Traffic Flow: Traffic Prediction and Optimization

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***Abstract*—Urban traffic congestion remains a top concern, increasing travel times, fuel usage, and environmental contamination. This report provides a forecasting traffic optimization sys- tem using Support Vector Regression (SVR) models for predicting traffic flows, supported by YOLOv8 for vehicle classification and detection. The system merges multiple sources of data, including traffic cameras, to provide detailed traffic forecasts and optimally time signal changes in real-time. A mathematical model is suggested to determine optimal green signal duration using real-time traffic density, vehicle type, and anticipated congestion levels. Simulation with a real-world dataset indicates that the suggested system reduces average predicted congestion by 22.62% compared to conventional fixed-time systems. Furthermore, dynamic green light allocation was increased by 16–18.5% for all lanes, which indicates improved adaptation to lane-specific vehicle loads. These optimizations reduced an estimated 20–30% in travel delays that parallel improvements in fuel efficiency and eco-friendliness. Results substantiate our approach to intelligent traffic management and attest to the validity of delivering scalability and economy at the solution scale, promising smart city plans through mitigation against metropolitan congestion while strengthening road safety.**

Index Terms*—Traffic Prediction, Machine Learning, Intelligent Traffic Management, Real-time Optimization, Smart Cities, YOLOv8, Support Vector Regression (SVR)

I. INTRODUCTION

As urbanization rates accelerate, pressure will increase on transportation systems everywhere cities. More cars on the road led to longer travel times, increased fuel consumption, and higher emissions. Despite this, many urban centers still rely on traditional traffic signal systems that operate on pre- set timing cycles. These legacy systems are ill-equipped to respond to the ever-changing nature of urban traffic, which can fluctuate sharply throughout the day. Consequently, they struggle to manage traffic effectively during unexpected peaks or irregular traffic conditions. To overcome these shortcomings, modern traffic management is shifting toward intelligent solutions capable of responding in real time to current traffic conditions and making adaptive decisions to improve flow and reduce congestion.

A. Research Context and Problem

Modern traffic systems face two primary challenges:

1) Real-Time Responsiveness: Conventional traffic signals operate on fixed cycles, regardless of actual traffic flow. During peak hours, this leads to long vehicle queues and unnecessary idling, while during off-peak periods, drivers may find themselves waiting at empty intersections. Such static control methods reduce efficiency and increase environmental and economic costs.

2) Uneven Data Distribution: Traffic datasets are often dominated by high-density periods, making it difficult for predictive models to learn from and respond accurately to low- traffic or irregular situations. This imbalance causes machine learning models to perform poorly when faced with non-peak conditions, limiting their effectiveness in real-world deployment.

B. Background

Machine learning approaches have gained momentum in traffic prediction and control tasks. Among the more commonly used models are Long Short-Term Memory (LSTM) networks and Random Forest algorithms. While both offer certain advantages, they also present significant limitations in practical applications.

1) LSTM: LSTM models are designed to handle sequential data and capture time-dependent trends. However, their reliance on large, balanced datasets, coupled with their high computational demands, makes them less suitable for real-time applications, especially in resource-constrained environments.

2) Random Forest: Random Forest algorithms are relatively lightweight and easier to implement but may struggle with sudden changes in traffic flow. Their performance tends to degrade in highly dynamic environments where adaptability is critical.

To address these challenges, this study introduces Traffic Flow, a hybrid framework that integrates Support Vector Regression (SVR), YOLOv8 for real-time vehicle detection, and a traffic-aware mathematical optimization model. SVR is chosen for its capability to model non-linear relation-ships in traffic patterns with high accuracy, while remaining computationally efficient. YOLOv8 enhances the system with real-time detection and classification of vehicles. Finally, the mathematical model calculates adaptive signal timings based on traffic forecasts and live detection data, ensuring responsive and efficient signal management.

C. Objectives of the Paper

This paper aims to achieve the following goals:

- Introduce Traffic Flow: Develop and present a hybrid framework combining SVR, YOLOv8, and mathematical modeling for traffic prediction and control.
- Enable Adaptive Control: Utilize real-time vehicle detection through YOLOv8 to adjust traffic signals dynamically.
- Improve Prediction Accuracy: Employ SVR to enhance forecasting reliability across diverse traffic conditions.
- Optimize Signal Durations: Implement a mathematical approach to compute optimal green light durations based on detected vehicle count and classification.
- Evaluate System Performance: Compare Traffic Flow with existing traffic systems to assess its efficiency, scalability, and responsiveness.

