TRAFFIC MANAGEMENT USING GNN AND MAB WITH SDN ORCHESTRATION

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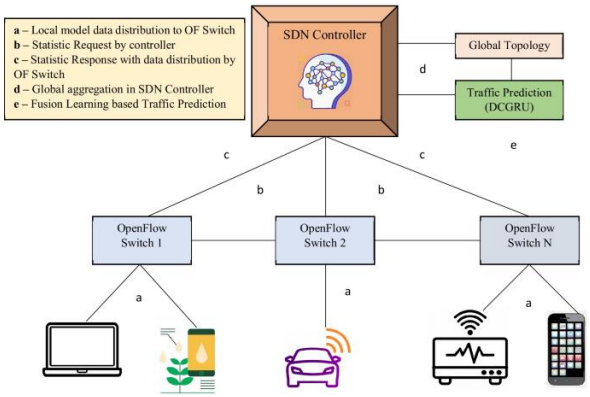
Phase 5 Submission Document

Project Title: Traffic Management

Phase 5: Project Documentation & Submission

Topic: In this section we will document the complete project and prepare it for submission.



TRAFFIC MANAGEMENT

Introduction:

- Traffic management is a critical task in software-defined IoT networks (SDN-IoTs) to efficiently manage network resources and ensure Quality of Service (QoS) for end-users. However, traditional traffic management approaches based on queuing theory or static policies may not be effective due to the dynamic and unpredictable nature of network traffic. In this paper, we propose a novel approach that leverages Graph Neural Networks (GNNs) and multi-arm bandit algorithms to dynamically optimize traffic management policies based on real-time network traffic patterns.

- Specifically, our approach uses a GNN model to learn and predict network traffic patterns and a multi-arm bandit algorithm to optimize traffic management policies based on these predictions. We evaluate the proposed approach on three different datasets, including a simulated corporate network (KDD Cup 1999), a collection of network traffic traces (CAIDA), and a simulated network environment with both normal and malicious traffic (NSL-KDD).

- The results demonstrate that our approach outperforms other state-of-the-art traffic management methods, achieving higher throughput, lower packet loss, and lower delay, while effectively detecting anomalous traffic patterns. The proposed approach offers a promising solution to traffic management in SDNs, enabling efficient resource management and QoS assurance.

Keywords:

Traffic management;anomaly detection;Intrusion detection;Network security;Internet of things;Network traffic analysis;Machine learning;SDN(software-defined networking);GNN(graph neural metwork);MAB(multi-armed bandit)

TECHNIQUES:

Traffic Data Collection:

Gather real-time traffic data using various sources like traffic cameras, sensors, and GPS data from vehicles.

Data Preprocessing:

Clean and format the collected data. This may include removing outliers, imputing missing values, and aggregating data.

Traffic Flow Analysis:

Analyze traffic patterns, congestion points, and identify areas with high traffic volume. Techniques like data visualization and time-series analysis can help with this.

Machine Learning Models:

Utilize machine learning algorithms for predictive analysis. Models like regression and time series forecasting can help predict traffic patterns.

Real-Time Monitoring:

Implement a system to monitor traffic in real-time. This may involve developing a dashboard that displays live traffic data and alerts for congestion or accidents.

Optimization Algorithms:

See optimization techniques to suggest traffic signal timings and lane management for improving traffic flow.

Data Visualization:

Create interactive maps and charts to visualize traffic data for better decision-making.

DATASETS:

Traffic Flow Dataset:

Real-time data from IoT sensors, including vehicle count and speed.

Weather Dataset:

Weather conditions, such as temperature, precipitation, and wind speed.

Environmental Dataset:

Environmental data, including air quality, noise levels, and road conditions.

Traffic Signal Data:

Real-time data from traffic signal controllers.

Historical Traffic Data:

Historical traffic data for training predictive models and understanding long-term traffic trends.

IMPORTING THE NECESSARY LIBRARIES:

1.Pandas:

For data manipulation and analysis, especially when working with structured traffic data.

2.NumPy:

Useful for numerical operations and working with arrays, which can be helpful for mathematical modeling.

3.Scikit-Learn:

A machine learning library that provides various algorithms for prediction and classification tasks.

4.TensorFlow or PyTorch:

For deep learning and neural network-based traffic prediction models.

5.Matplotlib and Seaborn:

For data visualization, which can help in presenting traffic data trends and patterns.

6.Folium:

A library for interactive mapping, which can be handy for visualizing traffic conditions on maps.

7.GeoPandas:

If your project involves geospatial data, GeoPandas can help with handling and analyzing geospatial data.

8.Statsmodels:

Useful for statistical analysis of traffic data, especially when looking at factors affecting traffic.

9.NetworkX:

If your project involves road network analysis, NetworkX is a powerful library for working with graphs and networks.

Proposed model:

Traffic management is a critical step in optimizing network performance by controlling the rate of data transmission. It can help to manage congestion and reduce packet loss, improving the overall quality of service (QoS) for end-users. In this section, we will discuss the traffic management component of the proposed model.

Traffic management involves regulating the flow of data through the network by introducing delays and buffering packets. This is typically achieved using a token bucket algorithm, where tokens are generated at a fixed rate and consumed by packets as they are transmitted. If the bucket is empty, packets are queued until sufficient tokens are available.

The token bucket algorithm can be represented mathematically as follows: At time *t*, the number of tokens in the bucket can be calculated as:

$$B(t)=\min(B(t-1)+r(t-tlast),Bmax)$$

where $B(t-1)$s the number of tokens at the previous time step, r is the token generation rate, t is the current time, $tlast$ is the time when the last token was generated, and $Bmax$ is the maximum bucket size.

When a packet of size P arrives at time t, it is immediately transmitted if there are enough tokens available in the bucket:

$$\text{if}B(t)\geq P\text{, thentransmitthepacket}$$

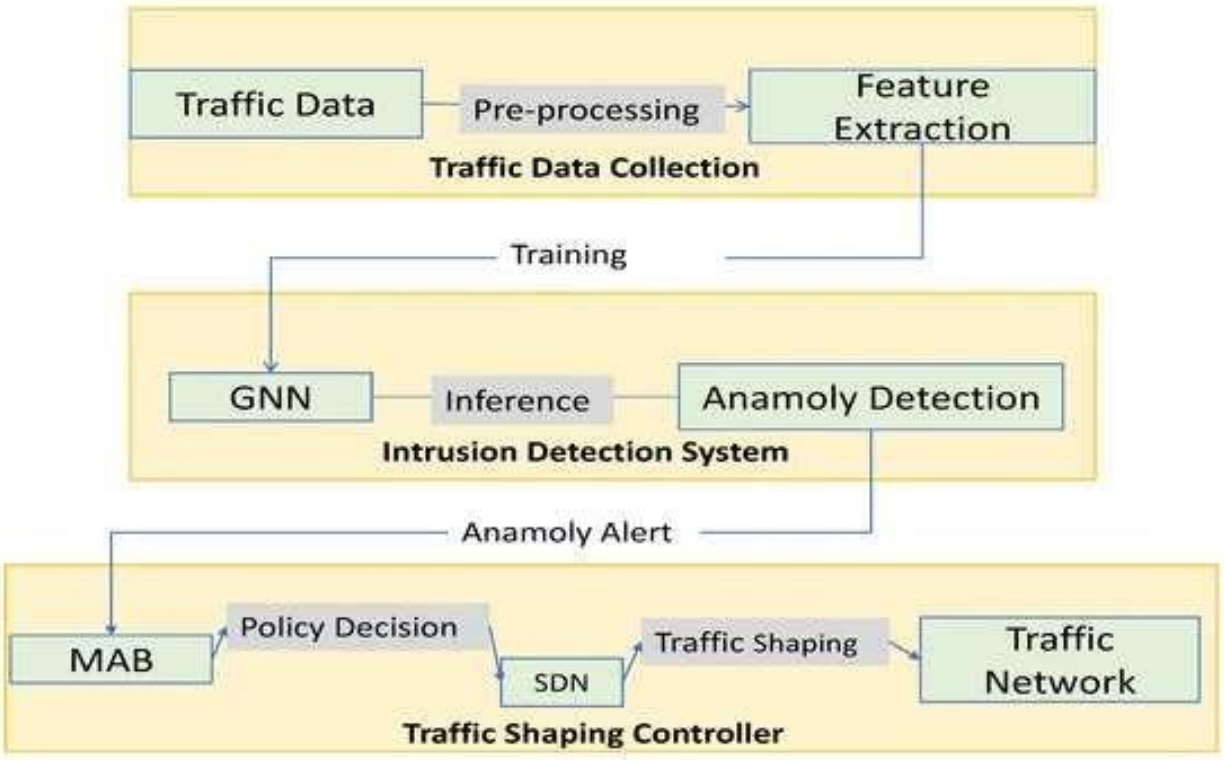
Otherwise, the packet is queued until sufficient tokens become available:

if$B(t)<P$, thenaddthepackettothequeueif ,thenaddthepackettothequeue. Packets in the queue are transmitted in order of arrival as soon as sufficient tokens become available.

