Traffic Prediction

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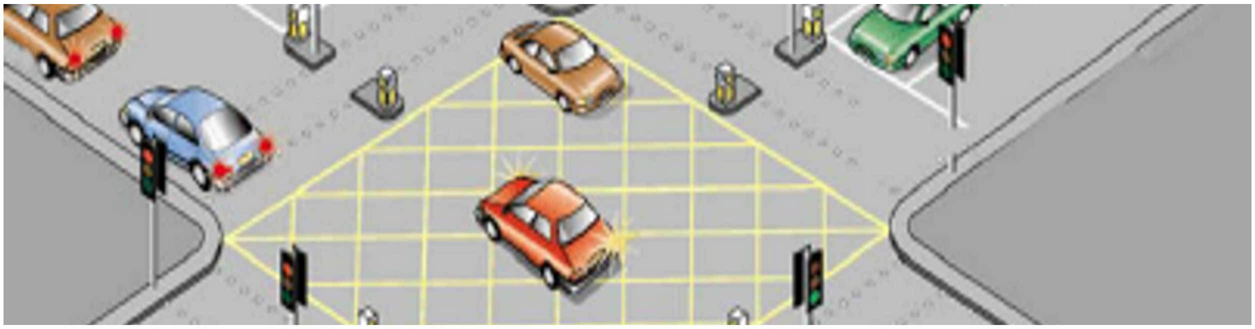
I. Introduction

Problem Statement:- Traffic prediction means forecasting the volume and density of traffic flow, usually for the purpose of managing vehicle movement, reducing congestion, and generating the optimal (least time- or energy-consuming) route. The task of detecting traffic for the next day, week etc.

Dataset:- The dataset contains 4 components (DateTime, Junction, Vehicles, id) across 48120 rows. The DateTime column shows the timestamp along with the respective date.

- DateTime - It shows the date and timestamp
- Junction - It tells the junction number for which vehicles are present
- Vehicles - It tells the number of vehicles
- id - It tells the id number of a timestamp

Dataset Link - Kaggle Dataset



II. Methodology

Overview:- We have implemented the following algorithms in our code: -

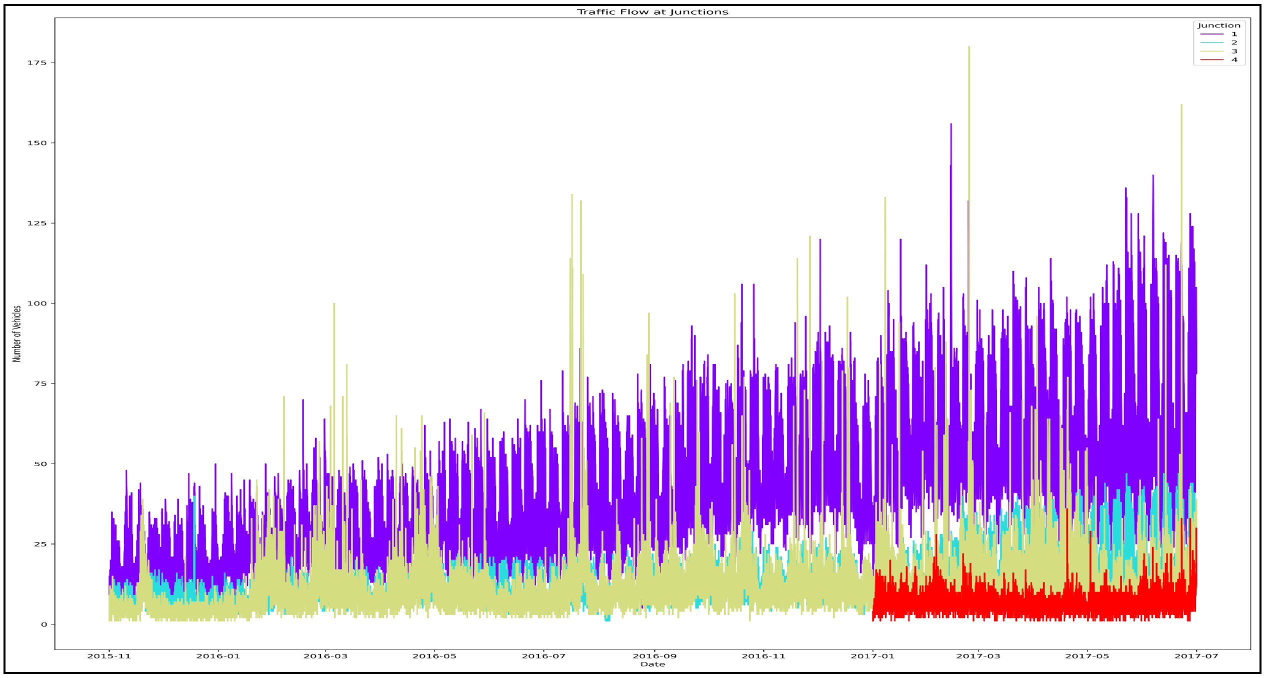
- *Decision Tree Regressor*
- *Linear Regression*
- *Random Forest Regression*
- *XGB Regression*
- *LGBM Regression*
- *Grid Search CV*

