TRAFFICSENSE: AN AI- POWERED SOLUTION FOR SAFER, SMOOTHER, AND SMARTED ROADS

SHUBALEKHA G , SHUBADHARSHAN R N , SREENIDHI K

, 220701275@rajalakshmi.edu.in,

220701274@rajalakshmi.edu.in

220701285@rajalakshmi.edu.in

Rajalakshmi Engineering College,
Chennai, Tamilnadu , India

***ABSTRACT* – AI-Traffic Sentinel Grid is a smart and adaptive solution for the problem of road rule violations and urban road safety management. This involves the use of AI, edge computing, and IoT devices. It involves the violation of specific people not wearing helmets, people not wearing seat belts, and signal jumper using real-time video analytics and behavioral data of people. It is observed that small monitoring cameras and sensors are placed at intersections of important roads and are updated in the cloud-based VIM that forecasts high-risk locations and violation prime periods. People can interact with the device through a simple application on their smartphone. The device automatically tracks incidents and provides safety warnings. It creates a feedback loop for humans that is on the network. The way of the present method is cost-effective, unobtrusive, and scalable. Road discipline and congestion and urban safety in large areas can be improved.**

I. INTRODUCTION

Not wearing helmets and following traffic signals and wearing seat belts have now become a problem for transporting in the city. New methods of controlling roads were expensive, unprofessional, and inefficient. In this situation, the AI-Traffic Sentinel Grid proposes a smart solution. It installs a grid of smart gadgets, powered by solar energy. Traffic Sentinel Grid detects traffic violations using cameras and sensors and sends immediate alerts and monitored centrally with one system. It also upgrades its photo with machine learning for the detection of numerous traffic threats and road congestion. Ordinary citizens and a smartphone app visually detect and report traffic law violations with drones. There is a 24-hour police drone live safety alert in the city center.

II. LITERATURE SURVEY

[1] AI traffic advisory system employs data-driven modeling, Physics-Informed Neural Networks (PINNs), and GPT-4 for real-time traffic forecasting. Machine learning with traffic flow conservation laws enhances the accuracy and reliability of the system. The users are welcomed by an NLP interface, which responds to questions as well as associated traffic information. It is founded on real traffic path data, approximating car density in position and time coordinates. The errors of estimation are removed by the application of a loss function, and traffic physics is described by applying Partial Differential Equations (PDEs) for facilitating prediction. The overall generalization ability is provided by the hybrid data-physics framework, stabilizing the model too. Traffic densities are categorized as being smooth, moderate, heavy, or jammed, and the user is provided with improved updates based on this categorization. Real-time update gives adaptive and dynamic traffic control. NLP operations are utilized in the system, supported by dependency on SpaCy and regex filters to analyze location and time information from the queries. The questions are preprocessed and cleaned before sending it for analysis to the PINN-TSE model. The answers are translated using GPT-4 support, and natural response is generated. For example, the query "What is 5 o'clock traffic on I-80?" would respond as a sentence "5o'clock traffic on I-80 will be moderate with a density of around 35 per kilometer." Azure AI Studio facilitates such interaction by virtue of real-time question solving. It is cross-checked and checked on test set and train set against the high-density I-80 NGSIM data set to avoid overfitting. Its performance measures are precision, accuracy, recall, and Root Mean Square Error (RMSE). Comparisons with the traditional traffic models are shown to offer improved real-time estimation ability. Traffic data are preprocessed and mapped onto Greenshield's speed-density model for deployment. PyTorch offers high-speed computation for real-time prediction. Hyperparameter tuning employed in favor of efficiency over accuracy is done via random search. It integrates real-time traffic information, user search detection, and then integrates it with GPT-4 to produce readable and easy-to-understand responses. It integrates physics-based simulation, artificial intelligence, and NLP and provides accurate, real-time traffic information to complement city commuting and planning manuals.

