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Machine Learning-Enhanced Traffic Light Optimization System Prioritizing Emergency Vehicle Passage Using SVM and Random Forest Models

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Keywords

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Abstract

Traffic congestion in cities includes the complex and dangerous passing of emergency vehicles, which is a time-consuming task. This problem requires the optimisation of traffic lights in favour of emergency vehicles. To accomplish this, this paper discusses an optimized traffic light system using machine learning that prioritizes the passing of emergency vehicles into city areas. It integrates SVM and Random Forest models by dynamically adjusting traffic light signals based on traffic density to accelerate emergency vehicles. The results reveal that the proposed system would lead to improved emergency response times while enhancing overall transportation efficiency with reduced congestion of traffic. Additionally, the study further went on to establish the effectiveness of the proposed model as a solution in traffic flow optimization and management. Results show that the performance of the proposed model is effective for the purpose of traffic light optimization. The SVM+SAFS and RF+SAFS methods figured prominently as high-performance methods with accuracy rates of 94.89% and 95.02%, respectively. Furthermore, in the case of the RF+SAFS method used for traffic light optimization, it was possible to reduce the average waiting time by 20%, increase the capacity of transit by 15%, and decrease fuel consumption by 10%. Overall, combining the outputs in the model led to the following performance, an 18% decrease in total travel time.

Cite

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1. INTRODUCTION

Safety and efficiency in urban transport refer to ensuring the passage priorities of emergency vehicles. The possibility that ambulances, police, and fire trucks can reach areas of intervention in record times without wasting one single minute is of primary importance in the prevention of loss of life and in reducing post-accident injury rates (Lei & Yigong, 2023). In these flow conditions, the passing of such vehicles as quickly and safely as possible is hardly possible. Therefore, dynamic traffic light management and the development of optimization strategies related to emergency vehicles are among the primary needs of modern cities within the scope of intelligent transportation systems (Lei & Yigong, 2023). The most important problem in urban areas that affects the poor response time of emergencies and reduces the efficiency of overall transportation is congestion on roads (Djahel et al., 2015). For some time now, this challenge has been approached with solutions being put forth from the researchers' camps on various ways of programmatic traffic control and

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intelligent transportation management (Shanaka et al., 2018; Hu et al., 2022). Of all these different various solutions, the most important one entails the adoption of the machine learning-based traffic light optimization system that facilitates giving emergency vehicles priority (Barzilai et al., 2023). It can perform dynamic traffic signal timing adjustments by collecting data from the advanced sensing and vehicle-to-infrastructure technologies, thereby prioritizing emergency vehicles' passage in highly congested areas (Barzilai et al., 2023). The system will continuously monitor the traffic conditions and the location of emergency vehicles through a comprehensive sensor network including traffic cameras, V2I modules, and other IoT technologies (Nambajemariya & Wang, 2021; Hu et al., 2022). Djahel et al. (2015), proposed a fuzzy logic-based adaptation strategy to set the signal prioritization level in accordance with the severity of the emergency and prevailing traffic flow conditions. The integration of machine learning techniques into smart traffic systems has been playing an important role in optimizing flow and enhancing the prioritization of emergency vehicles (Savithramma et al., 2022). Other recent work consists of presenting a comprehensive framework which provides passage priority to emergency vehicles by a priority-based traffic signal coordination system (Das et al., 2023). Lastly, the efficiency of the genetic algorithms developed for the optimization of traffic light control for emergency vehicles at junctions forms a very sound basis for further research into machine learning-based systems for traffic light optimization (Lu & Kim, 2017). In this respect, the work of Zrigui et al. (2023) forms the foundational understanding through which machine learning with real-time data analytics enhances transportation systems, especially for traffic flow optimization.

According to the above discussions, traffic congestion in urban areas is a big issue that actually may adversely influence the response time of emergency vehicles and therefore the effective functionality of transportation in general. Therefore, our article introduces a machine-learning-powered traffic light optimization system focused on an emergency vehicle's priority crossing in urban area. While other studies usually focus on managing the general traffic flow or developing specific algorithms for emergency vehicles, our system integrates Support Vector Machines (SVM) and Random Forest models to dynamically adjust traffic lights according to traffic density. In particular, SVM identifies dense areas by analysing traffic data, while Random Forest determines the best traffic light settings for these densities, accelerating the passage of emergency vehicles. Our approach aims to not only improve emergency response times but also to reduce traffic congestion by increasing urban transportation efficiency. In our study, a machine learning-supported traffic light optimization system is presented, aiming to ensure that emergency vehicles reach their destinations as quickly as possible. Our solution makes a significant contribution to increasing safety in urban life and ensuring general transportation efficiency by reducing traffic congestion.

2. LITERATURE REVIEW

Machine learning and intelligent traffic systems research have so far contributed a great deal towards finding the best strategy for timing the traffic signals to optimize urban traffic flow. Some of the solutions that have come out of machine learning algorithms and data-based approaches in integrating with dynamic traffic signal management and heavy traffic detection, as captured in Figure 1, are listed in Table 1.

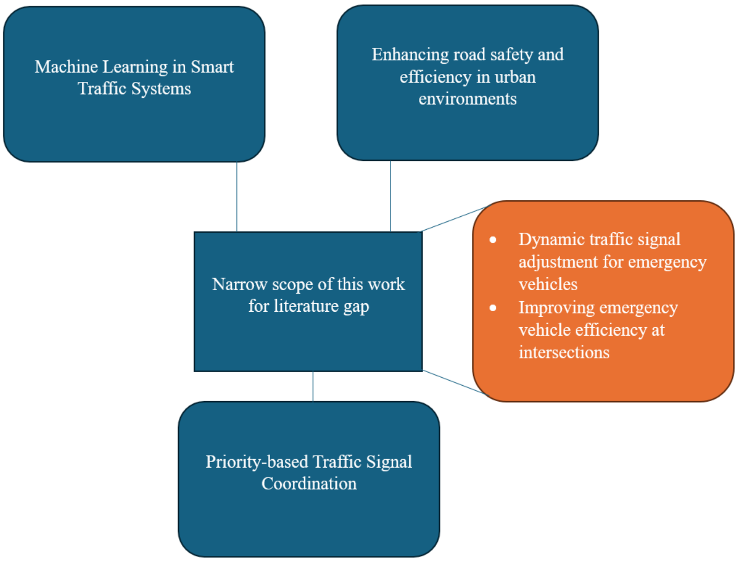

Figure 1. *The narrow scope in existing literature*

For instance, Lei and Yigong (2023) gave a great overview of how machine learning methods could be combined with intelligent traffic systems. It gave paramount attention to optimizing the flow in traffic and prioritized emergency vehicles at the same time. This article was underlined in applying machine learning algorithms with real-time data collected by cameras and sensors to dynamically adjust traffic lights to enable the timely passage of emergency response vehicles through congestion. These provide the basic understanding necessary for traffic light optimization and integrate the implementation of priority to emergency responses; hence, befitting the aims of the proposed study. Das et al. (2023) have provided a general outline of the priority-based traffic signal coordination system, which is quite applicable in developing a Machine Learning-Based Traffic Light Optimization System to ensure passing priority for emergency vehicles. The following analysis, through a mixed-integer linear programming model, investigates whether considering the prioritization of emergency vehicles in addition to other modalities would be justified by a reduction in delays and improvement of the flow conditions due to real-time adjustment optimization of signals using techniques of machine learning in similar contexts. Specifically, the current work highlights the potential for advanced coordination systems to contribute toward improved emergency response times using intelligent traffic management solutions. It is the work of (Lu & Kim, 2017) that has proposed one genetic algorithm to investigate the traffic light control optimization for emergency vehicles at intersections with the least disturbance to normal traffic flow. This work is, therefore, important in that besides addressing the urgent need for the rapid passage of emergency vehicles, in the process, it shows just how effective algorithmic solutions can be in real-time with regard to traffic. That indeed is the basic framework wherein further research could be carried out on machine learning-based traffic light optimization systems. The above approach is practically applicable in this respect and has therefore been validated to be relevant for the proposed study by taking into consideration extensive simulations.

