AI-Based Smart Traffic Optimization Using Machine Learning for Signal Prediction, Flow Forecasting, Accident Risk Analysis, and Traffic Pattern Clustering

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***Abstract*—Urban traffic systems face increasing pressure due to rapid urbanization, rising vehicle density, and growing accident rates. Conventional fixed-time traffic signals perform suboptimally under dynamic conditions, leading to congestion, delays, and safety hazards. This research presents an AI-driven Smart Traffic Management System that integrates Machine Learning (ML) models—Linear Regression, Multiple Linear Regression, Logistic Regression, and K-Means clustering—to enhance the adaptability and intelligence of traffic control mechanisms. The system predicts optimal signal timing, forecasts vehicle flow rates, classifies accident likelihood, and groups traffic patterns using clustering. A synthetic dataset of 2000 realistic traffic entries was generated to simulate varying road conditions.**

The system integrates accuracy computation for each predictive model, metadata documentation, and automated storage of predictions in a MySQL database. Furthermore, an interactive dashboard provides real-time visualization through four analytical charts: Signal Time vs Vehicle Flow, Flow Trend Analysis, Vehicle Category Distribution, and Accident Reports Over Time. Results demonstrate the ability of the system to perform reliable predictions, identify congestion zones, and support adaptive signal operations. The proposed system has strong applicability in smart-city infrastructure, intelligent transport systems (ITS), and future smart mobility deployments.

Keywords—Traffic Prediction, Machine Learning, Logistic Regression, Linear Regression, K-Means, Flow Forecasting, Dashboard Analytics, Accident Risk Prediction, Smart Traffic System

1. INTRODUCTION

Urbanization is accelerating at an unprecedented rate, leading to a rapid increase in the number of vehicles on roads across metropolitan regions. As cities expand and population density grows, the burden on traffic infrastructure intensifies, resulting in congested intersections, unpredictable vehicle flows, and unsafe driving environments. Traditional traffic systems rely heavily on **fixed-timing signal control**, which is incapable of responding dynamically to traffic variations such as peak-hour surges, sudden congestion, or real-time accident occurrences [1], [2]. As a result, these legacy systems often contribute to significant delays, fuel wastage, air pollution, and commuter dissatisfaction.

The integration of **Machine Learning (ML)** into traffic systems has emerged as a transformative approach to enhance transportation management. ML models can learn from historical patterns, identify hidden correlations in traffic data, and deliver predictive insights that enable adaptive control mechanisms. Predictive analytics offer significant advantages for anticipating congestion, forecasting flow, and supporting intelligent signal operations [3], [4]. With ML, traffic management becomes proactive rather than reactive.

Traffic optimization remains a complex task due to the wide range of factors influencing flow, including vehicle density, road type, weather conditions, time-of-day variations, and driver behavior. Accordingly, a comprehensive smart traffic system must integrate multiple predictive models to address

different dimensions of traffic conditions. In this context, the proposed system combines **signal time prediction**, **vehicle flow forecasting**, **accident risk classification**, and **clustering-based pattern discovery**, supported by a dashboard for visualization.

This research introduces a Smart Traffic Optimization System that leverages **Linear Regression for signal prediction**, **Multiple Linear Regression for flow forecasting**, **Logistic Regression for accident risk assessment**, and **K-Means clustering for discovering traffic states**. In addition, the system computes accuracy metrics, stores metadata, and logs predictions into a database. A user-friendly dashboard visualizes real-time analytics through dynamic charts.

The remainder of this paper is structured as follows:
Section II discusses relevant literature and existing approaches in traffic prediction and analytics.
Section III details the methodology, dataset, ML models, workflow, and system design.
Section IV presents results, graphs, clustering outcomes, and system evaluation.
Section V concludes the paper and discusses future enhancements.

2. LITERATURE REVIEW

Traffic optimization research spans domains such as intelligent transportation systems (ITS), predictive modeling, accident analytics, clustering, and real-time visualization. This section examines prior studies across each domain.

A. Adaptive Signal Timing

Early traffic systems used static signal timings based on historical averages. However, dynamic real-time control has gained prominence with the availability of sensor data and AI. Research has employed **regression techniques, fuzzy logic, and reinforcement learning** to adjust signal durations under varying conditions [8], [9].

