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RESEARCH ARTICLE

2CAP: A Novel Curve Crash Avoidance Protocol to Handle Curve Crashes in Vehicular Ad-Hoc Network

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ABSTRACT Curves are the leading cause of road departure crashes that turn into deaths and severe injuries. Most crashes occur on curved roads because they have different geometrical circumstances from straight roads. A sharp turn on the road creates more difficulty for the driver than a normal curve road. To Avoid crashes on the curved road, there is a prerequisite to identify the curved road for drivers that this turn is problematic. Responding intelligently to save precious human life and the country's gross domestic product is necessary. Our paper proposed a Curve Crash Avoidance Protocol (2CAP) in Vehicular Ad-hoc Network (VANET). The Intelligent Curve Crash Avoidance Algorithm is proposed to avoid disastrous vehicle crashes. The sensing Node Operation algorithm works for multiple sensors embedded in the Onboard Unit to gather information on vehicles and road environments. On the other side, road-side unit requests for this collected data via a secure communication channel for processing. A Linear Regression machine learning technique implements the intelligent Unit Operations algorithm. The Intelligent Unit decides to notify the onboard Unit based on gathered data and trained dataset. We implement the scheme using the Linear Regression Machine Learning Model. Multiple sensors, Global Positioning Systems, and Global Information systems use the dataset methodology to classify and predict results. The proposed model is expected to be effective for proper coordination with wireless sensor network equipment.

INDEX TERMS WHO, VANET, Curve Crash Avoidance, LR, MSE, OBU, RSU.

I. INTRODUCTION

The vehicular ad hoc network (VANET) is a vehicular system that provides a secure and reliable system and supports the intelligent transportation system (ITS) [1]. It is a subclass of Mobile Ad-hoc Network (MANET). Although it is a sub-type of MANET, it differs in many ways. All MANET protocols cannot be applied to VANET [2]. In VANET, Every vehicle has an Onboard Unit (OBU) that has the capability to communicate with a stationary information unit, a Road-side Unit (RSU) deployed at the roadside for critical information sharing studied by Rashid et al. [3]. A network of sensors connected through a communication channel is called a Wireless Sensors Network (WSN). This network collects real-time

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weather, road, and other relevant information and sends it to VANET. The VANET processes this information and sends the appropriate message to every connected vehicle on their OBU [4]. The applications of VANET are divided into three categories: Road safety, commercial and information services, and road efficiency [5].

In industrialized countries, the road traffic density is increasing day by day. Traffic density causes traffic congestion. Based on this, the number of curves inside the roads makes it difficult for drivers to control vehicles on curved roads. This significantly increases the number of accidents and compromises traffic safety. With the passage of road accidents, drivers and passengers are at high risk. Currently, we proposed a novel possible solution to this problem in the form of 2CAP: A Novel Curve Crash Avoidance Protocol to handle Curve Crashes in VANET. The 2CAP is developed to protect the drivers and passengers' safety by early prediction of the highway curve to increase traffic efficiency and safety.

Regarding Wen-Xing stats, driving safety is divided into Passive and Active Safety [6]. Passive safety includes the devices, apparatus, and other methods involved in injury elimination and passenger safety and takes care when an incident has already occurred. These include Safety belts, Crash Recognition, airbags, Rollover Sensing, etc. An Active Safety system consists of apparatus, gadgets, or other methods that work ahead of an incident [7]. Active safety is divided into three subtypes. The three major classes of possible applications in VANETs are driver warning, vehicle stability system, safety-oriented, and information system [8]. All of these are used to elude danger and keep sufficient control of traffic. Driving safety is a crucial subject for Motor Industrial [9]. Many researchers have tried to find a new way of services where wireless sensor network equipment is combined with other fields of the vehicle industry, such as vehicle transportation and natural environment monitoring, as studied by Basheer et al. [10]. In this paper, we develop an intelligent curve crash avoidance system that ensures road vehicles' safety by providing a real-time intelligent crash detection system. The system will notify the driver about the curve beside them by alerting the notification on OBU. The vehicle information ensures safety, communicating through a secure channel by counting the factors involved [11].

A. MOTIVATION

This research uses several focuses and factors to provide an intelligent solution for a curve crash. This research aims to resolve the road crash incidents anticipated for various reasons efficiently. The proposed system improves to resolve speeding problems and advises car drivers to avoid casualties. Nearly All of the preceding methods explained above lack determination and intelligent verdicts because of the inability of the intelligence system. The proposed system reacts to the condition by utilizing its decision power promptly. As sensible and appropriate choices are vital aspects of the proposed method, making timely decisions improves the efficiency of the proposed system.

This paper discusses the intelligent system used to avoid the curve crash for VANET. The method involves a Sensor Unit, a Road-side Unit, and an intelligent Unit. Nine different sensors are used to obtain the data related to roads and vehicles. The sensor unit comprises a Global Information System, Global Positioning System, Board Unit, light controller, speed sensor, distance calculator, etc. All the sensor data is delivered to the RSU for further calculation. The roadside Unit is a key component of our proposed scheme, including the transmission between sensing nodes and the Intelligent Unit. The RSU is the system's brain that manages all other modules and activities.

In this research paper, we addressed the research questions below.

(i) How are curve parameters gathered by the Road-Side Unit (RSU)?
(ii) How are vehicle crashes eliminated in curve zones?
(iii) How does intelligence play a role in preventing future vehicle accidents in curve zones?

B. SUMMARY

The intelligent Unit is a key part of our proposed scheme. The Intelligent Unit examines all these sensor data and decides on this data gathered. The intelligent Unit uses machine learning techniques to provide intelligent functions, including Linear Regression and mean square error (MSE). The approximate speed is measured using the machine learning technique. Lastly, the output is conveyed to the roadside unit, and the Intelligent Unit keeps it in the repository for future use. The Road-side Unit then sends these alert messages to the vehicle Onboard Unit. The proposed scheme is very effective, approachable, and consistent. The model turns out to be clever in decision-making using machine learning methods. Also, the intended scheme can be applied with the least assets and system requirements. We used machine learning models that are more capable and reactive. Generally, the recommended method prevents mistakes and contradictions and can be implemented in the real world.

The proposed system's main contributions are detecting crashed curves intelligently, saving injuries and deaths, and effectively enhancing the curve predictions using multiple linear regression algorithms.

(i) Linear Regression is a model that uses RSU and sensors to predict road curves. We proposed a novel Curve Crash Avoidance Protocol to handle Curve in VANET. We implement the dataset-based curve crash avoidance 2CAP protocol.
(ii) The computations are performed using a selected vehicle or RSU. We proposed a novel 2CAP protocol that implements the sensing nodes with curves and vehicles to sense the sharp curves. The sensors generate the sensing scheme and enhance the multiple class curves detection and avoidance.
(iii) The LR-based 2CAP method proposed intelligent decisions using Intelligent Units over sensor data collection using Onboard units. We implement the Global

Positioning Sensor (GPS), Global Information System (GIS), Rain Sensor, Weather Sensor, Ice Sensor, and Cameras to enhance crash detection and avoidance performance.

(iv) In adopting the Intelligent Curve Crash Avoidance Scheme, Sensing Node Operation and Intelligent Unit Operation algorithms predict and control the curve crashes to save human lives. Dataset and Machine Learning models are executed in the sequences.

