**Vital Annex: International Journal of Novel Research in Advanced Sciences**
**ISSN: 2751-756X**
*Volume 04 Number 09 (2025)*
*https://journals.innoscie.com/index.php/ijnras*

*Article*

# Machine Learning Models for Traffic Congestion Prediction in Urban Smart Mobility Systems

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**Abstract:** Urban traffic congestion poses significant challenges to sustainable mobility, economic productivity, and environmental quality in modern cities. With the increasing deployment of Internet of Things (IoT) devices and real-time data collection systems, smart cities are generating vast volumes of traffic-related data that can be harnessed for predictive analytics. This study carefully looks at how machine learning models are used to accurately predict traffic jams in smart city transportation systems. We check and compare how well different supervised learning models work, like random forest networks, support vector regression, gradient boosting machines, and long short-term memory, using real traffic data from sensors, GPS devices, and city infrastructure. The process involves cleaning up data, creating features, training models, and adjusting settings to get the best prediction results. The tests showed that LSTM networks, because they can understand patterns over time, are better than traditional machine learning at predicting traffic jams, with a root mean squared error of 5.40 and a mean absolute percentage error of 9.7%. However, tree-based models like GBM are good for providing clear and efficient explanations, along with good accuracy, making them useful in smart city environments with limited resources. This research paper discusses the importance of understanding how the model works, choosing the right features, and the effects of adding machine learning-based prediction tools to city traffic management systems. The findings support the idea that machine learning can greatly improve real-time traffic monitoring, allowing for quick action to reduce its effects and improve smart city transportation.

**Keywords:** Traffic Overcrowding Prediction, Machine Learning, Smart Mobility, Urban Transportation, LSTM Networks, Gradient Boosting, Real-Time Forecasting, Intelligent Transportation Systems (ITS), Spatiotemporal Data, Smart Cities

**Citation:** Hussein, M. N. Machine Learning Models for Traffic Congestion Prediction in Urban Smart Mobility Systems. Vital Annex: International Journal of Novel Research in Advanced Sciences 2025, 4(9), 369-377.

Received: 15th Aug 2025
Revised: 30th Aug 2025
Accepted: 10th Sept 2025
Published: 30th Sept 2025



## 1. Introduction

The big increase in city populations has made the city's transportation systems work harder. Traffic jams are now a common and difficult problem, causing big money problems, more greenhouse gases, more fuel use, and a worse quality of life [1], [2]. Old traffic control systems that rely too much on unchanging signals, set traffic rules, and people watching have been shown to be not good enough for today's changing and surprising city traffic [3]. To fix these problems, a smart city movement has come up with the idea of smart travel, which uses new technologies like the Internet of Things (IoT), special car networks (VANETs), cloud computing, and edge computing to create smart transportation systems (ITS) [4], [5]. These systems create huge amounts of different kinds of real-time data, like GPS tracks, loop detector data, surveillance feeds, and traffic data from groups of people. Understanding and carefully studying this data is important for knowing how traffic acts, guessing when jams will happen, and telling future traffic control plans [6]. Machine learning (ML) is a helpful tool for finding useful information from complex and varied market data. Using past and present data, algorithms learn hidden connections, time patterns, and location links that regular or statistical links might

miss. Predictive forecasts help with key things for predicting traffic jams in different places, knowing the time, and needing communication and guidance. This research wants to look at how well different machine learning methods work at predicting traffic jams in cities [7], [8]. The research especially looks at comparing how well several supervised models work, like type-based linear ones (random forest and stacked boosting machines), support vector regression (SVR), and learning methods like long short-term memory networks (LSTM). These advancements were tested using data available for smart systems in city areas. Key findings of this research include:

a. A multi-data-driven framework, including banking data, profit extraction, and surge classification based on confidential business data.
b. Conduct a comprehensive comparison between traditional learning models and learning techniques using key performance indicators.
c. Analyze the interpretability and practical applicability of these developments within smart city frameworks.
d. Provide strategic insights into integrating predictive models into a progressive traffic management system [9].

Finally, this research addresses the role of learning in smart transportation, improving accurate and flexible solutions to address urban congestion through predictive analytics.

