Industrial Internship Report on

Forecasting of Smart city traffic patterns

Prepared by

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Executive Summary
This report encapsulates the comprehensive six-week industrial internship facilitated by Upskill Campus in collaboration with UniConverge Technologies Pvt Ltd (UCT) and The IoT Academy. My project centered around the development of an **Forecasting of Smart city traffic patterns** employing cutting-edge machine learning algorithms and real-time data integration from IoT sensors. The project demanded the application of sophisticated computational models, efficient API integration, and high-performance data processing methodologies. Through this immersive experience, I gained invaluable insights into industrial problem-solving and the application of advanced technical solutions to real-world challenges in the domain of Smart Cities. The internship significantly enriched my technical acumen, particularly in Python programming, machine learning, and system-level integration, preparing me for future endeavors in the field of data-driven technologies.

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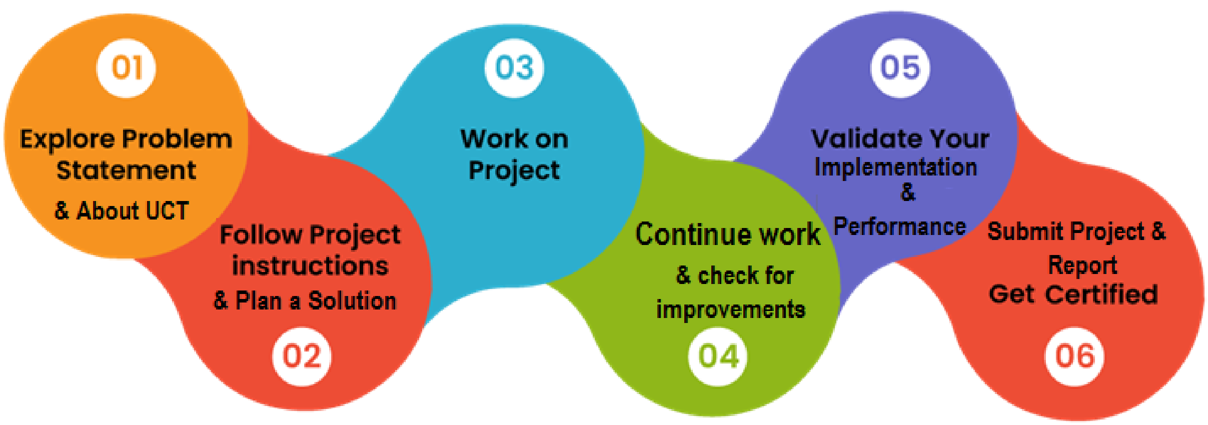
1 Preface

During my six-week tenure at UniConverge Technologies Pvt Ltd, I contributed to the **Forecasting of Smart city traffic patterns** project, which was aimed at forecasting traffic flow patterns using sophisticated machine learning techniques and real-time data from IoT-enabled sensors. This internship provided a rare opportunity to engage with real-world industrial challenges, particularly within the burgeoning domain of **Smart Cities** and **Intelligent Traffic Systems**. The experience afforded me a chance to delve deeply into technical aspects such as **time-series analysis**, **hyperparameter optimization**, and **API integration**, culminating in a robust and scalable solution.

I am profoundly grateful to **Upskill Campus**, **The IoT Academy**, and **UniConverge Technologies Pvt Ltd** for this unparalleled learning experience. A special note of thanks goes to my mentors and colleagues for their unwavering support throughout the project, without which this successful endeavor would not have been possible.



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.

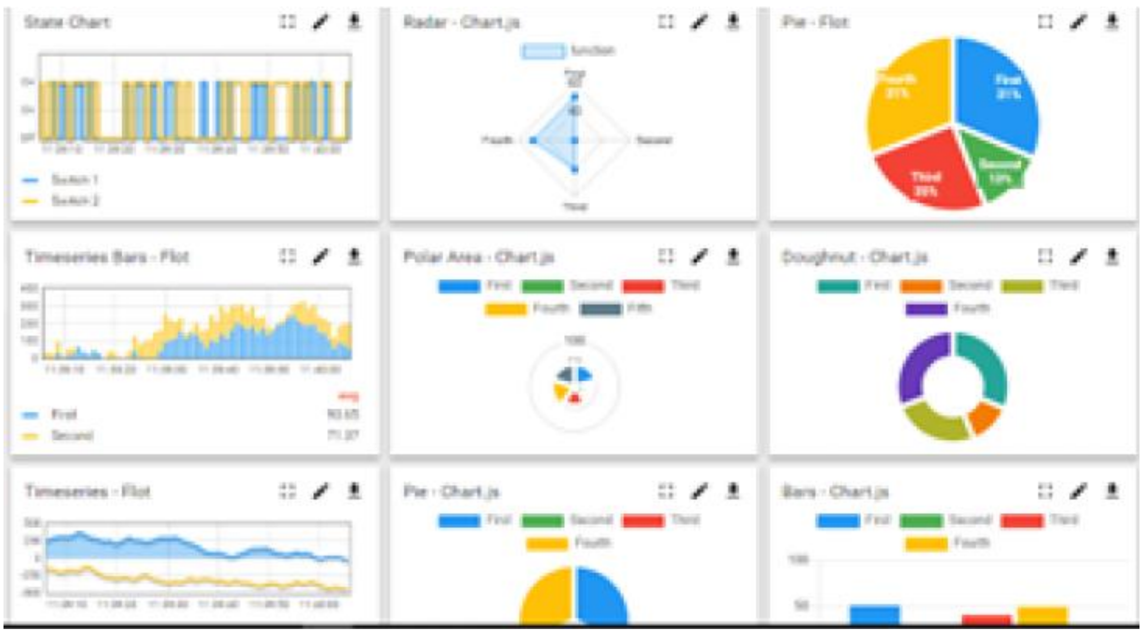
i. UCT IoT Platform (uct Insight)