Preprocessing:- It is important to clean the data before applying any model. The preprocessing steps involved are:-

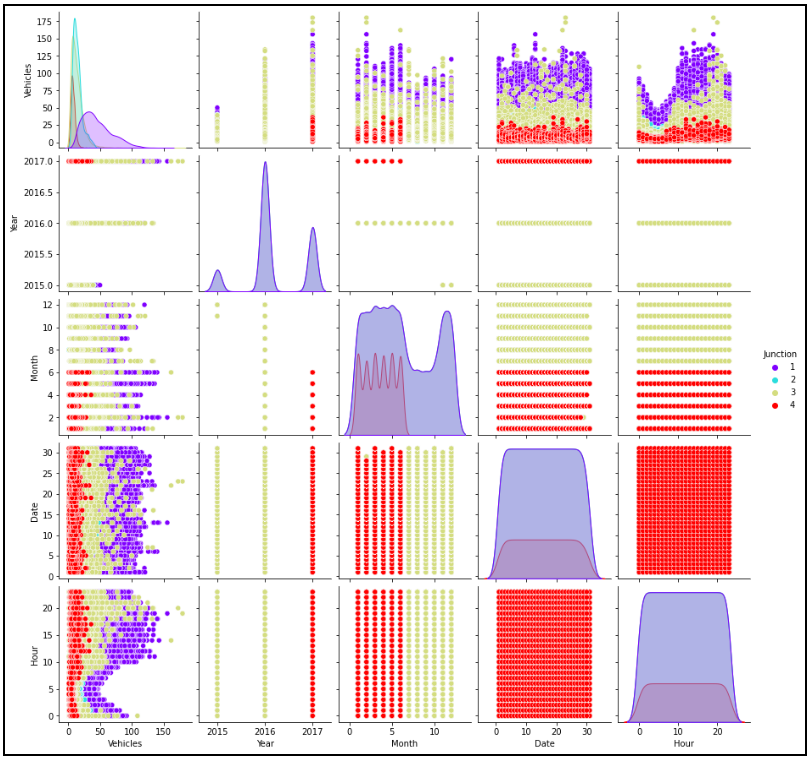
- *Dropping unnecessary columns (such as id)*
- *Conversion of date and time to DateTime format*
- *Adding more columns for the day of the week, date, month, year and hour*
- *Encoding the day of the week data column*
- *Creating different data frames for different junctions*
- *Splitting the data into train and test for different junctions and adding them to a list*

Visualization:- It is important to understand different aspects of every feature at a minute level before applying any model. The types of visualizations applied are:-

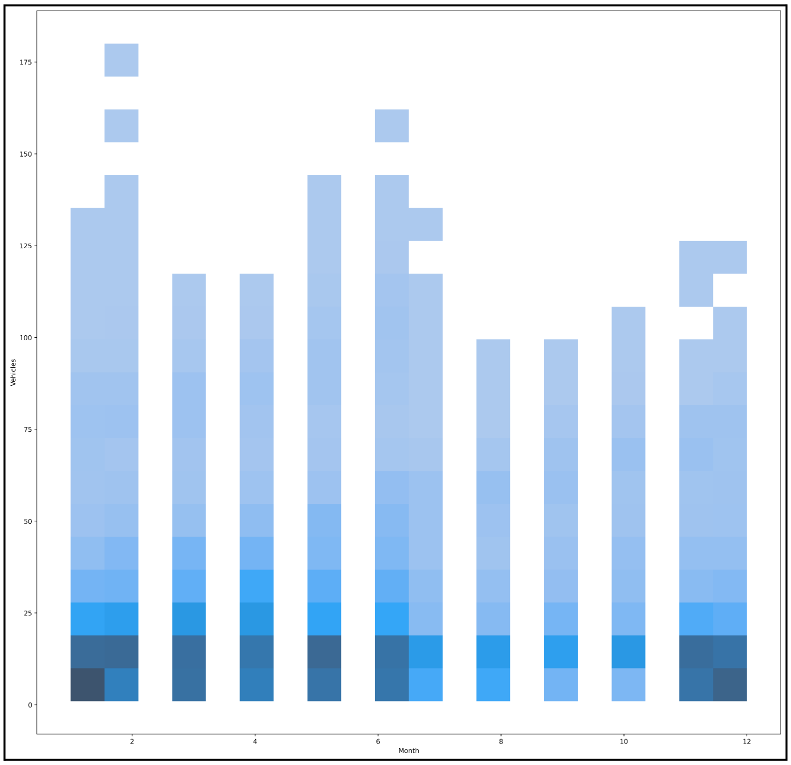
- *Traffic flow across different junctions across time-period*



