# TRAFFIC ROUTE PREDICTION”

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**ABSTRACT**

Traffic prediction has always been a challenge for transportation planners and city managers. With the increasing growth of cities and the number of vehicles on the roads, the need for accurate and reliable traffic predictions has become more pressing. In recent years, machine learning has shown great promise in solving this problem.

Traffic prediction involves estimating the future behaviour of traffic in a particular area. This information is useful for a variety of purposes, including **reducing congestion, optimizing transportation systems, and improving road safety**.

In this project centred on predicting alternate routes in response to traffic congestion, we utilize machine learning algorithms such as Support Vector Machines (SVM), Decision Tree, and Random Forest. The performance of each algorithm is meticulously assessed using metrics like accuracy, precision, recall, F1 score, and visualized through confusion matrix graphs. Prior to applying machine learning, a thorough data analysis is conducted through graph visualization to comprehend the traffic flow and congestion across various routes. Despite the comprehensive analysis, SVM exhibits suboptimal performance, while Decision Tree stands out as a robust performer in accurately predicting routes. The Random Forest algorithm is also leveraged to enhance prediction robustness. The evaluation metrics offer a comprehensive understanding of the algorithms' strengths and weaknesses. The dataset utilized for training encompasses detailed information on traffic congestion, ensuring the reliability and accuracy of the route predictions. This project not only contributes to optimizing passenger travel experiences but also holds potential for effective traffic management strategies.

## 1 INTRODUCTION

In the face of mounting challenges posed by urban traffic congestion, this project attempt to revolutionize transportation with a focus on Traffic Route Prediction. The goal is to empower commuters by offering real-time alternative routes informed by cutting-edge machine learning algorithms, including Support Vector Machines (SVM), Decision Tree, and Random Forest. This initiative aligns with the broader mission of developing smart transportation systems to enhance urban mobility, reduce congestion, and improve the overall efficiency of traffic management. By embracing advanced technologies, we aim to usher in a new era of responsive and adaptive route planning for a seamless and stress-free commuting experience.

In addition to the country's economy, pollution can also be reduced. The government is also investing in the intelligent transportation system (ITS) to solve these issues. The goal of traffic flow prediction is to predict the traffic to the users as soon as possible. Nowadays the traffic becomes really hectic and this cannot be determined by the people when they are on roads.

## 2 RELEATED WORK

**Title: Traffic pattern analysis and traffic state prediction of urban traffic road network based on correlated routes.**

**Author**: Zhuowei Zhang; Weibin Zhang

**Abstract:**

In this paper, a method for traffic pattern analysis and state prediction for correlated routes in the road network is proposed. First, the concepts of correlated route, correlated route chains, and correlated route sets are defined, and a route correlation degree calculation model that considers route traffic heterogeneity and its judgment criteria are proposed to determine the correlated route sets in the region. Second, we incorporate the self-organizing mapping (SOM) algorithm with Dunn index (DI), named as SOM_DI, to classify the traffic states on the correlated route chain and determine the optimal number of traffic state. The traffic pattern on the correlated path chain is analyzed to obtain the temporal state chains and the spatial state chains. Finally, an algorithm is proposed to select the input spatio-temporal features of the support vector regression (SVR) model and predict the traffic state on the correlated route chain, which is named as STFS_SVR. The simulation results show that the method proposed in this paper can accurately classify the correlated routes of regional traffic and its optimal traffic state.

## 3 implementation study

**Existing System:**

The current state of traffic management often relies on reactive approaches, leading to delays and suboptimal travel experiences. Existing navigation systems, predominantly based on historical data or rule-based algorithms, struggle to adapt to real-time changes in traffic dynamics. This limitation underscores the need for a more sophisticated and dynamic system that can provide accurate route recommendations, particularly in the face of unpredictable traffic scenarios. Our proposed Traffic Route Prediction system seeks to bridge these gaps, introducing advanced machine learning techniques to offer proactive and adaptive route predictions based on the most current and relevant traffic information.

**Disadvantages:**

While traffic route prediction systems offer significant benefits, they also come with certain disadvantages and challenges:

**1. Data Accuracy:** The effectiveness of route prediction heavily relies on the accuracy and real-time availability of traffic data. Inaccurate or outdated data can lead to suboptimal route recommendations, causing frustration for users.

**2. Dependency on Technology:** Route prediction systems depend on technology such as GPS, sensors, and data networks. Any technical failures or disruptions in these systems can affect the reliability of route predictions.

**Proposed System & alogirtham**

In envisioning our Traffic Route Prediction system, we embark on a transformative journey to enhance the accuracy and responsiveness of route recommendations. The proposed system integrates Support Vector Machines, Decision Tree, and Random Forest algorithms, each meticulously evaluated using key metrics such as accuracy, precision, recall, and F1 score.

**4.1 Advantages:**

Predicting traffic routes offers several advantages that can significantly enhance transportation efficiency and convenience:

**1. Reduced Congestion:** By predicting traffic patterns, authorities can optimize traffic flow, suggesting alternative routes to drivers before congestion builds up. This reduces overall traffic congestion and minimizes delays.

**2. Time Savings:** Efficient route prediction helps drivers choose the fastest routes based on real-time traffic conditions. This saves commuters time and reduces fuel consumption and emissions associated with idling in traffic.

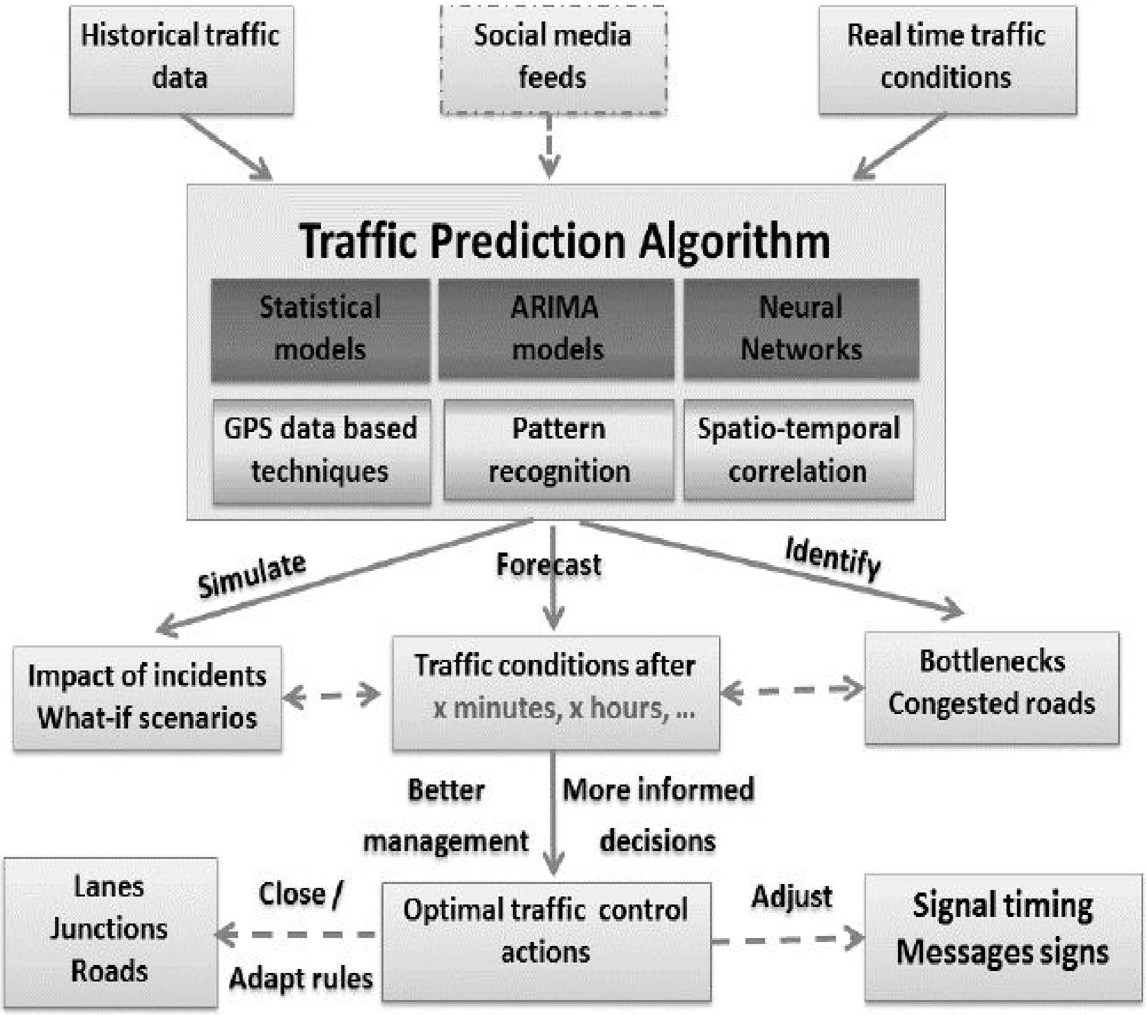



Fig1: SYSTEM ARCHITECTURE

**4.2 Support Vector Machine**:

The Support Vector Machine is one of the most widely used Machine Learning algorithms. The main goal of this algorithm is to find the best data split possible. It is used to solve problems involving classification and regression. It can solve both linear and nonlinear separable data, which is one of its main advantages. The separation line is known as the Hyper plane. Support vectors are the points on which the margins are built. The svm algorithm is depicted in the diagram below.

