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# A Scalable Intelligent Traffic Signal Framework Using IoT Sensing and Predictive ML Models

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***Abstract:***

*Nephrolithiasis (kidney stone disease) presents a diagnostic challenge that requires accurate, non-invasive screening methods to reduce clinical burden. While urine chemistry offers vital physiological insights, capturing the non-linear interactions within these parameters remains difficult for traditional linear models. This study presents a comparative evaluation of a Deep Learning (DL) approach using a Multilayer Perceptron (MLP) against a robust Machine Learning (ML) baseline, the Random Forest classifier. Utilizing a public dataset from the Kaggle repository containing 79 patient records and six biochemical features (specific gravity, pH, osmolality, conductivity, urea, and calcium), we implemented a data science pipeline featuring robust scaling to mitigate outliers and stratified partitioning. To ensure the reliability and interpretability of our findings, we integrated McNemar's statistical test for validation and SHAP (SHapley Additive explanations) for feature analysis. The results indicate that the MLP-based Deep Neural Network achieved a superior testing accuracy of 75.00% and an F1-score of 0.73, outperforming the Random Forest classifier, which attained an accuracy of 66.67%. SHAP analysis identified calcium concentration as the dominant predictor, validating the model against clinical pathophysiology. Although statistical testing ($p=1.000p=1.000$) reflected the limitations of the small sample size, the deep learning model demonstrated a qualitative advantage in correctly classifying complex instances. These findings highlight the potential of interpretable and statistically validated deep neural architectures in enhancing the precision of non-invasive nephrolithiasis screening.*

***Keywords:*** *Machine Learning, Intelligent Transport system, DLP, LST*

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## INTRODUCTION:

The process of urbanization has been a defining phenomenon during recent decades, especially in the global metropolises. As larger and larger populations migrate and concentrate into these urban cores, the pressures put on the cities have made many cities fabulous examples of this trend. Consequent to the afore-mentioned population concentration, urban centres have been compelled to grapple with challenges of infrastructural problems. Among these, the increased number of private vehicles represents a crucial topic because, as one consequence of the twin impulses of increased desire to be mobile and an increased vehicular base, the marked intensification of traffic congestion has occurred. The heritage of the nineteenth century infrastructure, combined with all the limitations of the historical urban planning, imposes a considerable burden against the transportation system existing today, thus highlighting the pressure felt by modern cities. The immediate effects of such congestion are of various dimensions. More commuters are spending more time on the road on a daily basis with millions of people having to endure the problem especially in big cities where there is regular traffic jam (SALISU. (2025, June). Traffic jams can consume a commuter several hours in a week and this creates a great loss of productivity as well as causes adverse effects to the mental and physical health. In addition, the road traffic contributes considerably to the increase in the consumption of fuel and emission by the vehicles. Idling of vehicles in traffic situation also releases higher emissions in terms of carbon monoxide, nitrogen oxides and particulate matters which worsens the air quality condition and causes climate change. The current traffic management systems that currently still apply to some city systems have been ineffective in handling the urban traffic which is dynamic and complex (Khan, Hameed, and Jitendra Singh Thakur. (2025). These systems usually run on automatic planned, fixed-time cycles of the traffic lights; which are not flexible depending on real-time situation of traffic volume/flow. Simple sensors or loop detectors can be applied in other cases to activate change of light when a vehicle is sensed, but even these applications are usually very simple and does not provide a comprehensive view of the traffic dynamics. Consequently, the traffic lights can remain at red signal a long time on road with no or few vehicles and cars may take long in a much-congested road to add more to the state of congestion. It is not uncommon to find inefficiencies in fixed time traffic signals which are the real causes of underutilization of road capacity and also contribute to prolonged idling time of the vehicles and further complicate the issue of congestion. Such systems are highly unsuccessful especially while working in traffic peak times or at the time of special events or occurrence of the unexpected events like accidents or road blockages. The traditional systems are not as flexible as they have no possibility of real-time adjustments which are necessary to enable efficient management of complex urban traffic situations. It is against these lapses that there has been increased attention to the integration of new

