Artificial Intelligence in Urban Traffic Noise Prediction: A Systematic Review

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ABSTRACT

The present work discusses the traffic noise prediction model based on Artificial Intelligence using Artificial Neural Networks (ANN), AI robot technology, and Intelligent Transportation Systems (ITS). This survey paper used a methodical review of the body of research on traffic prediction, with a particular emphasis on highlighting the most recent developments and untapped research opportunities in AI-based traffic prediction techniques which were used to look up papers in the IEEE Xplore, Web of Science, ACM Digital Library, and Scopus technology libraries. Taking into consideration a variety of input variables, such as traffic volumes, speed, and road conditions, these models are mainly designed with the goal of estimating road traffic noise levels. When compared to analytical techniques, machine learning algorithms have demonstrated good performance when used to model and predict a variety of variables. Artificial intelligence-based models have outperformed traditional and empirical models in traffic noise prediction due to its adaptive nature and capacity to manage non-linear properties. As a result, in contrast to nations with well-established empirical models, the application of AI-based methodologies provides an alternate strategy in nations with distinct traffic compositions and features. With the review, the explosive expansion of artificial intelligence (AI) offers potential for previously unheard-of productivity and creativity in controlling and organizing urban procedures and to serve as a solid resource for future urban traffic prediction using artificial intelligence (AI) research as well as an appropriate resource for readers to catch up on the state of the art rapidly.

Keywords: Artificial Intelligence (AI), Traffic noise, Artificial Neural Networks (ANN), AI robot technology, Intelligent Transportation Systems (ITS), Systematic Review

INTRODUCTION

In urban locations across the globe, traffic noise pollution has emerged as a pervasive and detrimental environmental issue (Tiwari et al., 2024). In addition to interfering with daily life, the continuous noise of cars travelling down streets and roads seriously compromises public health and welfare (Munzel & Daiber, 2018). The rapid advancement of passenger transit raises the risk of noise exposure (Vianna et al, 2015). This is most likely due to the fact that road traffic has more infrastructure coverage than air or rail transit (Ahmed et al., 2023). Scientific research has demonstrated that individuals' health is negatively impacted by high noise levels (Hahad et al., 2024).

Noise is an invisible contaminant that usually goes unnoticed, yet it clearly has detrimental impacts. Numerous health issues, including disturbed sleep, heart disease, and cognitive decline, have been linked to traffic noise (Gottesman et al, 2024). The interaction between the tyres of vehicles and the road surface is the main source of noise produced by traffic, accounting for a considerable portion of the total noise produced by traffic (Licitra et al., 2017). The method of traffic noise modelling should take into account the many contributing elements that contribute to the formation of traffic noise (Patel et al., 2022). The major important parameters that need to be included for traffic noise models are vehicle speed, traffic volume, and road geometry in order to assess their effects on noise levels (Yadav et al., 2023).

Physically monitoring traffic noise next to fast-moving highways can be expensive, time-consuming, or even impossible (Ahmed & Pradhan, 2019). Due to these difficulties, many statistical and regression models have been created by researchers, providing dependable and affordable techniques for estimating traffic noise with greater accuracy. These prediction models contribute to safer driving conditions and decision-making. Nonetheless, in affluent nations as well as those with comparable traffic patterns and driving behaviours, these empirical models are renowned for their great prediction accuracy (Sharma et al., 2016). However, due to local considerations such variances in road design, weather patterns, and traffic layout from one country to another, classical models are generally less accurate in areas with substantial variations in traffic patterns and features. Regression and empirical models have problems with generalisation in their forecasts (Hamad et al., 2017). Numerous mathematical and artificial intelligence models have been created in response to these problems in order to predict traffic noise in different countries and locations. Because artificial intelligence-based models are flexible enough to handle connections with non-linear features (Umar et al., 2024).

The planning and building of both highway and non-highway road projects, as well as figuring out how current changes in traffic patterns affect noise levels, depend heavily on traffic noise prediction models (Karami & Kashef, 2020). Numerous major noise prediction models have been created for individual countries based on their distinct traffic characteristics and road configurations, however, there is currently no worldwide consensus on a standardised index for evaluating road traffic noise (Tiwari et al., 2024). Models for predicting traffic noise are crucial resources for effectively controlling noise pollution. In the end, they improve the quality of life in cities and their environs by supporting sustainable urban growth, ensuring regulatory compliance, protecting public health, and assisting in decision-making. Many investigations have been conducted in an effort to design a model that can precisely forecast traffic noise levels (Staab et al., 2021).

