaches by retaining spatial correlations in the Long-Term Evolution network. With 200 epochs of training, the model had a test accuracy of 85.98%, better than traditional statistical and deep learning approaches in terms of efficiency as well as robustness. By introducing an effective graph-based learning mechanism, we enhance real-time traffic forecasting, adaptive network optimization, and mobility-aware resource allocation in Long Term Evolution networks. The result of Graph Neutral Network in real-world cellular networks, making them a promising approach for next-generation 5G and beyond network architectures

KEYWORDS: LTE – Long Term Evolution, GNN - Graph Neural Networks, GCN - Graph Convolutional Networks, RNN- Recurrent Neural Networks, GAT - Graph Attention Network, CNN – Convolutional Neural Network

I. INTRODUCTION

Cellular networks have evolved significantly over the past decades, providing essential connectivity for millions of users worldwide. With the advent of 4G LTE networks, mobile communication has reached unprecedented levels of reliability, speed, and efficiency [7][8]. However, the increasing demand for high-speed data, real-time applications, and seamless connectivity presents new challenges in network optimization, traffic forecasting, and resource allocation. Accurate cellular traffic prediction is a critical component in ensuring efficient network operations, mitigating congestion, and enhancing quality of service (QoS) for users [9][10][11]. Traditional machine learning-based models for LTE traffic prediction often rely on statistical and deep learning approaches such as regression models, RNNs, and CNNs While these models capture temporal dependencies, they fail to account for the spatial relationships inherent in cellular networks[12][13]. Since LTE networks are fundamentally structured as a graph of interconnected cell towers, traditional models often overlook spatial correlations, dynamic topology changes and inter-cell dependencies. These limitations lead to inaccurate traffic forecasts and inefficient resource allocation strategies [14][15]. To address these shortcomings, this work introduces a GNN - based approach for LTE cellular traffic prediction. Unlike conventional deep learning models, GNNs are specifically designed to process graph-structured data, making them ideal for modeling LTE networks [16][17][18]. The implementation leverages Graph GCN to learn spatial and temporal dependencies between LTE cells, capturing hidden patterns in network traffic fluctuations [19][20][21].

II. LITERATURE SURVEY

Cellular traffic prediction plays a critical role in optimizing resource allocation, load balancing, and congestion control in mobile networks. Over the years, various machine learning and deep learning techniques have been applied to predict LTE network traffic. However, these methods often fail to fully account for the spatial dependencies and dynamic topology that are inherent in cellular networks. This section reviews prior research in LTE traffic prediction and identifies

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their limitations, leading to the development of our Graph Neural Network (GNN)-based solution. Early research in LTE traffic forecasting relied on statistical methods like Auto-Regressive Integrated Moving Average (ARIMA) and Exponential Smoothing (ES) models [5]. These models aimed to predict LTE traffic based on historical trends and seasonal variations. Huang et al. (2016) proposed an ARIMA-based model to predict cellular traffic in urban environments, but it struggled with sudden traffic spikes and mobility-induced variations. Similarly, Zhang et al. (2017) applied Hidden Markov Models (HMM) to analyze network load fluctuations, but this approach failed to account for spatial dependencies between neighboring cell towers, limiting its effectiveness in multi-cell networks. The main limitations of these statistical models include their inability to handle non-stationary data, as LTE traffic is highly dynamic and influenced by varying user behavior, and their lack of spatial awareness, as they treat traffic in each cell independently without considering the correlation between neighboring cells. In an effort to improve forecasting accuracy, researchers turned to machine learning (ML) techniques such as Support Vector Machines (SVM), Random Forests (RF), and Gradient Boosting Trees (GBT). Sun et al. (2018) [14] employed SVM and Random Forests to predict LTE network congestion, achieving better performance than traditional statistical methods, though they still struggled with high-dimensional feature interactions. Wang et al. (2019) [17] introduced a Gradient Boosting Decision Tree (GBDT) model to predict LTE traffic, leveraging network quality parameters such as RSRP, RSRQ, and SINR. However, these ML models struggled to adapt to changing network topologies. The limitations of ML-based models are primarily their dependency on manual feature engineering, which is time-consuming and prone to error, and their limited ability to capture temporal patterns, as tree-based ML models are ineffective at modeling long-term dependencies that are essential for accurate traffic forecasting. With the rise of deep learning, researchers began exploring neural networks, particularly Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and Convolutional Neural Networks (CNNs), for LTE traffic prediction. Kim et al. (2020) [5] applied LSTMs to model time-series LTE traffic data, achieving improved long-term predictions compared to ML models. Chen et al. (2021) [6] enhanced LSTMs with attention mechanisms to improve forecasting stability. However, these models still ignored spatial dependencies and were computationally expensive.

