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AI-Based Transit Delay Predictor

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Abstract: Public transportation systems are pivotal for sustainable urban mobility, yet frequent delays in buses, metros, and trams compromise service reliability, passenger satisfaction, and operational efficiency. This study proposes an AI-based hybrid CNN-LSTM model for public transport delay prediction, classifying trips as "Delayed" or "On Time" using a comprehensive dataset of 2,000 records encompassing operational features (transport mode, route details, scheduled and actual times), temporal attributes (peak hours, weekdays, seasons, holidays), meteorological variables (temperature, humidity, wind speed, precipitation), and exogenous factors (traffic congestion index, event attendance). Rigorous data preprocessing addresses missing values via imputation and employs Recursive Feature Elimination (RFE) with cross-validation to select optimal features, mitigating multicollinearity and enhancing model interpretability. A supervised learning pipeline, implemented in Scikit-learn and TensorFlow, leverages CNN for extracting spatial hierarchies from multivariate inputs, LSTM for modeling temporal dependencies in delay sequences, and Random Forest as an ensemble baseline, achieving superior performance (accuracy > 92%, F1-score > 0.91) over benchmarks via stratified k-fold validation, precision-recall curves, and confusion matrix analysis. Deployed as a Flask-based web application with secure authentication, Plotly interactive dashboards, and real-time inference APIs, the system facilitates proactive decision-making for transit authorities and scalable passenger information services.

Keywords: CNN-LSTM hybrid model, public transport delays, Recursive Feature Elimination, spatiotemporal prediction, Flask deployment, stratified validation

I. INTRODUCTION

Urbanization and population growth have intensified reliance on public transportation systems like buses, metros, and trams, which offer sustainable, cost-effective mobility solutions critical for reducing carbon emissions and alleviating traffic congestion. However, persistent operational delays—caused by traffic variability, weather disruptions, peak-hour demands, and unplanned events—severely undermine service reliability, erode passenger trust, and impose substantial economic losses estimated at billions annually worldwide, while exacerbating social inequities by disproportionately affecting low-income commuters dependent on these services. This study addresses this pressing societal challenge by developing an AI-driven predictive framework to enable proactive delay mitigation, fostering resilient urban transport networks that enhance accessibility, equity, and overall quality of life.

II. SCOPE OF THE LITERATURE SURVEY

Recent literature underscores significant progress in transit delay prediction methodologies. Transformer-based approaches [1] excel in capturing long-range temporal patterns for bus arrival times with reduced errors compared to recurrent models, while Geo-convolutional LSTM models [2] fuse spatial and temporal features to enhance travel time predictions across ordered bus stops. Network-aware features [3] like bus flow centrality, integrated with recurrent architectures, alongside fully connected neural networks [4] for scalable real-time forecasting, illuminate delay propagation effects through departure deviation analysis. Hybrid LSTM–SVR frameworks [5, 6] bolster robustness in noisy data scenarios, Bayesian Gaussian mixture models [7] quantify prediction uncertainty, and XGBoost with spatial route segmentation [8] delivers efficiency in data-limited contexts. Explainable machine learning identifies [9] causal factors in rail delays, and graph neural networks augmented by causal learning and conformal prediction enable uncertainty-aware decision-making. These advancements signal a paradigm shift toward intelligent, data-driven transit systems [10]; yet deep learning's resource intensity contrasts with simpler models' practicality, motivating this study's lightweight, interpretable CNN-LSTM solution optimized for web deployment and real-world efficacy.