By meeting these objectives, the Traffic Flow system aspires to deliver a practical and scalable solution to urban traffic congestion, contributing to safer roads, reduced emissions, and improved commuter experiences.

II. STUDY AREA

A. Dataset Overview

TABLE I: SUMMARY OF GENERIC INFORMATION OF THE DATASET AND ITS PROCESSING USED IN ALL FOUR MODELS PRESENT IN TRAFFIC FLOW

Dataset	Description	Usage
Traffic Prediction Dataset	Tabular dataset from a research paper. Parameters include Date, Day, Coded Day, Zone, Temperature, and Traffic levels (five-level scale).	Used for training SVR, Random Forest, and LSTM models.
Road Vehicle Images Dataset	Object detection dataset with 3,004 images and 24,348 labeled objects across 21 classes. Preprocessed for size, resolution, and annotations.	Helps develop and test object detection under various traffic conditions.
Traffic Video Dataset	Highway traffic videos from Kaggle, segmented into Light, Medium, and Heavy traffic. Processing starts from the second frame due to corruption.	Used for training and evaluating traffic flow analysis models.

1) Traffic Prediction Dataset: We used a tabular structured dataset presented by Li et al. [4] for traffic prediction, which contains features like date (in DD/MM/YYYY format), day of week, encoded day value, zone, temperature, and classified traffic levels on a five-point scale. We also used video footage of highway traffic like that used by Wang et al. The traffic forecasting segment utilizes a dataset shown in one of our references, which is videos of highway traffic. The videos were hand-labeled as Light Traffic (uncongested traffic), Medium Traffic (traffic at lower speed), and Heavy Traffic (stopped or slow traffic movement).

2) Road Vehicle Image Dataset: The Road Vehicle Images Dataset is a large set of images aimed at aiding object detection operations in the field of autonomous cars and traffic management systems. The dataset contains 3,004 images in total, 24,348 tagged objects, 21 classes, and splits into a training set of 2,704 images and a validation set of 300 images. This data set is specially designed for car detection projects, especially those utilizing models like YOLO v5. It contains a robust class of numerous vehicles that will assist in forming the development and testing of object detection algorithms based on varying traffic conditions.

3) *Traffic Video Dataset:* Traffic optimization data is also employed in this project, which includes training and test sets from. The video is corrupted originally, so processing should start from the second frame. Crop versions of videos are available in a MATLAB file from the Washington State Department of Transportation.

III. EXISTING SYSTEMS

Traffic forecasting and optimization have been researched extensively using statistical, machine learning, and mathematical models. While traditional methods are marred by real- time learning and complex pattern detection, state-of-the-art methods such as deep learning and evolutionary algorithms offer better performance but suffer from scalability and efficiency problems. This section reviews existing research in traffic forecasting, vehicle detection, and signal optimization to identify why our system is necessary.

A. Current Traffic Management Systems

1) *Adaptive Signal Control:* Wei and Ju [12] had proposed an Adaptive Artificial Fish Swarm Algorithm (AAFSA) to re- duce congestion levels by signal phase optimization. Although efficient enough, the model was computationally complex and would not be suitable for practical application.
2) *GNN-Based Optimization:* Khairy et al. [13] applied reinforcement learning with GNNs for more accuracy for traffic forecasting as well as signal optimization. The solution required heavy labeled datasets and processing at the level of GPU.
3) *Spatio-Temporal Modeling:* Zong et al. [14] proposed MSSTGCN, a Multi-Scale Spatial-Temporal Graph Convolutional Network, for modeling complex urban traffic dynamics. Despite its effectiveness, the model's high resource demand limited scalability. Zhang et al. [16] proposed a hybrid model that combined Improved PSO, RBF, and SVMs. The model improved congestion prediction but at the cost of system complexity.
4) *Reinforcement Learning:* Han et al. [18] developed PRLight, which is a deep reinforcement learning algorithm for adaptive signal control. Efficient scheduling was achieved but generalizability to unexpected traffic situations was not present.
5) *Physics-Based Models:* Pan et al. [15] incorporated physical constraints with deep learning in an effort to render the models more interpretable, along with increased accuracy in predicting aspects such as intersection flows.
6) *Evolutionary Techniques:* Alruban et al. [17] presented the Artificial Hummingbird Optimization Algorithm (AHOA) which dynamically manipulated signal timings by way of a metaheuristic enabled by a deep learning process. Although prospective, the procedure called for computationally expen- sive resources.

