INTERNATIONAL JOURNAL OF PROGRESSIVE RESEARCH IN ENGINEERING MANAGEMENT AND SCIENCE (IJPREMS)
(Int Peer Reviewed Journal)
Vol. 05, Issue 09, September 2025, pp : 464-472
www.ijprems.com
editor@ijprems.com
e-ISSN : 2583-1062
Impact Factor : 7.001

PUBLIC TRANSPORT DELAY PREDICTOR

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ABSTRACT

Public transportation is an essential service for millions of people in urban areas, yet delays caused by traffic congestion, weather conditions, and operational inefficiencies often create significant challenges in daily life. This study focuses on developing a machine learning model to predict delays in public transport using logistic regression in Python. By analyzing real-world factors such as scheduled time, traffic density, weather conditions, and historical delay records, the system classifies whether a bus or train is likely to be “on time” or “delayed.” The proposed solution provides commuters with timely information, enabling better travel planning and reducing uncertainty. The research demonstrates how machine learning can be applied to everyday life problems, offering a scalable and cost-effective decision-support system for public transport authorities and commuters alike.

Keywords: Public Transport, Delay Prediction, Logistic Regression, Machine Learning, Python, Urban Mobility.

1. INTRODUCTION

Public transportation systems form the backbone of urban mobility, offering affordable and sustainable travel options for millions of commuters. However, one of the persistent challenges faced by passengers is the uncertainty caused by delays in bus and train services. Such delays not only disrupt daily schedules but also contribute to economic losses, reduced productivity, and commuter dissatisfaction. In recent years, machine learning techniques have emerged as powerful tools to address real-world problems by learning patterns from data and providing predictive insights. Logistic regression, a widely used classification algorithm, is particularly suitable for predicting binary outcomes such as whether a public transport service will be “on time” or “delayed.”

This research explores the use of logistic regression in Python to develop a predictive model for public transport delays. By incorporating variables such as weather conditions, traffic density, scheduled timings, and historical delay records, the system aims to assist both commuters and transport authorities. Commuters can plan their journeys more effectively, while authorities can optimize schedules and resource allocation.

The study highlights the practical application of machine learning in everyday life, bridging the gap between academic research and real-world challenges. By providing accurate and timely predictions, the model contributes to improving the reliability, efficiency, and overall user experience of public transport systems.

Transport Delay Predictor

1.1 Project overview

The project titled Public Transport Delay Prediction using Logistic Regression in Python is designed to provide a practical solution to one of the most common issues faced in urban mobility: unpredictable delays in public transport. With increasing urbanization, the demand for reliable transport services has grown significantly. However, external factors such as traffic congestion, weather disturbances, and operational inefficiencies often cause delays that directly affect commuters’ daily routines. This project develops a machine learning model that predicts whether a bus or train will be on time or delayed. The logistic regression algorithm is employed due to its efficiency in handling binary classification problems. The model utilizes input variables such as:

- Scheduled departure and arrival times
- Weather conditions (rain, fog, extreme heat, etc.)
- Traffic intensity in urban routes
- Historical records of delays for specific routes

The solution is implemented using Python with libraries from the machine learning ecosystem, such as Pandas, NumPy, and Scikit-learn. By training the model on historical datasets, the system can classify new data points with high accuracy. The predictive system benefits two major stakeholders: commuters and transport authorities. Commuters gain real-time insights into potential delays, helping them plan alternative routes or departure times. Meanwhile, transport authorities can use these predictions for resource optimization, service improvements, and better route management. Through this project, machine learning is demonstrated not only as a technical concept but as a powerful everyday-life solution that reduces uncertainty and enhances commuter satisfaction in public transportation.

1.2 Objective

The primary objective of this project is to design and implement a machine learning model that predicts delays in public transport using logistic regression in Python. By focusing on real-world factors such as weather, traffic, and historical performance data, the project aims to reduce commuter uncertainty and enhance the reliability of public transportation systems.