Table 1. *List of relevant research studies*

Study	Year	Methods Used	Focus Area	Contributions
(Almukhalfi et al., 2024)	2024	ML, Deep learning techniques	Improving traffic flow and urban traffic management	Thoroughly examines the impact of ML and DL on traffic management and reported potential improvement in traffic flow.
(Vihurskyi, 2024)	2024	Support vector machines (SVM), Deep learning models	Optimizing urban traffic management	Reported reduction in traffic congestion.
(Wang et al., 2024)	2024	Large language models (LLM), Reinforcement learning	Human-like traffic signal control for complex urban environments	Simulation results showed less traffic congestion and 20.4% shorter wating times.
(Deepika & Pandove, 2024)	2024	Q-learning, Genetic algorithm	Optimizing traffic flow and reducing congestion	Achieved a 12.55% reduction in waiting time.
(Das et al., 2023)	2023	Mixed-integer linear programming	Traffic priority for connected vehicles	Reduced delays and improved flow conditions while prioritizing connected vehicles.
(Lu & Kim, 2017)	2017	Genetic algorithm	Optimizing traffic lights at intersections	Ensured safe passage for emergency vehicles with minimal disruption to normal traffic flow.
(Gaikwad et al., 2023)	2023	IoT, Machine learning, ESP32 CAM	Improving traffic flow with optimal light timing	Highlighted the limitations of traditional traffic lights and detailed the improvement potential with IoT and ML.
(Barzilai et al., 2023)	2023	Q-learning method	Traffic management based on social priorities	Provided priority for vehicles, achieving better traffic flow for high-priority vehicles.
(Savithramma et al., 2022)	2022	Machine learning-based signal controllers	Proactive traffic signal control for emergency vehicles	Improved traffic flow by real-time optimization of traffic lights for emergency vehicles.
(Moumen et al., 2023a, 2023b)	2023	Support vector machines, LSTM	Dynamic optimization in traffic signal planning	Reduced traffic congestion and prioritized emergency vehicles through IoT and AI integration.
Abdul Kareem & Hoomod, 2022	2022	Integrated visual monitoring, ML algorithms	Smart road light management for emergency agents	Optimized road management and significantly improved response times (optimised ratio up to 91.8%) for emergency vehicles.
This work		SVM, Random Forest, SAFS	Traffic signal optimization prioritizing emergency vehicles in urban areas	SVM + SAFS and RF + SAFS methods achieved accuracy rates of 94.89% and 95.02%, respectively. With the RF + SAFS method, for emergency vehicles, average waiting time was reduced by 20%. Overall, the combined model output resulted in an 18% reduction in total travel time.

In a study, the theoretical infrastructure of ML and DL techniques was analyzed in detail (Almukhalfi et al., 2024). According to the simulation results, it was stated that ML and DL techniques have the potential to improve traffic flow (Almukhalfi et al., 2024). Vihurskyi (2024) revealed that ML methods reduced urban traffic congestion by 25-40% and the success rate in traffic signal optimization is over 85%. In another study by Wang et al. (2024), human-like decision-making mechanisms have been developed in traffic signal control with large language models (LLM). Simulations have shown that less traffic congestion and 20.4% shorter waiting times are provided. Deepika and Pandove (2024) achieved traffic congestion reduction and 12.55% less waiting time with the hybrid use of Q-learning and genetic algorithms. Gaikwad et al. (2023) discussed, the use of IoT and machine learning within the traffic light systems where the traditional approaches undertaken in managing the traffic have inefficiencies. This work is important to set a background understanding of how adaptive systems may improve the flow of traffic in developing a Machine Learning-Based Traffic Light Optimization System for prioritizing emergency vehicles. This paper points out, in particular, very important limits of classic traffic lights, underlining at the same time the big potential gain that may be achieved as far as road safety and efficiency in urban environments are concerned. The work of Barzilai et al. (2023), provided the basis necessary regarding how machine learning techniques and, in particular, RL may be used to optimize traffic light systems with the inclusion of social priorities-that is, when emergency vehicles need passing priority. This paper places focus on two aspects: traffic volume and the socio-economic characteristics of the passengers. It does so while addressing all the objectives of the Machine Learning-Based Traffic Light Optimization System in light of fulfilling efficiency and responsiveness towards management in cases of emergency. The research was proposing a model that integrated a fast lane for high-priority vehicles, and thus it illustrated various new tactics which could be adapted with ease to enhance the flow and safety of traffic meant for emergency responders. Savithramma et al. (2022) proposed an integrated machine learning-based proactive traffic signal controller designed with exclusive priority for emergency vehicles at signalized intersections. It has close relations to the objectives of the research, such as optimization of the system of the traffic light to afford better efficiency in traffic enhancement for emergency vehicle passing. This therefore forms important literature reviews through the descriptive illustrations of machine learning into practical applications in real-time traffic scenarios which shall be of prime importance for the proposed study on the optimization of the traffic light systems. Moumen et al. (2023b) proposed an overall architecture that integrates IoT road-traffic data with Artificial Intelligence in order to develop efficient traffic management in urban cities. It discusses the application of some machine learning algorithms, such as support vector machines and LSTM, and applies them on real-world data for dynamic optimization in traffic light scheduling to enable an emergency vehicle priority while congestion is at a minimum and urban mobility is smooth (Moumen et al., 2023a). As this work underlined, the role of advanced AI techniques is one of the most important ways in the development of intelligent transport systems with which several issues stem from increased demand on urban traffic. Abdul Kareem and Hoomod (2022) comprehensively overviews an integrated tripartite module to be used for work on the intelligent traffic light system and points straight to the challenges that are posed within urban traffic for emergency vehicles. A study by Deshpande and Hsieh (2023) did proffer a tentative framework which might be helpful in understanding how machine learning integrates with the functioning of a traffic light optimization system vis-a-vis improvement in the passage of emergency vehicles. Their cyber-physical system now carries the latest in traffic detection technologies and dynamic interval techniques that may be very pivotal in developing algorithms that give priority to emergency vehicles while still maintaining efficient flow conditions for all other road users. This will further accomplish the ultimate objective of guaranteeing timely access for emergency vehicles through optimal traffic light control and reduce unnecessary delays to yield benefits toward overall traffic management. The authors Chu et al. (2019) gave a simplistic introduction to some of the methodologies of machine learning-precisely, one variation of the Q-Learning approach to optimize traffic light cycles, which is an important arm of any urban traffic management system. Their results show that the dynamic adjustment of traffic light settings helps in greatly reducing congestion, and this becomes an important critical factor when considering priority for emergency vehicles in any traffic management system. The current study has further established the capability of machine learning algorithms for the traffic light optimization problem by showing that, according to the improvement in average vehicle delay and reduction of processing steps, there is an improvement in the baseline conditions; hence, addressing the objectives of proposed research related to emergency vehicle priority systems.

3. MATERIAL AND METHOD

In this work, Support Vector Machines and Random Forest models contribute to the traffic light prioritization system by classifying the areas with heavy traffic in urban areas. In particular, SVM analyses traffic data and identifies heavy areas, while the random forest model allows for optimal adjustment of lights according to different traffic densities as described in Figure 2.