Over the past thirty years, the modelling technique has been refined by investigating the potential applications of artificial intelligence principles in relation to various solutions for the problem of road noise (Baccoli et al., 2022). Artificial intelligence has been developed as a result of the growth and maturation of wireless communication and sensor technologies in recent years, and an increasing number of related technologies have been applied to the transportation sector (Boukerche et al., 2020). Data for the intelligent transportation system is gathered from a variety of sources, including social media, mobile phone signals, sensors, cameras, GPS (Global Positioning System), gearbox equipment, and other sources. These data bring the predictability and feasibility of intelligent transportation along with the intrinsic qualities of the transportation system (Lu, 2023). The present work discusses the traffic noise prediction model based on Artificial Intelligence using Artificial Neural Networks (ANN), AI robot technology and Intelligent Transportation Systems (ITS). This study contributes in assessing the reliability of AI-based models in traffic noise modelling in comparison to established empirical models across different countries; Identify potential input parameters used in traffic noise modelling and their significance in modelling traffic noise; Examine the various ways for monitoring parameters in the field and how they are applied as input parameters in AI-based models; and determine possible avenues for further investigation.

METHODS

Although there are a lot of relevant urban traffic forecast survey articles available, because there are so many different ways in the literature, most of them are concentrated on particular technical areas or subsets of the methodologies. However, not all polls link the most recent developments to real-world uses and potential avenues for further study. Furthermore, it is difficult for readers to evaluate the level of traffic prediction methodologies as of right now as a whole because these surveys are divided across different discipline-specific publications and publication sites. A review that takes the literature into account from all angles is required as the literature gets increasingly varied and interdisciplinary. Therefore, this survey paper's main contribution is to offer a thorough and methodical review of the body of research on traffic prediction, with a particular emphasis on highlighting the most recent developments and untapped research opportunities in AI-based traffic prediction techniques which were used to look up papers in the IEEE Xplore, Web of Science, ACM Digital Library, and Scopus technology libraries. The title was the only item in the keywords search area such as Artificial Intelligence (AI), Traffic noise, Artificial Neural Networks (ANN), AI robot technology, Intelligent Transportation Systems (ITS). After completing this step, duplicates were eliminated.

RESULTS

Artificial Neural Networks (ANN)

Numerous writers have studied artificial neural network (ANN) methods in recent studies. The ANN algorithms serve as the foundation for the most popular and effective heuristic techniques (Bravo-Moncayo, 2019; Genaro et al., 2010; Nourani et al., 2020; Khalil et al., 2019; Sharma et al., 2016; Tomi´c et al., 2016; Garg et al., 2015). The recent surge in interest in creating ANN models for challenging traffic noise prediction problems is due to their universal applicability in modelling, classifying, controlling, and predicting complex systems with a respectable degree of accuracy, insensitivity to noisy data, and tolerance to incomplete input data. Moreover, the neural network's black-box paradigm enables one to skip the initial phase, which involves applying specific physical rules pertaining to the acoustic wave propagation mechanism and associated boundary conditions. This feature is highly appealing because the initial steps towards incorporating the noise source representation, topography, and acoustic characteristics of the natural and urban environments (with appropriate refinement) could significantly affect how long it takes to fine-tune a physical model.

Nedic et al. (2014) presented an intriguing use of an ANN for traffic noise prediction. The authors selected the feed-forward (FF) BP system. The ANN was trained and evaluated in steady-state traffic situations on a Serbian motorway. The training and test sets comprised 70% and 30% of the entire dataset, respectively. The outcomes showed that the ANN algorithm performed better than any other statistical technique in forecasting traffic noise levels. However, Torija et al. (2012) presented a fascinating study on the application of a BP algorithm for forecasting the Leq,5′ short-term level and the evolution of the sound pressure level in the frequency domain for a physical characterization of the urban soundscape. The input data included traffic characteristics, street geometry, time of day and period, sound level stabilization time, and location characterization. The proportions of the training, validation, and test sets to the whole dataset were 80%, 5%, and 15%, respectively. They obtained a prediction error for Leq of less than 1.88% and for the spectral composition of less than 3.07%. Hamad et al. (2017) tested and calibrated sixteen distinct FF-BP ANN models to simulate traffic noise in a hot climate. The size of the training and test sets was 15% and 85% of the total dataset, respectively. To throw some insight on the black-box paradigm of the neural network, the scientists conducted a sensitivity analysis over the selected explanatory variables (distance from the edge of the road, volume and composition of light and heavy-duty vehicles, average speed, and roadway temperature).