[2] Urban congestion still remains at the top prompted by problems of overflow traffic, uncontrolled city growth, traffic accidents, and ineffective transport. Even when the traditional planning of infrastructure falls short on its own, the remedy is through green traffic conduct provoked by technologies. Fourth Industrial Revolution (4IR) technology of Artificial Intelligence (AI), Machine Learning (ML), Internet of Things (IoT), Software-

Defined Networking (SDN), and Blockchain offer better solutions to traffic. AI and ML enable real-time data analysis, predictive modeling, and adaptive traffic light control that reduce congestion by a considerable margin. Predictive analytics and traffic flow optimization are enhanced by machine learning algorithms, and traffic signal optimization is enhanced by deep reinforcement learning to reduce waiting time. IoT enables real-time capture of camera data and sensor data to provide end-to-end visibility of traffic as well as signal efficiency. Traffic policy formulation and traffic flow analysis need data-informed debates. Vehicle trajectory information and databases such as "Data on the Move" (DTM) facilitate traffic efficiency via simulation based on artificial intelligence and information exchange. Traffic components of systems include traffic sensing using cameras and sensors, computer decision-control supervisory systems, and analysis using unsupervised and supervised learning. Such operations facilitate effective traffic policy formulation and accident response plans. Leader 4IR technologies such as automation, real-time connected systems, and sharing economies such as carpooling and ride-sharing are transforming urban mobility. Data privacy, security, and city-level concerns in deploying solutions must be addressed. Some 4IR technologies must be combined to create an end-to-end traffic management system. While application is to facilitate traffic flow, AI-camera systems can be used to violation detection and thus feasible for mass traffic enforcement. This study proves the viability of an AI traffic system through the emphasis on the need for real-time information, AI-driven decision-making, and a systemic process of system designing. The higher the utilization of research and deployment of AI in traffic management, the higher the need being placed to leverage cameras and AI into traffic management to usher in the following increased and knowledge-based urban transportation networks.

[3] Effective traffic management is being negatively impacted by greater data complexity, VANET vulnerability, and inability to measure real-time road conditions. Aging infrastructure lacks the capacity to handle huge volumes of data from roads, sensors, and vehicles at the expense of congestion control and ITS. These issues can predict the anomalies in real time and correct them by speeding up the processing of data, computing the vehicle density correctly, and applying machine learning to avoid congestion and decrease the accident rate. The problem is solved by using VANETs to facilitate V2V and V2I communications. Real-time adaptation and sensing is facilitated by using Lambda architecture. DSRC facilitates enablement to OBUs and RSUs facilitate unstructured data to flow freely. Big data processing tools like Hadoop MapReduce and Apache Storm are utilized in order to process and analyze traffic data in real-time at an enormous scale. Machine learning algorithms also perform traffic forecasting and anomaly detection. Supervised and deep models like LSTMs and GRUs enhance the accuracy of forecasts with regression and classification. Sensing in the forms of cameras, speed sensors, and vehicle count sensors is employed for creating an instant database of the road condition. Anomaly detection approaches such as Space-Embedding Strategy for Anomaly Detection (SES-AD) and Local Recurrence Rate based Discord Search (LRRDS) identify abrupt break or disruption of long-range congestion with respect to comparison with traffic trends to regularized histories. System design comprises real-time traffic database, past-to-present condition comparison gateway, sensor integration, and dynamic route generation module. Traffic flow optimization and traffic congestion are optimized by load and vehicle balancing analysis and vehicle and load density. Sensor integration and anomaly detection mechanism also affect traffic violation detection directly because any type of anomaly in traffic always signifies that there is a violation. To achieve effective deployment, emphasis should be laid on creating a secure real-time database, real-time high-speed data management, and designing machine learning algorithms for effective anomaly detection. Synchronization of data processing network, communication network, and sensor network enables smooth monitoring of traffic and congestion control, hence making AI-based traffic solutions efficient and scalable.

