# Simulating Traffic Prediction on Urban Road Network using Machine Learning

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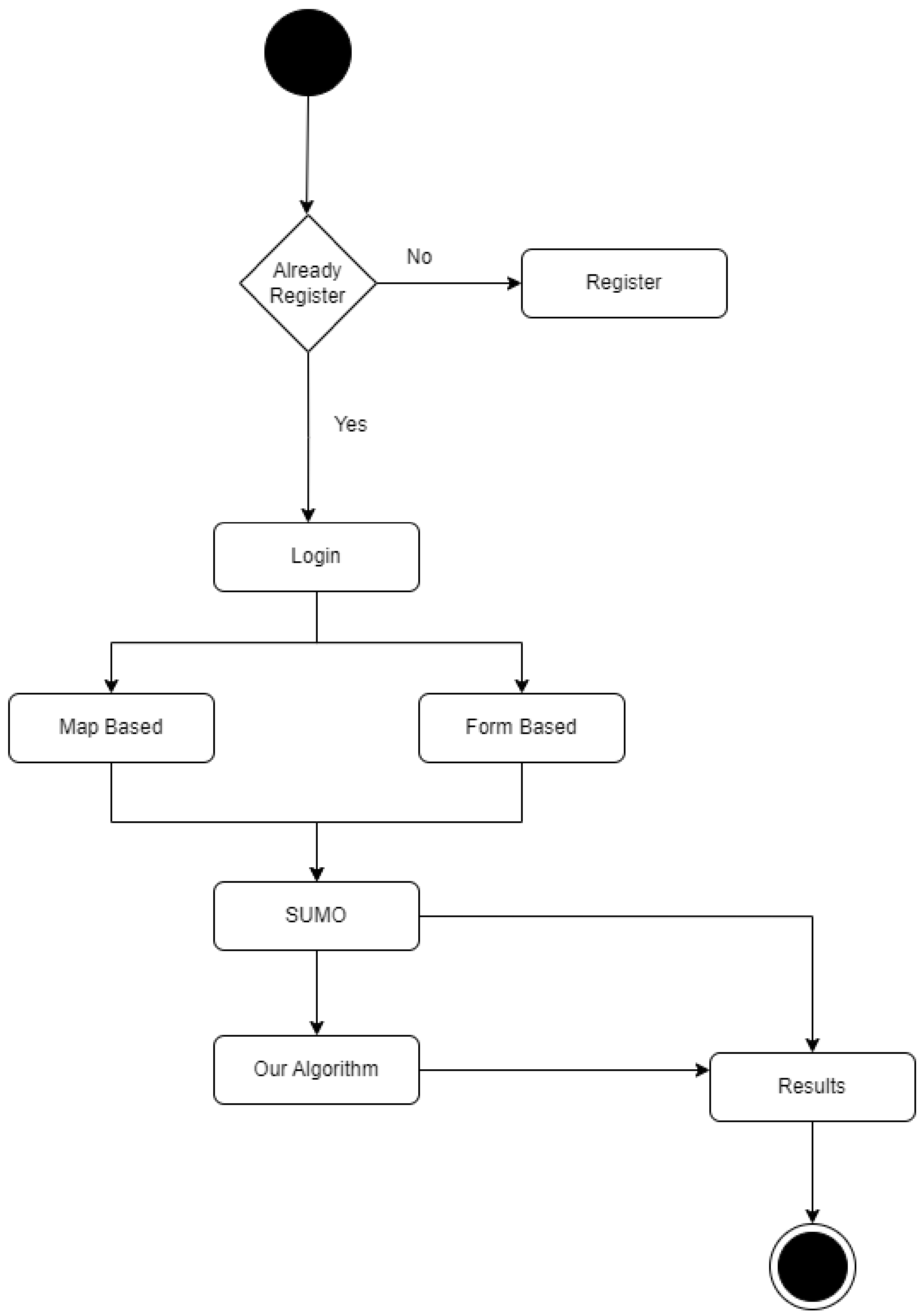
# Introduction

"Developing a web application allowing users to create and simulate custom traffic roads using SUMO. Integrating a machine learning algorithm for real-time traffic congestion prediction, providing users with insightful simulations through an intuitive interface."