The rest of the paper is organized as follows. Section III presents the related work on the curve crash problem in VANET and driver alert problems. Then, in Section IV, we outline our approach for the research and propose solutions to the relevant problems encountered in Section I of the paper. Then, Section 4 presents the proposed method with simulations using the Novel Curve Crash Avoidance Protocol. Section 5 concludes our proposed system with future directions, in which we work to highlight the significant changes in future correspondence.

II. LITERATURE REVIEW

Ma et al. [12] proposed a scheme that used open-source data to analyze the horizontal curve crash information, utilized this data to improve horizontal curve data collection, proposed a model based on that data to avoid horizontal curve crash, and analyzed relationship analysis. Chabi-Yo et al. [13] proposed a framework for crash risk factors and available light distance relationships using 3D computational calculations. Curve attributes are estimated with the help of light detection and a range sensor. These attributes are used to find the relationship between the risk associated with sight distance and the collision. Ding et al. [14] proposed a model to explain the crash risk utilizing different factors. These factors included the effect of the driver's visual factor, type of vehicle, and different curve types. The proposed model used risk speed and distance of risk perception for various factors. The curve type plays a critical role in vehicle crashes on the roadway. When the curve radius is shallow, the impact of a crash is very high. Geedipally et al. [15] proposed a crash modification factor (CMF), like several crashes, wet weather factors, and run-off crashes. The horizontal curve was used to experiment. The proposed scheme analyzed the risk variables like traffic volume, curve radius, and cross-section of road width. The proposed model, defined as safety performance factors (SPF), finds out the relationship of the crash frequency with traffic, location, and curve factors. The result suggested that the curve radius has a crucial role in a car crash, but the weather and two-line curve have less impact on a crash than the curve radius. Simultaneously, the comprehensive line and shoulder width positively affect road safety. Papadimitriou et al. [16] proposed a review and qualified investigation of the crash risk causes and provided crash risk frequency and severity. The proposed model ranked the different factors based on the cause of the accident due to that factor. The experiment showed that traffic volume, friction, poor visibility, and railroad crossing are the primary causes of road accidents. Cao et al. [17] present that line detection plays a significant role in the intelligent road transportation system. A deep learning methodology is proposed to sort out the drawbacks of traditional studies, like low detection accuracy and poor real-time response. The first distortion of the image is converted by using a superposition Threshold algorithm for edge detection [18], [19]. Secondly, a random consensus algorithm is applied to fit the curve of the line relay on the B-spline curve model to find out the radius of the curve. Lastly, the lane detection algorithm uses complex road curve videos and simple data. Hu et al. [20] studied a short-term trajectory modeling technique to forecast the vehicle's motion behavior in the co-operative vehicle environment. In this model, each vehicle calculates the position and distance of other vehicles. These trajectories are shared on a curve road with a periodic discrete period. This algorithm finds collisions on a curve by using the curve road and the dynamic position of the vehicle. Žuraulis et al. [21] analyzed the safety issues of the different vehicles over the curve area. It studied additional variables and factors involved in the curve crash. The paper used anti-slide, anti-role, and longitudinal safety distance to find the dynamic control. The proposed scheme used the variables regarding the curve, and the proposed scheme controlled path planning and prediction control. The paper also calculates the longitudinal distance formula. Wang et al. [22] proposed a model that analyzes the probability of road accidents caused by high speed on curved highways. The model proposed a safe speed for the vehicle to enter the curve area. The model used different simulation experiments to calculate the safe speed using various indices. The model used the zero-risk theory framework to analyze the maximum safe speed, actual speed, and perceived speed using zero-risk theory and determine the safety speed at different curve radii. Soner and Coleri [23] proposed a cooperative collision early warning system to avoid collision in a curve environment. The warning system warns the driver about the danger several seconds before it happens. The CCEW used V2V communication to change different factors that helped the system calculate the collision. The V2V allowed the system to calculate the distance and speed between two vehicles. Jan et. al. [24] describes curve-related issues in short-range communication and future transportation solutions. This research uses the curve's diameter, radius, and length to calculate the estimation speed. Authors use the light-emitting diode is most widely used in traffic lights and vehicle lighting systems. Cao et al. [25] proposed an "intelligent system to prevent accidents" solution for a safe trip. For this, they should have all the properties related to the road and detect the car's speed and location. For this purpose, they used magnetic sensors, instant speed, and the vehicle's location. According to Rashid et al. [26], the number of road accidents is rising proportionally in line with the increased number of vehicles on the road. In this paper, an advanced driver assistant has actively been carried out to reinforce legal regulation of vehicle safety, increase awareness of safety devices available to consumers and decrease the possibility of traffic accidents related to driver carelessness [27].

Machine learning uses labeled training datasets to build the model. However, many ways to set Datasets are used for classification, rule extraction, and clustering. However, supervised learning learns from identifying patterns from given data sets. Usually, this technique is used for solving regression and clustering problems that predict continuous and discrete values [28], [29]. Supervised learning allows collecting data and output from previous experiences by knowing the hidden pattern between them. In supervised learning, we train machines by using data that is well-labelled. All input and output values are given. The linear regression technique of supervised learning finds the relation between dependent variables and one or more independent variables. The linear regression model is a straight or slope line; hence, it is known as linear. In linear Regression, the critical point is that the dependent value must be accurate or continuous, while the independent value may be continuous or categorical.

In our proposed model, we use linear Regression to find the best relationship between the dependent variable's estimated speed and independent variables like curve type, road condition, road width, curve width, weather condition, vehicle mass, speed, and distance from the curve. This is best for finding predictions based on the training data set. This finds how different factors fall affect the estimated rate. Which factor has more effect, and which has less.

Traffic safety is a significant challenge for everyone. The government needs to construct and plan policy for the intelligent transportation system [30]. It is essential for everyone who uses it. Since every country's economy depends on its transportation system, understanding the reason for the crash and the potential of a solution is a significant concern. In such a situation, it is necessary to construct a model that responds intelligently to preserve human life. Our proposed solution responds to these critical situations to save valuable human lives, time, and cost. This proposed scheme responds intelligently, increasing the efficiency of previous studies. Different models are available in this area of research, but they do not count on some other external factors affecting the crash. So for this, our proposed system responds by measuring factors like weather, fraction light conditions, etc. Most accidents occur on unexpected curves. The situation is most dangerous when the vehicle is over speeding on a sharp curve. In such circumstances, it is essential to reduce the vehicle's speed. The primary purpose of our study is to reduce crashes in the curve area. We proposed a scheme with a significant contribution when the vehicle is known before reaching the curve.