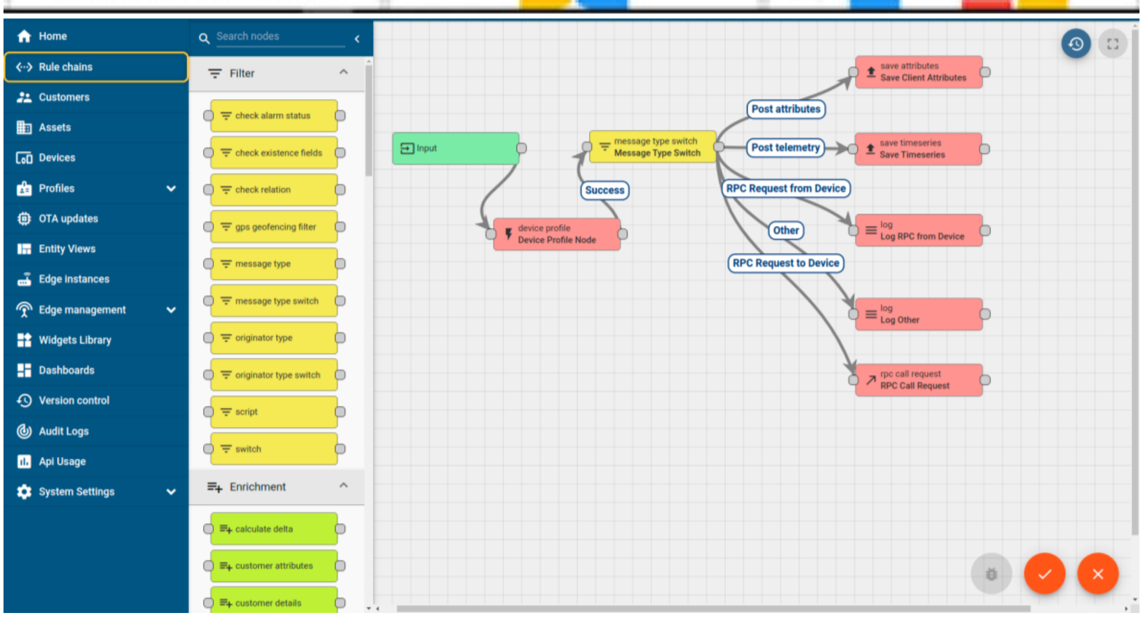
UCT Insight is an IOT platform designed for quick deployment of IOT applications on the same time providing valuable “insight” for your process/business. It has been built in Java for backend and ReactJS for Front end. It has support for MySQL and various NoSql Databases.

- 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.