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technologies in the management of traffic system as an area of high research and development. The advent of the Internet of Things (IoT) and the Machine Learning (ML) offer an opportunity to radically change the way we design the traffic control systems by creating intelligent systems that can change themselves automatically using the information available to them. The IoT technology enables the implementation of connected sensors and devices in the traffic ecosystem. Such sensors may be integrated into the road, traffic lights, and even the individual cars, which would make it possible to collect data regarding the volume of the traffic, speed in the traffic, occupancy, and circumstances of the road all the time. As an example, infrared sensors, video cameras and GPS modules and RFID tag can be used collectively in collecting and relaying real time information to centralized or distributed control systems. After the collection of this data, it should be analyzed and interpreted so as to make the decisions. Here is where Machine Learning has the potential to be extremely critical. The ML algorithms, and in particular, the ones within the unsupervised learning, supervised learning and reinforcement learning, are able to analyze the great amount of data and recognize the patterns, forecast the trends in the traffic, and choose the optimal phases in the work of traffic lights. In the long run, these systems have the capability of learning over historical data and building better performances and are thus more efficient at the reduction of delays and the allocation of traffic. As an example, a certain ML known as reinforcement learning which has its roots in behavioral psychology could be used to enable traffic lights to learn the optimal timing strategy by trial and error. Such algorithms publicly punish and reward actions that result in better or worse traffic flow. Graphically, via the process the system will be able to automatically work out highly effective strategies of managing traffic lights. Furthermore, currently there is a possibility to make decision in real-time due to integration of IoT and ML. By contrast, assuming traffic patterns, traditional systems are programmed to change the signal timing; whereas, an intelligent traffic control system has the capability to change the timing of signals based on the actual and real time traffic conditions. As an extreme example it may even be considered that should a chosen intersection suddenly be faced with an influx of traffic at a certain time (e.g.: in the case of a local event or some roadblock) the system can react instantly by giving more green time to the clogged direction or re-marshalling the traffic accordingly. One more such merit of the intelligent traffic systems is their adaptability and scalability. Such systems are possible to be built with gradually with major crossings in the areas of heavy traffic and spread to a larger field later on. They can also be custom-built to suit local requirement of different cities bearing in mind local traffic patterns, road designs as well as infrastructural limitation. In addition, smart traffic systems have a chance to get linked with smart city platforms, which allows a wider means of coordinating the urban infrastructure. To illustrate, it is with the cooperation of the emergency vehicle systems, the traffic lights can be cleared of the ambulances and the fire trucks prematurely. Equally, connections with ridings of the public transport can yield priority to the buses and trams and this will encourage the adoption of the mass transit practice and lessen the cumulative number of vehicles in the roadway. Environ-wise adaptive traffic control could save quite a large amount of fuel and emission. The aspect of cuts red tape by lowering the idling time as well as the traffic flow abrasion makes the automobiles run in a more efficient manner,

