Industrial Internship Report on

“Forecasting of Smart City Traffic Patterns”

Prepared by

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Executive Summary
This report provides details of the Industrial Internship provided by upSkill Campus and The IoT Academy in collaboration with Industrial Partner UniConverge Technologies Pvt Ltd (UCT). This internship was focused on a project/problem statement provided by UCT. We had to finish the project including the report in 6 weeks’ time. My project, titled 'Forecasting of Smart City Traffic Patterns,' aimed to optimize traffic control strategies for four city junctions. It focused on predicting traffic patterns during peak hours and holidays, ultimately contributing to enhanced traffic management. This internship gave me a very good opportunity to get exposure to Industrial problems and design/implement solution for that. It was an overall great experience to have this internship.

TABLE OF CONTENTS

1 Preface 3
2 Introduction 5
  2.1 About UniConverge Technologies Pvt Ltd 5
  2.2 About upSkill Campus 9
  2.3 About The IoT Academy 10
  2.4 Objectives 10
  2.5 References 10
  2.6 Glossary 10
3 Problem Statement 11
4 Existing and Proposed solution 12
5 Proposed Design/ Model 13
6 Performance Test 15
  6.1 Test Plan/ Test Cases 15
  6.2 Test Procedure 17
  6.3 Performance Outcome 19
7 My learnings 26
8 Future work scope 27

1 Preface

In the span of six weeks, I embarked on a transformative journey of hands-on learning and application through my internship experience. This internship not only deepened my understanding of the practical aspects of my field but also laid the foundation for my future career development.

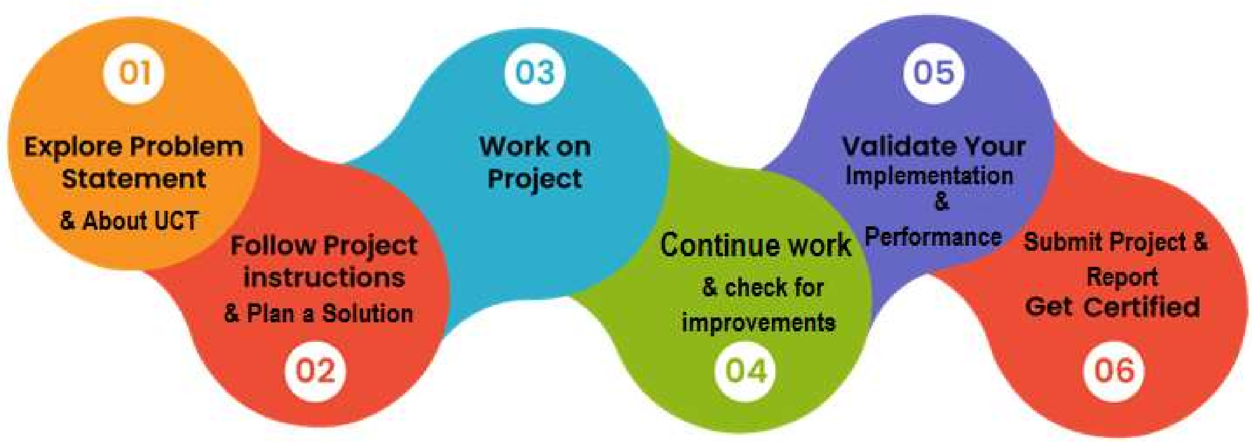
Throughout the internship, my focus was on the project titled 'Forecasting Smart City Traffic Patterns.' This project played a pivotal role in addressing traffic management challenges within urban landscapes. It involved predicting traffic patterns during peak hours and holidays, contributing significantly to the optimization of traffic control strategies for city junctions.

This internship has been a pivotal stepping stone in my career journey. It has allowed me to bridge the gap between theoretical knowledge and real-world application. The experience gained here has provided me with valuable insights and skills that are directly applicable to my future career aspirations.

The primary objective of my project was to forecast traffic patterns in smart cities. By understanding and predicting traffic flow during peak hours and holidays, I aimed to support efficient traffic management and infrastructure planning for the future. This project was not only intellectually stimulating but also aligned with the broader goal of transforming cities into smarter and more sustainable urban centers.

I am immensely grateful to upSkill Campus (USC), UniConverge Technologies Pvt Ltd (UCT) and The IoT Academy for providing me with this incredible opportunity. Their collaborative efforts with industry partners facilitated a dynamic learning environment, enabling me to work on real-world problems and gain practical experience.

The program was meticulously planned to ensure a well-rounded internship experience. It included a structured curriculum, expert guidance, and hands-on projects. The combination of coursework, mentorship, and practical application created a comprehensive learning journey.



During these six weeks, I acquired a wealth of knowledge and skills that extended far beyond the classroom. I delved into data science, machine learning, and data analysis, gaining proficiency in these areas. Additionally, I developed problem-solving abilities and learned to work effectively in a team. This internship has broadened my horizons and has been instrumental in my growth as a professional.

I extend my heartfelt gratitude to everyone who contributed directly or indirectly to my internship experience. I am thankful to my mentors and instructors for their guidance, my peers for their collaboration, and the industry experts who shared their insights. Your collective support has been invaluable.

To my juniors and peers, I encourage you to seize every opportunity for experiential learning. Internships like these provide a platform to apply classroom knowledge in real-world scenarios. Embrace challenges, ask questions, and never stop learning. Your determination and willingness to explore will pave the way for a successful and fulfilling career.

In conclusion, my internship journey has been an enlightening and enriching experience. It has equipped me with practical skills, fostered personal and professional growth, and instilled in me the confidence to tackle real-world challenges in my field. I look forward to applying these learnings in my future endeavors, contributing to the betterment of society, and striving for continuous improvement in my career.

2 Introduction

2.1 About UniConverge Technologies Pvt Ltd

A company established in 2013 and working in Digital Transformation domain and providing Industrial solutions with prime focus on sustainability and RoI.

