International Journal of
DATA SCIENCE AND IOT MANAGEMENT SYSTEM
Peer Reviewed, Referred & Indexed Journal
ISSN: 3068-272X www.ijdim.com Original Research Paper

LIVE DELIVERY DELAY PREDICTOR

[1] Farooqhussain Mohammed, [2] B Varsha, [3] P Sravan Kumar, [4] B Viswa Teja Goud
[1]AssistantProfessor, [234]Students
Department of IOT
Siddhartha Institute of Technology & Sciences, Narapally
farooqhussain.cse@siddhartha.co.in, 23tq1a6913@siddhartha.co.in, 23tq1a6910@siddhartha.co.in, 23tq1a6946@siddhartha.co.in

Abstract

The rapid growth of e-commerce, online food services, logistics, and on-demand delivery has increased the importance of accurate delivery-time prediction. Customers expect deliveries to arrive within the promised time, while delays can negatively affect customer satisfaction, operational efficiency, and business performance. Delivery time can be influenced by several factors, including traffic conditions, weather, distance, order volume, driver availability, route conditions, and time of day. Therefore, predicting potential delays before they occur can help organizations take corrective actions.

The proposed Live Delivery Delay Predictor is a real-time prediction system designed to estimate whether an active delivery is likely to be delayed. The system collects relevant delivery information such as current location, destination, distance, estimated travel time, historical delivery patterns, traffic conditions, weather information, and order status. These inputs are processed to generate an estimated arrival time and a delay-risk prediction.

The system can use machine-learning techniques to analyze historical delivery data and identify patterns associated with delayed deliveries. Features such as delivery distance, average speed, traffic level, route characteristics, delivery time, order preparation time, and historical performance can be used by the prediction model. The model produces an estimated delay probability or predicted delay duration that can be updated as new delivery information becomes available.

A centralized dashboard provides real-time visibility into active deliveries, predicted arrival times, delay probabilities, high-risk deliveries, and delivery-performance trends. When a delivery crosses a defined delay-risk threshold, the system can generate an alert for authorized logistics operators. Historical prediction results can also be stored and compared with actual delivery outcomes to evaluate and improve model performance.

The primary objective of the system is to provide early warning of potential delivery delays and support better logistics decision-making. By combining real-time data collection, machine-learning prediction, route information, monitoring, alerts, visualization, and historical analysis, the system can help delivery organizations improve operational efficiency and customer communication.

I. Introduction

International Journal of
DATA SCIENCE AND IOT MANAGEMENT SYSTEM
Peer Reviewed, Referred & Indexed Journal
ISSN: 3068-272X www.ijdim.com Original Research Paper

Delivery services have become an important part of modern commerce and daily life. E-commerce companies, food-delivery platforms, courier services, and logistics organizations manage large numbers of deliveries every day. Customers increasingly expect accurate delivery estimates and timely service. However, unexpected traffic, weather conditions, route changes, high order volumes, and operational problems can cause deliveries to arrive later than expected.

Traditional delivery systems often calculate estimated arrival times using fixed travel-time assumptions or basic route information. Although these approaches can provide an initial estimate, they may not adequately account for rapidly changing conditions. A delivery that is expected to arrive on time at the beginning of a journey may later encounter traffic congestion or other conditions that significantly increase the travel time.

Real-time prediction and machine learning provide opportunities to improve delivery-delay forecasting. A prediction system can combine historical delivery information with current operational conditions to estimate the likelihood of a delay. As new location and traffic information becomes available, the prediction can be updated continuously, allowing logistics teams to respond to changing circumstances.

The proposed **Live Delivery Delay Predictor** provides a centralized platform for monitoring active deliveries and predicting potential delays. The system collects information from delivery operations and processes it through a prediction model. The resulting delay probability, estimated arrival time, and predicted delay duration can be presented through an interactive dashboard.

The main objective of the system is to provide early visibility into delivery risks and support proactive decision-making. Logistics operators can use predictions to identify high-risk deliveries, communicate with customers, adjust delivery priorities, and improve route or resource planning. The system can also use historical outcomes to evaluate prediction accuracy and improve future delivery forecasting.

II. Literature Survey

Delivery-time prediction has been widely studied in transportation, logistics, e-commerce, and intelligent transportation systems. Traditional approaches often estimate travel time based on distance, average speed, route information, and historical travel patterns. Although these methods can provide useful baseline estimates, they may have limited ability to respond to rapidly changing traffic and operational conditions.

