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Artificial Intelligence based Smart Traffic Enforcement and Management System in urban areas

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Abstract

In the urban environment, traffic congestion has become a significant concern. Congestion negatively influences the economy, the environment, and the quality of life in general. Unfortunately, traditional traffic control systems fail to control traffic discipline due to inadequate human resource management and limited extension of current infrastructure, resulting in increased traffic congestion and road infractions.

This paper aims to create an intelligent system dashboard to make judgments on its own, detect congested areas and actual congestion locations, and plan alternative routes. The system should collect all available data from different cities and create forecasts based on the previous year's data. The designing Artificial Intelligence traffic controllers in our proposal can adapt to current data from sensors to perform constant optimizations on the signal timing plan for intersections in a network to minimize traffic congestions by using real-time traffic data, which is the main issue in traffic flow control today.

A new technology known as Radio Frequency Identification (RFID) has been introduced, which can be used in conjunction with the existing signalling system to provide real-time smart traffic control. Traffic congestion will be decreased as a result of the use of this innovative technology. In addition, bottlenecks and traffic violations will be spotted early, allowing for early preventative actions to be implemented, saving the motorist time and money.

Long-term decision-making is aided by traffic monitoring, mainly when designing transportation plans and budgets. It also helps law enforcement agencies identify the different types of traffic and take appropriate precautions, such as installing security cameras and other control mechanisms.

Keywords: proactive safety management: big data, machine learning; crash prevention;

1 Introduction

The growing number and type of vehicles have resulted in several road-related issues every year with rapid worldwide urbanisation. The global number of vehicles on the road is expected to be about twofold by 2040, putting tremendous pressure on the existing urban infrastructure (Marshall, 2022). Furthermore, as the number of vehicles increases, the likelihood of traffic offences rises, resulting in an increase in road accidents and injuries (Amiruzzaman, 2019). Traffic congestion and road crashes are the most complex challenges traffic management agencies face worldwide.

An essential component in mitigating severe traffic accidents is efficient traffic enforcement, which gives drivers the feeling that they are likely to be caught and sanctioned when they disobey the law (Elvik et al., 2009). Recent studies found that drivers respect traffic laws primarily due to enforcement concerns rather than safety considerations (Schechtman, 2016).

Intelligent Transportation Systems (ITS) and traffic management are tools that assist operators of urban transportation networks in managing traffic and transportation to achieve policy goals (Marshall, 2022). Therefore, smart urban planning projects strongly focus on traffic congestion control approaches.

Large–scale transportation networks can be better regulated using dynamic traffic light control, parallel computation simulated real-time path planning, and smart traffic police enforcement (Nama et al. 2021). ITS connects all of these technologies, making it an essential and trendy component of the burgeoning smart city concept. Smart applications, data collecting based on machine learning, analysis methodologies, intelligent and dynamic scheduling algorithms, and workable protocols are all part of ITS. Because their installation and maintenance involve a large expenditure, these leveraging technologies help manage available human resources and hardware components with software techniques rather than strict physical changes (Nama et al., 2021).

Using ITS principles to manage traffic control equipment, allocation, and scheduling of already available traffic control human resources optimistically according to runtime traffic conditions can assist solve the traffic congestion problem in the future (Nama et al. 2021). ITS solutions provide new vitality in traffic enforcement and solve traffic safety and efficiency issues with the emergence of AI, IoT and sensor technologies (Desouza,2020).

A typical traffic management system (TMS) involves three main stages; it entails the collection of traffic characteristics (such as speed, flow, and density) via sensors installed throughout the transportation network. Following that, these data are aggregated to obtain useful traffic statistics. The processed data is then used to generate traffic forecasting, incident detection, and other traffic statistics in the next step, Data exploitation. Finally, the Service Delivery stages provide consumers with information via various control devices (Jones,2020).

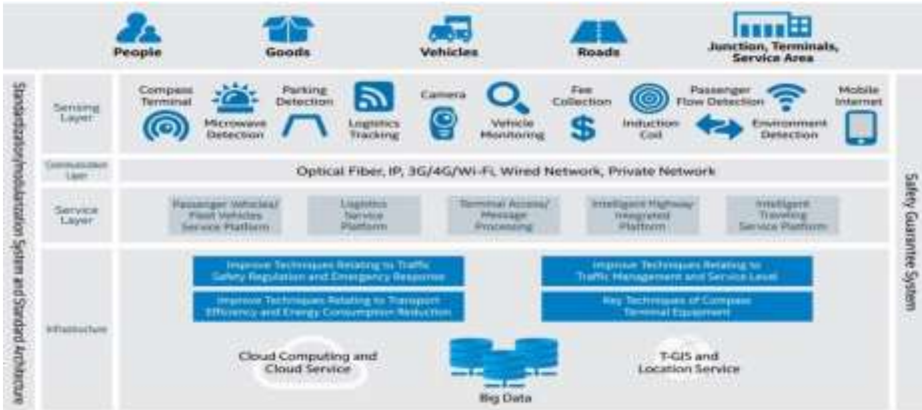

Fig. 1. Intelligent Transportation System with the IoT by Intel (Advantech, 2016)

In recent years, business and academic researchers have focused their efforts on utilizing modern communication technologies to improve the efficiency of TMS

Bhadra et al.,2016 applied an agent-based fuzzy logic technique for traffic control conditions involving multiple approaches and vehicle movements. Katiyar et al.,2011 developed strategies to integrate different dynamic data into Intelligent Transportation Systems.

Omar,2015 proposes an architecture that integrates the Internet of Things with agent technology into a single platform where the agent technology handles effective communication and interfaces among many heterogeneous, highly distributed and decentralized devices within the IoT. He presents a framework distributed traffic simulation model in NetLogo, an agent-based environment, for IoT traffic monitoring system using mobile agent technology.

Adler et al. 2014 provide a Multi-Objective Linear Programming (MOLP) approach for maximizing traffic police presence and proactive police action in areas prone to severe traffic crimes. However, this algorithm is designed for police vehicles, which require space and money, making it inefficient at minor intersections. Jones, 2020 proposed a Smart Traffic Management framework for future cities. The proposed framework combines different data sources and technologies to improve traffic prediction and incident detection systems.