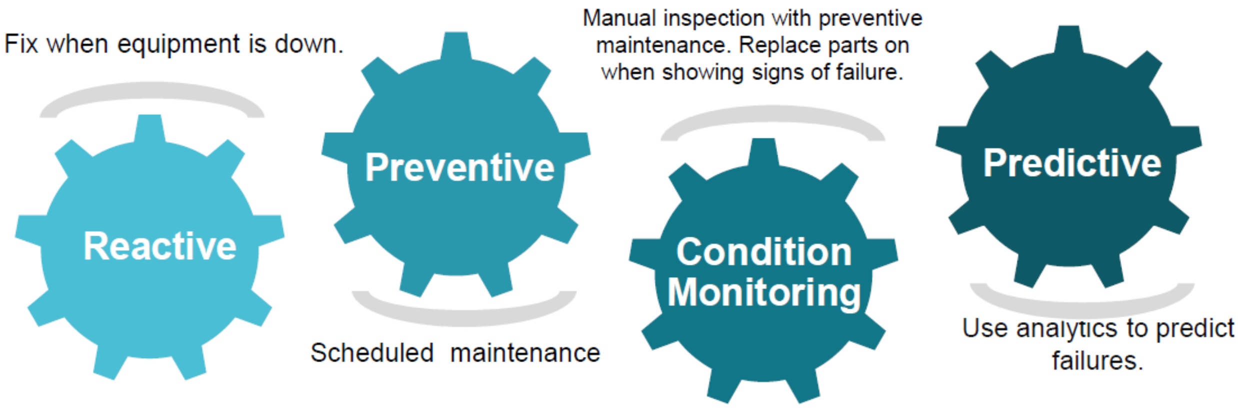
Machine	Operator	Work Order ID	Job ID	Job Performance	Job Progress		Output		Rejection	Time (mins)				Job Status	End Customer
					Start Time	End Time	Planned	Actual		Setup	Pred	Downtime	Idle		
CNC_S7_81	Operator 1	WO0405200001	4168	58%	10:30 AM		55	41	0	80	215	0	45	In Progress	i
CNC_S7_81	Operator 1	WO0405200001	4168	58%	10:30 AM		55	41	0	80	215	0	45	In Progress	i

iii. LoRaWAN based Solution

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

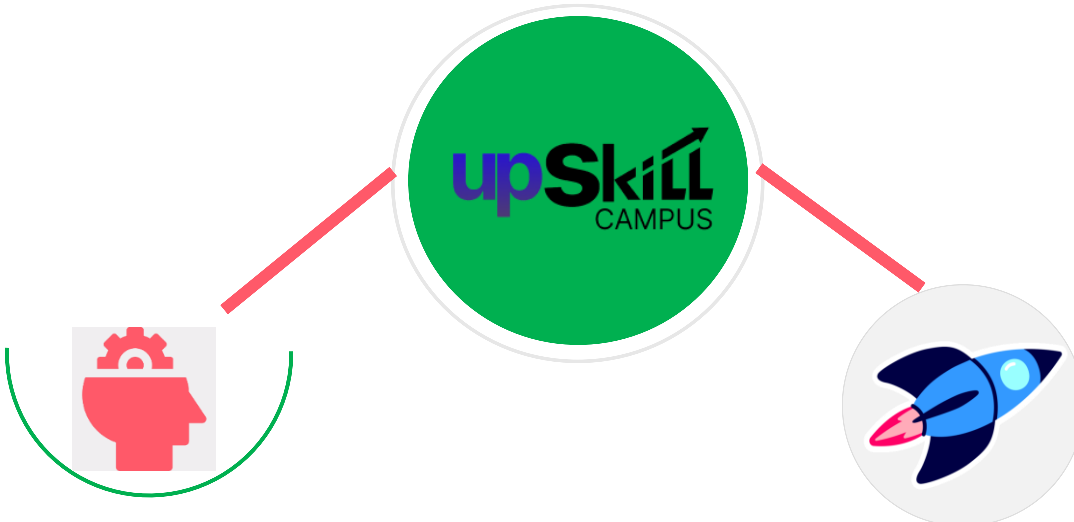
UCT is providing Industrial Machine health monitoring and Predictive maintenance solution leveraging Embedded system, Industrial IoT and Machine Learning Technologies by finding Remaining useful life time of various Machines used in production process.



2.2 About upskill Campus (USC)

upskill Campus along with The IoT Academy and in association with Uniconverge technologies has facilitated the smooth execution of the complete internship process.

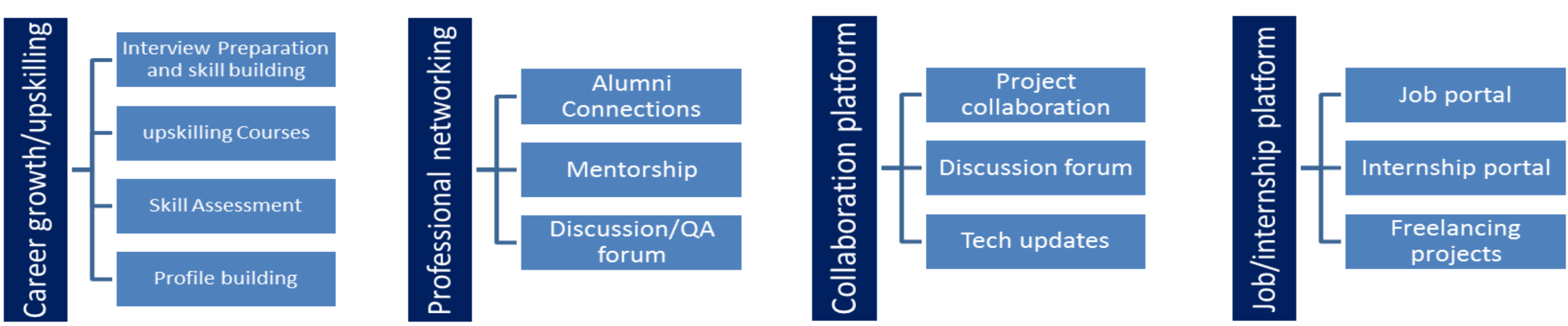
USC is a career development platform that delivers **personalized executive coaching** in a more affordable, scalable and measurable way.