Machine-learning approaches have been increasingly applied to travel-time and delivery-time prediction. Algorithms such as linear regression, decision trees, random forests, gradient-boosting methods, and neural networks can learn relationships between delivery characteristics and observed delivery times. These approaches can capture nonlinear relationships between factors such as distance, traffic, time of day, and delivery duration.

Real-time data has become an important component of modern logistics prediction. GPS locations, traffic information, weather conditions, route changes, and delivery-status updates can provide current information about an ongoing delivery. Combining historical information with real-time data can allow prediction systems to update estimated arrival times as the delivery progresses.

Research in intelligent transportation systems has also explored time-series and deep-learning techniques for travel-time prediction. Models based on recurrent neural networks and other sequential approaches can learn patterns from time-dependent traffic and movement data. However, model complexity, data requirements, computational resources, and interpretability must be considered when selecting an appropriate prediction approach.

Logistics optimization research has demonstrated that accurate delivery predictions can support better resource allocation and operational planning. Predicting potential delays can help organizations prioritize high-risk deliveries, adjust routes, allocate drivers, and communicate updated expectations. Integrating prediction with monitoring and alerting can therefore transform delivery management from a reactive process into a more proactive workflow.

Existing delivery platforms provide estimated arrival times and tracking features, but prediction accuracy may vary depending on the available data and modeling approach. Some systems may focus primarily on tracking the current location without explicitly estimating delay risk. The proposed system builds on these concepts by combining real-time delivery tracking, historical data, machine-learning prediction, delay-risk classification, alerts, visualization, and performance analysis.

III. System Analysis

System analysis for the proposed Live Delivery Delay Predictor focuses on the requirements for real-time delivery monitoring and prediction. The system should provide authenticated access for authorized logistics administrators and operators. It should collect delivery information such as current location, destination, distance, route, order status, and estimated arrival time. The system should also support relevant external data such as traffic and weather information where available. Historical delivery records should be stored to train and evaluate prediction models. A preprocessing module should clean missing, inconsistent, and duplicate delivery data before analysis. The prediction engine should estimate arrival time and potential delay based on available features. The system should calculate a delay-risk score and classify deliveries according to defined risk levels. A monitoring module should continuously update delivery information and refresh predictions. The dashboard should display active deliveries, predicted delays, arrival estimates, and high-risk orders. An alerting module should notify authorized operators when significant delay risks are detected. Finally, actual delivery outcomes should be recorded to evaluate prediction accuracy and improve future model performance.

Existing System

Existing delivery-management systems generally provide order tracking, route information, and estimated delivery times. These systems may calculate arrival estimates using distance, route data, average travel speed, and basic traffic information. However, simple estimation methods may not fully capture complex factors affecting delivery duration. Many systems primarily show the current delivery location without providing a dedicated delay-risk prediction. Operators may need to manually monitor deliveries and identify orders that appear likely to be delayed. Real-time changes in traffic, weather, driver availability, and order volume can make static estimates inaccurate. Historical delivery information may not always be effectively used for predictive analysis. Some systems provide limited visualization of delivery-risk trends. Alerts may be generated only after a delivery has already exceeded its expected time. Manual customer communication can therefore become necessary when delays occur. These limitations can make delivery management reactive rather than proactive. A predictive monitoring platform can help identify potential delays before they become actual service failures.

Disadvantages of Existing System

- Primarily focuses on tracking rather than prediction.
- Static estimates may become inaccurate as conditions change.
- Limited use of historical delivery patterns.
- Manual identification of high-risk deliveries.
- Limited real-time delay-risk analysis.
- Delays may be detected only after they occur.
- Limited integration of traffic and weather factors.
- Manual intervention may be required for many delayed orders.
- Limited predictive visualization and analytics.
- Difficult to compare predicted and actual delivery performance.
- Limited automated alerts for potential future delays.
- Reactive rather than proactive delivery management.

Proposed System

The proposed Live Delivery Delay Predictor provides a centralized platform for monitoring active deliveries and predicting potential delays in real time. The system collects delivery information including location, destination, route, distance, order status, estimated arrival time, and other permitted operational data. Relevant traffic and weather information can be incorporated when available. Historical delivery records are processed to identify patterns associated with successful and delayed deliveries. A preprocessing module cleans and transforms the collected information before sending it to the prediction engine. The machine-learning model analyzes delivery characteristics and generates an estimated arrival time and delay probability. The system continuously updates predictions as new delivery information becomes available. A risk-classification module categorizes deliveries into low, medium, and high delay-risk levels. The dashboard provides real-time visibility into active deliveries, predicted arrival times, delay probabilities, and high-risk orders. Alerts can be generated when the predicted delay exceeds configured thresholds. Actual delivery outcomes are recorded for model evaluation and performance analysis. Historical predictions can be compared with actual results to identify opportunities for improving the model. Overall, the proposed system supports proactive delivery management through real-time prediction, monitoring, alerting, and analytics.