# Contents

# Literature Review

## Research

The paper, titled "Traffic Dynamics Modeling in Buxton using Long Short Term Memory Networks," extends Yi et al.'s work by employing LSTM networks to predict traffic speed and estimate congestion propagation, showcasing their effectiveness in understanding and forecasting traffic dynamics.

## Learnings

Study underscores the prowess of Long Short Term Memory (LSTM) networks in modeling vehicle speed and predicting congestion in Buxton. The incorporation of multivariate features, such as vehicle flow rate and headway, significantly enhances the LSTM model's predictive capabilities, offering valuable insights for understanding and forecasting traffic dynamics.

# What We Learn

### LSTM Network Effectiveness:

Demonstrates the efficiency of Long Short Term Memory (LSTM) networks in modeling vehicle speed and predicting congestion in Buxton.

### Multivariate Feature Impact:

Highlights the enhanced predictive capabilities achieved by incorporating multivariate features, including vehicle flow rate and headway, in the LSTM model.

### Temporal Dependency Addressed:

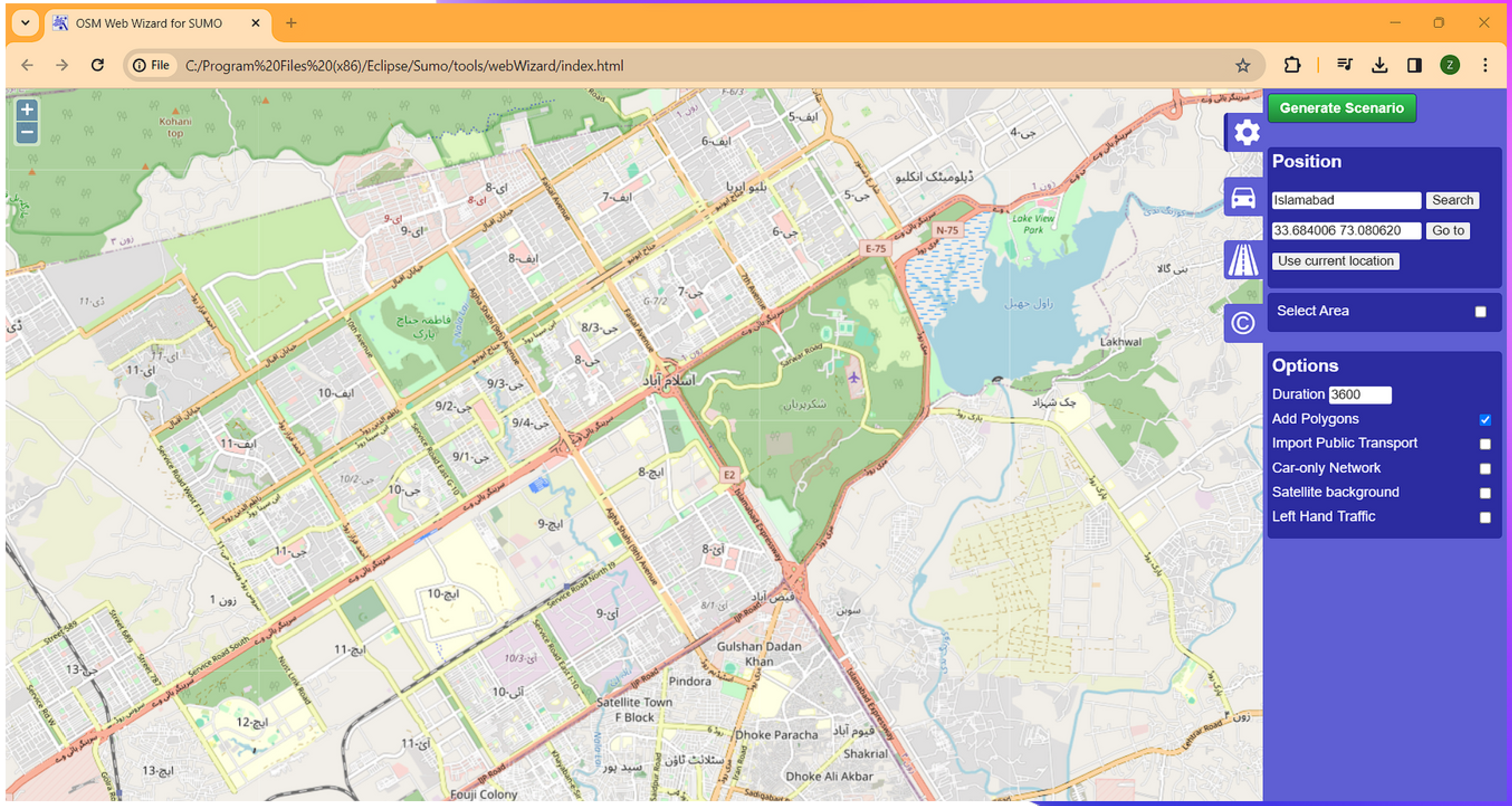
Discusses how LSTMs effectively address temporal dependencies, overcoming challenges associated with Back-Propagation Through Time (BPTT).

