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DELIVERY TIME SLA PREDICTION AND PERFORMANCE

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ABSTRACT

The **Delivery Time SLA Prediction and Performance** system is a data-driven application designed to analyze delivery operations and predict whether an order is likely to meet its defined Service Level Agreement (SLA). Delivery performance is an important factor in logistics, e-commerce, food delivery, and courier services because delays can affect customer satisfaction and operational efficiency.

The proposed system analyzes delivery-related information such as order time, dispatch time, pickup time, delivery time, distance, delivery location, vehicle type, traffic conditions, weather conditions, order priority, and delivery status. Data preprocessing techniques are applied to clean the collected dataset by handling missing values, duplicate records, inconsistent formats, and invalid entries.

The system calculates important performance indicators such as average delivery time, on-time delivery percentage, delayed orders, SLA compliance rate, and average delay duration. The dashboard can provide delivery performance analysis based on regions, delivery partners, order categories, time periods, and other available attributes. Interactive charts, graphs, tables, and KPI cards make the results easier to understand.

The prediction component uses historical delivery information to estimate the expected delivery time and determine the probability of an order meeting its SLA. Machine Learning models can identify relationships between delivery time and factors such as distance, traffic, weather, order volume, and time of day. The predicted results can help operations teams identify potentially delayed deliveries.

Overall, the proposed system combines delivery performance analysis with predictive analytics to provide useful operational insights. It can help organizations monitor SLA performance, identify causes of delays, and improve delivery planning. Future enhancements can include real-time GPS tracking, live traffic integration, automated alerts, route optimization, dynamic ETA prediction, and advanced forecasting models.

I. INTRODUCTION

Fast and reliable delivery has become an important requirement for modern logistics and e-commerce operations. Customers expect orders to be delivered within the promised time, while organizations need to manage transportation, delivery partners, traffic, and operational constraints. Service Level Agreements define expected delivery performance and provide measurable targets for delivery operations.

Delivery time can be influenced by several factors, including distance, traffic congestion, weather conditions, order volume, pickup delays, vehicle availability, delivery location, and time of day. Understanding these factors can help organizations identify reasons for SLA violations and improve operational planning.

Traditional delivery management systems primarily focus on order tracking, status updates, and basic delivery information. Although these systems provide operational visibility, they may not provide advanced analysis of SLA performance or predictive information about potential delays. Managers may need separate tools to analyze historical delivery records.

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Data analytics provides methods for calculating delivery KPIs and identifying operational patterns. Metrics such as average delivery time, SLA compliance rate, delay duration, and on-time delivery percentage can be used to evaluate performance. Visualization dashboards can make these metrics easier to understand and compare.

Machine Learning can further improve delivery management by predicting expected delivery time and identifying orders that may exceed their SLA. Historical delivery data can be used to train predictive models using factors such as distance, traffic, weather, order characteristics, and time information. The proposed system integrates performance analysis and predictive modeling into a centralized delivery analytics platform.

II. LITERATURE SURVEY

Delivery-time prediction has become an important research area in logistics and transportation analytics. Delivery datasets commonly contain information about orders, pickup and delivery timestamps, distance, location, vehicle details, traffic conditions, and delivery status. Researchers use these attributes to understand delivery patterns and estimate expected delivery times.

Traditional delivery-time estimation methods often use distance-based calculations and historical averages. These approaches are simple and easy to implement but may not capture complex relationships between traffic, weather, time of day, delivery density, and other operational factors. More advanced analytical approaches can provide improved estimates when sufficient historical data is available.

SLA monitoring is commonly used in logistics and service operations to measure whether deliveries meet predefined time commitments. Metrics such as on-time delivery percentage, average delay, SLA compliance rate, and late-order percentage can be used to evaluate operational performance. These measurements help organizations identify areas where delivery performance can be improved.

Machine Learning techniques have increasingly been applied to delivery-time prediction. Regression algorithms such as Linear Regression, Decision Trees, Random Forest, Gradient Boosting, and other predictive models can learn relationships between delivery characteristics and actual delivery time. Model performance can be evaluated using metrics such as MAE, MSE, RMSE, and R^2.

Traffic and weather conditions can have a significant effect on transportation and delivery operations. Integrating external information such as traffic conditions, weather conditions, and road characteristics can provide additional features for predictive models. Real-time information can also support dynamic ETA prediction.

Modern logistics analytics systems combine real-time tracking, historical performance analysis, predictive modeling, and visualization. Dashboards can display delivery KPIs and identify orders that may be delayed. The proposed system follows this approach by combining SLA performance analysis, delivery-time prediction, and interactive visualization in a single framework.

