

An efficient AI model for highway vehicle speed limit violation detection and real-time law-enforcing functionality

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Abstract

Traffic control at toll exit booths is unable to promptly apprehend speeders. Therefore, speeders get more self-assurance for overspeeding. According to different studies, data loss and transportation errors are significant challenges for traffic management systems. It significantly impacts data retrieval and anticipated outcomes. The integrity of data collection may be impacted by partial or whole data loss due to distinct transit problems. Consequently, due to the distorted data, the accuracy of detecting the overspeeding cars or drivers may be disrupted. However, the current literature fails to offer any integrated approach to resolve such issues. Therefore, this study offers an improved method for educating drivers against speeding. A challan is automatically issued following three highway speed offenses. It notifies the motorist before issuing the citation. The neighboring integrated network devices relay challan information to the traffic control office as the motorist passes the toll booth, traffic signal, or roadside site. Consequently, enhancing the psychological influence of exit booth enforcement on offenders to ensure compliance with payment. These psychological impacts dissuade speeders and augment fines. This project essentially involves a real-time, Internet of Things (IoT)-based artificial intelligence (AI) methodology for mitigating highway speeding. Enhanced simulated annealing (SA) improves the detection of speed limit violations and ensures data integrity. It features an effective error control mechanism to reduce transmission errors and data loss. The experimental results indicate that it offers greater predictive accuracy for speeds, displaying improved precision, recall, F1-score, and area under the ROC curve (AUC) score relative to current methodologies. Its power to produce improved information processing and diminished cyclomatic complexity (CC) confirms its temporal efficiency. The diminished information percentage, along with packet loss and an increased signal-to-noise ratio (SNR) value, illustrates its capacity to enhance data integrity.

Keywords

speed limit violators, psychological impact on violators, IoT-based real-time responsive AI approach, speed limit violation detection accuracy, data integrity, simulated annealing

I. Introduction

Lavish speed has constantly been identified as the primary cause of highway accidents, and this trend is increasing. High-speed driving conditions significantly increase the likelihood of catastrophic or fatal accidents. Severe accidents frequently arise from negligent driving. Exercising caution and alertness when driving will reduce the likelihood of negligent accidents. A significant factor in traffic accidents is distracted drivers. In recent decades, incidents resulting from inattentive driving have increased [1, 2]. Consistently prioritize focus on the roadways; this is a principle every driver should adopt. A hazardous combination of driving and multitasking, encompassing reading, replying to texts, and making phone calls. Roadways will be significantly safer for all if individuals adhere to the regulations. Notwithstanding the straightforwardness of the restrictions, individuals typically adhere to them. Always halt at red traffic signals to avert accidents. Ignoring a red light unlawfully may lead to a catastrophic incident, irrespective of your awareness of oncoming vehicles [3]. Exercising caution is preferable to experiencing remorse, as one's life holds greater significance than any justification. The absence of an instant legal enforcement mechanism is thought to promote drivers' disdain for traffic safety regulations and to foster dangerous driving behavior. Of all perilous driving behaviors, extreme speeding is the most dangerous. Conventional law enforcement aims to effectively deter overspeeding on roadways.

Nonetheless, inherent constraints of human law enforcement are progressively undermining its effectiveness. Frequently, due to high speed, it becomes challenging to determine an exit route, resulting in collisions with other vehicles [4, 5]. Such infractions of traffic regulations result in fatal accidents, perhaps causing the death of travelers on the highway. Figure 1 illustrates a standard vehicular collision caused by excessive velocity and infringement of traffic laws.

Numerous obsolete overspeed detecting technologies are presently in use. These include systems employing handheld or mounted light detection and ranging (LIDAR) weaponry, Closed-Circuit Television (CCTV) traffic cameras, speedometers, and analogous equipment [5–7]. To achieve optimal performance, most of these systems require installation throughout the entire length of the roadway, which can be an expensive undertaking. Furthermore, these duties generally necessitate continuous 24/7 monitoring, which introduces an additional challenge. Moreover, the enforcement of sanctions for drivers exceeding the speed limit is a protracted process, even upon their apprehension. The motorist continues their hazardous driving conduct, endangering themselves and others, so compromising the stated purpose [8]. A sophisticated system that reliably monitors drivers' compliance with speed rules and swiftly enforces penalties for infractions can exert considerable psychological effects on the driver, ultimately discouraging overspeeding. A sophisticated system of this kind would improve the safety of highway transportation. Thus, the prompt enforcement of laws

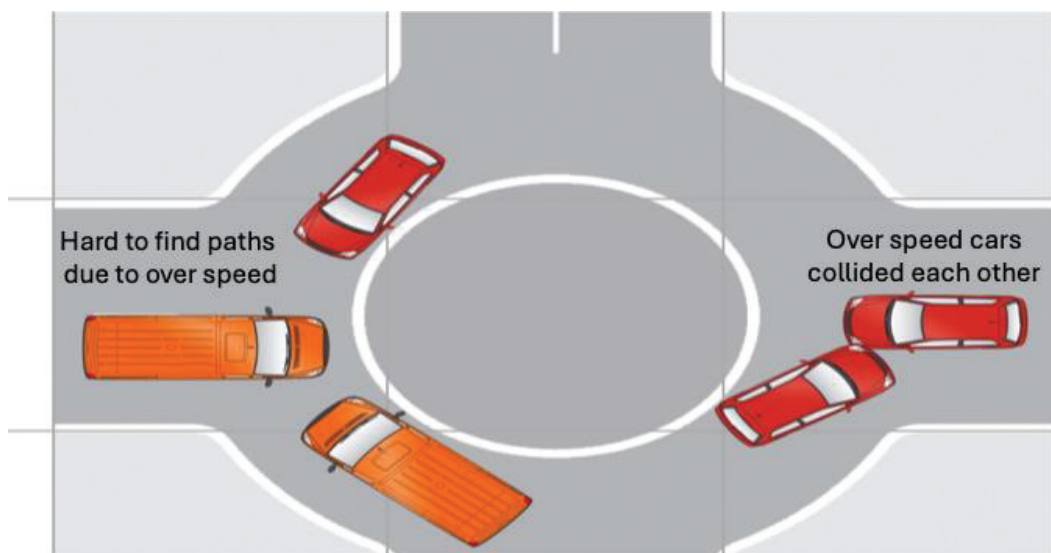


Figure 1: A typical road accident situation due to overspeeding and traffic rule violations.

at the departure booth might exert a significant psychological influence on offenders, functioning as an efficient means to educate drivers regarding the consequences of speeding infractions [9–11].

A notable risk is data loss due to various transmission issues, such as transmission errors, channel noise, and environmental interference. As a result, the received data is frequently irretrievable, either in part or in whole, at the destination [12–14]. Thus, it is a fundamental consideration for every data communication system. Traffic management systems require the transmission of image or textual data at various intervals to regulate traffic, monitor unauthorized cars, or identify traffic law breakers. As a result, in these professions, any occurrence of partial data loss may prevent the detection of speed limit violations or traffic regulations, hindering the proper regulation of the traffic management system. An error control mechanism is crucial for managing data errors and preventing data loss during the transfer of traffic information. A backup system is crucial for restoring original data in cases of inadvertent data loss or corruption during the transmission or processing of input traffic data

[15, 16]. A thorough evaluation of current real-time traffic management techniques is shown in Table 1.

Table 1 illustrates many issues associated with the existing traffic control and monitoring technologies. The limitations of the existing methodologies render them inappropriate for real-time traffic management. Moreover, these existing real-time traffic monitoring and control methods do not provide a means to generate real-time citations that could deter cars from exceeding speed limits.

This research presents an integrated module including Internet of Things (IoT) sensors to collect speed data directly from the vehicle to address the difficulties. It analyses speed data using an intelligent integration of artificial intelligence (AI) and a simulated annealing (SA) algorithm to properly forecast instances of speeding. The technology issues a warning to the driver upon exceeding the designated speed restriction and subsequently generates a citation after violating the specific speed limit on a particular highway during three consecutive instances. It additionally integrates a display device within the vehicle to present the warning or citation in real-time

Table 1: A compression of current approaches in real-time traffic management

Used approaches	Discussion
A unified digital framework for traffic conflict prediction using a deep learning approach [17].	This technique has promise to improve traffic management and road safety, despite constraints such as data heterogeneity, real-time processing, and model interpretation difficulty.
Automatic vehicle's number plate recognition using artificial neural network and fuzzy approaches. [4, 5].	- These methodologies are effective for real-time traffic management. - Efficacy of number plate scanning is entirely contingent upon the illumination and clarity of the plate and the effectiveness of the used scanning method.
Deep learning approaches, used for the network traffic surveillance and analysis [18, 19].	- These methods are effective for monitoring and analyzing traffic. - Certain applications for monitoring and analyzing network traffic encounter low efficacy in employing deep learning due to insufficient labeled data, resource-constrained networks, retraining challenges, and others.
Intelligent transportation systems enabled by the IoT: Real-time traffic surveillance and regulation management [20–22]	- Despite their efficacy in real-time traffic management, current methods are not environmentally friendly and fail to account for different road conditions. - Considering the constraints of the testing equipment and environmental factors, it is necessary to assess alternative scenarios and enhancements to the present testing method to validate the system.
Edge machine learning methodology for intelligent transportation systems in smart traffic management [19, 23]	- The primary obstacle with this strategy is the lighting conditions. - This advanced model is significantly hindered by inadequate lighting during data acquisition. - Moreover, connected vehicles can deliver real-time traffic conditions, enabling traffic lights to modify their timing in accordance with fluctuating traffic patterns.

IoT, Internet of Things.

to the driver. The processed data and the challan are transmitted to the traffic department through deployed Bluetooth devices located near toll booths, traffic lights, or designated areas along specified highways. It regulates transmission faults and data loss with an in-built transmission error control module. The auto-generated challan instills a psychological apprehension in drivers, thereby deterring them from exceeding speed limits. Essentially, it assists drivers in identifying causes following a warning displayed on the in-car gadget. Consequently, it has the potential to diminish deadly accidents on any highway.

a. Problem statement

Surpassing the speed limit on highways is a major contributor to fatal accidents. Numerous research papers over the years have proposed approaches and tactics to mitigate this issue [24–26]. These techniques can substantially mitigate the issue. Nonetheless,

1. None of these provides a mechanism for pre-screening unpaid speeding tickets to inhibit their access to the highway.
2. No traffic management office has implemented a consistent procedure for issuing summonses to speed limit violators.
3. The initiatives to deter reckless driving diminish in efficacy when it requires several days or weeks for the relevant authority to summon the offender.

b. Hypothesis

A comprehensive conceptual framework can be established to tackle instances of speeding offenses by motor vehicles utilizing IoT enabled AI technology [27–30]. Additionally, it would utilize a sophisticated SA technique to improve detection precision and data integrity. This design would facilitate the development of a very precise real-time system for recognizing and notifying specific instances of vehicles exceeding the speed limit. Moreover, it would enable the prompt enforcement of instant fines, such as citations, at toll exit booths, stations, or traffic offices. This system would restrict autos with unresolved speeding infraction summonses from utilizing the route [31].

c. Research questions

The subsequent inquiries emerge from the necessity to develop a sophisticated traffic system [32–34] for

monitoring highway speeders and enforcing immediate sanctions for habitual overspeeding:

1. How can we develop and construct a precise, real-time IoT based AI enabled system for detecting and warning vehicle over-speeding situations on highways, with minimal initial and recurring costs?
2. What is the optimal method for developing and executing an effective SA system that uses intelligent wireless scanning to accurately deter automobiles with outstanding speeding summonses from entering the highway?
3. How can we integrate real-time databases to ensure that when a driver exceeds the speed limit, they are promptly summoned for accountability at the toll booth, station, or traffic regulation office upon exiting the highway?