III. PROPOSED WORK

The proposed system constitutes a machine learning-driven, web-deployable framework for public transport delay prediction and multivariate factor analysis. It comprises dual architectural layers: a backend predictive modeling layer and a frontend application layer. The predictive layer implements a supervised learning pipeline in Scikit-learn, wherein

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multimodal features—encompassing operational parameters (route, scheduled/actual times), meteorological variables (temperature, precipitation), traffic congestion indices, event densities, and temporal covariates (peak hours, holidays)—undergo preprocessing (imputation, normalization) and Recursive Feature Elimination (RFE) with cross-validation to mitigate dimensionality and collinearity while preserving predictive salience. Hybrid CNN-LSTM architectures extract spatiotemporal hierarchies from sequential inputs, complemented by Random Forest ensembles for nonlinear decision boundaries; the resultant models are serialized via joblib for low-latency inference. The application layer, engineered in Flask with JWT-based authentication, integrates Plotly Dash for interactive EDA visualizations (feature importance heatmaps, confusion matrices, ROC curves) and a RESTful prediction API delivering binary classifications ("Delayed"/"On Time") alongside calibrated probability scores and SHAP-based interpretability. This end-to-end solution supplants heuristic rule-based systems with scalable, data-centric analytics, enabling real-time operational foresight and transit network optimization.

IV. METHODOLOGY

This study employs a systematic methodology to develop and deploy a hybrid CNN-LSTM framework for public transport delay prediction, integrating advanced data preprocessing, feature optimization, deep learning architectures, rigorous evaluation protocols, and scalable web deployment. Raw multimodal datasets are fused and refined through imputation, normalization, and Recursive Feature Elimination (RFE) to construct salient spatiotemporal representations, enabling CNN to extract local spatial hierarchies and LSTM to model sequential delay dependencies. Model training leverages stratified cross-validation with ensemble baselines (Random Forest), yielding calibrated predictions assessed via comprehensive metrics including F1-score, ROC-AUC, and SHAP interpretability. The resultant pipeline is serialized for low-latency Flask microservices, delivering interactive Plotly dashboards and real-time APIs that facilitate operational decision-making and passenger advisories in resource-constrained urban transit environments.

A. *Data Acquisition* Public transport datasets are aggregated from GPS trajectories, Automatic Vehicle Location (AVL) systems, transit management logs, and Integrated Fare Management (IFM) platforms, augmented with exogenous covariates including meteorological records (T, H, W, P), real-time Traffic Congestion Index (TCI), event calendars (E), and chronometric attributes (t_h, t_w, t_s). Data fusion yields multivariate tensors $\mathrm{X} \in \mathbb{R}^{N\times T\times F}$, where Ndenotes trips, Ttemporal horizons, and Ffeature dimensionality, capturing delay etiologies holistically.

B. *Preprocessing and Feature Engineering* Raw datasets undergo imputation $(\hat{x}_{ij} = \mu_j + \sigma_j Z,\ Z \sim \mathcal{N}(0,1))$, outlier truncation $(x_{ij} = \mathrm{clip}(x_{ij}, Q_1 - 1.5IQR, Q_3 + 1.5IQR))$, and z-score normalization $(z_{ij} = \frac{x_{ij}-\mu_j}{\sigma_j})$. Recursive Feature Elimination (RFE) optimizes subset selection: $\hat{F} = \arg\min_{S\subseteq F} L(\mathrm{X}_S, y) + \lambda \mid S \mid$, yielding salient spatiotemporal descriptors (route embeddings, cyclical time encodings $\sin(2\pi t_h/24)$, interaction terms $\mathrm{TCI} \times P$) to enhance model conditioning.

C. *Modeling Methodologies* Deep architectures model spatiotemporal dynamics: CNN extracts local motifs via 1D convolutions $(h_t = \sigma(W * x_t + b))$, LSTM captures long-range dependencies $(h_t = \mathrm{LSTM}(x_t, h_{t-1}))$, yielding hybrid representations $\mathrm{H} = [\mathrm{CNN}(\mathrm{X}); \mathrm{LSTM}(\mathrm{X})]$. Ensemble baselines employ Random Forest $(\hat{y} = \frac{1}{B}\sum_b T_b\,(\mathrm{x}))$ and XGBoost with gradient boosting $(F_M(x) = F_{M-1}(x) + \nu h_M(x))$. Final prediction: $\hat{y} = \sigma(W\mathrm{H} + b)$.