The first use of the Emotional ANN (EANN), a new generation of neural network techniques, for forecasting the equivalent noise level Leq,15′ from road traffic noise in Nicosia was published by Nourani and friends on 2020. According to the aforementioned study, traffic volume was shown to be the most significant contributing element, while the volume of heavy vehicles was found to be the least. Regarding the makeup of the test, validation, and training sets, nothing is said (Torija et al., 2012).

In order to anticipate highway traffic noise in an Indian setting, a multilayer feed forward BP neural network using the Levenberg–Marquardt algorithm. A site with unhindered traffic flow and no causes of disruption was chosen, with nighttime traffic levels excluded from the forecast. The suggested artificial neural network (ANN) model was applied to forecast 10 percentile levels (L10) and the corresponding continuous sound level in dB(A) by utilising the average hourly traffic flow numbers as raw data. Regression analysis compared with

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experimental values showed that the percentage training error for L10 and Leq ranged from − 5.1 to 2.6 and − 4.2 to 2.7, respectively, whereas for test samples, the error was between − 4.1% and − 0.1% for L10 and − 4.8% to 0.5% for Leq. Regression analysis did not perform as well as the ANN model. In fact, the ANN model's training error falls between − 0.8% and 1.0% for L10 and − 1.5% and 0.9% for Leq. In contrast, the error for testing samples is between − 1.7% and 1.8 for L10 and − 0.6% and 1.5% for Leq. 80% and 20%, respectively, of the 46 hourly recordings that made up the entire dataset were included in the training and test sets (Kumar et al., 2014).

A novel ensemble technique to combine the output of four distinct models in an effort to enhance Nicosia's traffic noise prediction capabilities. Four models were used: one was based on a traditional multilinear regression model, while the other three were AI-based (support vector regression method, neural network, and fuzzy). Measurements were taken at observation stations that were carefully chosen to minimise the amount of background noise that could be considered spurious throughout the day (nighttime was excluded). After that, the ensembled model was used to forecast the comparable sound level Leq, taking into account a 15-minute integration time and utilising average vehicle speed and traffic composition as input variables (Nourani et al., 2020).

Chen et al. (2020) created a neural network model for traffic noise prediction in a city with mountains. Experimental data collected on a municipal road in the hilly Chinese city of Chongqing was used to construct a multilayer feedforward artificial neural network (ANN) model. At observation stations that were carefully chosen to function in a situation with free-flowing traffic, measurements were taken. The comparable sound level pressure and per-vehicle noise levels were predicted using the suggested ANN model. The neural model significantly outperformed the empirical equations when compared to the Chinese standard HJ 2.4–2009.

A fundamental Multi-Layer Perceptron (MLP) model for hourly equivalent sound pressure level prediction was presented by Givargis and Karimi (2010). To find out if a neural network can be statistically employed to simulate traffic noise for Tehran's highways, the scientists compared their model to the CORTN model. The study's findings demonstrated that the MLP model could describe the traffic noise in a way that was consistent with the traditional statistical methodology of the CORTN model. Another prediction of continuous hourly Leq at various free-flow traffic locations in an Indian metropolis using four distinct soft computing methods: generalised linear model, decision trees, random forests, and neural networks. When it came to sound pressure level prediction, the Random Forests method fared better than the other methods (Singh et al., 2016).

AI Robot Technology

Some scholars have suggested employing AI robot technology for fusion design in order to make urban design more intelligent and innovative, and some scholars have already been active in the development of AI robot technology (Wang, 2022). Modern technological integration has become a game-changer in the ever-evolving sector of urbanisation. Another such revolutionary field is the use of novel elements that make use of autonomous robotic technologies for medium-scale city planning, heritage, and intelligence oversight. a chance to fundamentally rethink how we envision, arrange, and manage urban environments. Robots and machine learning offer a promising new route for medium-sized urban landscapes at the nexus of design and technology, characterised by unmatched knowledge, conservation, and profitability. The combination of these novel features offers an exciting future for medium-scale city growth, where intelligence and technology collaborate to build cities that are conducive to the welfare of populations, from bettering spatial organisation to rethinking approaches to managing municipal resources (Wang, 2024).

