AI ENHANCED SUPPLY CHAIN MANAGEMENT FOR TEA LEAVES IN AGRICULTURE

24-25J-303

SLIIT
FACULTY OF COMPUTING

Introduction

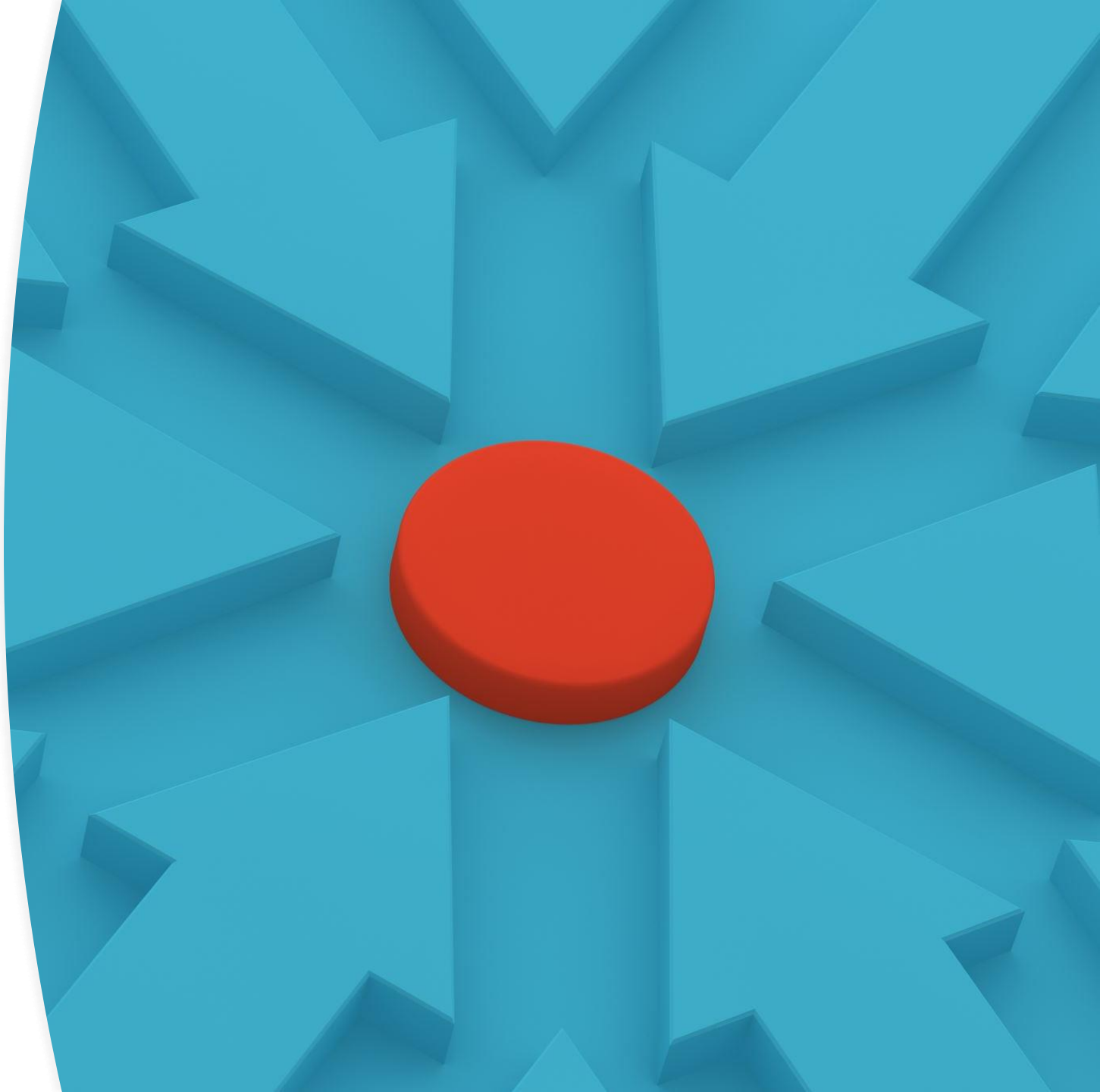
- Efficiently manages the journey of tea leaves from plantations to consumers.
- Involves key processes like sourcing, inventory management, labor planning, and logistics.
- Aims to reduce costs and minimize waste while maintaining quality.
- Ensures a steady supply of tea through streamlined operations.

Research Question

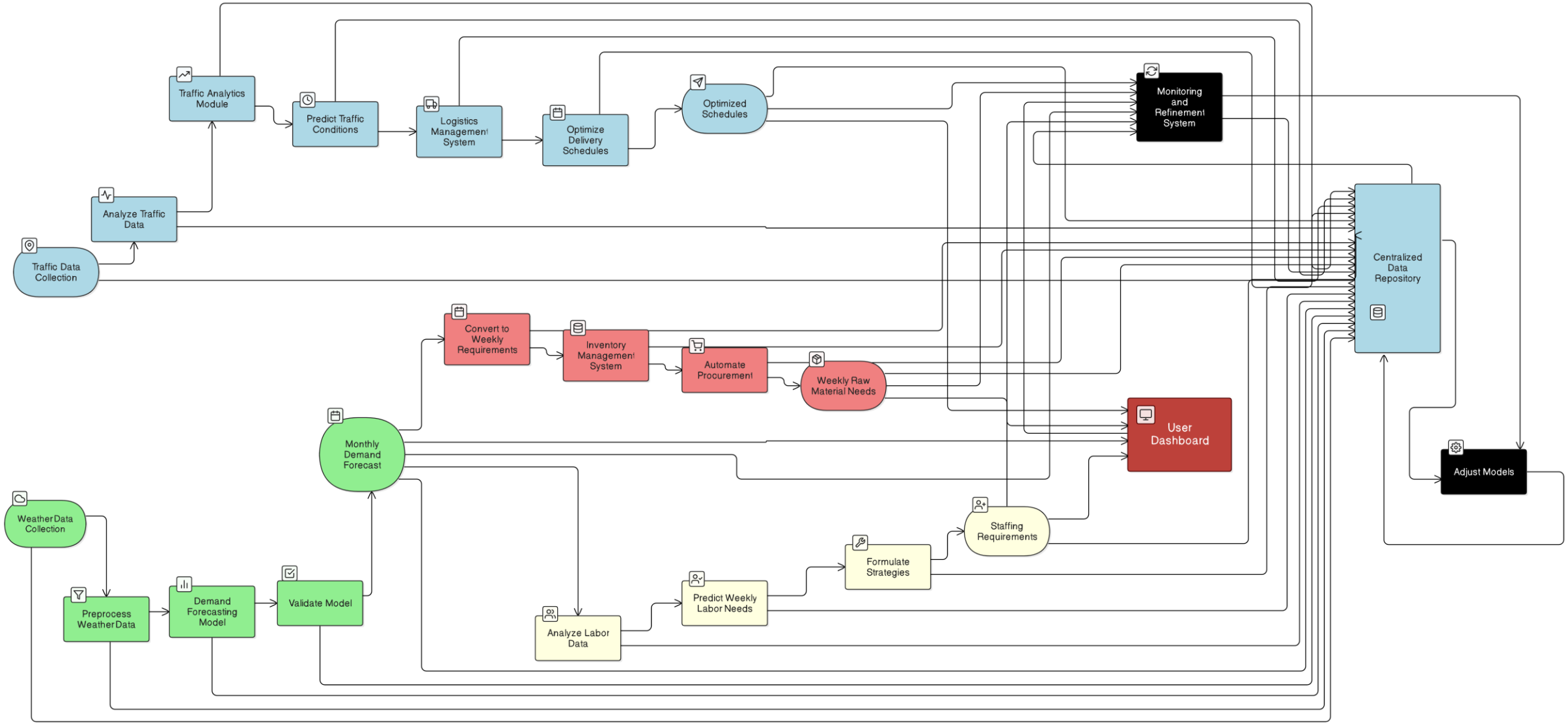
- How to accurately predict tea demand and raw material needs based on weather data and other predictive indicators.
- How to optimize inventory levels, reducing wastage and ensuring a steady supply of raw materials.
- How to manage and mitigate risks associated with labor shortages and ensure adequate staffing levels.
- How to enhance logistics operations by predicting traffic patterns and optimizing delivery schedules.

Objectives

Implementing a supply chain management system with AI automated technologies that we can aim to optimize operations, reduce costs, and improve overall service delivery in our tea production and distribution processes.



Overall System Diagram



IT21155970 | Madushan S.M.P.K.G.S

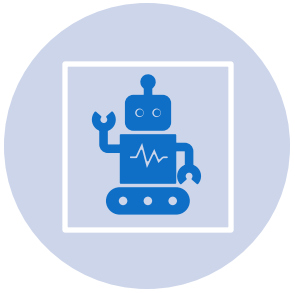
Specialization : Information Technology

Introduction & Background

Tea demand forecasting is a crucial part of aligning production with market needs

Traditional methods rely on historical data, leading to inaccuracies.

Key challenges include lack of real-time data, limited analytics, and poor focus on sustainability.



AI and machine learning offer precise forecasting, reducing waste and improving supply chain efficiency.

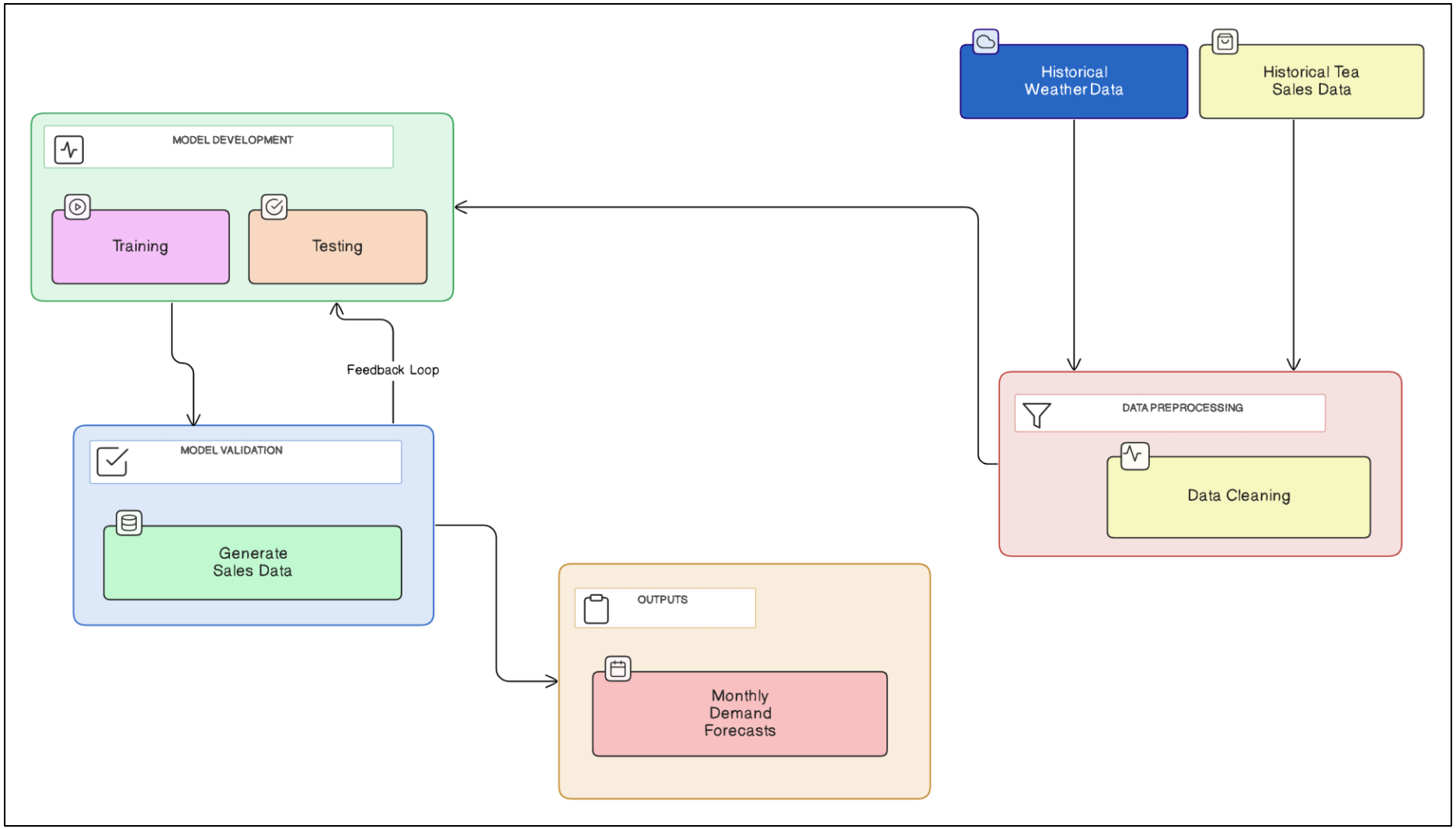
Research Question

- How can an AI-enhanced demand forecasting system address the challenges facing the tea supply chain?
  - ❖ Overreliance on historical data
  - ❖ Inaccurate demand forecasts
  - ❖ Inability to adapt to dynamic market and environmental factors
  - ❖ Increased wastage

Specific and Sub Objective

- Analyze historical demand data to identify key influencing factors.
- Select most appropriate machine learning algorithms for tea demand forecasting.
- Integrate real-time external factors such as weather, market trends into the forecasting model.
- Develop a demand forecasting model using machine learning techniques.
- Implement the model into a user-friendly web application for stakeholders.
- Validate the system through testing in real-world scenarios for reliability and effectiveness.