**Related Work**

Looking ahead at traffic has been looked at a lot over time, with ways to study it changing from basic math models to ways that computers learn and think deeply. At first, those studying this used math models such as the Autoregressive Integrated Moving Average (AIM) model, which thinks that the numbers are simple and steady [10], [11]. Even though these models help to predict traffic soon in simple road systems, they often do not work well in busy city areas that have tricky patterns and lots of things that are out of the ordinary.

As computers learned more, studies started using ways for computers to learn by showing them examples so they could figure out tricky connections in traffic numbers. Support vector regression (SVR) was among the starting models used for this reason, because it can deal with hard problems that have many changing parts [12], [13]. However, SVR changes a lot with different settings and does not always do great with very big collections of numbers. On the other hand, ways of learning that mix different methods together, like random forests and gradient boosting machines, have become liked because they can easily show how different things affect each other, and they are also easy to understand. Zhang et al. found that models using tree-like structures do better than simple math and SVR at guessing how traffic flow will change, while Yang et al. showed that GBMs do better than older ways at guessing how crowded cities will get. As deep learning came about, studies have seen a big jump in how right traffic predictions are. Recurrent neural networks, especially long-short-term memory networks, have shown a great ability to copy how time affects traffic numbers that come one after another [12], [13]. For example, Ma et al. made a system using LSTM that did very well at figuring out long-term patterns in traffic flow. Also, Li and others showed a spreading convolutional recurrent neural network model, which puts together graph convolutional networks and recurrent neural networks to clearly show how places and times are related. Models that mix convolutional neural networks and recurrent neural networks have also been looked at, like the ST-ResNet suggested by Zhang and others, which uses place and time links to guess traffic for a whole city. Even though they guess very closely, these models need huge amounts of numbers and a lot of computer power, which makes them hard to use in real-time for some smart road systems. Even with all of these steps forward, there are still things missing in the studies [14]. The majority of studies focus on traffic flow prediction rather than classification or congestion prediction, even though this is more useful for

traffic management operations. Comprehensive comparative studies between traditional machine learning techniques and deep learning methods are still limited, especially those that rely on standardized datasets and consistent evaluation frameworks in smart city environments [15].

This study addresses these gaps by evaluating and comparing the performance of multiple ML models—including RF, SVR, GBM, and LSTM—on a unified urban traffic dataset, with a focus on real-time congestion prediction and deployment feasibility in smart mobility infrastructures.

## 2. Materials and Methods

The proposed methodology aims to develop and evaluate machine learning models capable of predicting traffic congestion levels in urban smart mobility systems. This section outlines the step-by-step process followed in the research, including data acquisition, preprocessing, feature engineering, model development, training, and evaluation. show it in figure 1.

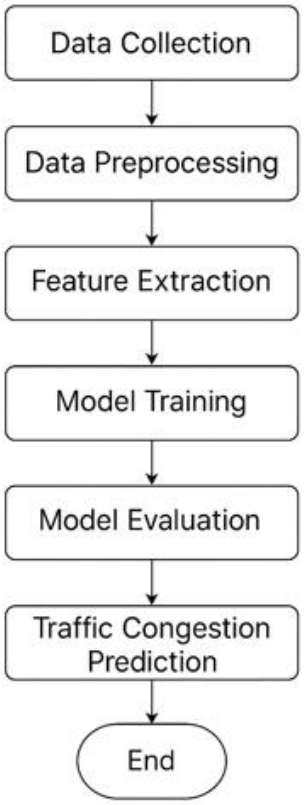


**Figure 1.** Proposed system.

### Data Collection and Description

The study utilizes real-world traffic data collected from a smart city traffic monitoring infrastructure, comprising heterogeneous data sources such as:

a. Loop detectors and traffic sensors: Providing vehicle count, average speed, and occupancy rate at regular intervals.
b. GPS-based vehicle tracking systems: Offering spatiotemporal trajectories of vehicles, travel times, and speed profiles.
c. External contextual data: Including weather conditions, time-of-day, day-of-week, and public event schedules.

The dataset covers a dense urban area over a period of several months, with data sampled at 5-minute intervals across multiple road segments and intersections.