d. Objectives

This study seeks to create a comprehensive conceptual model utilizing IoT technologies, big data analytics, and deep learning methodologies to identify instances of vehicles surpassing speed limits on highways [35–37]. The objective is to diminish the incidence of fatal traffic accidents and enhance awareness among vehicle owners and operators. Additional objectives can be emphasized on the need for the smart traffic overspeeding monitoring and law enforcement system:

1. IoT gadget can be deployed in vehicles to properly identify and report speed offenses.
2. A system enabling law enforcement to promptly dispatch text messages, including fines and summonses, upon detection of a traffic violation. The penalties are shown on the corresponding IoT device within the car. This system employs effective SA and a smart AI approach. This would promptly deter and caution the motorist.
3. Vehicles having three or more outstanding traffic citations can be swiftly and efficiently addressed to discourage drivers from repeatedly violating the established speed limit.

e. Novelty analyses and contributions

Currently, it is a prevalent practice to oversee highways. This results in several fatal traffic accidents. Consequently, infractions of highway speed limits must be identified immediately, and offenders should be penalized without delay [38]. Significant effort

has been invested in developing an IoT device that employs various machine learning and AI methodologies to address these issues instantaneously. Among the various methodologies, a prevalent strategy is the integration of you only look once (YOLO) with recurrent neural network (RNN), long short-term memory (LSTMs), and convolutional neural networks (CNNs) for time-series tracking [39, 40]. The inefficiency and imprecision of the conclusions produced by these methodologies in real-time are attributable to certain flaws. The numerous issues with YOLO-based real-time tracking include its limited intrinsic tracking skills, difficulties in managing small or overlapping objects, and insufficient object localization. In object detection, the YOLO model exhibits challenges with output precision despite its acclaim for temporal efficiency. The vanishing and exploding gradient issues arise concurrently in RNNs. During traversal of the network, the gradients employed in the learning phases of backpropagation may either significantly diminish (vanish) or substantially amplify (explode) [13]. Consequently, the RNN model encounters significant challenges in learning, resulting in unreliability and inconsistent outcomes. This is the reason LSTM performs effectively with sequential data. However, it also possesses other downsides, such as being computationally challenging and necessitating substantial time and financial resources for training. Moreover, overfitting is a prevalent problem, particularly with limited data. The computational inefficiency of CNNs, particularly in comparison to deep networks, constitutes a significant drawback of CNNs. Convolutional Neural Networks necessitate substantial processing resources due to the extensive number of convolutional operations and parameters involved [41–43]. The constraints established by the spatial hierarchy present an additional challenge for Convolutional Neural Networks. While they eliminate specific geographical data, pooling layers diminish feature map dimensions and confer translation invariance. CNNs frequently encounter difficulties with generalization and necessitate substantial quantities of labeled training data. Insufficient labeled datasets can lead to overfitting in CNNs, particularly in contexts such as uncommon disease diagnosis [14]. The issues with existing approaches can be resolved by integrating SA with artificial neural networks (ANNs), as outlined. A substantial body of research indicates that ANNs may readily adapt to novel activities and situations without necessitating reprogramming. Moreover, ANN is more straightforward to construct and implement for real-time data processing. Only one iteration is employed in the SA process. As a result, SA is

efficient and can yield optimal results with significant accuracy and adaptability [44–46]. Consequently, the optimal approach to address the existing issues with the proposed hardware configuration is to integrate ANNs with SA. This study significantly enhances prior attempts at real-time data collection by the utilization of a highly efficient motion sensor. It facilitates the effective transmission of processed challan information and speed data to the roadside device. The primary objective is to minimize data inaccuracies during the collection, processing, and transmission phases of the method.

II. Literature Review

The increasing frequency of reported incidents daily underscores the critical significance of speed monitoring devices. Every 30 s, an individual perishes in a vehicular collision. The predominant cause of most traffic accidents is insane speed relative to prevailing conditions. The demand for driver safety has risen with the emergence of new technology [19]. The World Health Organization (WHO) predicts that two-wheeler accidents will result in a higher number of fatalities than four-wheeler accidents. Injuries incurred in automobile collisions can differ significantly in severity and encompass a broad range. Monitoring a speeding car on a roadway and documenting the offense in real time are the two primary challenges to successful speed regulation [47–49]. The overspeed monitoring system and highway traffic safety have been the focus of numerous studies. Figure 2 illustrates a standard design for central monitoring.

Standard elements of an IoT system for monitoring highway traffic consist of devices for measuring vehicle speeds, devices for determining their positions, and networking devices for communication. Articles [16–19] employ a methodology for predicting vehicle velocities derived from floating car data (FCD). The capability for speed monitoring at much enhanced temporal and spatial frequencies is a key advantage of this technology [21]. This approach yields precise indicators of free flow speed. Regrettably, this technology does not permit real-time monitoring and measuring of speeds. The paper proposes an intelligent Radio Frequency Identification (RFID)-based approach for regulating vehicle access. This technology can efficiently resolve several challenges related to tracking and localizing vehicle movements on highways. However, monitoring objects or individuals without a tag is where this technology is deficient [21, 22]. Implementing self-exploration and self-monitoring in real-world vehicles is demonstrated in this work

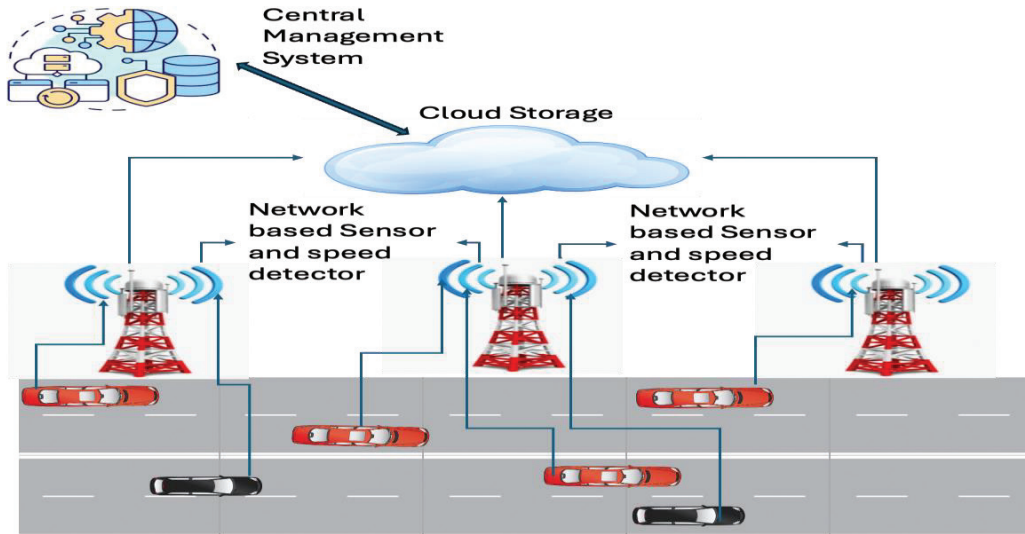


Figure 2: Central vehicle speed monitoring system [16].

using both on-board and off-board data sources. Regrettably, this approach is not suitable for real-time connections with remote servers. The article [4] presents a technique for vehicle detection and tracking using vision. It encompasses techniques for recognizing moving vehicles, tracking objects, categorizing vehicles, extracting foreground moving objects, and segmenting and subtracting background in the environment. Conversely, ambient noise during image acquisition may be erroneous or inappropriate for processing. Consequently, there exists a significant likelihood of obtaining erroneous results [51–53].

The studies [22–24] analyzed and ranked several traffic applications that can be addressed utilizing video-based systems, offering a fundamental overview of the subject. In the realm of Intelligent Transportation Systems (ITS) traffic applications, video-based technology provides the optimal solution universally. To get a high degree of user acceptance, it is advisable to implement and develop with a focus on objectives. Article [25, 54] proposes a wireless sensor network prototype utilizing the IoT for a traffic information monitoring system. This research verifies an innovative and user-friendly approach for monitoring traffic flow and classifying vehicles, utilizing wireless sensor networks and the IoT. The absence of test data across many situations and scenarios, along with insufficient internal communication, hinders the development of the expert monitoring system by the multi-embedded sensor system under multi-lane settings. A detailed WiTraffic, which employs commercially accessible WiFi devices, and real-world trials that gather data from local roads and highways over

a duration exceeding 1 week [25, 26]. This study is unable to effectively identify and categorize overlapping vehicles, as well as to execute lane identification and speed calculation for such vehicles. Bluetooth devices are economical network components ideally suited for communication in an IoT-based over-speed monitoring system. The power consumption of these Bluetooth devices is negligible, rendering them suitable for real-time applications. The authors in article [13, 38] monitor the traffic conditions utilizing a Low Energy linked Bluetooth device. This method can precisely assess a vehicle's speed in real-time. The input comprises limited V2X speed data and abundant Bluetooth occupancy data. The authors in article [13] developed a cooperative safety system for Vulnerable Road Users (CS4VRU) with a Bluetooth Low Energy link device. This technology offers a remote monitoring and alert system for vulnerable road. The system has been designed to function inside a varied communication network. In this network, vehicles function as mobile sensors, relaying their whereabouts to urban infrastructure over a specialized radio link known as IEEE 802.11p. This wireless standard is anticipated to establish the standard interface for automotive applications. However, these systems are incapable of delivering continuous monitoring for a particular vehicle during its journey [29, 55, 56].

This study [30] emphasized the growing prevalence of real-time traffic conflict prediction systems. These technologies are gaining prominence because of their proactive characteristics and their application in intelligent vehicles equipped with Advanced Driver

Assistance Systems (ADAS). A situation is deemed a traffic conflict when a safety metric, such as time-to-collision (TTC), surpasses a certain threshold. This study presents a novel approach for predicting traffic conflicts with deep learning [30, 31]. A centralized digital infrastructure was created to consolidate extensive data, including information obtained from in-vehicle sensors and highly aggregated traffic data. This methodology enabled us to demonstrate correlations between diverse surrogate safety measures (SSMs) obtained from data acquired by in-vehicle sensors and traffic variables such as density, flow, and speed. Examine TTC as a case in point. This study employed a region-based convolutional neural network (R-CNN)-assisted image processing technique to extract all vehicles in relation to the ego-vehicle from the video data and established several criteria to ascertain the output variable for each input [32–34]. This study fails to address the issue that networked vehicles can exchange active safety features, such as early conflict prediction, hence diminishing the probability of traffic accidents. These studies [35, 52] suggested a convolutional neural network utilizing accelerometer and gyroscope data to precisely estimate vehicle speed. This technique circumvents the drift problem inherent in dead reckoning systems and attains an accuracy of approximately 2 m/s. Accurate drift-free vehicle speed estimations are essential in automotive applications without internal wheel speed sensors or Global Positioning System (GPS). The proposed CNN technique is evaluated against a preexisting frequency analysis method utilizing extensive experimental data. The novel approach surpasses the frequency method, particularly in scenarios involving modest and rapid speed variations [36–38]. A unique method for speed prediction via deep learning with a convolutional neural network has been proposed, employing input from accelerometer sensors. The method outperformed previously proposed methods that employed frequency analysis, particularly in low-speed areas, and showed superior adaptability to speed fluctuations. Nonetheless, this endeavor lacks requisite precision and is unable to handle the vast dataset in real-time [50–54]. Table 2 is a comparison of several techniques employed to detect traffic violations or speed limit infractions on highways.

Table 2 compares the proposed methodology with several existing strategies employed to regulate various traffic-related offenses committed by vehicle operators, including speeding and violations of traffic regulations on highways. Several of these approaches utilized real-time data to generate challans or summons, thereby deterring drivers from

exceeding speed limits or violating traffic regulations, with the aim of mitigating the incidence of fatal road accidents. Data security is a critical feature of real-time data collecting and processing over wireless connections and remote servers [18, 27, 56]. Nevertheless, only a limited number of current methodologies have addressed data security and data loss during real-time traffic data processing, either fully or partially. Moreover, other approaches are simulation-based and utilize synthetic datasets to analyze and anticipate various traffic scenarios. Table 1 additionally contrasts the several platforms and methodologies for data processing, including deep learning, cloud-based solutions, and others. This project aims to design an efficient integrated device capable of intelligently processing oversteering data in real time without compromising data quality or incurring data loss. The suggested technique utilizes telematic data as input, processes it in real time via a wireless network, and promptly generates a summons to prevent the motorist from exceeding speed limits in real time [4, 12, 55]. Nonetheless, all these functionalities in the integration are lacking in other existing works.