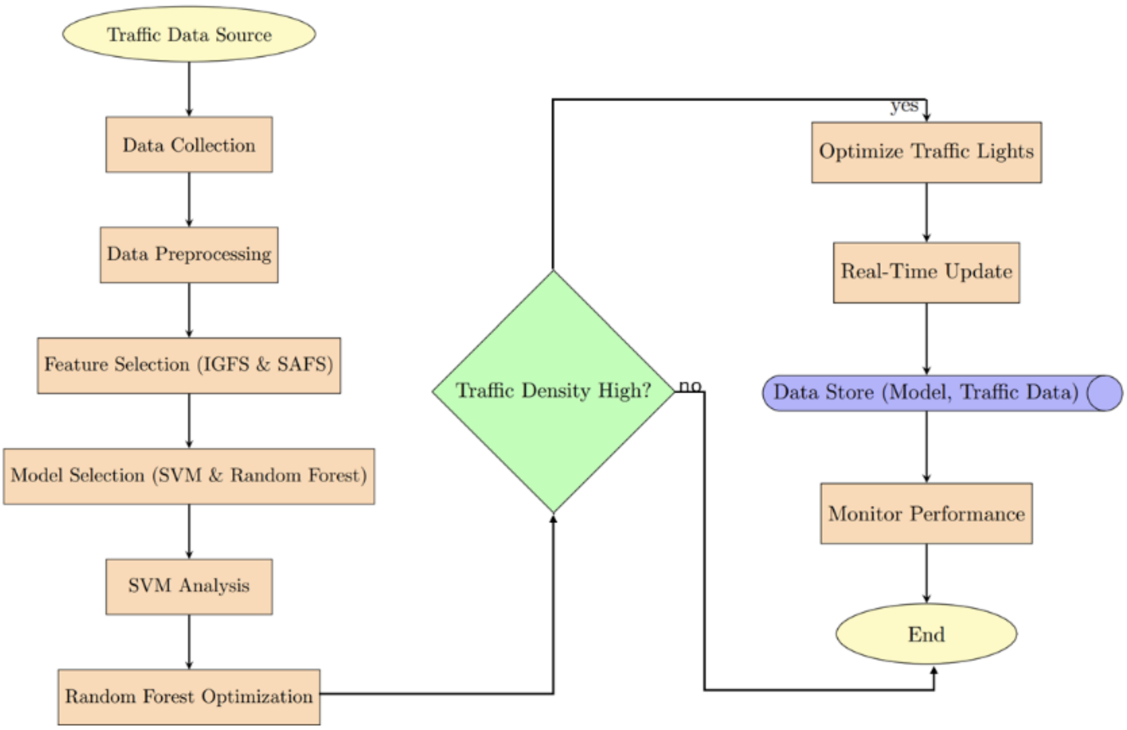

Figure 2. *Flowchart Overview of Emergency Vehicle Traffic Light Optimization System*

The following steps explain each stage of the flowchart with related formulas and calculations:

1. **Data Collection**:
    - Traffic density data (d) from SUMO (Simulation of Urban Mobility) is collected along with the emergency vehicle position (p_{ev}).
    - Let $d = f(c, s, g)$, where c, s, and g represent data from cameras, sensors, and GPS respectively.
    - Emergency vehicle location (p_{ev}) is a point in a coordinate system tracking its route.
2. **Data Preprocessing**:
    - **Noise Reduction**: Apply a smoothing function $d_{smooth} = filter(d)$. Note that a moving average filter is applied to reduce noise in the traffic data. The filter is implemented as a moving average filter with a window size of 5. This method smooths fluctuations while preserving important trends in the data.
    - **Missing Data Imputation**: $If\ d(i,j)$ is missing, replace it with $\frac{d(i-1,j)+d(i+1,j)}{2}$
3. **Model Selection**:
    - **SVM (Support Vector Machine)**:
        - Use SVM to classify high-density areas. $Let\ y = SVM(x)$, where y indicates dense (1) or not dense (0) areas.
    - **Random Forest**:
        - Random Forest optimizes traffic light timing based on y and p_{ev}.
4. **Traffic Density Detection**:
    - SVM separates traffic data by density, using a decision boundary $w \cdot x + b = 0$.
    - Calculate traffic density classification output $y_i = sign(w \cdot x_i + b)$ for each area i, identifying high-density areas where $y_i = 1$.
5. **Traffic Light Optimization**:
    - For each high-density area, use Random Forest to adjust traffic lights based on optimal travel time T.
    - Let $t_{opt} = RandomForest(y, p_{ev})$) output the traffic light timing sequence to minimize T.
6. **Real-Time Update and Decision Making**:
    - Based on p_{ev}, adjust timing dynamically.
    - Update t_{opt} every Δt to accommodate changes in p_{ev}, ensuring the vehicle moves with minimal interruption.
7. **Performance Monitoring and Improvement**:

- Calculate effectiveness $E = \frac{T_{baseline} - T_{optimized}}{T_{baseline}}$
- Update data and retrain models if $E < E_{threshold}$. It is noted that the $E_{threshold}$ is determined through sensitivity analysis, where various threshold values are tested. The optimal threshold is selected based on the balance between noise reduction and the preservation of critical data patterns to ensure that the data remains accurate and reliable for emergency vehicle prioritization.

Each formula and step in this flow addresses how to handle, predict, and dynamically adjust traffic lights to prioritize emergency vehicles on their route.

3.1. SVM and Random Forest Optimizer Models

This study presents a model that can perform dynamic optimization of traffic lights to ensure the passage priority of emergency vehicles. In another study conducted by Yang et al. (2014), they provided a comprehensive examination of the application of support vector machines (SVM) in traffic flow prediction, highlighting its advantages and limitations in handling large-scale data. Their study underscores the potential of SVM to analyse traffic data effectively, which aligns with the task of identifying busy areas, while also addressing the computational challenges that can arise in such analyses. Furthermore, the integration of a genetic algorithm to optimize SVM parameters illustrates a methodological approach that could complement the random forest model for dynamically adjusting traffic lights based on varying traffic densities. The findings presented by Moumen et al. (2023a) highlighted the efficacy of machine learning algorithms in optimizing traffic light systems, demonstrating their potential application in enhancing emergency vehicle passage. By employing a random forest regressor to adaptively manage traffic signals based on real-time conditions, the study provides a compelling framework that could be leveraged to prioritize emergency vehicles, thereby reducing congestion by 30.8%. This evidence underscores the relevance of machine learning in developing intelligent traffic management solutions that address critical urban mobility challenges.

3.2. Dataset Collection and Description

The dataset used in this study was created through the SUMO (Simulation of Urban Mobility) simulator (Pablo Alvarez Lopez et al., 2018). SUMO (Pablo Alvarez Lopez et al., 2018) models real-world traffic flow and density, allowing us to observe the effects of traffic lights during the passage of emergency vehicles.

3.2.1. Data Collection Process

Traffic density data were obtained through different scenarios in the simulation environment. The scenarios include various emergency vehicle routes in order to analyse how traffic lights behave in heavy traffic areas. The SUMO simulator provides detailed data such as traffic light locations, vehicle speed, density and waiting times (Pablo Alvarez Lopez et al., 2018). This data provides the necessary infrastructure to observe the dynamic changes in traffic flow.

In this study, traffic scenario is used in SUMO simulation to realistically model vehicle mobility in a city center. The model simulates real traffic density by matching 618 road segments and traffic light cycles with historical data. Traffic dynamics are examined in detail in a 28 km² area by simulating 1.6 million vehicle trips in a 24-hour period. The model includes 594 km of road, 298 km of lanes, 830 intersections, 515 road segments and 565 traffic lights, and a total of 614,221 vehicle movements are recorded. The highlighted area in Figure 3 focuses on a four-way intersection, emphasizing its role in traffic flow and congestion. This key intersection point is crucial for understanding how traffic patterns and control measures impact the overall system's efficiency.