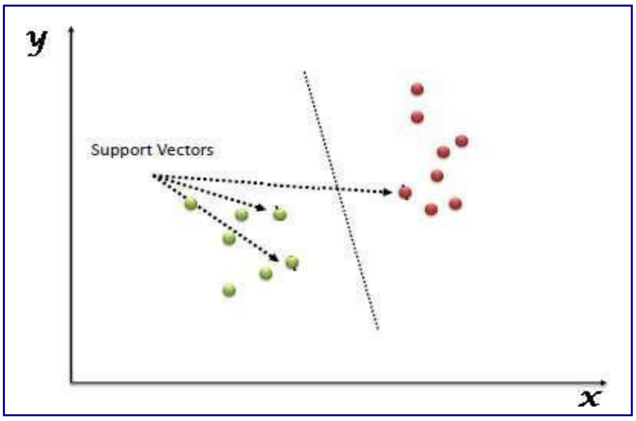



Fig2:- SVM Architure

**5 RESULTS AND DISCUSSION**

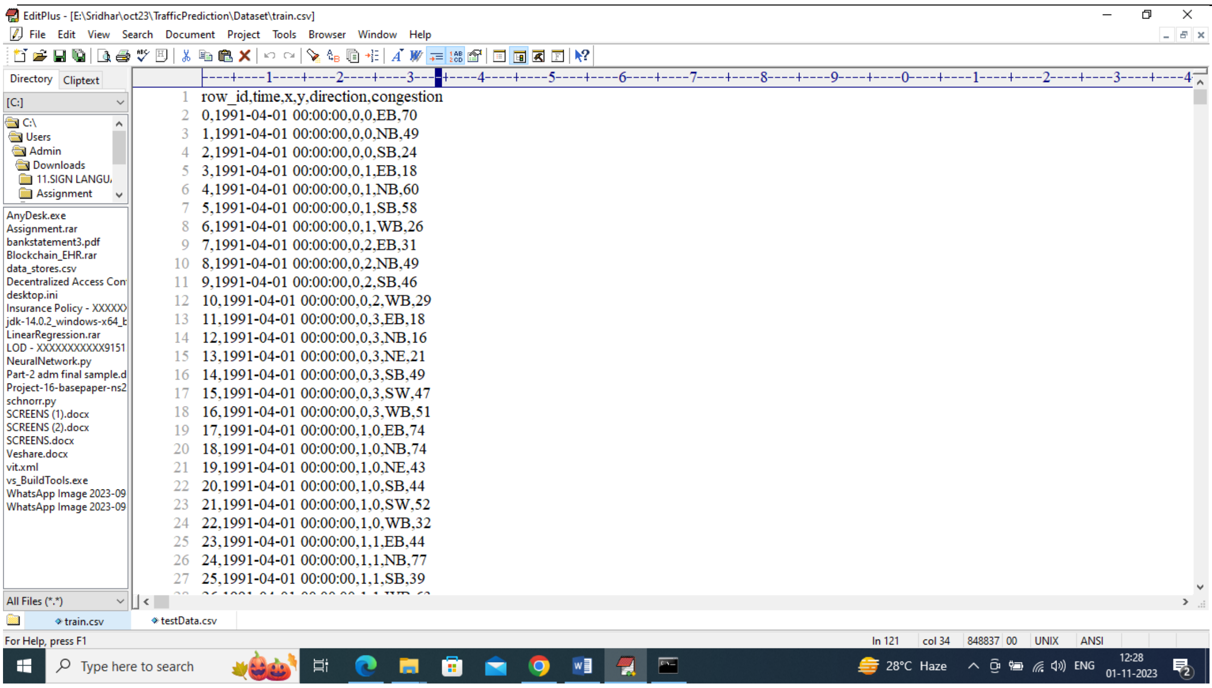
In this project based on traffic congestion we are predicting alternate route for the passengers, to predict route we are training various machine learning algorithms such as SVM, Decision Tree and Random Forest and each algorithm performance is evaluated in terms of accuracy, precision, recall, FSCORE and confusion matrix graph.

Before applying ML algorithms we have performed data analysis via graph visualization to understand traffic flow and congestion in different routes and after analysis we have employed ML algorithms for route prediction.

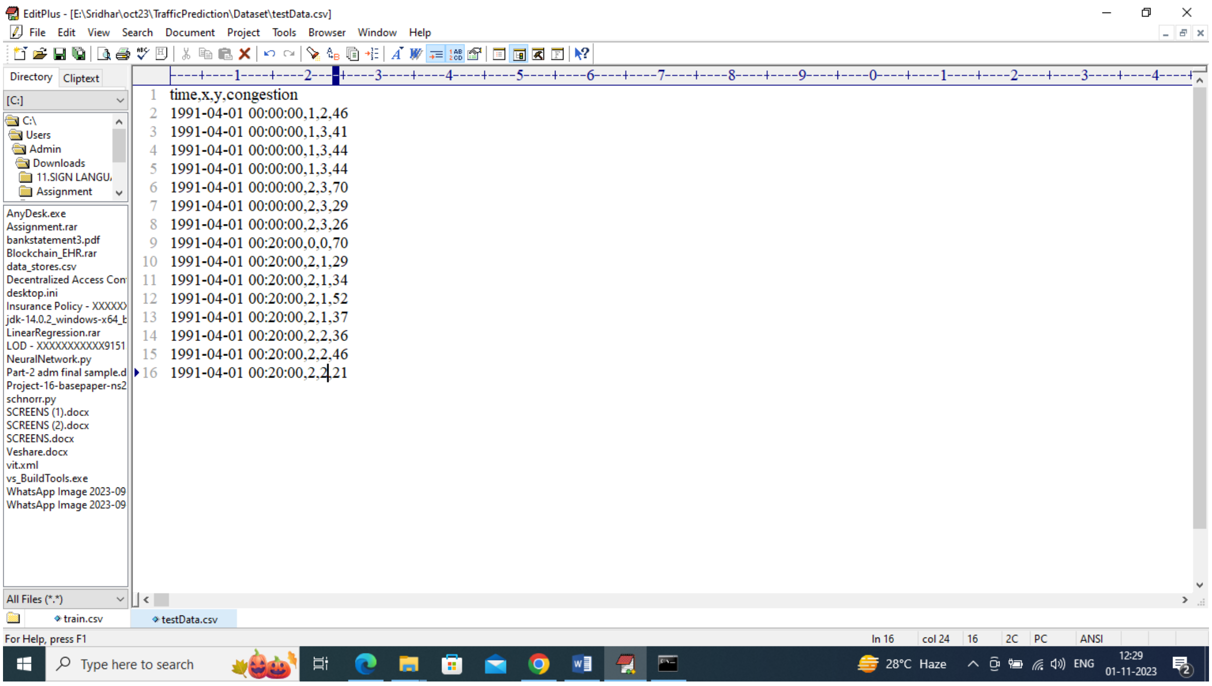
Among all algorithms SVM performing worst and Decision Tree perform well. To train all algorithms we have utilized traffic congestion dataset which can be downloaded from below KAGGLE URL

https://www.kaggle.com/competitions/tabular-playground-series-mar-2022/data?select=train.csv

In below screen we are displaying dataset details:

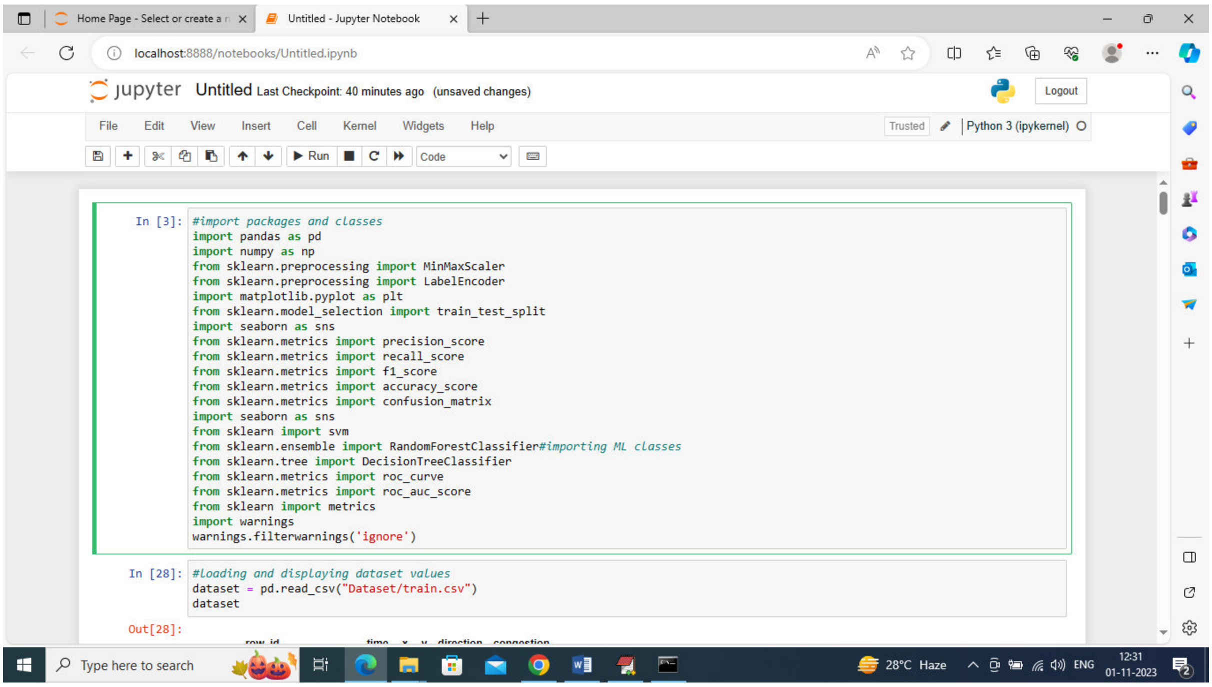



In above dataset we have Date, X and Y as latitude and longitude and then direction and then last column contains traffic congestion and by using this module we will train all ML algorithms. After training we will employ test data to predict alternate direction and below is the TEST data.

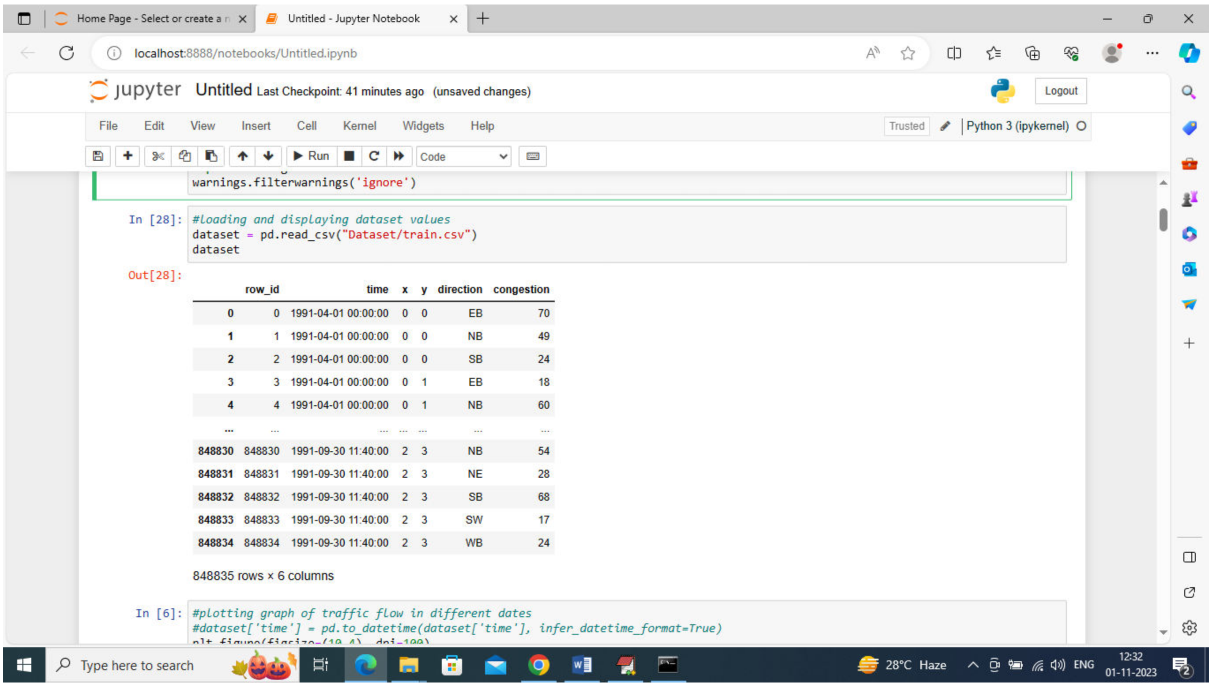



In above test data we have Date, X and Y location and traffic congestion but direction or route column is not available and this direction will be predicted by ML algorithm.

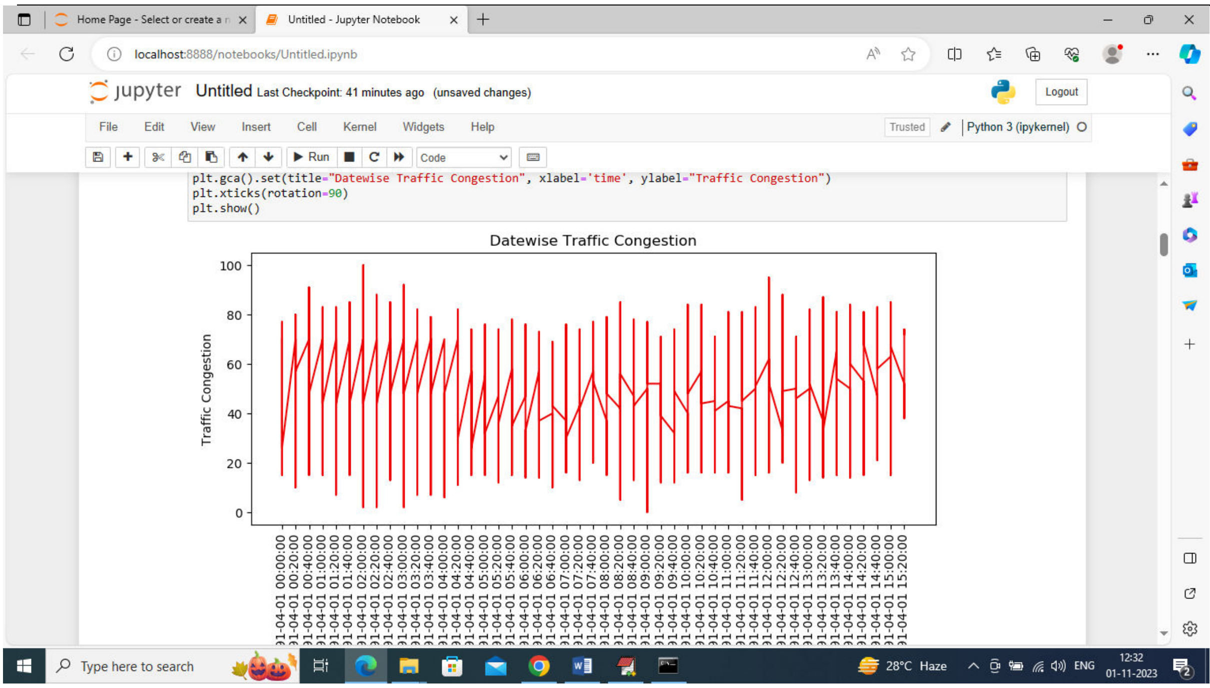
We have coded this project using JUPYTER notebook and below are the code and output screens with blue color comments.



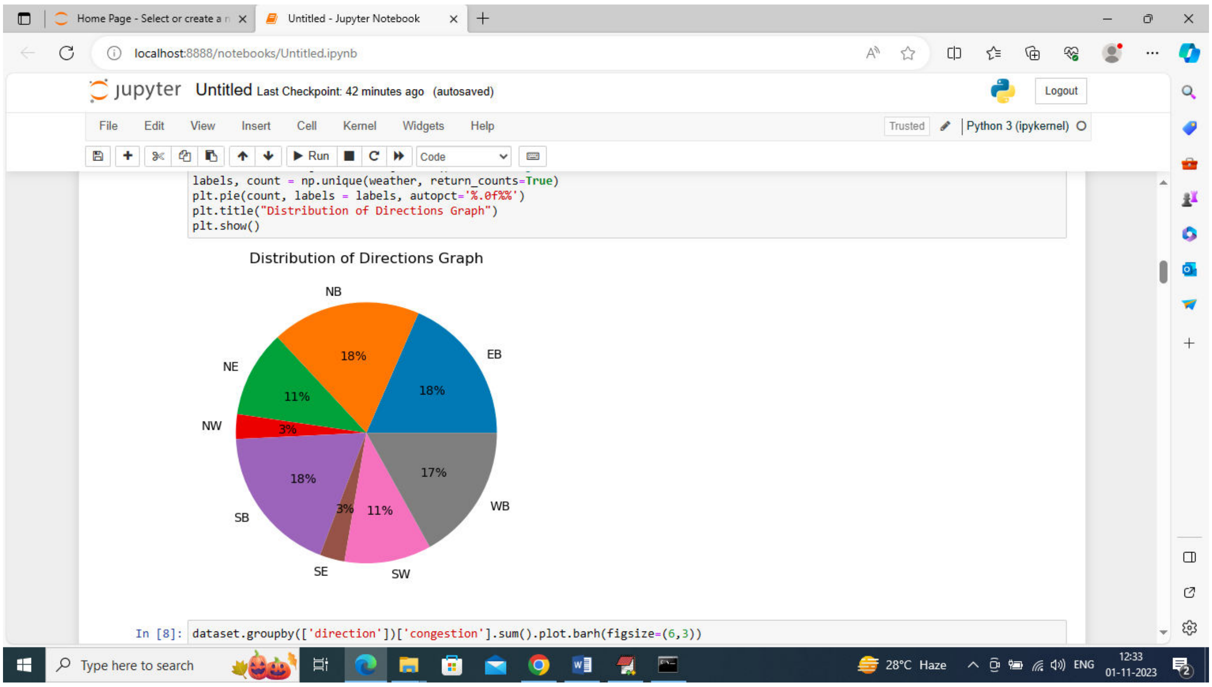

In above screen we are importing require python classes and packages.