This section analyzes various technologies that can be utilized individually or collectively to monitor and detect occurrences of high speeds on highways. This section also analyzes a select number of pertinent IoT-based research projects related to the issue of monitoring extreme speed on highways. These solutions provide the capacity to address various issues associated with highway traffic monitoring [13, 14]. Nonetheless, several problems persist in developing a system that minimizes implementation and maintenance costs while consistently detecting speed limit infractions on highways throughout the journey. It can simultaneously provide warnings and apply penalties on the motorist for exceeding a specified number of speed limit violations. Table 2 presents a comparison of various available approaches, emphasizing their strengths and drawbacks to clarify the current research gap.

a. Comparison of the proposed technique with other existing traffic management systems based on their efficiencies

The performances of the proposed integrated strategies are compared with existing approaches from contemporary literature to further evaluate the effectiveness of the suggested method, as presented in Table 3. Table 3 presents a comparison that

Table 2: Comparison of various traffic monitoring approaches for the highway

Publication details		Used approaches					Type of data set			Monitoring type			Offered	Prevent	
Year	Ref. No.	Deep and/ machine learning	Cloud/Fog/ network storage	Image processing/ pattern matching	Fuzzylogic	Block chain	Statistical method	Vehicular Ad-hoc network	Synthetic	Telematic	Real time	Vehicle over speed	Traffic rule violation	data security	data loss
2017	[13]		✓						✓			✓	✓		
	[15]						✓			✓	✓	✓			
2018	[33]	✓								✓			✓		
2019	[21]	✓								✓	✓	✓	✓		
	[25]							✓		✓	✓		✓	!	!
2020	[1]	✓								✓	✓		✓		
	[3]	✓							✓			✓		✓	✓
	[9]	✓								✓	✓	✓		!	!
	[12]	✓							✓				✓		
	[17]	✓							✓				✓		
2021	[39]	✓								✓	✓		✓		
	[45]	✓								✓	✓		✓	!	!
	[2]	✓				✓			✓		✓		✓	!	!
	[26]	✓								✓	✓		✓		
	[38]	✓								✓	✓		✓	!	!

(Continued)

(Continued)

Table 2: Continued

Publication details		Used approaches							Type of data set			Monitoring type			Offered	Prevent
Year	Ref. No.	Deep and/ machine learning	Cloud/Fog/ network storage	Image processing/ pattern matching	Fuzzylogic	Block chain	Statistical method	Vehicular Ad-hoc network	Synthetic	Telematic	Real time	Vehicle over speed	Traffic rule violation	data security	data loss	
2022	[11]	✓							✓	✓	✓		✓			
	[14]	✓							✓							
	[37]	✓							✓							
	[46]	✓							✓							
	[47]			✓					✓		✓		✓			
2023	[30]	✓								✓	✓		✓			
	[49]	✓								✓	✓		✓			
2024	[7]		✓							✓	✓		✓	✓	✓	
	[8]	✓								✓	✓	✓	✓			
	[19]	✓								✓	✓		✓	✓	✓	
	[28]	✓								✓	✓		✓			
	[32]			✓					✓		✓		✓			
	[41]			✓					✓		✓		✓			

(Continued)

Table 2: Continued

Publication details		Used approaches					Type of data set		Monitoring type			Offered	Prevent		
Year	Ref. No.	Deep and/ machine learning	Cloud/Fog/ network/ storage	Image processing/ pattern matching	Fuzzylogic	Block chain	Statistical method	Vehicular Ad-hoc network	Synthetic	Telematic	Real time	Vehicle over speed	Traffic rule violation	data security	data loss
2025	[5]							⊗	⊗					⊗	⊗
	[20]			⊗					⊗		⊗		⊗		
	[34]	⊗								⊗	⊗	⊗	⊗		
	[50]	⊗			⊗					⊗	⊗		⊗		
	Proposed	⊗	⊗							⊗	⊗	⊗		⊗	⊗
Here ⊗ denotes true, whereas ⊠ denotes the partially true.															

Herre ⊗ denotes true, whereas ⊗ denotes the partially true.

encompasses the intelligent and precise monitoring of vehicle speed on highways, alerts the driver when attempting to surpass the speed limit, imposes fines for repeated violations of the speed limit, ensures a security framework for data integrity, and offers a detailed cost estimation.

Table 3 illustrates that the suggested integrated technique effectively addresses all aforementioned characteristics. The alternative methodologies in the current literature are either incapable or only partially capable of addressing all these issues in a cohesive manner. A comprehensive study of the strengths and weaknesses of the current body of work is necessary to identify the existing gaps in the literature. This study aids in determining the suitable strategy to address the current gap in the literature. This section presents a detailed analysis of the diverse existing methods for regulating traffic-related offenses on highways, based on contemporary literature, highlighting their strengths and weaknesses in the following Table 4.

b. Impact of other existing intelligent systems on driver attitude

Contemporary car speed monitoring systems gather data using speed measurement sensors, evaluate the information, and issue alerts for exceeding speed limits [5, 13, 14]. Furthermore, most of these existing solutions lack a communication route with the traffic department. The current research provides limited insights into the integration mechanism of the traffic department; nonetheless, these approaches are insufficient to deter drivers from excessive expenditures and dangerous driving habits. As a result, these strategies do not evoke any apprehension among speeding motorists. Consequently, these advanced systems exhibit negligible influence on drivers who engage in hazardous behavior and persistently attempt to exceed speed limits in areas lacking traffic surveillance cameras. However, the increased warning generation due to speeding offenses on a certain highway is advantageous for cautious drivers. It aids them in sustaining an appropriate speed within the established limit, therefore mitigating the risk of adverse situations and serious accidents. Therefore, to alleviate irresponsible and lavish driving, these tactics must be amended through cooperation with traffic authorities.

c. Research gap analysis

The literature study indicates that current approaches are inadequate for a real-time monitoring system

Table 3: A summary of various challenges of cloud resource provisioning and their mitigation

Publication Year/ reference	Monitoring vehicle speed smartly and accurately	Warn the driver for violating the speed limit	Imposing a penalty for continuous speed limit violation	Security and integrity of traffic data	Cost efficiency of the used technique
2017 [13, 15]	○	●	○	●	●
2018 [33]	●	○	○	●	○
2019 [21, 25]	●	●	○	●	●
2020 [1, 3, 9, 12, 17, 39, 45]	●	●	●	●	○
2021 [2, 26, 38]	●	○	○	●	●
2022 [11, 14, 37, 46, 47]	●	○	○	●	●
2023–24 [7, 8, 9, 28, 30, 32, 41, 49]	●	○	○	●	●
2025 [5, 20, 34, 50]	●	○	○	●	●
Our Work (2025)	●	●	●	●	●

●→Fully Covered, ●→Partially Covered, ○→Not Covered

capable of detecting instances of overspeed violations. Nevertheless, there have been occurrences in which data gathered from highway traffic are unanalyzable due to ambient noise or substandard data quality [25, 26]. Consequently, a real-time IoT-driven AI model is essential for monitoring and regulating excessive speed in highway traffic. Further research and development are necessary to guarantee both accuracy and data integrity concurrently. Importantly, none of the proposed methods or strategies provides a structure or framework to restrict cars that have consistently exceeded speed limits from entering or accessing highways or expressways [28]. The literature review reveals a lack of studies on the real-time synchronization of overspeed violation data from multiple vehicles to issue summonses to drivers who violate speed limits at exit toll booths or stations [28, 29]. Furthermore, the study neglects to consider the critical issues of implementation and maintenance costs.

III. Proposed Technique

The primary aim of this research is to gather information on relevant prior art from available literature, conduct a survey to obtain user insights, requirements, and feedback, and use this data to develop and improve the proposed device. This study analyzes the advantages and disadvantages of the existing pertinent devices. After gathering the necessary information, the next phase was the development of an economical IoT device intended to measure and record the speed of a moving vehicle [7, 13]. This IoT device operates in conjunction with two additional components: the first component involves the installation of Bluetooth-enabled devices along roadways, including traffic lights, toll plazas, and other significant locations, to gather vehicle data and communicate maximum speed limits or other traffic-related information pertinent to specific highways for individual vehicles and traffic conditions. The information is then relayed from the roadside Bluetooth

Table 4: Comparison of various existing approaches for controlling overspeed vehicles

Related topics	Strength	Shortcomings
Forecasting the traffic issues in real-time [3, 9, 12, 17]	- A R-CNN model can forecast traffic conflicts by analyzing images captured by a single front-facing camera and identifying lane markings. - A collection of deep neural network models for predicting traffic conflicts is created from this data by integrating it with traffic characteristics and calculated SSMs.	- Unfortunately, the existing methodology does not provide a means to prevent data loss during transmission. - This technology yields low precision and is not especially effective for the real-time transmission of traffic data.
Real-time traffic tracking and management with IoT for adaptive transit systems [5, 25, 31].	- The objective of a strategic traffic management plan that integrates autonomous driving with the IoT is to alleviate traffic congestion. - Traffic flow dynamics results with an appropriate control strategy for vehicle-to-everything-enabled cars from a macro viewpoint.	- Challenges regarding the management of Intelligent Transportation Systems and the limited data transmission capabilities of IoT devices continue to exist. - The incorporation of data transport reliability must be integrated into this model additionally.
The IoT-based wireless sensor network framework for monitoring the traffic surveillance information [13, 16, 17].	- This algorithm analyzes test data to extract pertinent information, as significant signal noise during accelerometer monitoring complicates signal recognition. - It further employs a peak detector and a moving average smoothing filter to precisely identify each passing axle and calculate the time interval between two axles.	- Due to limitations of the testing apparatus and ambient variables, improvements to the current methodology are needed. - The absence of a mechanism to guarantee data integrity in this technique adversely impacts the accuracy and quality.
Optimizing the traffic management in today's transportation networks with innovative machine learning [5, 12, 14].	- The traffic signals are modified based on traffic calculations to reduce overall delay at the intersection. - The traffic lights may interact with adjacent signals to convey the total duration of delays. This delay facilitates the priority of traffic in essential areas such as schools, offices, and hospitals.	- Traffic trends can be forecasted via machine learning algorithms that examine both historical and current data. - Connected vehicles provide real-time data on the traffic situation, enabling traffic signals to evolve patterns.
A system of interlinked cars utilized for the intelligent transportation system for the urban areas [15, 16, 27].	- It presents an intelligent vehicular network for smart cities that selects routes via ad-hoc, real-time data, obtained from nearby vehicles. - It utilizes Android-powered smartphones equipped with Wi-Fi direct functionality as in-vehicle devices.	- This study does not aim to tackle communication issues, including delay, channel noise, and transmission failures. - A possible outcome is a reduction in output quality, while another is data corruption.
Intelligence-based traffic management systems for signalized crossroads including non-autonomous vehicles [6, 12, 16].	- This research presents a neural network capable of predicting delays for human-operated cars at signalized intersections. - An ANN will address complex tasks, including the processing of extensive datasets with variable inputs.	- It disregards the numerous issues that arise when transferring substantial volumes of data across locations. - The concerns may adversely affect both data quality and the accuracy of the proposed model.

(Continued)

Table 4: Continued

Related topics	Strength	Shortcomings
Utilization of IoT and multi-agent reinforcement learning, management of traffic lights might become automated [14, 32, 33].	- This work presents a reinforcement learning methodology for the deployment and control of traffic signals employing numerous agents. - The last phase involves developing an innovative reward function applicable in multiagent learning to effectively determine the optimal strategy for managing traffic light behaviors.	- It utilizes roadside gadgets and vehicle-to-everything connectivity to improve data for traffic scenario model learning. - Before implementing traffic signal control, the transportation system must be validated using a probabilistic model. - The accuracy and dependability of the method can be improved.