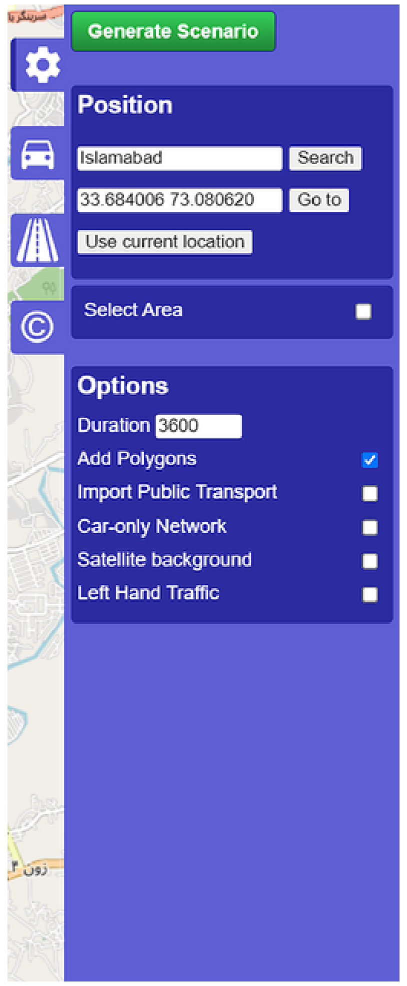
### Practical Application and Implementation:

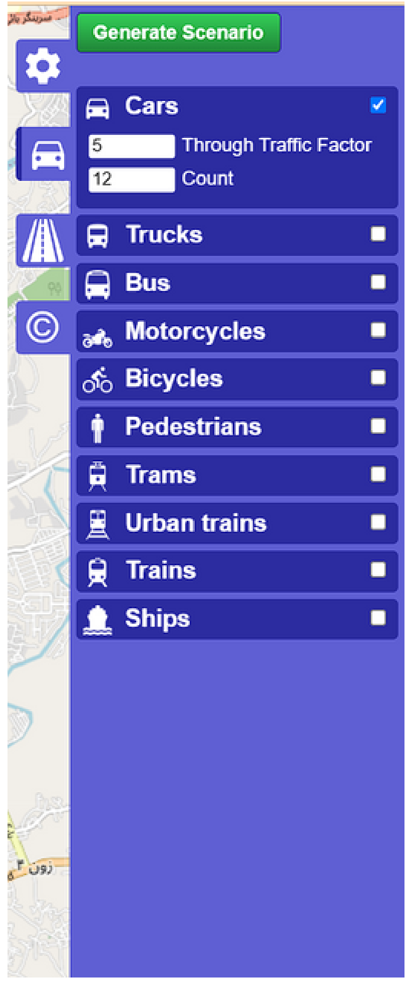
Showcases the practical application of the LSTM model using Keras, emphasizing the importance of careful hyperparameter selection for real-world traffic dynamics analysis.