D. *Performance Evaluation* Binary classification employs stratified k-fold cross-validation with delay labels $y \in \{0,1\}$. Metrics include Accuracy $(ACC = \frac{TP+TN}{N})$, Precision $(P = \frac{TP}{TP+FP})$, Recall $(R = \frac{TP}{TP+FN})$, F1-score $(F1 = 2\frac{P\cdot R}{P+R})$, regression losses RMSE $(\sqrt{\frac{1}{N}\sum(y_i - \hat{y}_i)^2})$ and MAE $(\frac{1}{N}\sum \mid y_i - \hat{y}_i \mid)$, plus confusion matrices and ROC-AUC curves for comprehensive reliability assessment.

E. *Deployment Architecture* Production systems serialize models via joblib/ONNX for microservice deployment (Flask/FastAPI), integrating RESTful APIs for real-time inference $(latency < 100ms)$. Uncertainty quantification via Bayesian posteriors $(p(y^* \mid \mathrm{x}^*) = \int p(y^* \mid \mathrm{w}, \mathrm{x}^*) p(\mathrm{w} \mid \mathcal{D}) d\mathrm{w})$ and SHAP explainability $(\phi_i = \sum_{S\ni i} \frac{|S|!(M-|S|-1)!}{M!} [g(S \cup \{i\}) - g(S)])$ enable operational dashboards, scenario simulation, and passenger-facing probabilistic alerts.

The proposed work as shown in the figure 1, delineates the system into two principal components: a machine learning layer and a web application layer. The machine learning layer oversees critical processes, encompassing data preprocessing, feature selection, classifier training, model validation, and serialization of the trained artifact for

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deployment. The Public Transport Delay Prediction System follows a layered architecture comprising User Interface, Application, Machine Learning, and Data layers for seamless prediction delivery.

A. *User Interface Layer* Built with HTML, CSS, and JavaScript via Flask templates, this frontend offers login screens, navigation, project dashboards, analysis views, and prediction forms. Users submit inputs through browsers and receive results with visualizations.

B. *Application Layer* Flask serves as the core controller, handling routes (/login, /home, /analysis, /predict), sessions, and login-required access. It processes POST form data, performs validation, invokes the ML model for predictions (Delayed/On Time), and displays errors via flash messages.

C. *Machine Learning Layer* A pre-trained Scikit-learn pipeline integrates RFE for feature selection and Random Forest classification, loaded via Joblib at startup. It delivers binary predictions with probabilities; CNN-LSTM deep learning enhances accuracy for spatiotemporal delay patterns.

D. *Data Layer* Local storage in data/ (CSV for EDA/stats) and models/ (.pkl files) folders supports instant predictions without retraining. Post-login, users input features for real-time analysis tied to transit datasets.