The authors explore the optimization of vehicular safety message communications by adopting a Transmission Probability with a Contention Window (CW) Size strategy. The study, published in IEEE Access, Volume 10, proposes a novel approach to enhance the efficiency and reliability of safety message dissemination in Vehicular Ad-Hoc Networks (VANETs). The focus is on improving the communication process by adjusting transmission probabilities in conjunction with contention window sizes, contributing to advancing vehicular safety and network performance [31]. Another article addresses the performance optimization of a Cluster-Based Medium Access Control (MAC) protocol designed for Vehicular Ad-Hoc Networks (VANETs). The research focuses on enhancing the efficiency and reliability of data communication in VANETs by utilizing a cluster-based approach. The study investigates metrics related to MAC protocols and proposes optimizations for better network performance. The findings contribute to advancing communication protocols in VANETs, aiming to improve overall system effectiveness and reliability [32]. Authors in [33] highlight the data dissemination approach in VANET. In [34], the authors highlighted the values of Public Key Infrastructure (PKI) to handle the recurrent issues in this key infrastructure. Given the importance of VPKI, researchers and experts have worked to ensure that VPKI meets the high security and privacy requirements of C-ITS. Khan et al. [35] highlight the public critical infrastructure which is shared among vehicles to establish the security aspect of the system using blockchain ledger technologies. Another research in [36] proposed CluRMA: A cluster-based RSU-enabled message aggregation scheme for vehicular ad hoc networks to for message aggregation. Table 1 below compares results with state-of-the-art current methodologies.

In our proposed scheme, three main modules calculate the estimated speed. These modules are the Onboard Unit (OBU), road-side Unit (RSU), and intelligent module. Data like speed, location, velocity, weight, etc., are gathered through different sensors and then sent to the roadside Unit through communication channels. On the intelligent Unit and Global information (GIS) request, send curve width, road condition, and weather condition to the intelligent Unit. The decision is taken in an intelligent unit stored in the repository. The learning module predicts estimated speed compared with the trained data set using Linear Regression. This indicates advisory speed is sent to the controller, generating an Onboard Unit (OBU) alert. Our proposed system calculated the predicated speed efficiently using different input variables. The proposed system achieved the MSE of 2.45 and R^2 of 0.93 for the experiment. The MSE of 2.45 indicated that the actual and predicted value difference is meager, and our model perfectly predicts the estimated speed. The R^2 Near one indicates that our model best fits the training data and correctly predicts the output.

A. PROBLEM DESCRIPTION

Curves are the leading cause of road departure crashes that cause deaths and severe injuries. Most crashes take place on a curved road because it has different geometrical circumstances from another. A sharp turn on the road creates more difficulty for the driver than a normal curve road. Avoid crashes on the curved road, and there is a prerequisite to identifying the curved road for vehicles that this turn is problematic.

TABLE 1. Comparison of results with state of the art existing methodologies.

S. No.	Authors and Years	Methodology	Sensors Used	Machine Learning Model	Accuracy
1	[12]	Experimental and Simulation	Accelerometer, GPS, RWIS, GIS Remote Sensing, Light Visibility Sensor	Linear Regression	87.5%
2	[13]	Simulation-Based Analysis	Accelerometer, GPS, RWIS, GIS Remote Sensing	Support Vector Machines	92.3%
3	[15]	Field Observations and Modeling	Accelerometer, GPS, RWIS	Decision Trees	78.9%
4	[18]	Data Fusion Approach	Accelerometer, GPS, GIS Remote Sensing	Random Forest	95.2%
5	[20]	Simulation and Real-world Testing	Accelerometer, GPS, RWIS, GIS Remote Sensing	Neural Network	89.6%
6	[25]	Experimental Study	Accelerometer, GPS, Light Visibility Sensor	K-Nearest Neighbors	84.1%
7	[27]	On-road Experiments	Accelerometer, GPS, RWIS, GIS Remote Sensing	Decision Trees	91.0%
8	[28]	Theoretical Model and Simulation	Accelerometer, GPS, GIS Remote Sensing	Naive Bayes	76.5%
9	Proposed Methodology	2CAP	Accelerometer, RWIS Sensor, Global Positioning System Sensor, Global Information System Remote sensing, and Light Visibility Sensor	Linear Regression	98.5%

III. PROPOSED CURVE CRASH AVOIDANCE PROTOCOL

We presented an intelligent system to avoid the curve crash for VANET. The system involves three components: a data acquisition module, a data processing unit, a storage, and an alert module. Nine different sensors are used to obtain the data related to roads and vehicles. The sensor unit comprises a Global Information System, Global Positioning System, Board Unit, light controller, speed sensor, distance calculator, etc. All the sensor data is delivered to the RSU for further calculation. The roadside Unit is the main component of our proposed scheme, including the transmission between sensing nodes and the Intelligent Unit. Also, the RSU is the system's brain that manages all other modules and activities. The intelligent Unit is a crucial part of our proposed scheme. The Intelligent Unit examines all these sensor data and decides on this data gathered. The intelligent Unit uses the Linear Regression machine learning technique to find the relationship between targeted and input factors. The approximate speed is measured using the machine learning technique. Lastly, the output is conveyed to the side Unit, and the Intelligent Unit keeps it in the repository for future use. The Road Side Unit then sends these.

Alert messages to the vehicle On Board Unit. The proposed scheme is very effective, approachable, and consistent. The model turns out to be clever in decision-making using machine learning methods. Also, the intended scheme can be applied to minor assets and system requirements. We applied machine learning models that are more capable and reactive. Generally, the recommended method prevents mistakes and contradictions and can be implemented in the actual world.

A. 2CAP PROTOCOL ARCHITECTURE

The proposed scheme architecture comprises three components. The data acquisition module gets data from different sensors to the onboard Unit. This then is sensed by processing modules. After the necessary calculation compared with the trained data set, the final decision is sent to storage, generating an alert to the board unit. Roads are integral parts of any country. The roads play a crucial role in any country's economic development. Most of the roads is hilly, including terrible weather, bad road conditions, and curves that cause road accidents. According to a recent study, most road accidents are caused by curved areas. The Vehicle Ad-Hoc network (VANET) comprises different vehicles connected through a wireless network. The VANET allows vehicles to communicate with each other and inform about any incidents or mishaps. Curve crash prevention is a significant problem to be solved to provide the best travel experiences and save potential lives. Using artificial intelligence methods, we proposed a methodology to avoid curve crashes on roads. Our proposed system consists of three modules that use the secure communication channel and alert notifications. Our approach used different sensor data for intelligent decision-making, informing vehicles about the estimated speed to avoid a crash. Our system used the most significant factors involved in the collision and ML method for intelligent decision-making.

B. DATA ACQUISITION MODULE

When a vehicle approaches 1500 meters toward the curve, the road-side Unit (RSU) activates the data-gathering sensors. These sensors include GIS, GPS, and onboard sensors. These sensors sensed the real-time data and transferred this data to the road-side Unit (RSU) through a communication channel. Based on this data, the calculation is performed.