[4] The present traffic management system employs manual control and fixed timing of signals, leading to congestion and inefficiency in the city. The primary problem is that traffic lights at most intersections are not coordinating with each other, thus congestion at one point is propagated to the whole system. Traffic police also provide real-time alternatives, which may or may not optimize traffic flow and at times increase congestion by blocking roads or diverting cars. To counter such problems, an Artificial Intelligence-based Traffic Management System has been proposed consisting of real-time monitoring, dynamic signal control, and AI-based violation identification. The system is capable of creating maximum traffic, minimizing violations, and increasing road safety. Unlike fixed-time traffic lights, the system utilizes AI-based algorithms to analyze current traffic congestion as well as dynamic signal timing modification. Heavy roads such as roads leading to offices, schools, or colleges receive extra green phases of light during rush hours so that free flow can be ensured without weakening the system. The system operates on the principles of computer vision and machine learning to enforce traffic rules automatically. The system detects violative actions such as helmetless riders, seatbeltless drivers, and speeding vehicles. The violations are detected and challans are issued automatically in an attempt to reduce the level of manual intervention and impose strict implementation of traffic rules. The most striking aspect of this model is that it is made up of networked traffic lights where light at one intersection is able to converse and coordinate with that on other intersections. This prevents congestion in the traffic flow on one location inhibiting the entire traffic network. There is even an equity policy to not close any road for an extended period of time, and at least one signal is kept green so that traffic flow is not severed and unnecessary delay is not wasted. With AI, real-time data analysis, and automated control integration, the platform maximizes traffic volume, road safety, and compliance. This reduces congestion, attains a Zero Violation Point, and provides an integrated and smart city traffic management platform.

[5] AI traffic management system utilizes automation, IoT,

and decision-making using data to ensure traffic flow and road safety. They have to battle the danger of accidents that happen due to hazardous driving styles and hacking of the traffic infrastructure.AI traffic management utilizes computer vision to encourage road safety using machine learning and real-time monitoring of traffic. Smart traffic lights themselves respond dynamically to levels of traffic congestion without abrupt braking and irresponsible driving, which lead to accidents. Automatic collection of fines for traffic violations strictly punishes traffic violations by tracking helmetless riders, seatbelt-less drivers, and speeders. Artificial intelligence-based analytics also improve security by identifying near-misses, irresponsible driving, and racing across traffic signals so that correction can be made in advance. Since AI-enabled traffic systems involve different road systems and rely on the cloud, they become vulnerable to being hacked. Traffic lights can be taken over by hackers and used to block traffic or cause accidents. Security cameras with system defects can be turned off by hackers, and road sensors can be inactivated, endangering public security. Apart from this, individual data collected for tracking cars and for policing are ultimately a casualty of illicit utilization and misuse, which is risky for security and protection of data. Reinforcement Learning (RL), a subset of AI, facilitates cyber security and traffic security. Real-time traffic light optimization, lane-change security improvement, and live feed filtering to prevent accidents are facilitated by RL-based systems. RL-trained AI IDS pre-trained in advance scan the network for malicious traffic and identify and prevent future cyber-attacks. Through integration of reinforcement learning, real-time safety verification, and auto-cyber security with AI for traffic control, traffic systems turn efficient, rugged, and safe. Along with guaranteed decongestion and decimation of accidents, guaranteed cyber security, a smart city traffic system that is safe and intelligent is contemplated.

[6] Congestion traffic is piling up because of population growths and therefore real-time congestion will be crucial to control traffic to perfection as well as in secure travel. Practically all types of prediction based on traffic models operate in big learning databases and exhausting calculations and therefore will become useless in use. An effort can hence be prevented from employing fuzzy system based on Greenshields because it employs minuscule data without being bogged down with excessive processes. It is an educable system and can operate in different levels of traffic with jam and non-jam operation modes with the provision for addressing uncertainty in traffic. The fuzzy logic system is founded on a formal process, converting real-time traffic speed and flow data to fuzzy sets, applying pre-specified "if-then" rules for relating, and finally converting fuzzy outputs to crisp levels of congestion. The Greenshields model provides a mathematical foundation for the derivation of these rules by deriving speed-flow-density relations. The output of the system is also contrasted with that of a polynomial regression model using real highway data. Two inputs and a single output to system design—traffic flow and traffic speed—traffic density or congestion level. Membership functions are used to establish fuzzification, and end product converted to actual congestion forecasts by a defuzzification unit. Quick, responsive congestion forecasting is the process, which does not require humongous databases and therefore hugely flexible to changing road conditions. This structure has several advantages, including low memory usage to estimate traffic congestion in real time and flexibility in adapting to various road types. The cascaded systems concept allows for the monitoring of broad stretches of highways, and cheap prediction of faraway traffic is possible. The system relies on highly developed traffic flow models and hence is accurate and dependable. Fuzzy logic in handling uncertain traffic data can be used directly to AI-based traffic management initiatives. Adaptability to varying circumstances, as a feature of this system, allows it to be used in real circumstances. Additionally, its concepts can be applied in infraction detection by controlling vehicular speed in terms of traffic flow to identify reckless or speeding infractions. Fuzzy logic coupled with sensor processing is a feasible and scalable technology for smart traffic monitoring.