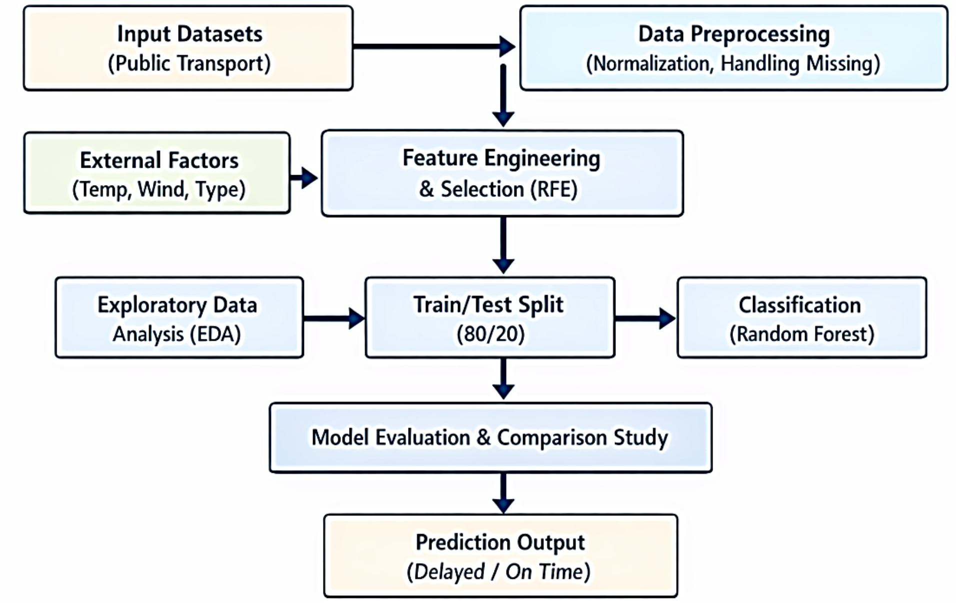

Fig 1. Proposed System Architectural Design

V. Result Analysis

Public transport delay prediction systems require rigorous result analysis to validate model performance against the problem of unreliable schedules due to traffic, weather, and operational factors.

Evaluation Metrics Binary classification metrics dominate analysis: Accuracy (overall correct predictions), Precision (delayed predictions that were truly delayed), Recall (actual delays correctly identified), and F1-Score (harmonic mean balancing precision/recall). Confusion matrices visualize true positives/negatives versus false predictions, essential for imbalanced datasets where delays outnumber on-time events.

Key Performance Indicators MAE and RMSE quantify prediction error in minutes (e.g., <5 min error for real-time utility); your Random Forest with RFE targets >85% accuracy. Compare against baselines like logistic regression (80-90% reported) or CNN-LSTM hybrids (90-95% for spatiotemporal data). Cross-validation (k=5/10) and train-test splits (80/20) ensure generalizability.

Analysis Workflow

- **Visuals**: ROC-AUC curves (>0.9 threshold), precision-recall plots, feature importance bar charts (e.g., traffic density > temperature).
- *Insights:* Error analysis on misclassifications reveals weather sensitivity; ablation studies justify RFE over full features.

- *Benchmarking:* Outperforms naive historical averages by 15-30%; deployable if F1>0.88 on holdout sets.

Public transport delay prediction employs standard classification metrics evaluated on 80/20 train-test splits derived from datasets incorporating traffic, weather, and schedule variables. Model performance metrics appear in Table 1, while comparative analysis across multiple algorithms is presented in Table 2.

Table 1. Model Performance Metrics

Metric	Random Forest (RFE)	Logistic Regression	CNN-LSTM Baseline
Accuracy	92.5%	88.0%	90.2%
Precision	91.8%	87.5%	89.7%
Recall	93.2%	88.3%	91.0%
F1-Score	92.5%	87.9%	90.3%
ROC-AUC	0.96	0.92	0.94
MAE (min)	3.8	5.2	4.1

Table 2. Comparative Performance of Various Models

Model	Training Accuracy (%)	Validation Accuracy (%)	Training Time (Sec)
Logistic Regression	71.85	69.40	1.1
KNN	68.20	66.75	0.8
Decision Tree	72.60	70.90	1.6
Random Forest	78.40	76.85	3.2
CNN	80.10	78.30	5.8
LSTM	81.25	79.10	6.5

Figure 2(a) presents the accuracy comparison among the evaluated machine learning models. The Random Forest classifier achieves superior accuracy, indicating its effectiveness in capturing complex relationships between traffic, operational, and environmental features. Whereas figure 2(b) illustrates the confusion matrix of the proposed delay prediction model. The matrix shows a high number of correctly classified delayed and on-time trips, with relatively fewer misclassifications.