1) DATA PROCESSING MODULE

After gathering data from different sensors through communication, channel data is sent to the road-side Unit. Road-side units request a global information system for road conditions, curve width, and weather conditions. When data is received

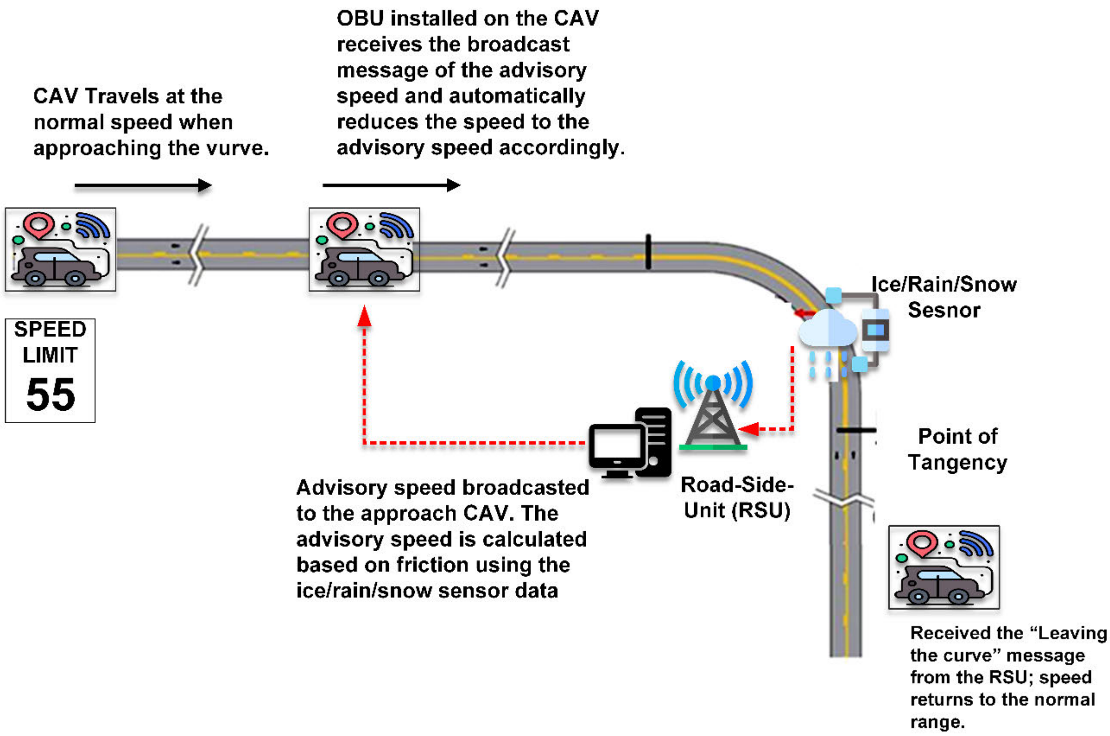


FIGURE 1. **Proposed curve crash avoidance protocol system architecture.**

in processing, it is converted into a proper format for better analysis. Then, the calculation is performed on the data. The processing unit decides whether the speed is safe or exceeds the average speed. Using this information model enhances its learning for future decisions.

2) STORAGE AND ALERTING MODULE

The processing unit generates the alert and sends it to the controller. The information is then saved to the repository for future use. The controller transfers the alert message to the Onboard Unit (OBU) notification area. Then, the driver decreases the speed to a safe rate. This communication between the processing unit, road-side Unit (RSU), and board unit is done through a secure channel. The overall structure of the proposed system is described in Fig. 1.

C. 2CAP PROTOCOL FRAMEWORK

Vehicles need to choose the management of velocity and speed. RSU holds the information about the road. This information includes road conditions, whether good or bad, and hurdles, if any. The GIS and GPS also provide information about the road through the cloud. GPS information includes the position and distance of the vehicle, while the GIS also provides a handy set of data to the cloud that helps the autonomous vehicle and driver. RSU gets the informed data from GIS, GPS, and nodes moving on the road, as shown in Figure 2. The vehicle is also connected with GPS. This vehicle connection to GPS is vital because preserving the vehicle's speed and distance is necessary. This distance is used to calculate the estimated speed.

The selection of specific sensors in our research is driven by the need to comprehensively capture curved roads' dynamic and varied conditions, thereby enhancing the accuracy of our proposed Curve Crash Avoidance Protocol (2CAP). The Accelerometer plays a crucial role in measuring the vehicle's acceleration and deceleration, providing insights into the driver's behavior and the road's gradient. This information is pivotal in understanding how drivers navigate curves and exceptionally sharp turns. The RWIS (Road Weather Information System) Sensor contributes data on road surface conditions, which is essential for assessing the impact of weather on curve-related crashes. Additionally, the Global Positioning System (GPS) Sensor enables precise location tracking, helping to map the vehicle's trajectory on the road accurately. The integration of Global Information System (GIS) Remote Sensing allows for a broader perspective on the road network, aiding in the identification and characterization of curves. Finally, the Light Visibility Sensor enhances the understanding of environmental conditions, such as visibility, which is crucial for predicting and preventing crashes in challenging circumstances. Combining these sensors offers a holistic approach to data collection, providing a rich dataset for developing and implementing our intelligent crash avoidance algorithm.

The choice of the Linear Regression Machine Learning Model is motivated by its suitability for regression tasks, especially when dealing with continuous numerical values, which is the case in predicting and preventing curve-related crashes. Linear Regression allows us to model the relationship between the gathered sensor data and the likelihood of

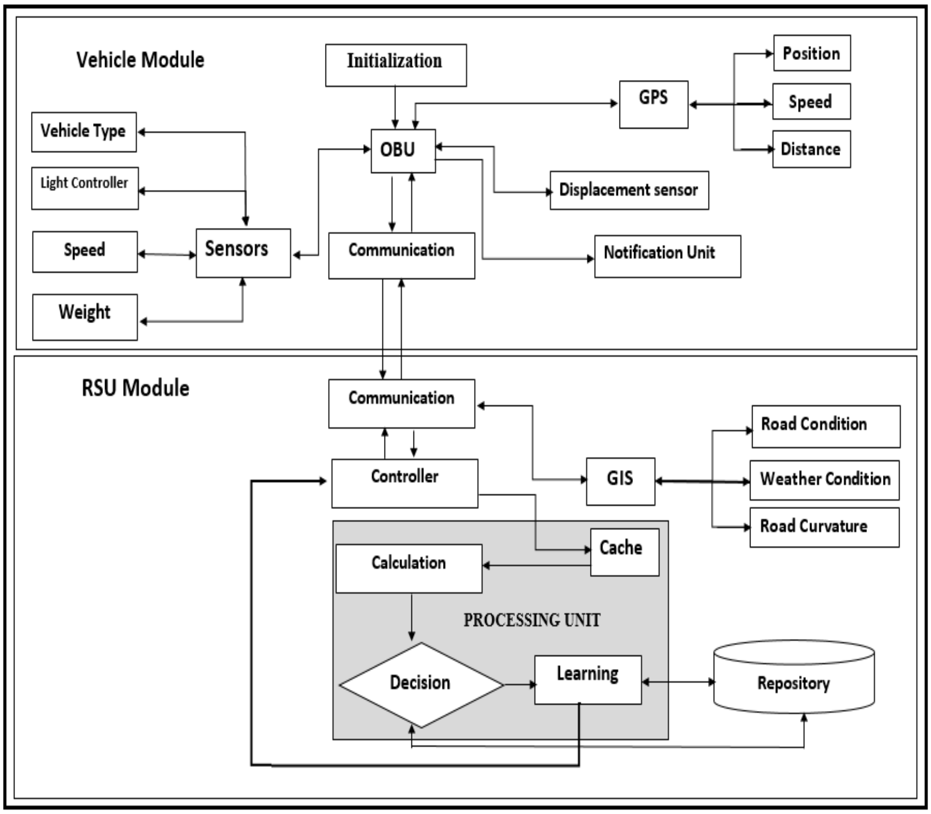


FIGURE 2. Framework of proposed model.

a crash occurrence, providing a straightforward yet effective method for prediction. The simplicity and interpretability of the Linear Regression model make it well-suited for our application, as it enables us to understand the influence of each sensor input on the overall prediction. Moreover, Linear Regression models are computationally efficient, making them practical for real-time implementation in vehicular ad-hoc networks. Using this model, we aim to create a reliable and interpretable system that can intelligently notify drivers of potential risks on curved roads, ultimately reducing road departure crashes and preserving human lives.