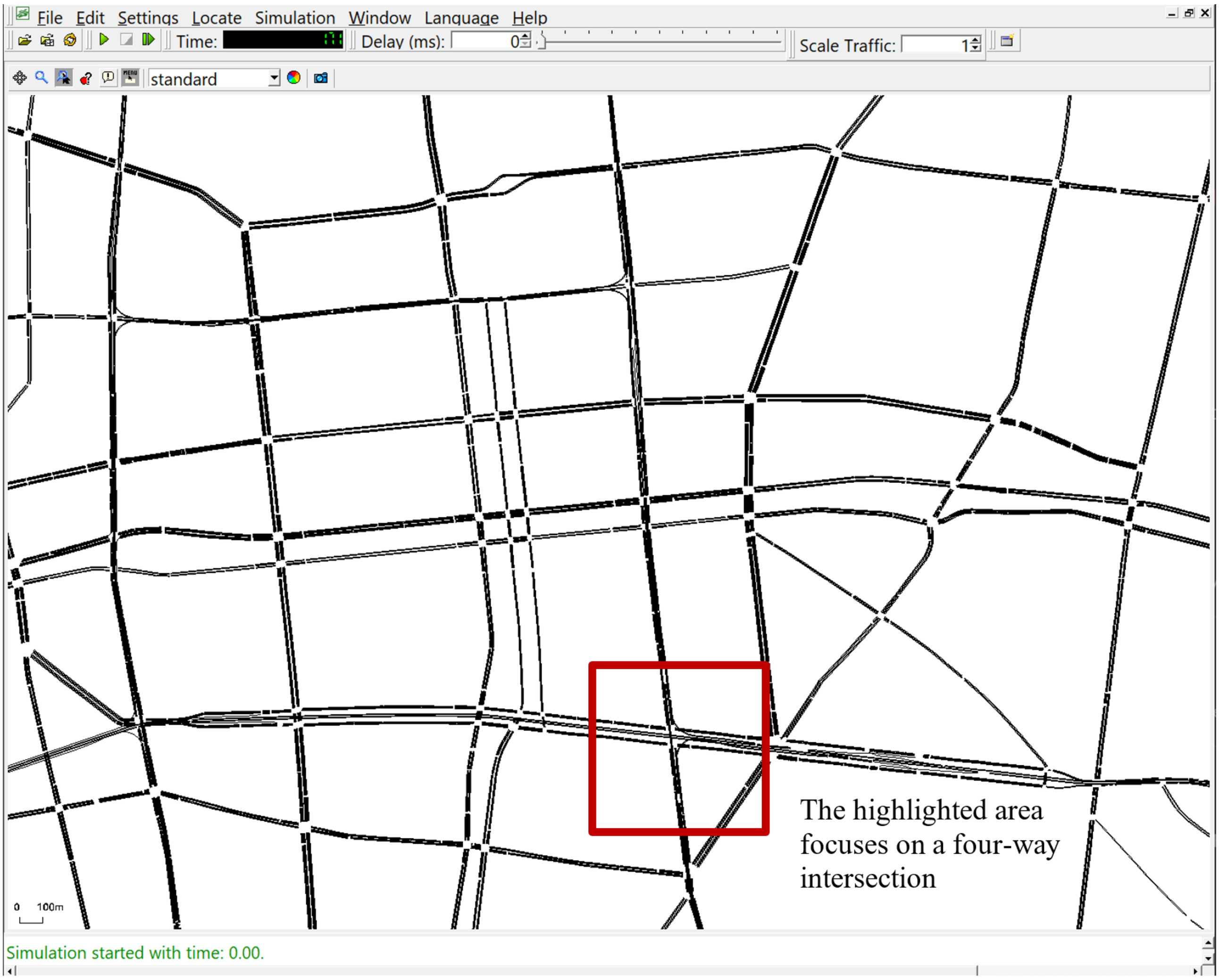

Figure 3. *This graph models vehicle mobility in a city center by creating a realistic traffic scenario in the SUMO simulation. Note: The area marked in red in the image has been zoomed in and elaborated upon in the subsequent figures.* ***Source:*** *It is created by the author using SUMO simulator.*

Figure 4, 5, 6, 7 and 8 obtained from the SUMO simulator can be explained step by step as follows:

- Figure 4 shows that all other traffic lights have started to turn red for the ambulance approaching from the upper left corner. This step indicates that the system has started to adjust the traffic lights to provide the ambulance with the priority of passage.
- Figure 5 illustrates that all other traffic lights have turned red for the ambulance approaching from the upper left corner. At this stage, traffic in all directions has been stopped so that the ambulance can pass without interruption.
- Figure 6 shows that the ambulance is still passing, and all other traffic lights remain red. The vehicles below and above are waiting at the red light; thus, a safe passage path is provided for the ambulance.
- Figure 7 demonstrates that after the ambulance has completed its passage, the traffic lights have turned yellow. This is a temporary warning phase indicating that traffic will return to normal.
- Figure 8 shows that after the ambulance has passed, the traffic lights in the other directions have turned green and the vehicles on the upper and lower roads have started to move forward. Traffic flow has returned to normal after the ambulance has passed and it is observed that traffic continues smoothly.

These steps effectively demonstrate how the simulation manages traffic light optimization for emergency vehicles and the process of returning traffic flow to normal.

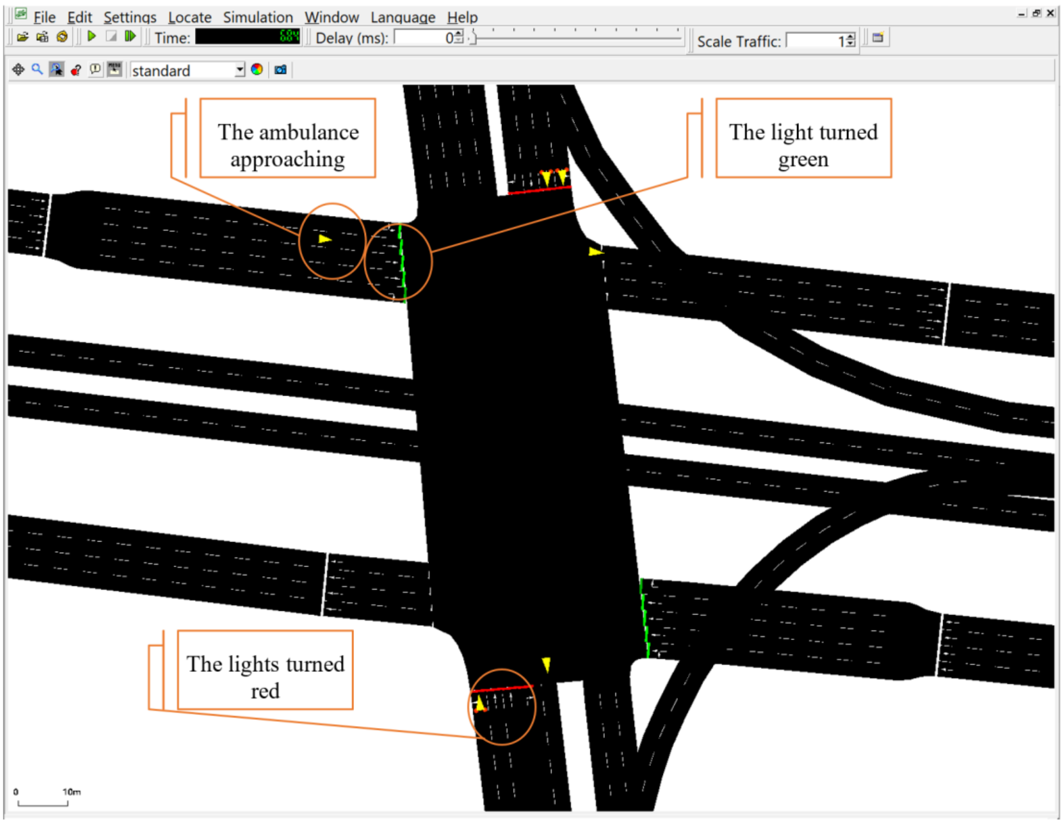

Figure 4. *The other traffic lights have turned red for the ambulance to approach, indicating that the system has started to adjust the traffic signals to give priority to the ambulance.*