Liu et al.2017 propose an architecture for better communication, reducing traffic congestion and developing the present urban traffic management with the help of rapidly emerging technologies such as fifth-generation (5G), software-defined networking (SDN), and mobile edge computing (MEC).

Nemade 2016 Implements a created video surveillance methodology that combines a two-line algorithm, vehicle classification using a Kalman filter, and headlight detection that considers various day and night situations as control factors, resulting in successful vehicle recognition and tracking. In addition, the detection of license plates aids in surveillance and security control.

Raj et al.2016 suggested a system for estimating traffic density using automated sensors, which can determine metrics such as volume and TMS (TMS). The data was gathered using a location-based sensor called The Infra-red Traffic Logger (TIRTL), which detects vehicles using infrared technology. They applied automated sensors machine learning approaches such as k-NN and ANN for traffic density prediction. They used the supervised and non-parametric k-NN and ANN algorithms individually on the TIRTL data.

Moreover, Various countries have formulated distinct traffic management development strategies worldwide, such as Saudi Arabia's 2030 vision, Singapore's "45-minute City" by 2040, Ukraine's 2030 strategy, etc. However, reducing traffic congestion by optimizing existing road capacities comes at a high expense, not to mention the enormous amount of time required to collect evidence for traffic offenses enforcement. Furthermore, gathering massive data to predict and regulate traffic is difficult, especially with traditional traffic systems (Marshall, 2022).

Camera-based systems are also starting to be deployed in American urban areas. They've become necessary components of automated toll collecting systems and traffic enforcement systems (Blumberg,2005). Massive extensions of these systems are already being considered, including systems that use GPS tracking devices in every registered car (Blumberg,2005).

In the USA, the city of Louisville adopted a crowdsourcing approach to encourage their citizens to participate in a smart city application (Blayney, 2016). They achieved this by joining Waze's Connected Citizens Program, where Waze exchanged traffic data with Louisville to identify congestion and improve the traffic situation.

The government of India has endeavored to develop and adopt artificial intelligence (AI) technologies. One example of how AI systems are being used in the public sector is the technology used to regulate traffic offences (Desouza, 2020).

The Florida Department of Transportation (FDOT) developed the WayCare model, which uses data from intelligent transportation system (ITS) devices and other sources and increasingly available big data and data analytics to improve the safety and mobility of Florida roadway networks. The model wre able to predict Sixty percent of crashes correctly (Wang,et al., 2020).

To create an efficient TMS, it is necessary to provide a continuous flow of information about the way traffic conditions evolve. Different algorithms have been employed for traffic management applications such as traffic flow forecasting and incident detection; these include time series models, traffic simulation models, and Artificial Intelligence Algorithms (Jones, 2020).

Dubai's traffic congestion is similar to that of many other big cities throughout the world, resulting in a significant economic cost of Dh 209,949 per km in fuel and time loss, as well as more than $790 million in lost person-hours. The monetary losses incurred as a result of this problem have been estimated to be Dh 4.6 billion every year, according to economic analysts. This data indicates that Dubai wastes more than 3% of its GDP due to traffic congestion. Furthermore, according to the Director of the Dubai Traffic Department, the department received 1,342 calls from the general public and police officers regarding various traffic infractions. While the radar cameras strewn throughout the city recorded 858 fines.

Our goal in this paper is to develop a smart system dashboard to make decisions on its own and perceive heavy traffic areas and actual location of congestion and plan alternative routes in UAE. The system gathers all available information about areas inside a city and makes predictions based on the previous year's data. This solution integrates a traffic enforcement system, traffic information release system, traffic flow collection and prediction system, as well as traffic management command and dispatch center.

The system should assist traffic management agencies in improving road safety, reducing congestions, responding to emergencies more effectively and making predictions on future traffic situations based on real-time data.

The remainder of the paper is organized as follows. Framework structure of the proposed traffic system is introduced in section 2. Section 3 describes the agent-based approach for the development of intelligent traffic information system. Discussion of the proposed traffic simulation framework is presented in section 6. Finally, section 7 is devoted to conclusions and future work.

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2 Proposed Smart Traffic

The main idea of system deployment as presented by Limsoonthrakul et al, 2021 As shown in Figure 2, the system architecture consists of four layers: Edge, processor, application, and user. Each layer of the architecture has a specific responsibility as defined by its name and only interacts with adjacent layers.

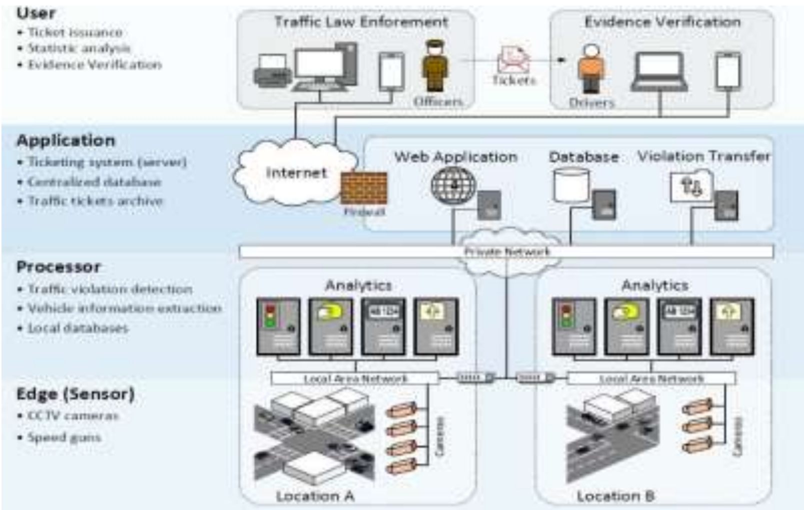


Fig. 2. Architecture Road Traffic Enforcement (Limsoonthrakul et al, 2021)

The main purpose behind the work in this paper is to develop a smart traffic management system dashboard. This system should develop the ability to assimilate and analyse Real-Time Traffic Information and historic trends to support decision making on traffic management strategies like creating traffic fines, sending aid or help in case of any accident, detecting traffic violation and stored them for future reference, showing necessary actions and precaution with time in order to control and manage the traffic congestion. The computing platforms products are used to build an end-to-end solution that enhances the user experience, improves reliability and security, and helps reduce operational costs.