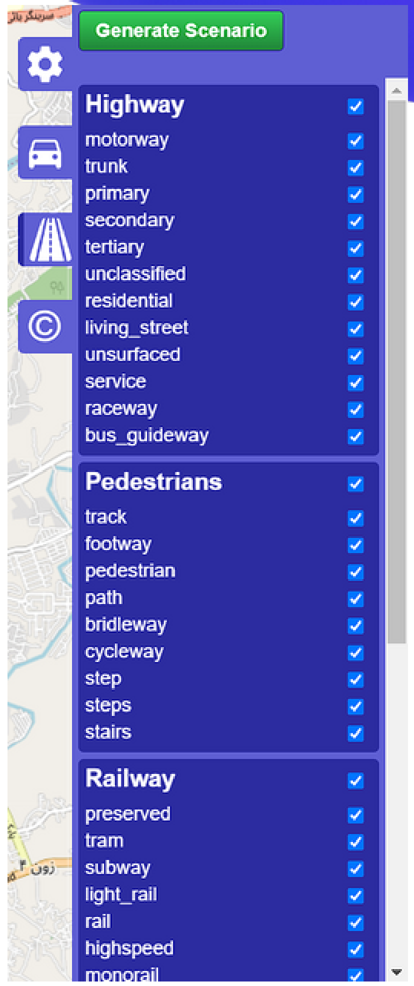
# OSM WEB Simulations

OpenStreetMap (OSM) is a collaborative and open-source mapping platform that empowers individuals worldwide to contribute, edit, and access geographical data. Unlike traditional mapping services, OSM relies on the collective efforts of its community to create a dynamic, detailed map of the world. Users can add and edit information such as roads, buildings, and landmarks, fostering a comprehensive and continually evolving resource. OSM serves as a versatile tool for a range of applications, from navigation and geographic analysis to disaster response and community planning, making it a valuable asset in the realm of open geospatial data.