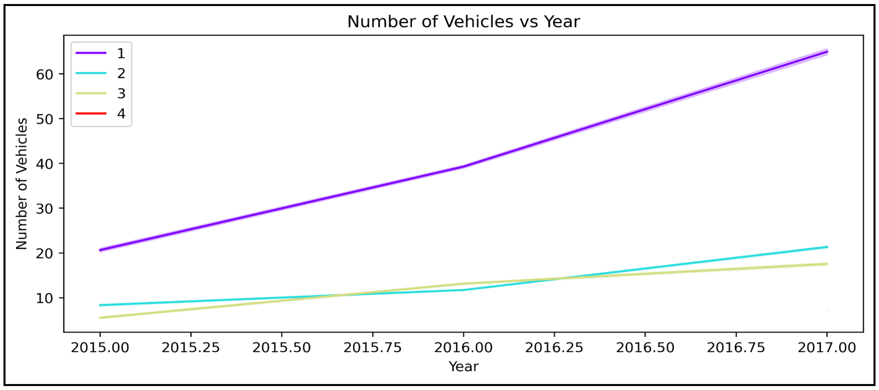
- *Pairplot of different features*

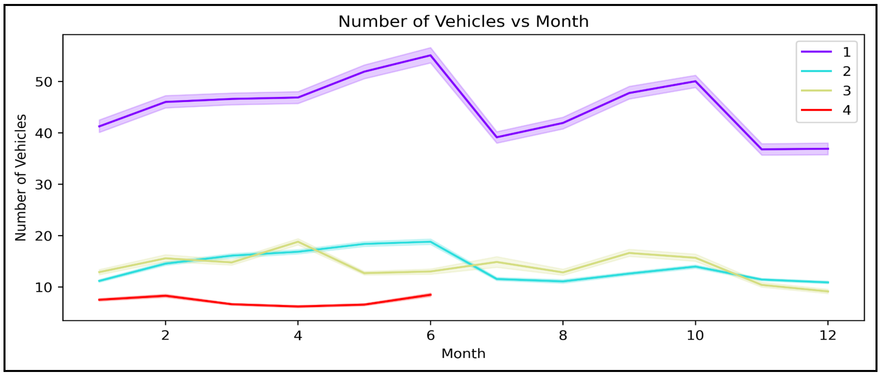


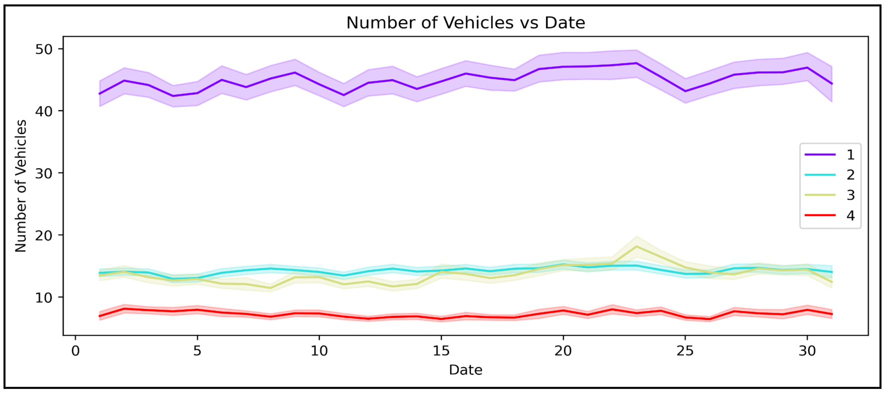
- *Histogram of month-wise traffic flow*