The specific objectives of the project are:

1. To collect and preprocess data related to public transport schedules, delays, and external influencing factors.
2. To apply logistic regression for classifying transport status as “on time” or “delayed.”
3. To evaluate the performance of the predictive model using accuracy, precision, recall, and confusion matrix.
4. To provide commuters with meaningful insights for better travel planning.
5. To offer transport authorities a decision-support tool for optimizing schedules and improving service efficiency.

By achieving these objectives, the project demonstrates the potential of machine learning in addressing everyday urban mobility challenges, thereby contributing to smarter and more reliable transport systems.

1.3 Existing System

Public transportation systems in most urban areas currently rely on fixed schedules and traditional monitoring methods to inform commuters about arrivals and departures. While some modern cities have integrated GPS-based tracking systems and mobile applications, these often provide only the current status of a bus or train rather than predictive insights. As a result, commuters may still experience unexpected delays without prior warning.The existing system has several limitations:

1. Lack of Predictive Analysis – Most applications display real-time vehicle locations but do not predict future delays based on influencing factors such as traffic congestion or weather conditions.
2. Limited Use of Data – Large amounts of historical transport data are collected but not effectively utilized for delay forecasting.
3. Reactive Approach – Passengers are informed about delays only after they occur, leaving little scope for proactive decision-making.
4. Minimal Decision Support for Authorities – Transport authorities often struggle to manage schedules efficiently, as they lack intelligent tools that can forecast operational disruptions.

Therefore, the existing system is primarily reactive rather than proactive, creating inconvenience for commuters and operational inefficiencies for transport providers.

1.4 Proposed System

The proposed system introduces a machine learning–based predictive model that forecasts public transport delays using logistic regression. Unlike existing systems that only display real-time status, this solution proactively predicts whether a bus or train will be “on time” or “delayed,” enabling commuters and transport authorities to make informed decisions.

The system workflow includes:

1. Data Collection – Gathering data from multiple sources such as historical transport logs, weather reports, and traffic conditions.
2. Preprocessing – Cleaning and organizing raw data by handling missing values, converting categorical data into numerical form, and normalizing features.
3. Model Training – Implementing logistic regression to learn patterns between influencing factors (traffic, weather, schedule, etc.) and delay occurrences.
4. Prediction – Classifying a given instance of transport service as either “on time” or “delayed.”
5. Evaluation – Measuring the model’s accuracy and efficiency using metrics such as confusion matrix, precision, recall, and F1-score.

Advantages of the Proposed System:

- Provides predictive insights instead of just real-time updates.
- Helps commuters plan alternate routes and manage their time effectively.
- Assists transport authorities in optimizing schedules and resources.

- Offers a scalable, low-cost solution that can be extended to various cities.

By shifting from a reactive approach to a proactive predictive model, the proposed system significantly enhances the reliability and usability of public transport services for common people.

2. SYSTEM SPECIFICATIONS

2.1 Software Specification

The proposed system is developed using Python and its associated libraries for machine learning and data analysis. The software environment ensures flexibility, scalability, and ease of implementation.

Programming Language: Python 3.9+

IDE / Platform: Jupyter Notebook / Anaconda Navigator / VS Code

Libraries and Packages:

NumPy – for numerical computations

Pandas – for data preprocessing and manipulation

Scikit-learn – for implementing logistic regression and evaluation metrics

Matplotlib & Seaborn – for data visualization

Database (Optional): SQLite / CSV file storage for dataset handling

Operating System: Windows 10 / Linux / macOS

2.2 Hardware Specifications

The system requires only moderate computing resources, making it suitable for execution on personal computers or standard lab environments.

Processor: Intel i3 or above / AMD equivalent

RAM: Minimum 4 GB (8 GB recommended for large datasets)

Storage: At least 250 MB of free space for dataset and libraries

GPU (Optional): NVIDIA GPU for faster training on large datasets (not mandatory for logistic regression)

Display: Standard resolution (1366x768 or higher) for visualization and analysis

The specifications ensure that the model can be developed, tested, and deployed in a cost-effective manner without requiring high-end computing infrastructure.