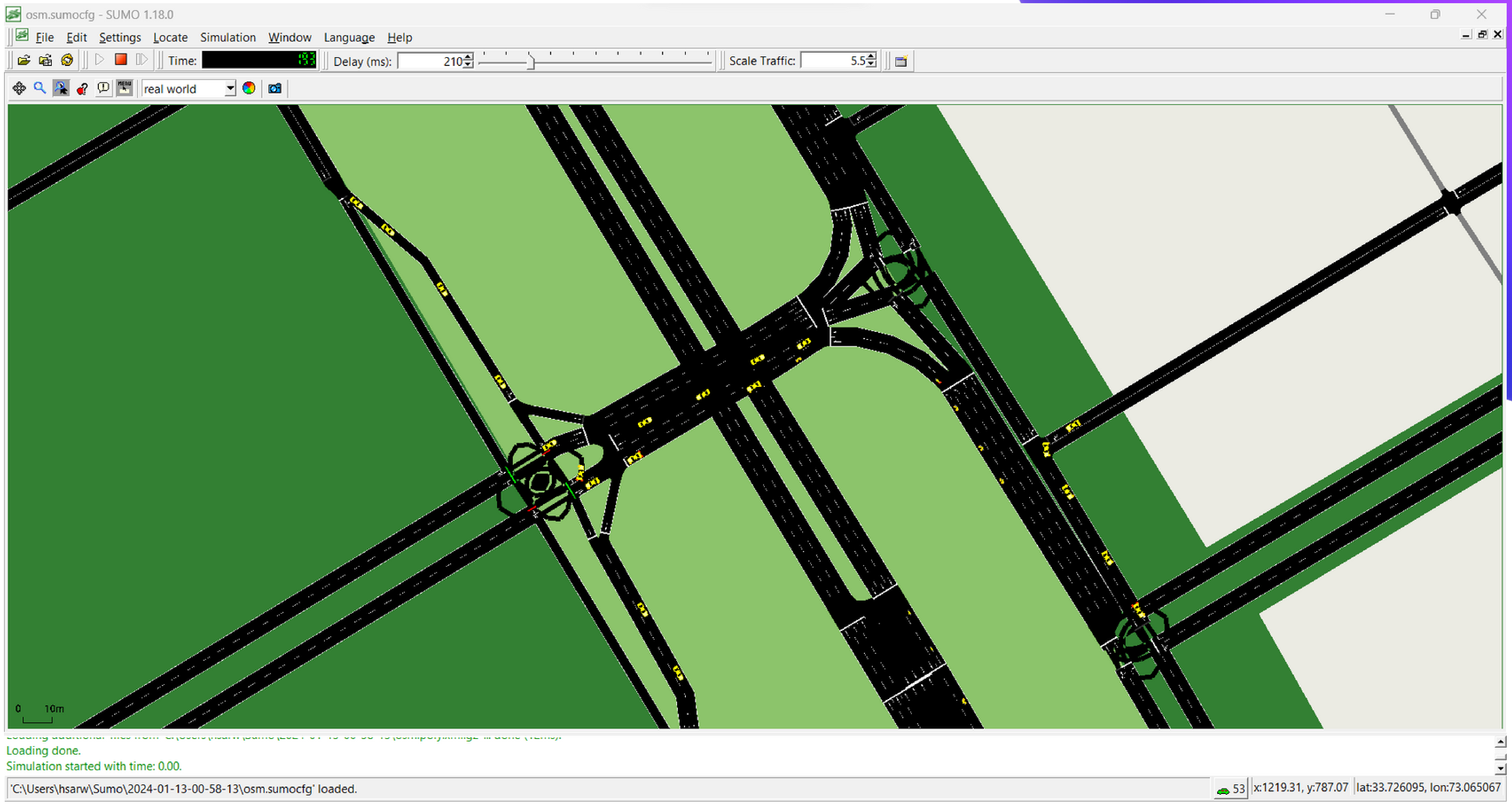


# Sumo Simulation



# Test Algorithm

# Test Algorithm

01

The algorithm utilizes a Long Short-Term Memory (LSTM) based Recurrent Neural Network (RNN) for sequential data modeling.

02

It processes feature sequences, including latitude, longitude, angle, and speed, to capture temporal dependencies in the time-series dataset.

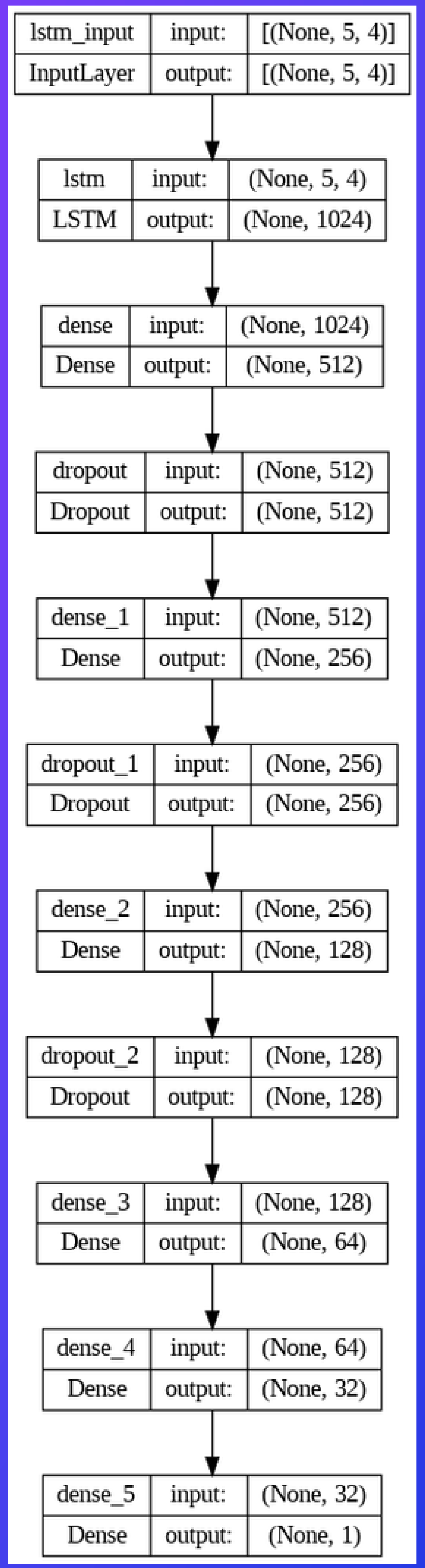
03

The architecture consists of an LSTM layer with 1024 units, followed by densely connected layers (512, 256, 128, 64) with ReLU activation. Dropout layers (0.5) are integrated to mitigate overfitting, and the model is trained using the Adam optimizer with a mean squared error loss function.