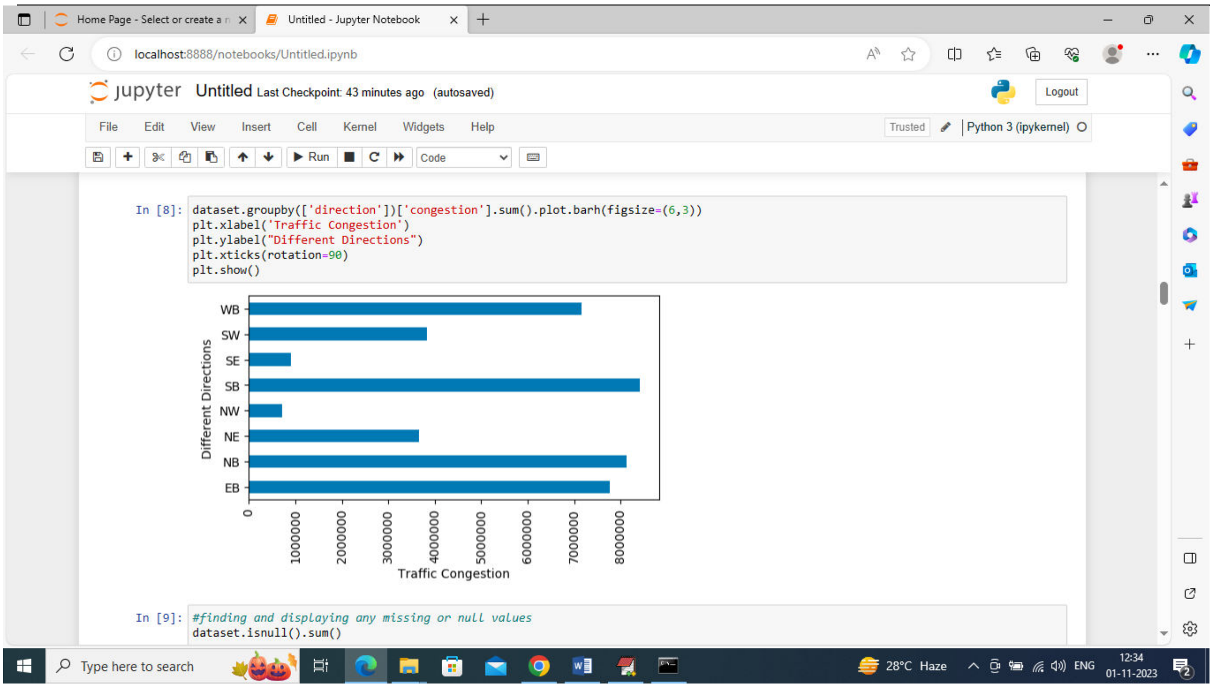

In above screen loading and displaying dataset values.



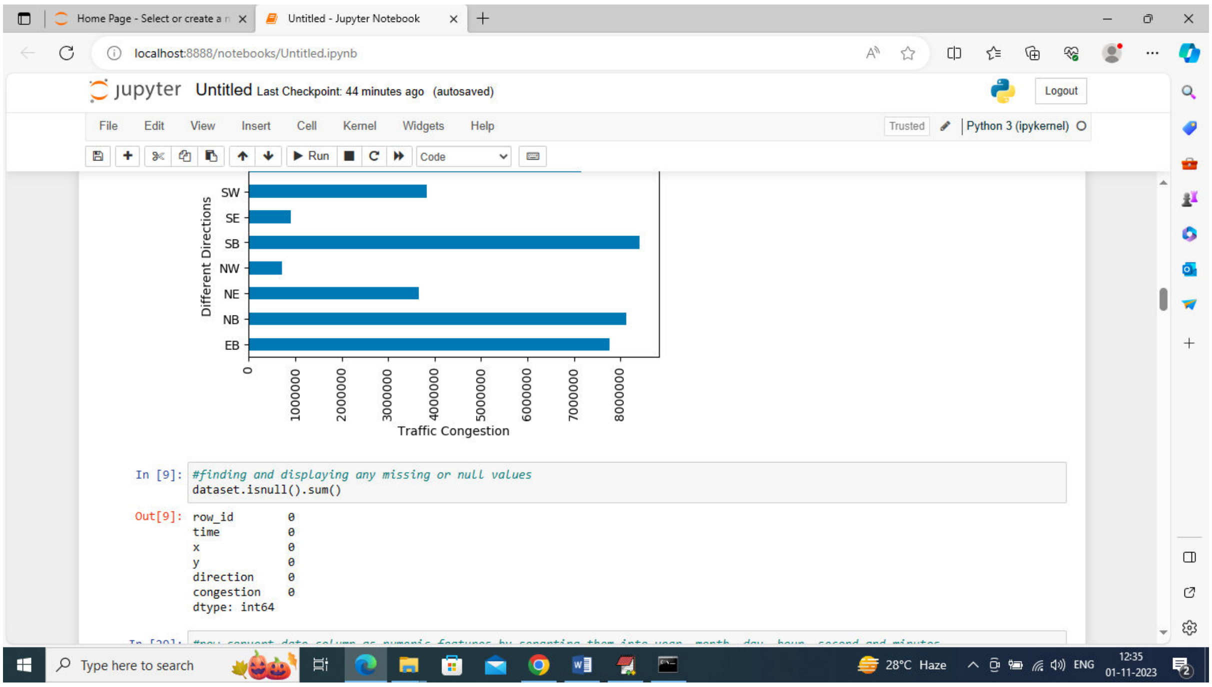

In above graph displaying traffic congestion on different dates where x-axis represents Date and y-axis represents traffic congestion.



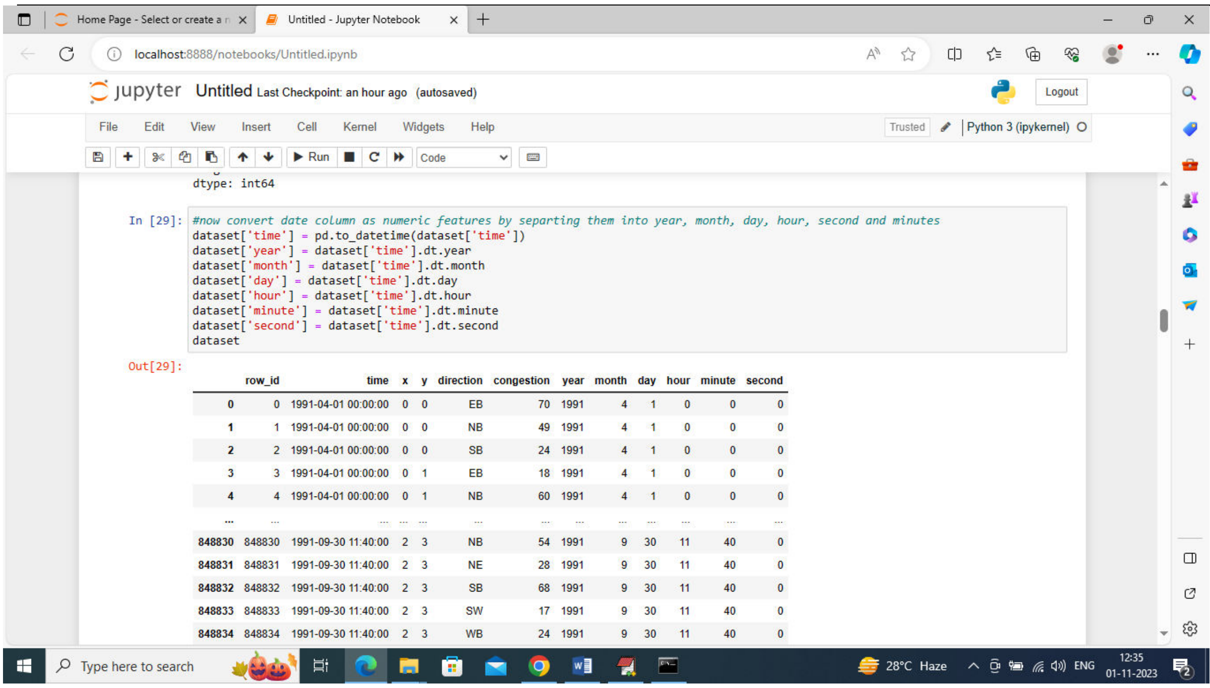

In above graph we are finding percentage of different directions or route exists in the dataset.