Fig. 1 illustrates the design of management and control in urban settings using robot technology. The use of robot is not only for environmental control but also traffic and building control as well as historical and cultural control. In terms of traffic control, the application of robot in urban intelligent management and control design used to analyze various type of traffic including static, motor vehicle, pedestrian and public transit.

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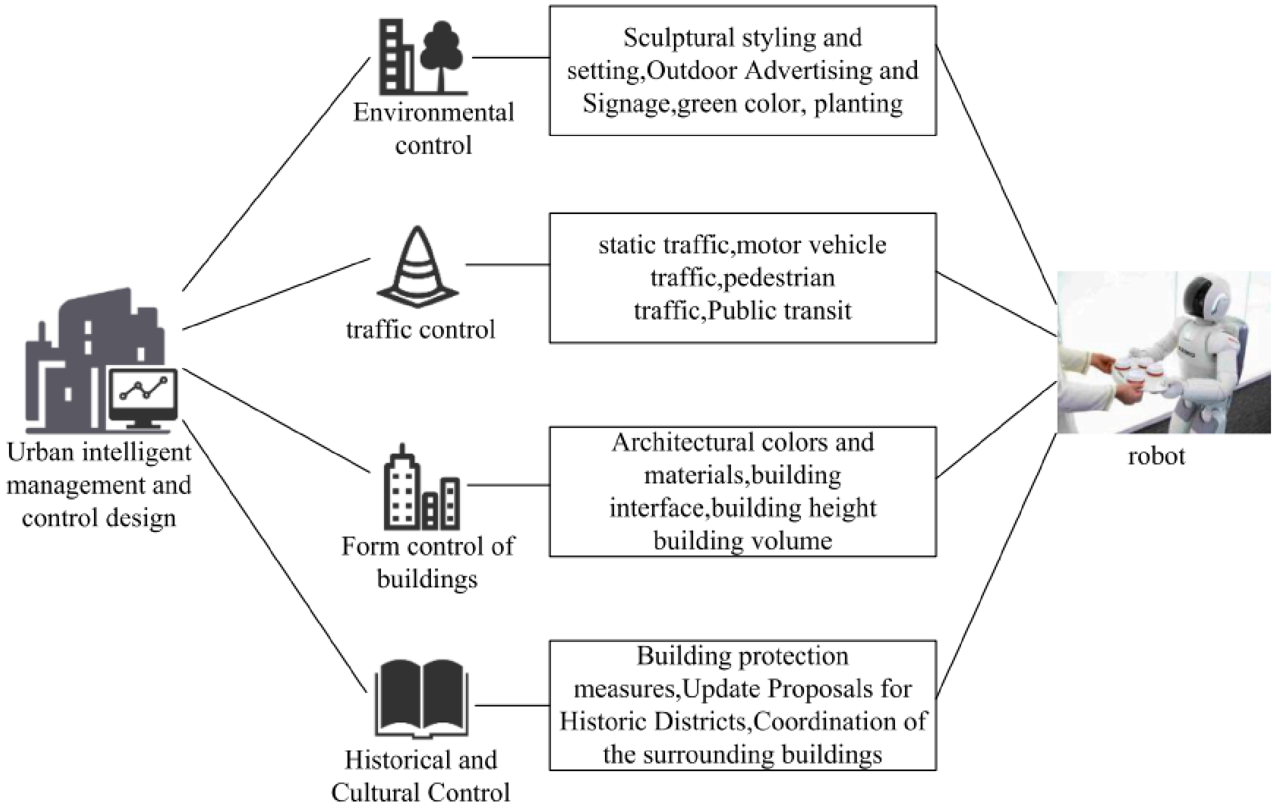

Fig. 1. Design content of urban intelligent management and control (Wang, 2024)

It was suggested in (Ponnusamy & Alagarsamy, 2021) that an IoRT system be developed in smart cities by integrating robotics and IoT sensor nodes. The system created a cloud platform that connects, shares, and exchanges traffic data between IoT sensor nodes and the cloud in order to obtain vehicle mobility data. The trials show that the IoRT system can improve traffic control, timely judgements about traffic flow, and collision-free traffic when compared to current smart city traffic management systems. While previous research has employed this kind of solution to lessen road-related problems, a number of difficulties remain unresolved. First of all, the sensors are unable to collect and send data to the processing unit due to malfunctions. For example, several sensors must be in closer proximity to the object they are intended to detect in order for them to collect data and function well. Furthermore, it is not practical to use a lot of IoT sensors because controlling them is expensive and time-consuming. As explained in detail in (Frank et al., 2019), employing Bluetooth or other short-range communication technologies eventually demands access points to be close to the sensor array in order to provide data. This increases system complexity.