Methodology System Diagram



Methodology

Data Collection

Collect historical sales and weather data

Model Development

Implement LSTM (Long Short-Term Memory) for demand forecasting.

System Design

Create an integrated platform with a web interface.

Testing and Validation

Perform unit testing, integration testing, system testing, and user acceptance testing.

Deployment

Deploy the forecasting system on cloud platforms with scalable architecture.

Methodology Evidence of Completion

Data Collection

name	datetime	temp	precip	demand_colombo	demand_gampaha	demand_kalutara
Colombo,Sri Lanka	2022-02-08	26.9	0	4684.416472	4959.196498	2696.764207
Colombo,Sri Lanka	2022-02-09	28.1	0	5208.775614	5514.313669	2998.631681
Colombo,Sri Lanka	2022-02-10	26.8	0.5	5495.497208	5817.853871	3163.693975
Colombo,Sri Lanka	2022-02-11	26.8	0.188	5495.497208	5817.853871	3163.693975
Colombo,Sri Lanka	2022-02-12	26.5	11.525	4826.494104	5109.608166	2778.556651
Colombo,Sri Lanka	2022-02-13	25.6	28.257	4969.840953	5261.363501	2861.079769
Colombo,Sri Lanka	2022-02-14	27.7	0.02	4730.906292	5008.413333	2723.527857
Colombo,Sri Lanka	2022-02-15	27.5	0	5256.562546	5564.903703	3026.142063
Colombo,Sri Lanka	2022-02-16	27.4	0	4683.11936	4957.823299	2696.017474
Colombo,Sri Lanka	2022-02-17	26.8	0	5311.323201	5622.876526	3057.667136
Colombo,Sri Lanka	2022-02-18	27.3	0.189	5306.971598	5618.269665	3055.161969
Colombo,Sri Lanka	2022-02-19	26.2	119.1	5608.454569	5937.437122	3228.722217
lombo,Sri Lanka	2022-02-20	26.6	0	6271.905594	6639.805073	3610.663274
Colombo,Sri Lanka	2022-02-21	27.6	0	4874.546037	5160.478745	2806.219592
Colombo,Sri Lanka	2022-02-22	27.4	0	4969.840953	5261.363501	2861.079769

Data preprocessing

```
# Preprocessing
## Clustering 'precip' into three classes
def cluster_precip(data, column_name):
    kmeans = KMeans(n_clusters=3, random_state=42)
    precip_values = data[[column_name]].values
    data['precip_cluster'] = kmeans.fit_predict(precip_values)

    # Map clusters to 'high', 'medium', 'low' based on the mean value in each cluster
    cluster_map = {
        cluster: label for cluster, label in enumerate(
            pd.DataFrame({'cluster': range(3), 'mean_value': kmeans.cluster_centers_.flatten()})
            .sort_values('mean_value')
            .assign(label=['low', 'medium', 'high'])['label'].to_dict()
        )
    }
    data['precip_cluster'] = data['precip_cluster'].map(cluster_map)
    return data

data = cluster_precip(data, 'precip')
```

Methodology Evidence of Completion

Training models using preprocessed datasets

```
# Training
for epoch in range(num_epochs):
    model.train()
    train_loss = 0.0
    for sequences, targets in train_loader:
        sequences, targets = sequences.to(device), targets.to(device).view(-1, 1)
        optimizer.zero_grad()
        outputs = model(sequences)
        loss = criterion(outputs, targets)
        loss.backward()
        optimizer.step()
        train_loss += loss.item() * sequences.size(0)

    train_loss /= len(train_loader.dataset)
    val_loss = 0.0
    model.eval()
    with torch.no_grad():
        for sequences, targets in val_loader:
            sequences, targets = sequences.to(device), targets.to(device).view(-1, 1)
            outputs = model(sequences)
            loss = criterion(outputs, targets)
            val_loss += loss.item() * sequences.size(0)

    val_loss /= len(val_loader.dataset)
    print(f'Epoch {epoch+1}/{num_epochs}, Train Loss: {train_loss:.4f}, Val Loss: {val_loss:.4f}')
```

```
Epoch 1/30, Train Loss: 0.0405, Val Loss: 0.0101
Epoch 2/30, Train Loss: 0.0140, Val Loss: 0.0125
Epoch 3/30, Train Loss: 0.0116, Val Loss: 0.0083
Epoch 4/30, Train Loss: 0.0104, Val Loss: 0.0076
Epoch 5/30, Train Loss: 0.0094, Val Loss: 0.0076
```

Methodology Evidence of Completion

Demand Forecasting for Next 6 Week

```
# prompt: next 6 week demand i need

# Predict the next 6 weeks' demand
next_six_weeks_demand = []
last_sequence = data.iloc[-sequence_length:][['precip_encoded', 'demand_scaled']].values
for _ in range(6):
    last_sequence = torch.tensor(last_sequence, dtype=torch.float32).unsqueeze(0).to(device)
    model.eval()
    with torch.no_grad():
        prediction = model(last_sequence).cpu().numpy()
    next_six_weeks_demand.append(scaler.inverse_transform(prediction).flatten()[0])
    # Update the last_sequence with the prediction for the next step
    last_sequence = np.roll(last_sequence.cpu().numpy()[0], -1, axis=0)
    last_sequence[-1] = prediction[0][0]

print(f"Predicted Demand for Next Six Weeks: {next_six_weeks_demand}")
```

```
Predicted Demand for Next Six Weeks: [4931.399, 5150.454, 5266.8804, 5332.1387, 5354.297, 5364.294]
```

```
[14] # prompt: total next 6 weeks demand

    total_demand = sum(next_six_weeks_demand)
    print(f"Total predicted demand for the next six weeks: {total_demand}")
```

```
Total predicted demand for the next six weeks: 31399.462890625
```

Used Techniques and Technologies

- Technologies
  - React Native
  - Pandas
  - Matplotlib
  - Sklearn
  - Torch
  - Flask Server
  - Numpy
  - Jupyter Notebook
  - Google Colab
  - Intellij Idea

- Techniques
  - Data preprocessing
  - Data Visualization

Functional, Non-Functional and Requirements

➢ Functional Requirements

- ❖ Collect and preprocess historical weather and sales data.
- ❖ Analysis to identify weather impacts on sales.
- ❖ Build and train machine learning models for demand forecasting.
- ❖ Validate accuracy with data.
- ❖ Generate monthly tea demand forecasts.

➢ Non-Functional Requirements

- ❖ Support multiple data sources and regions.
- ❖ High availability with minimal downtime .
- ❖ User-friendly interface with clear visualization.
- ❖ Encrypt sensitive data and implement access controls.

Completion of the project

60% Completion of the Components

- Integration of real-time data sources, including weather patterns and market trends
- Selection and optimization of machine learning algorithms for forecasting accuracy.
- Analysis of historical data to identify demand factors.
- Completion of the project model training and testing part.

40% Future Implementations

- Frontend dashboard design for monitoring and interactive visualization of forecasting outcomes.
- User training modules for maximizing system usability and adoption
- Testing and validation using expanded datasets from multiple regions.

References

[1] Gijo, E. V. (2011). Demand forecasting of tea by seasonal ARIMA model. *International Journal of Business Excellence*, *4*(1), 111-124.

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[4] Babai, M. Z., Boylan, J. E., & Rostami-Tabar, B. (2022). Demand forecasting in supply chains: a review of aggregation and hierarchical approaches. *International Journal of Production Research*, *60*(1), 324-348.

IT21106910 | Gimhani K.M.B.K

Specialization : Information Technology

Introduction and Background

Accurately estimating weekly raw material needs is essential for ensuring that procurement aligns with production schedules and market trends.

Traditional methods conventional approaches rely on manual processes and basic forecasting techniques, frequently leading to either excess stock or shortages.

Key challenges include the lack of seamless integration between monthly demand forecasts and weekly inventory planning, which often results in inefficiencies.

With AI and machine learning, businesses can forecast demand more accurately, automate procurement processes, and maintain optimal inventory levels with ease.

Research Question

How can an AI-enhanced inventory management system address the challenges in managing raw materials for tea production?

- Overreliance on static monthly forecasts
- Inaccurate raw material planning
- Inability to adapt to supply chain fluctuations
- Increased wastage of raw materials

Specific and Sub Objective

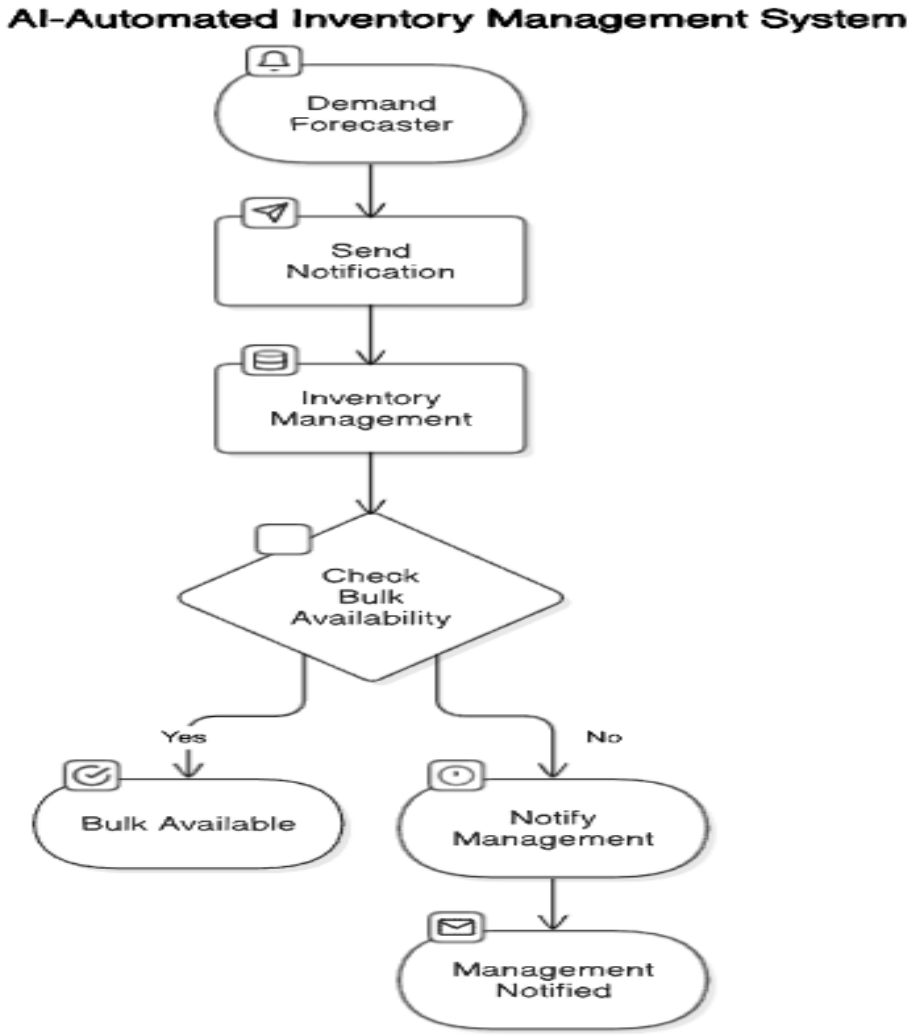
- **Specific Objective**

To develop an AI-driven inventory management system that converts monthly demand forecasts into precise weekly raw material predictions, ensuring optimal inventory levels with minimal waste.

- **Sub Objective**

Data Driven weekly conversion
Inventory optimization
Waste reduction and efficiency

System Diagram



Methodology

- **Data Collection and Analysis**

Monthly sales forecasts and historical data and integrate data with seasonal patterns and demand trends.

- **Model Development**

Implement LSTM (Long Short-Term Memory) to predict weekly raw material requirements based on monthly forecasts.

- **System Design**

Create an AI-Automated platform with a a user-friendly web interface for interaction.