04

The model predicts vehicle speed based on input features. The output consists of continuous speed values. Notably, the model achieves a low mean squared error (MSE) of 12 and a high R-squared (R2) score of 87%, indicating its effectiveness in accurately estimating vehicle speeds from the provided data.

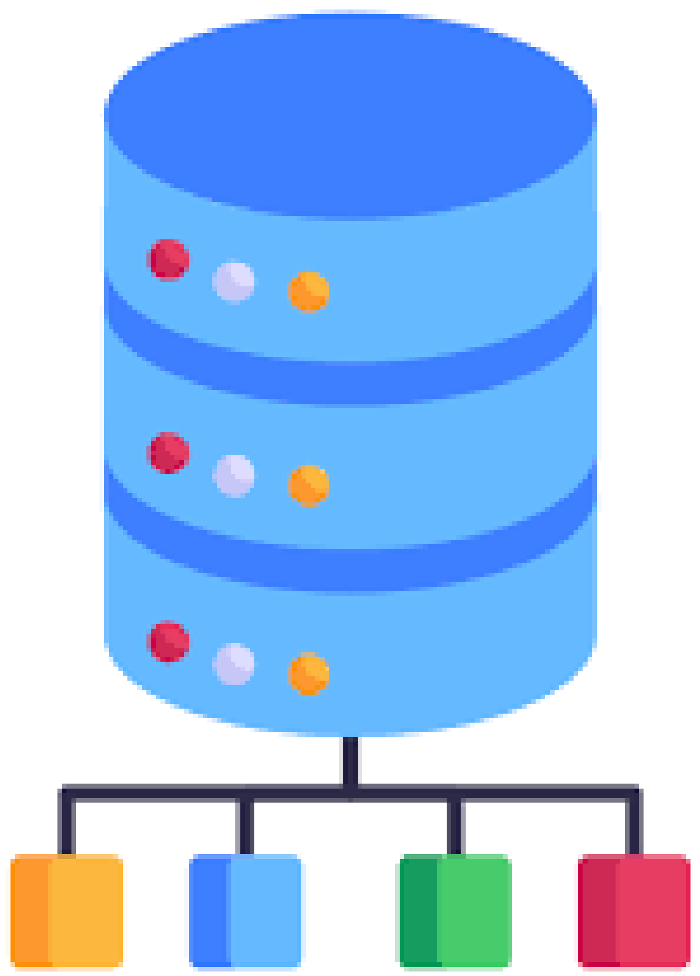
# Architechture:

# Dataset

This dataset records taxi and passenger movements in a specific area, offering details on location, speed, and direction. Unique identifiers for each taxi and passenger enable individual tracking. The dataset provides geographic coordinates, temporal details, and movement characteristics, offering valuable insights into transportation services efficiency in the specified region.

- **Time:** Elapsed time in seconds.
- **ID:** Unique identifier for entities (taxis or passengers).
- **Latitude:** Geographic coordinate representing north-south position.
- **Longitude:** Geographic coordinate representing east-west position.
- **Type:** Indicates whether it's a taxi or passenger.
- **Angle:** Direction of movement.
- **Speed:** Speed of the entity's movement.
- **Lane:** Positional information about the entity.
- **Pos:** Additional position information or identifier.



# Data Pre-Processing

### Data Preparation:

- Clean and preprocess the dataset to handle any missing or inconsistent values.
- Convert timestamp data into a usable format for time-series analysis.

### Feature Selection:

Identify relevant features for congestion prediction. In this case, focus on speed, time, and location data.