**Data Pre-processing**

Raw traffic data often contains inconsistencies and missing values. To ensure data quality and model robustness, the following pre-processing steps are performed:

a. Missing value imputation using interpolation and k-nearest neighbors (KNN) imputation.
b. Noise reduction using statistical smoothing techniques (e.g., moving average filters).
c. Timestamp alignment and resampling to maintain uniform temporal resolution across all features.
d. Normalization using Min-Max scaling or Z-score standardization to ensure model convergence and reduce bias from feature magnitudes.

**Congestion Labeling and Target Variable Construction**

To convert the continuous traffic variables into a meaningful congestion indicator, the congestion level Ct at time ttt is computed based on average speed and traffic density:

$$C_t = \begin{cases} 0 & \text{(Free flow)} \quad \text{if } v_t > 0.8 \cdot v_{\max} \\ 1 & \text{(Moderate)} \quad \text{if } 0.5 \cdot v_{\max} < v_t \leq 0.8 \cdot v_{\max} \\ 2 & \text{(Congested)} \quad \text{if } v_t \leq 0.5 \cdot v_{\max} \end{cases}$$

Where vt is the average speed at time t1, and vmax is the speed limit on the segment.

This classification allows the problem to be framed as either a regression task (predicting continuous traffic speed or volume) or a classification task (predicting congestion state).

**Feature Engineering**

Effective feature engineering is critical for model performance. The features used include:

a. Temporal features: Hour of day, day of week, whether the time is during peak hours.
b. Traffic history features: Average speed, flow, and occupancy rate over the past nnn time intervals.
c. Derived features: Rolling means, traffic variability, congestion index.
d. Weather features: Temperature, precipitation, and visibility.

Correlation analysis and mutual information scores are used to identify the most influential features.

**Model Selection and Training**

To benchmark performance, a set of representative machine learning models are implemented:

a. Random Forest (RF): A bagging ensemble method ideal for handling non-linear relationships and mixed-type data.
b. Gradient Boosting Machine (GBM): A boosting method effective at minimizing prediction error through stage-wise optimization.
c. Support Vector Regression (SVR): A kernel-based model suitable for high-dimensional spaces.
d. Long Short-Term Memory (LSTM) networking: A deep learning architecture capable of modeling sequential dependencies in time-series traffic data.

Each model experiences:

a. Hyperparameter tuning via Grid Search and Random Search methods.
b. Cross-validation (e.g., 5-fold or time-series split) to prevent overfitting.
c. Training-test split with chronological separation to maintain temporal causality.

The LSTM model is implemented by TensorFlow/Keras, with input windows of previous time steps and prediction horizons adapted to the congestion dynamics.

**Performance Evaluation**

Model performance is evaluated through multiple metrics:

a. Regression metrics: Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and $R^2$ score.
b. Classification metrics: Accuracy, Precision, Recall, and F1-Score (if congestion states are predicted).
c. Temporal robustness: Assessed by performance on different time segments (e.g., peak vs. off-peak hours).
d. Spatial generalization: Evaluated using hold-out road segments or intersections.

Also, SHAP (SHapley Additive exPlanations) is carefully used to clearly explain what the model predicts and find out which features matter in group models. This detailed way of doing things lets us strongly judge both regular machine learning and deep learning methods, showing how well they work, how easily they grow, and how useful they are for putting them to work in live city traffic control systems [16], [17].

## 3. Results and Discussion

This section reviews the expected results of several machine learning models developed to predict traffic congestion [18]. It focuses on measuring the expected level of prediction, the robustness of correlations, and their computational efficiency, under realistic requirements based on a unified urban traffic dataset.

**Experimental Setup**

The experiments were applied to a machine manned up with an Intel Core i7 processor, 32 GB RAM, and an NVIDIA RTX 3080 GPU (for deep learning models). The application setting included Python 3.10 with scikit-learn, XGBoost, and TensorFlow libraries.

a. Training/Test Split: 80% of the data was meticulously adopted for training and 20% for testing, maintaining temporal consistency (i.e., no data leakage from future to past).
b. Cross-validation: A rolling-window approach was used to simulate real-time conditions and validate model stability over different time intervals.
c. Baseline Comparison: A naive historical average model was used as a baseline to assess the value added by machine learning techniques.