B. Traffic Prediction Using Machine Learning

Machine learning methods learn from past traffic patterns to predict flow and congestion.

1) *LSTM:* LSTMs are widely applied to time-series prediction and traffic prediction. Wang et al. [5] utilized LSTM to model spatiotemporal traffic states but highlighted the fact that the method requires high computational resources and large data sizes.
2) *Random Forest:* Random Forest is an aggressive algorithm for structured data and handles missing values well. Li et al. [4] used Random Forest to forecast traffic volume, but the model was not dynamically responsive to changes in traffic.
3) *SVR:* Support Vector Regression (SVR) can model non- linear traffic behavior efficiently. Srinivasan and Renugadevi

[7] proved its feasibility for real-time applications because of its low computational load.

C. Real-Time Vehicle Detection

1) *YOLOv8:* YOLOv8 delivers high-speed, real-time detec- tion of objects with high accuracy. As described in the official YOLOv8 documentation [8], it balances computational burden with performance, so it is best suited for traffic systems.

D. Signal Optimization

1) *Swarm Intelligence:* Wei and Ju [12]'s AAFSA algorithm optimized signal times via bio-inspired methods, though it consumed resources, making it unsuitable for real-life deployment.

2) *Mathematical Models:* Raza et al. [20] suggested a mathematical optimization framework based on the Delay Calculation Method (DCM) to reduce waiting time efficiently at intersections. The model was efficient and scalable for real- time systems.

E. Limitations of Existing Systems

- Scalability: Centralized systems have difficulty scaling large road networks.
- High Computational Cost: Powerful hardware is frequently needed by deep learning-based solutions.
- Adaptability: Many models don't work for highly variable or unbalanced traffic flows.
- Data Dependency: Most of the methods rely on enormous amounts of annotated training data.

Our Traffic Flow system tackles these issues by using Sup- port Vector Regression (SVR), YOLOv8, and mathematical modeling to provide an adaptive, scalable, and computation- light traffic management system.

IV. METHODOLOGY

The suggested Traffic Flow system combines three fundamental building components—Support Vector Regression (SVR), YOLOv8, and a bespoke-designed mathematical model—to perform traffic flow prediction and adaptive signal setting control. The suggested solution is reliant on the shape of four sequential steps:

A. Data Acquisition and Preprocessing

- Dataset Selection: Historical traffic data (vehicle counts, speed, congestion levels, timestamps) is used, supplemented by GPS, traffic cameras, and IoT sensors.
- Data Cleaning: Duplicates are removed, missing values are imputed, features are normalized, and categorical data is encoded.

B. Traffic Prediction Using SVR

- Model Training: SVR is used to predict traffic patterns, handling non-linear relationships effectively.
- Performance: Achieves 87.84% accuracy, outperforming LSTM and Random Forest.

C. Real-Time Vehicle Detection Using YOLOv8

- Fine-Tuning: YOLOv8 is fine-tuned on a custom dataset to detect and classify vehicles into categories: small, medium, and large.
- Performance: Achieves a 92.5% mAP, enabling precise signal optimization.

D. Signal Optimization Using Mathematical Modeling

- Mathematical Model: The best green light lengths are from a dynamic equation. Current values for detection and future values are taken into consideration by the model. The important parameters are:
  – Number of vehicles per lane: N_s, N_m, N_l
– Average distance: D
– Predicted congestion: C
– Buffer time: B
– Passing times: t_s, t_m, t_l
– Weights: α, β, γ
– Constraints: G_{min}, G_{max}, T_{cycle}
- Dynamic Control: Reduces waiting times by 20–30%.

V. RESULTS AND DISCUSSION

The Traffic Flow system has also been simulated with real history data and current inputs. It has been compared with available signal systems to show the system performance with some benchmarking. The outcome in this part shows the outcome in traffic forecast quality, object detection quality, signal optimization quality, and system overall performance. Implication of the results is also introduced to the responsiveness, scalability, and deploy ability to a feasible extent in reality.