ANN, artificial neural network; IoT, Internet of Things; R-CNN, region-based convolutional neural network; SSM, surrogate safety measures.

device to a designated car. Similarly, the information concerning speeding and tickets is relayed from a designated car to the roadside Bluetooth apparatus. The second component is the inbuilt speed sensor in the vehicle, which continuously monitors the car's speed and relays this data to the primary processing unit or specified IoT device. The expected IoT device processes speed data obtained from roadside Bluetooth devices using Bluetooth connectivity [50].

The roadside Bluetooth device and the self-installed speed sensor collect data, which the IoT device processes to deliver warnings and fines to the driver as necessary. This suggested IoT gadget interfaces with the roadside Bluetooth system to collect highway traffic control data and relay vehicle information, including citations and other pertinent details. This processing phase primarily combines an ANN model with a SA method to accurately compute the overspeed data and enhance precision [34, 37]. In the last phase, an optimal error control approach has been developed and implemented into the proposed technique. This technology ensures accurate retention of speed violation data and effectively mitigates any data loss during the transfer of information from the local system (any vehicle) to the traffic monitoring department. The suggested error control solution can partially or fully restore lost information upon reception by the traffic management department from any local system, such as a vehicle. The next sections offer a thorough examination of each component of the suggested integrated techniques. The flowchart of the proposed model is shown in the following Figure 3.

a. Design of the proposed technique based on earlier information

The literature review indicates a notable inadequacy in the existing system for the real-time detection

and penalization of speeding by the appropriate authorities [23–26]. In the absence of a structure to impose sanctions for speeding, drivers are continually motivated to engage in this conduct. A survey was conducted concurrently to collect and evaluate the demand from various users, together with their comments and feedback concerning the necessity of the proposed device. Based on the literature analysis and public feedback, the suggested IoT sensors have been created with a compact rechargeable lithium battery and Bluetooth connectivity. The hypothetical placements of the proposed sensors around highways and toll gates are illustrated in Figures 4A–4D.

b. Design of the proposed ANN and SA

ANNs have acquired significance in numerous fields due to their functional similarities with biological systems. ANNs excel at generalizing ambiguous inputs, demonstrating fault tolerance, facilitating extensive parallelism, and solving non-linear problems. ANNs aim to offer mathematical frameworks for data processing that leverage existing knowledge bases. ANNs models can produce very precise solutions for situations that defy traditional methods and are mostly understood through empirical data. These models are created by experimental methodologies [13]. The internal design of the ANN is flexible in response to prevailing conditions due to a learning mechanism, and its ability for swift data processing and fault tolerance is ascribed to its significant parallelism. The obtained data are generalized to improve their relevance to new or varied datasets. The choice to employ ANN for the model development of this project was influenced by these factors [12, 13]. The applications of ANN in speed estimation for moving vehicles are widely employed because they successfully calculate vehicle speed while reducing errors and noise from the input

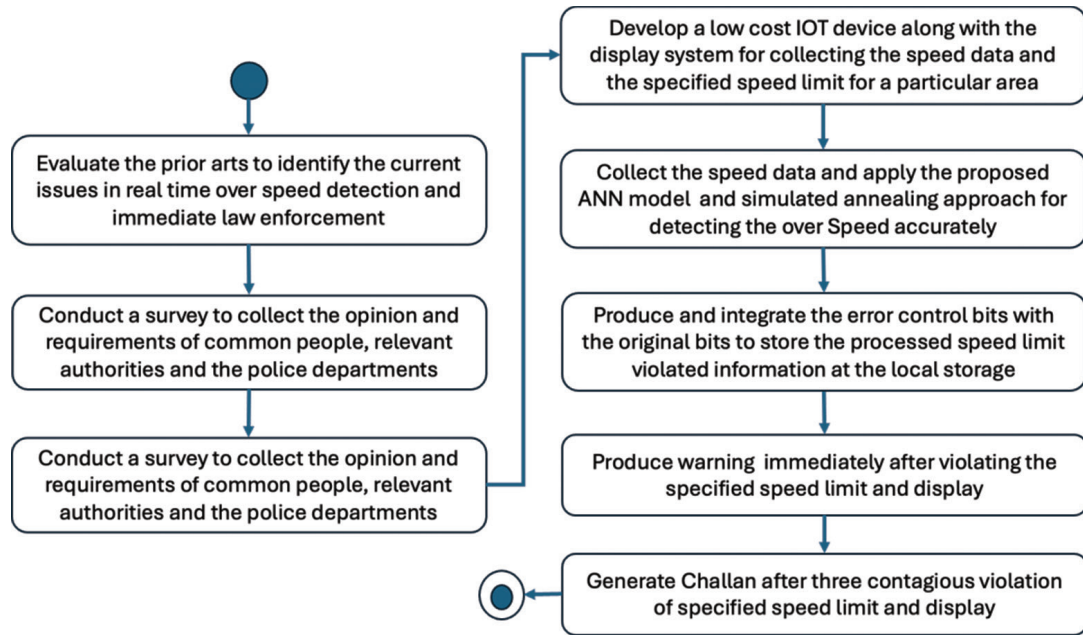


Figure 3: The proposed model. ANN, artificial neural networks; IoT, Internet of Things.



Figure 4: (A) Bluetooth device, installed at the traffic light, (B) Bluetooth device, installed at the toll booth entrance, (C) Bluetooth device, installed at the banner stand, and (D) Bluetooth device, installed at the road divider.

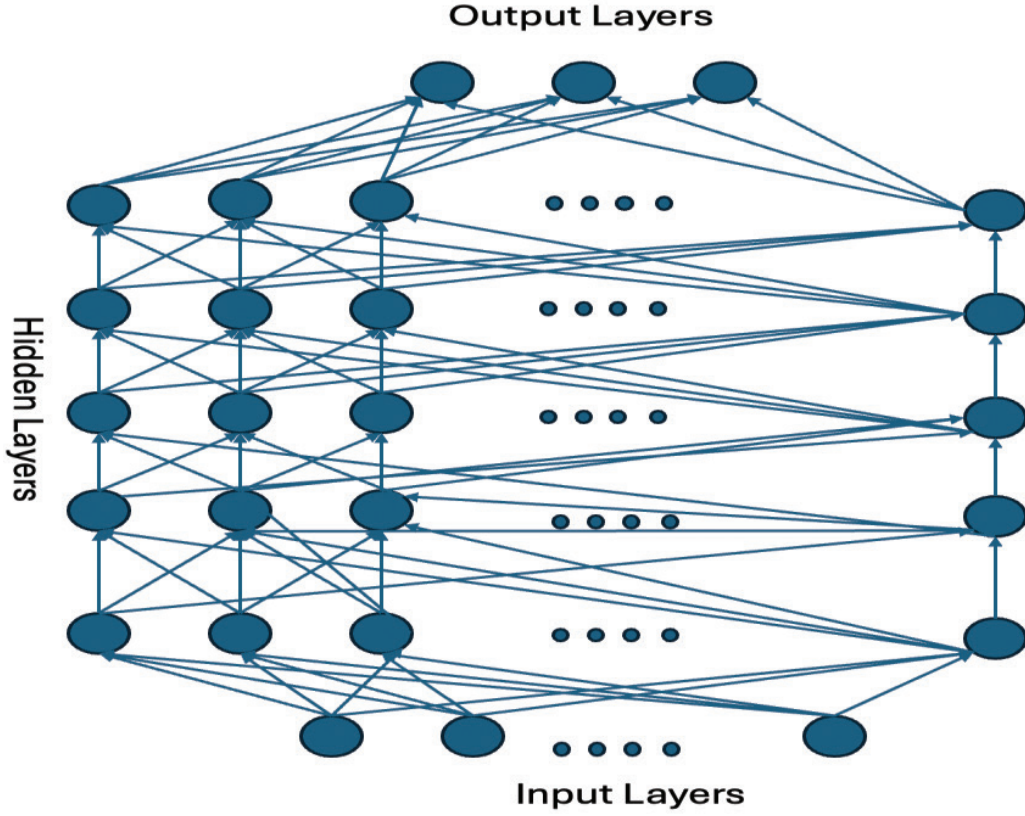


Figure 5: The anticipated ANN model. ANN, neural network.

data. The ANN operates best with a wide range of input data formats, including different types of sensor data. This study will utilize ANNs to develop a highway speed prediction model, which will subsequently be assessed using different personal vehicles.

At this phase of implementation, the proposed integrated methodology is amalgamated with an innovative design, an ANN, and a SA model [25–27]. Initially, the proposed architecture of an ANN is utilized to classify sensor data obtained from the vehicle's internal IoT components. The proposed architecture of the ANN comprises 150, 300, 300, and 30 hidden layers operating collaboratively. Seventy feature vectors were selected for this implementation, considering the dimensions of the input layer. The proposed ANN thus has three classes in its output dimension. Furthermore, the loss function distinctly intersects the entropy value in this implementation. A 10% dropout rate in each layer has been investigated to mitigate the overfitting problem. The adaptive movement estimation (ADAM) optimizer function and the rectified linear unit (ReLU) activation function are employed for each neuron. This model was created using Python through

the KERAS-Application Programming Interface (API) with TensorFlow operating in the background. Figure 5 illustrates that the proposed ANN model adheres to a conventional structure.

The first and second iterations of the projected ADAM model are represented by the exponential gradient (E_x) and the squared gradient (S_x). The hyperparameters α_1 and $\alpha_2 \in (0,1)$ control the rates of exponential decay. Here,

$$E_x = \alpha_1 \times E_{x-1} + (1 - \alpha_1) \times g(x) \quad (1)$$

$$S_x = \alpha_2 \times S_{x-1} + (1 - \alpha_2) \times g^2(x) \quad (2)$$

The inputs in this case are $(1, \dots, x_1, \dots, x_n)$, and the function $g(x)$, which adds up all the inputs biased to $\hat{E}_x$ and $\hat{S}_x$, calculates the output neurons. These are employed to further estimate the first and second iterations.

$$\hat{E}_x = \frac{E_x}{1 - \alpha_1^x} \quad (3)$$

$$\widehat{S}_x = \frac{S_x}{1 - \alpha_2^x} \quad (4)$$

Eq. (5) represents the final update parameter as $\gamma(x+1)$, which represents the final weight parameters, and $\gamma(x)$, which represents the previous weight parameters. If μ represents the learning rate, then ε (epsilon) is extremely small, preventing any division in this process by '0'. If ∂ , is any constant value, then we have,

$$\gamma_{x+1} = \gamma_x = \frac{\mu \times \widehat{E}_x}{\sqrt{\widehat{S}_x + \partial}} \quad (5)$$

All the hyperparameters in this projected model are set at $\mu = 0.001$, $\alpha_1 = 0.989$, $\varepsilon = e^{-09}$ and decay = 0.

b.i Avoidance of overfitting and underfitting issues

We addressed the overfitting issue in this research work in two distinct ways. L1 Least Absolute Shrinkage and Selection Operator (LASSO) and L2 regularization (Ridge) are acknowledged for their effectiveness in reducing overfitting [10, 37]. To alleviate the overfitting problem, we have utilized the dropout technique, which is distinct from L1 and L2 regularization methods. This comprehensive technique advocates for a 10% dropout in each layer to alleviate overfitting. Overfitting can be alleviated by stabilizing learning and improving convergence by the normalization of inputs at every layer [39]. To mitigate overfitting, we utilized a method that entails normalizing the input data. Underfitting presents a considerable obstacle for methodologies reliant on neural networks [39, 47]. To prevent this event, we conducted studies using a significant input data set. A range of hyperparameters, such as the activation function, model architecture, and the number of nodes per layer (e.g., the [ReLU]), can be modified to alleviate underfitting. The suggested approach proficiently tackles the issues of underfitting and overfitting.

b.ii Role of the SA for overspeed detection

SA, as an optimization technique, employs numerical models that accurately represent the data. A randomly generated model is systematically refined until it conforms to the data [22, 23]. Our methodology employs SA to identify and document overspending data derived from vehicle speed information obtained from the onboard speed sensor, alongside

the threshold speed limit gathered from roadside Bluetooth sensors. The suggested SA approach concurrently assesses if any vehicle exceeds the specified speed restriction on a particular highway. It also considers the traffic conditions and congestion levels of any highway, using calculations derived from this data. The congestion data are solely collected from the roadside Bluetooth device. A speeding notice is generated and dispatched by a thorough assessment of all pertinent factors. Furthermore, after the third consecutive speed limit violation on a certain highway, a citation is generated and sent to the adjacent roadside devices through Bluetooth communication. This information is then communicated to the traffic department, requiring the driver to pay the penalty at the next toll plaza or traffic control office. This section outlines the capabilities of the proposed SA method to enhance the precision in identifying instances of overspeed. It is essentially a method that uses probability to determine the ideal value. It is a metaheuristic approach utilized to evaluate the incidence of speed limit violations. The SA method for ascertaining overspeed from the input vehicle speed data is detailed in Algorithm-1.