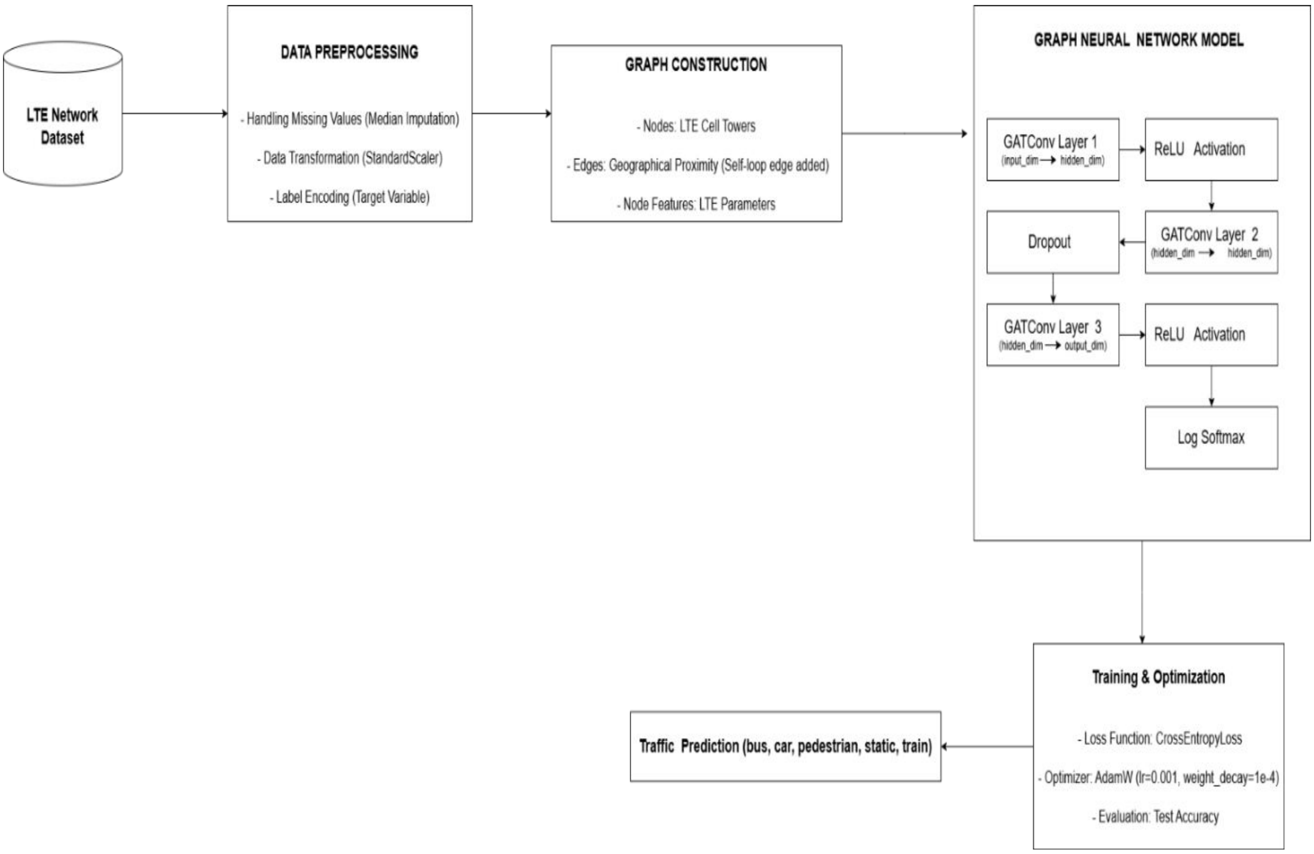

Fig 1 Overall Block Diagram of the proposed work.

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III. METHODOLOGY

A. Materials Used

Dataset: 4G Dataset labeled dataset (https://www.kaggle.com/datasets/aeryss/lte-dataset/)
Programming Languages: Python (with Torch, Torch Geometric, Scikit-learn, NumPy, Pandas, Seaborn.
Frameworks: Flask for API development, Bootstrap for frontend design, and SQLite for database management.
Hardware: NVIDIA GPU l, Intel-based CPU for testing and evaluation.
Development Tools: Visual Studios, Anaconda

B. Step by Step Procedure

Step 1 Data Preprocessing: Feature Selection Used: Longitude, Latitude, Speed, RSRP, RSRQ, SNR, CQI, RSSI, DL_bitrate, UL_bitrate, NRxRSRP, NRxRSRQ, Serving Cell_Distance and Vector Size is [166337, 13]
Merging Data: Multiple LTE signal datasets from different mobility scenarios (bus, car, pedestrian, etc.) were merged into a single Data Frame to create a comprehensive dataset.
Feature Engineering: Irrelevant columns such as timestamps and carrier information, were removed from the dataset.
Handling Missing Data: Missing values in the dataset were imputed using median imputation, a
statistically robust method to preserve data integrity while minimizing the influence of outliers
Normalization: Numerical features were normalized using the Standard Scaler to Normalization: Numerical features were normalized using the Standard Scaler to ensure uniformity in scale and prevent any single feature from dominating the model training process
Label Encoding: The categorical target feature (mobility type) was encoded into numerical labels with scikit-learn Label Encoder. This operation assigns each category a unique integer, making it possible to utilize it within the classification task. Once encoding is done, the initial 'target' column is removed and the encoded target column is used as the target feature for model training and assessment.