The suggested approach eliminates the requirement for several roadside sensors by integrating several on-board sensors into the ARC in order to address these issues. It guarantees ongoing detection by backup sensors in the event of a sensor failure. By using cameras to gather real-time traffic data, this system uses fewer sensors, which reduces complexity and costs. Additionally, Wi-Fi is used for effective communication, providing faster and farther-reaching connections between IoT devices and the cloud than alternative methods (Kheder & Mohammed, 2024).

Autonomous Robotic Cars, or ARCs for short, are vehicles that can function without the need for human interaction. It perceives its environment, navigates, and makes decisions based on real-time data using IoT sensors, software, and machine learning algorithms. According to (Balachander & Venkatesan, 2021; Gokasar et al., 2023), these cars have the power to completely transform transportation by lowering the number of accidents brought on by human error, increasing productivity, and improving accessibility. In order to maximise their driving behaviour, they can also converse with other cars, other drivers, and commuters. In order to assess the study's goals, the ARC was created utilising a variety of hardware and software components.

All the integrated components and the diagram of the system using Autonomous Robotic Cars can be seen from fig.2.

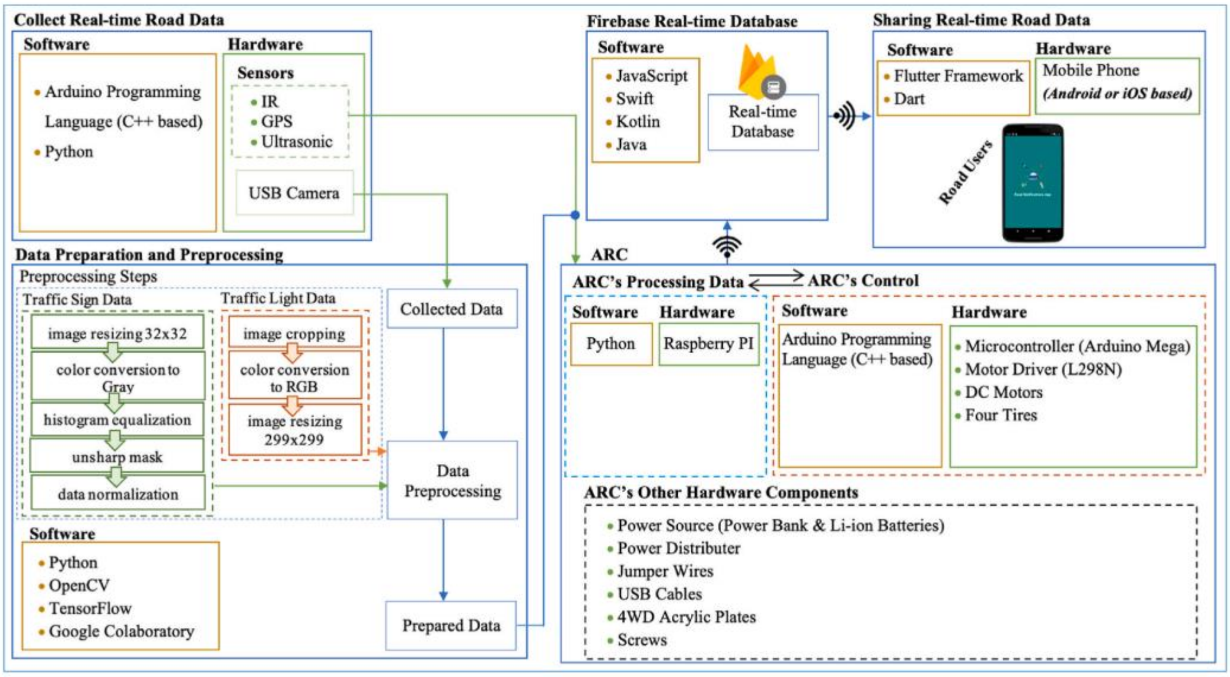

Fig. 2. General block diagram of the proposed system using Autonomous Robotic Cars (Kheder & Mohammed, 2024)