After calculating the penalty values for different scenarios using Algorithm-1, the final summons, or challan, is generated based on these penalty values. The resultant summon is thereafter displayed on the linked screen, accompanied by all pertinent information as illustrated in Figure 6.

SA may optimize many hyperparameters in any AI model and improve its architecture. To improve the performance of the proposed ANN model, the effectiveness of several hyperparameters, including ADAM and ReLU, is optimized using the recommended SA method. We employed SA to identify and document overspending information derived from vehicle speed data obtained from the onboard speed sensor and the threshold speed restriction provided by roadside Bluetooth sensors. In the domain of neural networks, any SA technique can explore the hyperparameter space, facilitating adjustments that improve performance. The suggested SA method concurrently assesses if every vehicle on a certain highway surpasses the established speed limit. Thus, the proposed SA method aids in determining the ideal hyperparameters that may be modified to improve the accuracy of overspeed detection. It also considers the traffic conditions and congestion levels of every highway, employing algorithms derived from this data. Furthermore, it contributes to reducing the mean squared error of the proposed integrated ANN model and enables accurate model training.

Algorithm-1: Simulated Annealing for Vehicle Overspeed Detection

Input Data: → Number of speed limit violation, epochs;
Result: → Generating Summon Accurately after violating the speed limit contagiously 3 times;

1. Let $S \leftarrow S_0$ be the initial solution where the driver violates the speed limit for the first time;
2. $T \leftarrow \text{epochs}$;
3. While $T > 0$ do
 - a. Calculate speed limit value from the road sensor and set it as the maximum speed limit (m);
 - b. While number of violation (n) < 3 do
 - (i) Select any other recorded speed (x_j) at the random basis in the next iteration;
 - (ii) If $x_j > m$
 - If the root is congested enough
 - Calculate the penalty value (P_j);
 - End if
 - If the root is not congested enough
 - Calculate the penalty value (P_k);
 - End if
 - Else if $e^{\frac{P_j - P_k}{k.T}} > \text{Random}(0,1)$, where k is any random integer
 - Calculate the penalty value (P_f);
 - Penalty $\leftarrow P_f$.
 - Break;
 - End if
 - End if
 - $T \leftarrow T-1$;
 - End While
 - End While

c. Design and incorporation of the proposed error control technique

As indicated in the introduction, data errors play a crucial role in any transportation system. The data are sometimes compromised or lost during transmission via unsecured networks due to variables such as channel congestion, restricted capacity, and environmental interference [16, 18]. The suggested integrated technique involves transmitting overspeed information from any vehicle to the roadside Bluetooth device and relaying highway-related information from the roadside Bluetooth device to the vehicle. Consequently, data loss may occur, allowing the true speed limit violation to evade punishment. Consequently, in the last stage of this implementation, an error control method is developed and incorporated with the suggested approach to guarantee the accuracy of data during its transfer from the local device to the roadside storage or from the roadside storage to the traffic department. The design of the proposed methodology and its integration with the suggested method are depicted in Algorithm-2. In this instance, we have utilized the final challan information as input and transformed it into a binary string to produce the error control bits during the inclusion phase.

Algorithm-2 produces the ultimate error control string by doing multiple rounds of Exclusive OR (XOR) and concatenation operations on various sets of input strings. Once the final error control bits generation and concatenation procedures are completed, the information is saved in a local IoT device. It can then be sent to the roadside storage device using a Bluetooth network.

c.i Effectiveness of the projected error control approach

Literature indicates that the efficacy of various data recovery methods in data distribution is not particularly satisfying. Some of them are not particularly effective in detecting and correcting numerous transmission faults when the volume of such errors is substantial [18, 29]. The low-density parity checking (LDPC) and standard Parity Checking approaches rely entirely on parity bits to identify fault locations. If both numerous original bits and parity bits are corrupted during data transmission, these methods fail to identify and rectify the original fault location. Moreover, forward error correction (FEC) techniques, particularly those utilizing Reed-Solomon and Cyclic Redundancy Codes,



Figure 6: The integrated module, installed inside the car.

Algorithm-2: Error Control Bits Generation and Incorporation

Input: →Contiguous two 8-bit string and denoted them Str_1 and Str_2 ;

Output: →The complete challan string with error control bits as $FinErr$

(1) Initialize $\langle FinErr \rangle = \emptyset$ and a string variable $temp = \emptyset$;

(2) for ($int m = 0; m < \overline{Str_1}; m++$) // concatenate both string

$$FinErr[m] = Str_1[m]$$

$$FinErr[Str_1 + m] = Str_2;$$

End for

(3) for ($int i = 0; i < \overline{Str_1}; i++$) //Performing XOR operation between both strings

$$temp[i] = Str_1[i] \oplus Str_2[i];$$

End for

(4) for ($int j = 0; j < \overline{temp}; j++$) // Concatenate $temp$ and the $FinErr$

$$FinErr[\overline{Str_1} + \overline{Str_2} + j] = temp[j];$$

End for

(5) Repeat Step-1 to Step-4 all rest of the strings;

(6) Concatenate all the strings in final single string $FinErr$;

primarily convey redundant information to mitigate data errors and losses. These methods effectively rectify the substantial amount of data mistakes encountered throughout the data retrieval procedure at the receiving end. Consequently, these methods impose significant data overhead on the communication. Future improvements can be instituted to boost accuracy and reduce data loss, hence contributing to a reduction in hazardous driving. This proposed work can be further enhanced. The experimental results indicate opportunities to enhance accuracy, decrease data loss, and further minimize transmission errors. Additionally, the utilization of a Graphics Processing Unit (GPU) might enhance processing speed concurrently. The proposed integrated technique can be enhanced to overcome these difficulties. The data overhead over the communication channel, potentially leading to additional data loss [42]. The error bit detection and correction method, such as Hamming Distance, can

manage a maximum of 8-bit faults. Nonetheless, these approaches are ineffective when the length of the error string exceeds 8-bits. Consequently, these strategies are not particularly useful in managing a substantial number of mistake bits. Conversely, the suggested XOR-based error control method can identify and rectify any number of erroneous bits with minimum data overhead. Moreover, it does not necessitate any retransmission of information, hence minimizing channel overhead. In contrast to other existing data recovery methods, it can restore information even if one or more bits are lost during transfer from its backup system. Consequently, the proposed method outperforms other existing systems in managing a substantial number of error bits while incurring reduced channel and data overheads.

d. Role and importance of the display device

The resulting summons or wordings are displayed on the display device when all the data has been processed using the recommended integrated approach. The major role of the display device is to notify drivers of the vehicle's speed and alert them when they surpass the authorized speed limit, allowing for speed regulation and the prevention of accidents or unfavorable situations. This display apparatus must be integrated into the vehicle to communicate information on speed limit violations, traffic infringement penalties, or alerts from the designated internal IoT device [13, 38]. The proposed method stipulates that the internal IoT device will transmit a warning to the display device upon any violation of speed restrictions, prompting it to exhibit a message. After three consecutive violations of the designated speed restriction, the display gadget generates a citation for the motorist. Figure 6 depicts the arrangement of the proposed display device.

Figures 4 and 6 illustrate that the internal IoT device interfaces with external sensors situated on the roads via Bluetooth devices in auto-pair mode. Bluetooth devices must be installed at every 1 km interval along the roads to capture and retain vehicular information. In the occurrence of a device malfunction, the alternative device can access the backup data with few or no complications. Conversely, communication delay presents a substantial challenge in these situations [11–13]. The employed Bluetooth device functions on a many-to-one communication mechanism, featuring a total of eight accessible channels. This enables concurrent communication with a maximum of eight

vehicles, rendering it appropriate for highway applications. The minimum data transfer rate of a Bluetooth device in a many-to-one or one-to-many setup is 800 kbps. This signifies that each channel of a many-to-one Bluetooth device can send data at a rate of 100 kbps. The proposed framework stipulates that the maximum size of each handshaking message shall be 5 KB. Consequently, transmitting a 5 KB message will need a maximum of 0.05 s. The operational range of the Bluetooth device employed in our proposed architecture is 100 m. A vehicle capable of reaching a maximum velocity of 240 km/hr may traverse 3.3 m in under 0.05 s. Even in particular circumstances, when the network speed diminishes to 4 kbps, it remains capable of communicating with a high-velocity car traveling at 240 km/hr. Consequently, in both instances, the proposed architecture may adeptly address the challenges with efficiency.

e. Retrieval of original information

The acquisition of unique information is crucial for any transportation system [46]. The suggested integrated system utilizes data from embedded speed sensors within the vehicle, which are subsequently analyzed through the combination of SA and ANNs to reliably identify specific speed limit infractions on designated highways. The output is further processed using the suggested error control technique, to which additional error control bits are incorporated for managing various sorts of data errors that occur during transmission. These error control bits also facilitate the creation of a backup system in the event of unintentional data loss. Consequently, the processed information (i.e., following the application of the proposed [SA] and [ANN]) must be extracted at the receiving end in its original format from the error-controlled string (*FinErr*). At this level, the utilized input string is the final error control string (*FinErr*). Each trio of 8-bit strings is consecutively delineated [8]. Perform the XOR operation on the initial two strings as per Algorithm-2, and evaluate the outcome against the third string. If the match is incomplete, eliminate both strings from the third string and thereafter compare the resulting strings with the original string to identify the appropriate combination of strings. Execute analogous methods for the residual segment of the string and consolidate all the extracted strings to reconstruct the original string. After extracting the original string, it must be reverted to its initial textual format for display on the device. Consequently, the original data, in the form of a challan or other documentation, is retrieved at the receiving end.

f. Key challenges in implementing the proposed model

Several challenges have arisen throughout the execution of the proposed model. The principal obstacles encountered in this research were related to the establishment of the hardware configuration. The proposed model is designed for detecting high speeds on highways. Consequently, we needed to obtain authorization from both the traffic department and the local police station to operate various car types at a designated speed during data collection. Additionally, the selection of sensors presented a significant challenge due to their varying ranges. Consequently, it was exceedingly challenging to determine which type of sensors would yield the most efficient results. The selection and deployment of Bluetooth devices presented a significant challenge in this research endeavor. The data reception and transmission capabilities of any Bluetooth device are significantly constrained. Accurate distance measuring is essential to yield precise results and reduce transmission errors. Consequently, the selection of an appropriate location and devices proved to be a formidable undertaking. The integration of communication between the speed detection sensors, display device, and the roadside Bluetooth apparatus was significantly transformative in this research as well. However, we have effectively surmounted these hurdles through our persistent efforts and the help of local authorities to create and evaluate the effectiveness of our suggested model across various dimensions.

g. Real-world deployment of the projected model

Assessing the real-time functioning of any IoT device is essential [50]. The prototype of the suggested model was installed in five different models of cars, such as Suzuki Swift, Tata Nexon, Hyundai Grand i10, Skoda Kylac, and Honda City 2023 models, and tested accordingly. All vehicles are evaluated on a traffic-free road in Panditwari, Dehradun (Uttarakhand) within a speed range of 70–100 km/hr due to specific traffic restrictions. The test runs for all these vehicles were undertaken for 2 hr daily over a period of 2 weeks. The Wireless Ultrasonic Sensor (Uno Minda 7687Q-028-11-M01 SPEED SENSOR For-BAJAJ-DISCOVER 125ST) was used to record the vehicle speed. A MacBook functions as the workstation for collecting vehicle speed data. Communication between the roadside Bluetooth device and the workstation has been established

by Bluetooth signals. The used Bluetooth device is a class-1 type of device which can cover, that is receive data or transmit data within a range of 100 m. The MICROUSB Compatible with Regold CR2016 Lithium Coin Button Battery 3v has been used in IOT sensor during the data collection operation. The installation of the Bluetooth device at the roadside and the integrated module was performed similarly to the representations in Figures 4A–4D and Figure 5. The results will be further analyzed in the results section to clarify the effectiveness of the proposed technique across multiple aspects.