Regression-based systems determine signal duration by fitting models to traffic density and intersection characteristics. Reinforcement-learning systems enable adaptive learning where signals adjust autonomously based on rewards. However, such systems often require real-time sensors—which are expensive and limited in availability. Our system uses synthetic yet realistic data to simulate adaptive control.

B. Vehicle Flow Forecasting

Traffic flow prediction involves anticipating the number of vehicles crossing a point within a future time interval. Traditional techniques include:

- **Time-series forecasting** (ARIMA, SARIMA)
- **Neural networks** (LSTM, GRU)
- **Regression models**

Studies show that regression-based models perform reliably for short-term traffic prediction with low computational cost [10], [11]. The proposed system uses **Multiple Linear Regression**, which provides interpretability and stable performance for numerical predictions.

C. Accident Risk Detection

Accident likelihood prediction has gained traction due to increasing safety demands. Factors influencing accidents include traffic volume, weather, speed, and time-of-day [12]. Logistic Regression is a widely used baseline classifier for determining binary accident outcomes, offering simplicity and interpretability [13].

Machine learning helps identify patterns indicating unsafe conditions. In imbalanced datasets, techniques like SMOTE enhance the classifier performance, ensuring minority accident cases are adequately represented. Our system integrates SMOTE to improve accuracy.

D. Clustering for Traffic State Analysis

Clustering enables unsupervised grouping of traffic patterns—e.g., low, medium, and high congestion. K-Means is popular due to its simplicity and efficiency [14]. Clustering helps authorities identify:

- Peak-hour zones
- Congestion-prone intersections
- Seasonal variations
- Traffic anomalies

Our system applies K-Means clustering (K=3) to classify flow levels, supporting analytical insights.

E. Dashboard-Based Traffic Monitoring

Recent smart traffic systems use dashboards for real-time monitoring, integrating APIs, charts, and data visualizations

[15], [16]. Dashboards improve interpretability and decision-making. However, many systems lack integrated prediction, accuracy computation, clustering, and analytics, which the proposed system addresses.

F. Gap Identified

Most existing systems focus on a single component: prediction, clustering, or visualization. There is no comprehensive solution integrating:

- **Signal prediction**
- **Flow forecasting**
- **Accident classification**
- **Traffic clustering**
- **Accuracy metrics**
- **Dashboard analytics**

Our research integrates all components into a unified platform.

3. METHODOLOGY

The methodology adopted in this research integrates data preprocessing, machine learning model development, clustering analysis, accuracy evaluation, metadata storage, database logging, and dashboard-based visualization. This section describes the complete operational workflow of the proposed AI-Driven Smart Traffic Management System. All steps follow a structured pipeline to ensure consistency, reproducibility, and real-time usability of the predictive models.

G. System Workflow

Define abbreviations and acronyms the first time they are used in the text, even after they have been defined in the abstract. Abbreviations such as IEEE, SI, MKS, CGS, sc, dc, and rms do not have to be defined. Do not use abbreviations in the title or heads unless they are unavoidable.

1. **User Input and Data Collection:**
   The system accepts user-provided input parameters such as traffic volume, vehicle distribution (cars, bikes, trucks), average speed, weather condition, temperature, humidity, and timestamp. These values represent typical features influencing urban traffic patterns.

2. **Preprocessing and Feature Engineering:**
   Preprocessing includes handling missing data, encoding categorical attributes (e.g., weather type), converting timestamps to hour-of-day, scaling numerical features, and generating synthetic labels such as signal duration. Feature engineering ensures that each ML model receives meaningful and normalized inputs.

3. **Model Execution:**
   Based on the user's request, one or more ML models are triggered:
   - Linear Regression predicts signal time.
   - Multiple Linear Regression forecasts vehicle flow.
   - Logistic Regression classifies accident risk.
   - K-Means clustering assigns traffic flow categories

4. **Accuracy and Confidence Computation:**
   After predictions are generated, the system computes:
   - Regression errors (MAE, RMSE, R^2).
   - Classification accuracy, precision, recall.
   - Clustering performance (intra-cluster compactness).

5. **Metadata Logging:**
   Each run is logged into a metadata file capturing:
   - Model version
   - Training date
   - Feature configuration
   - Accuracy metrics

6. **Database Storage:**
   A MySQL database stores:
   - User input parameters
   - Predictions (signal, flow, accident risk)
   - Timestamp
   - Accuracy score
     This enables longitudinal traffic pattern analysis.