- **Testing and Validation**

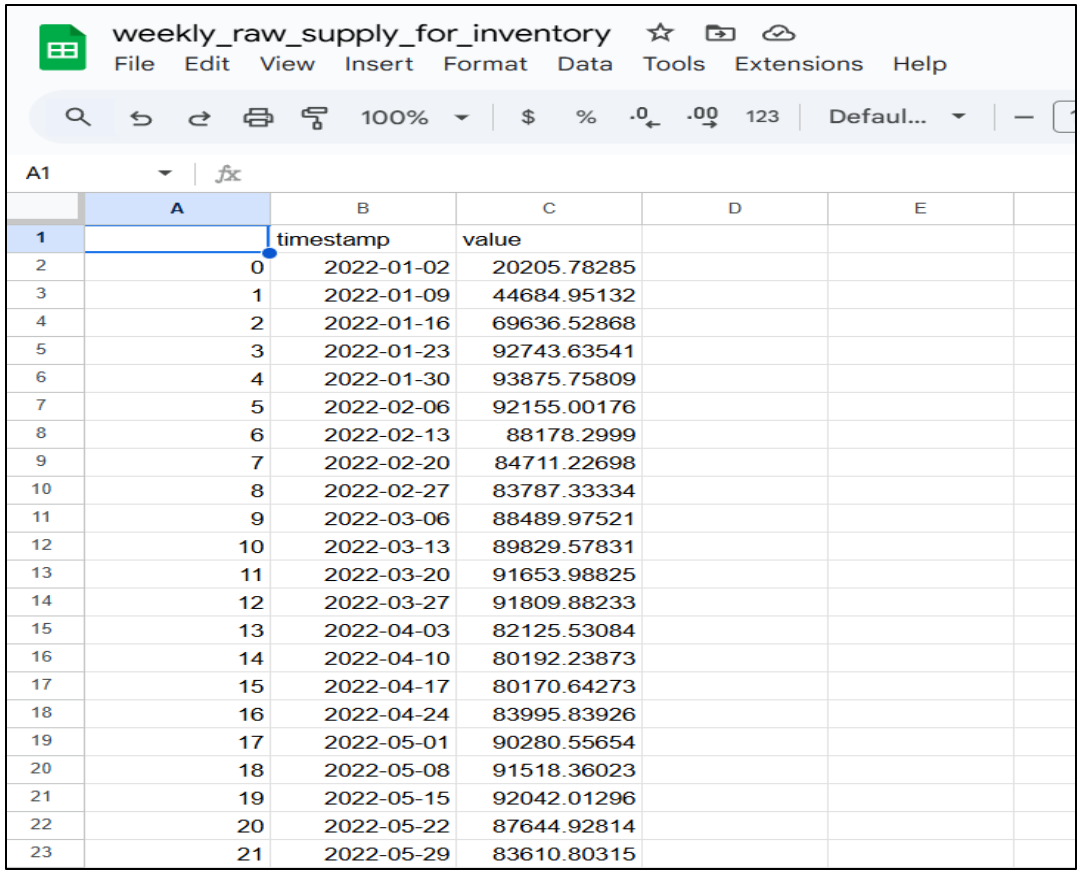
Performing unit testing, integration testing, system testing and user acceptance testing.

- **Deployment**

Deploying the inventory management system on scalable cloud platforms to ensure real-time forecasting and system scalability.

Methodology Evidence of Completion

Data Collection



	A	B	C	D	E
1		timestamp	value		
2	0	2022-01-02	20205.78285		
3	1	2022-01-09	44684.95132		
4	2	2022-01-16	69636.52868		
5	3	2022-01-23	92743.63541		
6	4	2022-01-30	93875.75809		
7	5	2022-02-06	92155.00176		
8	6	2022-02-13	88178.2999		
9	7	2022-02-20	84711.22698		
10	8	2022-02-27	83787.33334		
11	9	2022-03-06	88489.97521		
12	10	2022-03-13	89829.57831		
13	11	2022-03-20	91653.98825		
14	12	2022-03-27	91809.88233		
15	13	2022-04-03	82125.53084		
16	14	2022-04-10	80192.23873		
17	15	2022-04-17	80170.64273		
18	16	2022-04-24	83995.83926		
19	17	2022-05-01	90280.55654		
20	18	2022-05-08	91518.36023		
21	19	2022-05-15	92042.01296		
22	20	2022-05-22	87644.92814		
23	21	2022-05-29	83610.80315		

Data preprocessing

```
# Data preprocessing
values = data['value'].values.r  Loading...  1)
scaler = MinMaxScaler(feature_range=(0, 1))
scaled_values = scaler.fit_transform(values)
```

Methodology Evidence of Completion

Training models using preprocessed datasets

```
# Train the model
early_stopping = EarlyStopping(monitor='val_loss', patience=10, restore_best_weights=True)
history = model.fit(
    X_train, y_train,
    validation_data=(X_test, y_test),
    epochs=100,
    batch_size=16,
    callbacks=[early_stopping],
    verbose=1
)
```

```
Epoch 1/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 4s 73ms/step - loss: 0.6198 - val_loss: 0.3712
Epoch 2/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 14ms/step - loss: 0.5192 - val_loss: 0.2924
Epoch 3/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 10ms/step - loss: 0.4009 - val_loss: 0.1924
Epoch 4/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 14ms/step - loss: 0.2621 - val_loss: 0.0776
Epoch 5/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 10ms/step - loss: 0.0828 - val_loss: 0.0242
Epoch 6/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 10ms/step - loss: 0.0124 - val_loss: 0.0636
Epoch 7/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 14ms/step - loss: 0.0280 - val_loss: 0.0246
Epoch 8/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 12ms/step - loss: 0.0067 - val_loss: 0.0217
Epoch 9/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 15ms/step - loss: 0.0092 - val_loss: 0.0236
Epoch 10/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step - loss: 0.0055 - val_loss: 0.0296
```

Methodology Evidence of Completion

Weekly Forecasting(Raw Materials) for Next 6 Week

```
# Forecasting
last_sequence = scaled_values[-sequence_length:]
last_sequence = last_sequence.reshape(1, sequence_length, 1)

forecast = []
for _ in range(4):  # Predict the next 4 weeks
    pred = model.predict(last_sequence, verbose=0)
    forecast.append(pred[0, 0])
    # last_sequence = np.append(last_sequence[:, 1:, :], [[pred]], axis=1)
    last_sequence = np.append(last_sequence[:, 1:, :], pred.reshape(1, 1, 1), axis=1)
```

```
# Inverse scale the forecast
forecast = scaler.inverse_transform(np.array(forecast).reshape(-1, 1))
print("Forecasted Values:", forecast.flatten())
```

```
Forecasted Values: [67313.37  60918.293 58476.18  60361.625]
```

Used Technologies and Techniques

Technologies

- Flask Python
- TensorFlow
- sklearn
- numpy
- matplotlib
- pandas
- Model: LSTM

Techniques

- Data preprocessing
- Data Visualization

Functional, Non-Functional and Requirements

Functional Requirements

- Integrate and preprocess monthly sales forecasts to calculate baseline raw material demand.
- Analyze historical data to convert monthly forecasts into weekly requirements.
- Validate the system's prediction accuracy using historical and real-time data.
- Automate procurement processes based on weekly demand forecasts.

Non-Functional Requirements

- Interface should be user-friendly
- Application should be reliable
- Higher Accuracy of the results
- Results should be more efficiency

Completion of the project

60% Completion of the Components

- Integration of monthly sales forecasts to identify baseline raw material (raw tea) demand.
- Development of a methodology to convert monthly forecasts into weekly requirements using historical data analysis.
- Design and implementation of an automated inventory management system to calculate weekly raw material needs.
- Completion of the project model training and testing part.

40% Future Implementations

- Frontend dashboard design for real-time monitoring of raw material requirements and inventory levels.
- User training modules for maximizing system usability and adoption
- Include additional predictive capabilities, such as dynamic adjustments for seasonal trends and supply chain disruptions.

References

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IT21306990 | Wadigasinghe U.K

Specialization : Information Technology

Introduction & Background

- Optimizing delivery schedules by forecasting weekly traffic conditions to reduce delays and costs.
- Sri Lanka's tea industry faces significant logistical challenges, including traffic-related disruptions.
- Inefficient supply chain operations increase transportation expenses and affect delivery timelines.
- Predictive analytics and historical traffic data enable smarter scheduling and improved efficiency.

How can predictive analytics and historical traffic data be utilized to optimize delivery schedules, minimize transportation delays, and enhance the efficiency of the Tea Factory's supply chain operations?

Research Question

Methodology

Data Collection & Analysis

Gather historical traffic data and analyze patterns, including factors like weather and events affecting traffic.

Model Development & Integration

Develop predictive models using machine learning and integrate them into a delivery scheduling system.

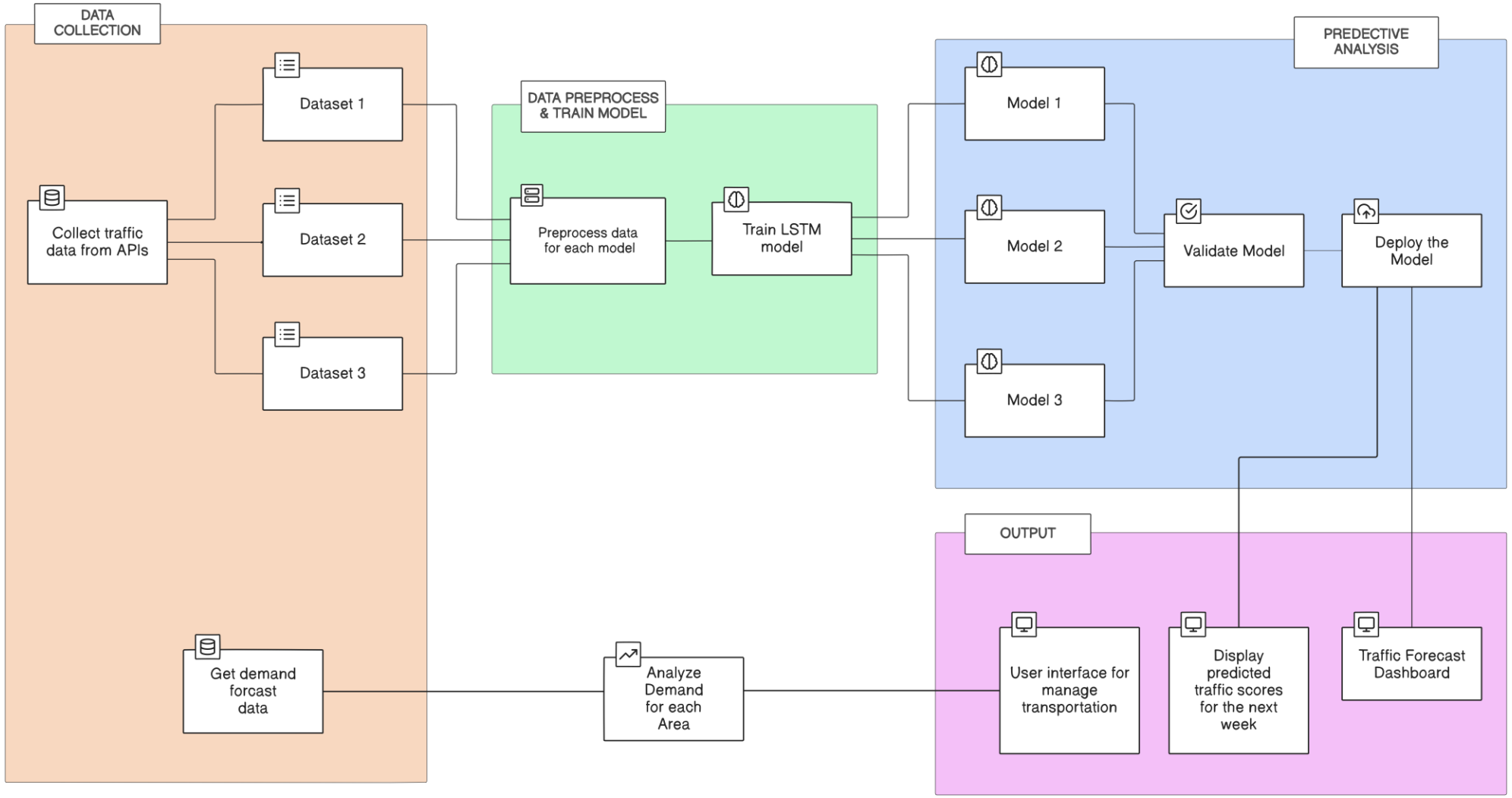
Testing & Validation

Compare model forecasts with actual traffic and evaluate the system's impact on delivery efficiency.

Deployment & Monitoring

Deploy the system in logistics operations and refine it continuously based on real-world feedback.

System Diagram



Objective

- Optimize logistics efficiency and reduce transportation costs for delivering tea to desired locations.

Sub Objectives

- Collect and analyze historical traffic data during critical delivery windows.
- Use predictive analytics to forecast traffic conditions for upcoming weeks.
- Adjust delivery schedules based on traffic predictions to improve timing and minimize costs.