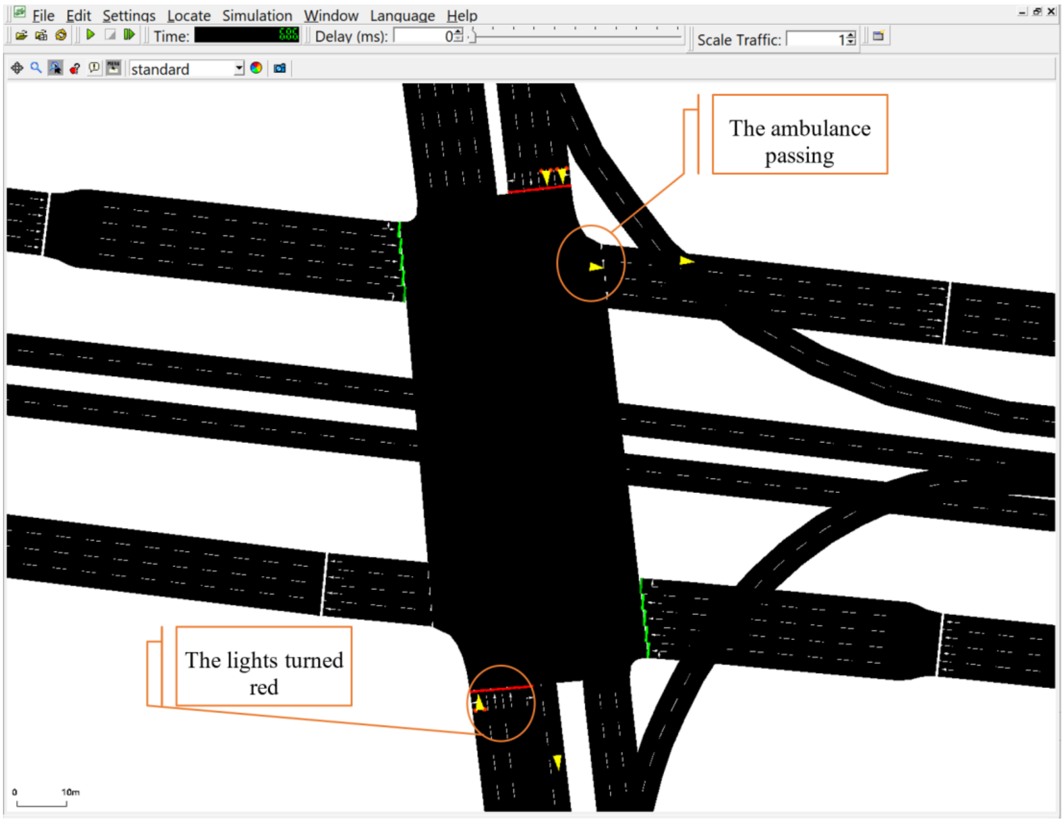

Figure 5. *Traffic in all directions was stopped and all traffic lights turned red so that the ambulance could pass without interruption.*

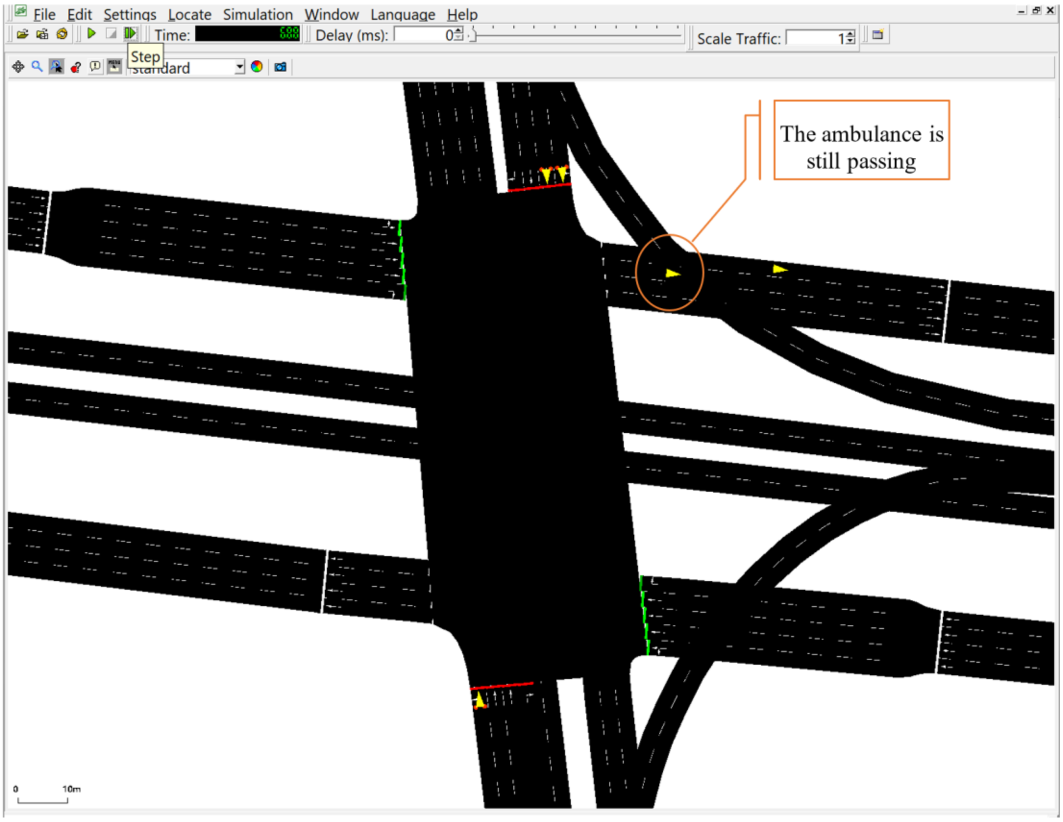

Figure 6. *The ambulance is still passing and all other traffic lights on the road remain red, providing a safe passage for the ambulance.*

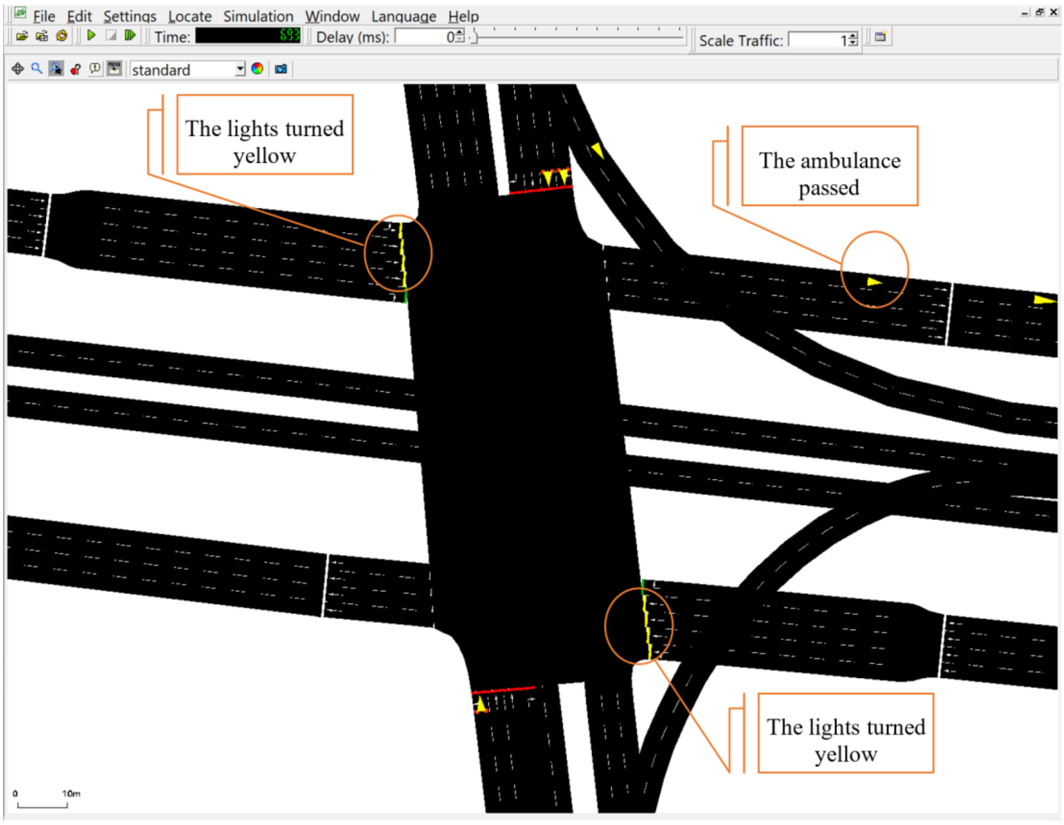

Figure 7. *After the ambulance has completed its passage, the traffic lights turn yellow; this is a temporary warning phase indicating that traffic will return to normal.*