For developing its products and solutions it is leveraging various **Cutting Edge Technologies e.g. Internet of Things (IoT), Cyber Security, Cloud computing (AWS, Azure), Machine Learning, Communication Technologies (4G/5G/LoRaWAN), Java Full Stack, Python, Front end** etc.

i. UCT IoT Platform (uct Insight)

UCT Insight is an IOT platform designed for quick deployment of IOT applications on the same time providing valuable "insight" for your process/business. It has been built in Java for backend and ReactJS for Front end. It has support for MySQL and various NoSql Databases.

- It enables device connectivity via industry standard IoT protocols - MQTT, CoAP, HTTP, Modbus TCP, OPC UA
- It supports both cloud and on-premises deployments.

It has features to

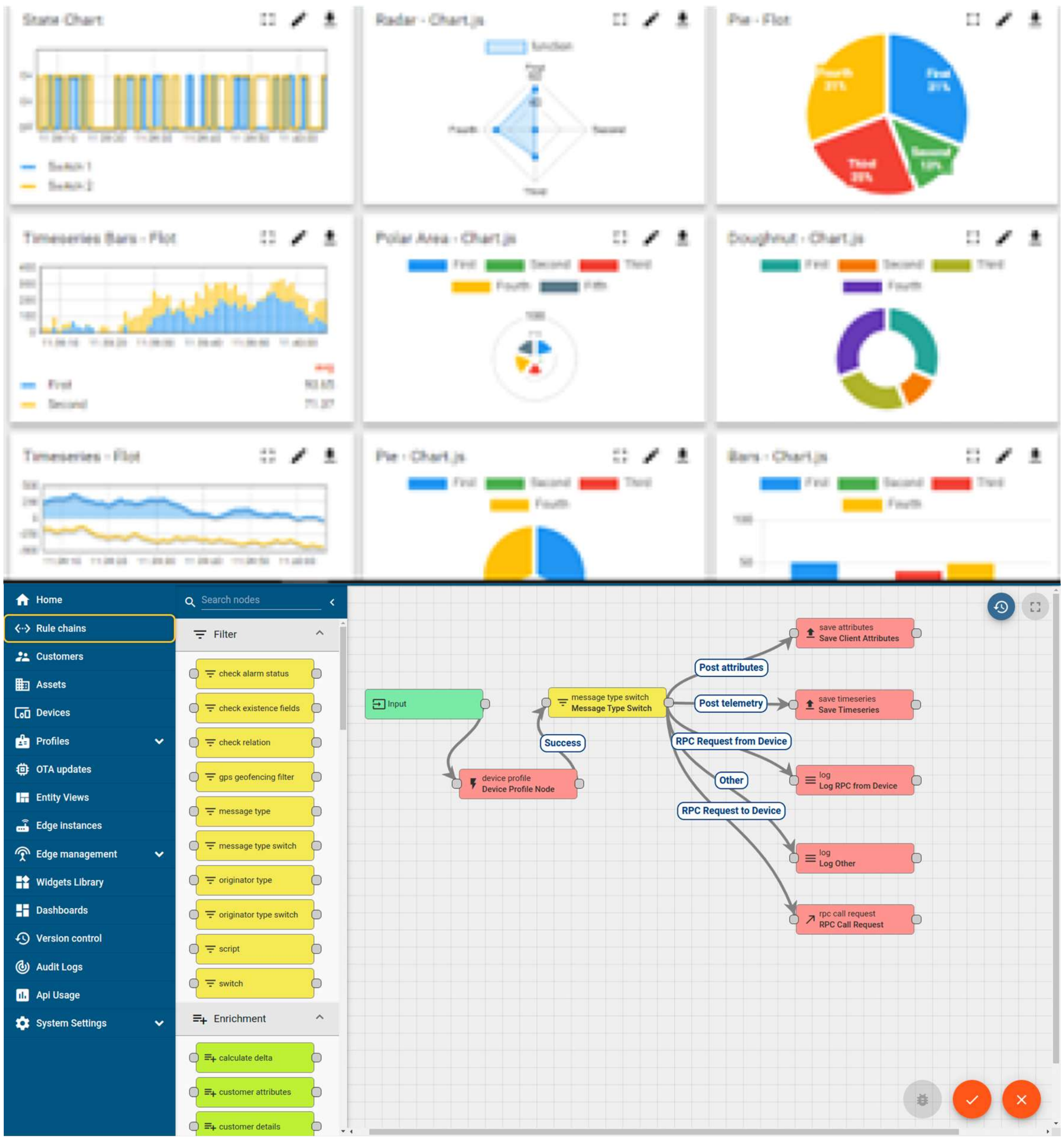
• Build Your own dashboard

• Analytics and Reporting

• Alert and Notification

• Integration with third party application(Power BI, SAP, ERP)

• Rule Engine



ii. Smart Factory Platform (FACTORY WATCH)

Factory watch is a platform for smart factory needs.

It provides Users/ Factory

- with a scalable solution for their Production and asset monitoring
- OEE and predictive maintenance solution scaling up to digital twin for your assets.
- to unleased the true potential of the data that their machines are generating and helps to identify the KPIs and also improve them.
- A modular architecture that allows users to choose the service that they what to start and then can scale to more complex solutions as per their demands.

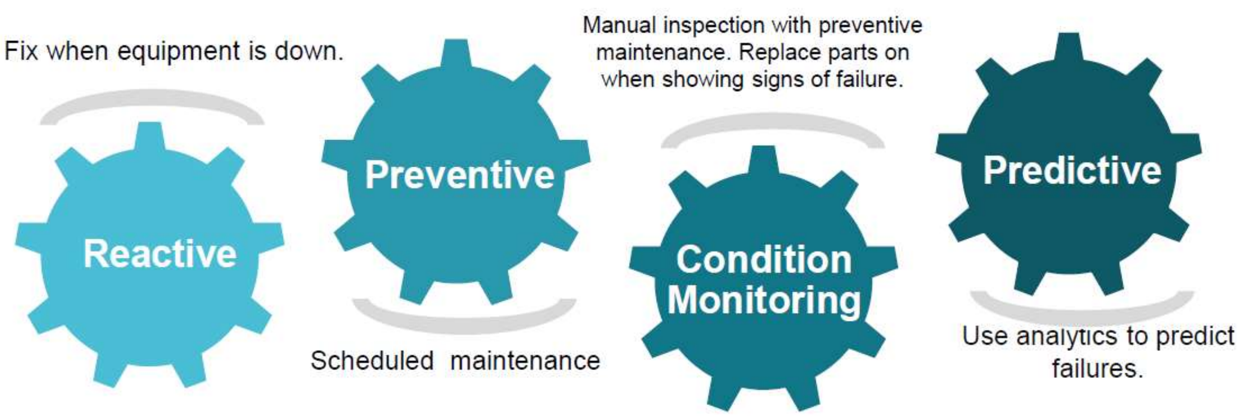
Its unique SaaS model helps users to save time, cost and money.