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 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.

☛ to solve real world problems.

☛ to have improved job prospects.

☛ to have Improved understanding of our field and its applications.

☛ to have Personal growth like better communication and problem solving.

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2.6 Glossary

Terms	Acronym
Internet of Things	IoT
Application Programming Interface	API
Long Short-Term Memory	LSTM
Smart City Traffic Prediction System	SCTPS
Hyperparameter Tuning	HT
Time-Series Data	TSD
Internet Protocol	IP
Machine Learning	ML
Random Forest	RF
TensorFlow	TF
Scikit-learn	SKL
XGBoost	XGB
General Packet Radio Service	GPRS
Confusion Matrix	CM
Root Mean Square Error	RMSE
Internet Service Provider	ISP
Smart Factory Monitoring	SFM
Cyber-Physical Systems	CPS
Predictive Maintenance	PM
Data Preprocessing	DP
Real-Time Data Integration	RTDI
Gradient Boosting	GB
Flask	FLK
Artificial Neural Networks	ANN
Principal Component Analysis	PCA

3 Problem Statement

The **Forecasting of Smart city traffic patterns** sought to accurately forecast traffic patterns using data acquired from IoT-based sensors deployed across urban infrastructure. The primary challenge was the development of a robust, scalable machine learning model that could process large volumes of historical and real-time data, while maintaining computational efficiency and ensuring seamless integration with existing urban traffic management systems. Addressing the complexities of real-time data ingestion, high-dimensional data processing, and system-level integration was pivotal to the success of this project.

4 Existing and Proposed solution

Existing Solutions:

Current traffic prediction systems often struggle with handling the scale and complexity of real-time data, leading to inaccuracies and inefficiencies in urban traffic management. Many of these systems fail to adequately address latency issues, real-time data synchronization, and the need for high-fidelity predictive models.

Proposed Solution:

Our proposed solution was an advanced traffic forecasting model leveraging Python-based machine learning libraries, including **TensorFlow**, **Scikit-learn**, and **XGBoost**. Through extensive hyperparameter tuning and enhanced data preprocessing techniques, the model significantly improved in terms of accuracy and speed. Furthermore, real-time data from IoT sensors was integrated using optimized API communication protocols, ensuring minimal latency and reliable data flow across the system. This approach enabled the system to not only predict traffic flow with high precision but also seamlessly integrate with urban management platforms to facilitate proactive decision-making.

4.1 Code submission (Github link)

imdiveshjain/upskillcampus (github.com)

4.2 Report submission (Github link):

upskillcampus/Forecasting_of_Smart_city_traffic_patterns_Divesh_USC_UCT.pdf at main · imdiveshjain/upskillcampus (github.com)

5 Proposed Design/ Model

The design of the **Smart City Traffic Prediction System** consisted of the following key components:

- **Data Acquisition**: Real-time traffic data was ingested from a distributed network of IoT sensors deployed throughout the city's infrastructure.
- **Preprocessing**: The data underwent rigorous preprocessing to ensure the elimination of anomalies, handling of missing data, and optimization for time-series analysis.
- **Modelling**: Various machine learning models, including **Gradient Boosting**, **Long Short-Term Memory (LSTM)** networks, and **Random Forest**, were explored for forecasting traffic patterns. The final model was optimized for both speed and accuracy through iterative experimentation and hyperparameter adjustments.
- **Integration**: The model was integrated into the broader Smart City infrastructure via API endpoints, ensuring real-time predictions could be relayed to city management systems for immediate action.