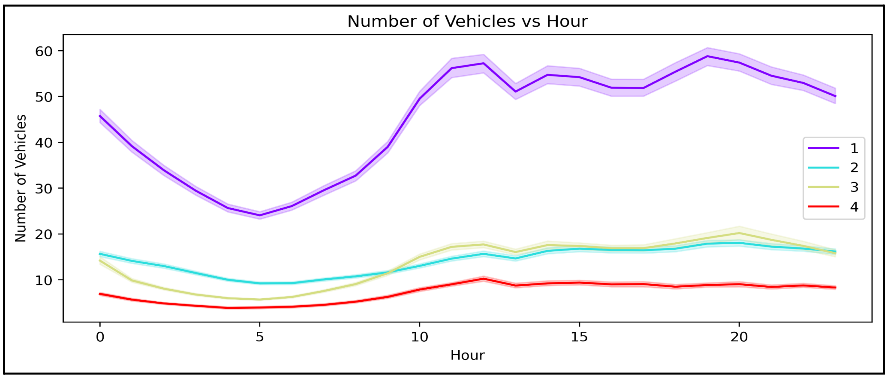


- *Lineplots for number of vehicles across the year, month, day and hour across different junctions.*

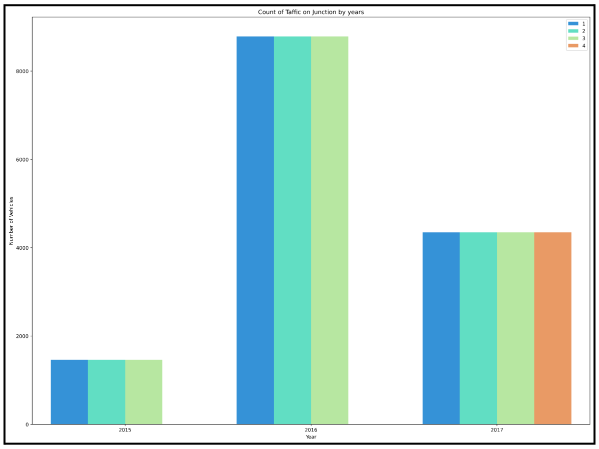




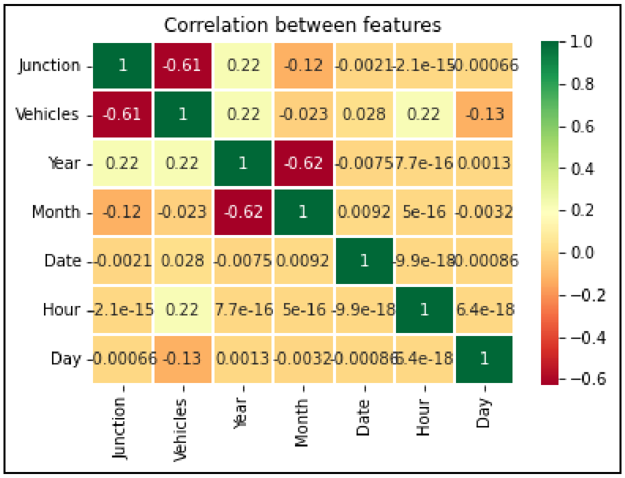




- *Countplot of traffic across different years*

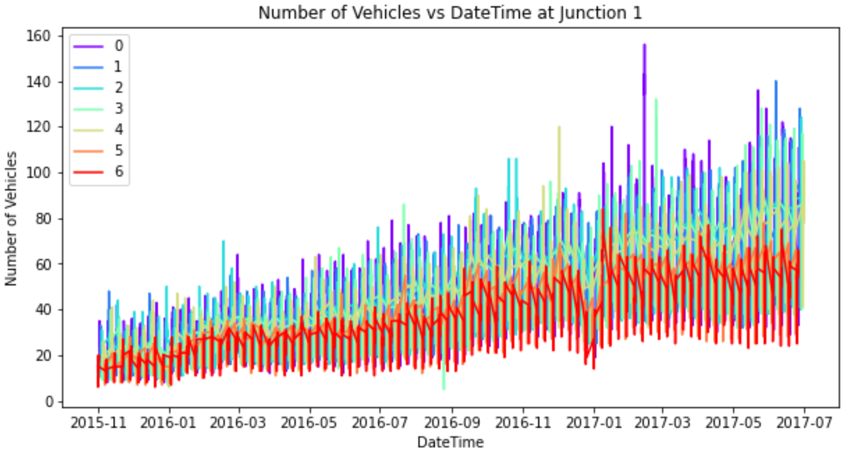


- *Correlation Heatmap for different features*

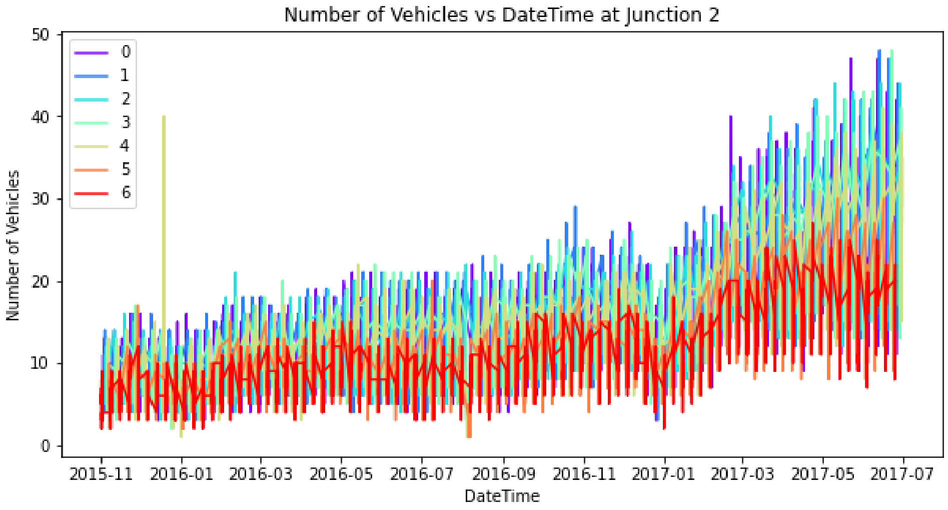


- *Plotting the number of vehicles across every day of the week for each junction.*