Step 2 Graph Construction:
Nodes: Each LTE cell tower in the LTE network is treated as a node in the graph.
Edges: Connections between towers are determined based on geographical proximity and handover interactions. Since this is single node processing and self-loop is created.
Node Features: Each node contains key LTE parameters such as RSRP, RSRQ, SNR, CQI, RSSI, bitrate, and user speed.

Step 3 GNN Model
GNN model based on GAT . GATs were chosen for their ability to learn the importance of neighboring nodes dynamically, allowing the model to focus on the most relevant spatial dependencies. The structure of the GNN model is comprises three GATConv layers, ReLU activation layers, and dropout layers:
GATConv Layer 1: Maps input features of dimension input_dim to a hidden representation of dimension hidden_dim.
ReLU Activation: Applies ReLU activation function after first GATconv layer
Dropout: Dropout layers with a probability of 0.5
GATConv Layer 2: Further refines the hidden representation, maintaining the same dimension hidden_dim.
ReLU Activation: ReLU activation function applied after second GATconv layer.
Dropout: Dropout layers with a probability of 0.5
GATConv Layer 3: Maps the refined hidden representation to the output space of dimension output_dim, corresponding to the number of traffic condition classes.
Log Softmax: Applies Log Softmax layer to produce the prediction.
The GNN model architecture can be formally defined by the following equations
GAT Convolutional Layer Equation

$$x'_i = \alpha_{i,i} W x_i + \sum_{j \in N(i)} \alpha_{i,j} W x_j$$

x'_i is the output feature vector of node i.
x_i is the input feature vector of node i.
N(i) is the set of neighbors of node i.
W is a learnable weight matrix.
$\alpha_{i,j}$ is the attention coefficient between nodes i and j.
Attention Mechanism Equation