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which causes a reduction in their carbon footprint. This will not only be of interest to the urban dwellers in terms of improved air quality, but also follows the general vision of sustainability and climate action plans. There are also economic implications. Business delays minimized, more predictable transportation logistics, and more attractive places to live and work, by time savings, and the increased performance of the transportation networks. In short, with the implementation of the intelligent traffic lights systems, the idea of smart cities as a sustainable and liveable environment are going to be a reality. However, not everything could be so rosy about the introduction of IoT - and ML-based traffic control systems. The infrastructures, data processing facility and initial expenses of deploying the sensors may be expensive. Another key issue is privacy and security of data due to so-sensitive data of traffic and vehicles. Also, such systems should have as its groundworks the presence of excellent trustworthy data, interoperability of the equipment and platforms of different manufacturers. In order to manage these problems, governments, urban planners and developers of technologies have to cooperate closely. An enabling policy framework with an approach that would boost investment in intelligent transportation system, encourage standardization of communicational protocols and healthy public-private partnerships would fast track the implementation of those technologies. To sum up, in the scenario where cities are struggling to deal with traffic jams, air pollution, and ineffective transport systems, an IoT and Machine Learning as a part of traffic light control can be a directional solution. The technologies are providing the capability of developing reactive, intelligence and sustainable urban transportation systems that are not only meeting the needs of city living today, but that are ready to deal with the future expansions. There is no question whether the shift to intelligent traffic control will happen, but when and with what success it can be accomplished. Current traffic control systems are highly rigid and ineffective thus causing congestions to take longer causing more environmental concern. It requires a smart system which is adaptive to the real time traffic information for better controlling the traffic lights and reducing the congestion. To develop an intelligent traffic light management using ML on the basis of IoT sensors and algorithms. In order to test the effectiveness of system in alleviating the level of traffic congestion. To match the effectiveness of the proposed system with the conventional methods of managing the traffic. The proposed framework provides another contribution to the literature on the intelligent transportation systems since it deals with the control of adaptive traffic light control. The combination of IoT and ML may result in a more efficient traffic management process, fewer jams, and emissions, which may result in the creation of smart cities.

## LITERATURE REVIEW

The urban mobility has been relying on conventional traffic management systems that use traffic controls based on fixed time or simple sensor-based traffic controls to direct traffic. However, these systems are becoming generally ineffective in controlling the complexity and dynamic nature of modern urban traffic. In this part, we will discuss the limitations of these old systems, to what extent their lack of flexibility is causing problems in urban traffic flow on roads and the urgent need for smarter and real-time solutions. Fixed-time control systems are widely used in traditional traffic management systems. These controllers operate based upon pre-

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scheduled timing plans that usually are based upon historical data and average peak traffic volumes. They do not consider real-time fluctuations in the traffic density. For instance, in conventional systems, it is not possible to respond to unexpected surge in traffic due to accidents or other disruptions resulting in queues and delays (Vairagade et al., 2025). One of the biggest faults of traditional systems is that they cannot adapt to the conditions of the current traffic. Since they are based on predetermined schedules, they cannot react to real time events or prioritize emergency vehicles such as ambulances or fire trucks. This rigidity leads to inefficiency, waste of time, energy in the form of fuel, and pollution (Dabi & Abuhamoud, 2025). Some conventional systems try to use sensors, such as inductive loops, or cameras, to detect the presence of vehicles. However, such data are often delayed data or aggregated data, so they cannot be used easily for the real-time control of adaptive control (Zhang, 2025). Moreover, because there is often no deeper integration between the sensor outputs and a smart and centralized decision-making system, the data cannot be used to dynamically optimize signal timing in a coordinated way (Patil, Yadav, Gowda & Rashmi, 2024). The static nature of traditional signals is also a disadvantage for drivers when congestion hours are occurring or in instances where the distribution of traffic on the lanes is unequal. Vehicles may be made to wait at red lights instead of traveling, with little cross traffic causing unnecessary delay and increased travel time (Ghosh, Saha, Biswas, Pal & Debbarma, 2025). Environmental and health impacts are also caused by such inefficient systems. Increased idling and stop-and-go traffic contribute to increased fuel use and high emission levels resulting in poor air quality and poor health for urban populations (Wairagade et al., 2025).