Intelligent Transportation System (ITS)

In the transportation system, ensuring the dependable transmission of information linked to traffic safety and management is the major design goal of vehicular networks (Sun et al., 2020; Sun & Samaan, 2021). It goes without saying that the primary obstacle to accomplishing this design aim is to mitigate the detrimental effects on data transmission caused by the extremely dynamic topology of automotive networks. The primary focus of current research efforts is on developing routing protocols (Goudarzi et al., 2019), data dissemination techniques (Begin et al., 2018), SDN-enabled VANET (Bhatia et al., 2019), handover systems (Sun et al., 2020) in order to meet this issue.

a. Internet of Vehicles (IoV)

Benefits coming from the introduction of traffic forecasting on-road car in the Internet of Vehicles (IoV), it is a provider of network resources and a user of associated vehicular networks. When an automobile offers network resources, its main function is to assist other cars in forwarding data by serving as a relay node or data carrier. It goes without saying that more network resources are available on a road stretch with higher traffic volumes. As a result, current methods for resolving the data transmission issue in the Internet of Vehicles (IoV) often follow a simple logic: they aim to maximise the data route's passage through high-traffic areas. Because it is simpler to locate replacement nodes on the road section with high traffic volume, this makes it possible to more easily recover the afflicted links locally when faced with changes in the network topology caused by relative movement between cars (Sun et al., 2020).

Currently, the majority of approaches include broadcasting different route discovery messages to investigate the system's short-term topology before using the associated routing metrics to choose the best path. However, because the topology in the Internet of Vehicles (IoV) environment is so dynamic, these reactive schemes must frequently explore the instantaneous topology of the system by broadcasting corresponding control messages. This will waste the limited transmission resources in IoV and add a significant amount of control overhead. However, the flooding problem that current approaches frequently encounter can be successfully

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mitigated by the use of traffic forecasting. This is because the vehicle can choose road segments with higher traffic flow to establish a more reliable data forwarding path by incorporating traffic flow prediction, which allows the vehicle to get the traffic flow of the relevant road segments prior to the commencement of data transmission (Boukerche et al., 2020). All that is required is a straightforward, greedy forwarding of the data on the matching designated road section. Thus, it is possible to greatly simplify the widely used technique of broadcasting routing discovery messages over a wide region for network topology study, which resolves the flooding problem. For example, the authors provided empirical evidence demonstrating how the introduction of traffic predictions can significantly improve the performance of data transmission in the vehicle network (Sun & Boukerche, 2020).

b. Data center/automobile cloud computing

The goal of automobile cloud computing is to increase the effectiveness of using in-car computer capability (onboard computing chipset). On the other hand, the on-board equipment's operating states vary amongst cars as a result of the various vehicle operating states. While some vehicles in a parking state have their on-board equipment in an idle state, other vehicles may need to execute extensive calculations and analysis on the observed data in order to put their respective computer units in a full load condition. Currently, related task solving efficiency can be greatly increased if the computing power of nearby idle vehicles that is relevant to the vehicle in full-load working condition can be utilised to jointly process the computing task of the working vehicle. This is precisely the objective of the application for automotive cloud computing (Sun et al., 2020).

As a result, as noted in (Douglas et al., 2019), the primary area of study in the field of VCC at this time is how to guarantee that, when the vehicle is in various motion states, it can efficiently explore and use the idle computing capacity of other players in the transportation system. In the meantime, the IoV is realised in the ITS system by the maturity of V2X communication technology, which is the base for deploying VCC as previously indicated. advantages brought about by traffic forecasting's introduction The advantages of introducing traffic prediction in the VCC field are clear.