The token bucket algorithm can be further optimized by adjusting the token generation rate based on network conditions. For example, if congestion is detected, the token generation rate can be reduced to prevent further congestion.

Data flow:

The Data flow of the proposed starts with the input data, which is passed through a feature extraction module to extract relevant features that will be used for traffic management. The extracted features are then passed to the GNN module, which is responsible for learning the complex patterns in the traffic data and predicting the optimal traffic-shaping policy.



GNN for Understanding Traffic Pattern:

Graph Neural Networks (GNNs) are a type of deep learning method that have recently gained popularity in the field of traffic analysis and prediction. GNNs are particularly effective in modeling and analyzing data that can be represented as graphs, which makes them well-suited for analyzing traffic patterns.

The basic idea behind GNNs is to learn a set of node and edge embeddings that capture the underlying structure of the graph. These embeddings can then be used to perform various downstream tasks, such as node classification, edge prediction, or graph clustering.

In the context of traffic analysis, GNNs can be used to model traffic flow data as a graph, where each node represents a road segment or intersection and each edge represents the flow of traffic between them. The GNN can then learn a set of embeddings that capture the underlying patterns of traffic flow, such as congestion, bottlenecking, and routing preferences.

The mathematical equations used in GNNs are typically based on messagepassing algorithms, which allow nodes in the graph to communicate and update their embeddings based on the embeddings of their neighbours. One commonly used message-passing algorithm is the Graph Convolutional Network (GCN), which is based on the following equation:

$$\{h(l+1)i=\sigma(\sum j\in\mathcal{N}(i)1cijW(l)h(l)j)$$

Necessary Steps To Follow:

1.Import Libraries:

Start by importing the necessary libraries.

Program:

```
import numpy as np import
pandas as pd  import
matplotlib.pyplot as plt
import seaborn as sns
import datetime import
tensorflow
from statsmodels.tsa.stattools import
adfuller from sklearn.preprocessing import
MinMaxScaler from tensorflow import keras
from keras import callbacks
from tensorflow.keras import Sequential  from tensorflow.keras.layers import
Conv2D, Flatten, Dense, LSTM, Dropout, GRU
, Bidirectional
from tensorflow.keras.optimizers import SGD from
tensorflow.keras.models import Sequential from
tensorflow.keras.layers import GRU, Dropout, Dense
from tensorflow.keras.optimizers import SGD from
tensorflow.keras import callbacks import math
from sklearn.metrics import mean_squared_error

import warnings
warnings.filterwarnings("ignore")
```

2.load the dataset:

Load your dataset into a pandas Dataframe.You can typically find traffic prediction datasets in csv format,but you can adapt this code to other format as needed.

Program:

```
data = pd.read_csv(“../input/traffic-prediction-dataset/traffic.csv”) data.head()
```

3.Data Exploration:

Perform data exploration to understand your data better.This includes checking for missing values,exploring the data's statistics, and visualizing it to identify patterns.

Program:

```
data["DateTime"]= pd.to_datetime(data["DateTime"]) data =
data.drop(["ID"], axis=1) #dropping IDs data.info()
```

4.Feature Engineering:

Depending on your dataset,you may need to create new features or transform existing ones.This can involve one-hot encoding categorical variables , handling date/time data,or scaling numerical features.

Program:

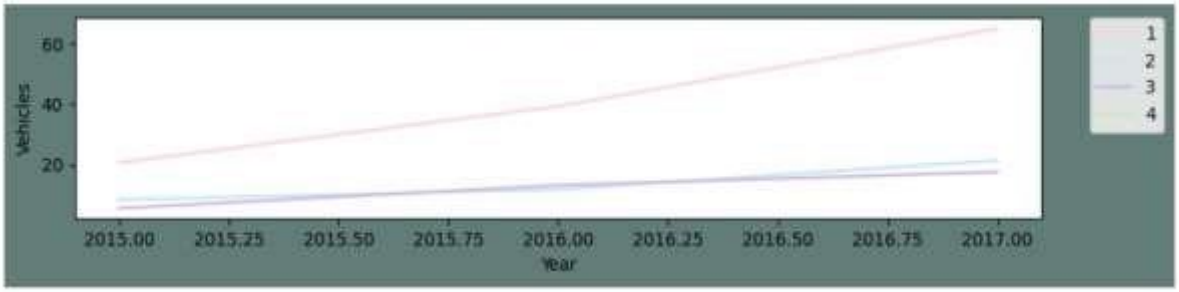
```
df["Year"]= df['DateTime'].dt.year
df["Month"]= df['DateTime'].dt.month
df["Date_no"]= df['DateTime'].dt.day
df["Hour"]= df['DateTime'].dt.hour df["Day"]=
df.DateTime.dt.strftime("%A") df.head()
```

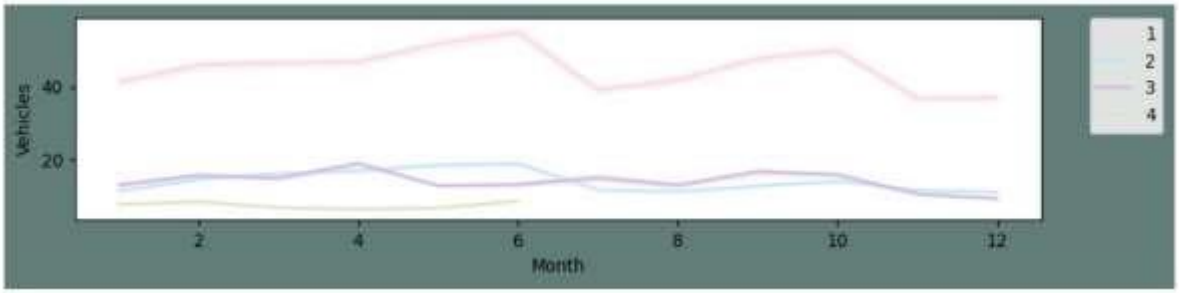
5.Exploratory Data Analysis(EDA):

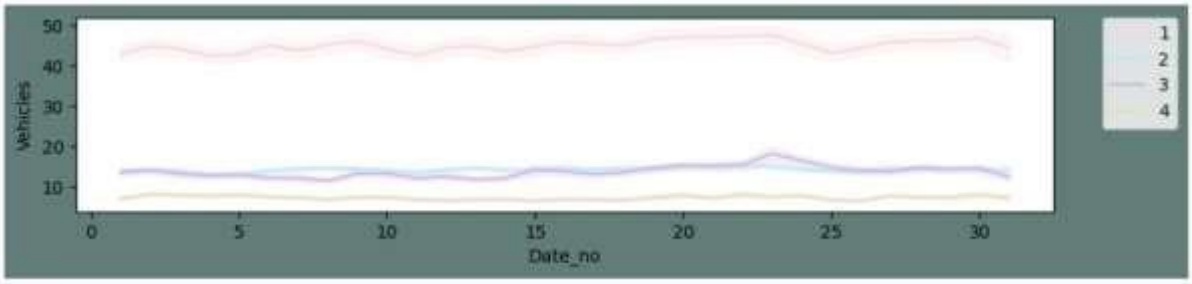
Perform data exploration to understand your data better.This includes checking for missing values,exploring the data's statistics, and visualizing it to identify patterns.

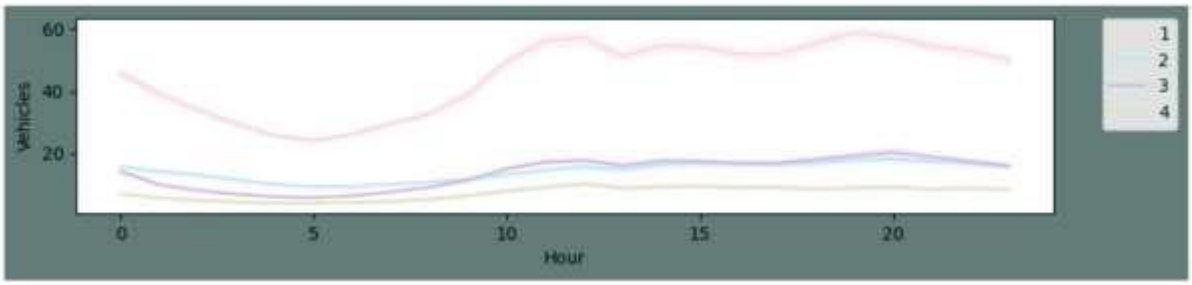
Program:

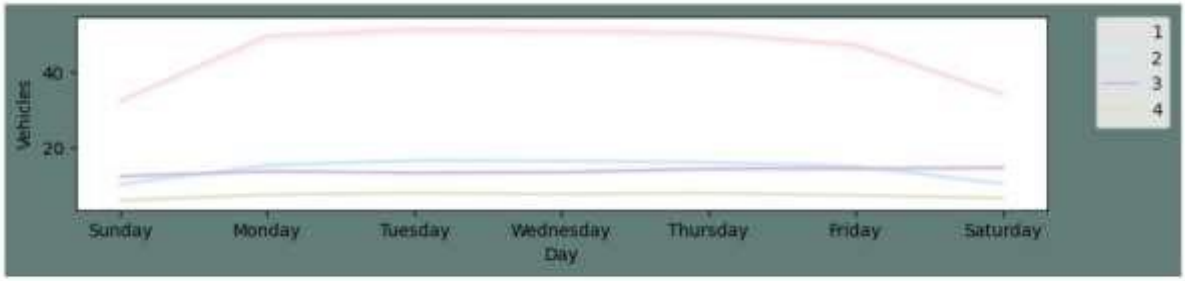
```
new_features = [ "Year","Month", "Date_no", "Hour", "Day"]
for i in new_features:
plt.figure(figsize=(10,2),facecolor="#627D78")
    ax=sns.lineplot(x=df[i],y="Vehicles",data=df, hue="Junction", palette=colo
rs )
    plt.legend(bbox_to_anchor=(1.05, 1), loc=2, borderaxespad=0.)
```