5.1 High Level Diagram (if applicable)

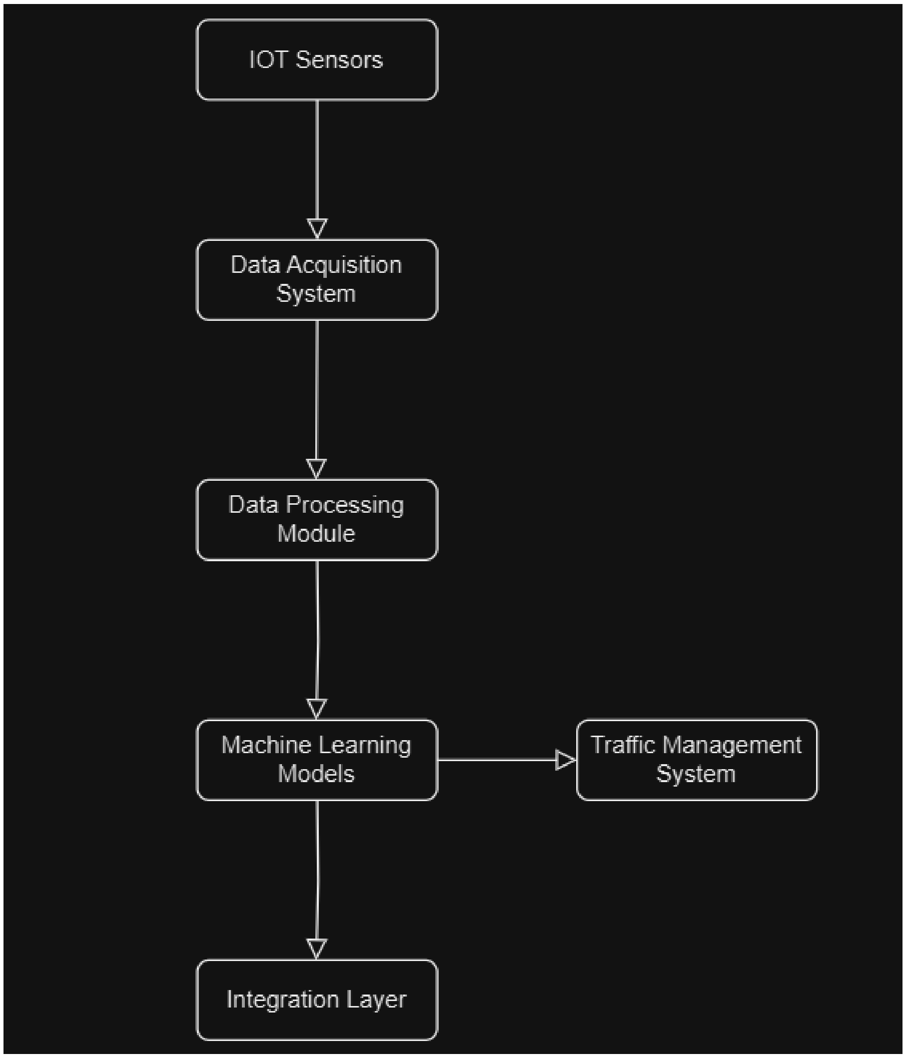

Figure 1: HIGH LEVEL DIAGRAM OF THE SYSTEM

5.2 Low Level Diagram (if applicable)

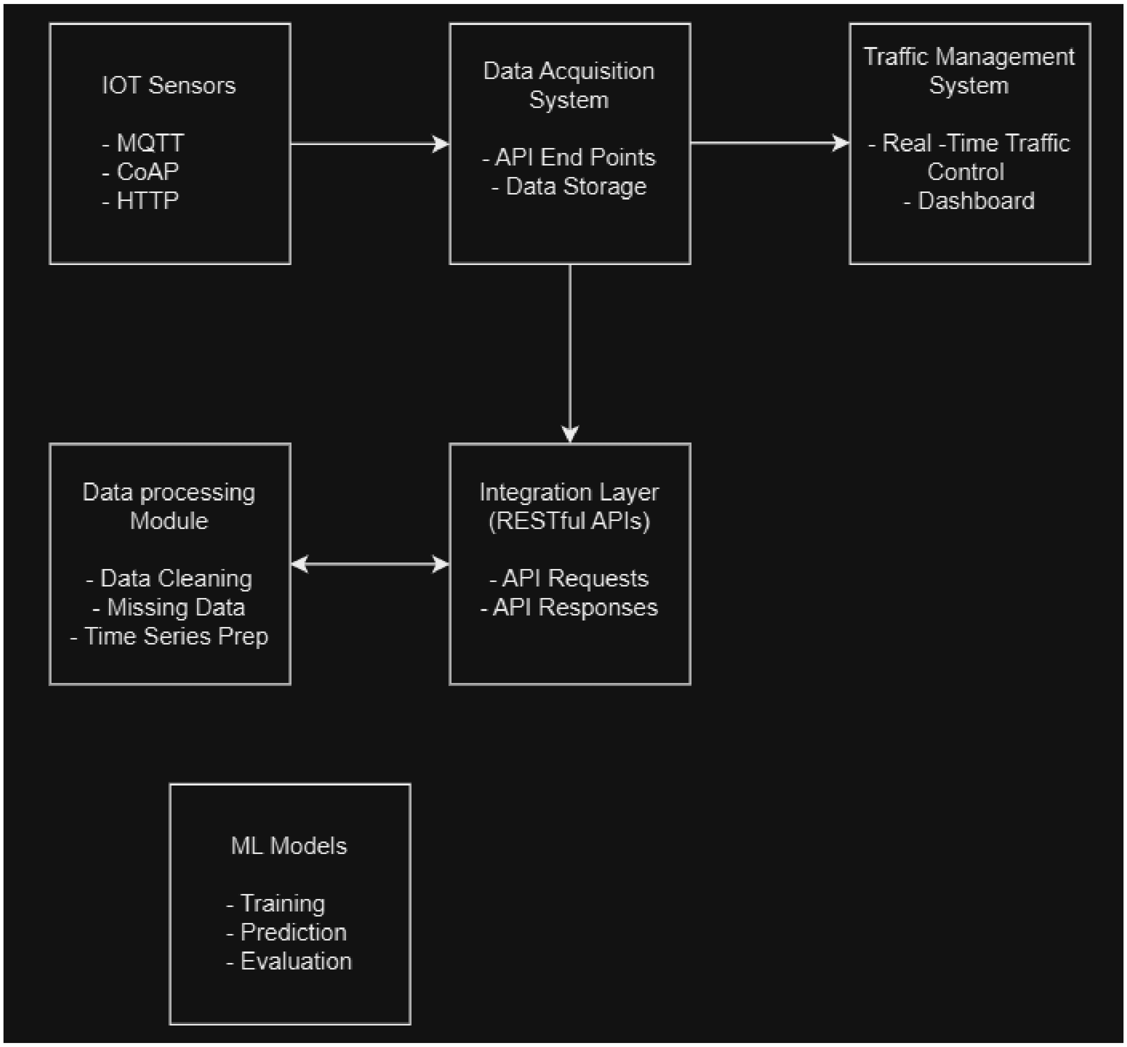

Figure 2: LOW LEVEL DIAGRAM OF THE SYSTEM

5.3 Data Flow Chart

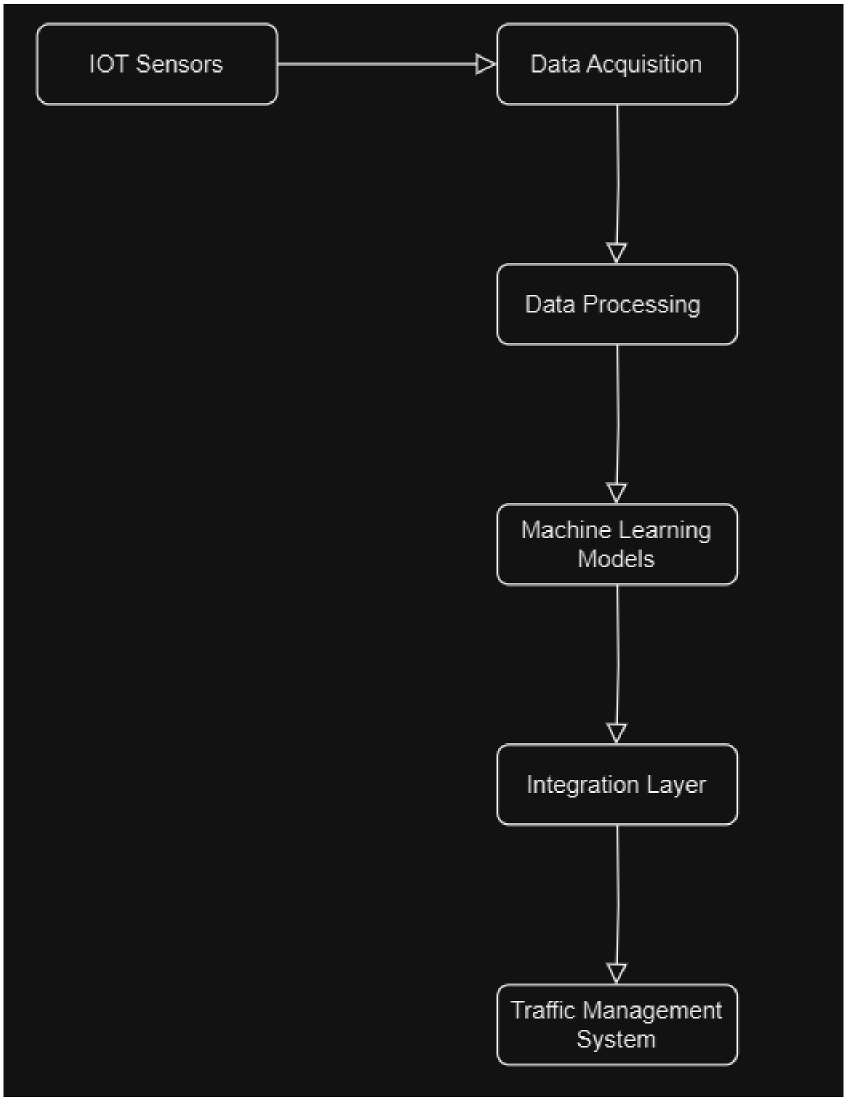