iii. LoRaWAN based Solution (LoRaWAN™)

UCT is one of the early adopters of LoRAWAN teschnology and providing solution in Agritech, Smart cities, Industrial Monitoring, Smart Street Light, Smart Water/ Gas/ Electricity metering solutions etc.

iv. Predictive Maintenance

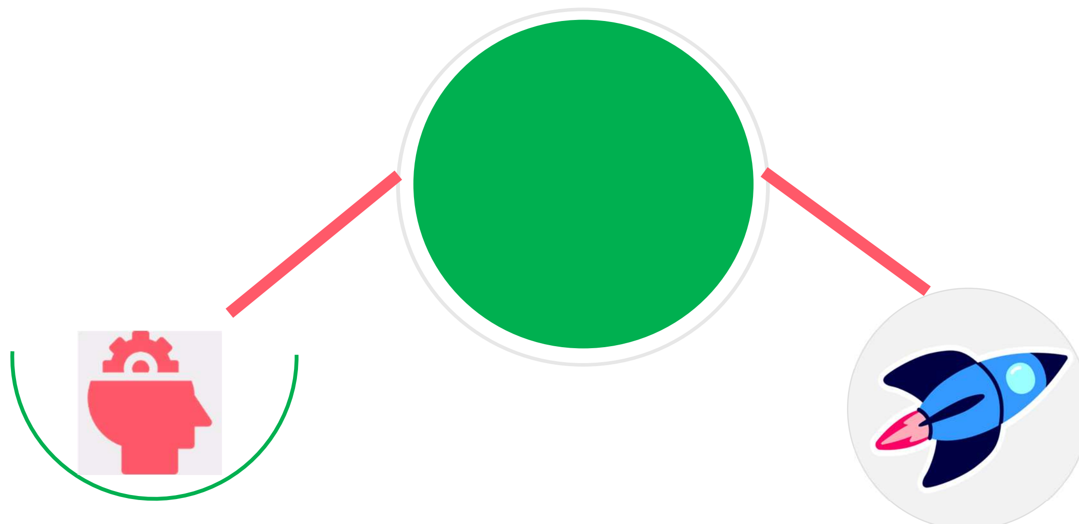
UCT is providing Industrial Machine health monitoring and Predictive maintenance solution leveraging Embedded system, Industrial IoT and Machine Learning Technologies by finding Remaining useful life time of various Machines used in production process.



2.2 About upskill Campus (USC)

upSkill Campus along with The IoT Academy and in association with Uniconverge Technologies Pvt Ltd has facilitated the smooth execution of the complete internship process.

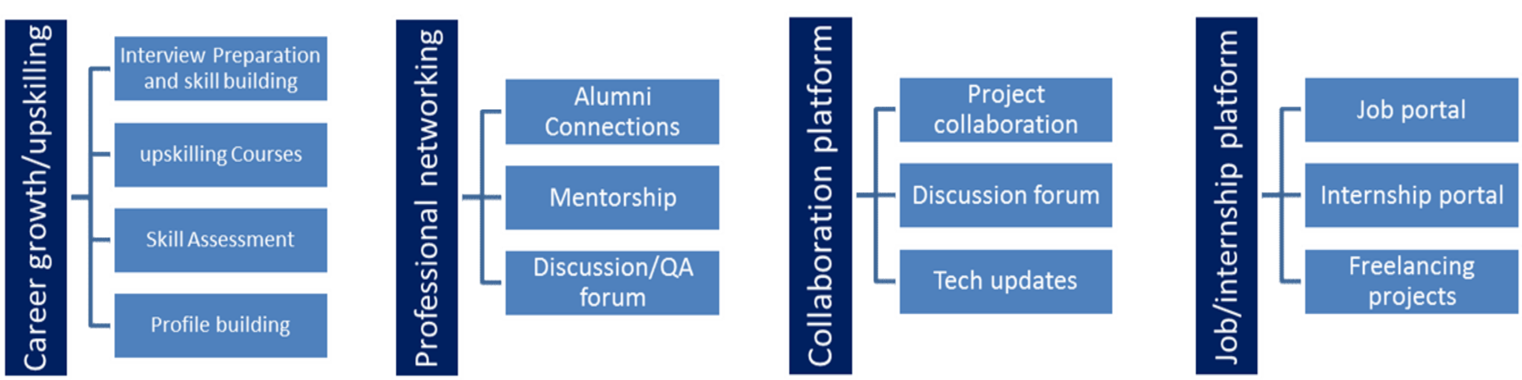
USC is a career development platform that delivers **personalized executive coaching** in a more affordable, scalable and measurable way.



Seeing need of upskilling in self paced manner along-with additional support services e.g. Internship, projects, interaction with Industry experts, Career growth Services

upSkill Campus aiming to upskill 1 million learners in next 5 year

https://www.upskillcampus.com/



2.3 About The IoT Academy

The IoT academy is EdTech Division of UCT that is running long executive certification programs in collaboration with EICT Academy, IITK, IITR and IITG in multiple domains.

2.4 Objectives of this Internship Program

The objective for this internship program was to:

☛ Get practical experience of working in the industry.

☛ Solve real world problems.

☛ Have improved job prospects.

☛ Have Improved understanding of our field and its applications.

☛ Have Personal growth like better communication and problem solving.