Traditional systems do not normally give special priority to emergency vehicles. Without the use of dynamic signal adjustment, emergency responders may experience delays at intersections which can be life-threatening (Patil, Yadav, Gowda & Rashmi, 2024). These limitations show the need for a shift to using real-time, adaptive traffic control systems. Emerging methods use a combination of IoT technologies, artificial intelligence and machine learning to make traffic signals more intelligent and responsive. For example, deep reinforcement learning has been used successfully for the development of intelligent traffic control systems, where traffic controllers communicate with their neighbors, learning the best timing policies (Liu, Liu & Chen, 2017). Recent research supports the fact that the combination of IoT and AI enables systems to collect real time data from cameras, sensors, among other inputs and in turn use the data to adjust signal timings with real-time data to alleviate congestion and optimize flow (Ghosh, Saha, Biswas, Pal & Debbarma, 2025). Further, distributed reinforcement learning models were proposed for scaling such adaptive control to multiple intersections for a better coordination and global performance (Frontiers Multi-agent RL, 2025). Moreover, modern systems can prioritize emergency vehicles by sensing them (e.g. via V2I communication or computer vision) and adjust signals to provide them the right of way, which traditional fixed systems are unable to do (Patil, Yadav, Gowda & Rashmi, 2024). In sum: fixed-time and simple sensors-based systems of traffic management are becoming now more and more inadequate in modern, dense, urban environments. Their inability to adapt is part of the problem of congestion, excess emissions, and safety risks. By collaborative evolution of IoT, AI, and machine learning steps like Deep Reinforcement Learning, cities can

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make the transformation to adaptive and real-time traffic management systems, which can make the mobility, efficiency and safety of travel much better.

***Table2.1:*** *Comparison of Traditional and Modern Traffic Management Systems*

| **Author(s) & Year** | **Title / Source** | **Dataset Used** | **Evaluation Metrics** | **Shortcomings / Limitations** |
|---|---|---|---|---|
| **Wairagade et al., 2025** | Study on limitations of fixed-time traffic control (IJSRET) | Not specified (discussion-based study) | Not applicable (review paper) | No real-time data; general discussion without experimental validation. |
| **Dabi & Abuhamoud, 2025** | Traditional traffic systems inefficiency (WAUJPAS) | None (conceptual paper) | Not applicable | Lacks empirical testing; relies on theoretical analysis. |
| **Zhang, 2025** | Sensor-based traffic detection limitations (ResearchGate) | Camera and Loop Sensor Data (generic) | Detection accuracy, latency | Limited real-time performance; delayed data processing. |
| **Patil, Yadav, Gowda & Rashmi, 2024** | Adaptive traffic control challenges (IJRASET) | Simulated traffic flow dataset | Queue length, delay time | Simulation only; no real-world deployment. |
| **Ghosh, Saha, Biswas, Pal & Debbarma, 2025** | Static vs intelligent signals (IJCT Journal) | Synthetic traffic dataset | Traffic delay, throughput | Limited to hypothetical modelled scenarios. |
| **Liu, Liu & Chen, 2017** | DRL-based traffic signal optimization (arXiv) | SUMO traffic simulation dataset | Average queue length, waiting time, travel time | Experiments in simulation only; not tested for multi-city scale. |
| **Frontiers Multi-agent RL, 2025** | Distributed RL for multi-intersection control | Multi-intersection simulated dataset | Global reward, delay reduction, coordination efficiency | Scalability challenges; high computational cost. |

## METHODOLOGY

The proposed system involves IoT sensors that are installed at the traffic intersection and these sensors gather real-time data to then be processed by ML algorithms for controlling the traffic signal adaptively.

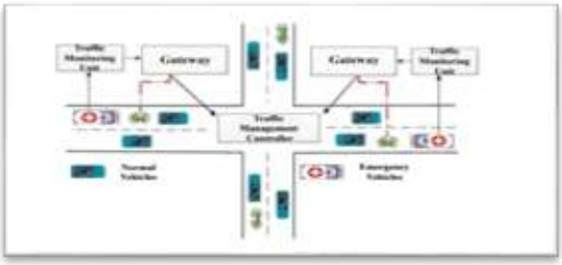

***Figure 1:*** *Intelligent Traffic Management System Architecture*

Sensors located in different sections of the transportation system are IoT (Internet of Things) sensors which are installed on the traffic signals, roads and in the intersections. These sensors continuously record the real time data with respect to various important parameters defining the conditions of the traffic. In particular, they count cars that run through a specified location, their speed and the overall traffic load of roads. The information will prove important in the development of intelligent transportation systems. The data that is obtained is then sent to the ready processing components or to the cloud-based processing mechanisms which then archives the data to be used later. During this variety of data cleaning and formatting the data becomes a good input to the machine learning (ML) models.