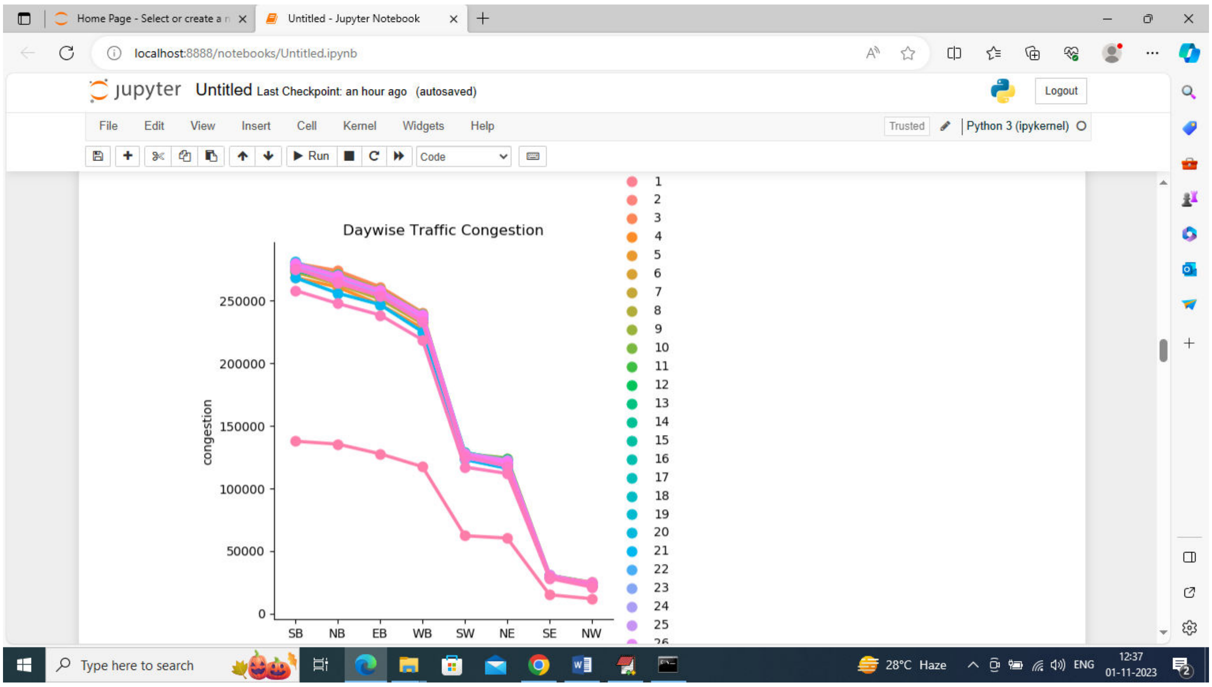

In above graph we are finding sum of traffic exists in each direction where x-axis represents traffic count and y-axis represents direction.



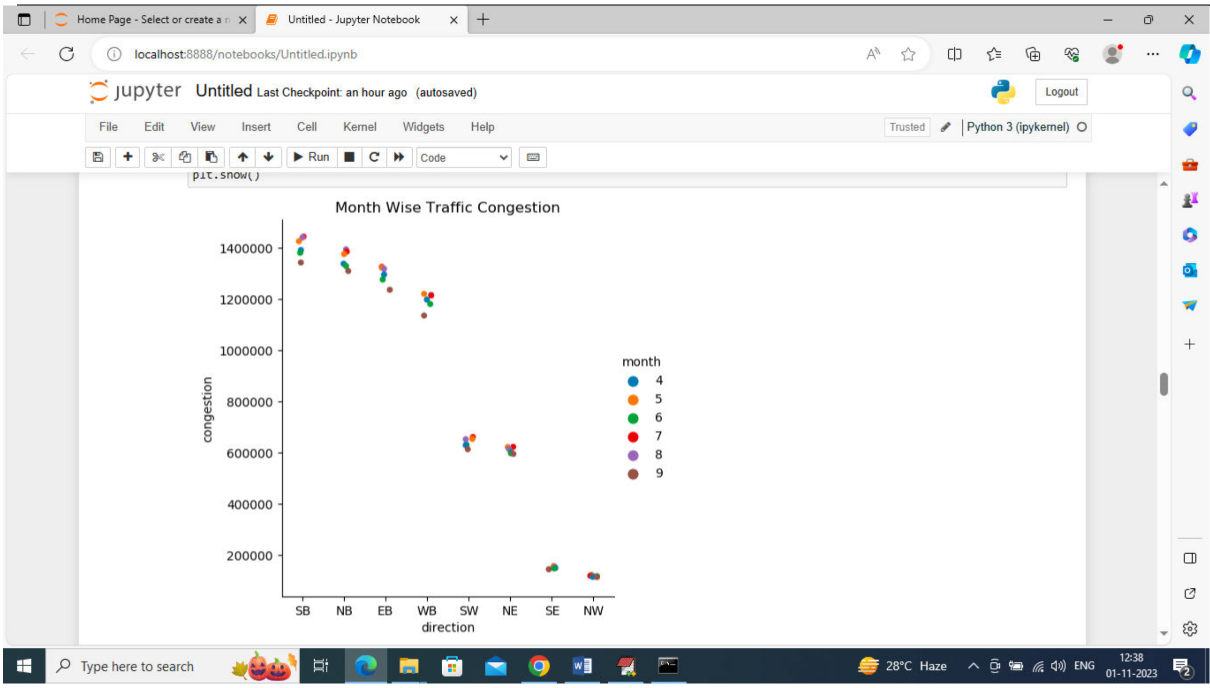

In above screen we are finding weather dataset contains any missing or null values but this dataset has no missing values.



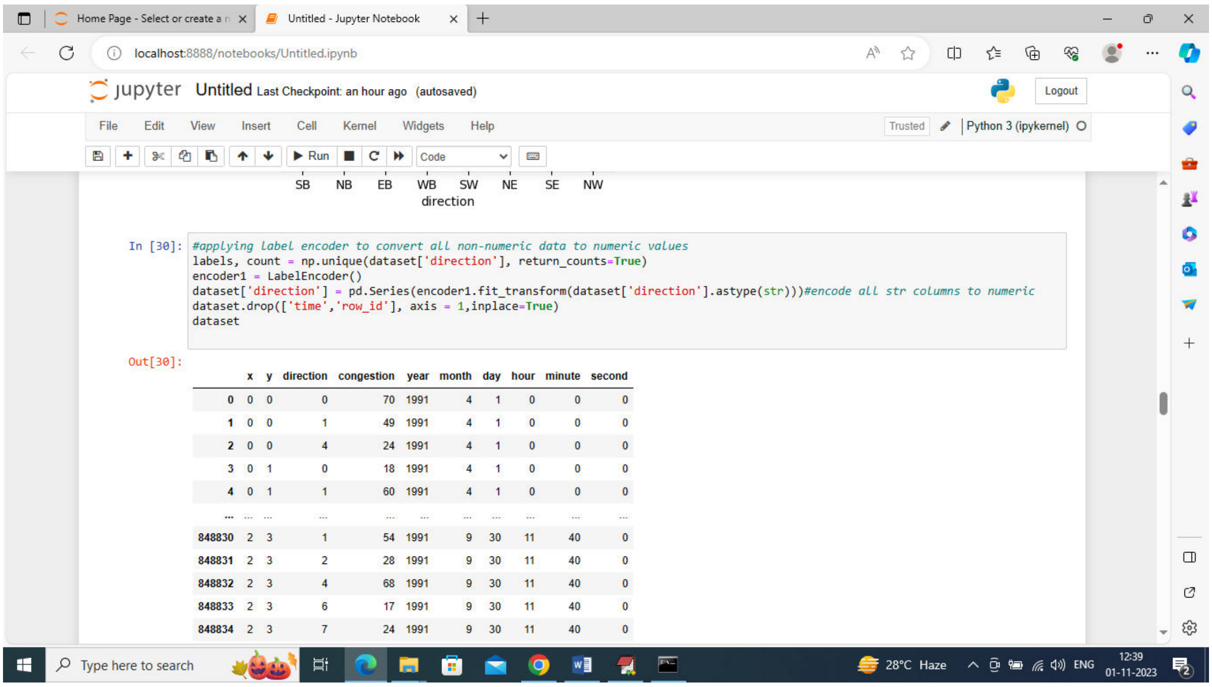

In above screen we are processing dataset to convert date into Day, Month and Year format so we can analyze traffic day or month wise and in above output we can see now dataset has day, year and month columns.