Advantages of Proposed System

- Provides real-time delivery-delay prediction.
- Identifies potential delays before they occur.
- Uses historical delivery data for predictive analysis.
- Can incorporate traffic and weather information.
- Continuously updates predictions during delivery.
- Provides delay-risk classification.
- Supports automated alerts for high-risk deliveries.
- Provides centralized real-time dashboards.
- Helps improve delivery planning and resource allocation.
- Supports comparison of predicted and actual delivery times.
- Improves customer communication and service reliability.
- Supports continuous improvement of prediction models.

IV. Methodology

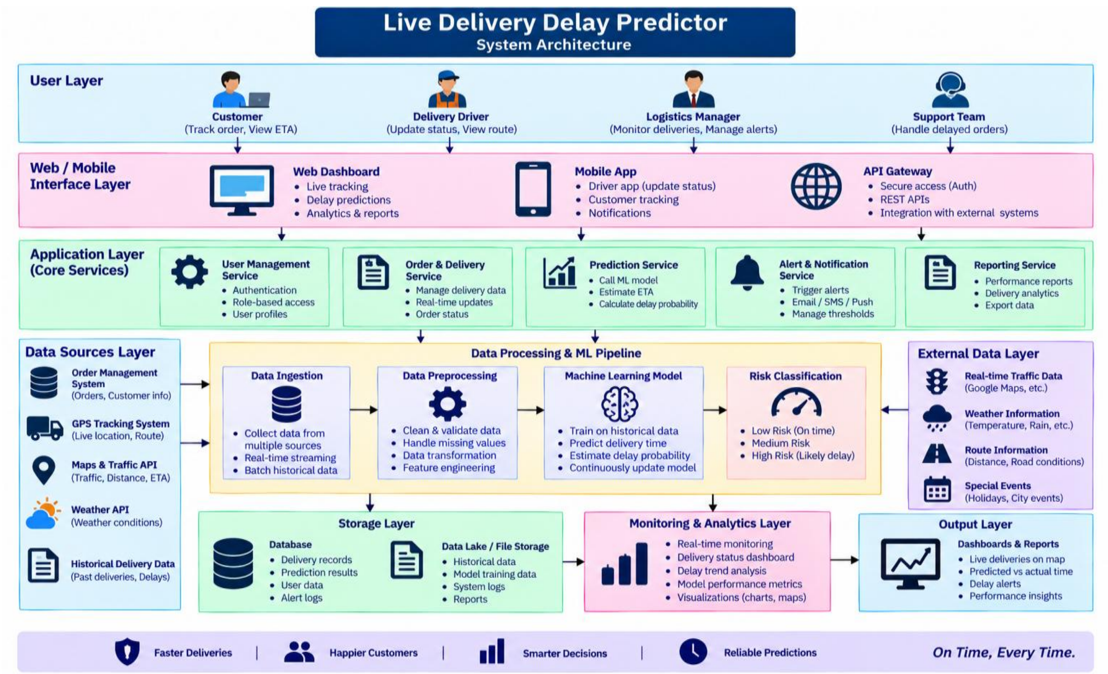
The methodology begins with authentication of the logistics administrator or authorized operator. Active delivery information is collected from approved delivery-management or tracking systems. Relevant features such as location, destination, distance, route, delivery status, and estimated arrival time are extracted. Where available, traffic, weather, and operational information are incorporated into the prediction process. Historical delivery records are collected and prepared for model training and evaluation. The preprocessing module handles missing values, inconsistent records, duplicate data, and feature transformation. A machine-learning prediction model is trained using historical delivery outcomes and relevant delivery features. When a delivery is active, its current information is passed to the prediction model. The model estimates the expected arrival time and probability or duration of a potential delay. A risk-classification module assigns an appropriate delay-risk level. The monitoring dashboard continuously displays updated delivery predictions and high-risk deliveries. Alerts are generated when configured delay-risk thresholds are reached. Actual delivery outcomes are recorded and compared with predictions to measure model performance. The model can then be periodically evaluated and improved using new historical delivery data.