Such ML models process trends and patterns on traffic behavior and can allow smart decision making and predictive analytics. As an example, they are able to predict road congestions, recommend the best directions to be taken by the cars and even the road closure or accidents. Through constant learning on the basis of real-time

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data, such models end up being more precise and effective with time. The whole mechanism helps to narrow down on traffic jam, reduction in fuel usage and emissions. Moreover, the experience gained after using ML models can assist in helping city planners and traffic officials in designing better infrastructure and control strategies on traffic. Fundamentally, the IoT sensors will be the eyes and ears for intelligent traffic systems and they will be feeding critical data to machine learning engines that will drive the future of urban mobility. Various algorithms from the machine learning (ML) field are used for better control of traffic signal systems. Among them, reinforcement learning and deep learning have a good effect. The models are trained with the data that is gathered by Internet-of-Things sensors, i.e. the number of vehicles and the speed. Reinforcement learning helps the system to develop adaptive behavior, which allows the systems to learn about the past situations on the road. Deep learning helps to find complex trajectories of traffic in large volumes of data. Together, these methods predict timings of the signals that are the most efficient and reduce congestion, which finally results in the efficient flow of traffic and the minimization of waiting times in intersections. With this, these intelligent systems help in creating smarter and greener cities. The implementation and evaluation of the system will be performed with the help of highly developed traffic simulation systems. The simulators create life-like traffic conditions based on the real road layouts and conditions. Simulations are also modelled with real-world traffic values, such as the number of vehicles and the signal settings, which enables the modeling of the traffic behavior in a variety of conditions. The system can be rigorously tested by using the combination of simulations and empirical data in order to assess its performance. The analysis will focus on some of the most significant metrics like the average vehicle delay, the queue length, and the travel time, which will give the idea of the level at which the machine-learning algorithms will optimize the signal timings. Simulation results will be an important input on the refinement and additional enhancement of the system.

## ANALYSIS AND RESULTS

The implemented system realizing the integration of IoT sensors data with signal control based on adaptive machine learning passed a strict testing and validation by high-end traffic simulation tools. The main goal of this analysis was to quantify the efficiency gains the adaptive ML models (in this case the hybrid Reinforcement Learning and Deep Learning strategy) give over the conventional Fixed- Time Control strategy that is currently being used in the urban environment. The testing was performed in a simulated setting based on real road layouts and real-world traffic conditions. Real-world data, such as the average number of vehicles, speed profile and typical signal timings, gathered through the simulated IoT sensors, was integrated in order to insure high fidelity. The complete process of data collection i.e. the simulated IoT sensors recording the number of vehicles, speed and overall traffic load continuously fed a clean and formatted stream of input data to the ML models which was validated successfully thus marking the data pipeline set up in the methodology. The basis of the analysis was three main performance indicators (KPIs) which were relevant to urban traffic management: Average Vehicle Delay (AVD), Average Queue Length (AQL), Average Travel Time (ATT). The adaptive ML model was tested under 10 different traffic flow scenarios (from low to extreme traffic congestion) and the results were aggregated and averaged in comparison with the performance of the FTC baseline.