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$\alpha_{i,j}$ = softmaxj(eij) eij = aT LeakyReLU(W xi || W xj)
eij is the attention weight between nodes i and j.
a is a learnable attention vector.
|| denotes concatenation.
LeakyReLU is the Leaky Rectified Linear Unit activation function.

Step 4 Model Deployment via Flask API
The trained GNN model was deployed as a RESTful API using the Flask framework to enable real-time LTE data input and prediction.The pre-trained GNN model (gnn_model.pth) and the StandardScaler (standard_scaler.pkl) were loaded into the Flask application.A web UI was developed using HTML
using HTML and Bootstrap to allow users to input LTE signal data.The application processes user input, transforms it into a graph object (in this single node setting, using the standard scaler and creating a self-loop), and feeds it to the GNN model for prediction.The predicted mobility type is retrieved from the GNN model and stored in an SQLite database along with the user input**.**

Step 5 Visualization & Analysis:
Database-Driven Insights: Historical predictions are stored in an SQLite database, which is then accessed to generate insightful visualizations. The application facilitates pagination to handle large datasets efficiently.
Graphical Analysis: The framework generates the following visualizations:
Pie Chart: Depicts the distribution of predicted mobility types across the dataset.
Bar Chart: Presents counts of each mobility class, providing a quantitative comparison.
Line Chart: Monitors the trend of each mobility class over time, which might be useful in the future for time-series-oriented analysis

IV. OBJECTIVES

Network (GNN) model specific to LTE traffic forecasting. This model will utilize graph-based learning to improve spatial awareness and general accuracy of predictions.
Address Limitations of Conventional Methods: Overcome the inherent shortcomings of traditional Machine Learning (ML) and Deep Learning (DL) models in addressing spatial interdependencies and dynamic network topologies. The GNN-based method will be designed to enhance adaptability to actual LTE network conditions.
Model LTE Cell Interactions through Graph-Based Learning: Create a graph model of LTE networks by representing cell towers as nodes and their connections as edges, allowing geographical and temporal dependencies to be incorporated into the predictive model.
Improve Prediction Accuracy and Support Real-Time Forecasting: Obtain high prediction accuracy via the optimization of the GNN architecture. The objective is to support real-time network traffic forecasting to enable proactive resource allocation, traffic congestion control, and network optimization.
Support Scalability and Generalizability: Test the performance of the model with real LTE traffic datasets. Evaluate the capacity of the model to scale well under different network conditions and traffic loads to ensure it can be used in various operational environments.
Compare Performance with Standard Models: Perform a comparative analysis with traditional ML and DL models such as LSTMs, CNNs, and Random Forests. Compare performance on accuracy, complexity, and resilience across various network conditions.

V. PROPOSED SYSTEM

To overcome the shortcomings of current methods, The introduce a GNN-based solution to LTE traffic prediction. This model takes advantage of graph-based learning for effective capture of spatial dependencies, dynamic topology, and real-time adaptability of LTE networks. In this framework, we represent the LTE network as a graph, where the nodes represent individual LTE cell towers and the edges between towers are based on proximity and handover interactions. The graph nodes are empowered with LTE attributes like Reference Signal Received Power (RSRP), Reference Signal Received Quality (RSRQ), Signal-to-Noise Ratio (SNR), Channel Quality Indicator (CQI), Received Signal Strength Indicator (RSSI), bitrate, and user speed [9]. Instead of viewing LTE data as separate time-series sequences, we utilize Graph Convolutional Networks (GCNs) to understand how cells close by shape LTE traffic scenarios. This approach makes it