III. SYSTEM ANALYSIS

The Delivery Time SLA Prediction and Performance system is designed to analyze delivery records and predict SLA compliance. The system accepts information such as order time, pickup time, delivery time, distance, location, traffic, weather, vehicle type, and delivery status. The input data is validated to ensure that required fields and supported formats are available. A preprocessing module handles missing values, duplicate records, invalid timestamps, and inconsistent data formats. Date and time attributes are transformed into useful features such as hour, day, weekday, and delivery period. The system calculates actual delivery duration using relevant timestamps. SLA compliance is determined by comparing actual delivery time with the predefined SLA target. The analytics engine calculates average delivery time, on-time delivery percentage, SLA compliance rate, and average delay. Performance analysis can be performed by region, delivery partner, vehicle type, order category, and time period. A Machine Learning model can be trained using historical delivery information to predict expected delivery time. The prediction module estimates whether a new order is likely to meet or exceed its SLA. Visualization components display performance metrics through charts, graphs, tables, and KPI cards. The final dashboard provides delivery insights and prediction results to authorized operational users.

Existing System

Existing delivery management systems primarily provide order tracking, delivery status, estimated delivery time, and basic operational reports. These systems allow users to monitor whether an order has been dispatched, picked up, or delivered. However, many basic systems provide limited analysis of historical SLA performance. Managers may need separate spreadsheets or analytics tools to calculate delivery-time statistics. Identifying the main causes of delivery delays can be difficult when multiple operational factors are involved. Traditional systems may provide an estimated delivery time but may not dynamically predict SLA violations using historical patterns. Comparing performance across regions, delivery partners, or time periods may require manual analysis. Static reports may also provide limited interactive visualization. Traffic and weather information may not be integrated into delivery analysis. Potentially delayed orders may not be identified early enough for operational action. Historical delivery data may be stored without advanced predictive analysis. These limitations create a need for an integrated platform that combines SLA monitoring, delivery performance analysis, and predictive modeling.

Disadvantages of Existing System

- Limited SLA performance analysis.
- Manual calculation of delivery metrics.
- Limited prediction of delivery delays.
- Difficult to identify potential SLA violations early.
- Limited analysis of delay factors.
- Traffic data may not be integrated.
- Weather information may not be considered.
- Limited interactive dashboards.
- Difficult to compare delivery-partner performance.
- Limited regional performance analysis.
- Static reports may provide insufficient insights.
- Separate tools may be required for predictive analytics.

Proposed System

The proposed Delivery Time SLA Prediction and Performance system provides a centralized platform for monitoring delivery performance and predicting SLA compliance. The system accepts historical delivery information containing order timestamps, pickup and delivery times, distance, location, vehicle type, traffic conditions, weather conditions, and order characteristics. The data validation module checks the structure, data types, timestamps, and required fields. The preprocessing module removes duplicate records and handles missing, invalid, and inconsistent

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values. Feature engineering generates useful attributes such as delivery duration, delivery hour, weekday, distance category, and SLA target. The system calculates important KPIs including average delivery time, on-time delivery percentage, SLA compliance rate, and average delay. Performance analysis compares delivery results across regions, partners, vehicle types, order categories, and time periods. The Machine Learning module uses historical delivery data to train a model for delivery-time prediction. The prediction module estimates expected delivery duration for new orders. SLA classification can determine whether an order is likely to meet or exceed its target delivery time. Interactive dashboards display KPIs, trends, delay analysis, and prediction results. The system can also highlight potentially delayed orders for operational attention. Overall, the proposed solution integrates delivery analytics and predictive SLA monitoring into one platform.

Advantages of Proposed System

- Provides centralized delivery performance analysis.
- Automates SLA calculations.
- Predicts expected delivery time.
- Identifies potentially delayed orders.
- Calculates SLA compliance percentage.
- Analyzes average delivery duration.
- Supports region-wise performance analysis.
- Supports delivery-partner comparison.
- Can incorporate traffic and weather information.
- Provides interactive dashboards.
- Reduces manual reporting effort.
- Supports data-driven delivery planning.