As previously stated, the key to putting VCC into practice is to effectively explore and utilise the IoV environment's idle data processing and storage capabilities. The traffic volume on a road section determines how much idle computing/storage capacity is possible on that segment (Sun et al., 2019). By knowing the expected traffic volumes on the relevant road sections, users of traffic forecasting can make an informed decision about whether or not to use VCC services on related road sections in order to solve corresponding computing tasks more quickly. As a result, that traffic flow prediction might be able to help with VCC application. For instance, further estimation of the possible dwell-time of the cloudlet within an arbitrary road segment based on the anticipated traffic flow data (Zhang et al., 2017).

c. Intelligent traffic management:

Enhancing the transportation system's operational efficiency is one of the primary design goals of the Intelligent Transportation System (ITS). At the moment, in order to achieve this objective is the creation of intelligent traffic control applications. There are two primary methods used to implement intelligent traffic management to guarantee that traffic moves as smoothly as possible within the permitted flow range of the traffic infrastructure, the first technique of real-time traffic flow control uses a traffic signal control (TSC) system to implement real-time dynamic adjustment of traffic flow (Meneguette & Nakamura, 2017). The current research trend in this topic focuses mostly on using reinforcement learning (RL) technology to determine the best signal control scheme through trial and error while following the appropriate reward functions. These techniques are essential for controlling the flow of traffic in the transport system and keeping it operating smoothly. However, this method's drawbacks are also readily apparent, it is ineffective when traffic volume surpasses the road's capacity. These techniques, however, are unable to relieve the current traffic congestion (Zhang et a., 2019).

In order to reduce the possibility of congestion at the macro level, the system can calculate the likelihood of congestion on the corresponding road segment and use this information to formulate the corresponding traffic

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management plan. This plan can then be used to directly adjust the capacity of the relevant road (e.g., setting tidal lanes) or control the corresponding traffic flow (e.g., diversion measures, increasing public transport capacity input within a specific time, etc.) (Li et al., 2014). It is important to note that the reactive approach, which handles microregulation and the proactive approach are complementary and essential in the transportation system, which is a complicated, large-scale system. As (Sun et al., 2020) described, even in cases where traffic flow is less than the capacity of the route, traffic congestion is unavoidable in the absence of a reasonable traffic signal control mechanism. Furthermore, a single intersection traffic bottleneck has the ability to set off cascading failures that could ultimately result in system-wide congestion.

d. Autonomous driving

Enhancing the driving safety of vehicles is essential to enhancing the system's overall safety as it is a vital component of the transportation network. The development of autonomous driving technology has thus been aided by the need to increase traffic safety. The current state of autonomous driving technologies can be roughly classified into two groups: The first type of technology is driving assistance, which has developed and is progressively being introduced to the market. It is associated with the movement state of the vehicle or the status of the driver. The majority of these techniques fall under the Level 1 autonomous driving category, such as lanekeeping/departure warning systems and driver drowsiness detecting systems. Some techniques, however, may be classified as Level 2 techniques, such as dynamic vehicular route planning. The other category consists of methods for identifying traffic conditions surrounding moving vehicles. This kind of technology focuses mostly on traffic-related objective identification of targets associated to traffic, such as animal detection (Mammeri et al., 2016), vehicle detection/model recognition (Zhao et al., 2017) and pedestrian detection (Brazil & Liu, 2019).