Intelligent Traffic Management System is specially designed and architecture to replace tedious manual process to track, regulate and analyses vehicle movements on roads to enforce traffic rules for the safety of people and citizens and their properties. It acts as a true decision support system for traffic planners and traffic law enforcement agencies such as State traffic police and Traffic Control and Management agencies.

System is based on deploying traffic cameras with Automatic Number Plate Recognition (ANPR) on accident-prone areas like intersections, crossroads, highways, flyovers and ramps enables operators to detect violations and verify incidents based on real-time monitoring. This system also involves developing a license plate recognition algorithm for developing both the traffic violation rate and the accident rate. This solution also offers an AR Panoramic Platform that is connected to all frontend devices and presents a new labelling display system. By utilizing this high-point monitoring system, traffic enforcement units can efficiently respond to traffic alerts and situations in time.

2.1 Smart Traffic Control System

The major components of the proposed are:

1. Hardware

- Lidar Sensor
- Speed Detection Camera
- OCR Cameras and Sensors
- RFIDs
- CCTV Cameras
- Ultrasonic Sensors
- Image Processing Techniques (OCR)
- Motion Sensor

2. Software

- Php (Laravel Framework)
- Python for AI
- Raspberry PI for ML
- Google Maps and google Analytics
- MySQL for Database Management System

2.2 Smart Traffic Control System

The proposed system uses big data analytics tools for studying stored historical data and for real-time data analytics. The combination of big data, cloud computing and internet of things (IoT) is utilized in the proposed design. We initially propose to collect our data using RFID mechanism, camera, and sensors. With the substantial growth of location data, data analytics plays a significant role in analyzing the data and in solving emerging problems in traffic management. The collected data can be used for performing various machine learning techniques. The storage data structure preferred is either multi-dimensional matrix or graphical representation The graphical analysis helps to take decisions for deciding whether or not speed breakers or road bumpers are required by correlating the accident information with the day to day traffic analysis.

The system acts as a true decision support system for traffic planners and traffic law enforcement agencies such as State traffic police and Traffic Control and Management agencies. The system has two main function that are Adaptive Traffic Control System and Traffic Enforcement System. The architecture of our proposed system is shown in figure 1.

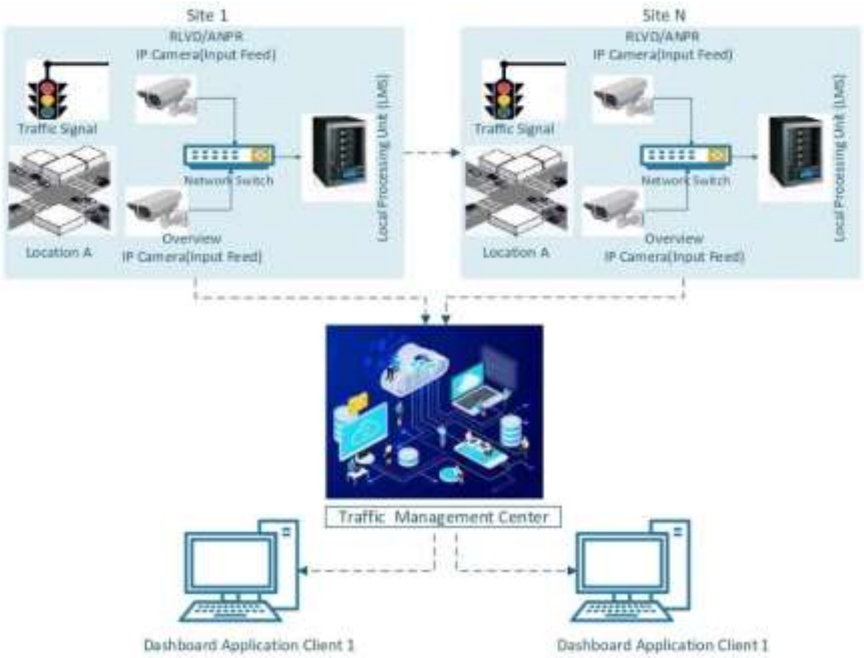


Fig. 1. The architecture of our proposed system

2.2.1 Smart Traffic Control System

The adaptive traffic control system will provide simulation based real time traffic flow modelling capability with the capacity to calculate traffic flows, Vehicle movements, and queues and turning movement along entire primary road transport network in the defined study area covering the STSC junctions.

The proposed solution has the radar-based sensors at junctions for detecting vehicles and assessing queue lengths, which communicates the information to locally installed controllers at the junctions. All local controllers shall in-turn be linked to software installed in a server, at the control room, which will bring coordination among all the junctions on a real time basis. The proposed solution uses sensor networks along with embedded technology. The timings of red and green lights at each crossing of road will be intelligently decided considering the traffic on all adjacent roads. Thus, optimization of traffic light switching increases road capacity and traffic flow and can prevent traffic congestions. The performance of intelligent traffic light controller is more efficient than the conventional controller in respect of less waiting time, more distance traveled by average vehicles and efficient operation during emergency mode.

The proposed STSC System it is composed by three subsystems including an RSU, an OBU, and a cloud center. Figure 2 shows the architecture of STSC System.

1. The RSU controller, connected to traffic signal control system
2. RSU periodically broadcasts the signal plan (cycle time, green split, current phase, current countdown
3. Controller, regarding it as one of the peripheral devices. To achieve this goal, a modularized system software architecture is designed as OBU (On Board Unit) RSU (Road Side Unit)