[7] Congestion represents a critical logistics challenge, creating pollution, delays, and loss of productivity. Short-term traffic attracts more attention from logistics managers than long-term predictions, but as real-time traffic information is stochastic and does not meet classical methods, an approach is described for the prediction of congestion probability and freeway bottleneck detection via a Discrete-Time Markov Chain (DTMC) model. The model successfully mimics randomness in traffic flow and generates transition probabilities among various traffic states, resulting in perceptive short-term predictions. The DTMC model utilizes real-time traffic data that is gathered through electronic toll collection (ETC) equipment based on open government data. The system aggregates and processes the data to establish traffic states by utilizing vehicle speed thresholds. One-step transition probability matrices are subsequently computed in order to estimate the congestion probability, while steady-state probabilities are utilized in identifying recurring traffic patterns. Its design consists of several important steps: pre-processing and aggregating traffic, estimation of traffic states, estimation of transition probabilities, and identification of long-term congestion patterns. Its open-data characteristic makes the model inexpensive and available. Probabilistic properties of DTMC allow accurate short-run prediction of congestion, which is especially beneficial for routing and traffic-flow optimization. It also identifies freeway bottlenecks, which are simple to respond to for effective road management. For artificial intelligence-based traffic control systems, probabilistic models allow a data-oriented method for traffic flow prediction. Congestion hotspots detection follows optimal traffic control. Further, incorporation of real-time monitoring information offers immediate reaction to the fluctuation of traffic patterns and, hence, system performance is enhanced. The principles of the model can also be used in violation detection. ETC device and sensor data can be used to detect cars driving at odd speeds or stopping at odd locations, both of which are indicators of possible traffic violations. By combining probabilistic modeling with real-time observation, this is a way of improving congestion management while facilitating automatic traffic law enforcement.

[8] The paper Online Incremental Machine Learning

Platform for Big Data-Driven Smart Traffic Management proposes an AI-based Smart Traffic Management Platform (STMP) to handle the increased complexity of city traffic with AI processing, Deep Reinforcement Learning (DRL), and real-time streams of data. The platform is economical and uses various data sources such as IoT sensors, social media, and historical records to optimize traffic control, reduce congestion, and enhance passenger comfort. Adaptive control strategies utilizing AI and data analysis of traffic allow the system to process real-time Bluetooth sensor data and social media data for freeway congestion monitoring, incidents, and accidents. Unlike rule-based traffic management, the AI model learns and adjusts dynamically in actual field conditions and predicts short-term incident impacts using machine learning strategies. Control by use of DRL was carried out and experimentally tested for a large-scale traffic network formed by 1,805 streets encircling a shopping district and regulating cycles of traffic lights using five diverse control programs. After over 500 simulation tests, the model forecasted an average waiting reduction of 50%, confirming performance in real-life traffic. Compared to the usual rule-based approaches to control, the DRL model learns dynamically from live high-dimensional data and is hence ideally suited to live traffic scenarios in the real world. Commuter emotion analysis from social media is also included under this work for collecting Twitter tweets that contain hashtags such as #VicTraffic and #MelbTraffic. Commuters' emotional intensity was monitored hour by hour, identifying peaks in negative emotion that occurred during times of peak traffic, and statistical confirmation gave a high correlation between traffic flow and emotional intensity. This allows the authorities to anticipate traffic strain and make specific interventions. The STMP system integrates streaming real-time data, AI, and reinforcement learning to optimize city traffic and is a multi-use, scalable smart city solution for congestion mitigation, disruption forecasting, and signal phase optimization. Next steps involve increased interpretability of AI and interaction with other sources of data such as CCTV-based visual data analytics, weather data for weather-aware traffic prediction, and public transport data for multi-modal traffic efficiency. This research highlights the revolutionary potential of AI-driven adaptive traffic systems to create more efficient, commuter-focused, and responsive urban transport systems.