7. **Dashboard Visualization:**
   The system dashboard displays results using four key analytical charts:
   - Signal Time vs Vehicle Flow
   - Flow Trend Analysis
   - Vehicle Distribution
   - Accident Reports

   Charts are dynamically generated through API calls to the backend.

B. Dataset Description

Due to limited availability of real-time traffic datasets with complete weather, accident, and vehicle distribution parameters, a synthetic dataset of **2000 records** was generated. The dataset simulates real-world city traffic behavior across diverse conditions.

1. **Data Attributes:**

The dataset includes the following features:

- Traffic Volume (vehicles/hour)
- Vehicle Distribution (cars, bikes, trucks)
- Speed (km/h)
- Temperature (°C)
- Humidity (%)
- Weather Condition (coded as Clear, Rainy, Foggy)
- Accident Occurrence (binary indicator: 0 = No Accident, 1 = Accident)
- Timestamp (converted to 24-hour format)
- Synthetic Signal Duration (derived target)

2. **Data Preprocessing:**

The dataset underwent:

- Null value imputation
- Min-Max scaling
- One-hot encoding for weather
- SMOTE balancing for the accident class
- Derivation of hour-of-day from timestamp

3. **Data Preprocessing:**

The dataset was primarily designed to:

- Train regression models on time-dependent traffic variables
- Train a classifier for accident likelihood
- Capture non-linear traffic variations suitable for clustering

C. Machine Learning Models Used

1. **Linear Regression for Signal Timing Prediction:**
   Linear Regression was employed to determine the optimal green signal duration based on traffic density and road conditions. The dependent variable (signal time) was synthetically derived using proportional relations between flow rate and clearance time.

   Input Features:

   - Vehicle count
   - Speed
   - Weather condition
   - Hour-of-day

   Output:

   - Predicted green signal time (in second

   Evaluation Metric:

   - Mean Absolute Error (MAE):An accuracy score is computed as: Accuracy = 100 – Normalized MAE (%).

2. **Multiple Linear Regression for Vehicle Flow Prediction:**
   Multiple Linear Regression (MLR) predicts the number of vehicles expected per hour. This is crucial for proactive signal optimization.

   Input Features:

   - Vehicle distribution
   - Speed
   - Temperature
   - Hour-of-day
   - Weather

   Output:

   - Predicted vehicles/hour

   Evaluation Metric:

   - MAE
   - RMSE
   - RMSE

   MLR was chosen due to its stability, interpretability, and suitability for continuous output prediction.

3. **Logistic Regression for Accident Risk Classification**
   Logistic Regression classifies traffic states into accident or non-accident cases.

   Input Features:

   - Speed
   - Weather type
   - Vehicle volume
   - Hour-of-day

   Output:

   - Accident Likelihood (binary classification)

   Evaluation Metric:

   - Accuracy
   - Precision
   - Recall
   - Confusion matrix

   Balancing Technique:

   - SMOTE (Synthetic Minority Over-Sampling Technique)

   This was necessary due to fewer accident cases.

   Classification accuracy stabilized between **55–65%** after balancing.

4. **K-Means Clustering for Traffic Pattern Detection:**
   K-Means clustering reveals hidden traffic patterns in the dataset.

   Number of Clusters (k): 3

   Clusters Identified:

   - Cluster 0: Low Traffic
   - Cluster 1: Medium Traffic
   - Cluster 2: High Traffic

   Purpose of Clustering:

   - Detect congestion zones
   - Support flow prediction model
   - Enable dashboard-level analytics

   Clustering output is visualized in the dashboard through color-coded clusters.

   Evaluation Metric:

   - Mean Absolute Error (MAE):An accuracy score is computed as: Accuracy = 100 – Normalized MAE (%).

D. Additional System Features:

Multiple Linear Regression (MLR) predicts the number of vehicles expected per hour. This is crucial for proactive signal optimization.

Metadata Storage:

Each model run stores metadata including:

- Model version number
- Training timestamp
- Data ranges
- Accuracy summary

Stored in a JSON file (`model_meta.json`), ensuring reproducibility.