2.5 References

[1] https://learn.upskillcampus.com/

[2] https://www.uniconvergetech.in/

[3] https://jesit.springeropen.com/articles/10.1186/s43067-023-00081-6

[4] https://journalofbigdata.springeropen.com/articles/10.1186/s40537-021-00542-7

[5] https://www.mdpi.com/2071-1050/14/7/4164

[6] https://www.mdpi.com/2624-6511/4/2/40

2.6 Glossary

Terms	**Acronym**
USC	upskill Campus
UCT	Uniconverge Technologies Pvt Ltd

3 Problem Statement

The problem statement revolves around forecasting traffic patterns in a smart city. The goal is to predict how traffic behaves, considering regular patterns and the influence of holidays and events. This aids in optimizing traffic management and future urban planning, aligning with the city's smart objectives. The project relies on data science and machine learning for accurate predictions.

The specific aspects and components of the problem statement include:

i. **Traffic Pattern Understanding:** The project necessitates a deep understanding of how traffic behaves within the smart city environment. This encompasses analyzing historical traffic data to identify recurring patterns, trends, and anomalies.

ii. **Influence of Special Occasions:** Beyond typical traffic patterns, the project must consider the influence of special occasions such as holidays and events on traffic. Understanding how these factors affect traffic is vital for accurate forecasting.

iii. **Smart City Objectives:** The project aligns with the broader goals of transforming the city into a smart city. Therefore, it contributes directly to achieving smart city objectives, such as efficient resource utilization and enhanced quality of life for residents.

iv. **Data-Driven Predictions:** The core challenge lies in developing a predictive model that can make accurate forecasts about traffic patterns. This involves the application of machine learning algorithms to historical and real-time traffic data.

v. **Infrastructure Planning:** The insights gained from accurate traffic predictions can inform future infrastructure planning. By anticipating traffic needs, city planners can make data-informed decisions about road expansion, traffic flow optimization, and other urban development projects.

Overall, the problem statement encompasses a multidisciplinary approach, combining data science, machine learning, urban planning, and smart city principles to create a holistic solution for better traffic management in a smart city context. This project's success hinges on the ability to develop an accurate and robust predictive model that can adapt to changing traffic conditions and contribute to the city's overall efficiency and sustainability.

4 Existing and Proposed solution

Existing Solutions and Limitations:

Currently, various traffic forecasting solutions exist, but they have certain limitations. Some solutions rely solely on historical traffic data without considering special occasions, leading to inaccuracies during holidays and events. Others might not adapt well to changing traffic patterns in evolving smart cities.

Proposed Solution and Value Addition:

Our proposed solution involves the development of a specialized traffic forecasting program. It considers historical traffic data, special events, and holidays to provide accurate predictions. Additionally, we plan to implement machine learning algorithms, specifically the Random Forest model, to enhance prediction accuracy. This approach adds significant value by offering precise traffic forecasts that facilitate efficient traffic management and infrastructure planning in the smart city.

4.1 Code submission (GitHub link):

https://github.com/junedmemon109/Forecasting-of-Smart-City-Traffic-Patterns

4.2 Report submission (GitHub link):

https://github.com/junedmemon109/Forecasting-of-Smart-City-Traffic-Patterns

5 Proposed Design/ Model

Designing a flow for forecasting traffic patterns using the Random Forest algorithm in machine learning involves several steps. Here's a proposed design flow for your "Forecasting of Smart City Traffic Patterns" project:

a. **Data Collection:**
   Gather historical traffic data, including features like time of day, day of the week, and holidays etc.

b. **Data Preprocessing:**
   Clean the data by removing duplicates and handling missing values.
   Perform feature engineering to extract meaningful features like year, month, day, hour, and weekday from the timestamp.
   Convert categorical variables into numerical representations using techniques like one-hot encoding.

c. **Data Splitting:**
   Divide the preprocessed data into training and testing sets (e.g., 80:20 or 70:30 ratio).

d. **Training the Random Forest Model:**
   Apply the Random Forest algorithm to the training data.
   The model will automatically select the best features and build multiple decision trees to improve prediction accuracy.
   Tune hyperparameters, such as the number of trees, maximum tree depth, and minimum samples per leaf, to optimize model performance.

e. **Model Evaluation:**
   Evaluate the trained Random Forest model using the testing data.
   Calculate metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and R-squared to assess the model's accuracy.

f. **Model Deployment:**
   Deploy the Random Forest model for traffic pattern forecasting using the entire dataset for training.
   Consider retraining the model periodically with new data to ensure it remains accurate over time.

g. **Prediction and Monitoring:**
   Utilize the deployed Random Forest model to forecast traffic patterns based on new input data.
   Continuously monitor the model's performance and update it as needed.

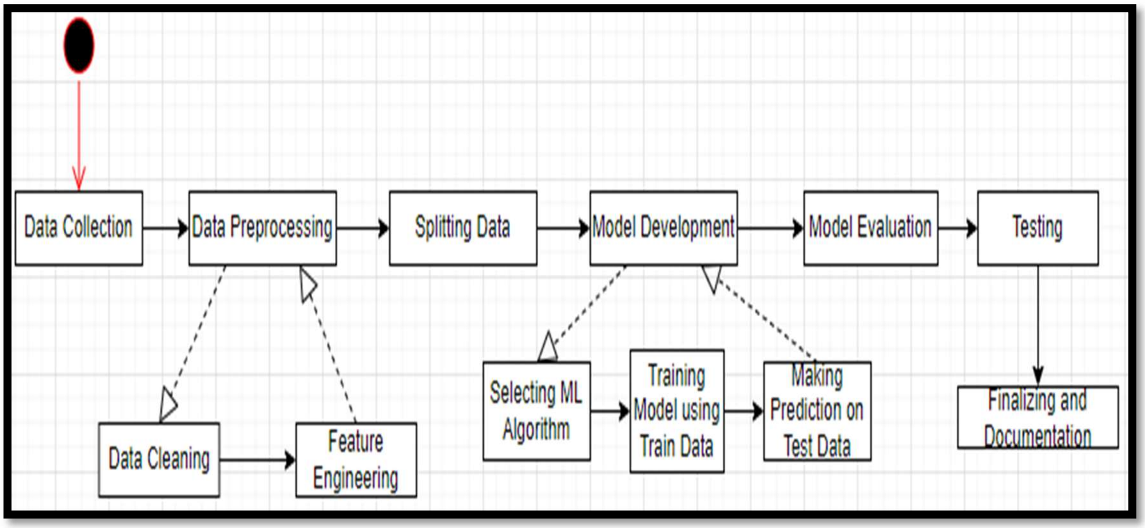


Figure 5.1: Flow Diagram

Advantages of Using Random Forest for Traffic Pattern Forecasting:

a. **Ensemble Learning:** Random Forest is an ensemble learning technique that combines multiple decision trees to make predictions. This ensemble approach typically results in more accurate predictions than individual decision trees.