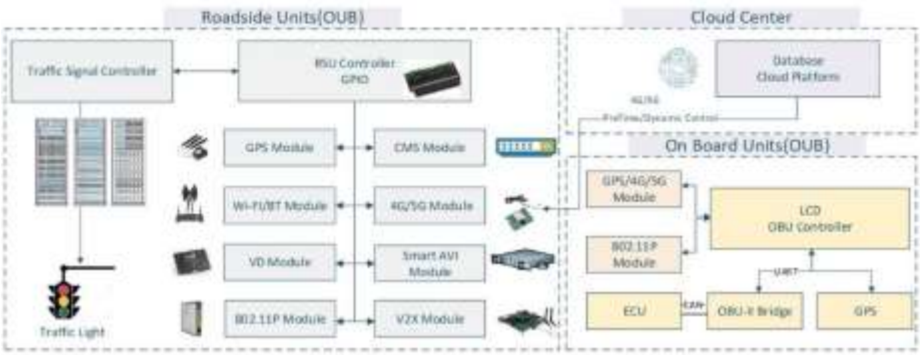


Fig. 2. The architecture of STSC System

2.2.2 Smart Traffic Control System

Traffic Enforcement Systems are automated or semi-automated systems through which traffic violations are captured and challans can be generated. They help in increasing compliance to traffic rules and reduce manual intervention in traffic enforcement activities. Traffic Violation detection system will have following solutions:

- ANPR - Automated Number Plate Recognition
- RLVD - Red-Light Violation detection

- SVD - Speed Violation detection
- E – Challan

The Monitoring System(ITMS) detects Licence plates (hence the Vehicles) in the camera FOV, and stores them in Database along with other information. With this information in hand, it generates various "events", e.g. ANPR, RLVD, Wrong way movement etc.

2.2.2.1 ANPR – Automated Number Plate Recognition

ANPR cameras shall provide the feed to the Command & Control center, where the ANPR server shall be located. The ANPR server shall process the image using OCR software for getting the registration number of the vehicle with highest possible accuracy. The system shall be able to detect, normalize and enhance the image of the number plate for detection of alpha numerical characters. System shall be able to identify stolen/ suspected vehicles by cross checking the numbers with vehicle database. ANPR software shall be integrated with video management system.

2.2.2.2 RLVD – Red Light Violation Detection

Red Light Violation Detection (RLVD) system is a system for capturing details of vehicles that have crossed the stop line at the junction while the traffic light is red. System shall be able to automatically detect red light through evidence camera units and other equipment. The information so captured shall be used to issue challans to the violators.

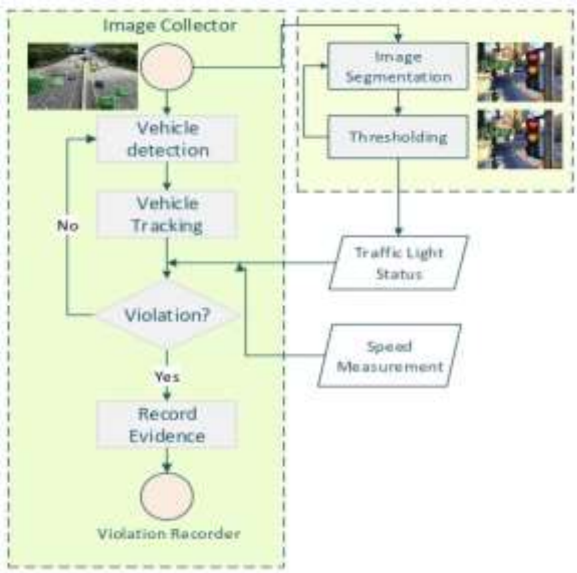


Fig. 3. Shows the architecture of the Smart Traffic Enforcement Systems

2.2.2.3 SVD – Speed Violation Detection

The SVD system will be used to automatically detect and capture vehicles violating the prescribed speed limit for the given road segment. The system will be capable of capturing multiple infracting vehicles simultaneously in different lanes at any point of time with relevant infraction data like speed of the vehicle, notified speed limit, date, time, location and registration number of the vehicle. This data will be transferred to the E-Challan system for further processing, tracing the ownership details of the infracting vehicle and printing of notices/challans.

2.2.2.4 E – Challan

The central Control room shall have an integrated e-Challan Module. Every red-light violation event / speed detection event will be processed by e-Challan module. The e-Challan system will be integrated with RTO databases which will fetch the owner details of the violating vehicle. The challan shall have all the details of violation such as date/time of violation, Place of violation, number plate image with OCR and associated evidence images with a unique challan ID.

3 Theoretical Background and Algorithm

Different algorithms have been employed for traffic management applications such as traffic flow forecasting and incident detection. With the purpose of creating an efficient TMS, it is necessary to provide a continuous flow of information about the way traffic conditions evolve over time.

A smart traffic management framework that exploits data from heterogeneous data sources to improve both traffic prediction and incident detection techniques, and provide real-time simulations of the road network. Different algorithms have been employed for traffic management applications such as traffic flow forecasting and incident detection. With the purpose of creating an efficient TMS, it is necessary to provide a continuous flow of information about the way traffic conditions evolve over time. Due to its importance, a wide number of researchers have studied and implemented a significant number of methods for the prediction of traffic flow and automatic identification of accidents. The following algorithm that are used in our system.

3.1.1 Traffic Signal Time in TMS

1. Effective Green Time: effective green time can therefore be defined as follows in Equation 1:

$$g = G + Y + R - (l_1 + l_2) \tag{1}$$

Where g is the effective green time,G is the actual green interval , Y is the actual kello change interval,R is the actual red clearance interval, $l_1$is the start-up lost time , and l_2 is the clearance lost time (all values in seconds)

2. Capacity

At signalized intersections, capacity for a particular movement is defined by two elements: the maximum rate at which vehicles can pass through a given point in an hour under prevailing conditions (known as saturation flow rate), and the ratio of time during which vehicles may enter the intersection. These are shown in Equation (2).

3. Cycle Length

$$c = s\left(\frac{g}{c}\right) \tag{2}$$

Where *C* is the capacity, s is the saturation flowrate of lane group in vehicles per hour, g is the effective green time for the movement in seconds, and C is the cycle length in seconds.

3.1.2 Traffic Accident and Prevention

The intersections between the nodes have a certain weight. When a value is passed through the input layer, the value is multiplied by the weight and summed to derive the total input nj to the unit, as shown in Equation (3)

$$n_j = \sum_i w_{ji} o_i \tag{3}$$

Where wji is the weight of the interconnection from the input unit i to another unit j, and oi is the output of i. The total input calculated using Equation (1) is transformed by the activation function to produce an output oj of j.