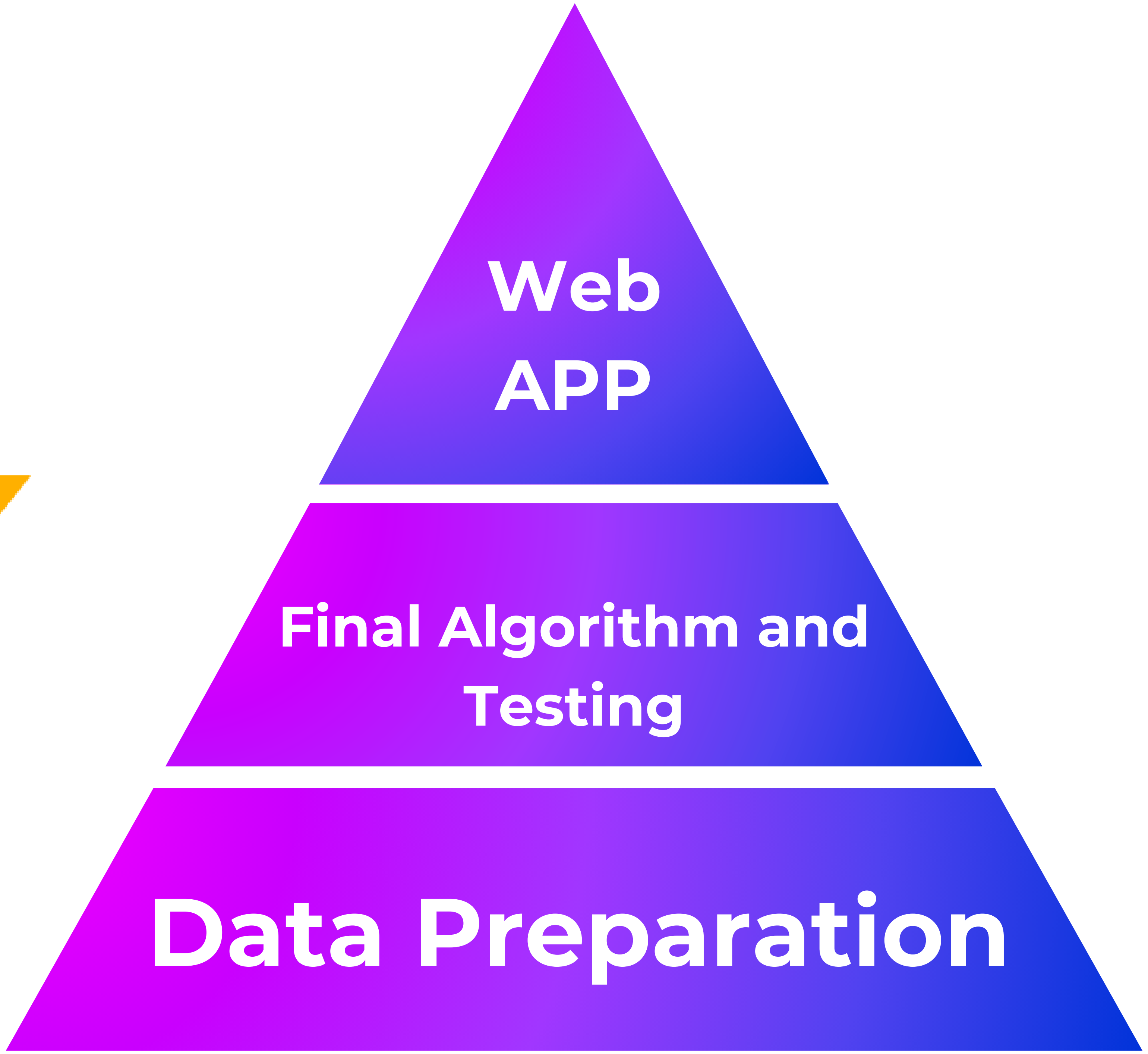
### Exploratory Data Analysis (EDA):

- Conduct EDA to understand the distribution of speed, detect outliers, and observe patterns over time.
- Explore how congestion correlates with specific times, locations, or other relevant factors.

### Temporal and Spatial Analysis:

- Analyze how speed varies temporally (e.g., hourly, daily, weekly) to identify peak congestion periods.
- Investigate spatial patterns by examining areas with consistently low speeds, indicating chronic congestion zones.

# Remaining Tasks



# Thank you
# Any Questions