b. **Feature Importance:** Random Forest provides a feature importance score, allowing you to identify which attributes have the most significant impact on traffic patterns. This information can inform decision-making in traffic management.

c. **Handling Nonlinear Relationships:** Random Forest can capture complex nonlinear relationships in traffic data without the need for extensive feature engineering.

d. **Robustness:** Random Forest is robust to outliers and missing values, making it suitable for real-world traffic datasets, which can be noisy and incomplete.

e. **Interpretable:** While Random Forest is not as interpretable as a single decision tree, it still offers insights into feature importance and can visualize feature relationships.

f. **Scalability:** Random Forest can handle large datasets and high-dimensional feature spaces, which is essential for traffic forecasting in smart cities.

In summary, the proposed Random Forest model offers a robust and effective solution for forecasting traffic patterns in smart cities. It leverages the ensemble approach, handles complex relationships, and provides insights into influential factors, contributing to improved traffic management and efficiency.

6 Performance Test

While the Random Forest algorithm offers several advantages, it's essential to assess its performance rigorously to ensure its suitability for traffic pattern forecasting in smart cities. The performance testing phase is critical in identifying potential constraints and validating the model's accuracy and efficiency.

6.1 Test Plan/ Test Cases

Test Plan for Forecasting Traffic Patterns using Random Forest Algorithm:

1. Test Objective:

Verify the precision, reliability, and scalability of the Random Forest-based traffic pattern forecasting model.

2. Test Environment:

Programming language: Python

Libraries: scikit-learn, pandas, numpy

Traffic dataset: Historical traffic data containing features like date, time, no. of vehicles, junctions, etc.

3. Test Data:

Prepare a dataset with historical traffic data, including known patterns and corresponding outcomes.

Split the dataset into training and testing sets (e.g., 70% training, 30% testing).

4. Test Cases:

a. Data Preprocessing:

i. Verify that the dataset is loaded correctly, and all required features are present.

ii. Check for missing or invalid values and ensure proper handling or imputation.

iii. Validate the normalization or scaling of numerical features if applicable.

b. Model Training:

i. Train the Random Forest model using the training dataset.

ii. Verify that the model has been trained successfully without any errors.

iii. Validate that the model has learned patterns and relationships from the training data.

c. Model Evaluation:

i. Apply the trained model to the testing dataset.

ii. Compare the predicted traffic patterns with the actual patterns in the testing dataset.

iii. Calculate evaluation metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and R-squared to assess the model's accuracy.

iv. Ensure that the model performance meets the defined acceptance criteria.

d. Model Validation:

i. Use Hyperparameter Tuning techniques assess the model's generalization capabilities.

ii. Verify that the model performs consistently across different subsets of the data.

iii. Ensure that the model does not overfit or underfit the training data.

e. Performance Testing:

i. Measure the training and prediction times to ensure they are within acceptable limits.

ii. Evaluate the model's performance on large datasets to validate scalability.

f. Boundary and Edge Cases:

i. Test the model's behavior with extreme or outlier values in the input features.

ii. Verify that the model handles unexpected or novel traffic patterns gracefully.

g. Integration Testing:

i. Validate the integration of the Random Forest algorithm with other components or systems.

ii. Verify the compatibility and data exchange between the traffic forecasting model and external systems.

6.2 Test Procedure

Test Procedure for Forecasting Traffic Patterns using Random Forest Algorithm:

1. Set up the Test Environment:

Install the required software and libraries (Python, scikit-learn, pandas, numpy, matplotlib, seaborn).

Configure the development environment with the necessary dependencies.

Ensure that the historical traffic dataset is available for testing.

2. Identify Test Data:

Select a subset of the historical traffic dataset for testing.

Split the dataset into training and testing sets (e.g., 70% training, 30% testing).

3. Preprocessing:

Load the training dataset into the system.

Perform any necessary preprocessing steps, such as handling missing values, normalizing or scaling features, and encoding categorical variables.

4. Model Training:

Implement the Random Forest algorithm using the scikit-learn library.

Train the Random Forest model using the training dataset.

Ensure that the training process completes without any errors or exceptions.

Validate that the model has been trained successfully by inspecting its attributes and structure.

5. Model Evaluation:

Load the testing dataset into the system.

Apply the trained Random Forest model to the testing dataset to predict traffic patterns.

Compare the predicted traffic patterns with the actual patterns in the testing dataset.

Calculate evaluation metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and R-squared to assess the model's performance.

Ensure that the model meets the defined acceptance criteria.

6. Performance Testing:

Measure the training and prediction times of the model to ensure they meet the performance requirements.

Evaluate the model's performance on larger datasets to assess scalability.

Identify any bottlenecks or performance issues and address them accordingly.

6.3 Performance Outcome

The performance outcome of the Random Forest Model for forecasting traffic patterns can vary depending on several factors, including the quality of the data, the complexity of the traffic patterns, the choice of features, and the tuning of the model parameters.

But before selecting the Random Forest Model, I concentrated on training and evaluating five distinct regression models using the processed dataset. These models encompassed different algorithms and approaches, allowing for comprehensive comparison and selection of the most suitable model.

1. Linear Regression:

This model captured linear relationships between features and the target variable.

Performance Metrics:

- Mean Absolute Error (MAE): 9.64
- Mean Squared Error (MSE): 162.93
- R-squared (R2): 0.60

2. Decision Tree Regression:

A Decision Tree Regression model was employed to capture complex non-linear relationships in the data.

Performance Metrics:

- Mean Absolute Error (MAE): 3.12
- Mean Squared Error (MSE): 22.60
- R-squared (R2): 0.94

3. Random Forest Regression:

The Random Forest Regression model combined multiple decision trees to improve predictive accuracy.