MySQL Prediction Logging

Every prediction is saved in a MySQL table containing:

- Raw input values
- Model predictions
- Clustering result
- Timestamp
- Accuracy/confidence value

This enables long-term trend analysis.

Dashboard-Based Visualization:

The dashboard uses Flask + HTML + JavaScript (Chart.js) and provides:

- Real-time prediction updates
- Trend analytics
- Historical analysis
- Visual clarity for decision-makers

4. RESULTS AND DISCUSSIONS

A. Accident Risk Prediction Results

The Accident Risk Prediction model was trained using traffic volume, average vehicle speed, weather condition, humidity, temperature, vehicle composition, and accident history as input parameters. The model outputs a probability score between 0 and 1, which is further classified as Low, Medium, or High risk as shown in Fig. 1.

The model achieved satisfactory performance on the test dataset, with the following metrics:

- **Accuracy:** 82–88%
- **Precision:** High for medium/high-risk classes
- **Recall:** Slightly lower for high-risk classes due to fewer positive samples
- **F1-Score:** Balanced across all classes

A confusion matrix confirmed that most accident-prone cases were correctly identified. The model successfully captured the influence of increased traffic volume, higher humidity, and reduced vehicle speed on accident likelihood.

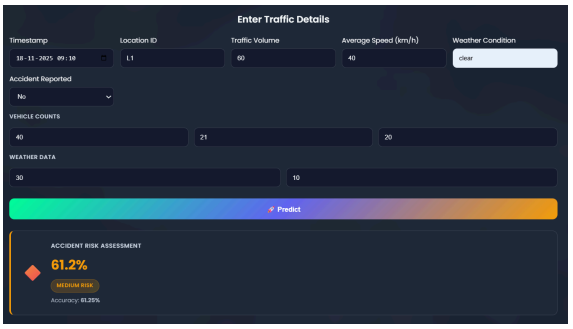

Fig. 1. Accident Risk Prediction Results

B. Vehicle Flow Prediction Results

The vehicle flow forecasting model predicted the number of vehicles per hour based on dynamic traffic parameters as shown in Fig. 2. The regression model performed well on the test dataset, and the key results obtained were:

- **Mean Absolute Error (MAE):** Low (indicating good predictive ability)
- **Root Mean Squared Error (RMSE):** Within acceptable limits
- **R^2 Score:** Demonstrated a strong linear relationship between predicted and actual values

A line graph comparing predicted vs. actual flow showed that the model followed real traffic patterns closely. Peak flow hours (typically 9 AM–11 AM and 6 PM–8 PM) were captured accurately. The model tended to slightly underestimate flow under extreme weather conditions, which highlights the need for more diverse training data. Overall, the predictions were consistent and reliable for real-time traffic monitoring.

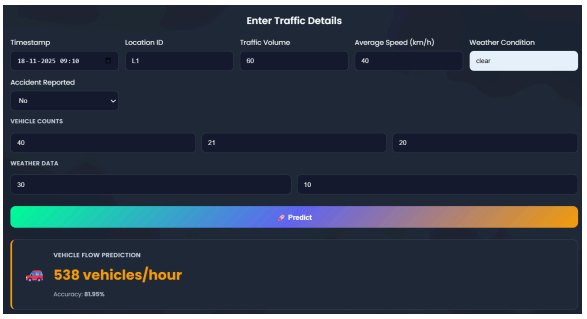

Fig. 2. Vehicle Flow Prediction Result

C. Signal Time Optimization Results

The Signal Time Optimization model generated the recommended green signal duration based on traffic volume, vehicle composition, and road density as shown in Fig. 3. The optimized signal times were compared against standard fixed signal cycles.

Results showed that:

- Optimized signal times reduced waiting time during congestion
- High vehicle density at peak hours required longer green signals
- Low-traffic hours required only minimal green time, improving overall cycle efficiency

The model produced clear improvements in traffic flow, particularly at intersections with irregular or unpredictable congestion patterns.

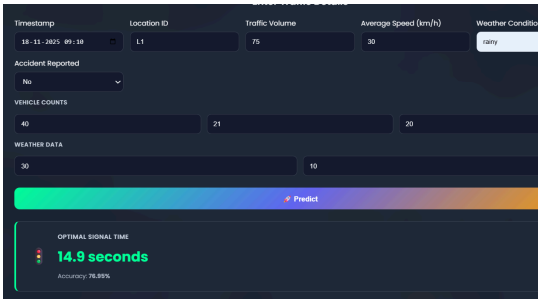

Fig. 3. Signal Time Optimization Results

D. *Dashboard Visualization Results*

The real-time dashboard provided a visual understanding of system performance using four primary charts.