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possible to capture spatial relationships between cell towers and model dynamics of traffic load variation [10]. The most valuable strengths of method are its potential to capture both spatial and temporal dependencies, adapt to the dynamics of LTE network topologies, and process real-time network changes. GCN-based model learns feature interactions automatically, bypassing the requirement for intensive manual feature engineering, and is more computationally efficient than LSTM and CNN models. Moreover, model yields mobility-aware predictions, which are essential for LTE network real-time adaptability . System implementation consists of building a graph in which nodes are LTE cell towers and edges are established based on cell distance and handover interactions. The boundaries are weighted by proximity and network conditions. The architecture consists of Graph Convolutional Layers (GCN Conv) to discover spatial dependencies, Fully Connected Layers (FC) for end traffic classification, and methods such as Dropout and Batch Normalization for avoiding overfitting. The model is trained on a purified LTE dataset covering different real mobility scenarios like static, pedestrian, car, and bus environments The used optimizer is Adam with learning rate 0.001, and the model is trained for 200 epochs with mini-batch gradient descent in order to be able to effectively handle large datasets. Post-training, our model yields a test accuracy of 85.98% with loss converged to 0.4064%. Graph- based method makes tremendous contributions to the existing conventional approaches through utilization of graph-based learning. In contrast to current models, our approach is capable of capturing spatial and temporal trends in LTE traffic, learn real-time network topological variations, and offer high accuracy (85.98%) while being computationally efficient. By graphically modeling LTE networks, our solution supports real-time traffic prediction, improved congestion control, and smart resource allocation. These features render GNN-based approach extremely efficient for next-generation mobile networks of LTE and 5G, providing a secure solution to manage future mobile networks[10].

VI. PERFORMANCE MEASURES

After 200 epochs of training, the GNN model achieved a test accuracy of 85.98% and a final loss value of 0.4064**.** The trained GNN model was tested on the dataset, and its performance was measured with different metrics. The model performed Test Accuracy: 85.98%**,** Recall:85.98%, F1-score:86%, Precision:88%

Accuracy=TP+TN/FP+FNTP+TN

Precision=TP/TP+FP

Recall=TP/TP+FN

F1=2×Precision×Recall/Precision+Recall

Class	Precision	Recall	F1 Score
bus	0.88	0.92	0.90
car	0.82	0.78	0.80
pedestrian	0.87	0.85	0.86
static	0.90	0.89	0.89
Train	0.95	0.92	0.94
AVG	0.88	0.8598	0.86

TABLE 1 Performance measures using classification report

VII. COMPARATIVE RESULT ANALYSIS

Model	Precision	Recall	F1-Score
Logistic Regression	0.72	0.70	0.71
Support Vector Machine	0.76	0.75	0.75
Decision Tree	0.78	0.77	0.77
GNN	**0.85**	**0.84**	**0.85**

TABLE 2 Performance evaluation of proposed framework compared to other state– of – the techniques

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VIII. GNN OUTPUTS

	Timestamp	Longitude	Latitude	Speed	Operatorname	CellID	NetworkMode	RSRP	RSRQ	SNR	...	RSSI	DL_bitrate	UL_bitrate	State	NRxRSRP	NRxRSRQ	ServingCell_Lon	ServingCell_Lat	ServingCell_Distance	target
0	2018.01.25_19.50.43	-8.466939	51.897914	46	B	2	LTE	-99	-14	-2.0	...	-82	1688	31	D	-100.0	-17.0	-8.464806	51.891945	679.6699999999996	bus
1	2018.01.25_19.50.44	-8.466616	51.897283	30	B	2	LTE	-99	-14	-1.0	...	-78	1688	31	D	-100.0	-17.0	-8.464806	51.891945	606.4099999999997	bus
2	2018.01.25_19.50.44	-8.466616	51.897283	30	B	2	LTE	-99	-14	-2.0	...	-78	1498	27	D	-100.0	-17.0	-8.464806	51.891945	606.4099999999997	bus
3	2018.01.25_19.50.46	-8.466616	51.897283	30	B	2	LTE	-98	-15	-1.0	...	-81	1286	24	D	-103.0	-18.0	-8.464806	51.891945	606.4099999999997	bus
4	2018.01.25_19.50.47	-8.466616	51.897283	30	B	2	LTE	-98	-15	-1.0	...	-91	548	20	D	-103.0	-18.0	-8.464806	51.891945	606.4099999999997	bus