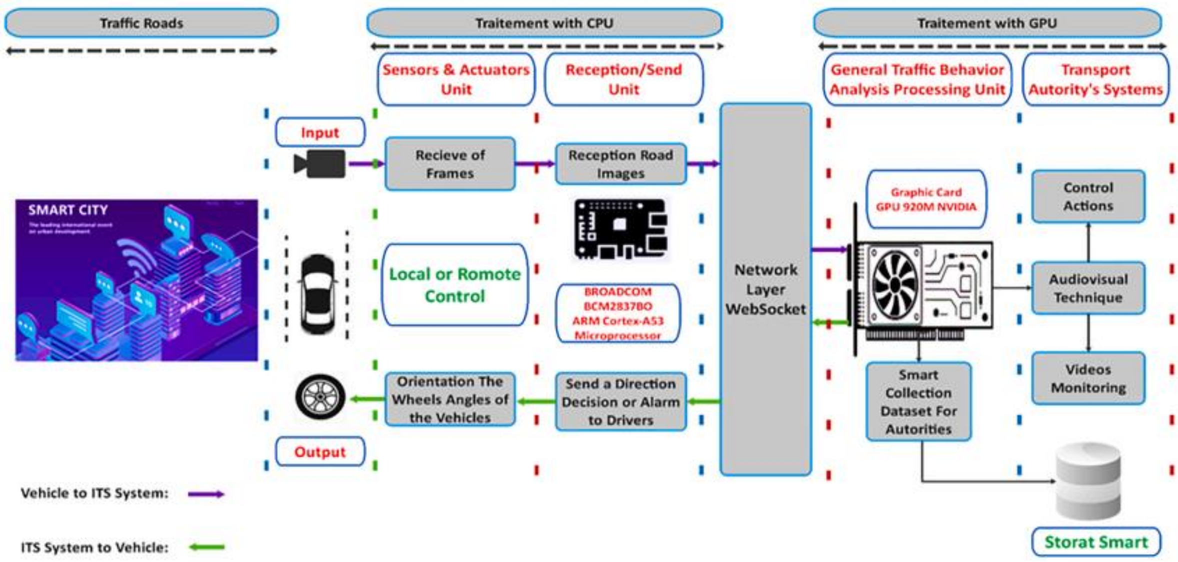

Fig. 3. General system of ITS (Barodi et al., 2023)

The general design of the suggested system is depicted in Fig. 3, and it consists of five key components. The first unit is made up of two main components: an actuator at the output that adjusts the angle of the wheels in three directions (right, middle, and left) and a camera at the input (sensor) that records a video of the road being crossed in order to identify the road's edges (left and right lines). The second unit is primarily a receiving and sending unit. It gets a sequence of photos from the video capture, and it sends the other units' returns (wheel orientation, authorities' warning, and alert). Within the ITS system, the third unit is the communication layer (WebSocket TCP/IP), which serves as a bridge between the processing units equipped with GPUs and CPUs. The study of high-speed road lines is made possible by the GPU (NVIDIA) graphics processor found in the fourth unit, the general traffic processing unit. The authority monitoring unit, which collaborates with the general unit, is the fifth unit. The authorities will respond by alerting the driver if the video analysis identifies that a road line is being crossed. If the driver does not respond appropriately, the ITS system will be triggered. The benefit of the ITS system is that it intelligently gathers and saves photographs. These images are identified by the calculated SA, which the traffic authorities can utilise at a later time (Barodi et al., 2023).

Future Research

Based on the review that have conducted, there are several recommendations for the future research related to traffic noise modelling using Artificial Intelligence. To evaluate its usefulness and dependability in traffic noise modelling, more research must be done. Additional independent factors such pavement type, street aspect ratio, vegetation, locale type, industry presence, building facade materials, acceleration and deceleration impacts, and barriers should be included in future studies. Future studies should also look into a microscopic method of traffic noise prediction, in which rolling and engine noise are modelled independently by outfitting a test vehicle to monitor each noise separately. Furthermore, the method's scalability and practicality are highlighted by the use of already-existing roadside video surveillance systems for data collection, which could establish a new benchmark for traffic noise measurement techniques. Additionally, it offers a strong framework to assist authorities in charge of traffic management and environmental protection in making well-informed decisions to reduce traffic noise pollution. This technique will be applied to more difficult noise estimation scenarios, such as social and industrial noise, after it has been developed in the field of traffic noise estimation.

CONCLUSION

Cities are the primary repositories of human culture and significant physical accomplishments. Given that a significant portion of this meso-scale, an examination of its architectural history and its intelligent management and control are especially crucial. In the current AI era, urban planning and architectural design face new issues as a result of the constraints of technology and ideas used in the creation of traditional cities. Artificial intelligence (AI) and urban planning work together to not only encourage innovation but also lay the groundwork for highly developed, adaptable, and people-centered neighbourhoods that can swiftly adapt to the shifting needs of their inhabitants. Together, they provide a workable future for transforming medium-sized communities and encouraging the harmonious coexistence of technology and human-centered lifestyles. With the review, the explosive expansion of artificial intelligence (AI) offers potential for previously unheard-of productivity and creativity in controlling and organising urban procedures.

More precisely, we first survey the existing work on urban traffic data, and then we thoroughly define the many data types used in traffic prediction and their constraints. After that, we offer a taxonomy and a summary of both traditional and modern traffic forecast techniques. Furthermore, we review various urban traffic prediction problems and examine the current literature-based methodologies with an emphasis on multivariate traffic using AI. Finally, some important issues are addressed along with potential avenues for future research. The purpose of this paper is to serve as a solid resource for future urban traffic prediction using artificial intelligence (AI) research as well as an appropriate resource for readers to rapidly catch up on the state of the art.

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ETHICAL APPROVAL

This research did not involve with any human subjects or animal.

COMPETING OF INTEREST DECLARATION

The authors have no competing interests to declare that are relevant to the content of this article.

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