Performance Metrics:

- Mean Absolute Error (MAE): 2.39
- Mean Squared Error (MSE): 12.56
- R-squared (R2): 0.97

4. Support Vector Machine (SVM) Regression:

This model aimed to capture non-linear relationships between features and the target variable.

Performance Metrics:

- Mean Absolute Error (MAE): 13.51
- Mean Squared Error (MSE): 458.67
- R-squared (R2): -0.13

5. Neural Network Regression:

A Neural Network model (MLPRegressor) was utilized to capture intricate patterns in the data.

Performance Metrics:

- Mean Absolute Error (MAE): 11.23
- Mean Squared Error (MSE): 223.78
- R-squared (R2): 0.45

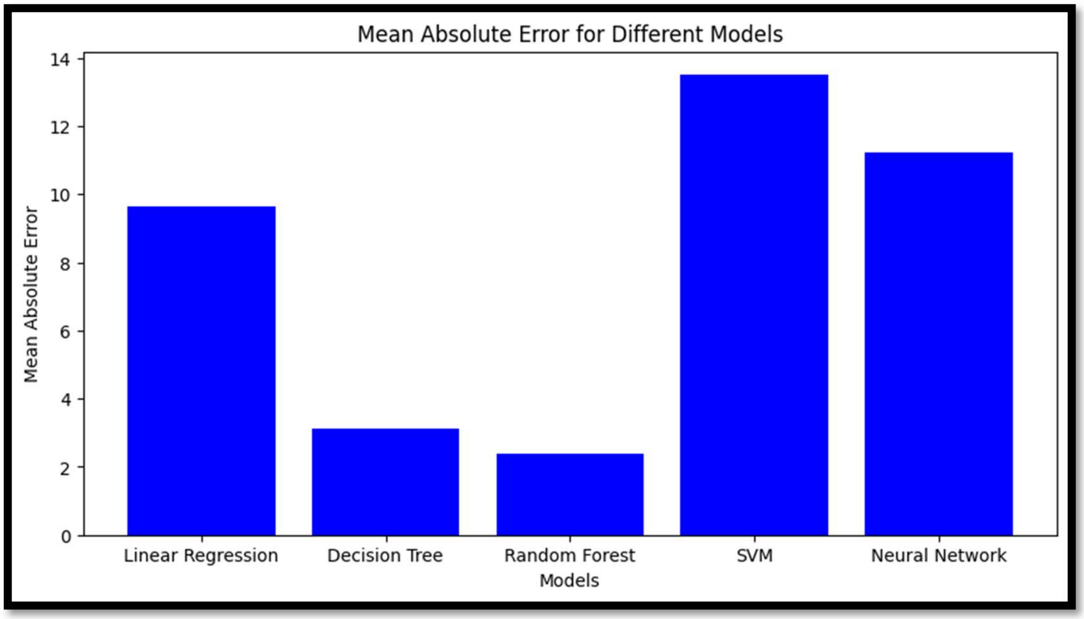


Figure 6.2: Mean Absolute Error for Different Models

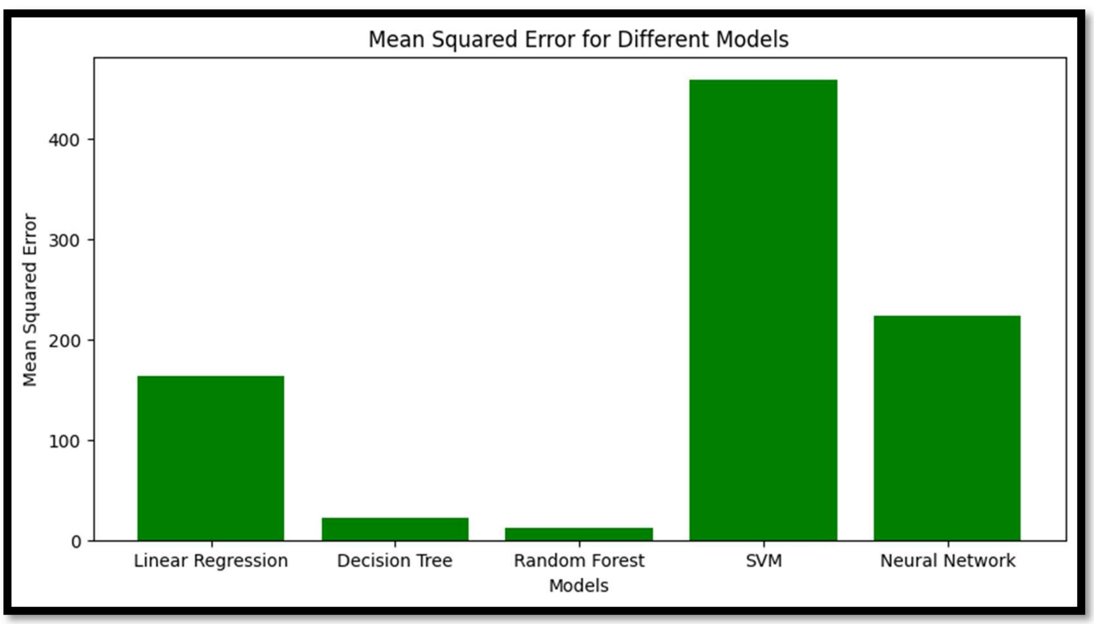


Figure 6.3: Mean Squared Error for Different Models

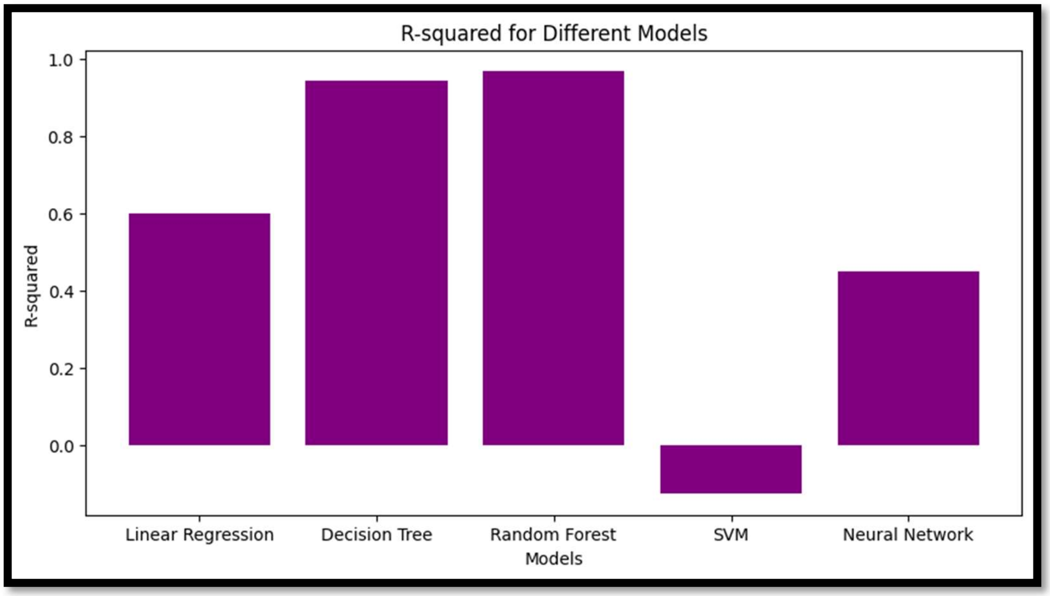


Figure 6.4: R-squared for Different Models

Based on these results, the Random Forest Regression model demonstrated superior performance, achieving the lowest MAE and MSE and the highest R2 score. This model is recommended for making accurate predictions on unseen data.

Hyperparameter Tuning:

For the Random Forest model, I applied hyperparameter tuning using Grid Search. This involved searching through various combinations of hyperparameters to find the optimal settings. The goal was to improve the model's performance by finding the best configuration.

After tuning the Random Forest model, I compared its performance before and after hyperparameter tuning. I calculated metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and R-squared to quantify the model's accuracy and predictive power.

Results and Findings**:**

Before hyperparameter tuning, the Random Forest model exhibited the following metrics:

- Mean Absolute Error: 2.3911

- Mean Squared Error: 12.5624

- R-squared: 0.9692

After hyperparameter tuning using Grid Search, the Random Forest model's metrics were:

- Mean Absolute Error: 2.3905

- Mean Squared Error: 12.5953

- R-squared: 0.9691

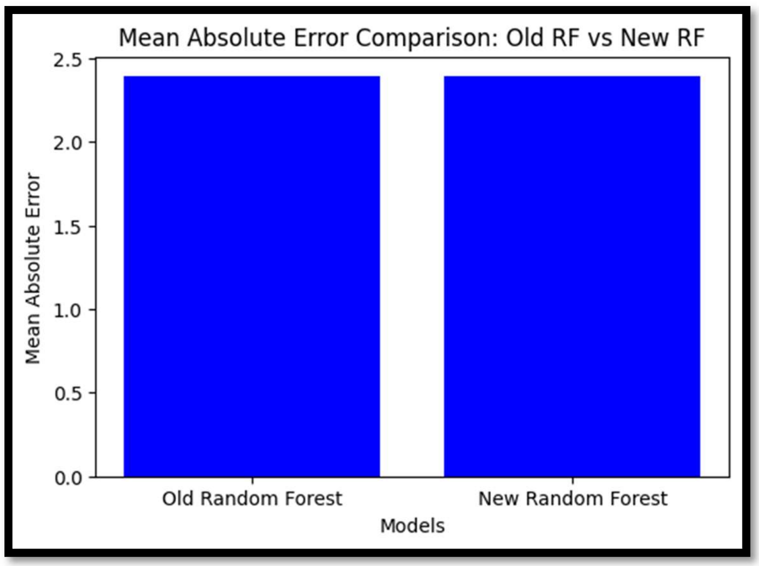


Figure 6.4: Mean Absolute Error Comparison: Old RF vs New RF

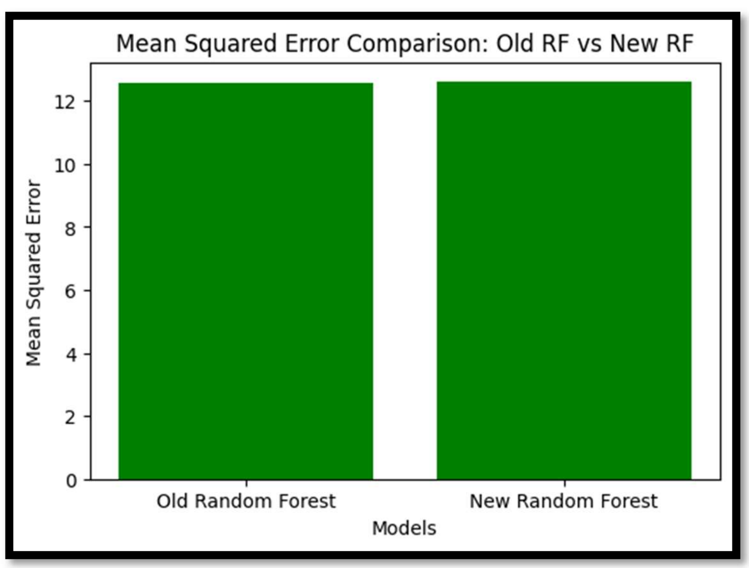


Figure 6.5: Mean Squared Error Comparison: Old RF vs New RF

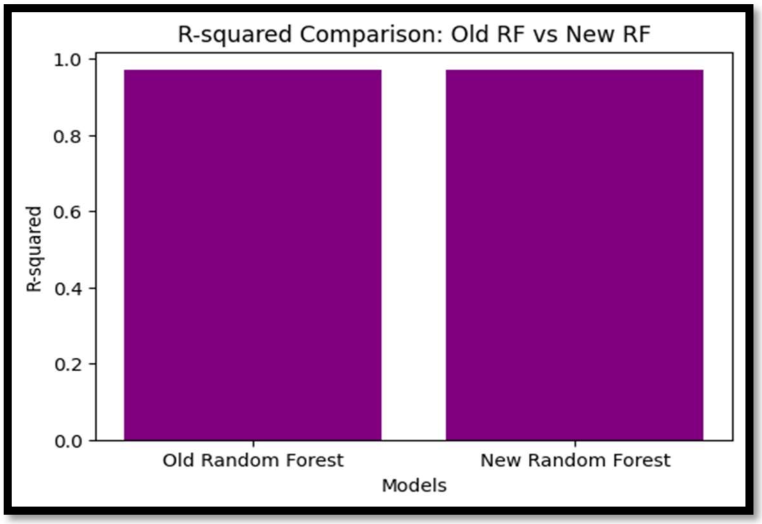


Figure 6.6: R-squared Comparison: Old RF vs New RF

Interestingly, the performance improvements were minimal after hyperparameter tuning. This suggests that the default hyperparameters of the Random Forest model were already quite suitable for our dataset. It's important to consider the trade-off between complexity and performance when tuning hyperparameters.

The performance outcome and test results provide valuable insights into the Random Forest model's effectiveness in traffic pattern forecasting. The presented visuals and metrics demonstrate the model's accuracy and capability to handle different junctions and scenarios.

Predicting on Unseen Data:

I began by preparing the unseen dataset (`test_df`), which contained data for which we needed to predict vehicle counts. Subsequently, I employed the previously tuned Random Forest model to predict the vehicle counts on these unseen instances.

Generating Final Predictions:

The predictions made on the unseen data were organized and stored in a structured format in a DataFrame named **`predictions_df`**. This DataFrame encompassed vital columns such as **`ID`, `Junction`, `Year`, `Month`, `Day`, `Hour`, `Weekday`, `IsHolidayOrEvent`, and**

`Predicted_Vehicles`. The purpose of this step was to encapsulate the results and prepare them for evaluation and potential future use.

Results and Findings:

The predictions on the unseen data have been successfully generated using the Random Forest model. The `**predictions_df**` DataFrame now holds the final predictions, and the associated columns provide valuable insights into the time, location, and predicted vehicle counts. These predictions serve as a critical aspect of our project, as they demonstrate the model's ability to generalize to new data.

index	ID	Junction	Year	Month	Day	Hour	Weekday	IsHolidayOrEvent	Predicted_Vehicles
0	20170701001	1	2017	7	1	0	5	0	67.0
1	20170701011	1	2017	7	1	1	5	0	60.0
2	20170701021	1	2017	7	1	2	5	0	43.0
3	20170701031	1	2017	7	1	3	5	0	38.0
4	20170701041	1	2017	7	1	4	5	0	32.0

Figure 6.7: First 5 rows of 'predictions_df'

7 My learnings

Throughout this internship, I've gained valuable insights and experiences that will significantly contribute to my career growth. Here's a summary of my key learnings and how they will benefit me:

i. **Data Science Fundamentals:** I've developed a strong foundation in data science, including data preprocessing, feature engineering, model selection, and evaluation. This knowledge equips me to tackle real-world problems by leveraging data-driven insights.

ii. **Machine Learning:** I've gained hands-on experience in training and evaluating various machine learning models, including regression and ensemble methods. Understanding the strengths and weaknesses of these algorithms is essential for effective problem-solving.

iii. **Hyperparameter Tuning:** The process of hyperparameter tuning using techniques like Grid Search has taught me how to optimize model performance. This skill is crucial in fine-tuning models for maximum accuracy.