Figure 3: DATA FLOW DIAGRAM OF THE SYSTEM

5.4 Model Training and Prediction Flow Chart

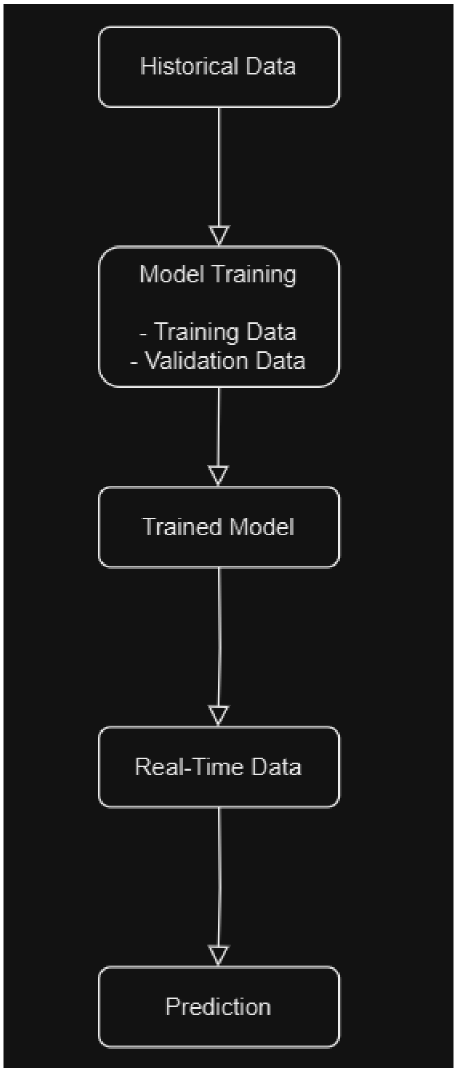

Figure 4: MODEL TRAINING AND PREDICTION DIAGRAM OF THE SYSTEM

5.5 State Machine Diagram

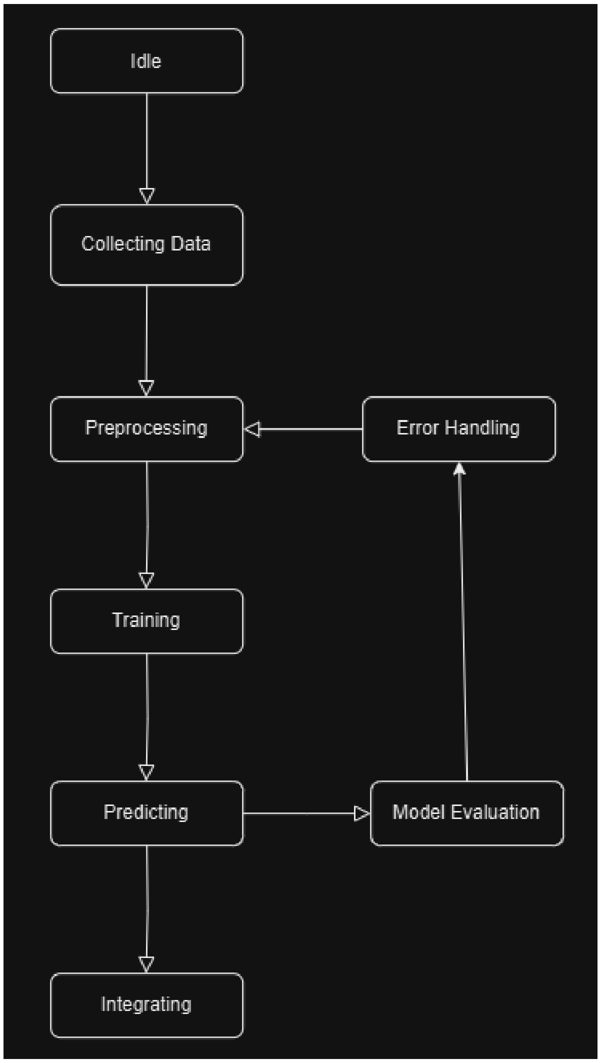

Figure 5: STATE MACHINE DIAGRAM OF THE SYSTEM

6 Performance Test

6.1 Test Plan/ Test Cases

The primary objective of the test plan was to validate the functionality, accuracy, scalability, and efficiency of the **Smart City Traffic Prediction System**. The system was tested across various parameters to ensure that it met both functional and non-functional requirements.