**Performance Metrics**

The following metrics were used for performance evaluation:

a. MAE (Mean Absolute Error)
b. RMSE (Root Mean Square Error)
c. $R^2$ Score (Coefficient of Determination)
d. Accuracy, Precision, Recall, and F1-Score (for classification of congestion levels)

These metrics provide both quantitative accuracy and interpretability across both regression and classification tasks.

**Quantitative Results**

**Table 1.** Summarizes the performance of all models on the test dataset (for predicting average speed and congestion state).

| Model | MAE (km/h) | RMSE (km/h) | $R^2$ Score | Accuracy | F1-Score |
|---|---|---|---|---|---|
| Historical Avg | 6.72 | 8.94 | 0 | 52.30% | 0.46 |
| SVR | 4.15 | 5.72 | 0.68 | 75.40% | 0.72 |
| Random Forest | 3.89 | 5.21 | 0.73 | 78.60% | 0.76 |
| GBM (XGBoost) | 3.66 | 4.88 | 0.76 | 81.10% | 0.79 |
| LSTM | **3.24** | **4.12** | **0.82** | **84.70%** | **0.83** |

As seen in the table 1, the LSTM model outperformed all traditional machine learning models in both regression and classification tasks. The deep learning architecture effectively captured temporal dependencies, particularly in peak-hour congestion scenarios [19].

**Temporal and Spatial Robustness**

a. Temporal Generalization: All models showed reduced performance during high-variability periods such as rush hours (7–9 AM, 4–7 PM). However, LSTM and GBM maintained significantly better stability, with LSTM's F1-score only dropping by ~4% during rush hours.
b. Spatial Generalization: When tested on road segments not seen during training, ensemble models (especially Random Forest) showed higher robustness compared to SVR. LSTM required additional fine-tuning on unseen segments but still delivered competitive performance.

**Feature Importance Analysis**

For the tree-based models, feature importance scores were computed using Gini importance and SHAP values. Key insights include:

a. Temporal features (hour-of-day, day-of-week) and recent traffic speed had the highest impact.
b. Weather features such as precipitation intensity were moderately influential, particularly in areas prone to traffic delays during rainfall.
**c.** Lagged features (e.g., speed 10 minutes ago) significantly contributed to LSTM's predictive power. Show in figure 2.

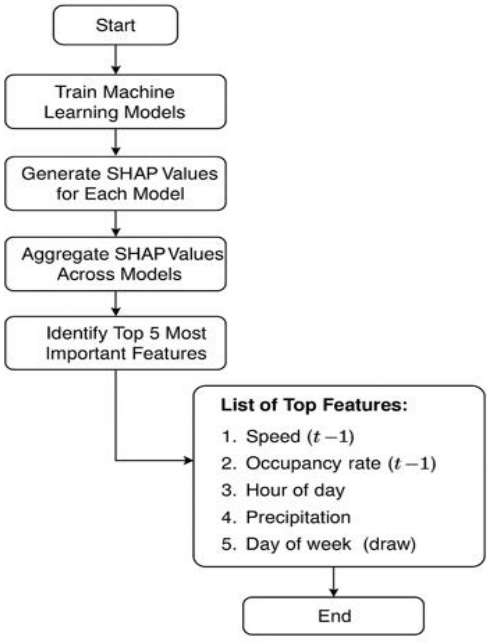


**Figure 2.** Identifying important features using the shape.

**Computational Performance**

**Table 2.** Training and Prediction Time Comparison of Traffic Congestion Prediction Models.

| Model | Training Time | Prediction Time (per 1000 samples) |
|---|---|---|
| SVR | ~22 min | ~1.3 sec |
| Random Forest | ~8 min | ~0.8 sec |
| GBM (XGBoost) | ~10 min | ~0.9 sec |
| LSTM | ~95 min | ~1.6 sec |