Functional requirements

- Collect and process historical traffic data from reliable sources.
- Generate accurate traffic predictions for upcoming weeks using predictive models.
- Provide optimized delivery schedules based on traffic forecasts.
- User interface for the transportation manager to manage vehicles, routes, and best delivery times.

Non-Functional requirements

- Ensure high accuracy and reliability of traffic predictions.
- Provide a responsive and user-friendly interface for the transportation manager.
- Ensure system scalability to handle increased data and additional logistics routes.
- Maintain data security and confidentiality throughout the system.

Evidence for Completion

Sub-objective 01

Collect historical traffic data using API

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P
1	query	way	distance(meters)	distance_label	origin	origin_coordinates	destination	destination_coordin	duration_min(minute	duration_max(minut	duration(minutes)	road_distance_timin	query_origin	query_destination	timestamp	datetime_utc
2	Watawala, Sri Lanka	Avissawella - Hatton	121644	122 km	GANKA'S PAWN BR	6.944946799999999	11 Bagatalle Rd, Co	6.900996, 79.85488	200	250	220	{"0": 0, "14": 1, "140	GANKA'S PAWN BR	11 Bagatalle Rd, Col	1717182000	05/31/2024 19:00:00
3	Watawala, Sri Lanka	Avissawella - Hatton	110150	110 km	GANKA'S PAWN BR	6.944946799999999	11 Bagatalle Rd, Co	6.900996, 79.85488	200	260	230	{"0": 0, "14": 1, "140	GANKA'S PAWN BR	11 Bagatalle Rd, Col	1717182000	05/31/2024 19:00:00
4	Watawala, Sri Lanka	Avissawella - Hatton	113674	114 km	GANKA'S PAWN BR	6.944946799999999	11 Bagatalle Rd, Co	6.900996, 79.85488	210	250	230	{"0": 0, "14": 1, "140	GANKA'S PAWN BR	11 Bagatalle Rd, Col	1717182000	05/31/2024 19:00:00
5	Watawala, Sri Lanka	Avissawella - Hatton	110150	110 km	GANKA'S PAWN BR	6.944946799999999	11 Bagatalle Rd, Co	6.900996, 79.85488	190	230	210	{"0": 0, "14": 1, "100	GANKA'S PAWN BR	11 Bagatalle Rd, Col	1717196400	05/31/2024 23:00:00
6	Watawala, Sri Lanka	Avissawella - Hatton	121644	122 km	GANKA'S PAWN BR	6.944946799999999	11 Bagatalle Rd, Co	6.900996, 79.85488	190	230	210	{"0": 0, "14": 1, "100	GANKA'S PAWN BR	11 Bagatalle Rd, Col	1717196400	05/31/2024 23:00:00
7	Watawala, Sri Lanka	Avissawella - Hatton	113674	114 km	GANKA'S PAWN BR	6.944946799999999	11 Bagatalle Rd, Co	6.900996, 79.85488	200	240	220	{"0": 0, "14": 1, "100	GANKA'S PAWN BR	11 Bagatalle Rd, Col	1717196400	05/31/2024 23:00:00
8	Watawala, Sri Lanka	Avissawella - Hatton	110150	110 km	GANKA'S PAWN BR	6.944946799999999	11 Bagatalle Rd, Co	6.900996, 79.85488	180	210	200	{"0": 0, "14": 1, "100	GANKA'S PAWN BR	11 Bagatalle Rd, Col	1717210800	06/01/2024 3:00:00
9	Watawala, Sri Lanka	Avissawella - Hatton	121644	122 km	GANKA'S PAWN BR	6.944946799999999	11 Bagatalle Rd, Co	6.900996, 79.85488	190	220	200	{"0": 0, "14": 1, "100	GANKA'S PAWN BR	11 Bagatalle Rd, Col	1717210800	06/01/2024 3:00:00
10	Watawala, Sri Lanka	Avissawella - Hatton	113674	114 km	GANKA'S PAWN BR	6.944946799999999	11 Bagatalle Rd, Co	6.900996, 79.85488	190	220	210	{"0": 0, "14": 1, "100	GANKA'S PAWN BR	11 Bagatalle Rd, Col	1717210800	06/01/2024 3:00:00
11	Watawala, Sri Lanka	Avissawella - Hatton	121644	122 km	GANKA'S PAWN BR	6.944946799999999	11 Bagatalle Rd, Co	6.900996, 79.85488	190	250	220	{"0": 0, "241": 27, "2	GANKA'S PAWN BR	11 Bagatalle Rd, Col	1717225200	06/01/2024 7:00:00
12	Watawala, Sri Lanka	Avissawella - Hatton	110150	110 km	GANKA'S PAWN BR	6.944946799999999	11 Bagatalle Rd, Co	6.900996, 79.85488	190	270	220	{"0": 0, "241": 27, "2	GANKA'S PAWN BR	11 Bagatalle Rd, Col	1717225200	06/01/2024 7:00:00
13	Watawala, Sri Lanka	Avissawella - Hatton	113674	114 km	GANKA'S PAWN BR	6.944946799999999	11 Bagatalle Rd, Co	6.900996, 79.85488	200	260	220	{"0": 0, "241": 27, "2	GANKA'S PAWN BR	11 Bagatalle Rd, Col	1717225200	06/01/2024 7:00:00
14	Watawala, Sri Lanka	Avissawella - Hatton	121644	122 km	GANKA'S PAWN BR	6.944946799999999	11 Bagatalle Rd, Co	6.900996, 79.85488	200	260	230	{"0": 0, "14": 2, "100	GANKA'S PAWN BR	11 Bagatalle Rd, Col	1717239600	06/01/2024 11:00:00
15	Watawala, Sri Lanka	Avissawella - Hatton	110150	110 km	GANKA'S PAWN BR	6.944946799999999	11 Bagatalle Rd, Co	6.900996, 79.85488	200	270	230	{"0": 0, "14": 2, "100	GANKA'S PAWN BR	11 Bagatalle Rd, Col	1717239600	06/01/2024 11:00:00
16	Watawala, Sri Lanka	Avissawella - Hatton	113674	114 km	GANKA'S PAWN BR	6.944946799999999	11 Bagatalle Rd, Co	6.900996, 79.85488	210	260	230	{"0": 0, "14": 2, "100	GANKA'S PAWN BR	11 Bagatalle Rd, Col	1717239600	06/01/2024 11:00:00
17	Watawala, Sri Lanka	Avissawella - Hatton	121644	122 km	GANKA'S PAWN BR	6.944946799999999	11 Bagatalle Rd, Co	6.900996, 79.85488	190	260	220	{"0": 0, "14": 1, "100	GANKA'S PAWN BR	11 Bagatalle Rd, Col	1717254000	06/01/2024 15:00:00
18	Watawala, Sri Lanka	Avissawella - Hatton	110150	110 km	GANKA'S PAWN BR	6.944946799999999	11 Bagatalle Rd, Co	6.900996, 79.85488	200	280	230	{"0": 0, "14": 1, "100	GANKA'S PAWN BR	11 Bagatalle Rd, Col	1717254000	06/01/2024 15:00:00
19	Watawala, Sri Lanka	Avissawella - Hatton	113674	114 km	GANKA'S PAWN BR	6.944946799999999	11 Bagatalle Rd, Co	6.900996, 79.85488	200	270	230	{"0": 0, "14": 1, "100	GANKA'S PAWN BR	11 Bagatalle Rd, Col	1717254000	06/01/2024 15:00:00
20	Watawala, Sri Lanka	Avissawella - Hatton	110150	110 km	GANKA'S PAWN BR	6.944946799999999	11 Bagatalle Rd, Co	6.900996, 79.85488	200	250	220	{"0": 0, "14": 2, "100	GANKA'S PAWN BR	11 Bagatalle Rd, Col	1717268400	06/01/2024 19:00:00
21	Watawala, Sri Lanka	Avissawella - Hatton	121644	122 km	GANKA'S PAWN BR	6.944946799999999	11 Bagatalle Rd, Co	6.900996, 79.85488	200	260	220	{"0": 0, "14": 2, "100	GANKA'S PAWN BR	11 Bagatalle Rd, Col	1717268400	06/01/2024 19:00:00
22	Watawala, Sri Lanka	Avissawella - Hatton	113674	114 km	GANKA'S PAWN BR	6.944946799999999	11 Bagatalle Rd, Co	6.900996, 79.85488	210	260	230	{"0": 0, "14": 2, "100	GANKA'S PAWN BR	11 Bagatalle Rd, Col	1717268400	06/01/2024 19:00:00
23	Watawala, Sri Lanka	Avissawella - Hatton	110150	110 km	GANKA'S PAWN BR	6.944946799999999	11 Bagatalle Rd, Co	6.900996, 79.85488	180	220	200	{"0": 0, "14": 1, "100	GANKA'S PAWN BR	11 Bagatalle Rd, Col	1717282800	06/01/2024 23:00:00
24	Watawala, Sri Lanka	Avissawella - Hatton	121644	122 km	GANKA'S PAWN BR	6.944946799999999	11 Bagatalle Rd, Co	6.900996, 79.85488	190	220	200	{"0": 0, "14": 1, "100	GANKA'S PAWN BR	11 Bagatalle Rd, Col	1717282800	06/01/2024 23:00:00
25	Watawala, Sri Lanka	Avissawella - Hatton	113674	114 km	GANKA'S PAWN BR	6.944946799999999	11 Bagatalle Rd, Co	6.900996, 79.85488	200	220	210	{"0": 0, "14": 1, "100	GANKA'S PAWN BR	11 Bagatalle Rd, Col	1717282800	06/01/2024 23:00:00
26	Watawala, Sri Lanka	Avissawella - Hatton	110150	110 km	GANKA'S PAWN BR	6.944946799999999	11 Bagatalle Rd, Co	6.900996, 79.85488	180	210	190	{"0": 0, "14": 1, "100	GANKA'S PAWN BR	11 Bagatalle Rd, Col	1717297200	06/02/2024 3:00:00
27	Watawala, Sri Lanka	Avissawella - Hatton	121644	122 km	GANKA'S PAWN BR	6.944946799999999	11 Bagatalle Rd, Co	6.900996, 79.85488	190	220	200	{"0": 0, "14": 1, "100	GANKA'S PAWN BR	11 Bagatalle Rd, Col	1717297200	06/02/2024 3:00:00
28	Watawala, Sri Lanka	Avissawella - Hatton	113674	114 km	GANKA'S PAWN BR	6.944946799999999	11 Bagatalle Rd, Co	6.900996, 79.85488	200	220	210	{"0": 0, "14": 1, "100	GANKA'S PAWN BR	11 Bagatalle Rd, Col	1717297200	06/02/2024 3:00:00
29	Watawala, Sri Lanka	Avissawella - Hatton	121644	122 km	GANKA'S PAWN BR	6.944946799999999	11 Bagatalle Rd, Co	6.900996, 79.85488	180	240	200	{"0": 0, "14": 1, "100	GANKA'S PAWN BR	11 Bagatalle Rd, Col	1717311600	06/02/2024 7:00:00
30	Watawala, Sri Lanka	Avissawella - Hatton	111889	112 km	GANKA'S PAWN BR	6.944946799999999	11 Bagatalle Rd, Co	6.900996, 79.85488	180	250	210	{"0": 0, "14": 1, "100	GANKA'S PAWN BR	11 Bagatalle Rd, Col	1717311600	06/02/2024 7:00:00
31	Watawala, Sri Lanka	Avissawella - Hatton	113674	114 km	GANKA'S PAWN BR	6.944946799999999	11 Bagatalle Rd, Co	6.900996, 79.85488	190	240	210	{"0": 0, "14": 1, "100	GANKA'S PAWN BR	11 Bagatalle Rd, Col	1717311600	06/02/2024 7:00:00
32	Watawala, Sri Lanka	Avissawella - Hatton	121644	122 km	GANKA'S PAWN BR	6.944946799999999	11 Bagatalle Rd, Co	6.900996, 79.85488	190	250	220	{"0": 0, "14": 1, "293	GANKA'S PAWN BR	11 Bagatalle Rd, Col	1717326000	06/02/2024 11:00:00
33	Watawala, Sri Lanka	Avissawella - Hatton	110150	110 km	GANKA'S PAWN BR	6.944946799999999	11 Bagatalle Rd, Co	6.900996, 79.85488	190	260	220	{"0": 0, "14": 1, "293	GANKA'S PAWN BR	11 Bagatalle Rd, Col	1717326000	06/02/2024 11:00:00
34	Watawala, Sri Lanka	Avissawella - Hatton	113674	114 km	GANKA'S PAWN BR	6.944946799999999	11 Bagatalle Rd, Co	6.900996, 79.85488	200	250	220	{"0": 0, "14": 1, "293	GANKA'S PAWN BR	11 Bagatalle Rd, Col	1717326000	06/02/2024 11:00:00
35	Watawala, Sri Lanka	Avissawella - Hatton	121644	122 km	GANKA'S PAWN BR	6.944946799999999	11 Bagatalle Rd, Co	6.900996, 79.85488	190	260	220	{"0": 0, "14": 2, "293	GANKA'S PAWN BR	11 Bagatalle Rd, Col	1717340400	06/02/2024 15:00:00
36	Watawala, Sri Lanka	Avissawella - Hatton	110150	110 km	GANKA'S PAWN BR	6.944946799999999	11 Bagatalle Rd, Co	6.900996, 79.85488	190	280	220	{"0": 0, "14": 2, "293	GANKA'S PAWN BR	11 Bagatalle Rd, Col	1717340400	06/02/2024 15:00:00