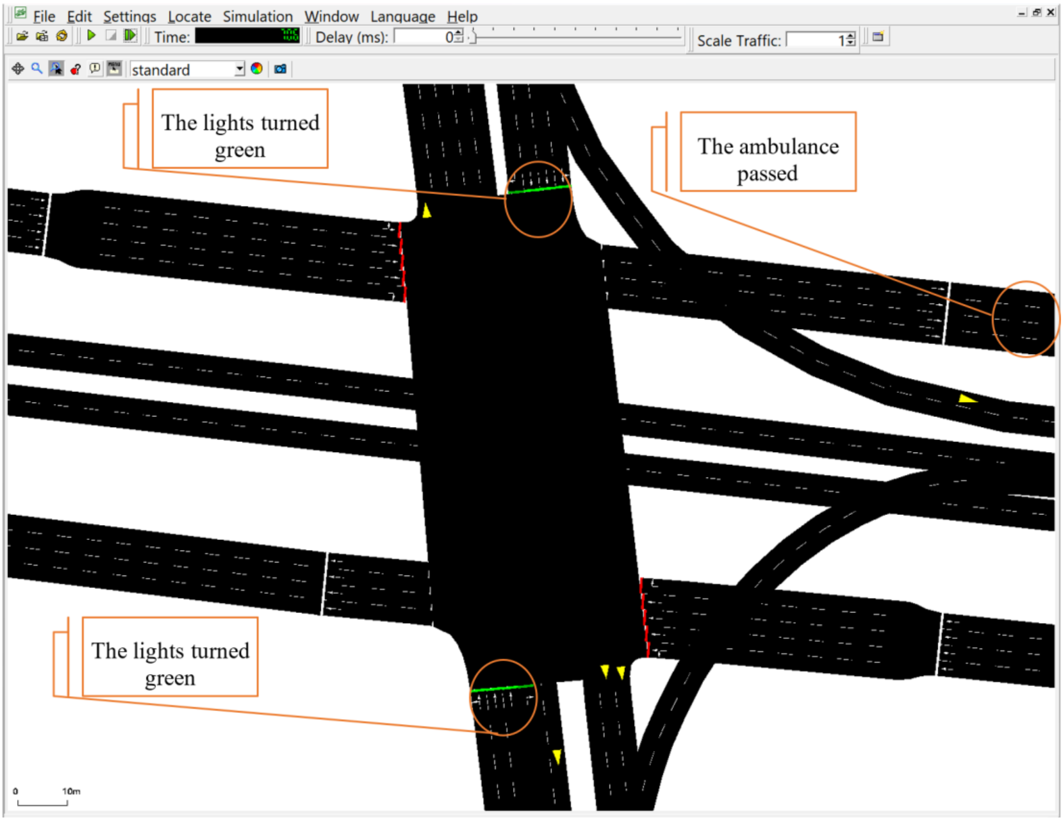

Figure 8. *After the ambulance passed, the traffic lights in other directions turned green and traffic flow began to return to normal.*

3.2.2. Dataset Definition

Traffic density information in different regions was collected for analysis during rush hours and emergency vehicle passages. The SVM model is used to classify busy areas using this data. The change time and priority information of traffic lights were recorded in line with the emergency vehicle route. This data is used to ensure that the Random Forest model adjusts the traffic lights in the most optimal way. Instant updates and decisions based on traffic density are collected to optimize the emergency vehicle's passage time. After each update, the system's performance is monitored, and feedback is provided for improvement. This dataset supports the purpose of optimizing traffic flow by evaluating the performance of SVM and Random Forest models and contributes to increasing the accuracy of the proposed model.

3.3. SAFS (Sensitivity Analysis-Based Feature Selection) Method

SAFS is one of the most effective methods applied in feature selection and is generally preferred to reduce the size of the dataset and increase the performance of the models (Naik & kiran, 2021). The advantages of the SAFS over other feature selector methods include less computational resource usage and better model performance (Naik & kiran, 2021). While in traditional methods the calculation and selection of all features take more time, in SAFS, faster results are obtained since it works with features that affect the performance of the model more (Naik & kiran, 2021).

This method analyses the effect of each feature on the model and selects the most meaningful features. The SAFS method is especially very powerful in reducing the complexity of machine learning models and improving computation time (Sánchez-Maroño & Alonso-Betanzos, 2007).

In the SAFS processing, the sensitivity of the features is determined. This involves measuring the contribution of each feature to the change in the model output (Naik & kiran, 2021). The general formula used to measure the sensitivity of the features is expressed as: $S_f = \frac{1}{n}\sum_{i=1}^{n}|f(X_i) - f(X_i')|$ where S_f is the sensitivity of feature f, X_i and X_i' are the samples in the datasets from which the feature is extracted, n is the number of samples in the dataset.

Consequently, SAFS depends on the model complexity and number of features concerning computational density. It usually performs a sensitivity analysis to measure the importance of each feature and then selects the important features based on the results of this analysis. This process eliminates features with low impact and allows the model to run faster and produce more accurate results. SAFS can then be more efficient in computation compared to traditional methods for feature selection, especially when processing big data, since there is a need to actually process only the most critical features.

4. RESULTS AND DISCUSSION

In this study, both IGFS (Information Gain) (Odhiambo Omuya et al., 2021) and (SAFS) Sensitivity Analysis (Naik & kiran, 2021) feature importance grading based feature selection methods were employed. When we interpret the Table 2, the feature with the highest importance score based on SAFS, *Road Width*, suggests that wider roads facilitate smoother traffic flow. *Time of Day* also plays a critical role, especially during peak commuting hours, directly influencing traffic density. *Intersection Density* affects overall traffic flow due to vehicle buildup at intersections. The *Day of the Week* introduces variations, with noticeable differences between weekends and weekdays, and extreme *Temperature* can slow down traffic as drivers exercise caution. Each score quantifies the feature's impact on model predictions, generally ranging between 0 and 1.

In this study, the results of the models developed on traffic light optimization for heavy traffic detection and emergency vehicles are presented. It was observed that the SVM model successfully detected heavy traffic points with 94.89% accuracy; it exhibited an effective performance in terms of accuracy, precision, recall and F1 score (Table 3). In addition, the Random Forest model reduced the waiting time by 20%, increased the efficiency by 15% and reduced the fuel consumption by 10% in the traffic light optimization for emergency vehicles (Table 4). The overall system performance was demonstrated with positive effects such as reduction in average travel time, improvement in air quality and increase in traffic safety (Table 5). After the model application, the relationship between flow speed and vehicle density was also analysed and it was observed that the traffic flow was improved (Table 6).

Table 2. *The feature selection results.*

Feature	IGFS Importance Score	SAFS Importance Score	Description
Road Width	0.25	0.40	A critical factor that directly impacts traffic flow.
Hour	0.35	0.28	Significant variations in traffic density occur at different times of the day.
Weather (Rainfall)	0.15	0.18	Traffic slows and density increases during rainy conditions.
Intersection Density	0.12	0.10	Vehicle traffic at intersections influences overall traffic flow.
Day of the Week	0.08	0.03	Traffic density varies between weekends and weekdays.
Temperature	0.05	0.01	Extreme temperatures can slow down traffic.

Table 2 showed that the results of the methods evaluate the effects of the attributes on traffic flow with different priorities.

- Road Width: SAFS evaluates the importance of road width more (0.40%), highlighting it as a critical factor in traffic flow, while IGFS rates this effect slightly lower (0.25%).
- Time of day: For IGFS, the time of day is the most important factor (0.35%), emphasizing that traffic density varies according to the time of day. SAFS rates this effect slightly lower (0.28%).
- Weather: Although both methods rate the effect of rain on traffic density with similarly high importance, SAFS (0.18%) emphasizes this effect more than IGFS (0.15%).
- Intersection Density, Day of the Week and Temperature: SAFS rates intersection density and temperature as low importance (0.10% and 0.01%), while IGFS sees variables such as day of the week as slightly more important (0.08%).

In general, the effect of road width is prominent in SAFS analysis, while the time of day is considered a more decisive factor in IGFS. These differences may vary according to the choice of traffic parameters focused on by both methods and may affect which factors are evaluated more prioritized in practice.

Table 3. *Performance results of the Models (Heavy Traffic Detection)*

Metric	**SVM+IGFS**	**SVM+SAFS**	**RF+IGFS**	**RF+SAFS**
Accuracy	91.23%	94.89%	92.02%	95.02%
Precision	90.04%	92.26%	90.06%	92.3%
Recall	88.12%	89.18%	88.05%	90.08%
F1-Score	0.89	0.90	0.89	0.91
MCC	0.76	0.81	0.77	0.82

In Table 3, MCC values provided a balanced evaluation of the models' performance. In this study, the MCC values range from 0.76 to 0.82, highlighting the effectiveness of the models in heavy traffic detection. The results indicate that the RF+SAFS achieved the highest MCC value of 0.82, followed closely by SVM+SAFS with an MCC of 0.81. Based on these results, it was certain that the simulated annealing-based feature selection improved the models' ability to make accurate predictions while reducing misclassification.