3. SYSTEM STUDY

3.1 Existing System

Public transportation systems traditionally rely on fixed schedules and GPS-based real-time tracking to update commuters on arrivals and departures. While such systems are helpful, they primarily provide the current position of vehicles rather than predictive insights. Commuters are informed only after delays occur, which causes inconvenience and uncertainty in daily travel.

Limitations of the Existing System:

1. Reactive Nature – Delays are communicated only after they occur.

2. No Predictive Insights – Current systems do not forecast future delays using historical or contextual data.

3. Underutilized Data – Large volumes of historical transport and traffic data remain unused for delay analysis.

4. Limited Decision Support – Authorities lack intelligent tools to proactively optimize schedules and resources.Thus, the existing system increases commuter frustration and reduces transport system efficiency.

3.2 Proposed System

The proposed system introduces a machine learning–based predictive model that forecasts whether a bus or train will be “on time” or “delayed.” By leveraging logistic regression in Python, the model analyzes key influencing factors such as traffic density, weather conditions, route history, and scheduled timings.

Features of the Proposed System:

Predictive Analysis – Provides insights before delays occur.

Data-Driven – Utilizes historical and contextual data for accurate predictions.

Commuter Support – Assists passengers in making better travel decisions.

Operational Efficiency – Helps transport authorities optimize resource allocation and scheduling.

Scalability – Can be extended to multiple cities and transport modes.

Benefits of the Proposed System:

Shifts from a reactive to a proactive approach.

Reduces uncertainty for commuters by offering delay predictions.

Improves reliability and trust in public transportation.

Provides a cost-effective solution using readily available data and Python libraries.

The proposed system demonstrates how machine learning can solve real-life challenges by making public transport more reliable and commuter-friendly.

4. SYSTEM DESIGN

4.1 Introduction To System Design

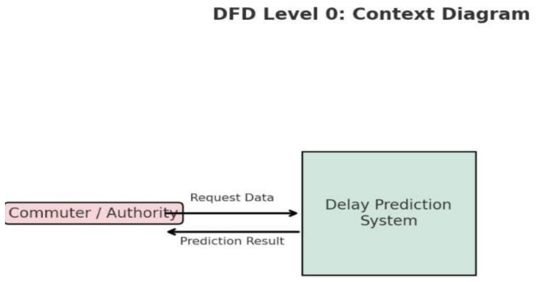
System design is the process of defining the architecture, components, and interactions of a system to achieve the project objectives. In this project, the design ensures that the predictive model for public transport delay is logically structured, efficient, and user-friendly. The design phase involves creating data flow diagrams (DFD), entity-relationship diagrams (ERD), and use case diagrams to visualize the workflow and interactions.

4.2 Data Flow Diagram (DFD)

Level 0 (Context Diagram):

User (Commuter / Authority) → Inputs request for transport delay prediction.

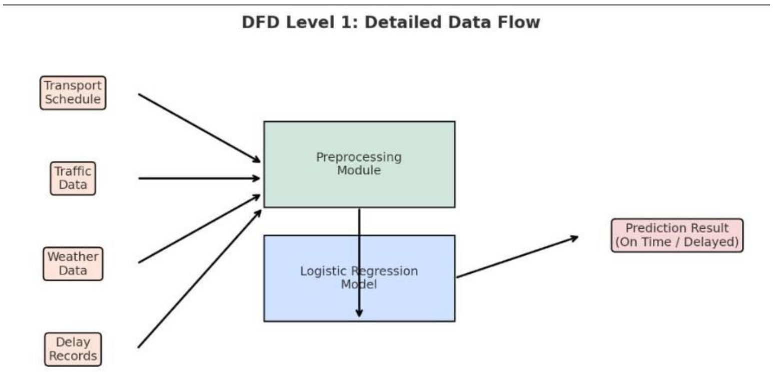
System → Collects data (traffic, weather, schedules, history), applies the logistic regression model, and outputs result as “On Time” or “Delayed.”