IV. METHODOLOGY

The methodology begins with collecting historical delivery records from an authorized logistics, e-commerce, courier, or delivery dataset. The collected data is validated to check its structure, required attributes, timestamps, and data completeness. Data preprocessing is performed to remove duplicate records and handle missing, invalid, or inconsistent values. Order, pickup, dispatch, and delivery timestamps are standardized into a common format. Delivery duration is calculated from the relevant timestamps. SLA compliance is determined by comparing the actual delivery duration with the defined SLA target. Feature engineering creates attributes such as delivery hour, weekday, distance category, traffic condition, weather condition, and order priority. Exploratory Data Analysis is performed to understand delivery-time distributions and identify delay patterns. Performance analysis calculates average delivery time, SLA compliance rate, on-time delivery percentage, and average delay. Different Machine Learning algorithms can be trained using historical delivery features to predict delivery duration. The models are evaluated using appropriate metrics such as MAE, MSE, RMSE, and R^2. A classification approach can also be used to identify whether an order is likely to meet its SLA. Finally, the analytical and predictive results are displayed through an interactive dashboard.

SYSTEM ARCHITECTURE

The system architecture consists of several interconnected layers that process delivery information and generate SLA performance and prediction results. The Data Source Layer provides order, pickup, dispatch, delivery, distance, location, vehicle, traffic, weather, and SLA information from authorized sources.

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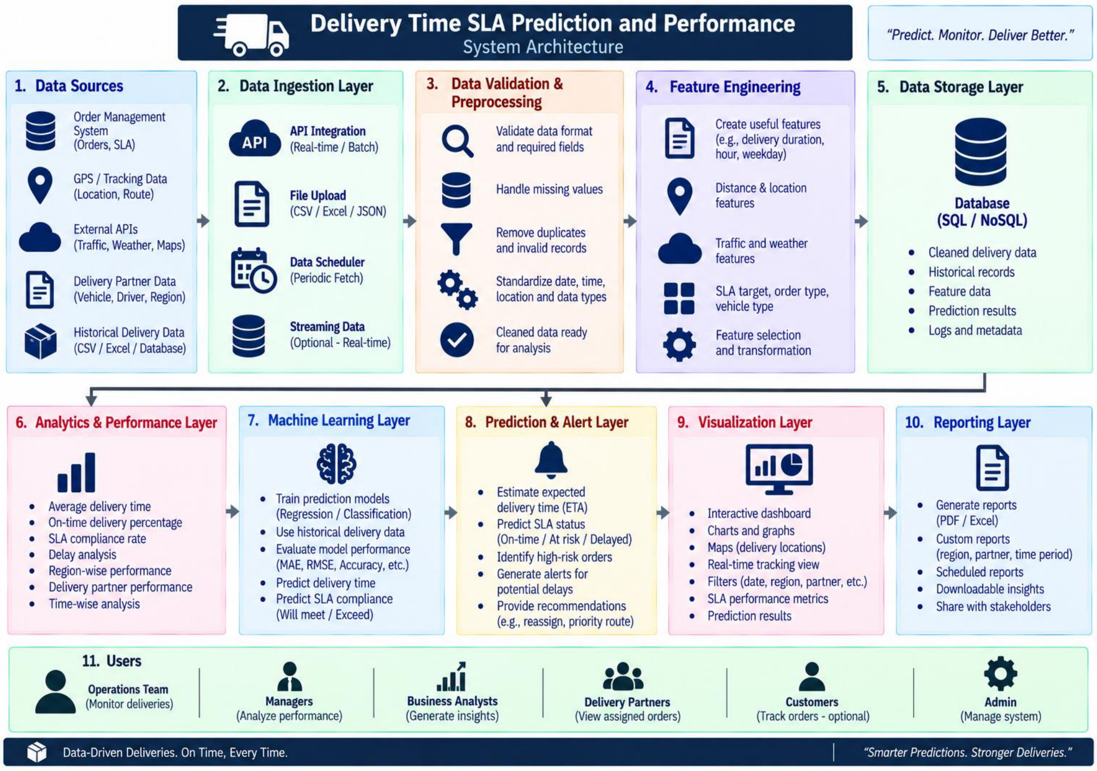

The Data Input Layer accepts information through CSV files, Excel files, databases, or APIs. The Data Validation Layer checks file formats, required fields, timestamps, and basic data quality. The Data Preprocessing Layer handles missing values, duplicate records, invalid timestamps, and inconsistent formats. The Feature Engineering Layer creates attributes such as delivery duration, delivery hour, weekday, distance category, and SLA target. The Data Storage Layer securely stores cleaned historical delivery records. The Performance Analytics Layer calculates delivery KPIs such as average delivery time, on-time percentage, SLA compliance, and average delay. The Delay Analysis Layer examines delivery performance across regions, partners, vehicle types, order categories, and time periods. The Machine Learning Layer trains and evaluates models for delivery-time prediction. The Prediction Layer estimates expected delivery duration and determines potential SLA compliance for new orders. The Alert Layer can identify potentially delayed orders for operational attention. The Visualization Layer presents results through dashboards, charts, graphs, tables, and KPI cards. The Reporting Layer generates delivery-performance summaries and analytical reports for authorized users.