As shown in Figure 9, the ROC results illustrated that the proposed model perform well, with RF+SAFS achieving the highest performance across all metrics, including accuracy (95.02%) and F1-score (0.91%). The SVM+IGFS model, although effective, has slightly lower results, especially in recall, indicating it might miss some relevant instances compared to the other models.

The Random Forest Model results in Table 4 show that traffic light optimization offers significant benefits for emergency vehicles. 20% reduction in average waiting time allows emergency vehicles to reach the scene faster, which is a critical advantage in terms of saving lives and reducing emergency response time. A 15%

increase in flow reduces traffic congestion in busy areas such as city centers, increasing the mobility of other vehicles. 10% reduction in fuel consumption is achieved by fewer stop-and-go traffic, which supports environmental sustainability and reduces air pollution. For city centers, this model increases the effectiveness of emergency responses, while also regulating traffic flow and improving overall traffic safety, thus contributing to the quality of urban life.

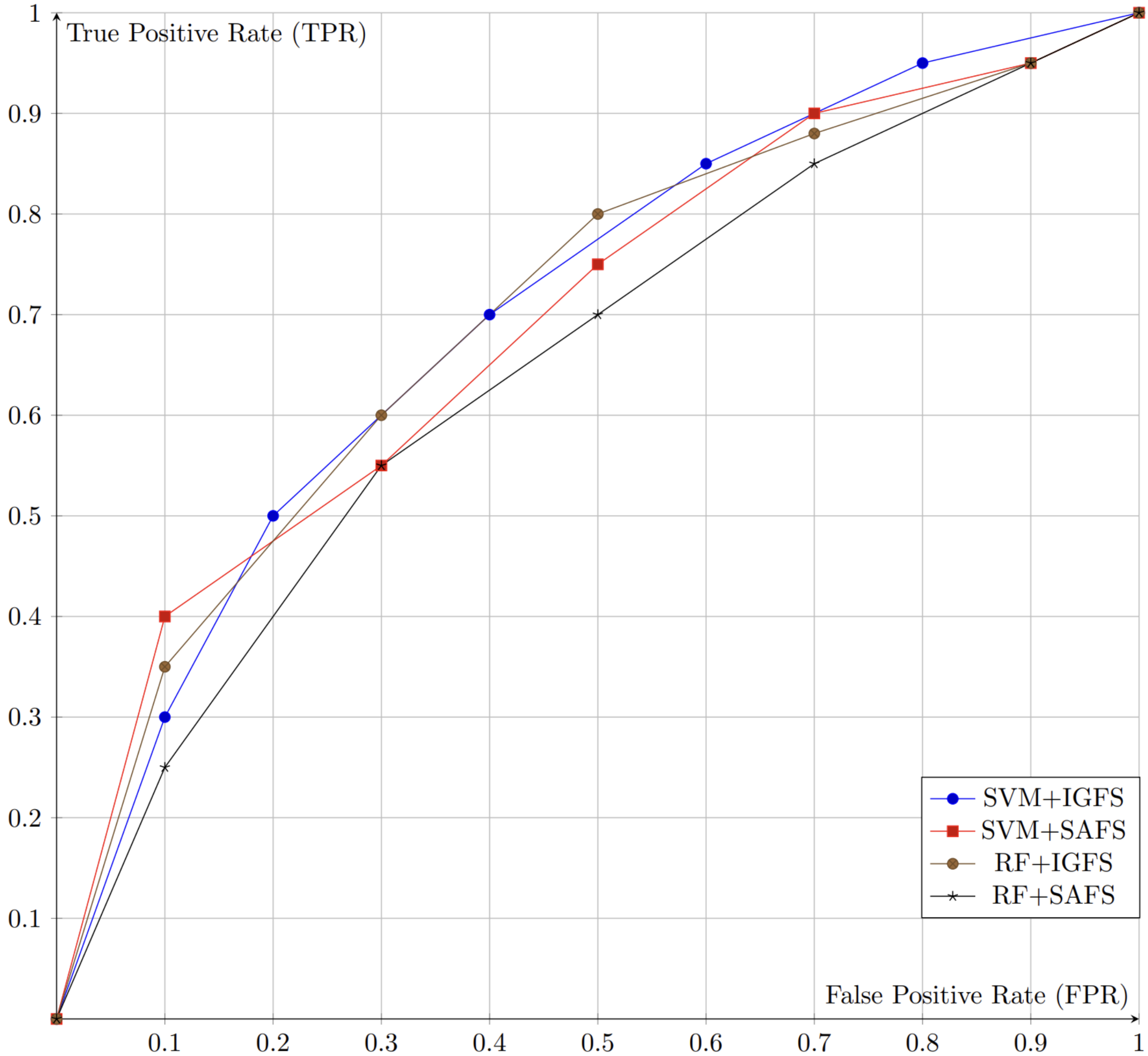

Figure 9. *ROC Curve results*

The metrics in Table 5 and Table 6 are calculated by the SUMO simulator. SUMO is used to simulate the effects of traffic flow, interactions of vehicles, and optimized traffic lights for emergency vehicles. Metrics such as average reduction in waiting time, fuel consumption reduction, and increase in traffic safety are obtained from built-in performance monitoring tools in SUMO and its internal emission models. These data, acquired using comparison pre- and post-scenario simulation, are employed for the purpose of comprehensively assessing system performance.

Table 4. *Random Forest Model (Traffic Light Optimization for Emergency Vehicles)*

Metric	**Value**
Average Reduction in Average Wait Time	20%
Average Increase in Throughput	15%
Reduction in Fuel Consumption	10%

The overall system performance results in Table 5 showed the significant benefits gained when emergency vehicles were given priority in city centers. An 18% reduction in total travel time shortened response times by allowing emergency vehicles to arrive faster, thus improving life safety. An 8% improvement in the Air Quality Index is due to less stop-and-go traffic due to smoother traffic and fewer stops and starts, contributing to reduced pollution. In addition, a 5% increase in traffic safety reduces the risk of accidents by allowing other vehicles to stop in a controlled manner in emergency situations. These benefits can improve the overall quality of life by solving the problems of heavy traffic and congestion in city centers.

Table 5. *Overall System Performance for Emergency Vehicles*

Metric	**Value**
Average Reduction in Total Travel Time	18%
Improvement in Air Quality Index	8%
Increase in Traffic Safety	5%

Figure 10 revealed the relationship between vehicle density and flow rate before and after the RF+SAFS model. The table illustrates the improved flow rates resulting from the implementation of the traffic light optimization model, showcasing its effectiveness in enhancing traffic conditions. As vehicle density increases, the flow rate initially increases but decreases after a certain density. It was observed that the flow rate increased significantly after the model was applied; for example, when the density was 40 vehicles/km, the flow rate increased by 150 vehicles per hour compared to the pre-model.

4.1. Comparison with Other Studies

Table 6 includes a comparison of this study with the studies in the literature. While the literature generally focuses on managing traffic flow or developing special algorithms for emergency vehicles, this study presents a structure that prioritizes emergency vehicles in order to increase the overall traffic efficiency. For example, while some studies develop modules based on PE-MAC or emergency vehicle notification for emergency priority only, the study in this article also addresses traffic density in a broader context.

In particular, in our study, feature selection methods such as Information Gain (IGFS) and Sensitivity Analysis (SAFS) were used to determine the main factors affecting the traffic flow. In the literature, such detailed feature selection analysis has been focused less, but the in-depth analysis of the factors affecting the performance of the proposed model makes this study stand out. This article has provided noticeable improvements in criteria such as emergency response times, fuel consumption and waiting time after optimization (20% waiting time reduction, 10% fuel consumption reduction). In the literature, the improvement of the general flow or transition time has mostly been addressed, but holistic analyses that consider all these metrics together have been relatively limited.