IV. Experimental Setup

The experiment setup has three parts: the first part comprises data set preparation, whereas the second part describes the hardware requirement and the final part includes the data preparation and software requirements. Each of the components are further discussed in the following subsection.

a. Data set preparation

During the data collection, Wireless Ultrasonic Sensor (Uno Minda 7687Q-028-11-M01 SPEED SENSOR For-BAJAJ-DISCOVER 125TH) were used to collect the speed data in JSON file format. After the completion of the test run of five different cars that is Suzuki Swift, Tata Nexon, Hyundai, Grand i10, Skoda Kylac, and Honda City 2023 models, along with the installed IOT device, the captured data stored in the local storage and preprocessed with the help of cleaning process to handle the missing values and normalized the data to create suitable input data that produces the accurate and desired output. Various libraries are added to make the processing unit very efficient and to support various input file formats. We considered various lighting conditions, including morning, evening, and afternoon, as well as sunny, overcast, and rainy weather, when preparing the dataset to obtain the input data under various circumstances. The test drive was conducted in low-density traffic conditions due to restrictions imposed by the local traffic authority.

b. Hardware setup

Wireless Ultrasonic Sensor (Uno Minda 7687Q-028-11-M01 SPEED SENSOR For-BAJAJ-DISCOVER 125TH) has been installed inside the car to collect the overspeed data. The IoT device that has been proposed is constructed using an LM339 from ON

Semiconductor, which is a Low Power Quad CPU, for the purpose of processing data, an Liquid Crystal Display (LCD) Unit (2.4 inches) for displaying the information, and an 8 GB storage unit for storing the processed data. Aside from that, the power has been supplied by a lithium battery with a voltage of 5 V and a life span of 2–3 years. However, in addition to that, a Many-to-One Bluetooth device and vehicle speed sensors (VSS) are utilized in order to record the speed of the vehicle at regular intervals. Every single component of the hardware is put together and put through its paces throughout the inspection process.

c. Software setup

In the software setup part, we have used Python within the KERAS API for implementing the projected ANN and SA part. Apart from that, simple Python programming has been used to develop and incorporate the proposed error control bits generation and the incorporation process. Simple integrated networking software and Point-to-Point protocol (PPP) is used to handle the Bluetooth devices. Finally, all the programs are implemented in windows 2010 platform.

d. Scalability and cost implications

The cost calculation of the proposed architecture has been conducted based on Indian market prices to assess its affordability. It comprises two modules: the cost of the integrated module, which will be situated within the car, and the cost of the many-to-one Bluetooth device, which will be positioned roadside. The expenses associated with the implementation, installation, and maintenance of both modules are presented in Table 5.

Consequently, the cost assessments in Table 5 indicate that both components for constructing the suggested model are economically viable for road users and transport authorities to implement the predicted design in practice. The display device is compact, and the Bluetooth device is highly portable and adaptable according to the available space within the vehicle or roadside, allowing for easy real-time deployment.

V. Implementation of Proposed Technique

The first step in putting the suggested method into practice was gathering previous data about different

Table 5: Cost estimation of the hypothetical architecture

Many-to-one Bluetooth device (for roadside)	Integrated module (for car)
1. Device cost: Rs. 2,000–3,000 (Max)	1. Uno Minda 7687Q-028-11-M01 SPEED SENSOR For-BAJAJ-DISCOVER 125ST-Rs. 300 (Max)
2. Lithium battery (Life 2–3 years): Rs. 600 (Max)	2. LCD display unit (2.4 in.): Rs. 1,000 (Max)
3. Installation and assemble cost: Rs. 2,000	3. Storage unit (8 GB): Rs. 1,000 (Max)
4. Maintenance cost: Rs. 0	4. One-to-many Bluetooth device: Rs. 800 (Max)
	5. LM339 - Low power Quad processor: Rs. 100 (Max)
	6. Lithium battery (Life 2–3 years): Rs. 600 (Max)
	7. Installation and assemble cost: Rs. 2,000
	8. Maintenance cost: Rs. 0
Total cost: Rs. 5,600 (Max)	Total cost: Rs. 6,700 (Max)

IoT devices that were available in the current literature. In accordance with subsection “Design of the proposed technique based on earlier information”, the strengths and weaknesses are thoroughly examined to investigate the present research gaps and the most recent requirements to close these gaps and optimize traffic safety. Following an examination of the existing research gap, the subsequent phase of implementation has been divided into six sections. First, in accordance with subsection “Design of proposed artificial neural network (ANN) and SA”, the architecture of the suggested ANN and SA has been set up. With reference to subsection “Avoidance of overfitting and underfitting issues”, the suggested method has been put into practice in a way that prevents overfitting and underfitting. Additionally, in accordance with subsection “Role of the SA for overspeed detection”, the role of the anticipated SA is examined and updated. Subsection “Design and incorporation of proposed error control technique” was then used to build and integrate the proposed error control strategy with the integrated system. The performance assessments in subsection “Effectiveness of the projected error control approach” are used to further improve the predicted error control technique. In accordance with the specifications listed in subsection “Role and importance of the display device”, the display device is further customized. Subsection “Retrieval of original information” aids in the retrieval of data from the recently constructed integrated system to assess its effectiveness. Subsequently, with the aid of paragraph “Key challenges in implementing the proposed model”, the main difficulties and current problems with the system have been examined and updated appropriately.

Subsequently, the newly integrated system was deployed in real-time utilizing paragraph “Real word deployment of the projected model” to confirm its actual performance. We designed our experimental setup during implementation with the assistance of section “Experimental setup”. Subsections “Data set preparation”, “Hardware setup”, and “Software setup” have been followed in the setup of the hardware, software, and data. Subsection “Scalability and cost implications” also aids in the system’s cost optimization and scalability.

VI. Result Analyses

The proposed integrated method is a novel and thorough conceptual framework for the real-time identification of speeding infractions utilizing IoT technology and AI capabilities [21, 22]. The objective is to reduce the incidence of fatal highway accidents and improve overall highway safety. Furthermore, it integrates a distinctive SA process alongside an error control system to improve accuracy and reduce data loss. An innovative method for issuing summonses for speeding violations at highway toll exit booths, serving as a quick consequence for those who violate speed regulations. This may significantly affect the driver’s psychology, heightening their awareness of the repercussions of exceeding the speed limit on the roadway. The system’s performance is assessed in the section focused on analyzing the results, specifically regarding its capacity to generate more precise information, enhanced processing speed, and a diminished incidence of data loss. The subsequent subsections provide a concise discussion of each component.

a. Evaluation to attain higher accuracy with various performance matrices

The effectiveness of the proposed combination, along with other AI techniques, in accurately detecting overspeed in formation has been tested in this sub-section. Here, the proposed integrated technique is designed by incorporating a unique ANN-based approach. Therefore, the capacity of the proposed integrated technique has been calculated and compared with some well-known AI techniques such as weighting and clustering outliers and internal cases detection (WCOID) [5], case method based on clustering and outliers and internal detection (COID) [27], Condensed Nearest Neighbor Rule (CNN) [7], RNN [26], R-CNNs [1, 9, 11] and instance-based learning (IBL) [21]. The accuracy percentage [9, 30, 49] for detecting overspeed information using different AI-based algorithms has been computed using the following Eqs (6) and (7).

$$\text{Accuracy Percentage} = \frac{\text{Total number of accurately retrieved instance}}{\text{total number attempt}} \times 100 \quad (6)$$

$$\Rightarrow \text{Accuracy Percentage} = \frac{TP + TN}{TP + TN + FP + FN} \times 100 \quad (7)$$

Where TP, TN, FP, and FN represent True Positive, True Negative, False Positive, and False Negative, respectively [5, 30]. An efficient system increases the accuracy percentage of detecting the overspeed information, or vice versa. Further plotting of the percentage of accuracy provided by the proposed combo as well as the other AI techniques, can be found in the following Figure 7.

The details of Figure 7 is further elaborated in the following Table 6 to make the accuracy percentage and the efficiency of the proposed integrated technique more visible.

Any deep learning model may be assessed for efficiency using many performance metrics, including precision, recall, F1 score, and area under the ROC curve (AUC) scores [9, 30, 49]. A deep learning-based strategy is deemed efficient in accurate prediction if it demonstrates superior precision, recall, F1 score, and AUC scores, or conversely. Consequently, the precision, recall, and F1 scores are computed using Eqs (8)–(10) as referenced in [9, 30, 49].

$$\text{Recall} = \frac{\text{True Positive}}{\text{Ture Positive} + \text{False Negative}} \quad (8)$$

$$\text{Recall} = \frac{\text{True Positive}}{\text{Ture Positive} + \text{False Negative}} \quad (9)$$

$$F1 \text{ Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (10)$$

The probability that a classifier favors a randomly chosen positive instance over a randomly chosen negative instance is denoted by the Receiver Operating Characteristic-Area Under the Curve (ROC-AUC) score. It evaluates the effectiveness of a binary classifier across all possible classification levels [49]. The performance analysis based on precision, recall, F1 score, and AUC scores for correct prediction is illustrated in Figure 8.

Table 7 that follows provides more details on the aspects of Figure 8, making the various AI methodologies more visible in terms of Precision, Recall, F1-Score, and AUC-Score, as well as the efficacy of the proposed integrated strategy.

Figure 7, Table 6, Figure 8, and Table 7 demonstrate that the suggested procedure yields superior Accuracy Percentage, Precision, Recall, F1-Score, and AUC-Score compared to other existing AI methodologies. These facts justify that the suggested strategy is efficient in providing superior prediction accuracy compared to existing methods. Consequently, the proposed combination surpasses other current AI methodologies for detecting speed limit infractions, as distinctly seen in Figure 7, Table 6, Figure 8, and Table 7. These findings indicate that the proposed combination can achieve both our first and second research objectives.

b. Analysis of its capacity to protect against data loss

Data loss is a critical feature that can occur during any transmission procedure. Data can be lost, either partially or fully, due to many factors such as limitations in the transmission channel, environmental noise, constraints of the network being used, channel congestion, and other similar reasons [5, 18]. Hence, in any traffic management or monitoring system, the loss of transmitted data poses a significant challenge in identifying drivers who exceed the speed limit or break other traffic regulations. Thus, in our research, we evaluated the effectiveness of the suggested combination and other known AI methods in minimizing data loss, using Eq. (11).

$$\text{Percentage of Data Loss} = \frac{\text{Actual Data Size} - \text{Retrieved Data Size}}{\text{Actual Data size}} \times 100 \quad (11)$$

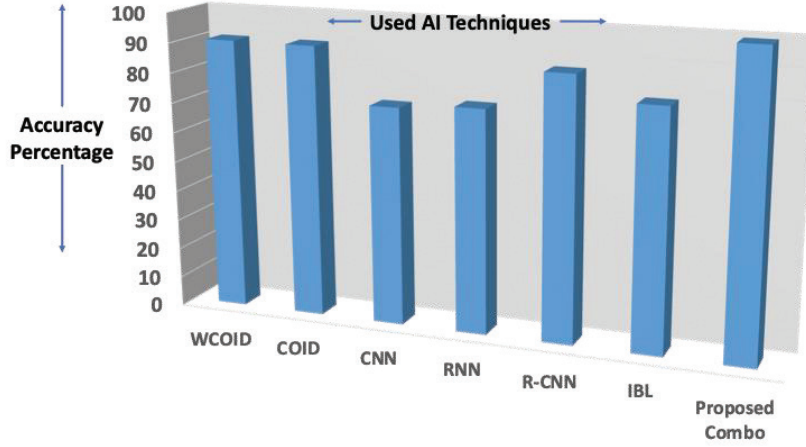


Figure 7: Accuracy percentage, provided by several AI methods for overspeed detection. AI, artificial intelligence; CNN, condensed nearest neighbour rule; COID, case method based on clustering and outliers and internal detection; IBL, instance-based learning; R-CNN, region-based convolutional neural network; RNN, recurrent neural network; WCOID, weighting and clustering outliers and internal cases detection.