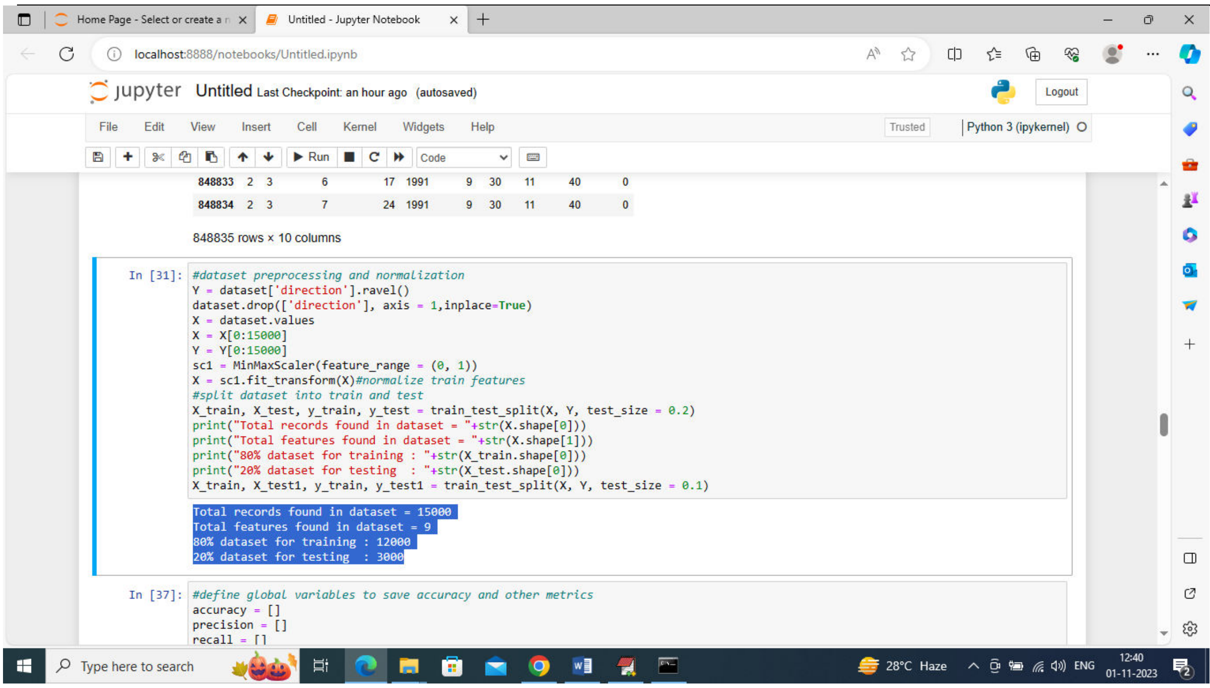

In above graph we are finding traffic day wise and each different color line represents different days traffic where x-axis is the direction and y-axis is the traffic congestion count.



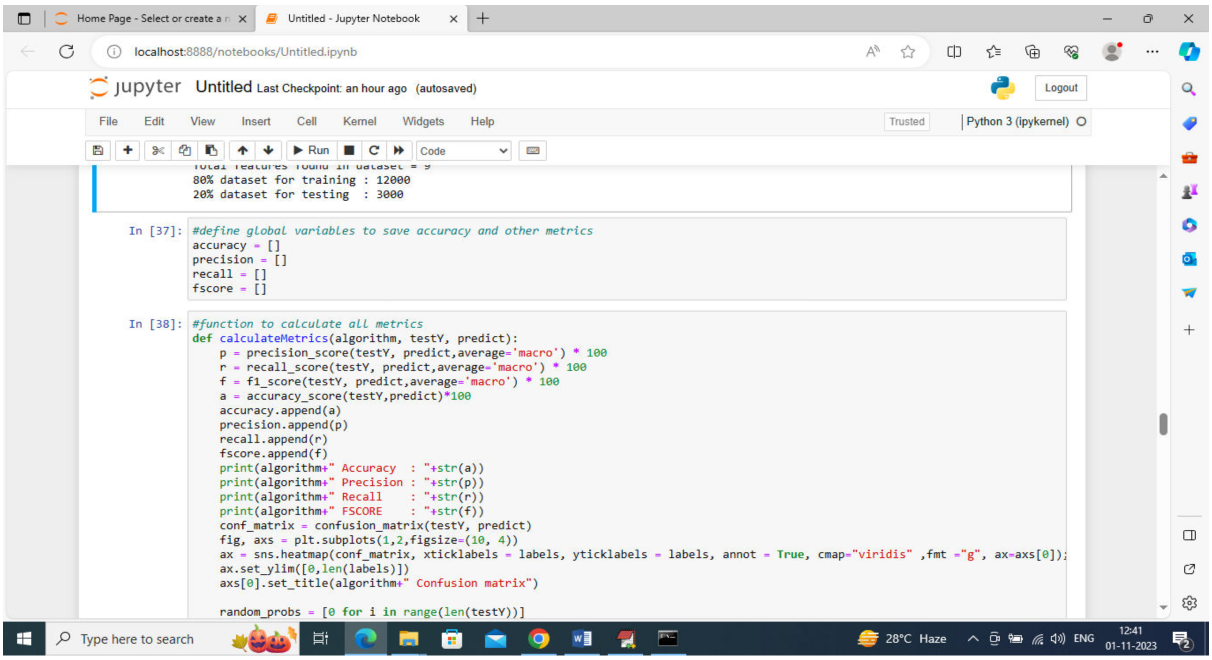

In above graph we are finding month wise traffic in different directions where x-axis represents direction and y-axis represents traffic congestion and different color dots represents months.



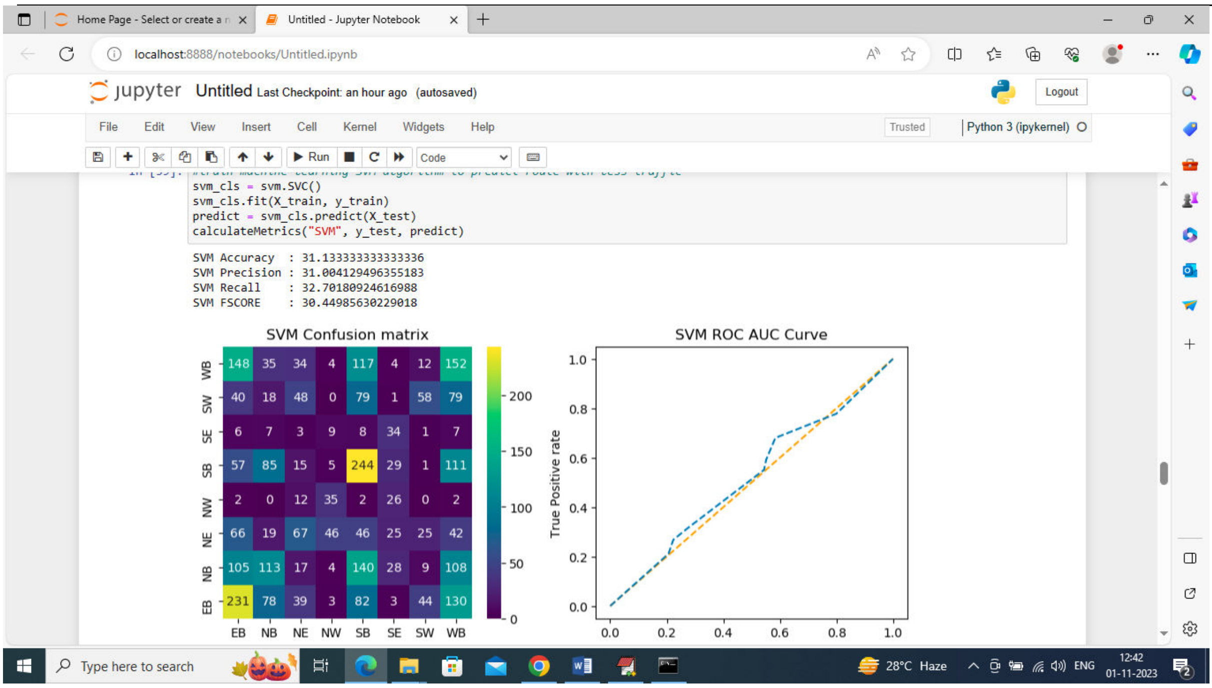

In above screen different directions are in string format so we have converted them into numeric format as ML will take all labels are numeric format so we have converted them into numeric labels.