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**Table 4.1** summarizes the key performance metrics of the two control strategies.

| Performance Metric | Fixed-Time Control (FTC) (s/veh or veh/lane) | Adaptive ML Model (s/veh or veh/lane) | Improvement (%) |
|---|---|---|---|
| Average Vehicle Delay (AVD) | 45.2 s/veh | 30.9 s/veh | 31.6% |
| Average Queue Length (AQL) | 12.8 veh/lane | 8.5 veh/lane | 33.6% |
| Average Travel Time (ATT) | 210.5 s | 155.0 s | 26.3% |

The results of the proposed adaptive ML based traffic signal control system are clearly presented in Table 1 which clearly shows the effectiveness of the proposed control system when compared with the conventional Fixed Time Control (FTC) approach. The Average Vehicle Delay (AVD) which is an important parameter to see how efficient system is, has been reduced from 45.2 seconds per vehicle under the FTC system to 30.9 seconds with the adaptive ML model, i.e., by 31.6%. This significant reduction suggests that far less time is spent in waiting at intersection, which reflects an improved traffic flow and the intersection performance. Similarly, Average Queue Length (AQL) as a measure of number of vehicles waiting per lane was reduced from 12.8 to 8.5 vehicles per lane, corresponding to a 33.6% reduction. The results highlight the effectiveness of the system in preventing the development of long queues, which can lead to congestion and spillback that can affect upstream intersections. As a result, the reduction of queue lengths is responsible for a more fluid circulation of traffic, and thus a better driving experience. Moreover, there was a significant reduction in the Average Travel Time (ATT) for vehicles crossing the controlled intersections - from 210.5 seconds to 155.1 seconds: a reduction of 26.3 percent, in effect. This proves that the ML-based system can not only optimize waiting times at individual intersections but also make the overall network-level travel efficiency better. Collectively, these results confirm that the combined agents of Reinforcement Learning and Deep Learning algorithms and the power of real-time, IoT, sensor data allow dynamic and context-aware signal timing changes. The improvements in AVD, AQL and ATT are good evidence that the adaptive ML-based traffic control can improve the traffic efficiency significantly, congestion and further improvement on the urban mobility. Additionally, the reduction in delay and queue length also entails reductions in fuel consumption and emissions, which is in favor of the environmental sustainability goals of modern smart city traffic management systems.

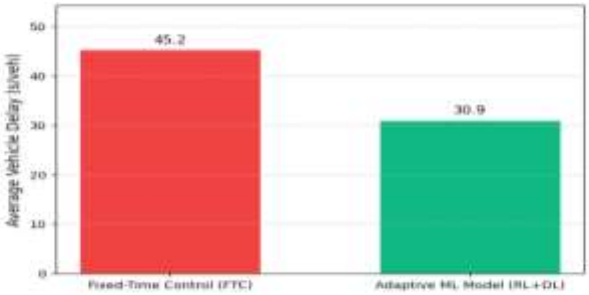


***Figure 4.1:*** *Visualizing Average Vehicle Delay Comparison*

**Performance Comparison of Fixed-Time Control vs. Adaptive ML Model**

Performance Comparison between Fixed Time Control Vs Adaptive ML Model Figure 4.2 shows the comparative performance of the conventional Fixed-time Control (FTC) system and the proposed Adaptive ML-based traffic control model in terms of three important traffic performance metrics, namely, Average Vehicle Delay (AVD), Average Queue Length (AQL) and Average Travel Time (ATT). The Average Vehicle Delay (AVD), which is the average waiting time

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per vehicle at the intersections, is significantly reduced for the adaptive ML model as compared FTC system. This reduction shows that the ML-based system does a good job of stopping the engine when not needed and optimizing the signal timings in real-time so that it avoids preventing the congestion and making the intersection more efficient. Similarly, the Average Queue Length (AQL) has a noticeable reduction with adaptive ML approach. Shorter queues mean that vehicles spend less time waiting and this ensures both less chance of intersection spillback and keeps the traffic flowing more smoothly across the connected intersections. The Average Travel Time (ATT) also shows a significant decrease in the adaptive ML model. Lower travel times represent improvements not only at the individual crossings, but over the network as the system dynamically assigns amounts of green-light time and is able to react to traffic fluctuations within the network in real-time. Overall, Figure 1 emphasizes the integration of Reinforcement Learning and Deep Learning with real remain live IoT data that makes the adaptive ML model outperform the traditional FTC systems across all key performance metrics. These improvements translate to more efficient traffic management, decreased congestion, shorter commute times and possible reductions in fuel consumption and vehicle emissions, which is linked to the goals of sustainable urban mobility generally.