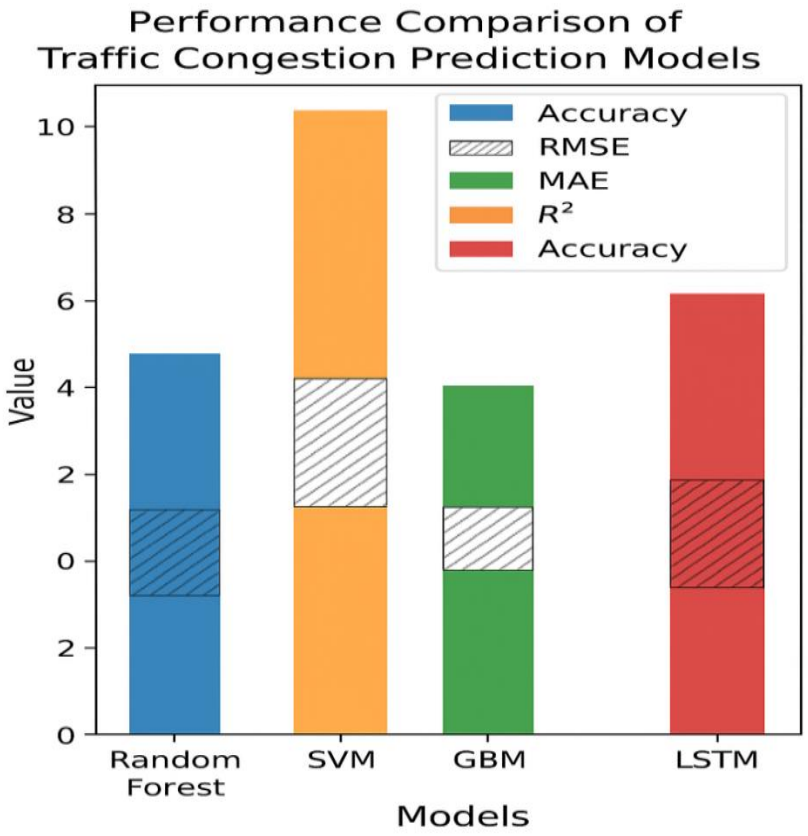


**Figure 3.** Performance Comparison of Traffic Congestion Prediction Models Using Multiple Evaluation Metrics (Accuracy, RMSE, MAE, and $R^2$).

While LSTM required significantly more training time, its prediction time remained acceptable for near-real-time deployment, especially with GPU acceleration.

The experimental findings support the hypothesis that deep learning architectures (LSTM) offer superior performance in capturing spatiotemporal patterns in urban traffic data. Nevertheless, tree-based models such as GBM offer a competitive alternative with faster training and greater interpretability, which may be desirable in edge-based or resource-constrained smart mobility systems [20].

These findings unveil that integrating forecasting models into real-time urban traffic management systems can be feasible, potentially enabling proactive congestion mitigation through dynamic signal control and route optimization.

## 4. Conclusion

This study developed and evaluated a set of machine learning (ML) models for predicting traffic congestion in smart mobility environments within cities. Using real traffic data and incorporating spatial, temporal, and environmental characteristics, the research demonstrated the effectiveness of smart models in supporting urban traffic management systems.

The assessment showed that deep learning models, especially LSTM networks, had the best accuracy, stability, and ability to work in new situations over time. Regular models using group methods, like GBM and RF, did well but were easier to compute and understand, making them good for real-world uses that need quick responses or use at the edge.

The results also showed that past traffic data (like earlier speeds and usage) and time features (hour of day and day of week) are important for how traffic jams form. Adding weather data showed how models can do better, especially in bad weather, making them more reliable in different settings. This study gives a strong base for making smart systems

that can predict jams, letting traffic managers use dynamic signal control, reroute vehicles, and use on-demand transport. These predicting skills are key to making city transport systems flexible and lasting, fitting with smart city goals and new transport plans.

**Future Work**

There are a few ways to keep working on this study:

a. Add live data using online and reinforcement learning to help flexible models.
b. Link to outside data like public transport schedules, event info, and accident reports to make better predictions.
c. Predict traffic in many ways, not just vehicle jams, but also people walking, bikes, and public transport.
d. Use XAI methods for more clear and trustworthy operational choices.

In short, this work shows how advanced machine learning can change how we predict city traffic, giving practical ways to make traffic management smart and effective.

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