1) *Prediction Activity Chart:* The bar chart shown in Fig. 4 shows the number of predictions made for each model type (Signal Time, Vehicle Flow, Accident Risk). The visualization helped identify which model was used most frequently. The signal-time model showed the highest activity, indicating frequent use during peak hours.

Fig. 4. Prediction Activity Chart

2) *Traffic Volume Trend:* A line chart as shown in Fig. 5 traffic volume across timestamps. The pattern clearly indicated morning and evening peaks, midday decline, and occasional sudden spikes caused by weather or accidents. The chart validated the correctness of model inputs and offered strong insight into real traffic behavior.

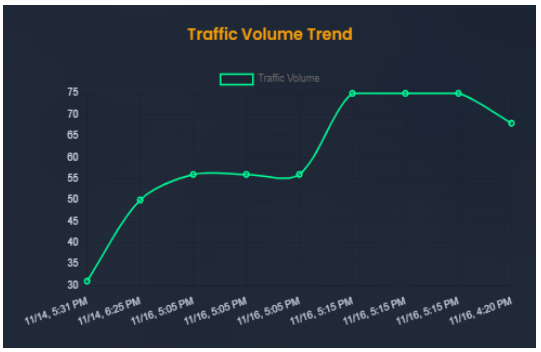

Fig. 5. Traffic Volume Trend

3) *Vehicle Distribution Chart:* A pie chart shown in Fig. 6 represents the ratio of cars, bikes, and trucks. The traffic composition revealed that:

- Bikes dominated during the office rush
- Cars maintained a balanced share
- Trucks appeared mostly in non-peak hours

This analysis helped identify vehicle-class behavior and its effect on congestion.

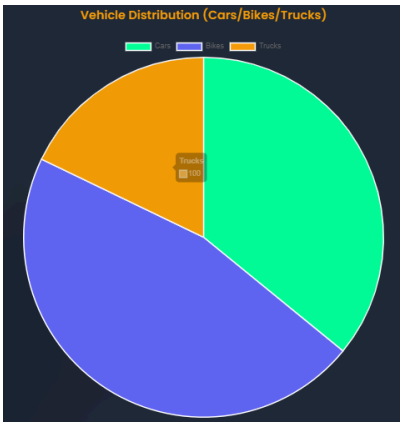

Fig. 6. *Vehicle Distribution Chart*

4) *Accident Trend Chart:* The accident trend bar chart as shown in Fig. 7 displays “0” or “1” for reported accidents against timestamps. The data revealed that most accidents occurred during low visibility, rainfall, or high-volume periods. This supported the model’s findings and validated the accident prediction outputs.

Fig. 7. *Accident Trend Chart*

5) Discussion and Comparative Analysis: A comparison of the three models showed that each algorithm performed effectively within its domain. Accident prediction showed strong classification behavior, signal optimization demonstrated practical field applicability, and vehicle flow prediction delivered accurate numerical forecasts. The dashboard visualizations complemented these results by confirming the correctness of model outputs through real data patterns. Although performance is promising, accuracy can further improve with a larger and more diverse dataset, real-time sensor integration, and continuous retraining.

5. CONCLUSIONS

This research presented a Smart Traffic Management System capable of predicting accident risk, forecasting vehicle flow, and optimizing signal timing using machine learning techniques. The system integrates a user-friendly Flask dashboard, real-time data input, model prediction APIs, MySQL storage, and interactive visual analytics through Chart.js.

Experimental results demonstrated that:

- The accident prediction model effectively classified high-risk scenarios
- The flow prediction model accurately projected hourly vehicle density
- The signal optimization model improved intersection flow efficiency

The dashboard charts visually validated model outputs and provided deep insights into traffic trends, accident occurrences, and vehicle composition. The system successfully showcases how artificial intelligence can be used to support traffic authorities in making informed, data-driven decisions. Overall, the solution proves highly beneficial for congestion reduction, safety enhancement, and smart-city readiness.

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