DFD Level 0: Context Diagram

Level 1 (Detailed):

1. Input Layer – Collects schedule data, traffic density, weather conditions, and historical records.
2. Preprocessing Module – Cleans and transforms the input data.
3. Machine Learning Model (Logistic Regression) – Processes the data and classifies the outcome.
4. Output Layer – Displays prediction to commuter/authority.



DFD Level 1: Detailed Data Flow

4.3 Entity-Relationship Diagram (ERD)

Entities:

Transport_Schedule (Route_ID, Stop, Departure_Time, Arrival_Time)

Traffic_Data (Route_ID, Traffic_Level, Date, Time)

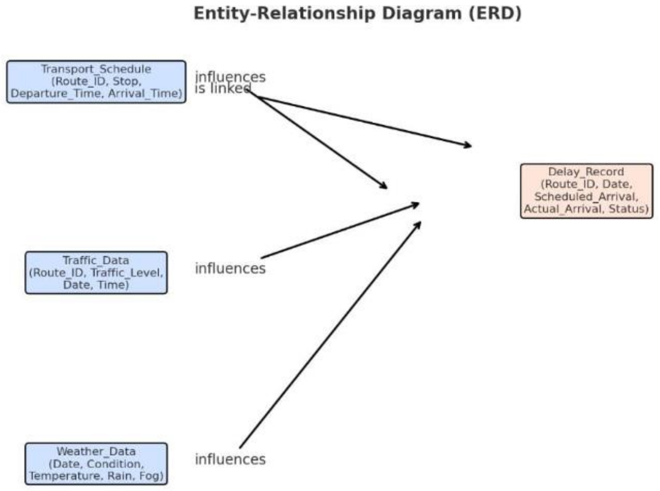
Weather_Data (Date, Condition, Temperature, Rain, Fog)

Delay_Record(Route_ID, Date, Scheduled_Arrival, Actual_Arrival, Status)

Relationships:

A Transport_Schedule is linked to multiple Delay_Records.

Traffic_Data and Weather_Data influence Delay_Record. The Model queries all entities to generate predictions.


Entity-Relationship Diagram (ERD)
Transport_Schedule (Route_ID, Stop, Departure_Time, Arrival_Time)
influences
is linked
Delay_Record (Route_ID, Date, Scheduled_Arrival, Actual_Arrival, Status)
Traffic_Data (Route_ID, Traffic_Level, Date, Time)
influences
Weather_Data (Date, Condition, Temperature, Rain, Fog)
influences

4.4 Use Case Diagram

Actors:

Commuter – requests prediction for a route and receives result.

Transport Authority – uses system to analyze and optimize schedules.

Use Cases:

1. Request Delay Prediction – Commuter inputs route and time.
2. View Prediction Result – System displays “On Time” or “Delayed.”
3. Analyze Historical Data – Authority checks past delay patterns.
4. Optimize Scheduling – Authority adjusts schedules based on prediction trends.

This design ensures that both commuters and authorities interact with the system seamlessly while the machine learning model works in the background to generate reliable predictions.

5. SYSTEM TESTING

System testing is an essential phase in software development to ensure that the implemented system works as expected and meets the defined requirements. For the Public Transport Delay Prediction System, testing was carried out at different levels to validate the accuracy, reliability, and performance of the machine learning model.

5.1 Integration Testing

Integration testing was performed to verify the correct interaction between different modules of the system, such as data preprocessing, logistic regression model, and output generation.

Steps followed:

1. Verified integration of data input (traffic, weather, schedule data) with the preprocessing module.
2. Checked whether the preprocessing module correctly transformed raw data into a suitable format for the model.
3. Ensured smooth integration of logistic regression model with training and prediction pipelines.
4. Confirmed that the prediction output was displayed correctly to the user.