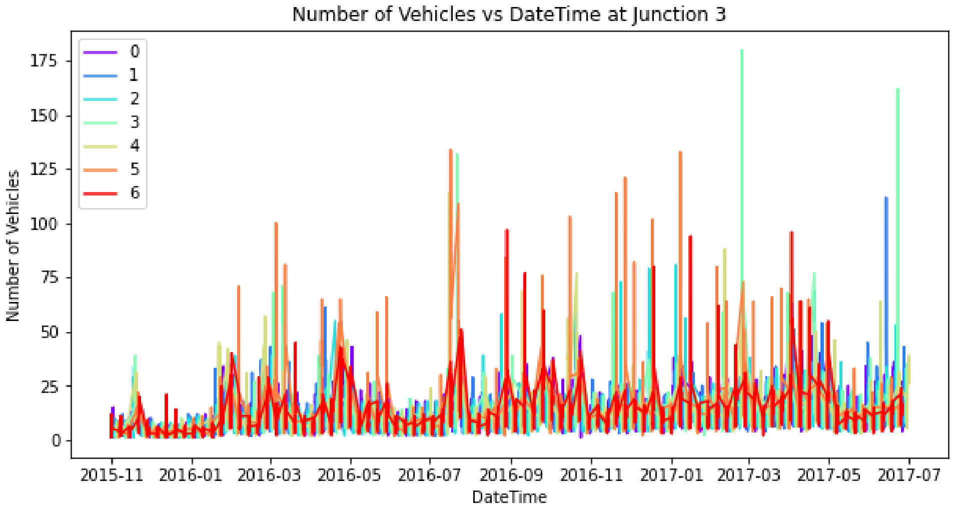
  ○ Junction 1



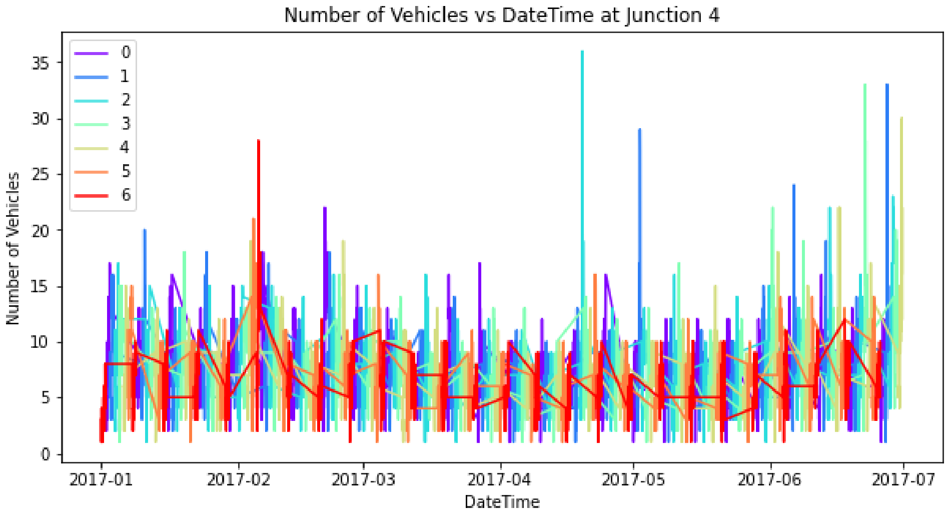
- Junction 2



- Junction 3



- Junction 4



Implementation:-

For Feature Selection, We see that our data has only date-time as a feature for every junction, which we then separate into 5 features namely, Year, Month, Date, Hour and Day. Since there were no redundant features, we do not employ a Feature Selection Algorithm.