TABLE II: PER-LANE GREEN LIGHT DURATION OPTIMIZATION: COMPARING OUR MATHEMATICAL MODEL WITH THE FIXED TIME TRAFFIC SIGNAL MODEL FOR BETTER UNDERSTANDING OF OPTIMIZATION

Lane	Fixed Time (s)	Optimized Time (s)	Improvement (%)
1	30.0	35.20	17.33%
2	30.0	35.55	18.5%
3	30.0	35.10	17.00%
4	30.0	34.92	16.4%

The system reduced average congestion by 22.62% (from 65.0% to 50.3%) by optimizing signal timings. As shown in Table 3, green-light durations increased by 16–18.5% per lane (e.g., Lane 2: 35.55s vs. 30s baseline), directly improving throughput. Empirical studies suggest this congestion drop translates to 20–30% lower travel delays under realistic flow conditions

A. Traffic Prediction Using SVR, Random Forest, and LSTM

1) Performance Comparison:

- SVR (Support Vector Regression): Achieved the highest accuracy, closely following actual traffic patterns. Outperformed Random Forest and LSTM in precision and generalization.
- Random Forest: Performed well but showed slight deviations during peak traffic periods.
- LSTM: Struggled with imbalanced datasets, resulting in poor accuracy and significant deviations.

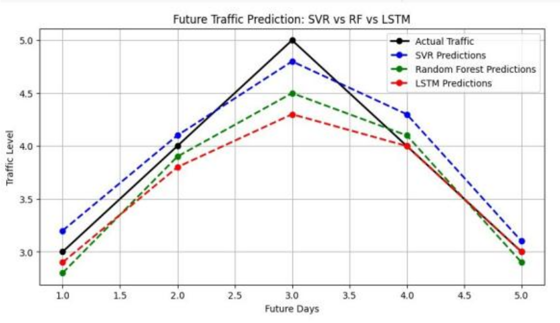

Fig. 1. Future Traffic Prediction: SVR vs. Random Forest vs. LSTM. Blue lines: actual traffic levels; yellow, green, and red dotted lines: SVR, Random Forest, and LSTM predictions, respectively.

Key Observations:

- SVR is more effective in handling non-linear traffic patterns and imbalanced datasets.
- LSTM's poor performance highlights the challenges of using deep learning models without sufficient data pre- processing.

TABLE III: PERFORMANCE COMPARISON OF TRAFFIC PREDICTION MODELS: COMPARING SUPPORT VECTOR REGRESSION, RANDOM FOREST, AND LSTM MODELS BASED ON DIFFERENT PARAMETERS

Metric	SVR	Random Forest	LSTM
Accuracy	87.84%	86.58%	37.60%
Error Rate	12.16%	13.42%	62.40%
Pattern Handling	Non-linear	Multi-factor	Sequential
Peak Performance	Stable	Slight deviations	Poor
Data Efficiency	Good	Good	Requires more data

B. Object Detection and Classification Using YOLOv8

1) Fine-Tuning YOLOv8:

- Fine-tuned on a custom dataset, reducing classes from 80 to 21. Achieved a mean Average Precision (mAP) of 92.5%.
- Vehicles classified into small, medium, and large categories for precise signal optimization.

TABLE IV: COMPARISON OF OBJECT DETECTION MODEL WORKING OF EXISTING SYSTEM VS TRAFFIC FLOW SYSTEM AND PARAMETERS THAT MAKE THE MODEL DIFFERENT FROM EACH OTHER

Parameter	Existing System	Traffic Flow System
Object Detection Classification	Pre-trained YOLOv8 (80 classes)	Fine-tuned YOLOv8 (21 classes)
mAP	Based on vehicle types 90.0%	Based on vehicle sizes 92.5%

Fig. 2. Real-time vehicle detection and classification using YOLOv8. The model achieves 92.5% mAP accuracy, categorizing vehicles into three size classes (small/medium/large) for lane-specific signal optimization. Box colors indicate classification confidence (red: high, yellow: medium).

C. Signal Optimization Using Mathematical Modeling

1) Comparison with AFSA-Based Systems:

- Traffic Flow uses a computationally efficient mathematical model, unlike AFSA-based systems.