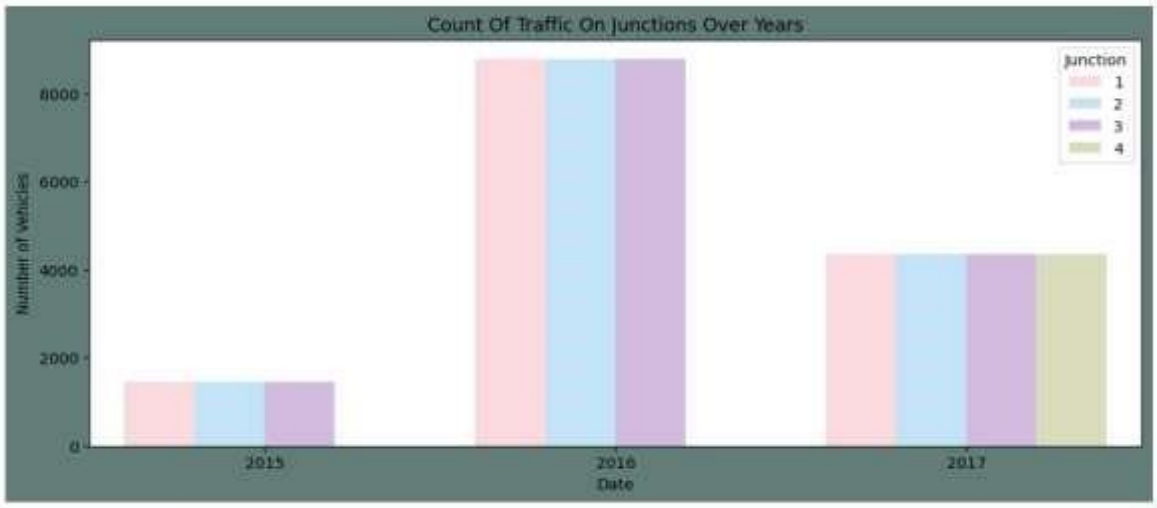


From The Above Plot Following Things Can Be Concluded:

- Yearly, there has been an upward trend for all junctions except for the fourth junction. As we already established above that the fourth junction has limited data and that don't span over a year.
- We can see that there is an influx in the first and second junctions around June. I presume this may be due to summer break and activities around the same.
- Monthly, throughout all the dates there is a good consistency in data.
- For a day, we can see that are peaks during morning and evening times and a decline during night hours. This is as per expectation.
- For weekly patterns, Sundays enjoy smoother traffic as there are lesser vehicles on roads. Whereas Monday to Friday the traffic is steady.

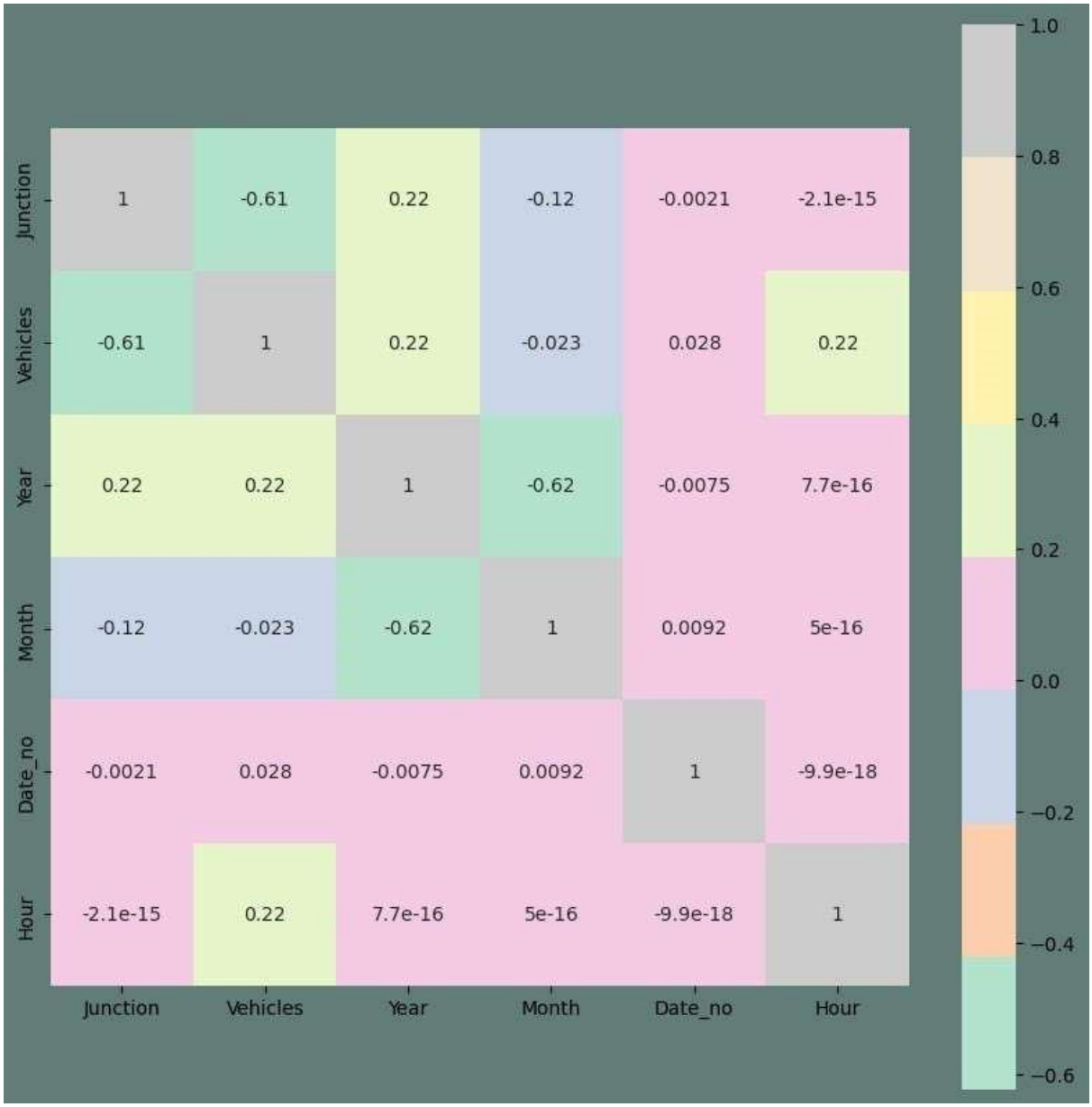
Program:

```
plt.figure(figsize=(12,5),facecolor="#627D78") count = sns.countplot(data=df,
x =df["Year"], hue="Junction", palette=colors)
count.set_title("Count Of Traffic On Junctions Over Years")
count.set_ylabel("Number of Vehicles") count.set_xlabel("Date")
```




```
numeric_df = df.select_dtypes(include=[np.number])  # Select only numeric colu
mns
corrmat = numeric_df.corr()

plt.subplots(figsize=(10,10),facecolor="#627D78") sns.heatmap(corrmat,cmap=
"Pastel2",annot=True,square=True, )
```