Now, The Models used:

- ***Decision Tree Regressor:*** *Decision tree builds regression or classification models in the form of a tree structure. It breaks down a dataset into smaller and smaller subsets while at the same time an associated decision tree is incrementally developed. The final result is a tree with decision nodes and leaf nodes.*
- ***Linear Regression:*** *Linear regression performs the task to predict a dependent variable value (y) based on a given independent variable (x). So, this regression technique finds out a linear relationship between x (input) and y(output)*
- ***Random Forest Regression:*** *A Random Forest is an ensemble technique capable of performing both regression and classification tasks with the use of multiple decision trees and a technique called Bootstrap and Aggregation, commonly known as bagging. The basic idea behind this is to combine multiple decision trees in determining the final output rather than relying on individual decision trees.*
- ***XGB Regression:*** *Extreme Gradient Boosting, or XGBoost for short, is an efficient ensemble learning algorithm via gradient boosting. It provides a parallel implementation of decision trees that are created in a sequential form, where weights play an important role.*
- ***LGBM Regression:*** *Light GBM is a gradient boosting framework that uses tree-based learning algorithms. Light GBM grows trees vertically while other algorithms grow trees horizontally meaning that Light GBM grows trees leaf-wise while other algorithms grow level-wise. It will choose the leaf with max delta loss to grow. When growing the same leaf, a Leaf-wise algorithm can reduce more loss than a level-wise algorithm.*

For tuning the hyperparameters, We have used ***Grid Search CV****, which uses a different combination of all the specified hyperparameters and their values and calculates the performance for each combination and selects the best value for the hyperparameters.*

III. Evaluation of Models

We have applied the above-mentioned algorithms for different junctions individually and recorded the test, train and RMSE scores.

- *For Junction 1:-*

Name of the Model Applied	Train Score	Test Score	RMSE Score
Decision Tree Regressor	0.84795	0.83595	0.06118
Linear Regressor	0.63901	0.63250	0.09157
Random Forest Regressor	0.84706	0.84275	0.05990
Grid Search CV (Random Forest Regressor)	0.99545	0.96399	0.02769
XGB Regressor	0.97506	0.96968	0.02630
Grid Search CV (XG Boost)	0.99829	0.97411	0.02430
LGB Regressor	0.96021	0.95929	0.03047
Grid Search CV (Light GBM)	0.98460	0.97538	0.02370

- *For Junction 2:-*

Name of the Model Applied	Train Score	Test Score	RMSE Score
Decision Tree Regressor	0.80671	0.78502	0.07196
Linear Regressor	0.54524	0.51561	0.10801
Random Forest Regressor	0.82137	0.80292	0.06889
Grid Search CV (Random Forest Regressor)	0.97937	0.90306	0.04832
XGB Regressor	0.93635	0.90692	0.04734
Grid Search CV (XG Boost)	0.93635	0.90692	0.04734
LGB Regressor	0.91571	0.90150	0.04870
Grid Search CV (Light GBM)	0.94186	0.91173	0.04610

- *For Junction 3:-*

Name of the Model Applied	Train Score	Test Score	RMSE Score
Decision Tree Regressor	0.38390	0.35075	0.04633
Linear Regressor	0.24722	0.24254	0.05005
Random Forest Regressor	0.40431	0.37868	0.04533
Grid Search CV (Random Forest Regressor)	0.96402	0.70860	0.03104
XGB Regressor	0.76980	0.63556	0.03471
Grid Search CV (XG Boost)	0.99937	0.73741	0.02946
LGB Regressor	0.63148	0.56083	0.03811
Grid Search CV (Light GBM)	0.87147	0.69041	0.03199