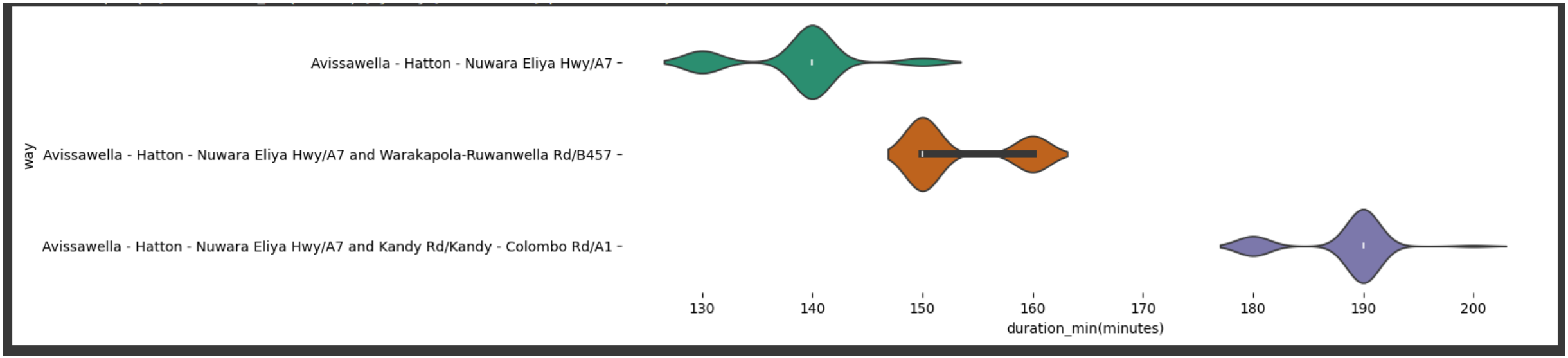
From Watavala to

- Colombo
- Kaluthara
- Gampaha(Nittambuwa)

Evidence for Completion

Sub-objective 02

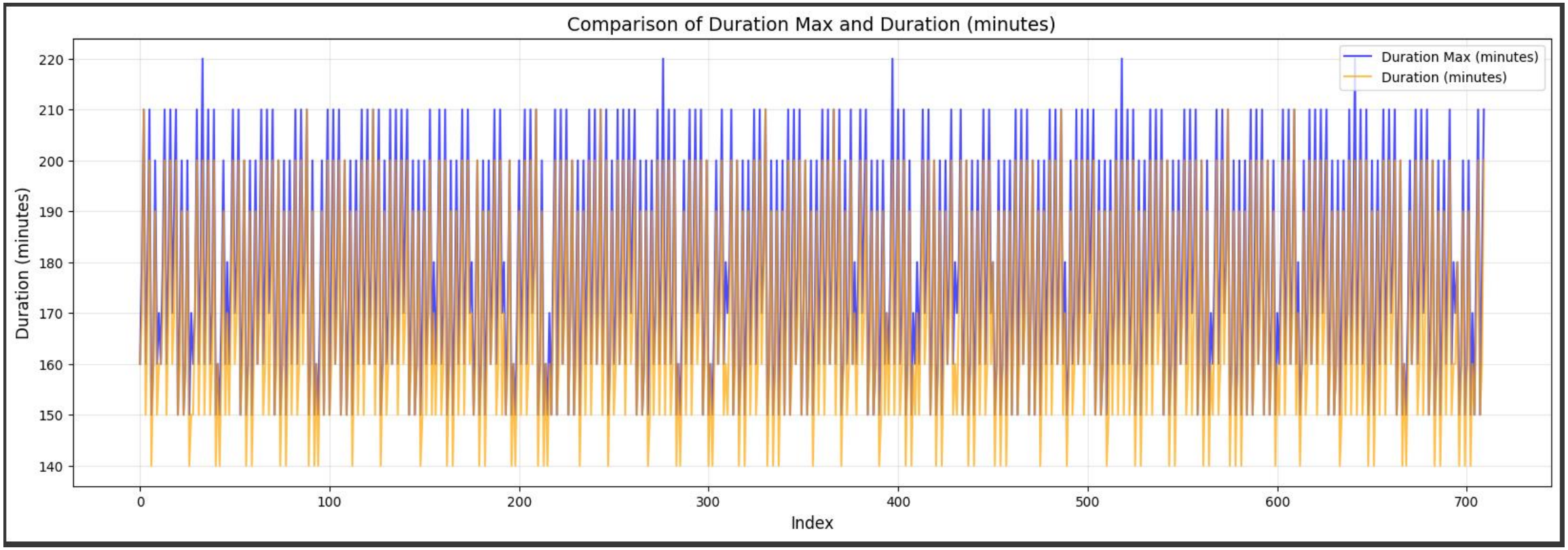
Selecting the best route with minimum time duration



Evidence for Completion

Sub-objective 02

select average duration/min duration/max duration to get good variation for training



Evidence for Completion

Sub-objective 02

Create final dataset for Model training

```
# Final dataset for model training

# Create a new dataframe with the desired columns
df_final = df_final2[['datetime_utc', 'duration_max(minutes)']]

# Display the first few rows to verify
df_final.head(20)
```

	datetime_utc	duration_max(minutes)
0	2024-05-31 18:00:00	250.0
9	2024-06-01 06:00:00	250.0
12	2024-06-01 10:00:00	260.0
15	2024-06-01 14:00:00	260.0
18	2024-06-01 18:00:00	250.0
27	2024-06-02 06:00:00	240.0
30	2024-06-02 10:00:00	250.0
33	2024-06-02 14:00:00	260.0
36	2024-06-02 18:00:00	250.0
45	2024-06-03 06:00:00	250.0

Colombo (Max duration)

```
# Final dataset for model training

# Create a new dataframe with the desired columns
df_final1 = df_filtered[['way', 'distance_label', 'datetime_utc', 'duration(minutes)']]

# Display the first few rows to verify
df_final1.head(20)
```

	way	distance_label	datetime_utc	duration(minutes)
0	Avissawella - Hatton - Nuwara Eliya Hwy/A7	80.9 km	2024-05-31 18:00:00	160.0
1	Avissawella - Hatton - Nuwara Eliya Hwy/A7 and...	92.8 km	2024-05-31 18:00:00	170.0
2	Avissawella - Hatton - Nuwara Eliya Hwy/A7 and...	103 km	2024-05-31 18:00:00	210.0
9	Avissawella - Hatton - Nuwara Eliya Hwy/A7	80.9 km	2024-06-01 06:00:00	150.0
10	Avissawella - Hatton - Nuwara Eliya Hwy/A7 and...	92.8 km	2024-06-01 06:00:00	160.0
11	Avissawella - Hatton - Nuwara Eliya Hwy/A7	80.9 km	2024-06-01 10:00:00	160.0
12	Avissawella - Hatton - Nuwara Eliya Hwy/A7 and...	92.8 km	2024-06-01 10:00:00	170.0
13	Avissawella - Hatton - Nuwara Eliya Hwy/A7 and...	103 km	2024-06-01 10:00:00	200.0
14	Avissawella - Hatton - Nuwara Eliya Hwy/A7	80.9 km	2024-06-01 14:00:00	150.0
15	Avissawella - Hatton - Nuwara Eliya Hwy/A7 and...	92.8 km	2024-06-01 14:00:00	170.0
16	Avissawella - Hatton - Nuwara Eliya Hwy/A7 and...	103 km	2024-06-01 14:00:00	200.0
17	Avissawella - Hatton - Nuwara Eliya Hwy/A7	80.9 km	2024-06-01 18:00:00	160.0
18	Avissawella - Hatton - Nuwara Eliya Hwy/A7 and...	92.8 km	2024-06-01 18:00:00	170.0
19	Avissawella - Hatton - Nuwara Eliya Hwy/A7 and...	103 km	2024-06-01 18:00:00	200.0
26	Avissawella - Hatton - Nuwara Eliya Hwy/A7	80.9 km	2024-06-02 06:00:00	140.0
27	Avissawella - Hatton - Nuwara Eliya Hwy/A7 and...	92.8 km	2024-06-02 06:00:00	150.0

Nittambuwa (Average duration)

```
# Final dataset for model training

# Create a new dataframe with the desired columns
df_final = df_final2[['datetime_utc', 'duration_max(minutes)']]

# Display the first few rows to verify
df_final.head(20)
```

	datetime_utc	duration_max(minutes)
0	2024-05-31 18:00:00	250.0
9	2024-06-01 06:00:00	260.0
12	2024-06-01 10:00:00	270.0
15	2024-06-01 14:00:00	270.0
18	2024-06-01 18:00:00	260.0
27	2024-06-02 06:00:00	250.0
30	2024-06-02 10:00:00	260.0
33	2024-06-02 14:00:00	270.0
36	2024-06-02 18:00:00	250.0

Kaluthara (Max duration)

LSTM Model for Traffic Prediction

Sub-objective 02

What is LSTM?

- A type of Recurrent Neural Network (RNN) designed for sequential data like traffic patterns.
- Addresses the vanishing gradient problem, enabling learning over extended time periods.

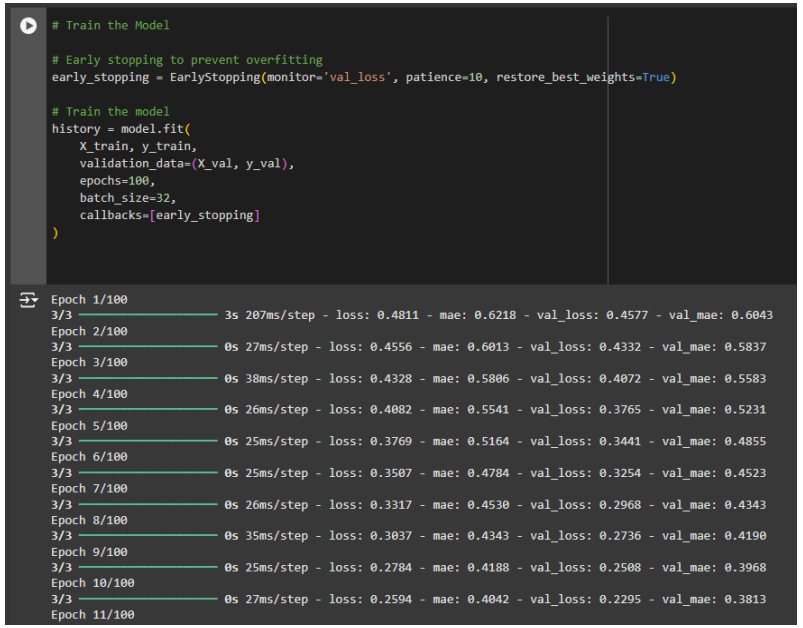
Key Features and Benefits:

- Retains past data and long-term dependencies to analyze traffic trends.
- Manages time-series data effectively, learning patterns like peak hours, holidays, and seasonal variations.
- Models complex, non-linear factors such as weather and events while being resilient to noisy or anomalous data.