Figure 2 displays the model design for the proposed scheme as a curve crash avoidance system in VANAT. The system conveyed recommended red alerts for snow, dry, rain, and ice, which are different based on the variable friction coefficient for roadway humidity conditions. The created system includes three elements: a data acquisition module, a data processing module, and a storage and alerting module. The data accusation module consists of automated sensors, including a sensing portion, a radio antenna, a microprocessor, and a battery. Different sensors are installed in the middle or roadside to detect whether a vehicle is coming. A controller collects and manages the detected data from the sensors and transmits it to the intelligent OBU using a multichip data transmission mode. A brilliant base station collects the sensed data from the sensors, examines and transforms it, and provides an alert message to the onboard vehicle unit. The intelligent Unit analyses this information and decides whether the speed is optimal.

D. PROBLEM FORMULATION

This section describes the algorithms for the proposed scheme. There are three algorithms for the proposed model. Algorithm 1 defines the Intelligent Curve Crash Avoidance Scheme, Algorithm 2 defines the Sensing Node Operation, and Algorithm 3 defines Intelligent Unit Operation. In the proposed architecture, the three components, i.e., the data acquisition module α^{acq}_{data}The data processing module β^{p}_{data}And Storage and alerting module γ^{s-a}_{data}. Sensors $(s_1, s_2, s_3 \ldots .s_n)$ sense data from vehicles fitted on the highway passed to α^{acq}_{data}. The collected α^{acq}_{data} is sent as processed to the processing module β^{p}_{data}. Equation 2 use $Y_{estimated}$ to calculate the estimated speed and awareness of the curve crash. The sensed data from equation 2 is passed to the machine learning module. ρ^{γ}_{data}. The final dataset is processed and provides the linear regression-based machine learning model with the ability to pass and respect the practical learning abilities. The data like weather w_iBad Road conditions $r - c_i$, and curves c_i Which causes road accidents and is the essential factor for classification using machine learning modules. All the formulated problems are considered in algorithms 1, 2, and 3 to solve the curve crash problem.

Initially, we set the vehicles $V = v_i, v_2, \ldots .., v_n$ to be used in the environment. These vehicles were driving highly with

TABLE 2. Notations with description.

Notation	Description
GIS	Global Information System for Road Weather Conditions
V_i	Collection of Every sensor data
D	Distance of Vehicle from the crashed curve
R	The curve shows the crash conditions.
V_i^R	The i^{th} the vehicle used in curve crash avoidance and detection.
OBU	The onboard Unit will show the crash curve avoidance notifications.
vd	Vehicular distance to show the actual distance
E	Energy Used in Vehicular Communication.
RSU_{sense}^{data}	RSU senses the data from vehicles to perform sensing operations.
$RSU_{controller}$	Initialize the RCU as the controller to control the curve crash operations through intelligent unit operations.
$PROCESS\_UNIT$	Initialize the processing unit that processes the intelligent operations performed in the proposed methodology.
ML_{Module}	Use a Machine Learning Module to perform ML Operations.
$Y_{estimated}$	$Y_{estimated}$ is the output variable depending upon different inputs ($X_{1,2,3\ldots n}$) and m is the magnitude of input values, and C is the equation constant.
MSE	MSE is used to find the actual and estimated values error. Figure 8 indicates that the error value was calculated using the MSE formula.
α_{data}^{acq}	Data Acquisition Module
$\beta_{data}^{p}.$	Processing Module
$\rho_{data}^{\gamma}.$	Machine Learning Module

the curve on the road. There are multiple attributes associated, such as $\varphi = \{curve_{type}, road_{cond}, road_{width}, curve_{width}, weather_{cond}, vhc_{mass}, speed, disf_{curve}, est_{speed}. Curve_{type}\}$ Shows the type of curve used; here, we have values from 10 to 50 for curve type. $road_{cond}$ Shows the actual road level with values from 4 to 8. $road_{width}$ shows the road width with values 5 to 20, with higher values. $Curve_{width}$ shows an actual curve with values associated with curves to handle the curve crash. $weather_{cond}$ Is it a parameter whose values are captured by a weather sensor and estimated by the machine learning algorithm? vhc_{mass} is another type that shows an actual mass with the load. Vehicle mass defines the solid group associated with the vehicle to deliver the actual performance. $speed$ is another parameter shown to display the speed in Kmph for every individual vehicle. $disf_{curve}$ shows the curve values from 10 to 50 are more diminutive and higher. est_{speed} shows the average estimated speed of every vehicle running on the road.

Based on the VANET configuration, we assume that we have N number of curves, i.e., $M = \{m_1, m_2, m_3 \ldots\ldots, N\}$. Every curve has the following attributes, i.e., $m_j = \left\{C_{type}^{lg}, \xi_w, C_d, V_{qty}^{p}\right\}$. where C_{type}^{lg} is the curve type with length attribute to show for vehicle passing through the curve, ξ_w demonstrates the vehicle passing rates of w_{th} road conditions, C_d Illustrates the total capacity of curve d in the condition. V_{qty}^{p} demonstrates the deployed quality of vehicles and passes through Curve $p$with the same capability to handle vehicles. Each C_{type}^{lg} consists of multiple curves with severe, less severe, and semi-severe conditions to pass multiple vehicles. Each microservice has its database and libraries to be executed during the execution. Due to limited page space, this paper shows a limited description of the notation, and the continuing notations are illustrated in Table 1. Equation 1 shows the vehicle curve decision using the suggested values.

$$\mathrm{D_{ij}} = \begin{cases} 1, & \mathrm{v_i} \leftarrow \mathrm{C_i} \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

Equation 2 shows the vehicle V_i passed from curve C_i. One indicates the positive passthrough of the vehicle through a curve C_i. Zero indicates the accident position of the vehicle through the curve C_i.

$$\sum_{q=1}^{N} \mathrm{D_{ij}} = 0 \cdot\dot{}\, 1 \tag{2}$$

E. ALGORITHM APPROACH FOR 2CAP PROTOCOL

This section describes the algorithms for the proposed scheme. There are three algorithms for the proposed model. Algorithm 1 is generic and explains overall processing. Later, Algorithm 2 describes the sensing operation, while Algorithm tells about intelligent processing and provides decision-making information as mentioned in Algorithms.

F. INTELLIGENT CURVE CRASH AVOIDANCE SCHEME

The overall structure of the proposed system is described in Figure 2. In this figure, different sensors acquire the input data from various sensors and then send it to OBU. The steps in algorithm 1 are as follows.