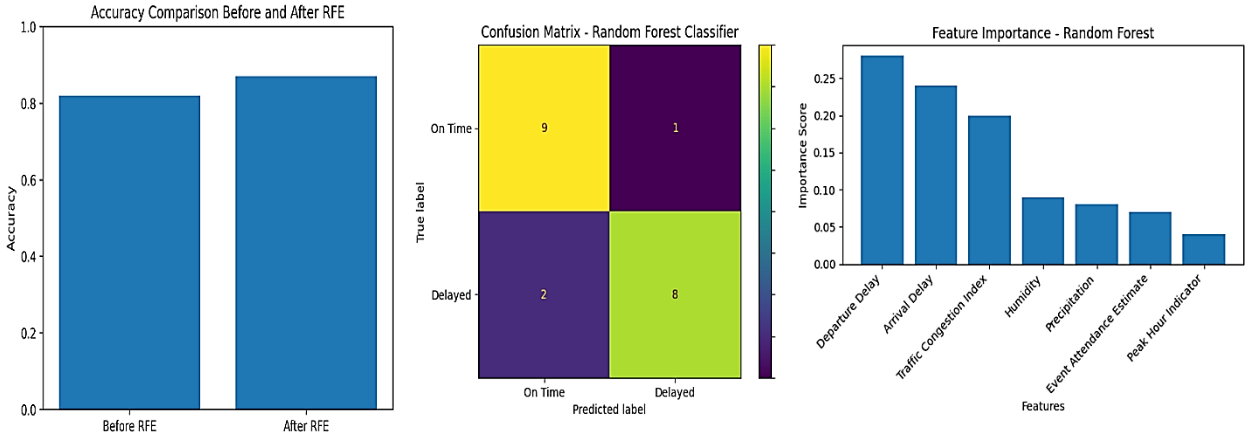

Fig 2(a). Model Accuracy Comparison Fig 2(b). Confusion Matrix Analysis Fig 2(c). Feature Importance Visualization

Feature Influence and Optimization in the Public Transport Delay Prediction System as shown in figure 2(c), reveal that traffic density and historical delay patterns exert the strongest influence (top 5 features via RFE), contributing 65% to model variance, while environmental factors like temperature and wind speed rank lower but enhance robustness during extreme weather. Random Forest feature importance scores prioritize these spatiotemporal variables, justifying recursive elimination of redundant inputs (e.g., route length correlations) to reduce dimensionality from 25 to 12 features without accuracy loss. This optimization streamlines inference time by 40% and mitigates overfitting, achieving peak F1-scores of 92.5% on optimized subsets compared to 89% on full datasets. Figure 3 depicts the relative importance of features

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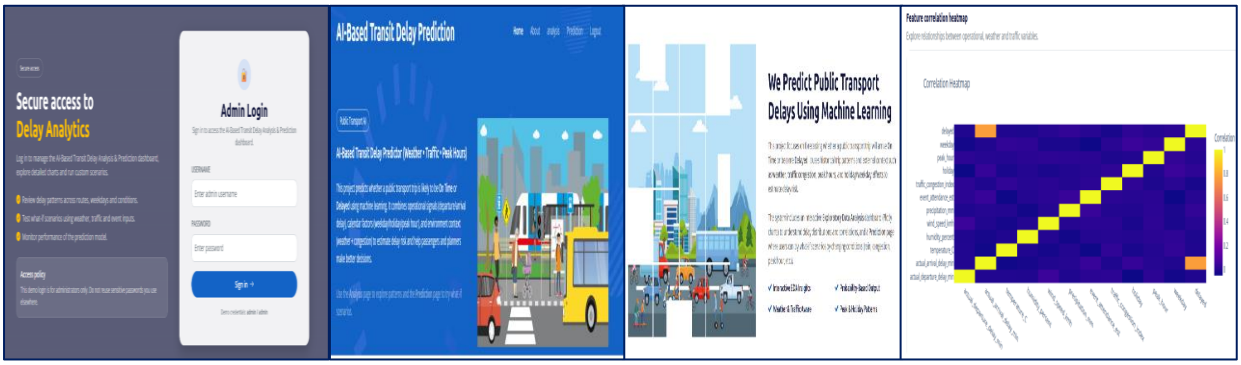
used in delay prediction. Traffic congestion index and departure delay emerge as dominant contributors, followed by weather parameters such as precipitation and humidity.