5 rows × 21 columns

Fig 2.1 Merge all Data Frames into a single Data Frame

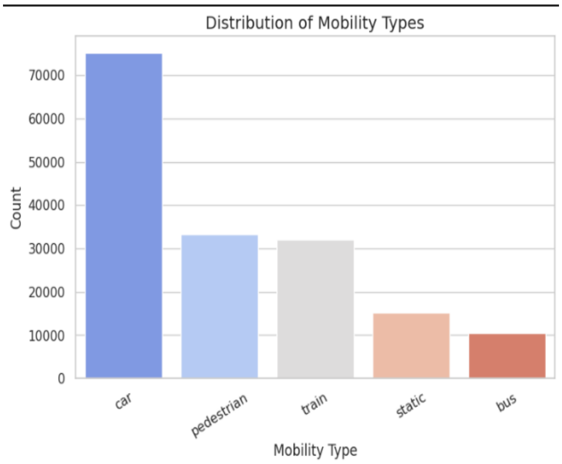

Fig 2.2 Distribution of Mobility Types

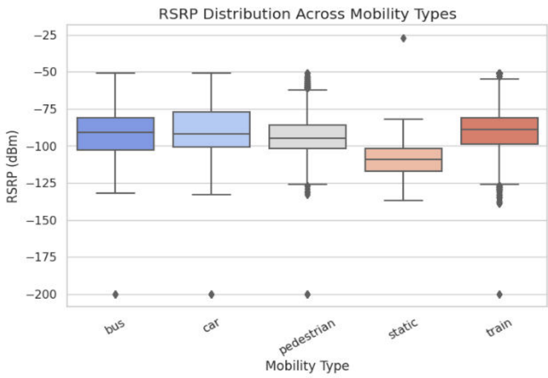

Fig 2.3 RSRP Distribution Across Mobility Types

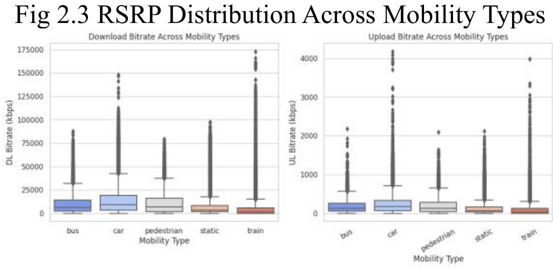

Fig 2.4 Download Bitrate Across Mobility Types of DL Bitrate (Download rate) and UL Bitrate(Uplink rate) at the device

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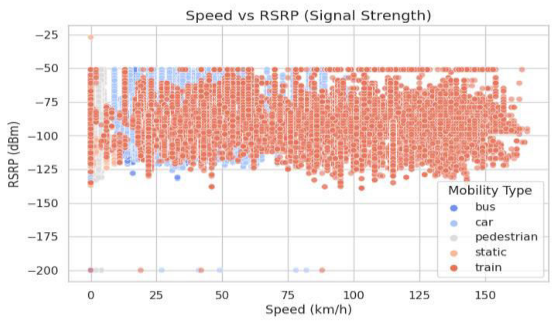


Fig 2.5 Speed vs RSRP (Signal Strength)

IX RESULT AND DISCUSSION

The system is structured as a three-step process to predict accurately and represent effectively. First, the users supply input by entering numerical data as comma-separated values into the input box. After clicking the "Predict" button, the Graph Neural Network (GNN) model trained on the data processes the input data and produces a predicted class label. This prediction would fall into one of several categories like car, pedestrian, bus, train, or static based on the input values. This auto-classification assists in rapid decision-making by making use of the learning done by the model from past data.

