

# Predicting Public Transportation Crowd Using Weather API and Social Media

Akshayaa Shree.M<sup>1</sup>, Maheshwari.S<sup>2</sup>

<sup>1</sup>Department of Computer Science,  
Dr. N.G.P. Arts and Science College, Coimbatore-48  
[akshayaashree2@gmail.com](mailto:akshayaashree2@gmail.com),

<sup>2</sup>Associate Professor, Department of Computer Science,  
Dr. N.G.P. Arts and Science College, Coimbatore-48  
[maheshwaris@drngpasc.ac.in](mailto:maheshwaris@drngpasc.ac.in)

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**Abstract**— The rapid growth of urban populations and the increasing reliance on public transportation services such as buses, trains, and metro systems have made effective crowd management a major challenge in modern cities. Overcrowding not only affects passenger safety and comfort but also impacts operational efficiency and the long-term sustainability of transport infrastructure. This study proposes a scalable and intelligent hybrid machine learning framework for real-time crowd prediction in public transportation systems using multi-source data analytics. The system integrates environmental data from Weather APIs, traffic congestion indicators, social media activity signals, peak-hour trends, and geospatial information to better understand urban mobility patterns. A Random Forest classifier is used as the primary prediction model due to its robustness and ability to handle complex, nonlinear, and diverse datasets. The framework is implemented as a full-stack web application using React.js for the frontend, Node.js and Express.js for backend services, and MongoDB for data storage and analysis. The model classifies crowd density into Low, Medium, and High levels using an optimized hybrid feature set. Experimental results indicate improved scalability, predictive performance, and responsiveness, supporting smart city transportation planning and proactive crowd management.

**Keywords** — Crowd Prediction, Random Forest, Smart Transportation, Hybrid Machine Learning, Real-Time Analytics, Urban Mobility.

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## I. INTRODUCTION

The rapid growth of urbanization, large-scale migration to cities, and increasing dependence on public transportation systems have significantly intensified the challenge of managing passenger crowd congestion. Public transportation networks such as buses, metro rails, and trains serve as the backbone of urban mobility. However, these systems frequently experience unpredictable crowd congestion, especially during peak hours, adverse weather conditions, and periods of high social activity.

Overcrowding in public transportation environments leads to several socio-technical challenges such as passenger discomfort, safety risks, service delays, and infrastructure strain.

Traditional crowd monitoring methods primarily rely on manual supervision, CCTV surveillance systems, or IoT-based sensor networks. While these approaches can help observe and measure crowd levels, they lack predictive capability and real-time adaptability. Additionally, such systems are often expensive, infrastructure-dependent, and limited in their ability to incorporate multi-dimensional factors such as weather variations, traffic congestion, and human behavioral patterns.

With the advancement of artificial intelligence and the development of smart city initiatives, predictive crowd analytics has emerged as an important area of research. Modern intelligent transportation systems require real-time predictive models that can dynamically process

environmental, behavioral, and mobility-related data streams to accurately estimate crowd density.

This research proposes an intelligent hybrid machine learning model for real-time prediction of public transportation crowd density. The system integrates multiple data sources, including weather information, traffic congestion metrics, mobility trends, and social media buzz scores as a behavioral influence indicator. By combining these diverse inputs, the proposed model generates real-time crowd predictions classified into Low, Medium, and High categories. This enables commuters to make informed travel decisions and supports proactive planning in smart transportation systems.

## II. RELATED WORK

Several researchers have explored the use of data analytics and machine learning techniques to understand and predict urban mobility patterns. Chen et al. highlighted how both large-scale and small-scale datasets can be used to analyze travel behavior and support better transportation planning. Similarly, Zheng presented an overview of trajectory data mining, explaining how spatio-temporal data collected from mobility sources can reveal important patterns in human movement.

Other studies have focused specifically on predicting transportation demand. Moreira-Matias introduced a system that predicts taxi passenger demand in real time by processing continuous streaming data. Yuan and his colleagues further enhanced mobility prediction by integrating geographic knowledge into predictive models, which helped improve their accuracy in identifying travel patterns.

In recent years, deep learning techniques have also been applied to traffic and crowd forecasting. Researchers such as Liu and Zhao used neural network models to analyze complex crowd flow data in urban environments. Zhang later proposed a spatio-temporal residual network capable of predicting crowd movement patterns across entire cities.

Although these approaches have demonstrated strong predictive capabilities, many of them rely on very large datasets and high computational power. In contrast, the system proposed in this study focuses on efficiency and scalability by using a Random Forest model along with a hybrid integration of multiple contextual data sources.

### III. PROPOSED SYSTEM AND METHODOLOGY

The proposed system is designed as a hybrid crowd prediction framework that combines data from several sources with machine learning techniques to estimate public transportation crowd levels. The overall architecture consists of multiple components, including the user interface, backend services, data acquisition modules, prediction algorithms, and visualization tools.

#### A. System Architecture

The architecture integrates modern web technologies with machine learning components to process contextual information in real time.