Evidence for Completion

Sub-objective 02

Train each three models using preprocessed datasets



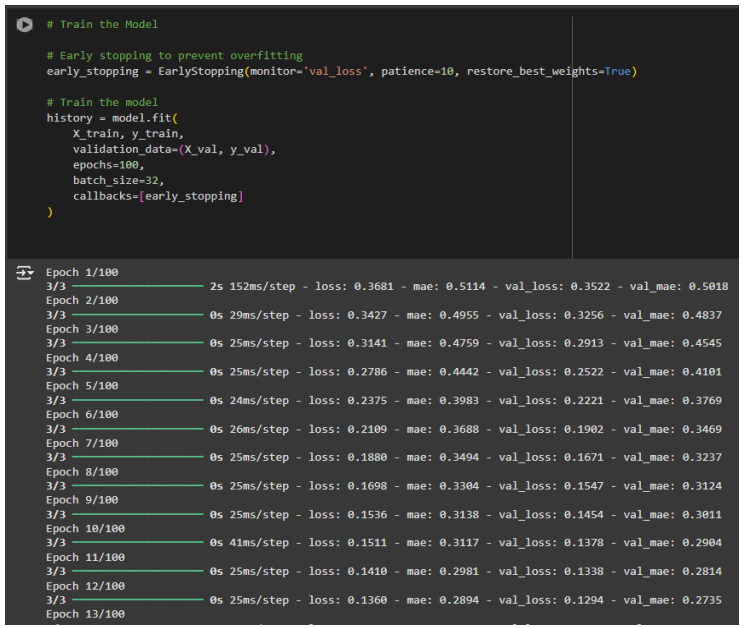
```
# Train the Model

# Early stopping to prevent overfitting
early_stopping = EarlyStopping(monitor='val_loss', patience=10, restore_best_weights=True)

# Train the model
history = model.fit(
    X_train, y_train,
    validation_data=(X_val, y_val),
    epochs=100,
    batch_size=32,
    callbacks=[early_stopping]
)
```

```
Epoch 1/100
3/3 ━━━━━━━━━━━━━━━━━━━━ 3s 207ms/step - loss: 0.4811 - mae: 0.6218 - val_loss: 0.4577 - val_mae: 0.6043
Epoch 2/100
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 27ms/step - loss: 0.4556 - mae: 0.6013 - val_loss: 0.4332 - val_mae: 0.5837
Epoch 3/100
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 38ms/step - loss: 0.4328 - mae: 0.5806 - val_loss: 0.4072 - val_mae: 0.5583
Epoch 4/100
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 26ms/step - loss: 0.4082 - mae: 0.5541 - val_loss: 0.3765 - val_mae: 0.5231
Epoch 5/100
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 25ms/step - loss: 0.3769 - mae: 0.5164 - val_loss: 0.3441 - val_mae: 0.4855
Epoch 6/100
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 25ms/step - loss: 0.3507 - mae: 0.4784 - val_loss: 0.3254 - val_mae: 0.4523
Epoch 7/100
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 26ms/step - loss: 0.3317 - mae: 0.4530 - val_loss: 0.2968 - val_mae: 0.4343
Epoch 8/100
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 35ms/step - loss: 0.3037 - mae: 0.4343 - val_loss: 0.2736 - val_mae: 0.4190
Epoch 9/100
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 25ms/step - loss: 0.2784 - mae: 0.4188 - val_loss: 0.2508 - val_mae: 0.3968
Epoch 10/100
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 27ms/step - loss: 0.2594 - mae: 0.4042 - val_loss: 0.2295 - val_mae: 0.3813
Epoch 11/100
```

Colombo



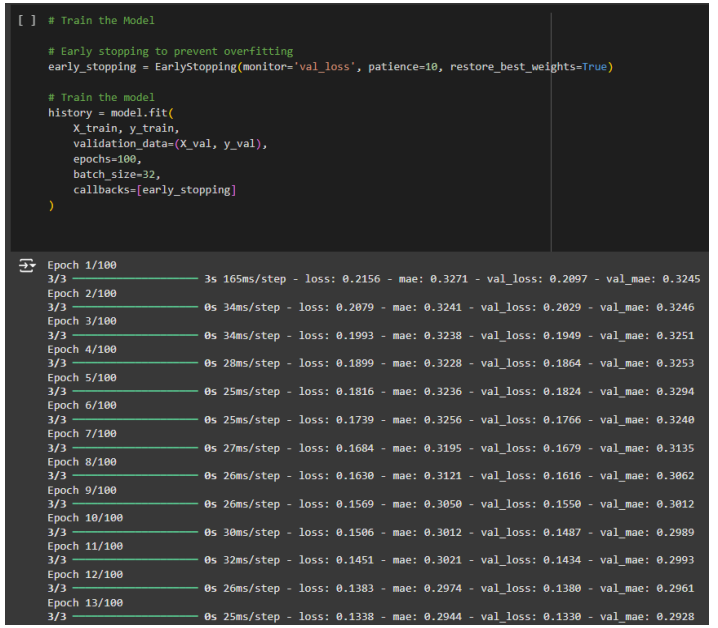
```
# Train the Model

# Early stopping to prevent overfitting
early_stopping = EarlyStopping(monitor='val_loss', patience=10, restore_best_weights=True)

# Train the model
history = model.fit(
    X_train, y_train,
    validation_data=(X_val, y_val),
    epochs=100,
    batch_size=32,
    callbacks=[early_stopping]
)
```

```
Epoch 1/100
3/3 ━━━━━━━━━━━━━━━━━━━━ 2s 152ms/step - loss: 0.3681 - mae: 0.5114 - val_loss: 0.3522 - val_mae: 0.5018
Epoch 2/100
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 29ms/step - loss: 0.3427 - mae: 0.4955 - val_loss: 0.3256 - val_mae: 0.4837
Epoch 3/100
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 25ms/step - loss: 0.3141 - mae: 0.4759 - val_loss: 0.2913 - val_mae: 0.4545
Epoch 4/100
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 25ms/step - loss: 0.2786 - mae: 0.4442 - val_loss: 0.2522 - val_mae: 0.4101
Epoch 5/100
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 24ms/step - loss: 0.2375 - mae: 0.3983 - val_loss: 0.2221 - val_mae: 0.3769
Epoch 6/100
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 26ms/step - loss: 0.2109 - mae: 0.3688 - val_loss: 0.1902 - val_mae: 0.3469
Epoch 7/100
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 25ms/step - loss: 0.1880 - mae: 0.3494 - val_loss: 0.1671 - val_mae: 0.3237
Epoch 8/100
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 25ms/step - loss: 0.1698 - mae: 0.3304 - val_loss: 0.1547 - val_mae: 0.3124
Epoch 9/100
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 25ms/step - loss: 0.1536 - mae: 0.3138 - val_loss: 0.1454 - val_mae: 0.3011
Epoch 10/100
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 41ms/step - loss: 0.1511 - mae: 0.3117 - val_loss: 0.1378 - val_mae: 0.2904
Epoch 11/100
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 25ms/step - loss: 0.1410 - mae: 0.2981 - val_loss: 0.1338 - val_mae: 0.2814
Epoch 12/100
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 25ms/step - loss: 0.1360 - mae: 0.2894 - val_loss: 0.1294 - val_mae: 0.2735
Epoch 13/100
```

Nittambuwa



```
[ ] # Train the Model

    # Early stopping to prevent overfitting
    early_stopping = EarlyStopping(monitor='val_loss', patience=10, restore_best_weights=True)

    # Train the model
    history = model.fit(
        X_train, y_train,
        validation_data=(X_val, y_val),
        epochs=100,
        batch_size=32,
        callbacks=[early_stopping]
    )
```

```
Epoch 1/100
3/3 ━━━━━━━━━━━━━━━━━━━━ 3s 165ms/step - loss: 0.2156 - mae: 0.3271 - val_loss: 0.2097 - val_mae: 0.3245
Epoch 2/100
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 34ms/step - loss: 0.2079 - mae: 0.3241 - val_loss: 0.2029 - val_mae: 0.3246
Epoch 3/100
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 34ms/step - loss: 0.1993 - mae: 0.3238 - val_loss: 0.1949 - val_mae: 0.3251
Epoch 4/100
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 28ms/step - loss: 0.1899 - mae: 0.3228 - val_loss: 0.1864 - val_mae: 0.3253
Epoch 5/100
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 25ms/step - loss: 0.1816 - mae: 0.3236 - val_loss: 0.1824 - val_mae: 0.3294
Epoch 6/100
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 25ms/step - loss: 0.1739 - mae: 0.3256 - val_loss: 0.1766 - val_mae: 0.3240
Epoch 7/100
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 27ms/step - loss: 0.1684 - mae: 0.3195 - val_loss: 0.1679 - val_mae: 0.3135
Epoch 8/100
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 26ms/step - loss: 0.1630 - mae: 0.3121 - val_loss: 0.1616 - val_mae: 0.3062
Epoch 9/100
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 26ms/step - loss: 0.1569 - mae: 0.3050 - val_loss: 0.1550 - val_mae: 0.3012
Epoch 10/100
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step - loss: 0.1506 - mae: 0.3012 - val_loss: 0.1487 - val_mae: 0.2989
Epoch 11/100
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 32ms/step - loss: 0.1451 - mae: 0.3021 - val_loss: 0.1434 - val_mae: 0.2993
Epoch 12/100
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 26ms/step - loss: 0.1383 - mae: 0.2974 - val_loss: 0.1380 - val_mae: 0.2961
Epoch 13/100
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 25ms/step - loss: 0.1338 - mae: 0.2944 - val_loss: 0.1330 - val_mae: 0.2928
```

Kaluthara

Used Techniques and Technologies

- **Technologies**
  - React Native
  - Python
  - TensorFlow
  - Flask Server
  - Node Server
  - Jupyter Notebook
  - Google Colab
  - Intellij Idea

- **Techniques**
  - Data preprocessing
  - Data Visualization

Completion of the project

65% Completion of the Components

- Collect and analyze historical traffic data during critical delivery times.
  Data preprocessing for train the model.
- Train the LSTM model for each selected three locations.

35% Future Implementations

- Get demand tea amount data for each delivery from demand forcasting system
- Implement user interface for Transportation.

References

1. Kechagias, Evripidis P., et al. "Traffic flow forecasting for city logistics: A literature review and evaluation." International Journal of Decision Support Systems 4.2 (2019): 159-176.
2. Chen, Yi-Ting, et al. "Pragmatic real-time logistics management with traffic IoT infrastructure: Big data predictive analytics of freight travel time for Logistics 4.0." *International Journal of Production Economics* 238 (2021): 108157.
3. Bhattacharya, Arnab, et al. "An intermodal freight transport system for optimal supply chain logistics." *Transportation Research Part C: Emerging Technologies* 38 (2014): 73-84.
4. Gurnak, Vitalii, Lyudmila Volynets, and Ilona Khalatska. "Intellectualization of logistic supply chains on the basis of forecasting volumes of cargo transportation." *MATEC Web of Conferences*. Vol. 294. EDP Sciences, 2019.
5. Al Moteri, Moteeb, Surbhi Bhatia Khan, and Mohammed Alojail. "Economic growth forecast model urban supply chain logistics distribution path decision using an improved genetic algorithm." *Malaysian Journal of Computer Science* (2023): 76-89.

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Specialization : Information Technology

Introduction and Background

Forecast weekly labor needs by area to prevent and manage labor shortages, ensuring smooth operations.

With AI and machine learning, Analyze historical labor data and external factors, develop predictive models, and implement strategies like temporary staffing and production adjustments.

A proactive labor management system that addresses shortages before they impact production.

Complex supply chains, data quality issues, and unpredictable risks make Supply Chain Risk Management a difficult but essential task.

Research Question

How can real-time data help in managing labor shortages and ensuring smooth operations?

- Real-Time Tracking
- Immediate Adjustments
- Data-Driven Decisions
- Optimization

Specific and Sub Objective

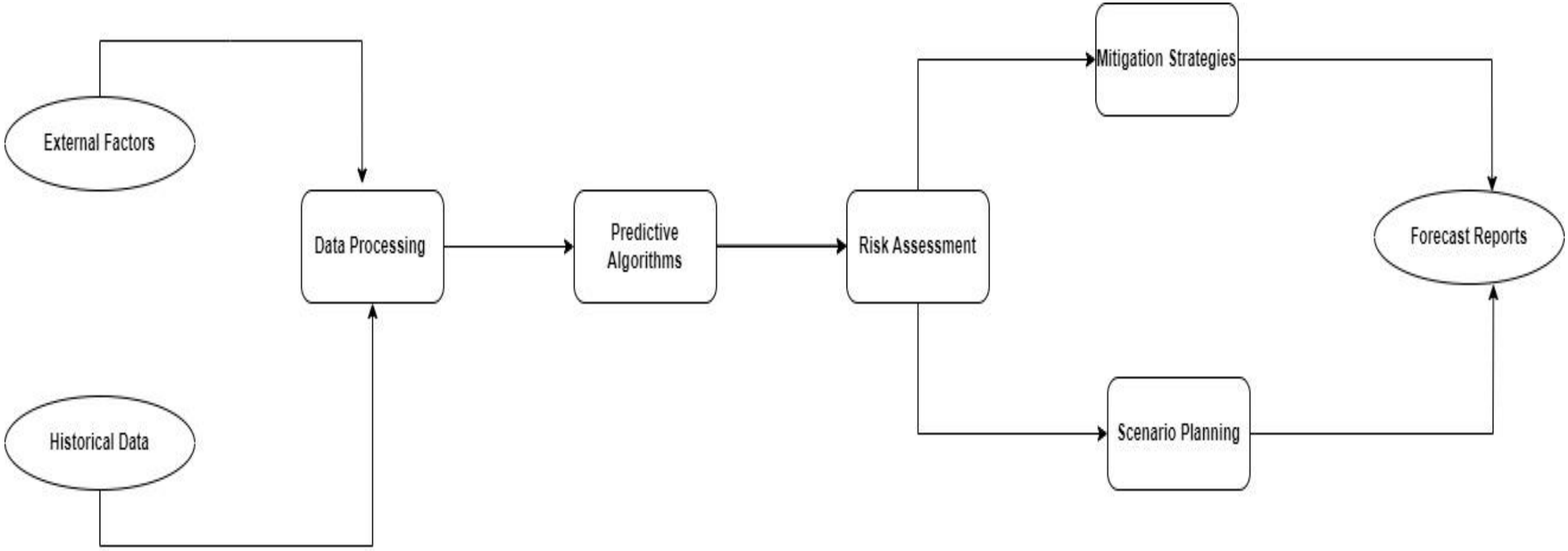
- **Specific Objective**

To develop a predictive labor management system that forecasts weekly labor needs by area, using historical data and external factors to mitigate labor shortages and ensure continuous production.