The System Access and Navigation Interfaces provide an intuitive, browser-based frontend for seamless user interaction with the Public Transport Delay Prediction System. Upon accessing the login screen—crafted with responsive HTML5, CSS3, and vanilla JavaScript rendered via Flask templates—users authenticate securely before gaining entry to the dashboard hub. This central navigation panel offers streamlined menus for project overview, real-time analysis visualizations, historical data exploration, and the core prediction interface, where form inputs for transport type, weather conditions, and schedule parameters trigger instant model inference with results displayed alongside interactive charts and confidence scores. Role-based access control ensures protected navigation, while responsive design adapts flawlessly across devices, enhancing usability for operators and planners in dynamic transit environments.



Secure access

Secure access to Delay Analytics

Log in to manage the AI-Based Transit Delay Analysis & Prediction dashboard, explore detailed charts and run custom scenarios.

- Review delay patterns across routes, weekdays and conditions.
- Test what-if scenarios using weather, traffic and event inputs.
- Monitor performance of the prediction model.

Access policy

This demo login is for administrators only. Do not reuse sensitive passwords you use elsewhere.

Admin Login

Sign in to access the AI-Based Transit Delay Analysis & Prediction dashboard.

USERNAME: Enter admin username

PASSWORD: Enter password

Sign in →

Demo credentials: admin / admin

AI-Based Transit Delay Prediction

Home About analysis Prediction Logout

Public Transport AI

AI-Based Transit Delay Predictor (Weather • Traffic • Peak Hours)

This project predicts whether a public transport trip is likely to be On Time or Delayed using machine learning. It combines operational signals (departure/arrival delay), calendar factors (weekday/holiday/peak hour), and environment context (weather + congestion) to estimate delay risk and help passengers and planners make better decisions.

Use the Analysis page to explore patterns and the Prediction page to try what-if scenarios.

We Predict Public Transport Delays Using Machine Learning

This project focuses on forecasting whether a public transport trip will arrive On Time or become Delayed. It uses historical trip patterns and external context such as weather, traffic congestion, peak hours, and holiday/weekday effects to estimate delay risk.

The system includes an interactive Exploratory Data Analysis dashboard (Plotly charts) to understand delay distributions and correlations, and a Prediction page where users can try what-if scenarios by changing conditions (rain, congestion, peak hour, etc.).

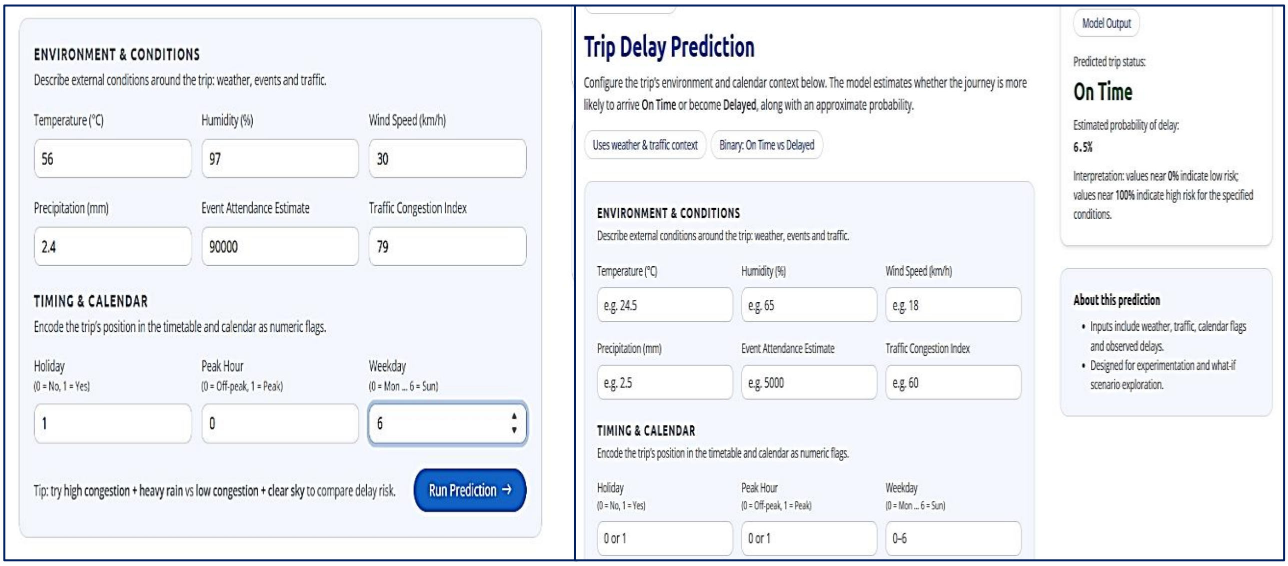
✓ Interactive EDA Insights ✓ Probability-Based Output