1. Initialization and Data Sensing:
   a. Activate RSU if the vehicle distance (vd) is less than or equal to 1500m.
   b. Initialize sensing node, capture sensor data, and request data from RSU.
2. Data Transmission and Session Handling:
   a. Send the collected data (I+MSG) to RSU and handle errors by requesting data again.
   b. Expire the session if the vehicle distance exceeds 1500m. Otherwise, continue the data transmission.
3. RSU Controller Activation and Data Collection:
   a. Activate the RSU controller and collect data such as location, distance, speed, curve information, and road weather.
   b. Initialize the RSU processing unit (PU), estimate speed, make speed decisions, and add data to the repository.
4. Controller Activation and Decision-Making:
   a. Activate PU and controller for Onboard Unit (OBU) and make speed decisions based on collected data.
   b. De-activate the RSU controller, display warnings on OBU, and alert the driver.

Algorithm 1 Intelligent Curve Crash Avoidance Scheme

Input: Sensor Data (V_i), *lec*, *long*, Weight (W), Distance (D), Curve (R), GIS (*RoadWeather*).
Process: $EST = F(I)$
Output: *Display EST on Notification Unit*
Steps
1. $if\,(vd \leq 1500m)$
2. $\quad active(RSU)$
3. $initialize \rightarrow sensing\_node()$
4. $while(energy\,(E) \rightarrow remains)$ do
5. $If\,(vd \leq 1500m)$
6. $\quad Active(RSU)$
7. $\quad$ while($capture\ I\ value$)
8. $\quad RSU_{request} \leftarrow data\_sensing()$
9. $session(created)$
10. $\quad Initialize(RSU\ sensors)$
11. $\quad notify(OBU\ sensor)$
12. $\quad request(GPS\ data)$
13. $Data \leftarrow I + MSG$
14. $MSG \leftarrow$ "*Datasend*"
15. $if\,(error)$
16. $Request - again()$
17. *else*
18. $Session(expire)$
19. *else*
20. $\quad Sleep$
21. *End while*
22. Activate $\leftarrow RSU_{controller}$
23. Sense $\leftarrow RSU^{data}_{controller}$
24. $send(long, lat, distance, speed, R, RC)$
25. $RWIS_{send}(visibility, humidity, weather - data)$
26. $OBU_{send}(mass, VI, light - condition)$
27. $GIS_{sends}(type, Curve - width)$
28. $RSU_{initialize} \leftarrow ProcessingUnit(PU)$
29. $\quad PU_{RSU} \leftarrow Activate()$
30. $\quad computer_{PU} \leftarrow Estimate_{speed}$
31. $\quad Decide - speed()$
32. $\quad add_{repository}()$
33. $\quad send\ (data) \rightarrow controller$
34. $Activate(PU)$
35. $Controller_{OBU}()$
36. $decision_{speed}()$
37. De-activate $\leftarrow RSU_{controller}$
38. $Display_{warning}(OBU)$
39. $Alert_{OBU}(driver)$
40. *End*

G. SENSING NODE OPERATION

Algorithm 2 describes the sensing node's operations in detail. As RSU demands the sensor data, the sensor starts detecting for a specific period. The gathered data then shift to RSU, and sensors change their state to sleeping mode to save energy. The below steps explain algorithm 2.

1. Initialization and Sensing Node Setup:
   a. Initialize the sensing node and start a timer for sensing operations.
   b. Begin sensing using the sensor until the timer expires or sensing fails.
2. Data Transmission and Alert Handling:
   a. If sensing is successful, generate data (I+MSG) and transmit it to the RSU.
   b. If sensing fails, generate an interrupt, alert the RSU, and activate sleep mode.
3. Sleep Mode Activation:
   a. Activate sleep mode to conserve energy and pause sensing operations.
   b. End the sensing node operation.

Algorithm 2 Sensing Node Operation

Input: Sensor Data (V_i), *lec*, *long*, Weight (W), Distance(D), Curve (R), GIS (*Road Weather*).
Output: *Sensing Node Operation*
Steps
1. Start
2. while(RSU^{data}_{sense}) do
3. $Initialize \rightarrow Sensor_{Node}$
4. $\quad start\_timer(T)$
5. $\quad start_{sensing}\ (sensor)\ toExpire_{time}$
6. $\quad if\,(sensing == fail)$
7. $\quad generate(interrupt)$
8. $\quad Send_{alert} \leftarrow RSU$
9. else
10. $\quad generate_{data}$
11. *When*
12. $\quad Data \leftarrow I + MSG$
13. $\quad MSG \leftarrow$ "*datasense successfully*"
14. $\quad Transmit_{data} \rightarrow RSU'$
15. $\quad start\_timer(T)$
16. End while
17. $Activate^{Mode}_{Sleep}()$
18. End;

H. INTELLIGENT UNIT OPERATION

In Algorithm 3, the RSU sends the variable information to the intelligent Unit (IU) for speed calculation. The IU directs the sensor information as an input variable to machine learning models and initializes the model for speed calculation. The model (Linear Regression) used these input values and their intelligence (pre-training) to estimate safe speed. If the estimated speed is more significant than the vehicle speed, the IU adds this information into the repository and aborts the process. If the calculated system speed is less than the vehicle's, the Unit generates a speed warning to the RSU unit. After sending the notification, it added speed to the dictionary. The intelligent unit processing aborted. The below steps explain the algorithm 3.

1. Initialization and Machine Learning Module Activation:

   a. Initialize the RSU controller's PROCESS_UNIT and activate the Machine Learning (ML) module.
   b. Set parameters (LR, MSE, r^2), fetch values from the repository, and start the training process with linear Regression.
2. Speed Estimation and Repository Management:
   a. Calculate Estimated Speed ($Speed_E$) using the trained model, compare with the actual speed (V_i).
   b. Add data to the repository, and if the estimated speed is less than the actual speed, abort the process; otherwise, generate an alert, send data to RSU, and repeat the loop.
3. Deactivation and Process Completion:
   a. De-activate the process until further input.
   b. End the unit operations for intelligent management.

Algorithm 3 Intelligent Unit Operation

Input. Sensor Data (V_i) lec, long, Weight (W), Distance(D), Curve (R), GIS (Road Weather).
Output. *Unit Operations for Intelligent Management*
Steps
1. $RSU_{controller} \rightarrow Init_{PROCESS\_UNIT}$
2. $PROCESS\_UNIT(initialized)$
3. while $(estimated_{speed})$ do
   a. $PROCESS\_UNIT \leftarrow Cache\_value$
   b. $Activate \rightarrow ML_{Module}$
   c. $init_{parameters}(LR, MSE, r^2)$
   d. $fetch_{value}(repository)$
4. **Start Training Process:**
5. $Linear - Regression(Model) \leftarrow Training$
6. $Continue - Complete - Iterations()$
7. $Training - Stop()$
8. **Calculation-E-Speed**
9. $if\,(Speed_E < V_i)$
10. $add_{repository}()$
11. $process_{abort}()$
12; else
13. $add_{repository}()$
14. $alert_{generate}()$
15. $send() \rightarrow RSU_{controller}$
16. End Loop;
17. $Process() \rightarrow Deactivate_{until}()$
18. End;