- **Sub Objective**

- Data-Driven Labor Forecasting
- Labor Allocation Optimization
- Real-Time Risk Monitoring

System Diagram



Used Technologies and Techniques

Methodology

- **Data Collection and Analysis**

Collect historical labor data and external factors (e.g., weather, events) that influence labor availability. Clean and prepare the data for analysis.

- **Predictive Modeling**

Develop forecasting models to predict weekly labour needs by region using historical data and external factors.

- **Labour Shortage Mitigation Strategies**

Create strategies to address labour shortages, such as temporary staffing, flexible schedules, and adjusting production processes.

- **Real-Time Risk Monitoring and Adjustment**

Implement real-time monitoring to track labor availability and adjust plans based on unexpected changes or disruptions.

- **System Integration and Deployment**

Integrate the forecasting and monitoring system with existing tools, and deploy it in stages, ensuring smooth operation and user adoption.

Functional, Non-Functional and Requirements

Fuctional Requirements

•Collect and integrate historical labor data and external factors (e.g., weather, events).

•Predict weekly labour requirements by region using predictive models.

•Detect potential labor shortages based on forecasted needs.

•Suggest mitigation strategies (temporary staffing, flexible scheduling, etc.).

Non-Functional Requirements

•Interface should be intuitive and easy to use.

•Application should be reliable with minimal downtime.

•Forecasting models should provide accurate labor predictions.

•System should process data and deliver predictions efficiently.

Evidence for Completion

	A	B	C	D	E
1	datetime	precip	Labours_stateA	Labours_stateB	Labours_stateC
2	2022-02-01	6.375	284	190	93
3	2022-02-02	0	296	194	97
4	2022-02-03	0	293	198	92
5	2022-02-04	0	297	191	97
6	2022-02-05	0.103	291	189	90
7	2022-02-06	0.2	294	196	92
8	2022-02-07	0	298	192	92
9	2022-02-08	0	290	196	99
10	2022-02-09	0	290	199	90
11	2022-02-10	4.073	292	194	94
12	2022-02-11	0.542	291	194	98
13	2022-02-12	22.948	270	184	84
14	2022-02-13	31.191	257	178	83
15	2022-02-14	1.548	292	195	97
16	2022-02-15	0.083	294	198	94
17	2022-02-16	0	297	194	97
18	2022-02-17	0	292	197	91
19	2022-02-18	0.312	291	190	95
20	2022-02-19	119.974	175	119	58
21	2022-02-20	0.423	297	192	97
22	2022-02-21	0.676	292	197	95
23	2022-02-22	0	293	190	90
24	2022-02-23	3.837	292	193	95
25	2022-02-24	10.031	280	188	95
26	2022-02-25	0.042	296	196	91
27	2022-02-26	3	291	192	90
28	2022-02-27	2.362	289	188	91
29	2022-02-28	0	298	190	95

- Collect data set labour avalability of monthly

Evidence for Completion

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
1	name	datetime	tempmax	tempmin	temp	feelslikemax	feelslikemin	feelslike	dew	humidity	precip	precipprob	precipcover	preciptype	snow
2	Watawala, Sri Lanka	2022-02-01	34.1	18.5	27	38	18.5	28.4	20.8	72	6.375	100	4.17	rain	
3	Watawala, Sri Lanka	2022-02-02	31.1	18.6	26	34.3	18.6	27.4	20.3	72.1	0	0	0	rain	
4	Watawala, Sri Lanka	2022-02-03	29.1	19.2	25.7	33.7	19.2	27.2	21.7	79.4	0	0	0	rain	
5	Watawala, Sri Lanka	2022-02-04	31.1	17.6	25.3	34.7	17.6	26.7	20.8	78.4	0	0	0		
6	Watawala, Sri Lanka	2022-02-05	33.1	15.8	26.5	38	15.8	29.1	22.2	79.2	0.103	100	4.17	rain	
7	Watawala, Sri Lanka	2022-02-06	34.1	22.1	27	36.2	22.1	28	20.1	69.9	0.2	100	4.17	rain	
8	Watawala, Sri Lanka	2022-02-07	33.1	17.6	26.8	34.7	17.6	27.7	19.4	66.8	0	0	0	rain	
9	Watawala, Sri Lanka	2022-02-08	33.1	19	25.9	34.1	19	27	20.1	72.9	0	0	0		
10	Watawala, Sri Lanka	2022-02-09	34.1	17.3	26.7	34.7	17.3	27.5	19.4	66.2	0	0	0		
11	Watawala, Sri Lanka	2022-02-10	31.1	21.1	26.3	35.6	21.1	27.6	22.9	82.6	4.073	100	12.5	rain	
12	Watawala, Sri Lanka	2022-02-11	30.1	19.3	26	35.2	19.3	27.9	23.9	89	0.542	100	12.5	rain	
13	Watawala, Sri Lanka	2022-02-12	31.6	19.1	25.1	38.1	19.1	26.7	23.1	89.8	22.948	100	20.83	rain	
14	Watawala, Sri Lanka	2022-02-13	29.1	17.7	24.7	32.9	17.7	25.6	22.5	88.7	31.191	100	20.83	rain	
15	Watawala, Sri Lanka	2022-02-14	33.1	19	26.6	36.2	19	28.2	21.9	77.7	1.548	100	8.33	rain	
16	Watawala, Sri Lanka	2022-02-15	33.1	17.8	26.6	35.4	17.8	27.8	20.6	71.9	0.083	100	4.17	rain	
17	Watawala, Sri Lanka	2022-02-16	33.1	17.7	26.2	34.7	17.7	27.1	19.8	70.5	0	0	0		
18	Watawala, Sri Lanka	2022-02-17	33.1	18.6	25.9	35.6	18.6	26.9	19.3	69.5	0	0	0		
19	Watawala, Sri Lanka	2022-02-18	32.1	16.3	25.8	36.7	16.3	27.6	21.1	76.4	0.312	100	4.17	rain	
20	Watawala, Sri Lanka	2022-02-19	28.1	19.5	25.3	32.8	19.5	26.6	23.8	91.8	119.974	100	16.67	rain	
21	Watawala, Sri Lanka	2022-02-20	31.1	18.2	25.6	34.7	18.2	27.6	22.4	84	0.423	100	8.33	rain	
22	Watawala, Sri Lanka	2022-02-21	30.1	19.6	26.4	36.3	19.6	28.9	23.4	84.6	0.676	100	4.17	rain	
23	Watawala, Sri Lanka	2022-02-22	30.1	17.2	26	34.3	17.2	27.7	22.6	83.1	0	0	0	rain	
24	Watawala, Sri Lanka	2022-02-23	31.1	19.4	26.3	35.2	19.4	27.6	22	79.7	3.837	100	8.33	rain	
25	Watawala, Sri Lanka	2022-02-24	33.1	19.2	26.9	35.4	19.2	28.1	21.3	74.5	10.031	100	8.33	rain	
26	Watawala, Sri Lanka	2022-02-25	34.1	19.6	26.2	38.2	19.6	27.3	21	74.4	0.042	100	4.17	rain	

Getting monthly weather forecaster data from Watawala area

Evidence for Completion

	datetime	precip	Labours_stateA	Labours_stateB	Labours_stateC
0	2022-02-01	6.375	284	190	93
1	2022-02-02	0.000	296	194	97
2	2022-02-03	0.000	293	198	92
3	2022-02-04	0.000	297	191	97
4	2022-02-05	0.103	291	189	90

```
# Select relevant columns
data = data[['datetime', 'precip', 'Labours_stateA']]
data.head()
```

	datetime	precip	Labours_stateA
0	2022-02-01	6.375	284
1	2022-02-02	0.000	296
2	2022-02-03	0.000	293
3	2022-02-04	0.000	297
4	2022-02-05	0.103	291

Area A

	datetime	precip	Labours_stateA	Labours_stateB	Labours_stateC
0	2022-02-01	6.375	284	190	93
1	2022-02-02	0.000	296	194	97
2	2022-02-03	0.000	293	198	92
3	2022-02-04	0.000	297	191	97
4	2022-02-05	0.103	291	189	90

```
# Select relevant columns
data = data[['datetime', 'precip', 'Labours_stateB']]
data.head()
```

	datetime	precip	Labours_stateB
0	2022-02-01	6.375	190
1	2022-02-02	0.000	194
2	2022-02-03	0.000	198
3	2022-02-04	0.000	191
4	2022-02-05	0.103	189

Area B

	datetime	precip	Labours_stateA	Labours_stateB	Labours_stateC
0	2022-02-01	6.375	284	190	93
1	2022-02-02	0.000	296	194	97
2	2022-02-03	0.000	293	198	92
3	2022-02-04	0.000	297	191	97
4	2022-02-05	0.103	291	189	90

```
# Select relevant columns
data = data[['datetime', 'precip', 'Labours_stateC']]
data.head()
```

	datetime	precip	Labours_stateC
0	2022-02-01	6.375	93
1	2022-02-02	0.000	97
2	2022-02-03	0.000	92
3	2022-02-04	0.000	97
4	2022-02-05	0.103	90

Area C

Getting availability labors in each areas

Evidence for Completion

Train each three models using preprocessed datasets

```
Epoch 1/50
25/25 ━━━━━━━━━━━━━━━━━━━━ 4s 29ms/step - loss: 0.7093 - mae: 0.8276 - val_loss: 0.1484 - val_mae: 0.3809
Epoch 2/50
25/25 ━━━━━━━━━━━━━━━━━━━━ 1s 13ms/step - loss: 0.0560 - mae: 0.1981 - val_loss: 0.0144 - val_mae: 0.1158
Epoch 3/50
25/25 ━━━━━━━━━━━━━━━━━━━━ 0s 13ms/step - loss: 0.0125 - mae: 0.0769 - val_loss: 0.0067 - val_mae: 0.0735
Epoch 4/50
25/25 ━━━━━━━━━━━━━━━━━━━━ 1s 12ms/step - loss: 0.0141 - mae: 0.0773 - val_loss: 0.0039 - val_mae: 0.0446
Epoch 5/50
25/25 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step - loss: 0.0112 - mae: 0.0667 - val_loss: 0.0035 - val_mae: 0.0378
Epoch 6/50
25/25 ━━━━━━━━━━━━━━━━━━━━ 0s 12ms/step - loss: 0.0104 - mae: 0.0647 - val_loss: 0.0040 - val_mae: 0.0463
Epoch 7/50
25/25 ━━━━━━━━━━━━━━━━━━━━ 1s 12ms/step - loss: 0.0108 - mae: 0.0682 - val_loss: 0.0041 - val_mae: 0.0472
Epoch 8/50
25/25 ━━━━━━━━━━━━━━━━━━━━ 1s 11ms/step - loss: 0.0103 - mae: 0.0652 - val_loss: 0.0037 - val_mae: 0.0403
Epoch 9/50
25/25 ━━━━━━━━━━━━━━━━━━━━ 0s 12ms/step - loss: 0.0103 - mae: 0.0643 - val_loss: 0.0040 - val_mae: 0.0464
Epoch 10/50
25/25 ━━━━━━━━━━━━━━━━━━━━ 1s 11ms/step - loss: 0.0118 - mae: 0.0759 - val_loss: 0.0046 - val_mae: 0.0533
```