Table 6: Accuracy percentage offered by distinct AI approaches

Used AI techniques	Accuracy percentage
WCOID	90.7
COID	90.6
CNN	72.5
RNN	74.2
R-CNN	87.1
IBL	79.3
Proposed combo	99.2

AI, artificial intelligence; COID, case method based on clustering and outliers and internal detection; IBL, instance-based learning; RNN, recurrent neural network; R-CNN, region-based convolutional neural network; WCOID, weighting and clustering outliers and internal cases detection.

Eq. (11) states that a data transmission strategy is considered efficient to boost data integrity if it has a reduced percentage of data loss. The efficacy of the proposed combination, as well as other AI approaches, in protecting against data loss has been calculated and presented in Figure 9.

Further information about the elements of Figure 9 can be found in Table 8, which also emphasizes the effectiveness of the suggested integrated and other systems in terms of their ability to deliver a lower proportion of data loss.

Figure 9 and Table 8 illustrate that the suggested integrated strategy exhibits the lowest proportion of information loss compared to other relevant methodologies. Therefore, we may assert that enhancing data integrity is efficient. The efficacy of any error control strategy can be assessed using the signal-to-noise ratio (SNR) [16, 42]. An error control strategy that provides superior SNR values is deemed efficient in minimizing data errors and improving data integrity. The SNR can be computed using the subsequent Eq. (12).

$$\text{SNR}_{\text{dB}} = 10 \times \text{Log}_{10} \left\{ \frac{\sum_n i^2(n)}{\sum_n [i^2(n) - t^2(n)]} \right\} \quad (12)$$

In Eq. (12), $i(n)$ represents the mean value of the output where n is any number. Here, the performance of the proposed integrated technique to reduce data error has been calculated in terms of SNR with the help of Eq. (12) and plotted in Figure 10. Consequently, the performances of some well-known error controlling approaches from the contemporary literature have been calculated in terms of their capacity to produce higher SNR values and plotted in Figure 10 further for drawing a comparison among them.

Table 9, which also highlights the efficacy of the proposed integrated and other systems in terms of their capacity to produce a higher proportion of SNR Decibel (DB), provides more details regarding the components of Figure 10.

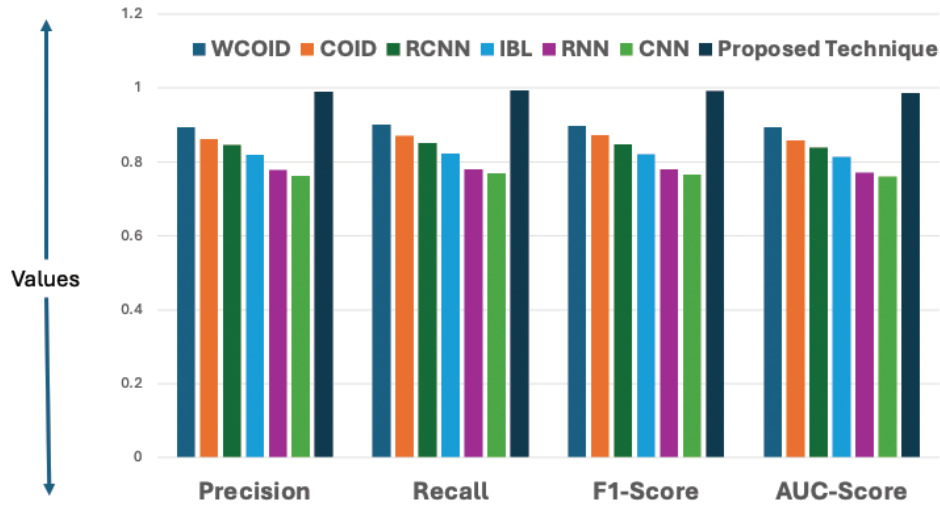


Figure 8: Comparison of different AI approaches in terms of precision, recall, F1-score, and AUC-score. AI, artificial intelligence; AUC, area under the ROC curve; CNN, condensed nearest neighbour rule; COID, case method based on clustering and outliers and internal detection; IBL, instance-based learning; R-CNN, region-based convolutional neural network; RNN, recurrent neural network; WCOID, weighting and clustering outliers and internal cases detection.

Table 7: Comparison of AI techniques in terms of their capacity to produce precision, recall, F1-Score, and AUC-Score

Used techniques	Precision	Recall	F1-score	AUC-score
WCOID	0.89	0.91	0.89	0.87
COID	0.85	0.88	0.87	0.85
R-CNN	0.83	0.85	0.86	0.83
IBL	0.81	0.83	0.85	0.81
RNN	0.78	0.79	0.79	0.78
CNN	0.76	0.78	0.78	0.76
Proposed technique	0.98	0.99	0.99	0.99

AI, artificial intelligence; AUC, area under the ROC curve; CNN, condensed nearest neighbour rule; COID, case method based on clustering and outliers and internal detection; IBL, instance-based learning; R-CNN, region-based convolutional neural network; RNN, recurrent neural network; WCOID, weighting and clustering outliers and internal cases detection.

Figure10 and Table 9 demonstrate that the suggested error control strategy provides a greater SNR value compared to existing error control methods. Consequently, it can mitigate data loss by reducing various transmission faults. Additionally, the efficacy of information regeneration in the proposed integrated methodology has been compared with that of established methodologies in the present literature, specifically regarding their percentage of packet loss estimated post-implementation.

Literature indicates that the assessment of information loss percentage reveals the strengths and limitations of a transportation system, as well as the efficacy of error control techniques in mitigating information loss. The literature identifies several prominent methodologies, including LDPC, Reed-Solomon error correction, FEC, error correction and lost bit generation through Hamming distance computation, and Cyclic Redundancy Checking [44, 48]. Consequently, the percentage of packet loss

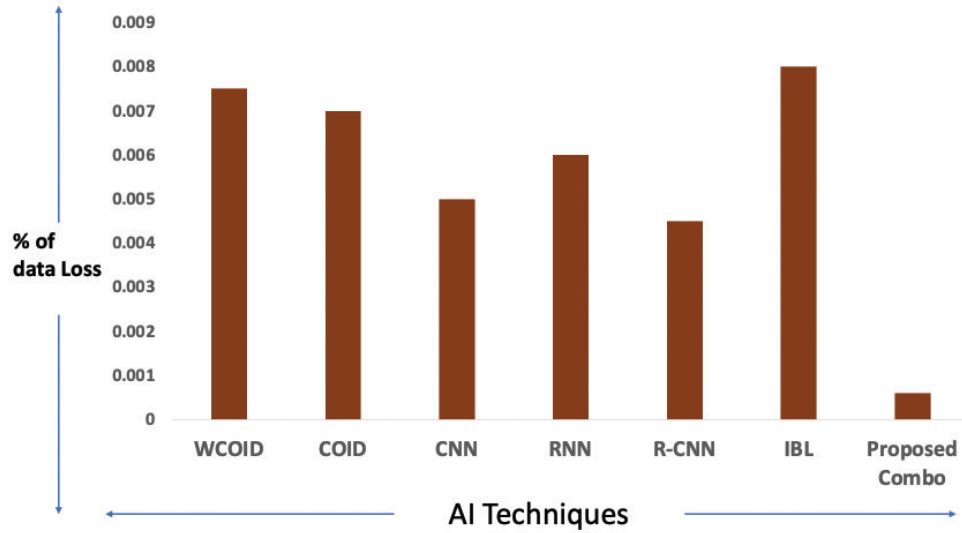


Figure 9: Percentage of data loss provided by different AI-based methods during data transmission. AI, artificial intelligence; CNN, condensed nearest neighbour rule; COID, case method based on clustering and outliers and internal detection; IBL, instance-based learning; R-CNN, region-based convolutional neural network; RNN, recurrent neural network; WCOID, weighting and clustering outliers and internal cases detection.

Table 8: Comparison of AI techniques with their data loss percentage

AI techniques	% of data loss
WCOID	0.0075
COID	0.007
CNN	0.005
RNN	0.006
R-CNN	0.0045
IBL	0.008
Proposed combo	0.0006

AI, artificial intelligence; CNN, condensed nearest neighbour rule; COID, case method based on clustering and outliers and internal detection; IBL, instance-based learning; R-CNN, region-based convolutional neural network; RNN, recurrent neural network; WCOID, weighting and clustering outliers and internal cases detection.

has been computed for the suggested method and the current methods utilizing the following Eq. (9).

$$\text{Percentage of Packet Loss} = \left(\frac{\text{Total Transmitted Packets} - \text{Total Retrieved Packets at Receiving End}}{\text{Total Transmitted Packets}} \right) \times 100 \quad (13)$$

Per the convention, a data recovery method is deemed efficient if it results in a reduced percentage

of packet loss or the opposite. Consequently, the efficacy of the suggested method and other current methods to diminish the packet loss percentage has been assessed using Eq. (13). The sample information size is determined by the capacity of the input storage device, ranging from 2 GB to 5 GB throughout the transmission procedure. The percentage of packet loss across all transmissions has been computed using Eq. (13) for all transmission phases; their average has been calculated and plotted in Figure 11.

Table 10, which also highlights the efficacy of the proposed integrated and alternative systems in terms of their capacity to deliver a lower fraction of packet loss, provides more details regarding the components of Figure 11.

Figure 11 and Table 10 demonstrate that the proposed combination effectively reduces the proportion of packet loss compared to other existing techniques. Consequently, Figure 8, Table 7, Figure 9, Table 8, Figure 11, and Table 10 demonstrate that the proposed integrated technique effectively minimizes data loss by yielding a reduced proportion of packet loss and data loss while providing an enhanced SNR. It yields a reduced proportion of data loss, diminished packet loss, and an enhanced SNR relative to other established alternatives. Consequently, the proposed amalgamation can fulfill our second objective of this research.