iv. **Problem Solving:** I've learned to approach complex problems systematically, breaking them down into manageable steps. This problem-solving mindset will be invaluable in my future endeavors.

v. **Communication Skills:** Preparing reports and documentation has enhanced my communication skills. Being able to convey technical concepts clearly is essential in any data-related role.

vi. **Project Management:** Managing a project from problem understanding to model deployment has provided me with project management experience. This skill will be beneficial in coordinating and executing data-driven projects in the future.

vii. **Collaboration:** I've had the opportunity to collaborate with peers and mentors, learning from their experiences and perspectives. Collaboration is key in the professional world, and this experience has honed my teamwork abilities.

These learnings collectively position me as a well-rounded data scientist and provide a solid foundation for my career growth in the field of data science and machine learning. I'm confident that the skills and knowledge I've acquired during this internship will enable me to make meaningful contributions in future data-driven projects and roles.

8 Future work scope

While I've made significant progress during this internship, there are several areas where future work and enhancements can be explored to further improve the solution and address additional aspects of the problem:

i. **Advanced Models:** Experiment with more advanced machine learning models, such as time series forecasting models, to potentially improve prediction accuracy.

ii. **Incorporate Weather Data:** Include weather-related features, such as temperature, precipitation, and humidity, to account for weather conditions' impact on traffic patterns.

iii. **Real-time Predictions:** Develop a real-time traffic prediction system that continuously updates predictions based on incoming data, allowing for dynamic traffic management.

iv. **Integration with Traffic Control Systems:** Explore the integration of predictive traffic data with traffic control systems to enable proactive traffic management and optimization.

v. **Scalability:** Ensure that the solution can scale to handle data from additional junctions and cities, making it adaptable to larger smart city initiatives.

vi. **User-Friendly Interface:** Develop a user-friendly interface or dashboard for city planners and traffic management authorities to visualize and interact with the predicted traffic patterns.

vii. **Anomaly Detection:** Implement anomaly detection algorithms to identify unusual traffic patterns or incidents, which can trigger alerts or interventions.

viii. **Evaluation Metrics:** Explore additional evaluation metrics specific to traffic prediction, such as traffic congestion indices or route optimization measures.

ix. **Deployment in Smart Cities:** Collaborate with smart city initiatives to deploy and test the predictive traffic system in real-world urban environments.

x. **Cost-Benefit Analysis:** Perform a cost-benefit analysis to assess the economic impact of implementing the proposed solution in terms of reduced congestion, fuel savings, and improved transportation efficiency.

These future work scopes present exciting opportunities to enhance the predictive traffic system's capabilities and contribute to more efficient and smarter urban transportation management. By addressing these areas, we can continue to refine and optimize the solution for the benefit of cities and their residents.