System Architecture

The system architecture consists of several interconnected layers designed to provide real-time delivery monitoring and predictive analysis. The User Layer contains logistics administrators, delivery operators, managers, and authorized customer-support personnel. The Web/Mobile Interface Layer provides authentication, delivery monitoring, dashboards, prediction results, alerts, and reporting functions. The Application Layer manages users, delivery records, business logic, prediction workflows, configuration, and system logging. The Data Collection Layer receives

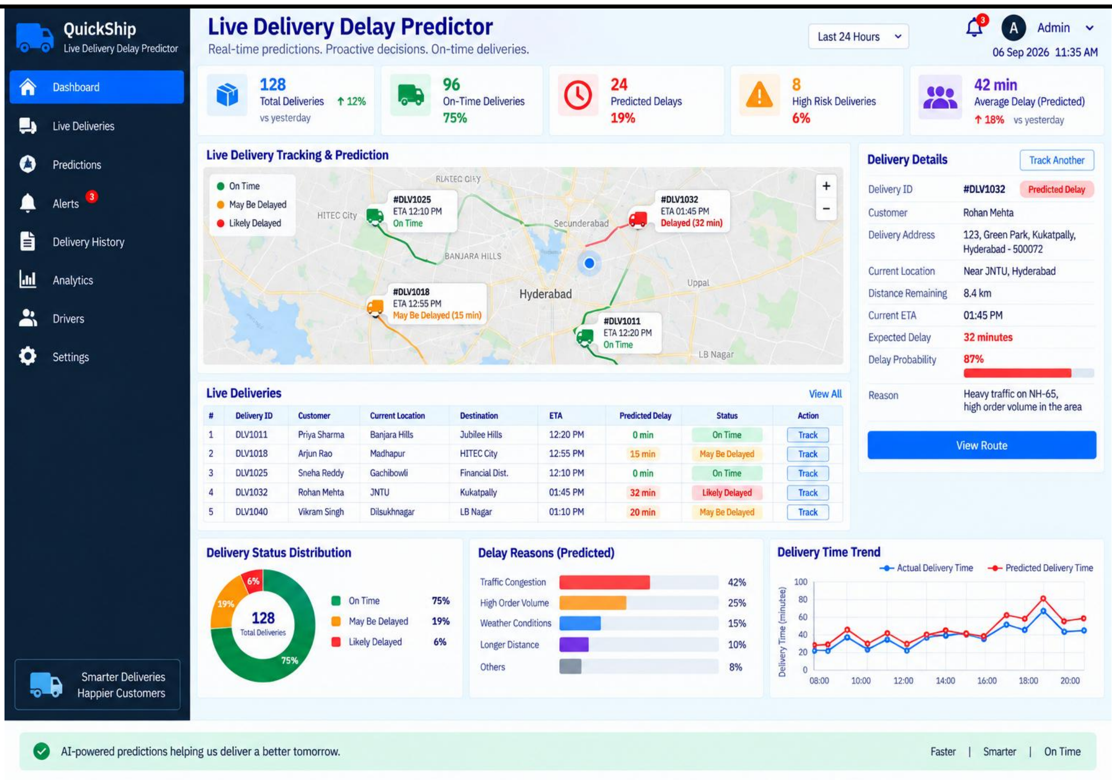
International Journal of
DATA SCIENCE AND IOT MANAGEMENT SYSTEM
Peer Reviewed, Referred & Indexed Journal
ISSN: 3068-272X www.ijdim.com Original Research Paper

permitted information from delivery-management systems, GPS tracking services, order systems, and other approved data sources. The External Data Layer can provide relevant traffic, weather, route, and location information where available. The Data Preprocessing Layer validates, cleans, transforms, and combines delivery and external data before prediction. The Feature Engineering Layer derives useful attributes such as distance, travel speed, elapsed delivery time, traffic conditions, time of day, and historical delivery characteristics. The Prediction Engine uses a trained machine-learning model to estimate expected arrival time and potential delay probability or duration. The Risk Assessment Layer converts prediction results into delay-risk categories such as low, medium, and high. The Alerting Layer generates notifications when high-risk delay conditions or configured thresholds are reached. The Database Layer stores delivery records, historical outcomes, prediction results, risk scores, alerts, and model-performance information. The Analytics and Visualization Layer displays active deliveries, delay trends, prediction accuracy, risk distributions, and operational statistics. The Reporting Layer generates delivery-performance reports and prediction-analysis summaries. The overall architecture follows the workflow Collect → Process → Predict → Classify → Monitor → Alert → Evaluate, enabling proactive delivery-delay management.