[9] Traffic Management and Data Fusion in ITS using Artificial Intelligence is adopting future technologies like cloud computing, Internet of Things (IoT), and Artificial Intelligence (AI) to facilitate traffic management at high speed. As population and vehicle growth has risen with a resultant increase in traffic, real-time data-based decision-making is the demand of the hour for avoiding jams, enabling smooth flow of traffic, and ensuring road safety. Traffic Flow Analysis (TFA) is also required in traffic pattern observation and estimation of traffic congestion levels, to inform policymakers to make traffic regulation and mobility interventions for the city. Data Fusion (DF) also consolidates all traffic sources into one complete surveillance system that eliminates uncertainties and improves the accuracy of traffic prediction. ITS data collection includes a wide variety of technologies from computer vision and cameras to track cars as well as automate traffic violation detection, GPS and probe cars to track traffic in real time, and radar and loop detectors to measure speed and density. Social media and crowd-sourced information offer further details of road closures, crashes, and live traffic, with Automatic Vehicle Identification (AVI) Bluetooth and Remote Traffic Microwave Sensors (RTMS) helping detect cars, provide route guidance, and introduce smart parking. ITS operationality is predicated on multi-modal traffic sensing technologies including fixed sensors and their applications (loop detectors, cameras, radars) for the measurement of vehicle volume and road occupancy, mobile sensors and their applications (GPS, probe vehicles, mobile applications) for measurement of real-time traffic, and infrared or microwave sensors for the detection of vehicle movement in poor visibility. Crowdsourced information and social media are employed for the purpose of increasing situational awareness. Given that single-sensor solutions will yield low-quality or wrong information, multimodal sensing and data fusion methods are at the foundation of more precise control, estimation, and traffic forecasting methods. Concatenating the several pieces of information makes the information credible and accurate by cross-validation, enhances real-time traffic estimation, lessens the possibility of omitting key information, and offers well-decisioned replies to traffic planners and traffic managers. Experiments verify GPS convergence with loop detectors for the improvement of more precise prediction of traffic streams and AVI Bluetooth convergence with car detectors for the improvement of congestion sensing and prediction of traffic states. Altogether, AI-powered data convergence in ITS makes traffic control easy to improve efficiency and reliability so that there are intelligent, responsive urban mobility solutions.

[10] Traffic congestion is growing with the increase in vehicles and traditional traffic flow control techniques are limited to respond to the present-day complexity in traffic. The understanding of mixed traffic flow made up of ordinary and networked vehicles is necessary for traffic control in the future. This study proposes a modeling framework that combines an advanced Intelligent Driver Model (IDM) for non-connected cars with driver memory effects and a derivative model of Cooperative Adaptive Cruise Control (CACC) for connected cars. The CACC model is a nonlinear dynamic headway policy supporting enhanced coordination through vehicle-to-vehicle (V2V) communication. Simulation tests through MATLAB investigate queue time, congestion length, and overall properties of traffic flow. Spatiotemporal heat maps represent the variations in speed, while fundamental diagram analysis explains the efficiency of traffic. It is demonstrated through this study that with an increase in connected vehicle penetration, traffic efficiency increases dramatically as congestion is reduced and road utilization is enhanced. The proposed framework simulates mixed traffic dynamics with satisfactory accuracy and thus is an extremely good tool to simulate traffic control plans. The integration of V2V communication and connected car technology aligns with the goals of traffic management in the modern era. Equipped with the ability to exchange real-time data related to acceleration, position, and speed, dynamic traffic manipulation is feasible and optimizes flow overall. Moreover, multiple situations of

market penetration for connected vehicles can be determined through simulation, which will benefit future city planning and infrastructure investments. This model is best suited to AI-driven traffic systems because it identifies the contribution of connected vehicle technology to congestion management. Real-time data for decision-making enables anticipatory traffic control. Data shared between connected vehicles can also detect hazardous driving patterns, such as sudden acceleration or tailgating, and flag them as potential traffic violations. Data obtained through CACC systems also can assist in reconstructing accident scenes, enhance safety on the road and operations of law enforcers.