I. TIME COMPLEXITY OF PROPOSED METHOD

The Proposed Method worked on multiple components like Intelligent Curve Crash Avoidance Scheme, Sensors Node Operations, Intelligence Unit Operations, Machine Learning, and Resource Matching. All these components are treated separately to utilize the time complexity of these components. (1) Intelligent Curve Crash Avoidance Scheme: We expect that any curve is avoided and detected using LR, AHP, and TOPIS methods for curve avoidance. The computed time complexity of the Intelligent Curve Crash Avoidance Scheme is $O(ExT)$. E is the Curve Crash Avoidance Scheme sensing criteria, and T is OBU's estimated curve handling technique. (2) Sensors Node Operations: In node sensing using vehicle sensors, the RSU demands the sensor's data, and the sensors detect and send data to the RSU for a specific time. The gathered data then shift to RSU, and sensors change their state to sleeping mode to save energy by using $O(mlogn)$. N is the number of sensor nodes, and M is the exploited method to get energy and generate messages. (3) Intelligence Unit Operations: All the RSUs and Vehicles are scheduled for speed computations. IU is used to compute the speed and check for the ML module. However, the time complexity we have measured is $O(logM).O(logM) + N$. This time complexity is for all IUO servers according to their descending order of price and load for the sensing process. Nshows the tasks swapping process in the time complexity of the different ML training processes. (4) Machine Learning and Resource Matching: The ML operations using LR for the proposed sensor nodes data are predicted to avoid any curve through the proposed system. The time complexity for the Machine Learning and Resource Matching for the proposed system is $O\,(MLxR)$.

IV. PERFORMANCE EVALUATION

To evaluate the performance of proposed systems using the Intelligent Curve Crash Avoidance Scheme, Sensing Node Operation, and Intelligent Unit Operation, we generate a practical dataset, and results are captured using a Linear regression-based application. Table 3 defines the stimulation parameters with their description.

TABLE 3. Simulation parameters.

S.No.	Parameters	Used Values
1	Windows OS	LINUX OS
2	Language	Python 3.6, JAVA, XML
3	Processor	X64 bit
4	Platform	Google Collaboratory
5	Simulation Time	14 Hours
6	Simulation Repetition	180 Times
7	Instance	12 GB NVIDIA Tesla K80
8	Libraries Used	TensorFlow, Karas, Cuda, matplot
9	Sensors Used	Accelerometer, RWIS Sensors, GPS, GISR, Light Visibility.
10	Service	ML-based system
11	$B_{MCC}^{wj(up)}$	50 ≈ 1200 Mbps
12	$B_{MCC}^{wj(down)}$	1200 ≈ 50 Mbps

	A	B	C	D	E	F	G	H	I
1	curve_type	road_condition	road_width	curve_width	weather_cond	vhc-mass	speed	disf_curve	est_speed
2	12	8	5	5	8	2268	51	15	30
3	48	6	10	10	6	750	53	50	31
4	40	4	20	20	4	500	55	45	32
5	32	4	20	20	4	500	57	35	33
6	36	4	20	20	4	4523	59	41	34
7	27	4	20	20	4	500	60	30	34
8	30	8	5	5	8	4523	62	50	33
9	30	8	5	5	8	2268	64	32	35
10	30	8	5	5	8	1500	66	30	36
11	12	8	5	5	8	2268	68	15	33
12	48	6	10	10	6	750	70	50	35
13	40	4	20	20	4	500	71	45	38
14	30	8	5	5	8	4523	95	50	42
15	30	8	5	5	8	2268	97	32	42
16	30	8	5	5	8	1500	99	30	43
17	12	8	5	5	8	2268	100	15	45
18	48	6	10	10	6	750	102	50	45
19	40	4	20	20	4	500	104	45	47
20	32	4	20	20	4	500	106	35	47
21	36	4	20	20	4	4523	108	41	48

FIGURE 3. Dataset with variables.

Based on the parameters in Table 3, the simulation results are gathered using four distinct parts. (1) Sensor implementation part, (2) Dataset Generation and Preprocessing Part, (3) ML-based Linear Regression Implementation framework, and (4) Algorithms Comparison and Results generation part. The next section describes the sensing nodes used in the research to effectively detect the Curve Crash Avoidance Protocol to handle Curves in Vehicular Ad-Hoc Networks.

A. SENSING MODULES

A sensor is a device that detects environmental changes and transmits them to the system in a human-readable form to be used for future decisions.

B. ACCELEROMETER

An accelerometer is a sensor used to measure the acceleration of a vehicle. The vehicle's acceleration depends on the rest or motion of the body, while coordinate acceleration depends on body coordinates. This sensor is attached near the vehicle's wheel and calculates the acceleration using tire movement. This sensor helped us to find the actual speed of the vehicle.

C. RWIS SENSOR

Federal Highway Administration Authority USA reports that 1.4 million highway crashes occur yearly under worse conditions. Sometimes, the weather has a significant impact on road conditions. The sensor must get a different weather condition factor for real-time results. These sensors provide weather conditions like wet, icy, snowy, flooded, and light visibility. This sensor is installed on the roadside unit (RSU) and sends data to the processing unit [33].

D. GLOBAL POSITIONING SYSTEM SENSORS

The type of sensor in a satellite-based navigation system uses 24 satellites revolving around the orbits to provide the earth with position, velocity, and timing information [34].

E. GLOBAL INFORMATION SYSTEM REMOTE SENSING

This type of sensor provides us with a continuous and constant source of information about the earth. GIS gives us a complete analysis of the earth's surface and information on many things' functionalities for our understanding. These types of sensors give us accurate information about a vehicle and geometrics statistics of the curve. This analysis is helpful for decision-making for road safety and saving lives [35].

F. LIGHT VISIBILITY SENSOR

Light visibility sensor finds the intensity of atmospheric transparency and convert it to range in many human forms so that human eyes can see maximum distance. They offer a regular process for assessing visibility range when compromised by fog, cloud, smoke, snow, or other rainfall. Uses for visibility sensors include road condition evaluations [36].

G. DATASET DESCRIPTION

We required specific parameters to perform experiments over linear Regression and machine learning to construct labeled training and testing datasets. As we work on a novel technique to solve curve crash parameters, getting a parameterized dataset for a specific problem is challenging because little or no work has yet been done on the defined issue in VANET. All the required attributes are listed in Figure 3. The required dataset contains all the variables of our interest. In the dataset, we use 15,000 rows of data with parameters like *curve_type*, *road_condition*, *road_width*, *curve_width*, *weather_cond*, *vhc − mass*, *speed*, *dist_curve*, *est_speed*. The parameters are labeled according to the problem and machine learning model. Also, it requires too many resources and time to collect real-time data, so managing such a dataset in real-time was impossible. Therefore, we get the required dataset from authentic and precompiled datasets already available on Kaggle.

1) DATASET DETAIL

The different variables used in the above dataset are explained in Table 3. The curve type is described in Table 4. The critical Curve indicates that the curve is dangerous and has a sharp turn. At the same time, the critical curve represents the curve angle between 11-45 degrees and a critical turn. The average and very good indicated a standard curve.

TABLE 4. Different curve type.

Curve Type		
Severity	Curve Angle	Dataset Value
Very Critical	10 Degree	40-52
Critical	45 Degree	27-39
Normal	100 Degree	13-26
Very Good	150 Degree	0-12

2) ROAD CONDITIONS

The road condition with different severity levels is clarified in Table 5. The terrible road condition indicates that the road is dangerous to ride. Bad situations also mean lousy road conditions, while ordinary and excellent conditions imply exceptionally smooth and rutted roads.