Random forests represent an ensemble machine learning technique. A random forest model employs an advanced decision tree analysis method to overcome overfitting issues, which is a drawback of decision tree analyses [34]. In the learning process, a random forest model generates classification trees by selecting subsets of the given dataset and randomly selecting subsets of variables for prediction. The number of trees is set in advance, and the average results for each tree are derived as the final outputs, based on the results generated in each tree. The learning process of random forests using bootstrap sampling consists of the following steps: (i) generate trees and datasets from the training dataset by sampling the bootstrap, (ii) train a basic sorter for the trees, (iii) combine the basic sorter (i.e., tree) into one sorter (i.e., random forest), and (iv) derive the final results of prediction by the majority voting rule. The observed values in the random forest that are not included in the learning process are considered out-of-bag (OOB) values, and they are used in the model validation. OOB values are used to estimate the predicted values and classify variables that cause anomalies. The number of times OOB values are selected in all trees varies for each tree, and the expected values are different for each tree. The probability of correctly predicting the OOB values for each observation in the original category, i.e., category k, can be calculated using Equation (4)

$$Prob_k(x_i) = \frac{\sum \in \overline{OOB_\iota} - I[y(x_{i,}, T_j) = k]}{|OOB_i|}, for\ k \tag{4}$$

Where i is an indicator that is set as 1 and 0 when the value in the parenthesis is true and false, respectively. y where i is an indicator that is set as 1 and 0 when the value in the parenthesis is true and false, respectively. y

where i is an indicator that is set as 1 and 0 when the value in the parenthesis is true and false, respectively y(xi- Tj) is the predicted category, and Tj is the jth decision tree among the generated trees T, in the forest. OOBi represents a group of decision trees that are not used in the learning process and are bagged as an observed variable. If a set of decision trees does not include xi , the ratio of the number of decision trees predicting xi to category k is Probk(xi). For a random forest, the Gini importance is computed and used to indicate the importance of the independent variables. At each node τ within the binary trees t of the random forest, the optimal split is found using the Gini impurity i(τ), which indicates how well a potential split separates the samples of the two categories in a particular node. Let pk = nk n represent the fraction of nk samples from category k = {0, 1} among the total n samples at node τ. The Gini impurity i(τ) can be calculated using Equation (5).

$$i(\tau) = 1 - P_1^2 - P_0^2. \tag{5}$$

The change in i(τ), Δi, which can be attributed to the splitting and transmission of the samples to two subnodes τl and τr (with sample fractions pl = nl n and pr = nr n , respectively) based on a threshold tθ for variable θ, can be calculated using Equation (6).

$$\Delta i(\tau) = i(\tau) - p_1 i(\tau_1) - p_r i(\tau_r) \tag{6}$$

In the search for all variables θ available at the node and all possible thresholds tθ, the pair {θ, tθ} leading to the maximum Δi is determined. The change in the Gini impurity resulting from the optimal split, Δiθ(τ, T), is recorded and accumulated for all nodes τ in all trees T in the forest for all θ values, as shown in Equation (7).

$$I_G(\theta) = \sum_T \sum_\tau \Delta i_\theta(\tau, T) \tag{7}$$

The Gini importance IG indicates how often a particular variable θ is selected for a split and the contribution of this value to the classification problem. This study adopts the scikit-learn package in Python, an open-source programming language software that provides a user-customizable random forest model [35]. 2.1.3. Gradient Boosting Decision trees Gradient boosting decision trees are decision tree models that can prevent overfitting and demonstrate an enhanced prediction accuracy [36]. In gradient boosting decision trees, F(x) is assumed to be an approximation function of the output y based on a set of input variables x. The squared error function is applied as the loss function L to estimate the approximation function, as indicated in Equation (8).

$$L(\mathrm{y}, \mathrm{F}(x)) = [\mathrm{y} - \mathrm{F(x)}]^2 \tag{8}$$

Assuming that the number of splits is J for each regression tree, each tree partitions the input space into J disjoint regions R1m, . . . , Rjm and predicts a constant value bjm for region Rjm. In this case, each decision tree exhibits the additive form, as indicated in Equation (9).

$$h_m(x) = \sum_{i=1}^{J} b_{jm} I(x \in R_{jm}) \tag{9}$$

$$I = \begin{Bmatrix} 1 & if \ \mathrm{x} \in R_{jm} \\ 0 & otherwise \end{Bmatrix}$$

Using the training data, the gradient boosting model iteratively constructs M decision trees h1(x), . . . , hM(x). The updating approximation function Fm(x) and gradient descent step size ρm can be defined using Equation (10) and (11) and the optimal γjm can be calculated using Equation (12)

$$\mathrm{F}_m(\mathrm{x}) = F_{m-1}(\mathrm{x}) + \rho_m \sum_{i=1}^{\mathrm{J}} b_{jm} \mathrm{I}(x \in R_{jm}) \tag{10}$$

$$\rho_m = \underbrace{\text{argmin}}_{\rho} \sum_{\mathrm{i}=1}^{\mathrm{N}} L(y_i, F_{m-1}(\mathrm{x}_i) + \rho_m \sum_{i=1}^{\mathrm{J}} b_{jm} \mathrm{I}(x \in R_{jm})) \tag{11}$$

With a separate optimal γ_{jm} for each region bR_{jm}, b_{jm} can be discarded. Equation (10) can be expressed as equation (12).

$$\mathrm{F}_m(\mathrm{x}) = F_{m-1}(\mathrm{x}) + \sum_{i=1}^{\mathrm{J}} \gamma_{jm} \mathrm{I}(x \in R_{jm}) \tag{12}$$

And the optimal γ_{jm} can be calculated using equation (11)

$$\gamma_{jm} = \underbrace{\text{argmin}}_{\gamma} \sum_{x \in R_{jm}} \mathrm{L}(\mathrm{y_i}, F_{m-1}(\mathrm{x}_i) + \gamma) \tag{13}$$

$$= \underbrace{\text{argmin}}_{\gamma} \sum_{x \in R_{jm}} (\widetilde{y_\imath} - \gamma)^2$$

$$\text{where} \quad \widetilde{y_\imath} = -\left[\frac{\partial \mathrm{L}(\mathrm{y_i}, \mathrm{F}(\mathrm{x}_i))}{\partial \ \mathrm{F}(\mathrm{x_i})}\right]_{F_m(x) = F_{m-1}(\mathrm{x})}$$