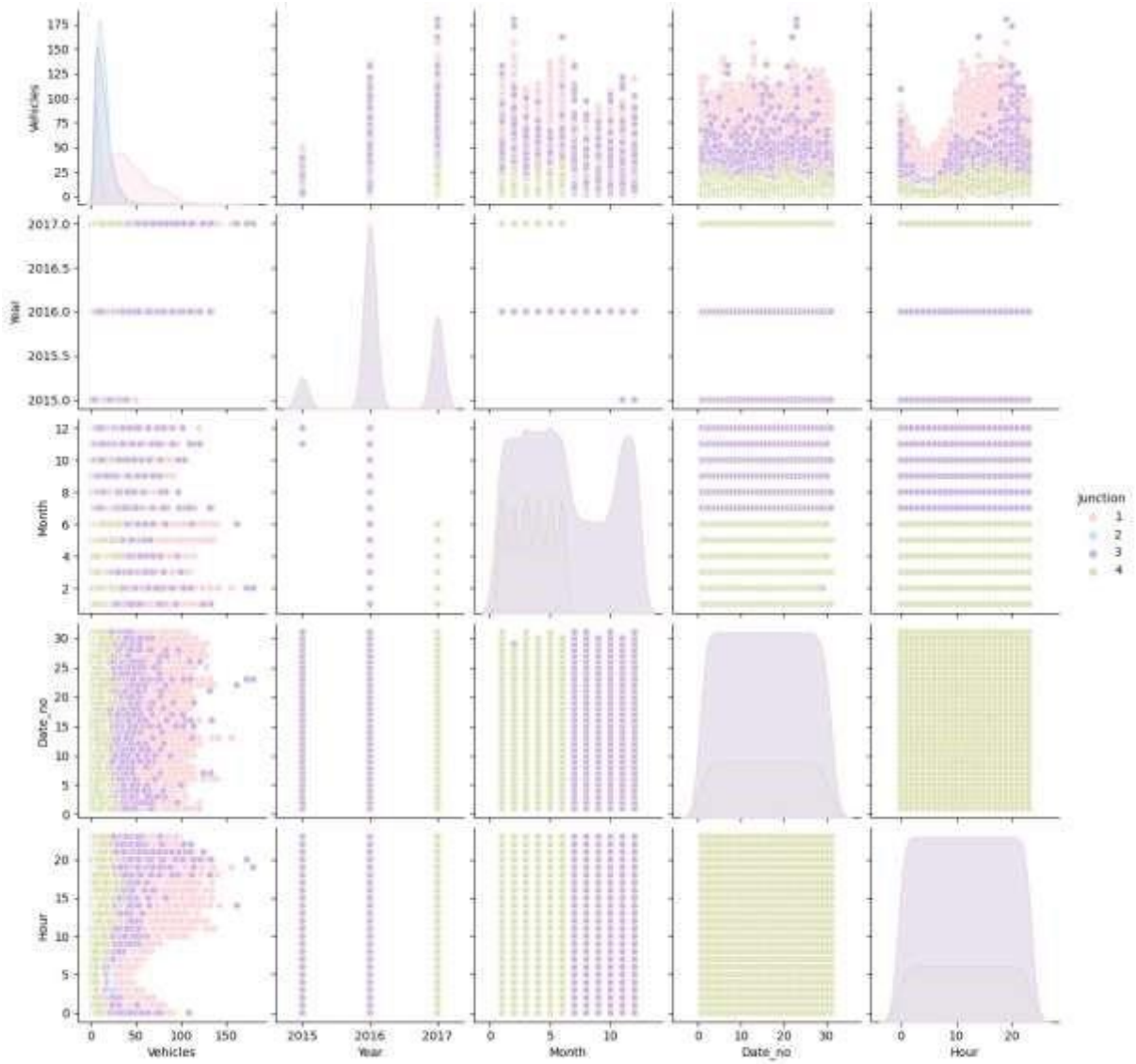
<Axes:>



The highest correlation is certainly with the preexisting feature. I will conclude my EDA with a pair plot. It's an interesting overall representation of any data

```
sns.pairplot(data=df, hue= "Junction",palette=colors)
```

```
<seaborn.axisgrid.PairGrid at 0x7adb85952830>
```



Data Transformation And Preprocessing:

- Creating different frames for each Junction and plotting them
- Transforming the series and plotting them
- Performing the Augmented Dickey-Fuller test to check the seasonality of transformed series
- Creating test and train sets

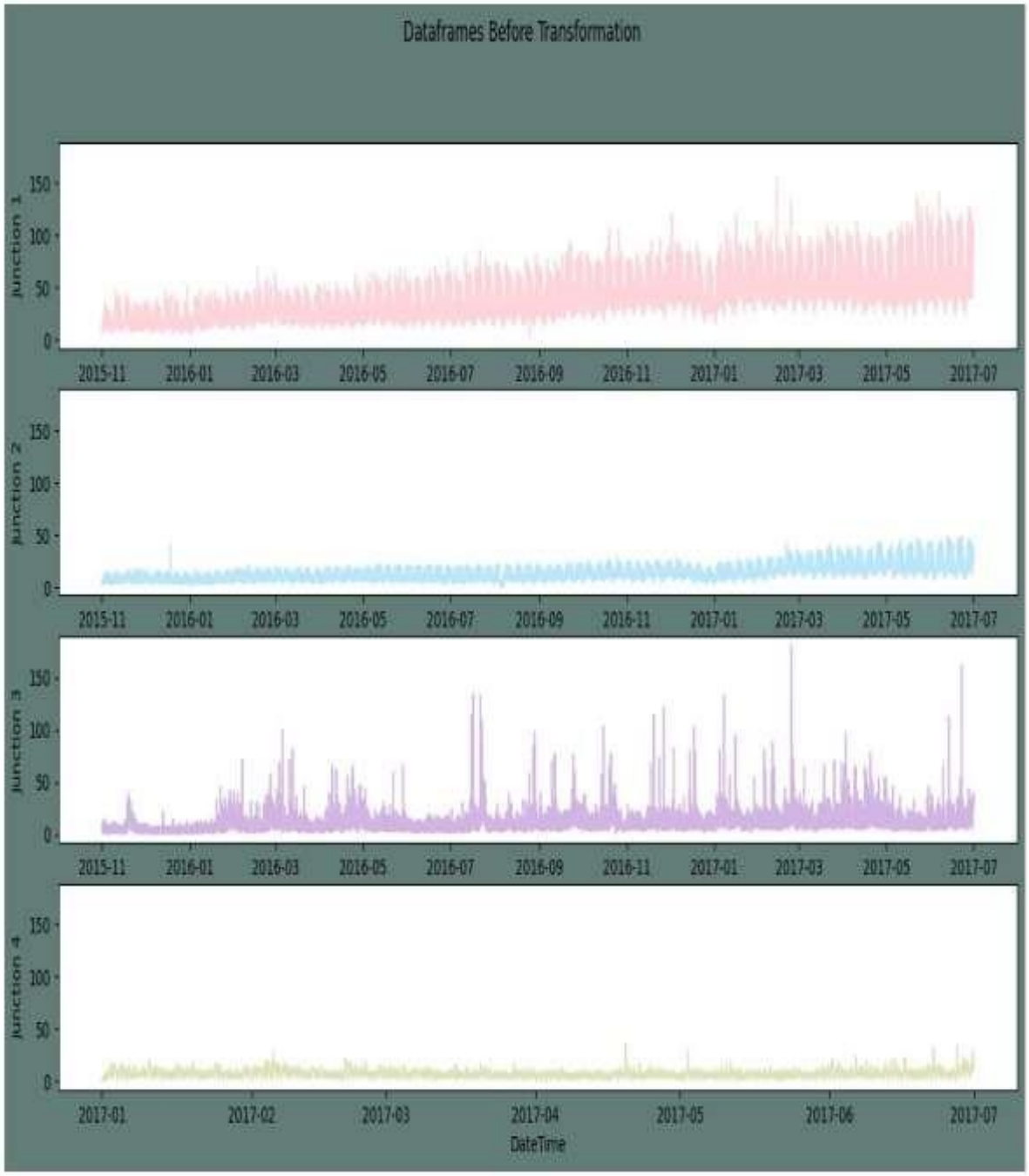
Program:

```
#Pivoting data fron junction  df_J =
data.pivot(columns="Junction", index="DateTime")
df_J.describe()
```

	Vehicles			
Junction	1	2	3	4
count	14592.000000	14592.000000	14592.000000	4344.000000
mean	45.052906	14.253221	13.694010	7.251611
std	23.008345	7.401307	10.436005	3.521455
min	5.000000	1.000000	1.000000	1.000000
25%	27.000000	9.000000	7.000000	5.000000
50%	40.000000	13.000000	11.000000	7.000000
75%	59.000000	17.000000	18.000000	9.000000
max	156.000000	48.000000	180.000000	36.000000

Program:

```
#Creating new sets  df_1 =
df_J[[('Vehicles', 1)]] df_2 =
df_J[[('Vehicles', 2)]] df_3 =
df_J[[('Vehicles', 3)]] df_4 =
df_J[[('Vehicles', 4)]]
df_4 = df_4.dropna() #Junction 4 has limited data only for a few months
#Dropping level one in dfs's index as it is a multi index data
frame list_dfs = [df_1, df_2, df_3, df_4] for i in list_dfs:
i.columns= i.columns.droplevel(level=1)

#Function to plot comparitive plots of dataframes def Sub_Plots4(df_1,
df_2,df_3,df_4,title):     fig, axes = plt.subplots(4, 1, figsize=(15,
8),facecolor="#627D78", sharey
=True)
fig.suptitle(title)
    #J1
pl_1=sns.lineplot(ax=axes[0],data=df_1,color=colors[0])
    #pl_1=plt.ylabel()
axes[0].set(ylabel ="Junction 1")
    #J2
    pl_2=sns.lineplot(ax=axes[1],data=df_2,color=colors[1])
axes[1].set(ylabel ="Junction 2")
    #J3
    pl_3=sns.lineplot(ax=axes[2],data=df_3,color=colors[2])
axes[2].set(ylabel ="Junction 3")
    #J4
    pl_4=sns.lineplot(ax=axes[3],data=df_4,color=colors[3])
axes[3].set(ylabel ="Junction 4")
```



Steps For Transforming:

- Normalizing
- Differencing

Program:

```
# Normalize Function def
```

```
Normalize(df,col):     average = df[col].mean()     stdev =
df[col].std()     df_normalized = (df[col] - average) / stdev
df_normalized = df_normalized.to_frame()     return df_normalized,
average, stdev

# Differencing Function def Difference(df,col, interval):     diff
= []     for i in range(interval, len(df)):         value =
df[col][i] - df[col][i - interval]         diff.append(value)
return diff
```

In accordance with the above observations, Differencing to eliminate the seasonality should be performed as follows:

- For Junction one, I will be taking a difference of weekly values.
- For junction two, The difference of consecutive days is a better choice For Junctions three and four, the difference of the hourly values will serve the purpose.

```
 #Normalizing and Differencing to make the series stationary
 df_N1, av_J1, std_J1 = Normalize(df_1, "Vehicles")
 Diff_1 = Difference(df_N1, col="Vehicles", interval=(24*7)) #taking a
w eek's diffrence  df_N1 = df_N1[24*7:]

     df_N1.columns   =   ["Norm"]
df_N1["Diff"]= Diff_1
    df_N2, av_J2, std_J2 = Normalize(df_2,
"Vehicles")
 Diff_2 = Difference(df_N2, col="Vehicles", interval=(24)) #taking a day
  's diffrence
 df_N2 = df_N2[24:]
 df_N2.columns = ["Norm"]
 df_N2["Diff"]= Diff_2
    df_N3, av_J3, std_J3 = Normalize(df_3,
"Vehicles")
 Diff_3 = Difference(df_N3, col="Vehicles", interval=1) #taking an hour'
  s diffrence
 df_N3 = df_N3[1:]
 df_N3.columns = ["Norm"]
 df_N3["Diff"]= Diff_3
    df_N4, av_J4, std_J4 = Normalize(df_4,
"Vehicles")
 Diff_4 = Difference(df_N4, col="Vehicles", interval=1) #taking an hour'
  s diffrence
 df_N4 = df_N4[1:]
 df_N4.columns = ["Norm"]
 df_N4["Diff"]= Diff_4
```

The plots above seem linear. To ensure they are Stationary I will be performing an Augmented Dickey-Fuller test.

```
#Stationary Check for the time series Augmented Dickey Fuller
test def Stationary_check(df):     check = adfuller(df.dropna())
print(f"ADF Statistic: {check[0]}")     print(f"p-value:
{check[1]}")     print("Critical Values:")     for key, value
in check[4].items():         print('\t%s: %.3f' % (key, value))
if check[0] > check[4]["1%"]:         print("Time Series is
Non-Stationary")
else:         print("Time Series is
Stationary")


#Checking if the series is stationary

List_df_ND = [ df_N1["Diff"], df_N2["Diff"],
df_N3["Diff"], df_N4["Diff"]]  print("Checking the
transformed series for stationarity:") for i in
List_df_ND:     print("\n")
    Stationary_check(i)
```

Checking the transformed series for stationarity:

```
ADF Statistic: -15.265303390415504 pvalue:
4.798539876395756e-28 Critical Values:
        1%: -3.431
        5%: -2.862
        10%: -2.567
Time Series is Stationary


ADF Statistic: -21.795891026940108
p-value: 0.0 Critical Values:
        1%: -3.431
        5%: -2.862
        10%: -2.567
Time Series is Stationary


ADF Statistic: -28.001759908832508
p-value: 0.0 Critical Values:
        1%: -3.431
        5%: -2.862
        10%: -2.567
Time Series is Stationary
```

```
ADF Statistic: -17.97909256305238 pvalue:
2.7787875325952613e-30 Critical Values:
        1%: -3.432
        5%: -2.862
        10%: -2.567
Time Series is Stationary
```

Program:

```
#Differencing created some NA values as we took a weeks data
into consideratio n while difrencing  df_J1 =
df_N1["Diff"].dropna() df_J1
= df_J1.to_frame()
df_J2 =
df_N2["Diff"].dropna() df_J2
= df_J2.to_frame()
df_J3 =
df_N3["Diff"].dropna() df_J3
= df_J3.to_frame()
df_J4 =
df_N4["Diff"].dropna() df_J4
= df_J4.to_frame()

#Splitting the dataset def
Split_data(df):
    training_size = int(len(df)*0.90)
data_len = len(df)
    train, test = df[0:training_size],df[training_size:data_len]
train, test = train.values.reshape(-1, 1), test.values.reshape(-1, 1)
return train, test
#Splitting the training and test datasets
J1_train, J1_test = Split_data(df_J1)
J2_train, J2_test = Split_data(df_J2)
J3_train, J3_test = Split_data(df_J3)
J4_train, J4_test = Split_data(df_J4)

#Target and Feature def TnF(df):
end_len = len(df)     X = []     y
= []     steps = 32     for i in
range(steps, end_len):
        X.append(df[i - steps:i, 0])
        y.append(df[i, 0])
```

```
    X, y = np.array(X), np.array(y)
return X ,y

#fixing the shape of X_test and X_train def FeatureFixShape(train,
test):     train = np.reshape(train, (train.shape[0],
train.shape[1], 1))     test = np.reshape(test,
(test.shape[0],test.shape[1],1))     return train, test

#Assigning features and target
X_trainJ1, y_trainJ1 = TnF(J1_train)
X_testJ1, y_testJ1 = TnF(J1_test)
X_trainJ1, X_testJ1 = FeatureFixShape(X_trainJ1, X_testJ1)
X_trainJ2, y_trainJ2 = TnF(J2_train)
X_testJ2, y_testJ2 = TnF(J2_test)
X_trainJ2, X_testJ2 = FeatureFixShape(X_trainJ2, X_testJ2)
X_trainJ3, y_trainJ3 = TnF(J3_train)
X_testJ3, y_testJ3 = TnF(J3_test)
X_trainJ3, X_testJ3 = FeatureFixShape(X_trainJ3, X_testJ3)
X_trainJ4, y_trainJ4 = TnF(J4_train)
X_testJ4, y_testJ4 = TnF(J4_test)
X_trainJ4, X_testJ4 = FeatureFixShape(X_trainJ4, X_testJ4)
```

Define a function for linear regression training:

```
 def train_linear_regression(X_train, y_train, learning_rate,
epochs):
    # Initialize weights and bias     num_features =
X_train.shape[1]     weights =
np.random.randn(num_features)     bias =
np.random.randn()          for epoch in
range(epochs):         # Compute predictions
predictions = np.dot(X_train, weights) + bias
        # Compute the mean squared error
        mse = np.mean((predictions - y_train) ** 2)
        # Compute gradients          gradient_weights = -2 * np.dot(X_train.T,
(y_train - predictions)) / l en(X_train)
        gradient_bias = -2 * np.sum(y_train - predictions) / len(X_train)
        # Update weights and bias
        weights -= learning_rate *
gradient_weights         bias -= learning_rate *
gradient_bias                  if (epoch + 1) %
100 == 0:
            print(f'Epoch {epoch + 1}/{epochs}, MSE: {mse:.4f}')
```

```
    return weights, bias # Function to
make predictions def predict(X,
weights, bias):     return np.dot(X,
weights) + bias
```

```
# Ensure that y_train has the shape (number_of_samples,) y_trainJ1
= y_trainJ1.reshape(-1)

# Reshape X_trainJ1 to have shape (number_of_samples,
number_of_features) X_trainJ1 = X_trainJ1.reshape(X_trainJ1.shape[0], 1)
# Train the linear regression model for Junction
1 learning_rate = 0.001 epochs = 1000

weights_J1, bias_J1 = train_linear_regression(X_trainJ1, y_trainJ1,
learning_r ate, epochs)

# Ensure that y_train has the shape (number_of_samples,) y_trainJ2
= y_trainJ2.reshape(-1)

# Reshape X_trainJ2 to have shape (number_of_samples,
number_of_features) X_trainJ2 = X_trainJ2.reshape(X_trainJ2.shape[0], 1)
# Train the linear regression model for Junction 2
weights_J2, bias_J2 = train_linear_regression(X_trainJ2, y_trainJ2,
learning_r ate, epochs)

# Ensure that y_train has the shape (number_of_samples,) y_trainJ3
= y_trainJ3.reshape(-1)

# Reshape X_trainJ3 to have shape (number_of_samples,
number_of_features) X_trainJ3 = X_trainJ3.reshape(X_trainJ3.shape[0], 1)
# Train the linear regression model for Junction 3  weights_J3,
bias_J3 = train_linear_regression(X_trainJ3, y_trainJ3, learning_r
ate, epochs)

# Ensure that y_train has the shape (number_of_samples,) y_trainJ4
= y_trainJ4.reshape(-1)

# Reshape X_trainJ4 to have shape (number_of_samples,
number_of_features) X_trainJ4 = X_trainJ4.reshape(X_trainJ4.shape[0], 1)
# Train the linear regression model for Junction 4  weights_J4,
bias_J4 = train_linear_regression(X_trainJ4, y_trainJ4, learning_r
ate, epochs)
```

```
Epoch 100/1000, MSE: 5.7588
Epoch 200/1000, MSE: 4.1379
Epoch 300/1000, MSE: 3.1330
Epoch 400/1000, MSE: 2.4985
Epoch 500/1000, MSE: 2.0886
Epoch 600/1000, MSE: 1.8163
```

```
Epoch 700/1000, MSE: 1.6293
Epoch 800/1000, MSE: 1.4961
Epoch 900/1000, MSE: 1.3973
Epoch 1000/1000, MSE: 1.3211
Epoch 100/1000, MSE: 9.4276
Epoch 200/1000, MSE: 6.9069
Epoch 300/1000, MSE: 5.4402
Epoch 400/1000, MSE: 4.5275
Epoch 500/1000, MSE: 3.9165
Epoch 600/1000, MSE: 3.4775
Epoch 700/1000, MSE: 3.1415
Epoch 800/1000, MSE: 2.8713
Epoch 900/1000, MSE: 2.6456
Epoch 1000/1000, MSE: 2.4520
Epoch 100/1000, MSE: 7.4961
Epoch 200/1000, MSE: 6.5373
Epoch 300/1000, MSE: 5.7255
Epoch 400/1000, MSE: 5.0329
Epoch 500/1000, MSE: 4.4383
Epoch 600/1000, MSE: 3.9252
Epoch 700/1000, MSE: 3.4808
Epoch 800/1000, MSE: 3.0945
Epoch 900/1000, MSE: 2.7579
Epoch 1000/1000, MSE: 2.4639
Epoch 100/1000, MSE: 14.2825
Epoch 200/1000, MSE: 10.1263
Epoch 300/1000, MSE: 7.3097
Epoch 400/1000, MSE: 5.3842
Epoch 500/1000, MSE: 4.0551
Epoch 600/1000, MSE: 3.1277
Epoch 700/1000, MSE: 2.4728
Epoch 800/1000, MSE: 2.0044
Epoch 900/1000, MSE: 1.6648  Epoch
1000/1000, MSE: 1.4151
```