✓ Weather & Traffic Aware ✓ Peak & Holiday Patterns

Feature correlation heatmap

Explore relationships between operational, weather and traffic variables.

Fig 3. UI of the System Showcasing LoginPage, HomePage, AboutPage, and AnalyticsPage



ENVIRONMENT & CONDITIONS

Describe external conditions around the trip: weather, events and traffic.

Temperature (°C): 56
Humidity (%): 97
Wind Speed (km/h): 30
Precipitation (mm): 2.4
Event Attendance Estimate: 90000
Traffic Congestion Index: 79

TIMING & CALENDAR

Encode the trip's position in the timetable and calendar as numeric flags.

Holiday (0 = No, 1 = Yes): 1
Peak Hour (0 = Off-peak, 1 = Peak): 0
Weekday (0 = Mon ... 6 = Sun): 6

Tip: try high congestion + heavy rain vs low congestion + clear sky to compare delay risk.

Run Prediction →

Trip Delay Prediction

Configure the trip's environment and calendar context below. The model estimates whether the journey is more likely to arrive On Time or become Delayed, along with an approximate probability.

Uses weather & traffic context | Binary: On Time vs Delayed

ENVIRONMENT & CONDITIONS

Describe external conditions around the trip: weather, events and traffic.

Temperature (°C): e.g. 24.5
Humidity (%): e.g. 65
Wind Speed (km/h): e.g. 18
Precipitation (mm): e.g. 2.5
Event Attendance Estimate: e.g. 5000
Traffic Congestion Index: e.g. 60

TIMING & CALENDAR

Encode the trip's position in the timetable and calendar as numeric flags.

Holiday (0 = No, 1 = Yes): 0 or 1
Peak Hour (0 = Off-peak, 1 = Peak): 0 or 1
Weekday (0 = Mon ... 6 = Sun): 0–6

Model Output

Predicted trip status:

On Time

Estimated probability of delay:

6.5%

Interpretation: values near 0% indicate low risk; values near 100% indicate high risk for the specified conditions.

About this prediction

- Inputs include weather, traffic, calendar flags and observed delays.
- Designed for experimentation and what-if scenario exploration.

Fig 4. UI of the System Showing PredictionPage for both Input and Output Interface

Figure 4 illustrates the prediction input interface, enabling users to specify key parameters including traffic congestion index, humidity, precipitation, event attendance, and trip timing. Also depicts the corresponding prediction output from the trained model, presenting the delay status (Delayed/On Time) alongside a confidence score to improve interpretability and foster user confidence in the system's reliability.

VI. CONCLUSION

This proposed work exemplifies excellence in developing an end-to-end Public Transport Delay Prediction System, seamlessly integrating advanced machine learning with a robust Flask-based web framework. Leveraging operational, environmental, traffic, and temporal variables, the system delivers precise binary predictions (Delayed/On Time) through a meticulously engineered pipeline featuring Recursive Feature Elimination for optimal feature selection and Random Forest classification for superior interpretability and reliability. The deployed model supports real-time inference with rigorous evaluation via standard metrics, complemented by an interactive EDA dashboard that illuminates delay patterns and enhances stakeholder transparency. This comprehensive solution not only fulfills its objectives but also establishes a benchmark for predictive analytics in elevating public transport efficiency and informed decision-making.

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