Gradient boosting decision tree build the model sequentially and update it by minimizing the expected value of loss function. To avoid overfitting and increase the prediction accuracy. A learning rate strategy is applied. The learning rate is used to scale the contribution of each tree model by introducing a factor $\varepsilon(0 < \varepsilon \leq 1)$,as indicated in equation (12).

$$\mathrm{F}_m(\mathrm{x}) = F_{m-1}(\mathrm{x}) + \varepsilon. \sum_{i=1}^{\mathrm{J}} \gamma_{jm} \mathrm{I}\big(x \in R_{jm}\big), \varepsilon(0 < \varepsilon \leq 1) \tag{14}$$

3.1.3 Traffic Violation and Prediction

Correlation analysis helped to determine that property damage and alcohol were correlated (17%). Similarly, contributed to accident and property damage were correlated (34%); contributed to accident and personal injury were correlated (37%). The correlation values were calculated using the following equation (see equation 13)

$$r_{xy} = \frac{\sum_{n}^{i=0} (x_i - \bar{x})(x_i - \bar{x})}{\sqrt{\sum_{n}^{i=0} (x_i - \bar{x})^2 \sum_{n}^{i=0} (y_i - \bar{y})^2}} \tag{15}$$

Where, rxy is the correlation value between variables, x and y, P is the symbol for "sum up", xi is the individual value of variable x, x¯ is the mean of variable x. Similarly, yi is individual value of variable y, y¯ is the mean of variable y

In this analysis linear regression was used to verify some of the prediction made by the WEKA software. The regression equation can be expressed as (see Equation 14)

$$y_i = a + bx_i + c \tag{16}$$

Where, Y is the dependent variable that the equation tries to predict, X is the independent variable that is being used to predict Y , xi ∈ X, and i = 1, 2, 3, ..., n, yi ∈ Y , and i = 1, 2, 3, ..., n, a is the Y -intercept of the line, b is the slope, and c is a value called the regression residual, which can be calculated by |yi−yi |, where ˆyi is the expected value of y. The values of a and b are selected so that the square of the regression residuals is minimized.

Table 1. Linear Regression analysis

Model	R	R^2	Adjusted model	Std. Error of the Estimation
1	0.404	0.163	0.163	0.125

Reliability vale were calculated using equation below (see Equation 17)

$$\alpha = \frac{N \times \bar{c}}{\bar{v} + (N-1) \times \bar{c}} \tag{17}$$

Where, N is the number of items¯c is average iter-item covariance and¯v is average variance. The reliability of four attributes (i.e., personal injury, property damage, alcohol, and contributed to the accident) was 0.435.

3.1.4 Current Prediction for Violation, Traffic Fine and Accidents

Violation 12 month = (Mean of Prev. Year + Current Year Mean + Same month of Prev. Value)/3

Traffic Fine 12 month = (Mean of Prev. Year + Current Year Mean + Same month of Prev. Value)/3

Accidents12 month = (Mean of Prev. Year + Current Year Mean + Prev. Year Single month value)/3

Example:

Prev Year = [500,400,600,700,450,550,440,550,400,380,500,560]

Current Year = [500,40,]

Mean of Prev. Year = 502

Mean of Prev. Year = 270

Same month of Prev. Value = 400, because current month is Feb so prev. year month record was 400

Prediction = (502+270+400)/3 => 390

And so for next month March, April…….. etc

4 Implementation and Discussion

The first phase of deployment was launched in 2020 at United Arab countries(UAE). The Smart Traffic Enforcement and Prediction System (STEP) Dashboard (as shown in figure 3) is an Intelligent, automated system that controls the traffic by sensing the situation automatically makes instant decisions, and helps decision-makers to take decisions on the various situations that occur on the road. STEP is to take advantage of the technologies to create more Intelligent transportation systems. The solution will eliminate or at least minimize the traffic congestion, environmental pollution, lesser accidents, and violations.

The central management server application receives all the data from across the edge devices. This valuable data feed is passed on to a command center via an API to provide relevant information. The dashboards are used by the city managers and analyst to monitor the system or the city how it works as a whole. The dashboard includes a graphical interface to query this huge data set.

Fig. 4. STEP Dashboard

4.1 Prediction system

The system will calculate and count the number of violations (figure 5), traffic fines, and accidents each year and will predict the results of next year based on the previous year's record which will help to enforce traffic rules and regulations. Figure 6 shows Yearly Accident Violation and Prediction.

Fig. 5. Yearly Accident Violation and Prediction

4.2 Violation Monitoring

It will analyze each vehicle if they are violating any traffic rules and report back to the system admin in form of notifications and alerts. The system will be smart enough to determine if the violation occurred (as shown in figure 6) or not and will save the cause of violation for future reference and help predict the system.

Fig. 6. Yearly Violation, Comparison and Prediction

4.3 Sensor System

The sensor system will sense the traffic intensity on each pole and location, which will count the number of vehicles on the road each passing through the junction of the pole then this data will be sent to the traffic command centre for further processing. Figure 7 shows Vehicles Flow Graph.

Fig. 7. Vehicles Flow Graph

4.4 Real-time Monitoring

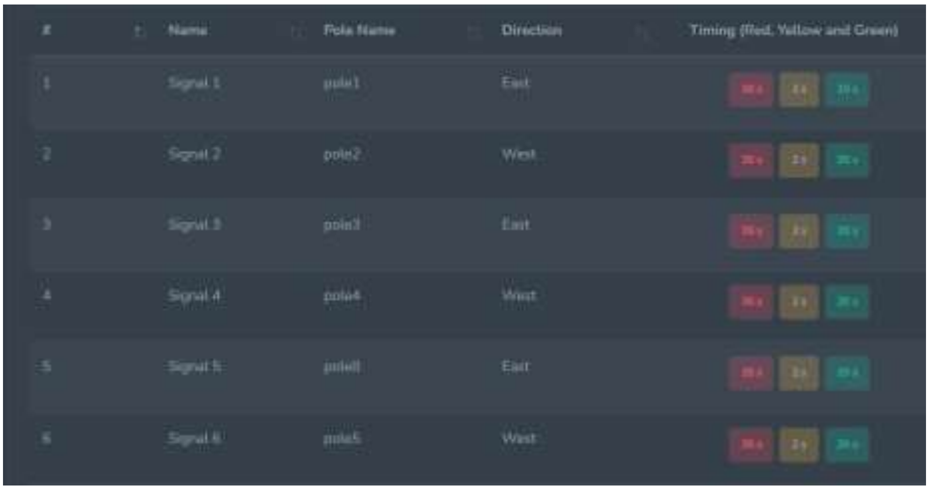
An IoT real-time traffic monitoring will dynamically control the traffic signal time in case of traffic congestion and density and then the information will be sent to the server for further processing and it will provide daily reports through web application based, the system will analyse each vehicle on the road and keep track of them in real-time in case of emergency like accidents as shown in figure 8.