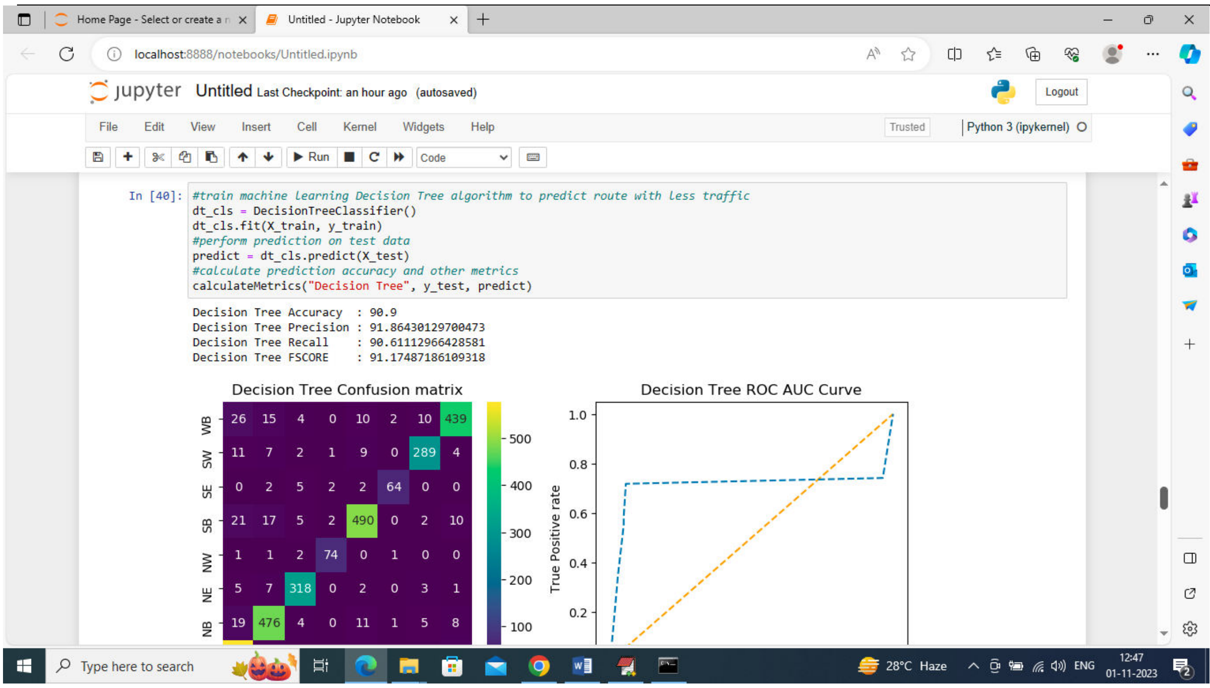

In above screen we are processing dataset such as normalization and then splitting into train and test where application using 80% dataset for training and 20% for testing and in blue colour we can see train and test size.



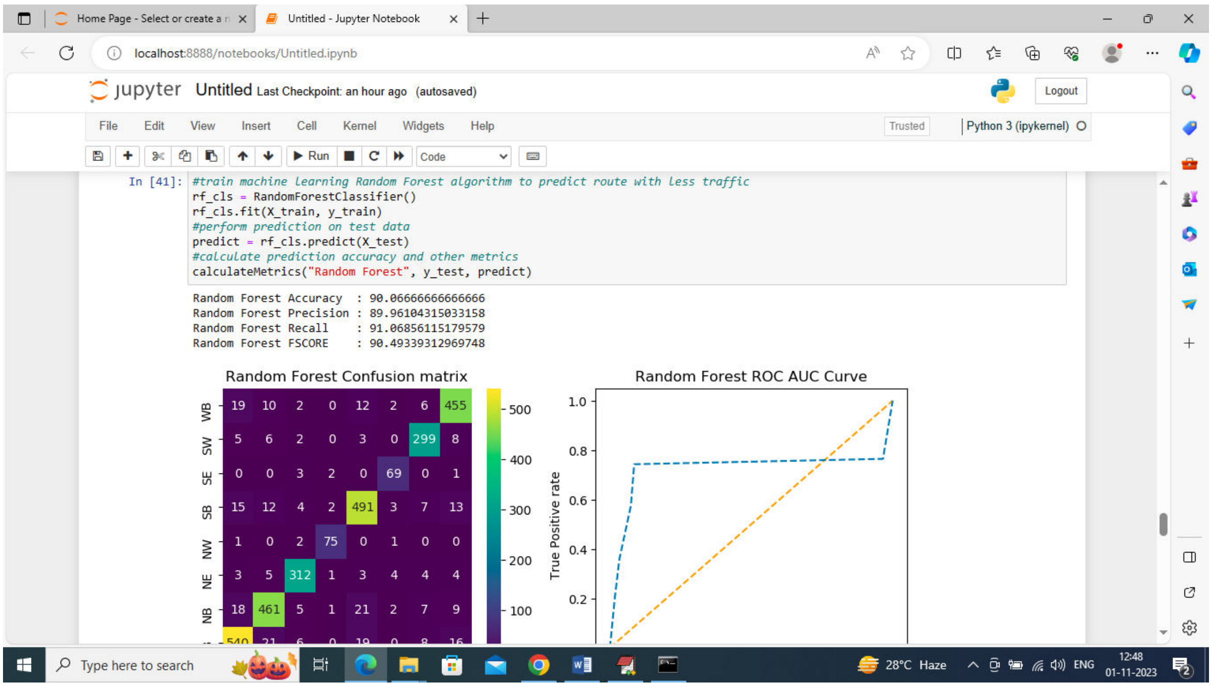

In above screen defining function to calculate accuracy and other metrics.



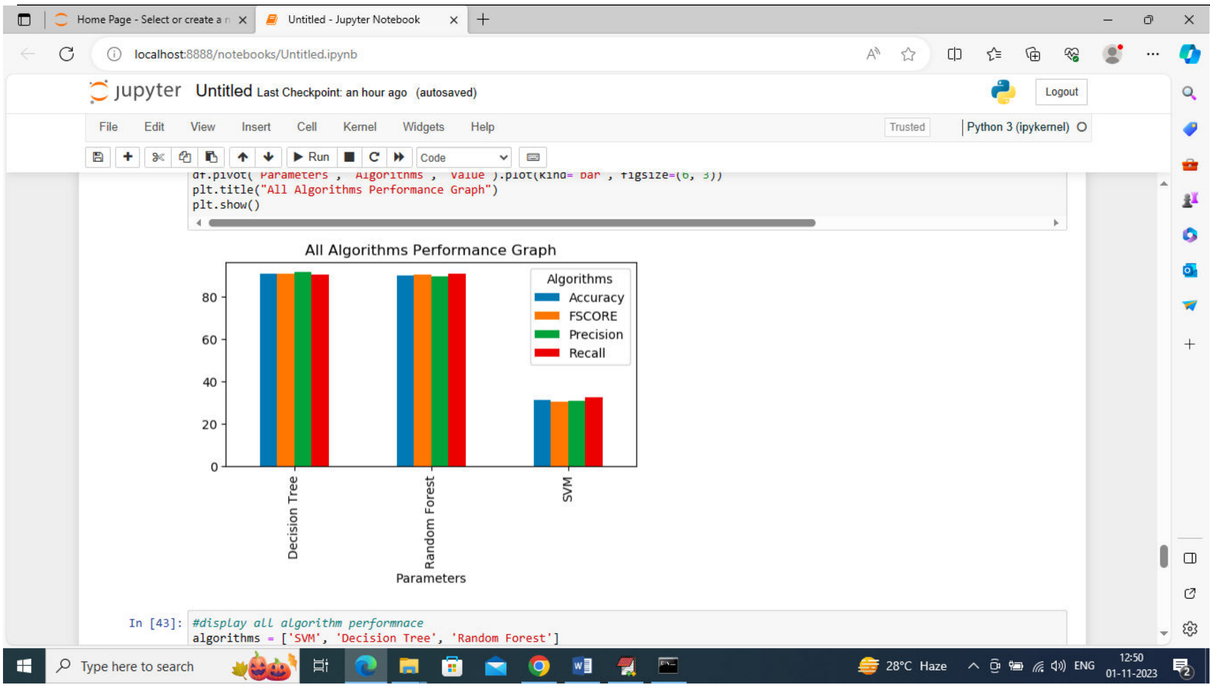

In above screen training SVM algorithm and after training SVM got 30% accuracy and can see other metrics also. In confusion matrix graph x-axis represents Predicted Labels and y-axis represents True Labels and all boxes in diagnol represents correct prediction count and remaining boxes represents incorrect prediction counts and from above graph we can notice SVM predicted many records incorrectly. In ROC curve graph x-axis represents False Prediction and y-axis represents True Predictions and if blue line comes on top of orange line then predictions are correct and if goes below orange line then predictions are incorrect and in above graph we can see only few predictions are correct.