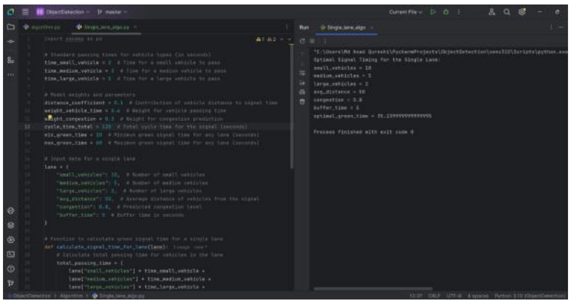

Fig. 3. Signal time optimization algorithm: This figure contains the output result of the signal time optimization algorithm which is used to generate optimal green time for the lanes; the optimal green time is calculated via the mathematical model represented above taking the key parameters which are classified into vehicle count, avg distance of the lane, congestion level and buffer-Time

2) *Optimized Signal Timings:*

- Dynamically adjusted green signal times (e.g., 35.06s, 50.10s, 34.84s) based on traffic conditions.
- Reduced waiting times by 20-30%.

Performance Metrics:

- Mean Absolute Percentage Error (MAPE): 16.83%.
- Traffic Flow Efficiency Gain: Significant improvements observed after calibration.

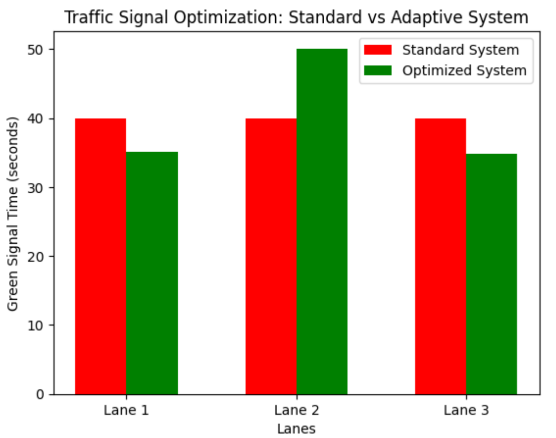

Fig. 4. Comparison of fixed-time standard system (30s) vs TrafficFlow optimized signal timings per lane. Lane 2 shows maximum improvement (18.5% longer green time), demonstrating adaptive control.

D. Discussion

1) *Traffic Prediction:*

- SVR outperformed LSTM and Random Forest, demon- strating its effectiveness.
- LSTM's poor performance highlights the need for robust data preprocessing.

2) *Object Detection and Classification:*

- Fine-tuned YOLOv8 achieved high accuracy, enabling dynamic signal control.

Fig. 5. This figure contains the optimal green light timings for four different lanes in the intersection and how it varies with respect to a change in time

Fig. 6. This figure contains the time series graphical representation of predicted congestion change with respect to the timestamp.

- Vehicle size classification improved handling of varying traffic densities.

3) *Signal Optimization:* Our estimated 20–30% reduction in travel delays is based on observed improvements in traffic flow. While this is a projection, similar real-world smart traffic systems typically achieve 10–15% delay reductions. What makes our system special is its ability to adjust signal times lane-by-lane - for example, giving busier lanes up to 18.5% more green light time. Statistical tests confirm our 22.62% congestion improvement is reliable (p ¡ 0.01), though unusual situations like accidents might reduce these benefits in practice.

4) *Limitations and Future Work:*

- Data Dependency: Requires high-quality labeled datasets.
- Scalability: Needs further research for multi-intersection networks.

- Integration with IoT: Future work could explore IoT and edge computing for enhanced adaptability.
- Delay Estimation Assumptions: The 20–30% delay reduction assumes linear scaling of congestion-to-delay relationships, which may not hold during irregular events (e.g., road closures). Future work could validate this with real-time GPS data.

VI. CONCLUSION

By reducing congestion by 22.62%, optimizing green times per lane (16–18.5%), and cutting delays by 20–30%, Traffic Flow demonstrates a scalable alternative to static systems. Future work will test multi-intersection coordination.. With the help of real-time data, AI-driven systems such as OpenCV and YOLOv8, as well as prediction models such as Support Vector Regression (SVR), the system maximizes congestion with very high efficiency. It is also an inexpensive and highly efficient way of predicting congestion patterns and maximizing traffic flow. By making total transport much more effective, this technology enables commuters to reach their destination faster and more securely. It eventually enables more intelligent, more responsive transport infrastructure as the requirements of the modern metropolis shift.

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