V. Result and Output

International Journal of
DATA SCIENCE AND IOT MANAGEMENT SYSTEM
Peer Reviewed, Referred & Indexed Journal
ISSN: 3068-272X www.ijdim.com Original Research Paper



VI. Conclusion

The Live Delivery Delay Predictor provides a real-time and intelligent approach to identifying potential delivery delays before they occur. By analyzing delivery information such as location, distance, route conditions, traffic, weather, order status, and historical delivery patterns, the system can estimate expected arrival times and identify deliveries that may require attention.

The proposed system improves traditional delivery tracking by combining machine-learning-based prediction, real-time monitoring, delay-risk classification, alerts, and visualization. Instead of simply showing the current location of a delivery, the platform provides predictive insights that help logistics teams take proactive action when a delay is likely.

The centralized dashboard makes it easier to monitor active deliveries, compare predicted and actual delivery times, identify major causes of delays, and prioritize high-risk orders. Historical delivery data can also be used to evaluate prediction accuracy and continuously improve the prediction model.

Overall, the system can serve as an effective solution for logistics management, e-commerce delivery operations, courier services, and real-time delivery monitoring. Future enhancements can include advanced deep-learning models, live traffic integration, dynamic route optimization, customer notifications, driver performance analytics, and automated resource allocation. By enabling proactive decision-making, the system can contribute to faster deliveries, improved operational efficiency, and better customer satisfaction.

References

[1] Kumar, R. D., Prudhviraj, G., Vijay, K., Kumar, P. S., & Plugmann, P. (2024). Exploring COVID-19 through intensive investigation with supervised machine learning algorithm. In Handbook of Artificial Intelligence and Wearables (pp. 145-158). CRC Press.
[2] Swathi, B., Vijay, K., Sushanth Babu, M., & Dinesh Kumar, R. (2024, November). Machine Learning Techniques in Cloud Based Intrusion Detection. In The International Conference on Artificial Intelligence and Smart Environment (pp. 557-564). Cham: Springer Nature Switzerland.
[3] Sv satyakrishna, shirisha rangu ,bhargavi nalacheruve.(2024) Prospective investigation on colorectal cancer with SMOTE on machine learning Algorithm
[4] Dr.G.Vishnu Murthy, BhargaviNalacheruve 1Professor, Department of computer Science & engineering, Anurag University, TS, India. 2Student, Department of computer Science & engineering, Anurag University, TS, India.
[5] V. N. S. Manaswini, K. K, C. Nigam, S. S. Ali, R. Niranjana, and Suman, “Real-Time Object Detection in Drone Surveillance Using YOLOv5,” in Proc. 2025 3rd Int. Conf. IoT, Communication and Automation Technology (ICICAT), Gorakhpur, India, 2025, pp. 1–6, doi: 10.1109/ICICAT68430.2025.11414670.
[6] B. Soundarya, V. N. S. Manaswini, M. Ayyakrishnan, R. D. Kumar, “Contextual Analysis of Big Data Analytics in Intelligent Transportation Frameworks,” in Intersection of Artificial Intelligence, Data Science, and Cutting-Edge Technologies: From Concepts to Applications in Smart Environment, Lecture Notes in Networks and Systems, vol. 1353, Cham: Springer, 2025, doi: 10.1007/978-3-031-88304-0_79.
[7] R. D. Kumar, V. N. S.Manaswini, “Applications of blockchain in smart cities: detecting fake documents from land records using blockchain technology,” in Blockchain for Smart Cities, Elsevier, 2021, pp. 105–117, doi: 10.1016/B978-0-12-824446-3.00017-X.
[8] Tejavath Veeramma, Badarla Anil, Guguloth Ravinder, “An advanced movie recommender using collaborative filtering and sentiment analysis,” International Research Journal of Modernization in Engineering Technology and Science, vol. 7, no. 7, July 2025, doi: 10.56726/IRJMETS81618.
[9] Ravi Kumar Banoth, Ramana Murthy B V, “Automatic crop recommendation system using LightGBM and decision tree machine learning models,” Journal of Machine and Computing, vol. 5, no. 1, pp. 343, Jan. 2025, doi: 10.53759/7669/jmc202505026.
[10] Ravi Kumar Banoth, Dr. B.V. Ramana Murthy, “Smart agriculture through IoT and machine learning for analyzing carbon footprints,” in Proc. Int. Conf. Computer Science and Communication Engineering (ICCSCE), Apr. 2025.
[11] Ravi Kumar Banoth, B. V. Ramana Murthy, “Soil image classification using transfer learning approach: MobileNetV2 with CNN,” SN Computer Science, vol. 5, art. no. 199, 2024, doi: 10.1007/s42979-023-02500-x.