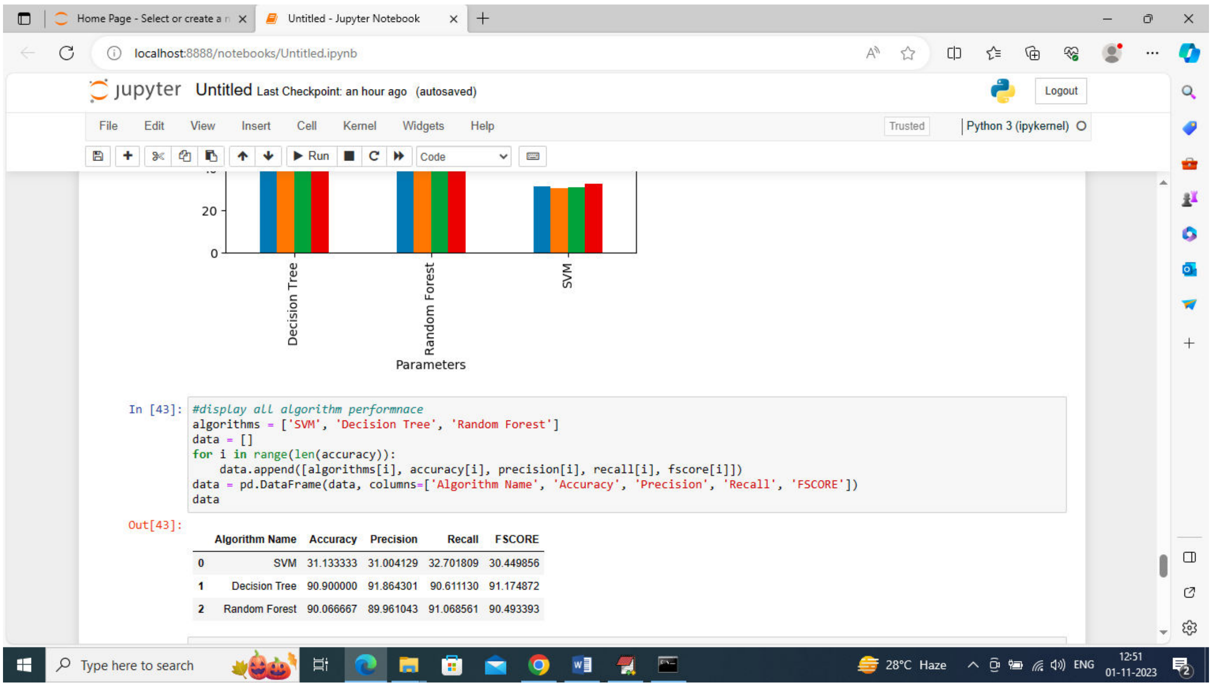

In above screen training decision tree and it got 90.9% accuracy and can see other metrics and results graph.



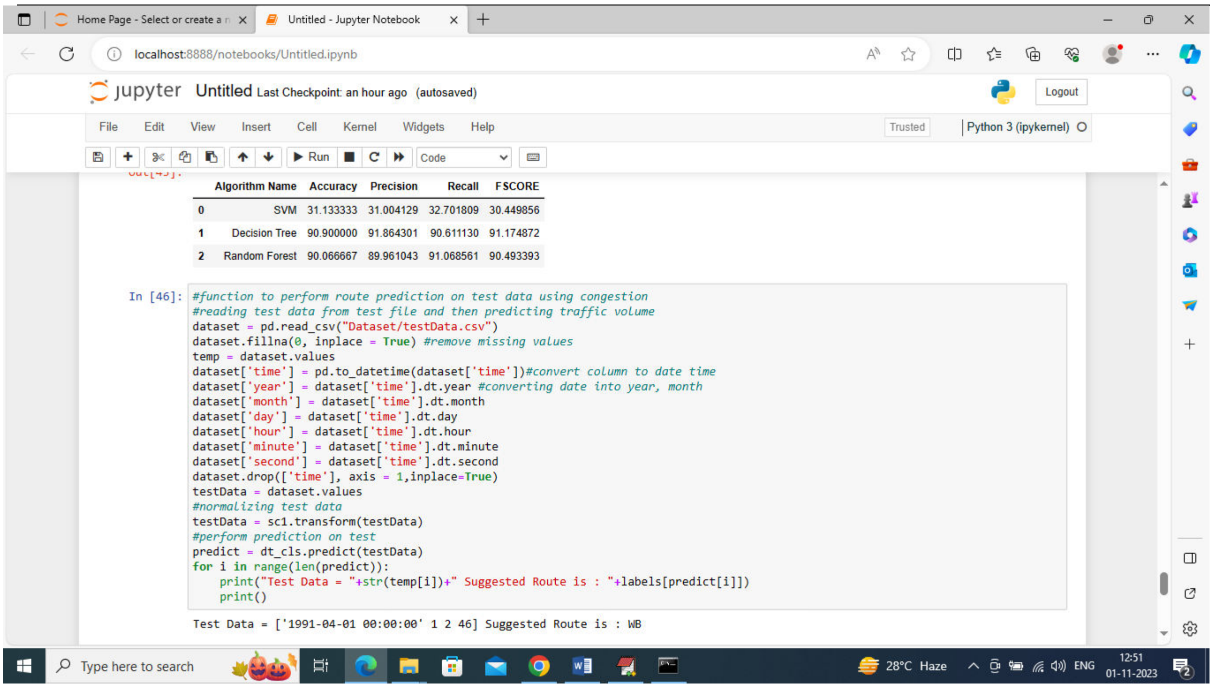

In above screen training Random Forest and it got 90.06% accuracy and can see other metrics also and in above confusion matrix graph in diagnol we can see many records are correctly predicted and in all blue boxes only few are incorrectly prediction. In ROC graph also we can see only few predictions are incorrect.



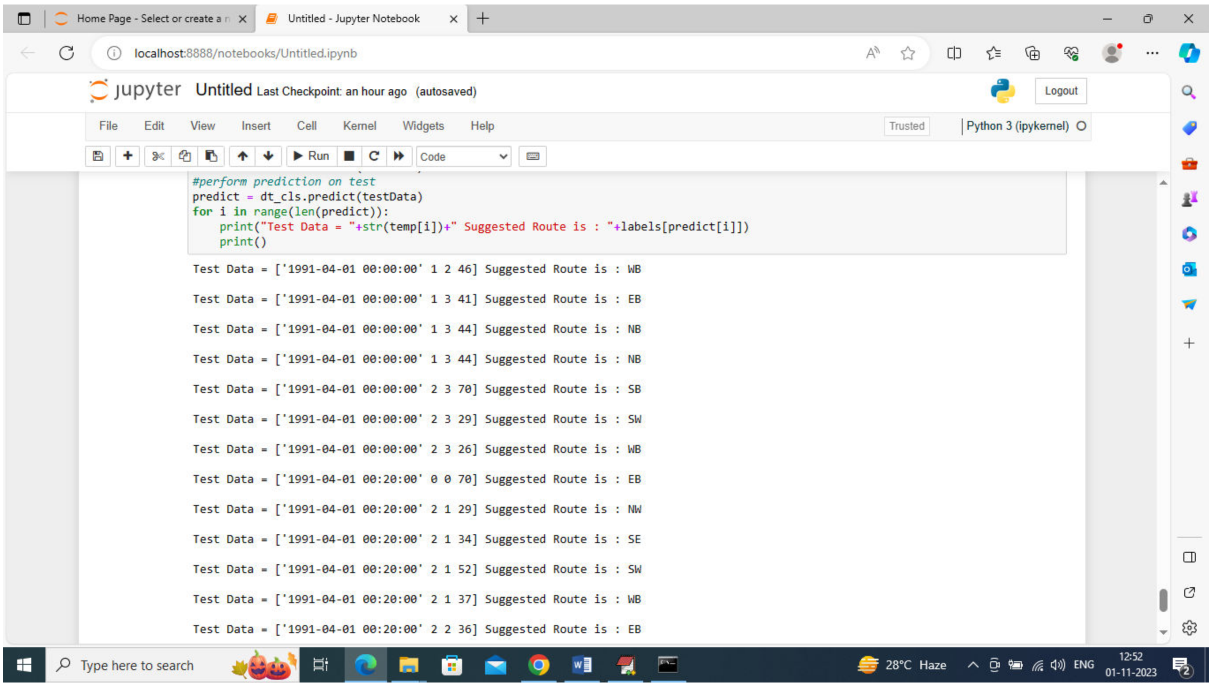

In above graph x-axis represents algorithm names and y-axis represents accuracy and other metrics in different color bars and in all algorithms Random Forest and Decision Tree work best.




In above screen can see all algorithm performance in tabular format.




In above screen we are defining function to read TEST data and then perform route prediction on test and after execution above block will get below output




In above predictions in square bracket we can see the TEST data where last value is traffic congestion and based on that congestion we can see suggested Route as WB or NB or SE etc.

**Note:** The direction of travel of the roadway. EB indicates "eastbound" travel, for example, while SW indicates a "southwest" direction of travel.

## 6. CONCLUSION AND FUTURE WORK

## CONCLUSION

In conclusion, our Traffic Route Prediction project represents a significant leap forward in addressing the persistent challenges of urban traffic congestion. Through the integration of advanced machine learning algorithms such as Support Vector Machines, Decision Tree, and Random Forest, we have endeavored to provide commuters with real-time alternative routes, enhancing the overall efficiency of traffic management. The comprehensive evaluation of these algorithms using accuracy, precision, recall, and F1 score metrics has revealed the prowess of Decision Tree in predicting routes amid dynamic traffic conditions.

The analysis, coupled with graph visualization techniques, has afforded us deeper insights into traffic flow dynamics, enriching the predictive capabilities of our system. While the Support Vector Machines exhibited suboptimal performance, the robustness and adaptability of our proposed system, especially leveraging the strengths of the Decision Tree algorithm, showcase the potential to revolutionize route planning in urban environments.

## 7. REFRENCES

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