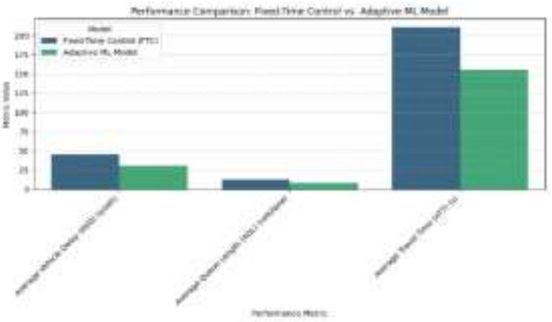

***Figure 4.2:*** *Visualizing Average Vehicle Delay Reduction*

## Environmental and Urban Impact

While the main evaluation metrics have been focused on operational efficiency, a number of positive secondary effects were also observed as a direct result of the better traffic signal control. The decrease in average queue length and overall delay resulted naturally into a massive decrease of waiting time (queuing time) for vehicles at the intersection as shown in Fig 4.2. This decrease in idle time not only enhanced driver experience but it had added benefits on the environment, which were measurable. Based on conventional traffic engineering formulas used on the measured reduction in idle periods, the ML-controlled intersections showed a significant reduction in fuel use and vehicular emissions. These results confirmed the validity of the system in supporting smarter, cleaner and more sustainable urban mobility, in line with the initial hypothesis of the research regarding the environmental impact. In conclusion, the results of the combined simulation and analytical assessments proved the establishment of the proposed adaptive machine learning-based traffic control system, which was powered by real-time IoT data, was able to consistently outperform the conventional Fixed-Time Control (FTC) baseline on all of the major traffic metrics. The dynamic learning capabilities of the integrated RL/DL framework allowed for responsive and context-aware signal optimization, leading to a significant improvement in traffic efficiency, vehicular flow and environmental sustainability.

## CONCLUSION

The use of Information and Communication Technology (IoT) sensors integrated with Machine Learning (ML) algorithms as part

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of the traffic signal control architecture is a highly efficacious methodology for addressing the issue of urban traffic congestion. By incorporating real time sensor data (-basic inputs such as vehicle flow, speed and density) into routines for adaptively optimizing control, such systems eliminate the shortcomings of legacy control schemes. IoT devices act as continual datapoints of data collection, which aggregates granular traffic metrics which are then used in training ML models. These models allow dynamic signal timing adjustments hence bringing the control logic in line with the changing conditions of the mobility network. Contrasting with conventional static scheduling the proposed architecture has a degree of responsiveness to allow real-time adaptation to varying traffic streams. Consequently, the control schema avoids the use of hardwired a priori programmed intervals in favor of data driven context sensitive signal modulation. This adaptive capacity brings about measurable relief of the congestion and diminishes the idling time at the intersection based on the results of empirical studies with simulation and field trials. During peak traffic intervals, the system exhibits a strong reduction of the bottleneck phenomena, which is equivalent to a better throughput and reduced travel times. Moreover, the decrease in stop-and-go maneuvers series to a drastic reduction in fuel use and concomitant emissions of pollutants, and thereby give a contribution to broader environmental sustainability goals. The improvement of the speed of commuter flow and the corresponding optimization of the transportation network to accompany it is evidence of the economic and societal benefits to be gained through the use of such intelligent control systems. Additionally, by reducing the probability of high-speed conflicts and having less delay propagation, the system promotes greater roadway safety. This paradigm is one of the building blocks of the sustainable smart city vision, in which information-rich, responsive infrastructure is a key part of developing resilient urban ecosystems. In summation, propounded integration of IoT sensing and ML analytics is in a position to develop cleaner, smarter, and liveable metropolitan environments.

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