[11] The Multiple Hypotheses Detection and Tracking system is suggested to improve vehicle tracking and detection for Moroccan urban traffic surveillance. The system integrates YOLO-based detection, Kalman filtering, and data association techniques to facilitate accurate tracking under adverse conditions such as occlusions, illumination variations, and cluttered environments. The MHDT procedure involves video frame to sequence conversion, vehicle detection in every frame with bounding boxes, vehicle tracking via Kalman filtering and data association, and writing out their trajectories at the output. To the convenience of its construction, MoVITS dataset was established and holds 75,230 annotated images. The dataset accounts for real-world situations encountered in Moroccan urban traffic, such as occlusions and varying lighting conditions. MHDT was constructed using C++ under Qt Framework and OpenCV and run on a Linux system powered by an Intel i7-8700K CPU, 16GB of RAM, and an NVIDIA GTX 1080 Ti GPU.MHDT was evaluated on 1,263 to 15,300 frames with a 15 FPS frame rate video. High resolution 2456×2054 Highway sequence containing 6,225 frames was tested on which the framework performed well in tracking with high accuracy. It solved it with a good solution in vehicle scale variations, rotation, braking, and occlusion. Vehicle orientation and position prediction were well completed. Detection is executed by image rescaling to 416×416 and model processing on the YOLO basis, while tracking is executed on a computational complexity of $O(b^3 + b^2 + b)$. Detection efficiency is quantified as the precision with which correct vehicles are extracted and distinguished from the false ones. The MHDT model outperforms SORT and MDP in tracking precision in challenging urban settings. Its ability to provide reliable tracking makes it an important traffic observing and policing tool. Future improvement will include the analysis of vehicle traces to detect offenses in terms of directional changes to further improve traffic control and safety on roads.

[12] Traffic congestion results in significant economic losses, and it is challenging to develop adaptive traffic signal control systems (TSCSs). The majority of deep reinforcement learning (DRL) methods, such as Deep Q-Networks (DQN), do not work well in multi-agent environments with numerous signals appearing simultaneously. Centralized traffic signal systems are subject to high information transmission costs and single-point failure, while distributed systems have high communication cost in sharing information. For such challenges to be addressed, the introduction of a traffic light control system using the Dual Targeting Algorithm (DTA) is recommended. The system enhances multi-agent system learning performance through independent control of traffic lights that reduces information transmission costs and improves overall efficiency. The approach reinforces successful experiences to avoid concurrent learning issues and leverages variations in levels of congestion to predict neighboring signal behavior without explicit communication. The system applies DRL approaches, i.e., DTA and DQN, and is tested via traffic flow simulation by the Simulation of Urban Mobility (SUMO) software. Each TSCS agent in every intersection is an individual agent with a Q-value estimation from a neural network and experience storage by a replay buffer. Traffic signal phases, lane congestion levels, congestion disparities, and average vehicle speed constitute the state definition, whereas optimizing total vehicle waiting times constitutes the reward design. Results indicate that this approach significantly reduces waiting times at intersections, improves learning speed and convergence, and ensures stable performance in multi-agent systems. It also reduces communication costs and is less susceptible to simultaneous learning problems compared to conventional approaches. For traffic control systems based on AI, use of DRL to adaptive signal control is highly relevant. Decentralized control of the system aligns with distributed architectures, and estimation of congestion fluctuation without explicit communication enhances efficiency. Information collected by the system, such as vehicle speed and congestion level, can also be used for traffic violation detection. Cars traveling at risky speeds during heavy traffic hours can be detected and marked, so traffic law enforcement becomes more efficient. This essay presents an efficient approach to adaptive traffic control which can be embedded in AI traffic management systems.

[13] Road accidents are a ubiquitous feature worldwide, and they cause severe trauma, loss of life, and economic wastage. ITS takes advantage of the utilization of Artificial Intelligence (AI), data fusion, and machine learning to analyze the causes of crashes, anticipate dangerous incidents, and suggest the optimal possible countermeasures to avoid road accidents. An AI-driven decision support system for the correlation of crash causes and related safety measures through real-time traffic management and policy making is brought to light through this study. AI-driven ITS is dependent on the collection of data from sensors and other sources such as surveillance cameras across traffic that sense the movement of vehicles, red-light running, and near-miss incidents. Speed, braking, and lane position are monitored through telematics data and GPS data, but road conditions, fog, rain, and visibility problems are monitored with weather and environmental sensors. Police reports and crash records give information on where accidents happen, and driver monitor systems detect distraction, fatigue, and hazardous driving maneuvers. Combined as a whole, these data sources, ITS constructs forecasting models that detect areas and conditions under which crashes are likely to happen. Computer programs examine vast reservoirs of data to determine important contributory factors like road condition, e.g., poor light, sharp bends, and potholes; factors related to vehicles like brake failure and tire blowout; weather-related factors making driving difficult; and traffic stream movements leading to bottlenecks and rear-end crashes. Driver behaviors like