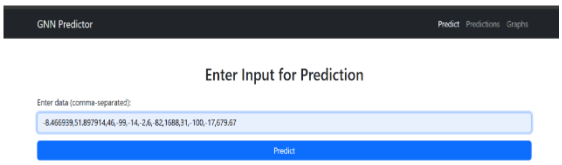
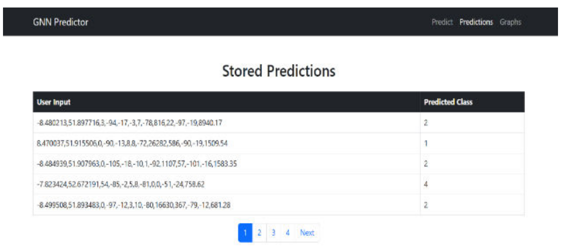


Fig 3.1 Users enter numerical data as comma-separated values in the input box

The second step involves maintaining transparency and traceability by registering the predicted class and the related user input in an orderly table. This makes it possible for users to recall past predictions, confirm model accuracy, and identify trends over time. Recording predictions also aids in model refinement to enhance reliability for subsequent use.



User Input	Predicted Class
-8.480213,51.897716,3,-94,-17,-3,7,-78,816,22,-97,-19,8940.17	2
8.470037,51.915506,0,-90,-13,8,8,-72,26282,586,-90,-19,1509.54	1
-8.484939,51.907963,0,-105,-18,-10,1,-92,1107,57,-101,-16,1583.35	2
-7.823424,52.672191,54,-85,-2,5,8,-81,0,0,-51,-24,758.62	4
-8.499508,51.893483,0,-97,-12,3,10,-80,16630,367,-79,-12,681.28	2

Fig 3.2 The predicted class is stored in a table, along with the corresponding user input.

Visualization of the prediction output for easier interpretation is the ultimate step. Several graphical representations are created to offer insights into the forecasted data. A pie chart shows the percentage distribution of different forecasted classes, offering a clear indication of how often each category occurs. A bar chart displays the number of predictions per class, enabling frequency analysis and comparison across various categories. In addition to this, a line chart is employed to present the trend of predictions over time so that the repeated patterns and fluctuations in data can be easily observed.

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Such visualizations further improve the general understanding of the performance of the model and aid users in making data-driven decisions effectively.

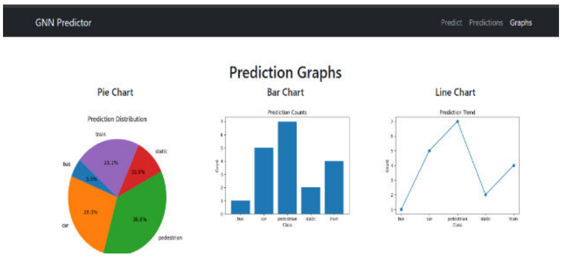

Fig **3.3** The system generates graphs to summarize the prediction results

X. CONCLUSION

The proposed GNN-based LTE traffic prediction model represents a major advancement in network traffic forecasting by addressing the limitations of traditional methods. It effectively captures spatial dependencies and adapts to dynamic topologies, improving accuracy and reliability. However as mobile networks continue evolving toward 5G, 6G, and intelligent edge computing, further enhancements can improve scalability, real-time deployment, and multi-modal learning. By integrating real-time edge inference, dynamic graph learning, multi-modal data fusion, and anomaly detection, the model can develop into a fully autonomous, self-optimizing cellular traffic prediction system. Th ese improvements will play a crucial role in shaping next-generation mobile networks, leading to smarter, more efficient, and secure wireless communications

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