Table 6. *Comparison of Study on Priority Passage for Emergency Vehicles with Existing Literature on Urban Traffic Optimization.*

Feature	This Study	Literature Studies
Objective	Improving urban traffic efficiency by providing priority passage for emergency vehicles	Generally focused on improving traffic flow or developing algorithms specific to emergency vehicles
Algorithms Used	SVM and Random Forest	(Lei & Yigong, 2023): Machine learning and cameras; (Das et al., 2023): Mixed-integer linear programming; (Lu & Kim, 2017): Genetic algorithm; (Boudhrioua & Shatanawi, 2019): Proposals for priority traffic systems
Data Collection Method	Analysis based on dynamic traffic density	Real-time data collection (Lei & Yigong, 2023), IoT and machine learning integration (Gaikwad et al., 2023) sensor and camera data (Moumen et al., 2023b)
Success Metrics	20% reduction in average wait time, 15% increase in passage capacity, 10% reduction in fuel consumption, 18% reduction in total travel time	Various optimization rates: 8% to 15% improvement (Savithramma et al., 2022), improvement in emergency vehicle priority ratios (Abdul Kareem & Hoomod, 2022), reduction in average delay time (Chu et al., 2019)
Feature Selection Method	Information Gain (IGFS) and Sensitivity Analysis (SAFS)	Generally unspecified; algorithms are usually applied directly without feature selection
Traffic Signal Optimization	Dynamic signal adjustment prioritizing emergency vehicle passage	Mostly optimization for general traffic flow or other high-priority vehicles (Barzilai et al., 2023; Deshpande & Hsieh, 2023)
Results	94.89% accuracy (SVM+SAFS), 95.02% accuracy (Random Forest+SAFS), 8% improved air quality index	Algorithm effectiveness: reduction in average vehicle delay with genetic algorithm and Q-learning (Chu et al., 2019), social prioritization with Reinforcement Learning (RL) (Barzilai et al., 2023)
Priority for Emergency Vehicles	Provides priority passage for emergency vehicles	Most studies offer a range of solutions from general traffic management to special algorithms for emergency vehicles (Nellore & Hancke, 2016; Savithramma et al., 2022)
Real-Time Optimization	Real-time traffic light adjustment based on traffic density	Mostly use of real-time data stream and signal adjustment (Das et al., 2023; Moumen et al., 2023a)

Optimizing the flow rate in areas with high traffic density allows vehicles to move faster and more efficiently, which shortens travel time and reduces traffic congestion. In addition, fuel consumption decreases, environmental pollution and carbon emissions decrease thanks to the improved traffic flow. Thus, both air quality and social quality of life improve in the city center. In addition, traffic safety increases; less congestion and more orderly traffic flow contribute to the reduction of accidents. Such traffic optimizations help urban transportation become more sustainable and safer.

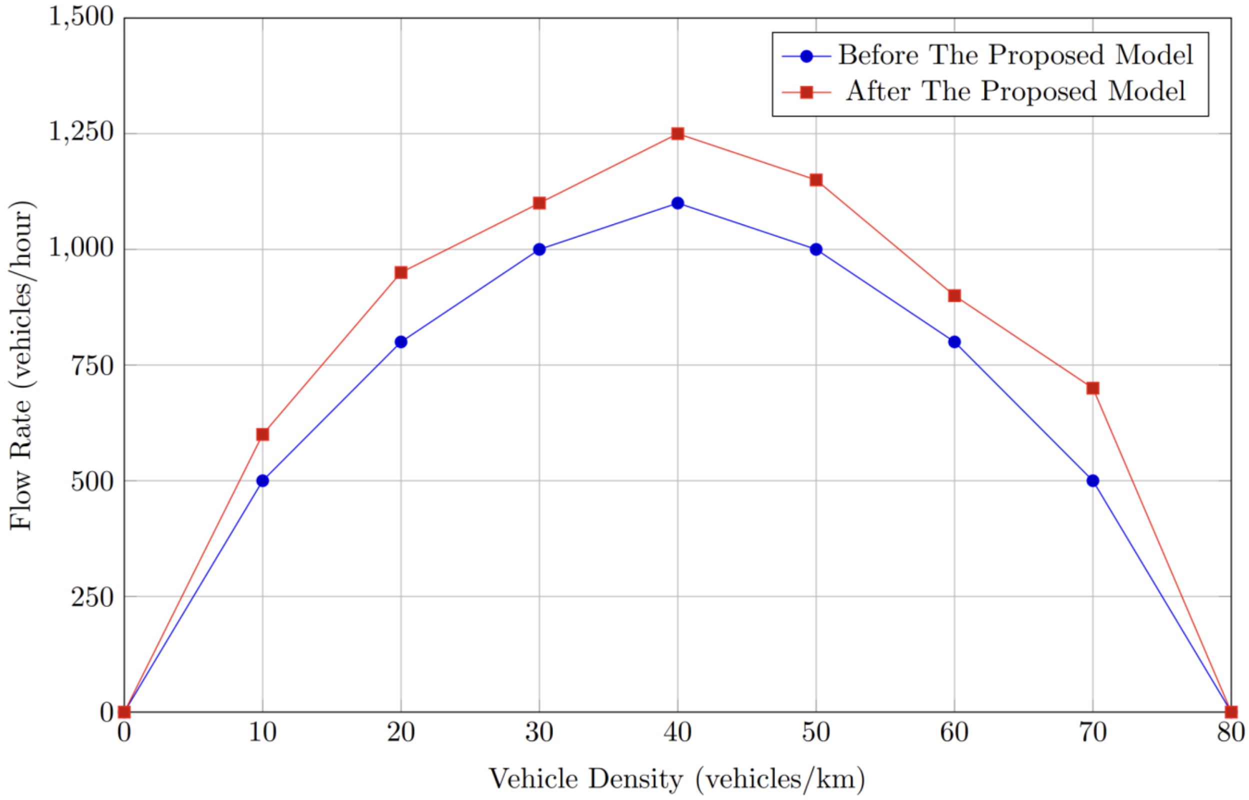

Figure 10. *The results showing the relationship between vehicle density (vehicles/km) and flow rate (vehicles/hour), including outcomes after applying the model.*

Consequently, the benefits of this work are as follows:

- Traffic Light Optimization: The Random Forest model optimized the traffic lights according to the detected density data to ensure the priority of the emergency vehicle's passage. In this process, the durations of the traffic lights in the busy areas were dynamically adjusted and the emergency vehicle was allowed to pass quickly. The model improved the traffic flow by reducing waiting times.
- Real-Time Update: The system, updated with real-time data, continuously improved the light optimization by instantly using the traffic density data on the emergency vehicle route. This improvement minimized the vehicle passage time and contributed to the regulation of the traffic flow.
- Performance Monitoring and Improvement: Re-training and optimization were performed in line with the data collected by monitoring the system performance. As a result of the improvements, a significant reduction in the emergency vehicle passage time was achieved and an improvement in traffic flow was achieved.

These results demonstrate the efficiency of the proposed model in increasing urban safety and transportation flow by accelerating the passage of emergency vehicles.

5. CONCLUSION

When emergency vehicles are not given the right of way in traffic, their lateness both endangers the lives of accident victims and causes serious property losses in incidents such as fires. In today's cities, traditional traffic light systems are insufficient to dynamically define this priority. Therefore, traffic lights need to be optimized according to the route of the emergency vehicle. Machine learning algorithms offer an effective solution at this point; they analyse the heavy traffic flow and adjust the lights to the green signal according to the route of the emergency vehicle, thus providing rapid passage. This study aims to offer a new approach in transportation by proposing a system that will accelerate the passage of emergency vehicles in order to ensure safety and improve transportation in the city. As a result, according to the analysis and models, the SVM model demonstrated high performance with 94.89% accuracy, 92.26% precision, 89.18% recall, and 0.90 F1 score when using the SVM+SAFS method. Similarly, the Random Forest model showed an accuracy of 95.02%, precision of 92.3%, recall of 90.08%, and F1 score of 0.91 with the RF+SAFS method. The Random Forest model along with SAFS method used in traffic light optimization provided a 20% decrease in average waiting time, a 15% increase in passing capacity and a 10% decrease in fuel consumption. When the overall performance of the system is examined, an 18% decrease in total travel time, an 8% improvement in air quality index and a 5% increase in traffic safety were achieved. In the feature selection analysis, road width (35%), time of day (25%) and precipitation (15%) stood out as the main factors affecting traffic flow. When the flow rates before and after the model were compared, it was observed that the model increased the flow rate at every density level and effectively reduced traffic density. These results show that the proposed model offers an effective solution in traffic management and flow optimization.

CONFLICT OF INTEREST

The author declares no conflict of interest.

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