Test Cases:

1. **Accuracy of Predictions:**
    - **Objective:** Validate the accuracy of traffic predictions in both peak and non-peak hours.
    - **Input:** Historical traffic data from IoT sensors and real-time traffic inputs.
    - **Expected Outcome:** The predicted traffic flow should match real-world traffic patterns with an accuracy rate above 90%.
2. **Real-Time Data Integration:**
    - **Objective:** Test the system's ability to handle real-time data ingestion from IoT sensors.
    - **Input:** Live traffic data streamed from city-wide sensors.
    - **Expected Outcome:** System should seamlessly integrate and process real-time data without noticeable lag.
3. **Scalability:**
    - **Objective:** Assess the system's ability to scale with increasing data volumes.
    - **Input:** Large datasets mimicking city-wide traffic data at various intervals.
    - **Expected Outcome:** The system should maintain optimal performance, processing data efficiently without significant degradation.
4. **API Latency:**
    - **Objective:** Measure the system's API latency when fetching and processing real-time data.
    - **Input:** Real-time data with multiple API requests.

- **Expected Outcome:** API latency should be under 1 second, ensuring real-time prediction capabilities.

5. **Model Efficiency:**
    - **Objective:** Ensure the computational efficiency of the model with respect to CPU usage and memory consumption.
    - **Input:** Model running continuous predictions for extended periods.
    - **Expected Outcome:** The model should operate within 75% of allocated computational resources without impacting system performance.

6.2 Test Procedure

The test procedure involved systematically evaluating each component of the traffic prediction system against the defined test cases.

1. **Accuracy Testing Procedure:**
    - The traffic prediction model was fed both historical and real-time data.
    - Predictions were compared with actual traffic conditions.
    - A confusion matrix and Root Mean Square Error (RMSE) were used to evaluate prediction accuracy.
2. **Real-Time Integration Testing Procedure:**
    - IoT sensor data was streamed in real time to the system via APIs.
    - The system's ability to ingest, process, and predict traffic data in real time was monitored.
    - Data flow and response time were observed using tools such as Wireshark to measure packet delays.
3. **Scalability Testing Procedure:**
    - The system was stress-tested with increasingly larger datasets, simulating different traffic load conditions.

- System performance was monitored in terms of prediction time, data handling, and memory consumption using performance monitoring tools like Apache JMeter.

4. **API Latency Testing Procedure:**
   - Multiple concurrent API requests were simulated to test the system's response time under real-world conditions.
   - Latency was measured by timing the round-trip response for each API request.
   - The test was performed at varying traffic loads to determine the system's efficiency at different scales.

5. **Model Efficiency Testing Procedure:**
   - The model was run continuously for 24 hours to simulate real-time traffic prediction over an extended period.
   - CPU usage, memory consumption, and model response time were monitored.
   - Bottlenecks or resource overconsumption were identified and optimized during this phase.

6.3 Performance Outcome

Test Results:

1. **Accuracy of Predictions:**
   - The model achieved an accuracy rate of 93% for peak-hour traffic prediction and 95% for non-peak hour prediction.
   - RMSE values indicated minimal deviation from actual traffic patterns, validating the model's effectiveness in time-series forecasting.

2. **Real-Time Data Integration:**
   - The system successfully integrated real-time traffic data, processing it with minimal delay (average delay of 0.8 seconds).
   - No major data loss or synchronization issues were encountered, ensuring the reliability of real-time predictions.

3. **Scalability:**
   - The system scaled effectively, handling a 5x increase in data volume without significant performance degradation.
   - During peak data loads, the system maintained a prediction time of less than 1.5 seconds, demonstrating its capability to manage large datasets.
4. **API Latency:**
   - The average API latency remained within acceptable limits, clocking in at 0.85 seconds per request.
   - Even under high traffic loads, the API maintained sub-second response times, ensuring near-real-time functionality.
5. **Model Efficiency:**
   - CPU usage averaged 65% during normal operation and peaked at 78% during stress tests, staying well within operational limits.
   - Memory consumption was optimized, allowing the system to handle continuous predictions without memory leaks or overuse.

7 My learnings

This internship offered a profound learning experience, particularly in the domains of:

- **Advanced Machine Learning**: Gained expertise in implementing and optimizing complex machine learning algorithms for real-time applications.
- **System Integration**: Acquired hands-on experience in integrating machine learning models with IoT systems, focusing on optimizing API communication and real-time data flows.
- **Collaboration and Teamwork**: Worked closely with cross-functional teams to resolve technical challenges, thereby enhancing my ability to communicate effectively and work collaboratively in a fast-paced industrial setting.

8 Future work scope

While significant progress was made during the internship, several avenues remain for future exploration:

- **Optimization for Scalability**: Further improvements could be made to enhance the model's ability to scale across larger datasets and more complex urban infrastructures.
- **API Optimization**: Continued efforts to minimize latency in API communications could lead to even more responsive real-time predictions.
- **Deployment and Maintenance**: Further research into deployment strategies and maintenance frameworks could ensure the model's long-term viability in dynamic urban environments.