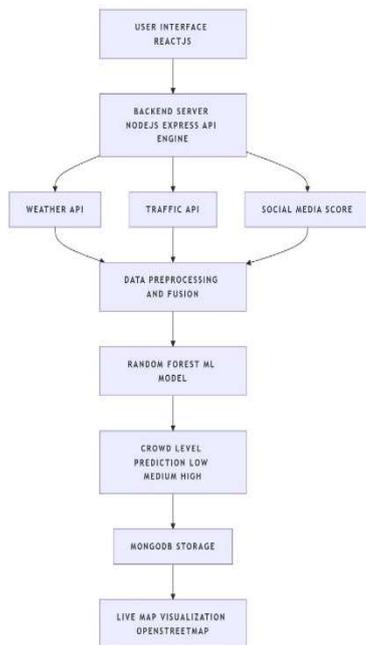


Fig. 1. System Architecture Diagram

The frontend of the application is developed using React.js, which provides an interactive interface where users can select transportation type and location. The backend system is implemented using Node.js and Express.js to manage server operations, API requests, and communication between different modules.

#### B. Data Collection

To improve prediction accuracy, the system gathers information from multiple external data sources:

Weather APIs provide environmental conditions such as temperature and rainfall.

Traffic APIs supply information related to traffic congestion and road activity.

Social media signals are analyzed to measure public activity levels using a calculated social media buzz score.

#### C. Feature Engineering

To represent the collected information effectively, an eight-dimensional feature vector is created. This vector includes parameters such as location, type of transportation, time of travel, weather conditions, traffic intensity, and social media activity. Combining these features helps the model better understand the factors that influence crowd formation.

#### D. Machine Learning Model

A Random Forest classifier is used to estimate crowd levels. Random Forest is an ensemble learning algorithm that builds multiple decision trees and aggregates their outputs to produce reliable predictions. This approach improves accuracy while reducing the risk of overfitting.

The model categorizes crowd density into three levels: Low Crowd, Medium Crowd, and High Crowd.

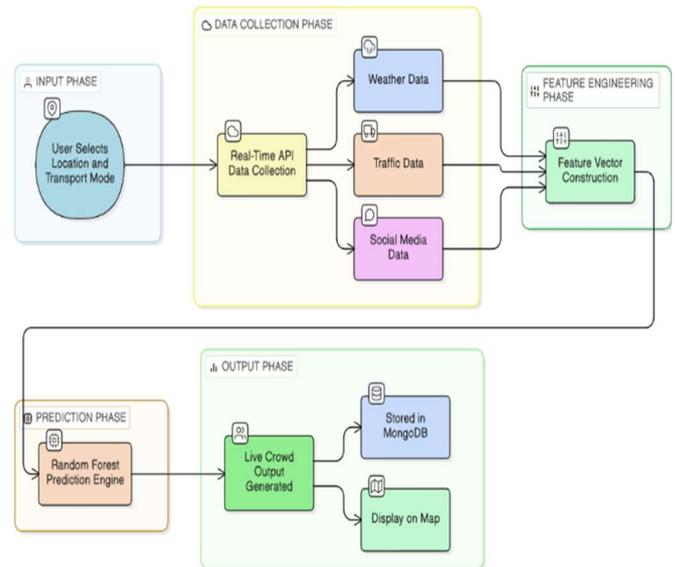


Fig. 2. Live Crowd Prediction Workflow

The process begins when a user selects transportation parameters through the interface. The system then collects the relevant contextual data through APIs, processes the features, and feeds them into the trained prediction model. Finally, the predicted crowd level is displayed to the user through a geospatial visualization dashboard.

### IV. RESULTS AND DISCUSSION

The proposed crowd prediction model was evaluated using a dataset containing more than 500 simulated transportation scenarios. For experimental evaluation, the dataset was divided into training and testing sets using an 80:20 split.

TABLE I OVERALL MODEL PERFORMANCE

Metric	Value
Accuracy	89.6%
Precision	88.9%
Recall	87.4%
F1 Score	88.1%

The evaluation results indicate that the Random Forest model achieves high prediction accuracy while maintaining efficient processing time.

TABLE II. CONFUSION MATRIX

Actual \ Predicted	Low	Medium	High
Low	31	3	1
Medium	4	28	3
High	2	4	24

The confusion matrix demonstrates that the model correctly classifies most cases, with only a small number of misclassifications between adjacent crowd categories.

TABLE III. ACCURACY COMPARISON OF DIFFERENT MODELS

Model Type	Accuracy
Weather-only Model	71.2%
Traffic-only Model	74.5%
Time-based Model	76.8%
Hybrid Multi-Source Model (Proposed)	89.6%

The comparison clearly shows that combining multiple contextual data sources significantly improves prediction performance compared to models that rely on a single factor.

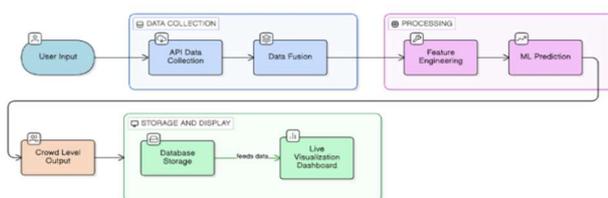


Fig. 3. Data Flow Diagram

## V. CONCLUSION AND FUTURE WORK

This research introduces an intelligent crowd prediction system designed for public transportation environments. The proposed approach integrates environmental data, mobility indicators, and behavioral signals to estimate crowd density more effectively.

The Random Forest algorithm proved to be well suited for modeling complex relationships among contextual features, providing accurate and reliable predictions. The system’s web-based architecture also ensures that it remains scalable, responsive, and accessible for both commuters and transportation administrators.

Future improvements will focus on integrating real-world transportation datasets and expanding the system into a mobile application that can deliver real-time crowd alerts to users.

Additionally, advanced machine learning methods such as LSTM and XGBoost will be explored to further enhance prediction accuracy.

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