speeding, handheld mobile phone operation, wrong lane change, and driver fatigue errors are also a major contributory factor. Random Forest, Deep Neural Networks (DNNs), and Support Vector Machines (SVMs) AI methods predict the reasons for crashes and probabilities of an accident happening. Multilabel classification method on a Deep Neural Network is employed to project traffic accident causes to corresponding countermeasures such that automatic identification of risky locations, proposing multiple countermeasures, and dynamic updating based on changing trends are facilitated. AI-ITS provides countermeasures in certain areas such as road infrastructure upgrade with intelligent traffic signals through adaptive signal timing, pedestrian protection systems through LiDAR sensors, and dynamic lane markings through LED signs. Automatic emergency braking, lane departure warning, and blind spot detection as vehicle safety features prevent accidents. Fatigue detection by AI-based face recognition, distraction detection by mobile phones, and speed limit setting by AI-based speed governors are achieved by driver monitoring systems. AI-based solutions provide a safer and more efficient transportation system through accident minimization and proactive prevention of accidents.

[14] This research addresses traffic congestion in cities using a new multi-intersection traffic signal control model. The new model incorporates reinforcement learning (RL) and deep Q-learning networks (DQN) and is reinforced by multi-head attention (MHA) mechanisms and graph convolutional networks (GCNs). The objective is to overcome the limitations of conventional passive control that lacks the ability to respond to dynamic and intricate traffic conditions. The research starts by formulating the traffic signal control problem as a Markov decision process using RL to build an adaptive control strategy. A single-agent model is then established based on DQN and further optimized to the RELight algorithm for the optimization of decision-making. For the application of the model to the multi-intersection scenario, the article proposes the ABSTLight model, in which MHA and GCNs coexist to provide collaborative optimization between neighboring intersections. The model facilitates the agents learning from one another and, in so doing, improves control efficiency as a whole. The research performs large-scale experiments on real-world and simulated data to test the performance of the proposed models. The optimal parameters of the reward function are used to test the RELight algorithm, and it is compared with other competing algorithms. The ABSTLight model is subject to ablation studies to ensure that its constituent components are effective and compared with state-of-the-art techniques. Results confirm that the ABSTLight model yields excellent traffic flow efficiency with the highest throughput of 195 vehicles/min, the shortest queue length of 4.31 vehicles, the shortest average delay of 1.23 minutes, and the shortest average travel time of 2.07 minutes. The model also records high attention values for adjacent intersections, which reflects satisfactory coordination. The average green wave time of 4 minutes and peak of 5 minutes signifies the capability of the model in maximizing signal coordination.The work given here is an important contribution to the field of intelligent transportation systems because it introduces a reliable and adaptive solution for the multi-intersection traffic signal control problem.

[15] Urban traffic congestion is among the most significant issues for city planners, both environmentally and logistically. Proper scheduling of traffic lights is crucial to counteract these problems. This paper introduces a mathematical programming model and a firefly-based rolling horizon (FBH) strategy for traffic signal timing optimization in an adaptive traffic-responsive control system, which can learn and react to real-time traffic conditions. The mathematical model introduced is designed to reflect the subtle physical constraints of urban intersections such as road length, lane capacity, vehicle class, and optimal queueing size. The model is designed to solve small-sized problems optimally. In consideration of the reality that computational capacities would be paralyzing on large-sized instances in the real world, the authors formulated the FBH heuristic. FBH algorithm, which is based on firefly movement, supports determination of optimal solutions through iterative searching and optimization of traffic signal cycle. The metaheuristic derives inspiration from iterative solution searching throughout the planning horizon, subdividing the horizon into minimum intervals and sequentially searching for each. It is possible to explore the space of the solution more effectively in dynamic traffic networks through this method. One of the FBH algorithm's unique characteristics is "matrix of all possible phases," which allows the solution to be feasible by avoiding conflicting traffic signal settings. The matrix helps the algorithm in choosing compatible phases combinations for unobstructed traffic flow. The computational time of the mathematical model and FBH heuristic are validated and compared through the use of the SUMO traffic simulator. The simulation considers factors such as average queue length, waiting time, and travel time and is a measure of the performance of all solutions. A case study based on a real scenario is also utilized in an other attempt to further validate the practicability of the proposed schemes under real-world application, and the effectiveness of traffic signal timing optimization and urban traffic congestion reduction. The research emphasizes the necessity of adaptive traffic control systems in managing the challenges of modern urban transport.