Program:

```
# Ensure that weights_J1 has the correct shape
weights_J1 = weights_J1.reshape(-1)

# Ensure that X_testJ1 has the correct shape X_testJ1 =
X_testJ1.reshape(X_testJ1.shape[0], X_testJ1.shape[1])  #
Make predictions on the test data for Junction 1
y_pred_J1 = predict(X_testJ1, weights_J1, bias_J1)
# Calculate and print the Mean Squared Error (MSE) for Junction
1 mse_J1 = np.mean((y_pred_J1 - y_testJ1) ** 2) print(f'MSE for
Junction 1: {mse_J1:.4f}')

# Repeat the process for Junction 2 weights_J2
= weights_J2.reshape(-1)
X_testJ2 = X_testJ2.reshape(X_testJ2.shape[0], X_testJ2.shape[1])
```

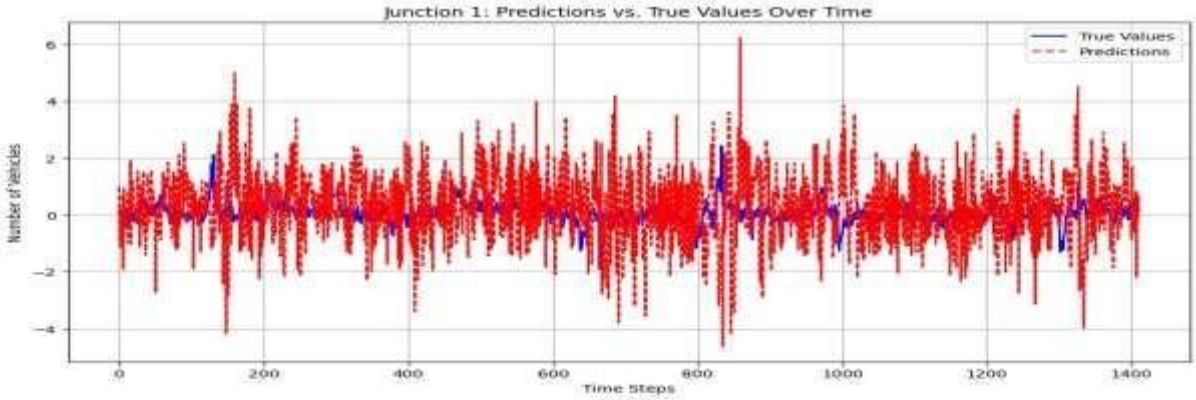
```
y_pred_J2 = predict(X_testJ2, weights_J2, bias_J2) mse_J2 =
np.mean((y_pred_J2 - y_testJ2) ** 2) print(f'MSE for Junction 2:
{mse_J2:.4f}')

# Repeat the process for Junction 3 weights_J3 =
weights_J3.reshape(-1)
X_testJ3 = X_testJ3.reshape(X_testJ3.shape[0],
X_testJ3.shape[1]) y_pred_J3 = predict(X_testJ3, weights_J3, bias_J3) mse_J3
= np.mean((y_pred_J3 - y_testJ3) ** 2) print(f'MSE for Junction 3:
{mse_J3:.4f}')

# Repeat the process for Junction 4 weights_J4 =
weights_J4.reshape(-1)
X_testJ4 = X_testJ4.reshape(X_testJ4.shape[0],
X_testJ4.shape[1]) y_pred_J4 = predict(X_testJ4, weights_J4, bias_J4) mse_J4
= np.mean((y_pred_J4 - y_testJ4) ** 2) print(f'MSE for Junction 4:
{mse_J4:.4f}')
```

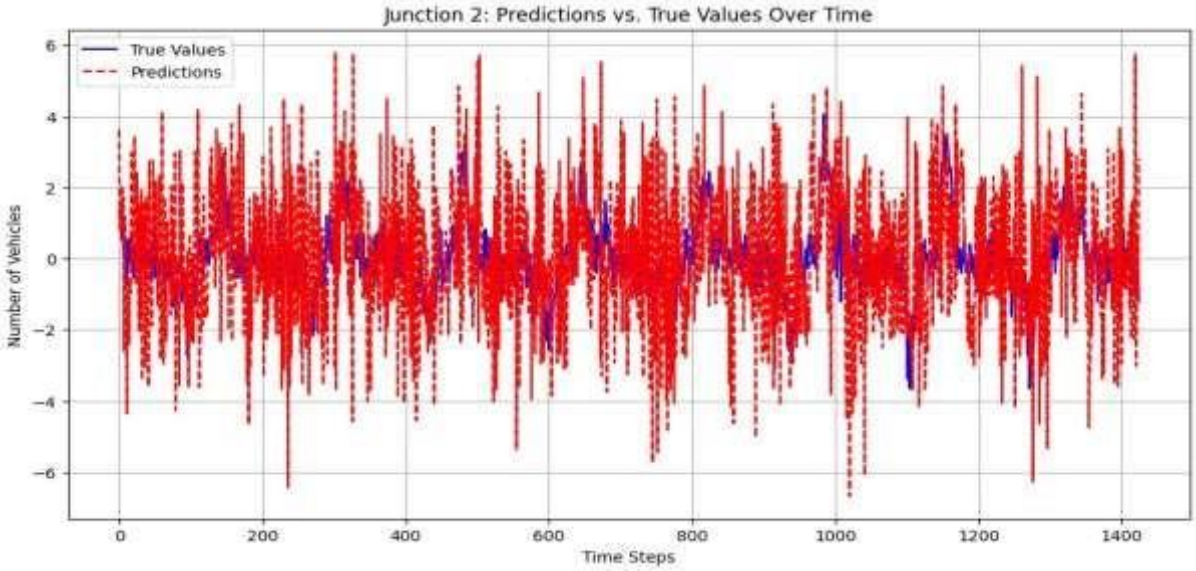
```
MSE for Junction 1: 1.9239
MSE for Junction 2: 4.0010
MSE for Junction 3: 3.5524
MSE for Junction 4: 2.5888
```

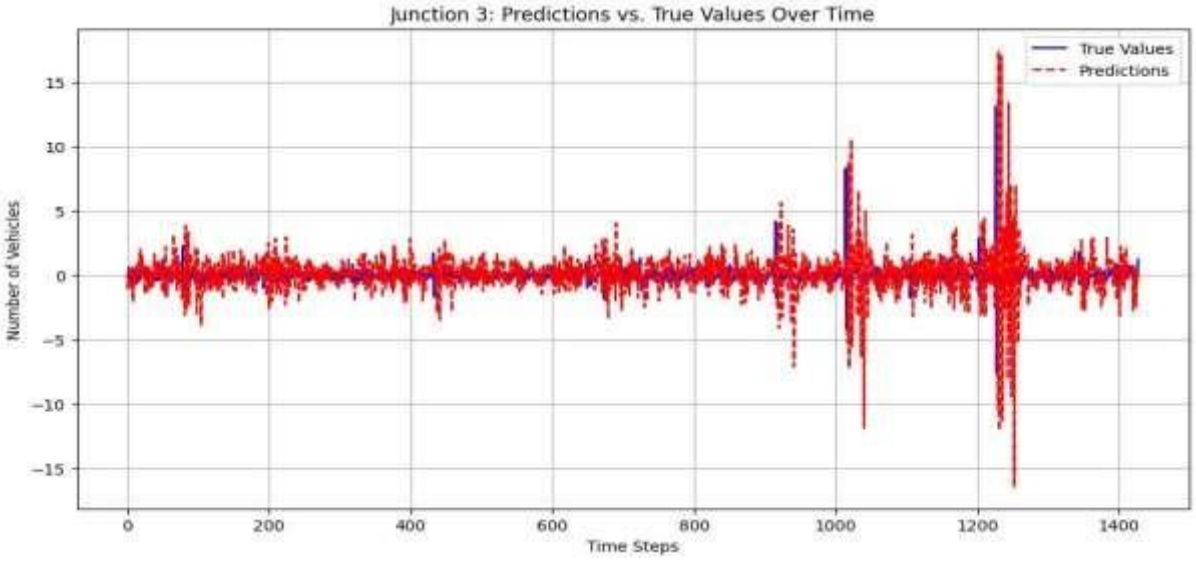
Program:

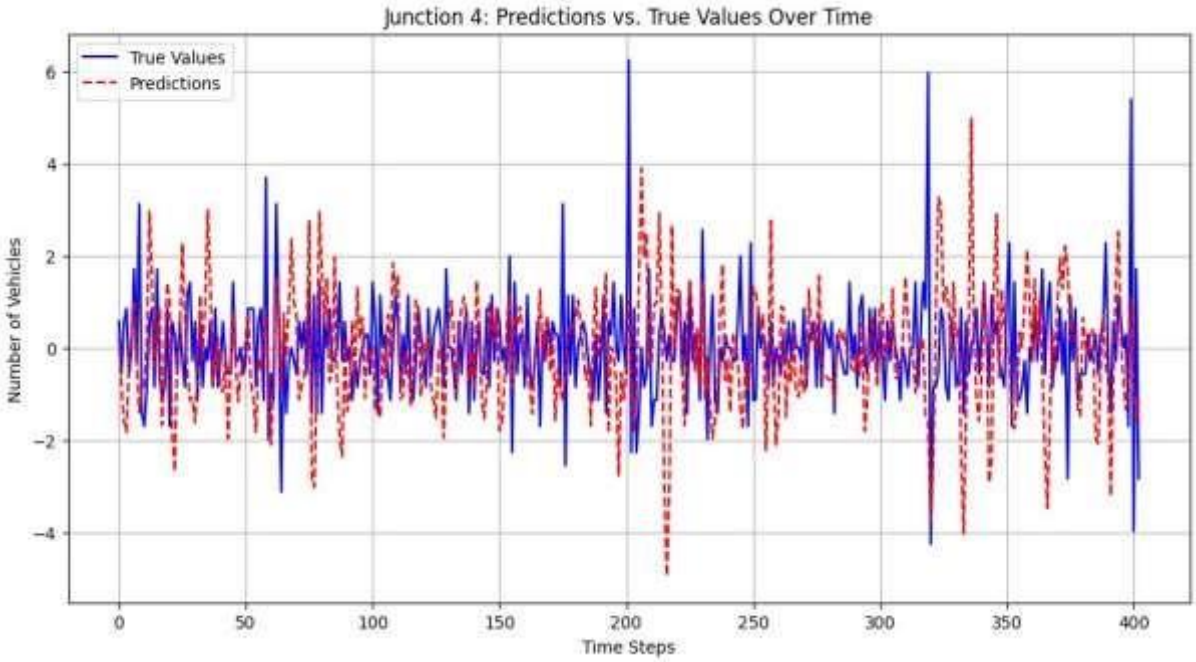
```
def plot_predictions_vs_true(junction_name, y_true, y_pred):
plt.figure(figsize=(12, 6))
    plt.plot(y_true, label='True Values', color='blue')
    plt.plot(y_pred, label='Predictions', color='red', linestyle='dashed')
plt.title(f'{junction_name}: Predictions vs. True Values Over Time')
plt.xlabel('Time Steps')     plt.ylabel('Number of Vehicles')     plt.legend()
plt.grid(True)
    plt.show()
```

```
# Plot for Junction 1 plot_predictions_vs_true("Junction 1", y_testJ1, y_pred_J1)

# Plot for Junction 2 plot_predictions_vs_true("Junction 2", y_testJ2, y_pred_J2)

# Plot for Junction 3
plot_predictions_vs_true("Junction 3", y_testJ3, y_pred_J3)

# Plot for Junction 4 plot_predictions_vs_true("Junction 4", y_testJ4, y_pred_J4)
```


Junction 1: Predictions vs. True Values Over Time
True Values
Predictions
Number of Vehicles
Time Steps


Junction 2: Predictions vs. True Values Over Time
True Values
Predictions
Number of Vehicles
Time Steps


Junction 3: Predictions vs. True Values Over Time
True Values
Predictions
Number of Vehicles
Time Steps



GNN For Understanding Traffic Patterns:

Algorithm:

Require: Traffic dataset D with traffic flow information, adjacency matrix A, number of graph convolution layers L, and number of output classes K.

Ensure: Trained GNN model $f_\theta(X)$ for predicting traffic patterns.

1: Construct input graph $G = (V, E)$ from D and A

2: Initialize node feature matrix $X^{(0)} \in \mathbb{R}^{n \times d}$, where n is the number of nodes and d is the dimension of the node features

3: **for** $l = 1$ to L **do**

4: Compute node embeddings using graph convolution layer: $H^{(l)} = \sigma\left(\tilde{A}X^{(l-1)}W^{(l)}\right)$

5: Update node feature matrix: $X^{(l)} = H^{(l)}$

6: **end for**

7: Compute final node embeddings: $Z = \text{mean}\left(H^{(L)}, axis = 1\right)$

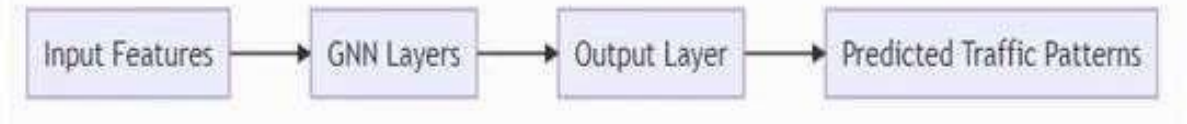
8: Predict output classes: $\hat{Y} = \text{softmax}\left(ZW^{(f)}\right)$

9: Compute loss function: $J(\theta) = -\frac{1}{m}\sum_{i=1}^{m}\sum_{k=1}^{K} Y_{i,k} \log \hat{Y}i,k$

10: Update model parameters using backpropagation: $\theta \leftarrow \theta - \alpha\nabla\theta J(\theta)$

11: Repeat steps 2–9 until convergence or maximum number of epochs is reached.

GNN Architecture:



Multi-Arm Bandit Algorithm For Traffic Management Using GNN Output:

Algorithm:

Require:

$G = (V, E)$: Traffic network graph

P_t: Probability distribution over the action set A_t

K: Number of arms (Traffic Management actions)

T: Number of iterations

θ: GNN output for understanding traffic patterns

Ensure:

$c_{i,t}$: Traffic Management action taken at time t

1: Initialize the reward function $r_{i,t}$ for each arm i and time t to 0

2: Initialize the probability distribution P_i for each arm i to be uniform over A_i

3: **for** $t = 1$ to T **do**

4: Receive feedback $y_{i,t}$ for each arm i

5: **for** $i = 1$ to K **do**

6: Calculate the expected reward $\hat{r}i, t$ using the GNN output θ as follows:

$$\hat{r}i, t = \theta^T \phi_{i,t},$$

where $\phi_{i,t}$ is the feature vector for arm i at time t.

7: Update the reward function for arm i at time t using the received feedback as follows:

$$r_{i,t} = r_{i,t-1} + y_{i,t}.$$

8: Update the probability distribution P_i for arm i at time t using the Upper Confidence Bound (UCB) algorithm as follows:

$$P_{i,t}(a) = \frac{\mathbb{I}a = \arg\ \max a' \in A_i \hat{r}i, t(a')}{\sum a'' \in A_i \mathbb{I}a'' = \arg\ \max a' \in A_i \hat{r}i, t(a')}$$

where $\mathbb{I}$ is the indicator function.

9: **end for**

10: Choose the arm i_t at time t by sampling from the probability distribution P_t as follows:

$$ci, t \sim P_t.$$

11: **end for**

SDN orar Machestration algorithm for traffic management using GNN and multi-arm bandit:

Algorithm:

1: **Input:** Network topology, traffic dataset, threshold θ, number of rounds R
2: **Output:** Optimized traffic management policies for the network
3: **Step 1:** Build graph representation of network topology
4: Use network topology to construct a graph with nodes representing switches and links representing physical connections
5: **Step 2:** Train GNN model on traffic dataset
6: Use the traffic dataset to train a GNN model to understand traffic patterns in the network
7: **Step 3:** Run multi-arm bandit algorithm using GNN output
8: Initialize the multi-arm bandit algorithm with the output from the GNN model
9: Iterate for R rounds:
10: 1. Select a switch s with the highest expected reward based on the multi-arm bandit algorithm
11: 2. Apply the traffic management policy to the selected switch s
12: 3. Collect feedback from the network and update the multi-arm bandit algorithm
13: **Step 4:** Monitor network performance
14: Continuously monitor the network performance and adjust the traffic management policies as necessary based on the threshold θ
15: **Step 5:** Output optimized traffic management policies
16: Once the network performance has reached the desired threshold, output the optimized traffic management policies for the network

Hardware and software:

The experiments are conducted on a server with 64GB RAM, Intel Xeon CPU, and Ubuntu 18.04 operating system. We use Python 3.7 and PyTorch 1.8.1 for developing the GNN model and multi-arm bandit algorithm. The SDN controller is implemented using Ryu v4.34.