Fig. 8. System Real-time Tracking

4.5 Adaptive Traffic

The conventional and old approaches of traffic signals work on the principle using fixed timing at the Traffic poles. That means traffic poles at each junction will be pre-decided with a fixed interval of time so that there will be a fixed time for red, green, and orange lights on each road. Similarly, all the junctions will be working synchronously (An automatic system with a pre-set timing). The conventional system once had a greater advantage but now, because of the ever-increasing population, more vehicles are on the city roads which drastically increased the waiting time at each junction. Increased waiting time means, more fuel consumption, and more environmental pollution thus it creates severe health issues for the general public. At the same time, this system doesn't have any procedure to provide information about the volume of traffic congestion.

ATCS has resolved all the disadvantages of the conventional system. It captures the volume of traffic flow at each arm of the road and dynamically determines the timing of traffic signals based on AI. It uses keen Machine Learning (ML) algorithms for this purpose. The system captures the traffic volume in real-time from each arm of the junction and sends the data feed to a Dedicated Server. The dedicated server is having an Artificial Intelligence (AI) engine, which receives alike input from multiple junctions across the city. The data received is been handled by the AI engine and with the help of Machine Learning algorithms, it determines how much time needs to be set at each junction in the city to ensure a stable and hassle-free vehicle drive. ATCS system provides real-time information regarding the traffic congestion at different segments of the city and the same can be informed through the general public through digital information boards along the city roadside (see figure 9).



#	Name	Pole Name	Direction	Timing (Red, Yellow and Green)
1	Signal 1	pole1	East	[illegible]
2	Signal 2	pole2	West	[illegible]
3	Signal 3	pole3	East	[illegible]
4	Signal 4	pole4	West	[illegible]
5	Signal 5	[illegible]	East	[illegible]
6	Signal 6	pole5	West	[illegible]

Fig. 9. Traffic Signal Control System

4.6 Red Light Violation (RLVD)

In RLVD, there will be a detection camera/ evidence camera (see figure 10) that will be capturing the image of the vehicle which are violating the red signal at the same time, the ANPR camera will capture and decode the vehicle license plate. Evidence camera will capture both the Vehicle position as well as the Traffic red light as proof of violation. Once all the systems are in place, the identified violations based on the ANPR system will be recorded in a dedicated server from where a ticket/ challan will be automatically generated and sent to the Vehicle Owner through e-mail/ SMS/ by post.

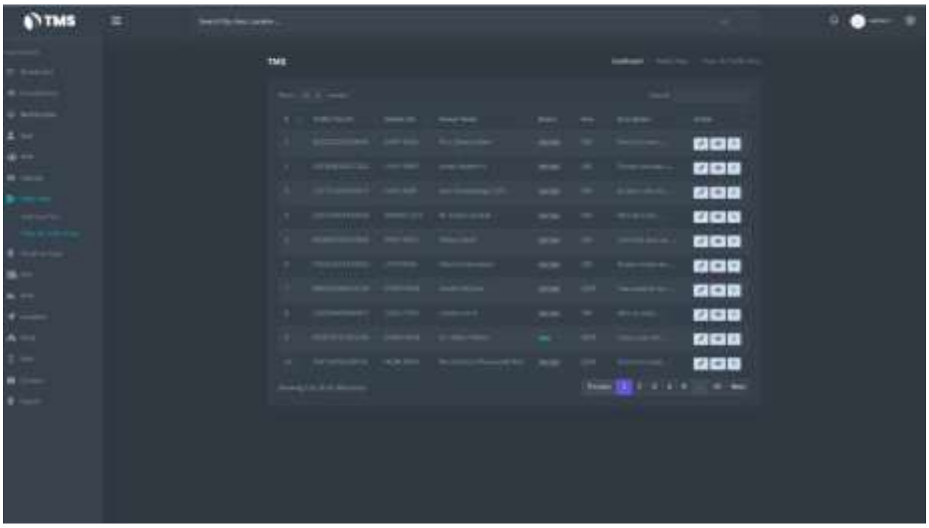


Fig. 10. Red light Violation

4.7 Tracking System

The tracking system (figure 11) is one of the main features, in which every single vehicle is being observed and watched closely which will help the driver and guide them for a safer journey, it includes road condition, alternate route guidance, provides security and privacy.

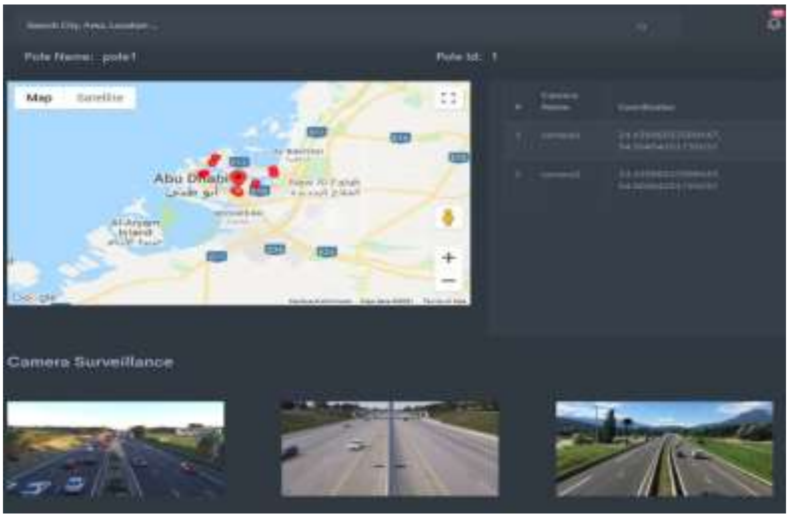


Fig. 11. Tracking System

4.8 Automatic Number Plate Recognition

Automatic Number Plate Recognition (ANPR) System is one of the traffic enforcement solutions which uses Optical Character Recognition (OCR) technology for identifying and examining the license plate of vehicles. Images of the Vehicle are captured through a CCTV camera and the captured image is analysed using dedicated computer software. Once the software recognizes the characters with the help of OCR, it will automatically give the number on the screen. ANPR helps in identifying the details of stolen vehicles like when, where, and through which route the stolen vehicle has gone.