III. METHODOLOGY

• ADMIN LOGIN MODULE

One admin module functionality provides an authenticated facility to log in using the officials' credentials. New users who are officials must establish a secure account by providing confirmed identity information to enroll. On successful login, administrators can track reports of infractions, modify system parameters (infraction levels), and access the Violation Intelligence Map (VIM) for scheduling enforcement action. Information processed here will be aggregated into the central cloud system.

• VIOLATION DETECTION MODULE

Intelligent camera and IoT device real-time traffic video is processed at the edge node by machine learning computer vision models. The system checks violation data — it detects events such as helmet-less riding, no seatbelt, and jumping over the red light — prior to sending confirmed events to the central cloud platform. Smart contracts ensure violation records are stored in integrity without tampering.

• VIOLATION RECORDING AND ALERT SYSTEM

When there is a violation, data (images, timestamps, and vehicle descriptions) is kept safe. Data packets are encrypted with asymmetric algorithms like RSA, and each violation is tagged with a specific hash by a secure algorithm like SHA-3. The vehicle's registered owner is informed in real-time through the mobile app, and violation data is kept in a distributed ledger-like database for the sake of accountability, transparency, and later analysis.

IV. PROPOSED SYSTEM

Today's traffic management is an independent system of traffic lights, CCTV cameras, manual enforcers and control rooms each working in silos. Very little data sharing occurs, slow reporting and erratic monitoring of offences take place, so compliance and free flow of traffic are adversely affected. Offences such as helmet riding, seatbelt failure and jumping the lights go unchecked or unpunished.

The project is a dream of a decentralized AI-driven traffic violation management system. It combines edge-computer vision models deployed at critical intersections, motion and heat sensors to sense vehicle and riders, and Violation Intelligence Map (VIM) in the cloud for central analysis and predictive alert. Ground-based units are augmented by smart drones monitoring traffic congestion patterns and violation hotspots. A user-friendly cellular phone application facilitates public involvement by leveraging the abilities of many users to report, receive real-time violation alerts, and view individualized safety messages. The system is effective,

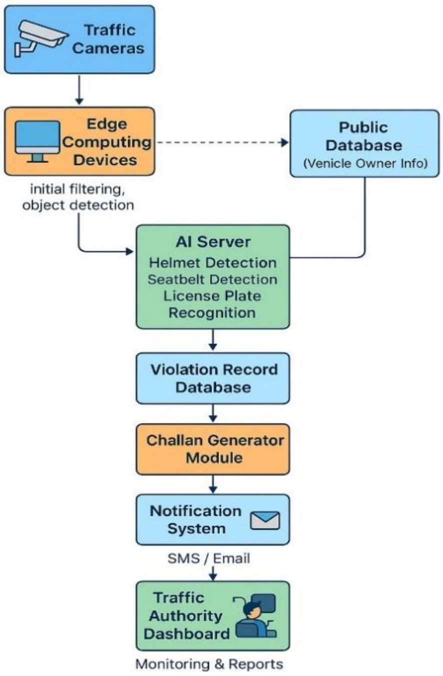

Fig. 1. Architecture Diagram

scalable, and proactive deterrent-focused instead of reactive punishment-constrained with a final objective towards Zero Violation Points and improved road safety.

V. CONCLUSION

The problems with enforcement of road rules by manual traditional methods have been addressed. Various research articles and online sites were read and objectives were sought. System structure and operation flow for the said AI-based system for traffic violations have been known. Inefficient and limitations associated with traditional systems of traffic enforcement have been explained in Phase I. Various e-journals and articles were read, and a few objectives were sought. The plan of system integration and structure has been drawn up. Proposed work installation, testing, and result analysis have been accomplished successfull

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