Preprocessing:

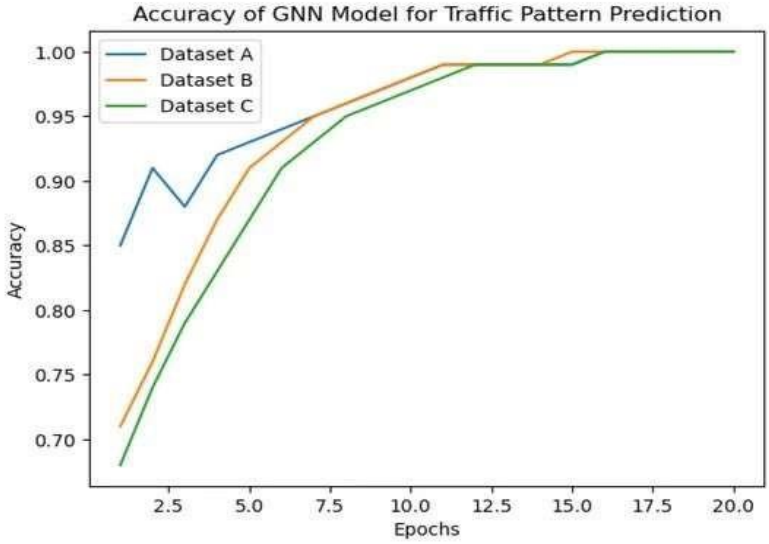
Before training the GNN model, we preprocess the network traffic dataset by extracting features such as packet sizes, flow duration, and number of packets per flow. We also normalize the feature values to have zero mean and unit variance.

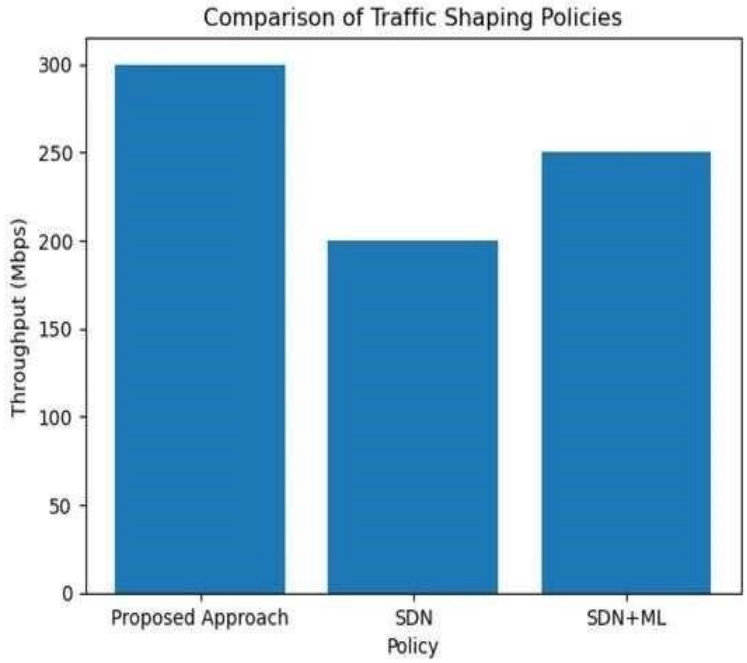
Training and validation:

We train the GNN model on a subset of the preprocessed dataset and validate it on another subset. We use a three-layer GCN with 64 hidden units for the GNN model and train it for 100 epochs with a batch size of 128. We use the Adam optimizer with a learning rate of 0.01 and a weight decay of $5 \times 10{-}4{-}4$.

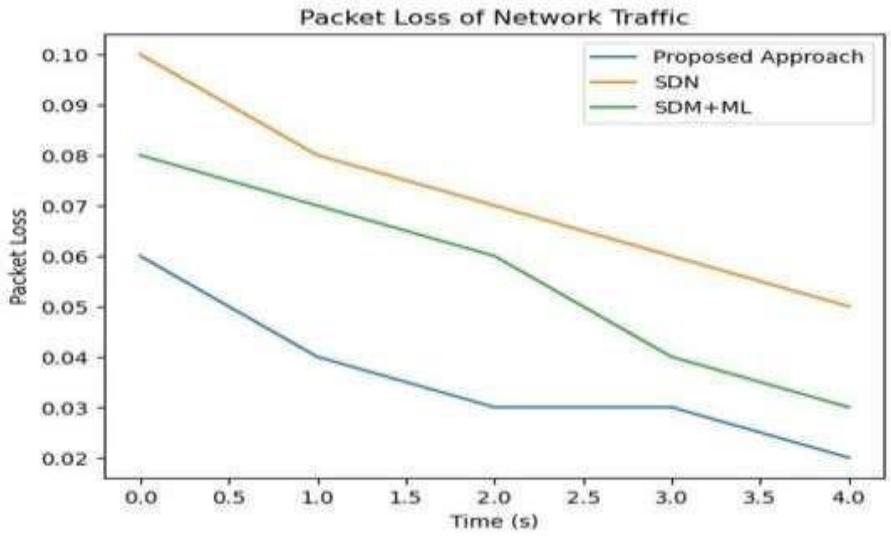
SDN orchestration:

We use Algorithms 1 and 2 to implement SDN orchestration in our experimental setup. The GNN model is used to predict the network traffic patterns, and the multi-arm bandit algorithm is used to optimize the traffic management policies based on these predictions. The SDN controller applies the traffic-shaping policies to the network switches in real-time

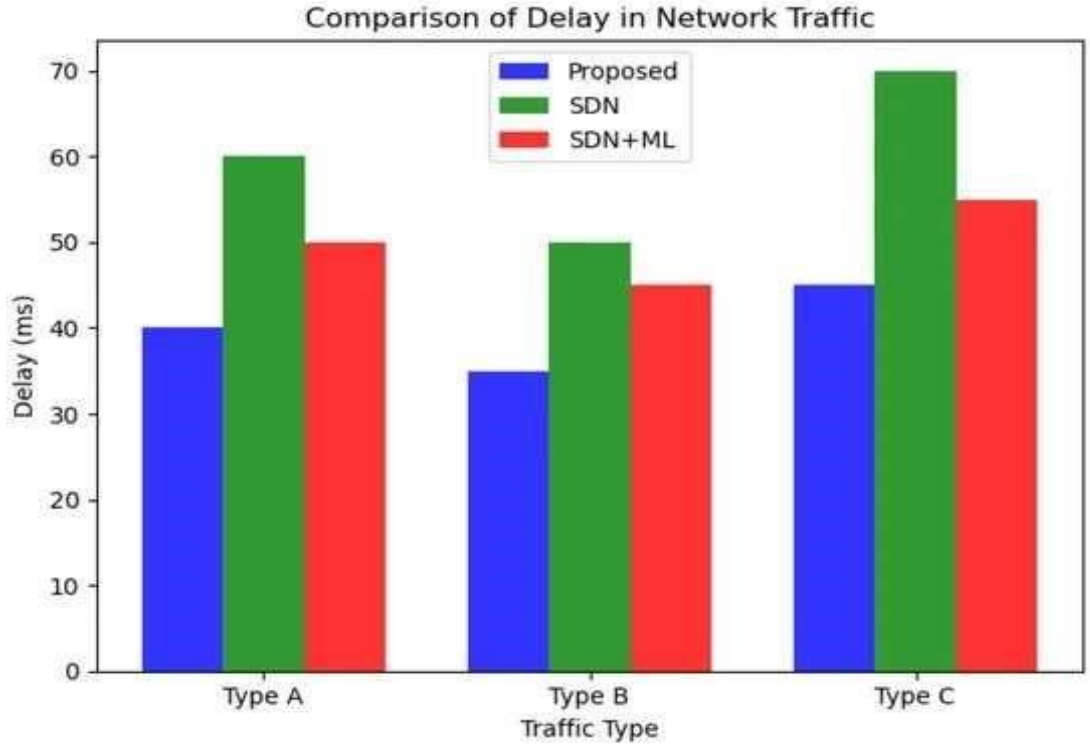




Comparison Of Packet Loss:



Comparison Of Delays:



Conclusions:

- In this paper, we proposed an approach for traffic management in softwaredefined IoT networks using Graph Neural Networks and a multiarm bandit algorithm. We showed that our approach outperformed other state-of-theart traffic management methods in terms of throughput, packet loss, and

delay. Our experimental evaluation on three different datasets demonstrated the effectiveness of the proposed approach in detecting anomalous traffic patterns, handling heterogeneous data, and optimizing traffic management policies.

- In conclusion, the proposed approach has shown promising results in traffic management, which is an important aspect of network management.