4.9 Violation Detection

Using speed violation Cameras, the system will record every single vehicle and store proof of violation in our secure database for which can be used later for sending speeding tickets and traffic fines. The system will detect that behaviour and alert the system admin for decision making, if the admin is not available to make a decision it will automatically make the decision and then inform the admin and maintain its logs so that the system admin can revert back or acknowledge that decision. Figure 12 shows violation detection system.

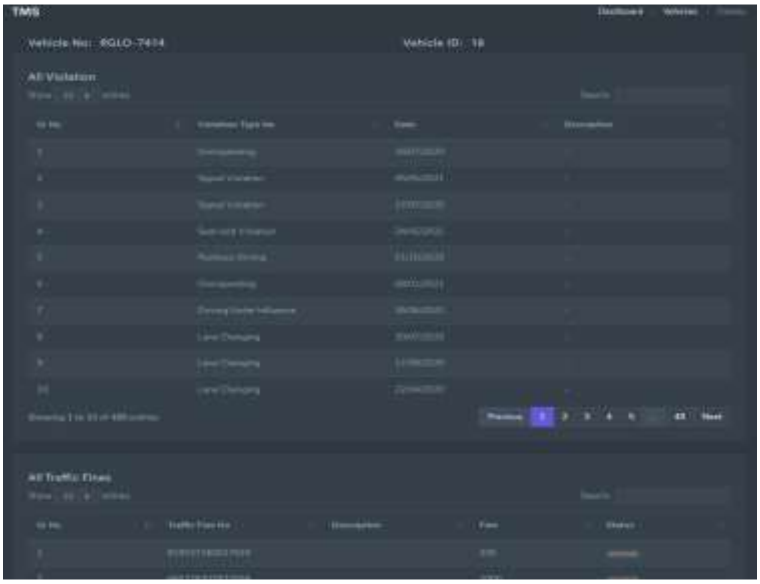


Fig. 12. Violation Detection System

4.10 Centralized Command Centre

All requests are handled from central command and control, all system administration tasks are being controlled by the centralized command. Every single piece of data related to traffic will be stored on our database on our secure Dedicated servers. Central command is responsible for all the security and maintenance for the system and provides all the help the authorities need (see figure 13).

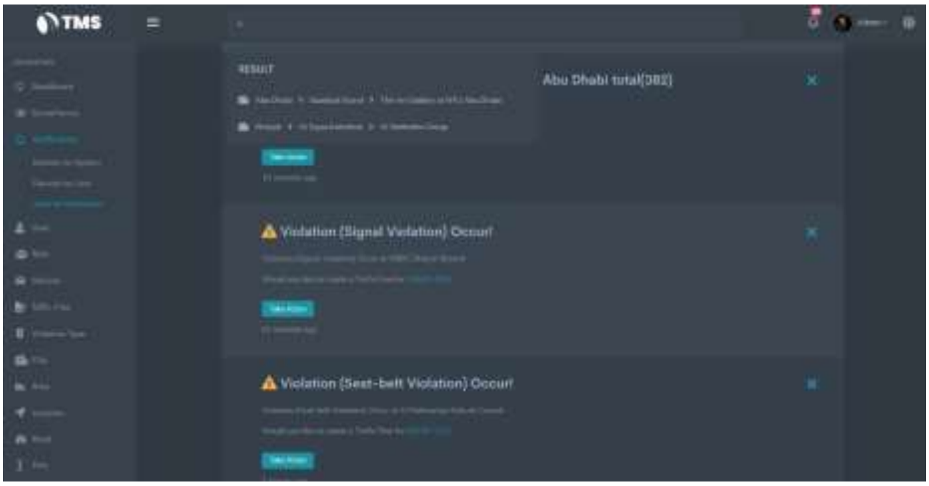


Fig. 13. Notification Alerts

5 Conclusion

The study presents the problems created by traffic congestion in metropolitan regions around the world. Congestion has a negative impact on a country's financial status, the environment, and, as a result, general quality of life.

We proposed the Smart Traffic Enforcement and Prediction System (STEP) platform, a cost-efficient smart traffic enforcement and prediction system. The proposed system provides a new technique of monitoring traffic flow that aids in the improvement of traffic conditions and resource utilization. Furthermore, utilizing real-time traffic monitoring data, the transportation administration department may detect potentially risky situations in real-time and take appropriate action to prevent traffic congestion and reduce the frequency of accidents, assuring road traffic safety.

The Machine learning-based congestion prediction algorithm that uses Logistic Regression gives a simple, accurate and early prediction of the traffic congestion for a given static road network which can be considered as a graph. The proposed architecture employs key technologies: Internet of Things, RFID, wireless sensor network (WSN), GPS, cloud computing, agent and other advanced technologies to collect, store, manage and supervise traffic information

Thus, for any developing or developed country, STEPS plays a crucial role in shaping the city traffic to the next level by reducing traffic violation & congestion. In addition, it will reduce the cost of the existing system and help the administration enforce the traffic rules and regulations more effectively.

Technological advancement in traffic management and real-time traffic police scheduling will shift police focus from enforcement to proactive work and eventually reduce the wastage of time, money, and fuel of the general public in long traffic jams. it is based on the real-time traffic density at major and minor crossroads to reduce traffic jams and enable smooth traffic flow.

Traffic management technology advancements and real-time traffic police scheduling will move police attention from enforcement to proactive work to decrease traffic congestion and enable smooth traffic movement across the city.

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