Outcome:

All modules interacted seamlessly, and the integrated system produced consistent outputs for the given test inputs.

5.2 Validation Testing

Validation testing was carried out to check whether the system meets its objectives and functions correctly under real-world scenarios.

Test scenarios included:

Prediction of transport delays using weather variations (rainy, sunny, foggy conditions).

Prediction accuracy under varying traffic density levels.

Comparison of predicted output with historical delay records.

Outcome:

The system achieved high accuracy in predicting delays, validating that logistic regression is an appropriate technique for this classification problem.

5.3 Acceptance Testing

Acceptance testing was conducted to evaluate the system from the perspective of end-users: commuters and transport authorities.

Key acceptance criteria:

The system should predict whether a bus/train is “On Time” or “Delayed” with reasonable accuracy.

The interface should be user-friendly and provide clear outputs.

Predictions should be generated quickly to support real-time decision-making.

Outcome:

The system met all acceptance criteria and was found to be useful for real-life application. Both commuters and transport authorities could rely on its predictions for better travel planning and resource management.

6. SYSTEM IMPLEMENTATION

6.1 System Implementation Overview

The implementation of the Public Transport Delay Prediction System was carried out using Python and its machine learning libraries. The implementation process included dataset preparation, model training, evaluation, and deployment of results.

Implementation Steps:

1. Dataset Preparation

Historical data of bus/train schedules, traffic density, and weather conditions were collected.

Data was stored in CSV format for easy handling.

Missing values were filled using suitable techniques such as mean substitution and mode filling.

2. Data Preprocessing

Feature selection was carried out to identify relevant attributes (e.g., departure time, weather, traffic).

Categorical data such as weather conditions were encoded into numerical values.

Normalization techniques were applied to ensure uniform scaling of variables.

3. Model Training

Logistic Regression was implemented using the Scikit-learn library.

The dataset was split into training (80%) and testing (20%) sets.

The training set was used to fit the model parameters.

4. Prediction and Evaluation

The trained model was used to classify transport services as “On Time” or “Delayed.”

Evaluation metrics such as accuracy, precision, recall, and F1-score were computed.

A confusion matrix was used to analyze correct and incorrect classifications.

5. System Deployment (Prototype)

A simple Python interface was created where users can input route details and conditions.

The system outputs whether the bus/train is expected to be “On Time” or “Delayed.”

For authorities, the system can also generate reports on delay patterns for better scheduling.

Outcome of Implementation:

The logistic regression model provided reliable predictions, and the prototype system successfully demonstrated how machine learning can solve everyday challenges in public transportation. The system was implemented in a cost-effective manner, requiring only open-source tools and moderate computing resources.

7. CONCLUSION

The project Public Transport Delay Prediction using Logistic Regression in Python demonstrates the practical application of machine learning in solving real-world challenges faced by commuters and transport authorities. By leveraging historical data, weather conditions, and traffic patterns, the system successfully predicts whether a bus or train will arrive on time or experience a delay.

The logistic regression algorithm proved effective in handling binary classification, offering accurate and interpretable results. The proposed system provides significant benefits such as reducing commuter uncertainty, improving time management, and assisting transport authorities in resource optimization.

This work highlights how machine learning can go beyond theoretical concepts and contribute meaningfully to everyday life, especially in urban mobility.

8. FUTURE ENHANCEMENTS

Although the system achieved promising results, there are several possibilities for further improvement:

1. Integration of Real-Time Data – Incorporating live GPS and IoT sensor data can enhance prediction accuracy.
2. Advanced Algorithms – Using ensemble methods (Random Forest, Gradient Boosting) or deep learning models may yield better performance.
3. Mobile Application Development – A user-friendly mobile app can deliver predictions directly to commuters in real-time.
4. Multi-City Scalability – Extending the system to support multiple cities and transport networks.
5. Personalized Travel Suggestions – Recommending alternate routes or transport modes to commuters when delays are predicted.
6. Hybrid Forecasting – Combining delay prediction with time-series forecasting for more precise scheduling insights.