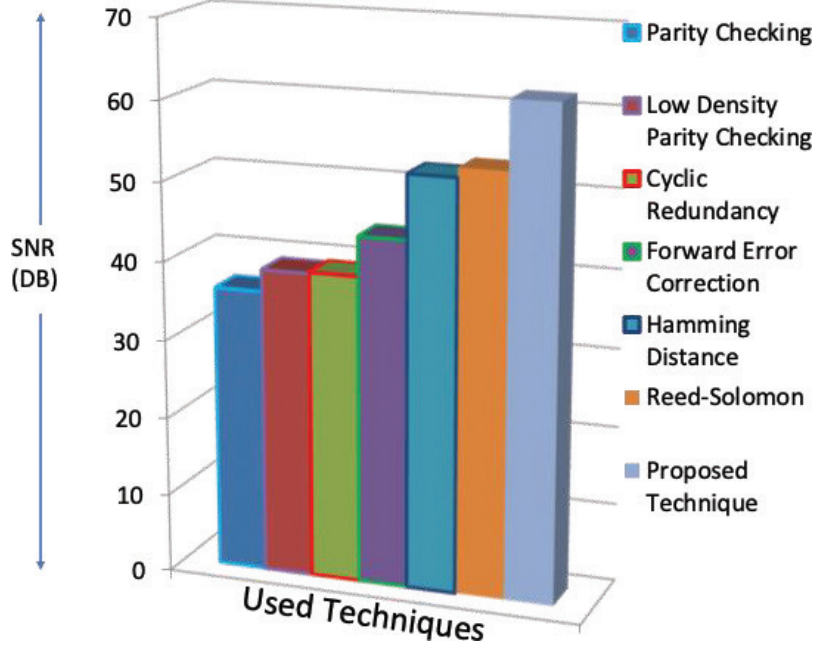


Figure 10: SNR_{dB} , offered by various error control techniques. SNR, signal-to-noise ratio.

c. Analysis of its time efficiency

The temporal efficiency of information processing is crucial for every information processing system. In our method, the primary concern is the processing time, as faster information processing can prevent the car driver from exceeding the speed limit or breaching any defined speed restrictions on the highway. The processing efficiency of an information processing system can be determined by calculating its ability to generate lower cyclomatic complexity (CC). The CC [16, 27, 42] can be used to quantify the efficiency of the system being utilized and its ability to solve certain tasks related to the source problem. Typically, the measurement involves creating a Control Flow Graph of the software module to determine the overall count of linearly independent pathways within the module [20]. The CC can be determined with the following Eq. (14).

$$CC = (N - T + (2 \times C)) \quad (14)$$

The CC represents the number of edges on the control flow graph. The number of nodes in the graph is given by N , whereas T represents the number of linked components in the graph, and C represents the number of connected components. The table

Table 9: Comparison of distinct error control techniques along with their SNR (DB)

Used techniques	SNR (DB)
Parity checking	36.1
Low density parity checking	38.9
Cyclic redundancy	39.1
Forward error correction	44.1
Hamming distance	52.2
Reed-Solomon	53.4
Proposed technique	61.95

DB, Decibel; SNR, signal-to-noise ratio.

provided, Table 11, outlines the meanings associated with different ranges of CC.

Among the AI approaches we've covered so far, Table 11 shows that the proposed combination has the lowest CC. The proposed integrated method is exceptionally successful in reducing time complexity and processing information efficiently. The Processing Capacity [44, 48] can be quantified by its capability to manage a specific volume of information per second, enabling the assessment of the temporal efficiency of

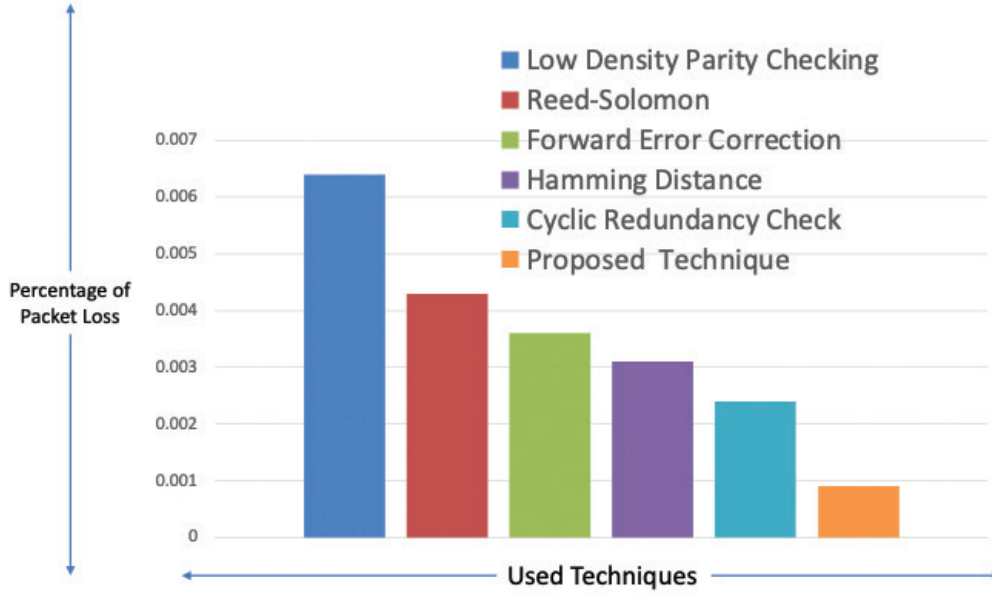


Figure 11: Percentage of packet loss offered by various data retrieval schemes. FEC, forward error correction; LDPC, low-density parity checking.

various AI systems. Utilizing Eq. (10), one can determine the computation of processing capacity as follows.

$$\text{Processing Capacity} = \frac{\text{Number of information}}{\text{Total Processing Time in Second}} \quad (15)$$

The convention dictates that a technique with high processing capacity is time-efficient, and conversely, a technique with low processing capacity is time-inefficient. Thus, utilizing Eq. (15), we can calculate the information processing capability of the suggested combination alongside other pertinent existing AI methodologies, as illustrated in Figure 12.

More information on the elements of Figure 12 can be found in Table 11, which also emphasizes the effectiveness of the suggested integrated and alternative systems in terms of their ability to offer higher information processing capacity.

The findings presented in Figure 12 and Table 12 demonstrate that the proposed combination provides a greater capacity for information processing than the other AI techniques that are already in use. Since this is the case, Figure 12, Tables 12 and 11 provide evidence that the proposed combination is significantly more effective and efficient in terms of processing the information when compared to the other AI systems

that are currently in use. As a result, these discoveries provide support for the third purpose of this research.

d. Worst-case scenario discussion for the proposed technique

The intended outcome can be attained by placing Bluetooth devices at every 1 km interval along the route to capture vehicle information. Should any device malfunction under any circumstances, the alternative device can supply backup data with minimal error rates or without mistakes altogether. Conversely, communication delay is a significant concern in such circumstances. Consequently, we will evaluate the network robustness of our proposed design utilizing the information from references [6, 29, 42].

- The used many-to-one Bluetooth device consists of eight communication channels, that is, it can communicate with a maximum of eight cars at a time, which is sufficient for the highways. The minimum communication rate of a many-to-one or one-to-many Bluetooth device is 800 kbps, which means each channel of a many-to-one Bluetooth device can communicate at 100 kbps.
- As per the proposed model, each handshaking message size will be a maximum of 5 KB. Hence,

Table 10: Comparison of distinct error control techniques along with their packet loss percentages

Used techniques	Percentage of packet loss
Low density parity checking	0.0064
Reed-Solomon	0.0043
Forward error correction	0.0036
Hamming distance	0.0031
Cyclic redundancy check	0.0024
Proposed technique	0.00091

Table 11: CC table for different AI approaches

Applied AI techniques	CC
WCOID	5
COID	6
CNN	4
RNN	4
R-CNN	4
IBL	7
Proposed combo	2

AI, artificial intelligence; CC, cyclomatic complexity; CNN, condensed nearest neighbour rule; COID, case method based on clustering and outliers and internal detection; IBL, instance-based learning; R-CNN, region-based convolutional neural network; RNN, recurrent neural network; WCOID, weighting and clustering outliers and internal cases detection.

- the transportation of a 5 KB message will take a maximum of 0.05 s.
- c. The range of the used Bluetooth device in our hypothetical architecture is 100 m.
- d. An over-speeded car with 240 km/hr (maximum) can travel 3.3 m in 0.05 s.

If certain circumstances, the network speed comes down to 4 kbps, then it can also communicate with an overspeeded car which is running at 240 km/hr. Hence, in both cases, the proposed architecture can handle.

VII. Conclusion

Traffic accidents on or near highways are a leading cause of mortality in countries, such as India. There are instances when conventional policing and law enforcement mechanisms cannot accommodate the rising volume of automobiles on highways. The deployment of intelligent technology rooted in the IoT is essential in this context to monitor and proactively mitigate hazardous driving behaviors. The prompt legal repercussions imposed on a driver for reckless driving exert a psychological impact on the driver's mindset, deterring him from adopting hazardous driving behaviors. Our proposed methodology aims to mitigate incidents on highways resulting from drivers exceeding safe speeds for prevailing conditions. Implementing this technology is expected to enhance roadway safety and transform travel into a pleasurable and memorable experience. This research also encompasses the prevention of manipulation with IoT overspeed detection systems. The IoT overspeed

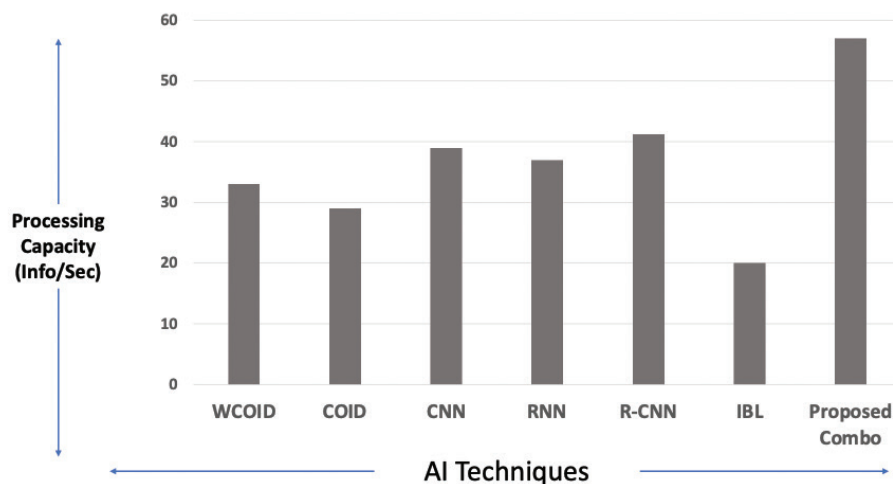


Figure 12: Information processing capacity of different AI approaches. AI, artificial intelligence.

Table 12: Comparison of various AI techniques along with their capacity for information processing

AI techniques	Processing capacity (Info/second)
WCOID	33
COID	29
CNN	39
RNN	37
R-CNN	41.2
IBL	20
Proposed combo	57

AI, artificial intelligence; CNN, condensed nearest neighbour rule; COID, case method based on clustering and outliers and internal detection; IBL, instance-based learning; R-CNN, region-based convolutional neural network; RNN, recurrent neural network; WCOID, weighting and clustering outliers and internal cases detection.

detection system is located within the user's vehicle. The system may cease operation while the vehicle is in motion due to either inadvertent failure or deliberate intervention by the owner. Consequently, this research must also investigate the approach for recognizing vehicles on the highway that possess a defective IoT overspeed detection system.

VIII. Future Direction

The suggested method is used to prevent drivers from exceeding the speed limit on any roadway in order to reduce collisions and guarantee the safety of both drivers and passengers. The experimental findings show that these goals are successfully met by the proposed study. The traffic data is typically not fully recoverable at the receiving end due to network errors and data loss. As a result of breaking traffic laws and compromising traffic safety, it is exceedingly challenging to find and penalize the driver who has been observed driving on the highway. To address these kinds of problems, the proposed study minimizes data loss and corruption. Additionally, it provides an effective way to control the different transmission problems and a backup data creation mechanism. Every system, nevertheless, has provisions to make it better. To penalize the offender and increase the accuracy of identifying the driver who has exceeded the speed limit, future enhancements

can be implemented. The accuracy of the suggested model can be improved by increasing the number of epochs and applying a more suitable activation function. Additionally, lessen data loss, which will help to cut down on dangerous driving. Effectively reducing different transmission defects and minimizing data loss and corruption can be achieved by the implementation of more effective error control mechanisms. So, using a GPU could also increase processing speed at the same time. It is possible to improve the suggested integrated technique to get beyond these obstacles. Thus, there is still room to improve the suggested method.

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