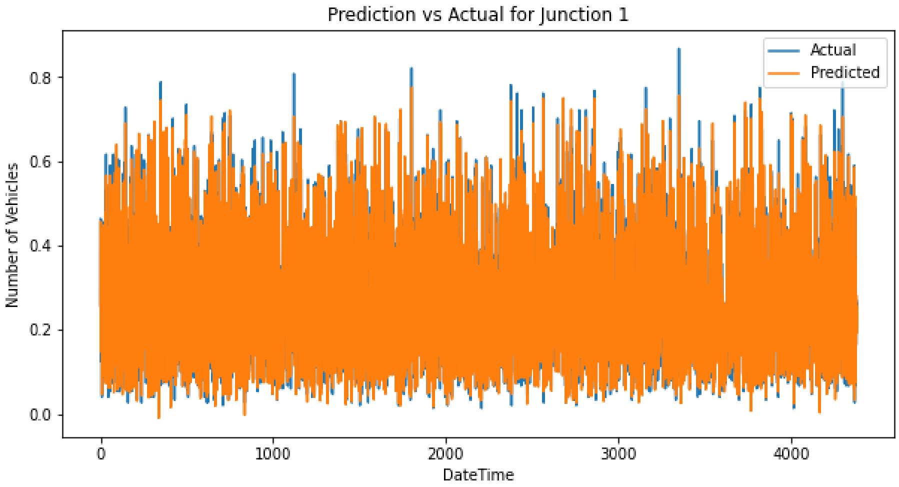
- *For Junction 4:-*

Name of the Model Applied	Train Score	Test Score	RMSE Score
Decision Tree Regressor	0.49650	0.42116	0.07954
Linear Regressor	0.19975	0.20613	0.09315
Random Forest Regressor	0.52271	0.43272	0.07874
Grid Search CV (Random Forest Regressor)	0.80133	0.49095	0.07459
XGB Regressor	0.79586	0.48834	0.07478
Grid Search CV (XG Boost)	0.79586	0.48834	0.07478
LGB Regressor	0.65620	0.51469	0.07283
Grid Search CV (Light GBM)	0.70091	0.52373	0.07215

IV. Result & Analysis

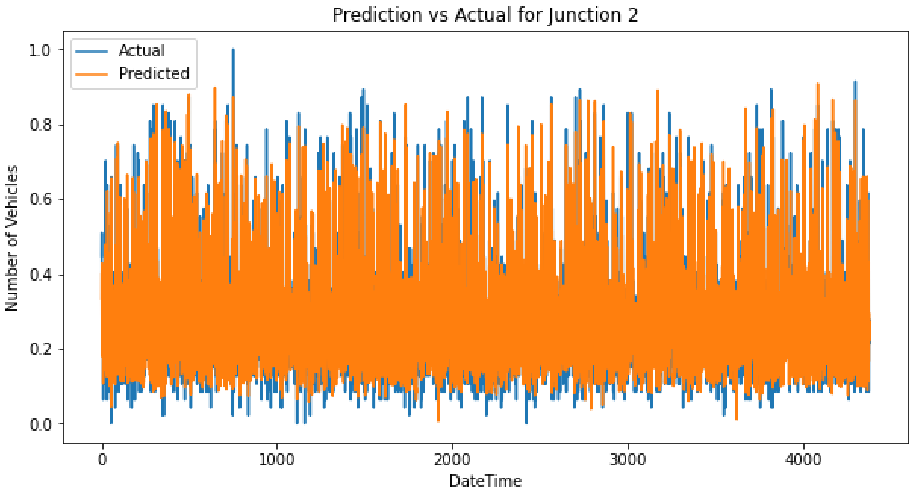
After analyzing through various models and junctions, a conclusion can be made to know which is the best model for a junction. The conclusion is :-

- **Junction 1** - *Light GBM after hyperparameter tuning with GridSearchCV*



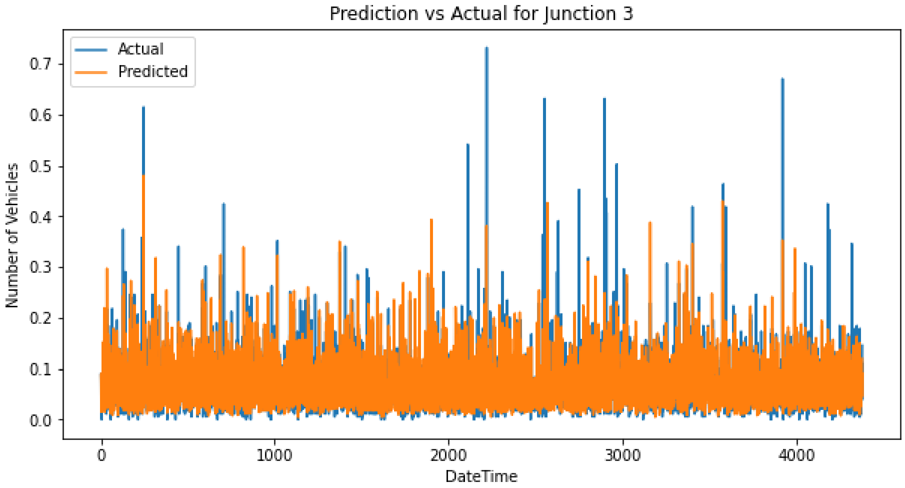
Accuracy score for the model GridSearchCV(lightgbm) on the train set: ***0.9846079330767183***
Accuracy score for the model GridSearchCV(lightgbm) on the test set: ***0.9753823289109363***
RMSE score for the model GridSearchCV(lightgbm) on the test set: ***0.023702447113830984***