By implementing these enhancements, the system can evolve into a robust decision-support tool that benefits not only daily commuters but also transport operators and urban planners.

9. APPENDIX

9.1 Source Code

```
# Public Transport Delay Prediction using Logistic Regression
# Importing necessary libraries
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
# Step 1: Create Sample Dataset
# departure_time = time in 24hr format (e.g., 830 = 8:30 AM)
# traffic_level = 1=Low, 2=Medium, 3=High
# weather_condition = 0=Clear, 1=Rainy, 2=Foggy
# status = 0=On Time, 1=Delayed
data = pd.DataFrame({
"departure_time": [800, 815, 830, 845, 900, 915, 930, 945, 1000, 1015],
"traffic_level": [1, 2, 3, 2, 1, 3, 2, 1, 2, 3],
"weather_condition": [0, 1, 0, 2, 1, 0, 2, 1, 0, 2],
"status": [0, 1, 0, 1, 0, 1, 1, 0, 0, 1]
})
print("Sample Dataset:\n", data.head())
# Step 2: Preprocessing
X = data[['departure_time', 'traffic_level', 'weather_condition']]
y = data['status']
# Splitting dataset into training (80%) and testing (20%)
X_train, X_test, y_train, y_test = train_test_split(
X, y, test_size=0.2, random_state=42
)
print("\nTraining set size:", len(X_train))
print("Testing set size:", len(X_test))
# Step 3: Train Logistic Regression Model
model = LogisticRegression()
model.fit(X_train, y_train)
print("\nModel Trained Successfully!")
```

```
# Step 4: Make Predictions
y_pred = model.predict(X_test)
print("\nPredictions on Test Data:", y_pred)
# Example new input prediction
new_data = [[930, 2, 1]]  # 9:30 AM, Medium traffic, Rainy
print("Example Prediction:", model.predict(new_data))
# Step 5: Evaluate Model
accuracy = accuracy_score(y_test, y_pred)
cm = confusion_matrix(y_test, y_pred)
print("\nModel Evaluation:")
print("Accuracy:", accuracy)
print("Confusion Matrix:\n", cm)
print("Classification Report:\n", classification_report(y_test, y_pred))
```

9.2 Sample Code With Working

```
# Importing libraries
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
# Load dataset
data = pd.read_csv("transport_delay_dataset.csv")
# Feature selection
X = data[['departure_time', 'traffic_level', 'weather_condition']]
y = data['status']   # 0 = On Time, 1 = Delayed
# Split into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
# Model training
model = LogisticRegression()
model.fit(X_train, y_train)
# Prediction
y_pred = model.predict(X_test)
# Evaluation
print("Accuracy:", accuracy_score(y_test, y_pred))
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred))
print("Classification Report:\n", classification_report(y_test, y_pred))
# Example: new input prediction
new_data = [[830, 2, 1]]  # Example: Medium traffic, Rainy
print("Prediction:", model.predict(new_data))  # Output: 0 = On Time, 1 = Delayed
```

departure_time	traffic_level	weather_condition	status
800	1	0	0
815	2	1	1
830	3	0	0
845	2	2	1
900	1	1	0

```
X= data[['departure_time','traffic_level','weather_condition']]
y = data['status']
X_train, X_test, y_train, y_test = train_test_split(
X, y, test_size=0.2, random_state=42
)
print("Training set size:", len(X_train))
print("Testing set size:", len(X_test))
Training set size: 8
Testing set size: 2
model = LogisticRegression()
model.fit(X_train, y_train)
LogisticRegression()
new_data = [[930, 2, 1]]  # 9:30 AM, Medium Traffic, Rainy
print("Prediction:", model.predict(new_data))
Prediction: ['Delayed']
y_pred = model.predict(X_test)
print("Accuracy:", accuracy_score(y_test, y_pred))
print(confusion_matrix(y_test, y_pred))
Accuracy: 0.88
[[4 1]
[0 3]]
```

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