V. RESULT AND OUTPUT

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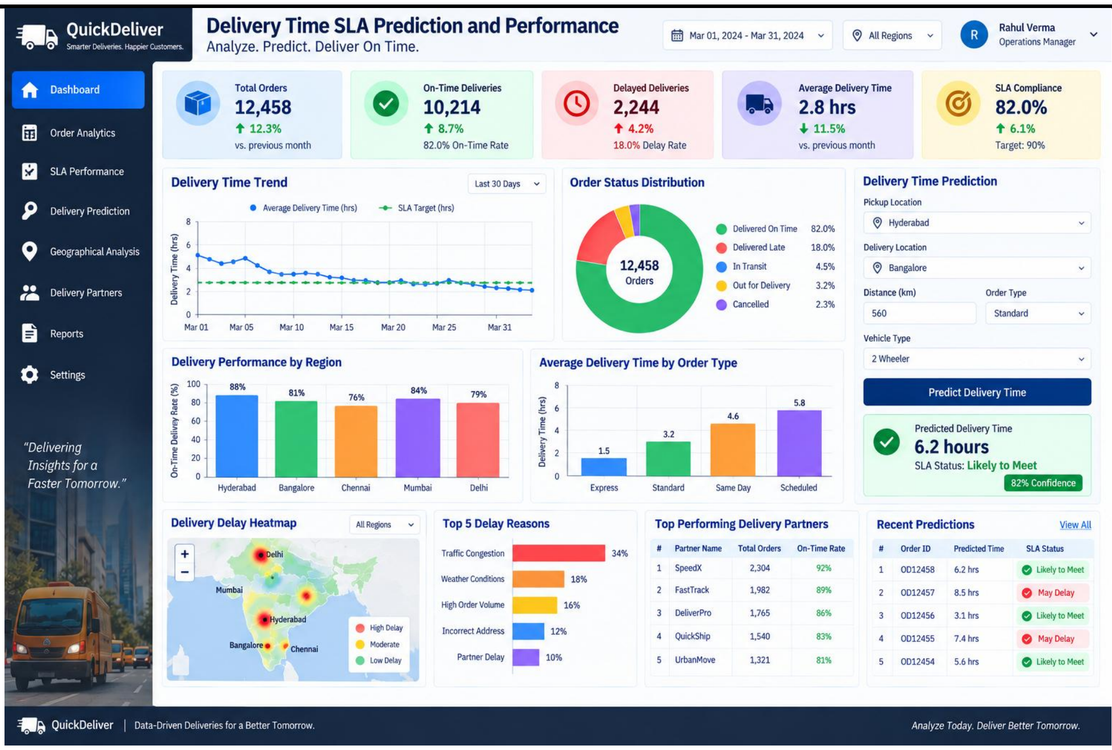

VI. CONCLUSION

The Delivery Time SLA Prediction and Performance system provides a data-driven solution for analyzing delivery operations and predicting whether orders are likely to meet their defined Service Level Agreements. The system combines data preprocessing, performance analysis, visualization, and Machine Learning techniques to transform delivery records into useful operational insights.

The system analyzes important factors such as delivery time, distance, order type, vehicle type, delivery location, traffic conditions, weather conditions, and SLA targets. It calculates key performance indicators including average delivery time, on-time delivery percentage, delayed deliveries, SLA compliance rate, and average delay duration.

The interactive dashboard presents delivery information through KPI cards, delivery-time trends, order-status charts, regional performance graphs, delay heatmaps, delay-reason analysis, and delivery-partner performance tables. These visualizations help users understand delivery operations and identify areas where delays occur.

The prediction module estimates the expected delivery time for new orders and determines whether an order is likely to meet its SLA. By identifying potentially delayed deliveries in advance, the system can support better operational planning, prioritization, and resource allocation.

In the future, the system can be enhanced with real-time GPS tracking, live traffic and weather APIs, dynamic ETA prediction, route optimization, automated delay alerts, driver-performance analysis, and advanced Machine Learning models. These improvements can make the platform more responsive and useful for efficient delivery management and SLA monitoring.

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