Area A

```
Epoch 1/50
25/25 ━━━━━━━━━━━━━━━━━━━━ 3s 24ms/step - loss: 0.4903 - mae: 0.6819 - val_loss: 0.0312 - val_mae: 0.1729
Epoch 2/50
25/25 ━━━━━━━━━━━━━━━━━━━━ 1s 17ms/step - loss: 0.0254 - mae: 0.1271 - val_loss: 0.0116 - val_mae: 0.1017
Epoch 3/50
25/25 ━━━━━━━━━━━━━━━━━━━━ 0s 16ms/step - loss: 0.0125 - mae: 0.0778 - val_loss: 0.0058 - val_mae: 0.0638
Epoch 4/50
25/25 ━━━━━━━━━━━━━━━━━━━━ 1s 20ms/step - loss: 0.0104 - mae: 0.0681 - val_loss: 0.0069 - val_mae: 0.0731
Epoch 5/50
25/25 ━━━━━━━━━━━━━━━━━━━━ 0s 18ms/step - loss: 0.0105 - mae: 0.0725 - val_loss: 0.0052 - val_mae: 0.0586
Epoch 6/50
25/25 ━━━━━━━━━━━━━━━━━━━━ 1s 19ms/step - loss: 0.0095 - mae: 0.0644 - val_loss: 0.0042 - val_mae: 0.0469
Epoch 7/50
25/25 ━━━━━━━━━━━━━━━━━━━━ 1s 19ms/step - loss: 0.0118 - mae: 0.0703 - val_loss: 0.0037 - val_mae: 0.0396
Epoch 8/50
25/25 ━━━━━━━━━━━━━━━━━━━━ 1s 20ms/step - loss: 0.0095 - mae: 0.0673 - val_loss: 0.0037 - val_mae: 0.0387
Epoch 9/50
25/25 ━━━━━━━━━━━━━━━━━━━━ 0s 14ms/step - loss: 0.0115 - mae: 0.0700 - val_loss: 0.0037 - val_mae: 0.0376
Epoch 10/50
25/25 ━━━━━━━━━━━━━━━━━━━━ 0s 12ms/step - loss: 0.0106 - mae: 0.0667 - val_loss: 0.0037 - val_mae: 0.0339
Epoch 11/50
25/25 ━━━━━━━━━━━━━━━━━━━━ 0s 12ms/step - loss: 0.0094 - mae: 0.0624 - val_loss: 0.0036 - val_mae: 0.0354
Epoch 12/50
25/25 ━━━━━━━━━━━━━━━━━━━━ 0s 13ms/step - loss: 0.0104 - mae: 0.0607 - val_loss: 0.0037 - val_mae: 0.0373
Epoch 13/50
25/25 ━━━━━━━━━━━━━━━━━━━━ 1s 12ms/step - loss: 0.0081 - mae: 0.0617 - val_loss: 0.0039 - val_mae: 0.0420
Epoch 14/50
25/25 ━━━━━━━━━━━━━━━━━━━━ 0s 14ms/step - loss: 0.0086 - mae: 0.0644 - val_loss: 0.0041 - val_mae: 0.0458
Epoch 15/50
25/25 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step - loss: 0.0107 - mae: 0.0668 - val_loss: 0.0037 - val_mae: 0.0369
Epoch 16/50
25/25 ━━━━━━━━━━━━━━━━━━━━ 0s 12ms/step - loss: 0.0081 - mae: 0.0603 - val_loss: 0.0038 - val_mae: 0.0390
```

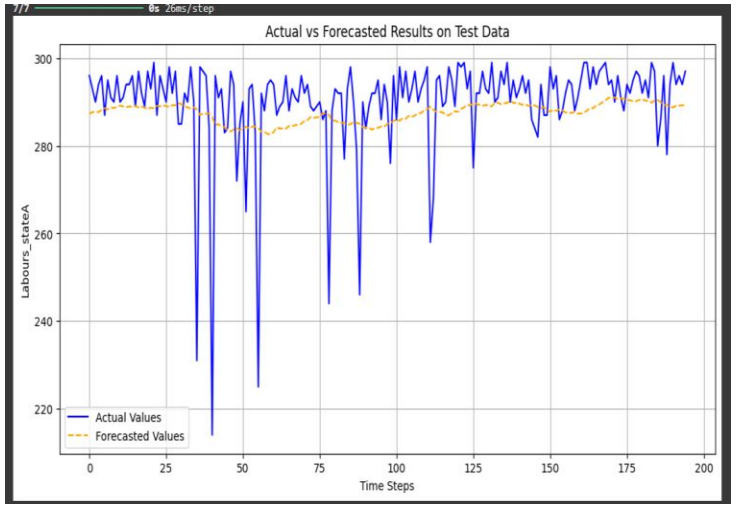
Area B

```
Epoch 1/50
25/25 ━━━━━━━━━━━━━━━━━━━━ 5s 39ms/step - loss: 0.4102 - mae: 0.6030 - val_loss: 0.0163 - val_mae: 0.1054
Epoch 2/50
25/25 ━━━━━━━━━━━━━━━━━━━━ 0s 18ms/step - loss: 0.0195 - mae: 0.1057 - val_loss: 0.0054 - val_mae: 0.0520
Epoch 3/50
25/25 ━━━━━━━━━━━━━━━━━━━━ 1s 18ms/step - loss: 0.0133 - mae: 0.0759 - val_loss: 0.0054 - val_mae: 0.0548
Epoch 4/50
25/25 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step - loss: 0.0089 - mae: 0.0664 - val_loss: 0.0064 - val_mae: 0.0624
Epoch 5/50
25/25 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step - loss: 0.0101 - mae: 0.0691 - val_loss: 0.0056 - val_mae: 0.0565
Epoch 6/50
25/25 ━━━━━━━━━━━━━━━━━━━━ 1s 13ms/step - loss: 0.0109 - mae: 0.0712 - val_loss: 0.0052 - val_mae: 0.0524
Epoch 7/50
25/25 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step - loss: 0.0114 - mae: 0.0728 - val_loss: 0.0052 - val_mae: 0.0522
Epoch 8/50
25/25 ━━━━━━━━━━━━━━━━━━━━ 1s 11ms/step - loss: 0.0123 - mae: 0.0702 - val_loss: 0.0059 - val_mae: 0.0589
Epoch 9/50
25/25 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step - loss: 0.0098 - mae: 0.0709 - val_loss: 0.0052 - val_mae: 0.0522
Epoch 10/50
25/25 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step - loss: 0.0102 - mae: 0.0689 - val_loss: 0.0052 - val_mae: 0.0527
Epoch 11/50
25/25 ━━━━━━━━━━━━━━━━━━━━ 0s 13ms/step - loss: 0.0089 - mae: 0.0651 - val_loss: 0.0054 - val_mae: 0.0549
Epoch 12/50
25/25 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step - loss: 0.0104 - mae: 0.0677 - val_loss: 0.0052 - val_mae: 0.0526
```

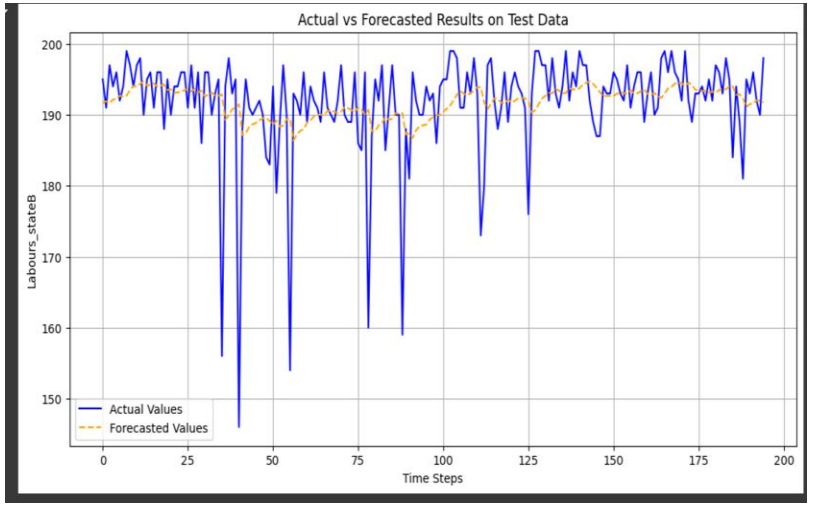
Area C

Evidence for Completion

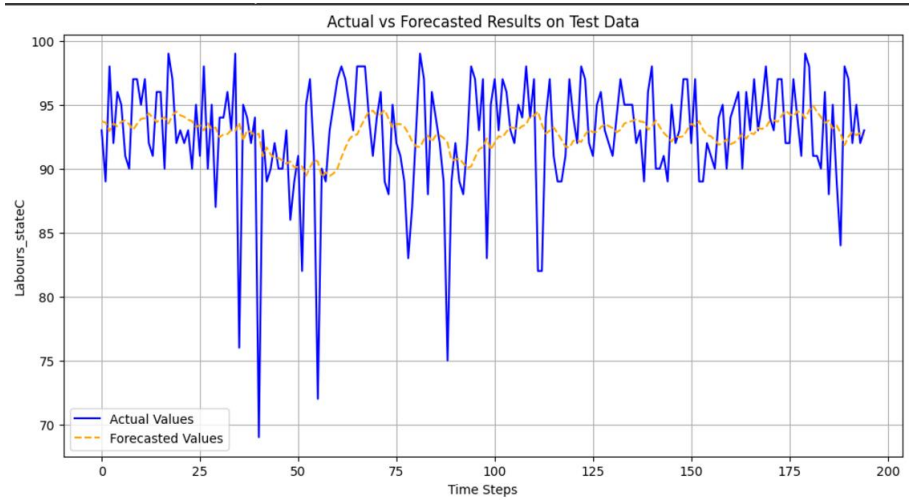
Actual vs forecasted results on test



Area A



Area B



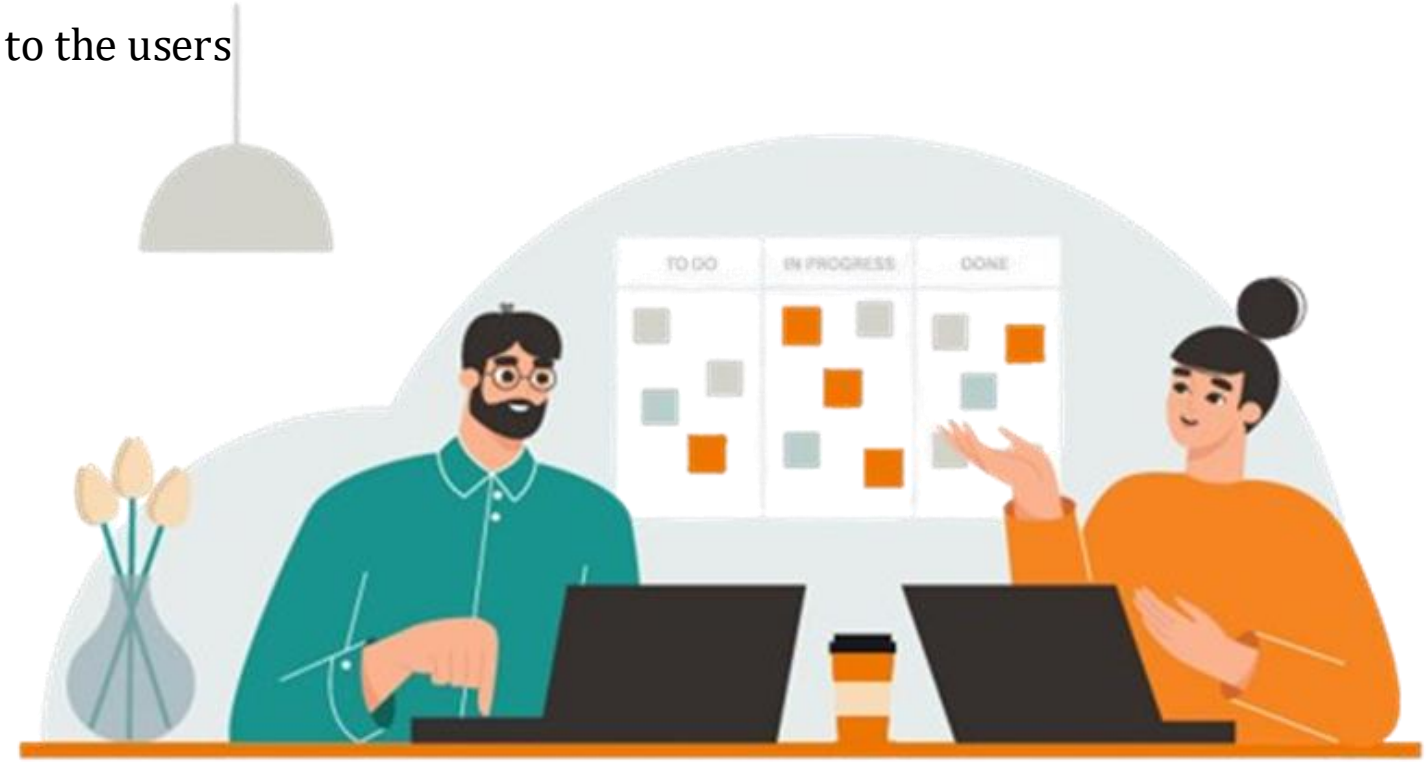
Area C

Completion of the project

- Collect and analyze labour data and weather data
  Data preprocessing for train the model.
- Train the LSTM model for each selected three areas.

Next Expected Progress

- Have to use that trained models and when shortage is not enough in specific area , the other area should be assign labours
- Have to create Interfaces and dashboards to the users
- Connect with the database



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