- **Junction 2** - *Light GBM after hyperparameter tuning with GridSearchCV*



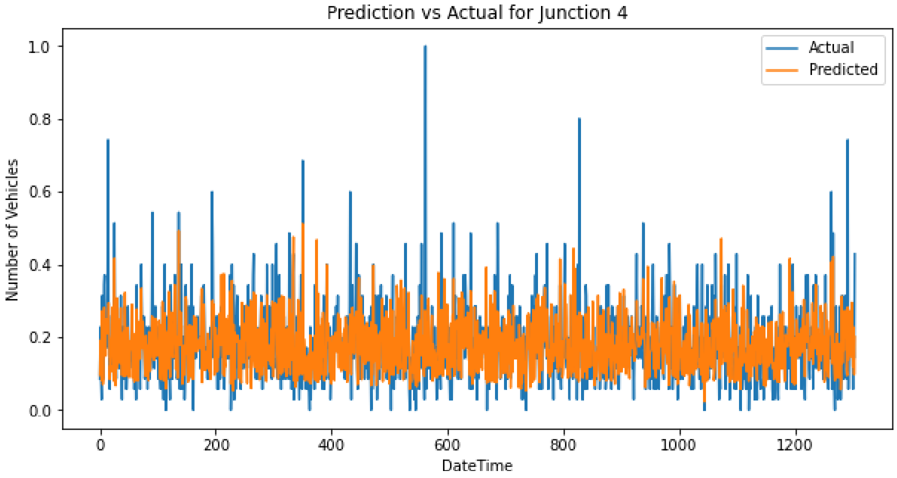
Accuracy score for the model GridSearchCV(lightgbm) on the train set: ***0.9418674199141464***
Accuracy score for the model GridSearchCV(lightgbm) on the test set: ***0.9117378990695377***
RMSE score for the model GridSearchCV(lightgbm) on the test set: ***0.04610918678100267***

- **Junction 3** - *Random Forest Regressor after hyperparameter tuning with GridSearchCV*



Accuracy score for the model GridSearchCV(lightgbm) on the train set: ***0.9640296641946572***
Accuracy score for the model GridSearchCV(lightgbm) on the test set: ***0.7086006232467421***
RMSE score for the model GridSearchCV(lightgbm) on the test set: ***0.031044055027950327***

- **Junction 4** - *Light GBM after hyperparameter tuning with GridSearchCV*



Accuracy score for the model GridSearchCV(lightgbm) on the train set:
0.7009171982881327
Accuracy score for the model GridSearchCV(lightgbm) on the test set:
0.5237397514165021
RMSE score for the model GridSearchCV(lightgbm) on the test set:
0.07215436594321141

V. Web Application and Pipeline

We implemented an end-to-end pipeline using the python pickle library. The four best models for four different junctions were saved along with the preprocessing done on the data using the pickle library and the four ".pkl" model files were created.

Then, we converted our directory into a pipenv environment and installed all the necessary libraries.
We created a python file where we used the Python StreamLit library to render our website server which included a home page (predictions page) which takes the input features from the user in the form of radio buttons. Features input by the user:

- *Year*
- *Month*
- *Date*
- *Hour*
- *Junction*

We import all the four saved models in our py file and select which model to apply according to the Junction information provided by the user and finally return the rounded off predictions (Number of Vehicles) to the user.

VI. References

- Decision Tree Regressor | RandomForestRegressor | XGBoost | LightGBM | LinearRegression
- Pattern Classification by Richard O. Duda, Peter E. Hart, David G. Stork
- Vehicle Dataset | Kaggle
- Seaborn Plots | Seaborn Docs
- Article on Traffic Prediction | www.alexsoft.com

VII. Appendix

The learning and planning were done as a team. The individual contributions are as given

- **Ayush Abrol (B20AI052):** *Data Visualization and exploratory analysis, GridsearchCV XGboost and RandomForest regressors, Pipeline Implementation and Web Application Development, Report.*
- **Aryan Tiwari (B20AI056):** *Data Preprocessing, Decision tree and Linear regression and GridsearchCV LightGBM, Code Optimization and Documentation, Report.*
- **Neehal Bajaj (B20AI026):** *Junction-Wise Data Visualization and analysis, LGBM, XGB, randomForest implementation without GridsearchCV, Report.*

VIII. Acknowledgement

We would like to express our sincere gratitude towards **Dr. Richa Singh** for guiding us through this course and helping us in grasping all the aspects of the various concepts covered. Furthermore, We are grateful to our Teaching Assistants for helping us in clearing all our doubts and guiding us all the way through the course. Finally, we would like to thank our institute, Indian Institute of Technology, Jodhpur, for providing us with the opportunity to work on this project.