TABLE 5. Parameters used for road conditions.

Road Condition		
Severity	Road Condition	Dataset Value
Very Critical	Tracks	7-8
Critical	Muddy	5-6
Normal	Patched	3-4
Very Good	Smooth	1-2

3) ROAD WIDTH IN RANGE

Table 6 describes the road width variable as the data limits. The mountain and rural roads have minimal widths ranging from 2 to 12 meters. At the same time, highway roads have multiple road lines and have a width of 19-25 meters.

TABLE 6. Road width in range in meters.

Road Width		
Severity	Road Type	Dataset Range(meters)
Mountain	Tracks	2-6
Rural	Two Way Road	7-12
Urban's	One Way Road	13-18
Highways	Multi-Lane Road	19-25

4) WEATHER CONDITIONS

The weather condition variable has different attributes that are described in Table 7. The awful weather conditions are foggy, and the line of sight is poor. Bad conditions also indicate rainy weather, while normal and good weather conditions indicate an excellent line of sight.

TABLE 7. Weather condition parameters.

Weather Condition		
Severity Level	Weather Type	Dataset Value
Very Bad	Foggy	7-8
Bad	Rainy	5-6
Normal	Sunny	3-4
Very Good	Pleasant	1-2

5) VEHICLE WEIGHT

The vehicle weight has the following severity points described in Table 8. The table represents vehicle types, from cumbersome to lightweight vehicles, based on their weight.

TABLE 8. Vehicle weight description.

Vehicle Weight		
Vehicle Type	Category	Dataset Value
Very Heavy	Type O	2269-4536
Heavy	Type N	1589-2268
Normal	Type M	906-1588
Light Weight	Type S	500-905

6) CURVE WIDTH

The curve condition has the following attributes in Table 9 on the next page. Different curve conditions regarding their difficulty level are explained here. The extreme and critical curve level describes the very high difficulty level. At the same time, inadequate and typical represents the average difficulty level.

TABLE 9. Curve width detail.

Curve Width		
Severity	Curve Type	Dataset Value
Extreme	Deviation Curve	16-20
Critical	Reverse Curve	11-15
Bad	Compound	6-10
Normal	Simple Curve	0-5

7) VEHICLE SPEED

The actual speed of vehicle capture from the sensor is explained in Table 10. The extreme speed limits indicate the

TABLE 10. Vehicle speed(km/hr).

Vehicle Speed		
Severity	Speed Range	Dataset Range (Km/h)
Extreme	Over 80	81-100
Fast	Over 60	66-80
Normal	Over 50	51-65
Ideal	Blow 50	30-50

vehicle's excessive speed could cause damage. In comparison, fast speed indicates a vehicle's speed is over 60 km/h. The ideal speed is less than 50 for the vehicle in the curve area.

8) CURVE DISTANCE

The vehicle's distance from the curve is the distance (Meter) of the automobile from the angle explained in Table 11. The sensor calculates this to represent the vehicle's distance from the angle. The within 25 meters indicates the vehicle is very close to the curve, while over 45 means the vehicle is far away from the curve area.

TABLE 11. Distance from curve (meters).

Curve Distance		
Severity	Representation	Dataset Range (Meters)
Closest	Within 25	15-25
Close	Over 25	26-35
Away	Over 35	36-45
Far Away	Over 45	46-55

Table 12 describes the overall summary of the dataset values and their actual resource specification of the LR-based algorithms. It describes dataset descriptions and their implementations.

TABLE 12. Dataset description summary and cost.

Dataset Parameters	$T_{w,i}$(MB)	Communication Cost	N
Curves	40.2	4G:0.7$	650
Raod Conditions	31.2	3G:2.5$	790
Road Width	25.1	4G:1.5$	650
Weather Conditions	52.8	5G:5$	900
Vehicle Weight	16.5	5G:2.6$	830
Curve Width	24.8	3G:2.5$	700
Vehicle Speed	64.3	3G:2.5$	560
Curve Distance	36.3	3G:2.5$	900

H. COMPARISON FRAMEWORK AND APPROACHES

The obtained results are compared with existing approaches for final active considerations. The below-mentioned considerations are made to compare the results and design the hypothesis.

- **Hypothesis-1/Baseline-1:** We implement the VANET-based Python Linear Regression Framework and implement the proposed model. We use linear regression (LR) to calculate the estimated speed for the vehicle using defined parameters in section B's dataset description. The studies have implemented the [comparison papers 2] frameworks for testing results. The hypothesis aims to train the LR model over 1800 dataset samples to find the relationship between the variables.
- **Hypothesis-2/Baseline-2:** The system is trained and tested on a Google Collaboratory instance because the model requires enormous computation time. Different mechanical sensors are embedded in the onboard Unit, gathering information about the vehicle and road environment. The adopted strategies are] [39], [40] used to test and compare the testing results. The aim is to sense the road conditions and apply the Intelligent model to avoid road accidents in the proposed system. Accident avoidance is based on variable resources.

I. PERFORMANCE METRICS

This paper's experimental results show the implementation components for the proposed solution. Table 2 describes the components' collaboration with parameters and values to be used in the implementation. In this experiment, we take the dataset described in Figure 3, and its attributes are defined in the "Dataset Description" section. Every vehicle that passes from high should handle the curve severity. Equation 3 shows the experimental setup in VANET with curve avoidance and processing ratio.

$$\mathrm{V_d^{a,i}} = \mathrm{P_{a,i}} + \gamma + \mathrm{P_{a,i}} \tag{3}$$

The vehicle reached the deadline to curve for $V_d^{a,i}$ They were required to cross the curve and check the early prediction of curve values. γ depicts the early prediction of crash avoidance on curves using LR with values of 0.2, 0.4, 0.6, 0.8, and 1. These show the different prediction results, with 0.2 lowest prediction and 1 with the highest predicted values, i.e., $\gamma 1$, $\gamma 2$, $\gamma 3$, $\gamma 4$, and $\gamma 5$. The algorithm performance is evaluated using equation 4, and we verify the algorithm performance throughout the performance metrics. Relative

Percentage Division (RPD) statistical analyses are performed to compute the recital division method. Equation 4 defines the RPD estimation for the proposed technique.

$$\mathrm{RPD}(\%) = \frac{\mathrm{V_a^*} + \mathrm{V_a}}{\mathrm{V_a^*}} \times 100\% \tag{4}$$

where, V_a shows the objective function.

J. 2CAP IMPLEMENTATION

We use ML-based IDE PyCharm Community Edition to set up the environment on the intel core i7 10^{th} Generation system. Figure 4 shows the implementation description of the experimental setup with application and scenario. Initially, we imported the libraries for linear regression: NumPy and matplotlib. After implementing the libraries, the dataset is imported into the implementation with the main components. The standardization process is performed on the dataset with unit standard deviation. The standardization in this model is performed using Equation 5.

$$\frac{x - \mu}{\sigma} \tag{5}$$

After the effective standardization, the parameters are utilized from the dataset, as mentioned in Figure 3. At first, we deal with feature vectors; secondly, we deal with weights or parameters. The dependent and independent parameters are selected from the 1800 lines of the dataset.

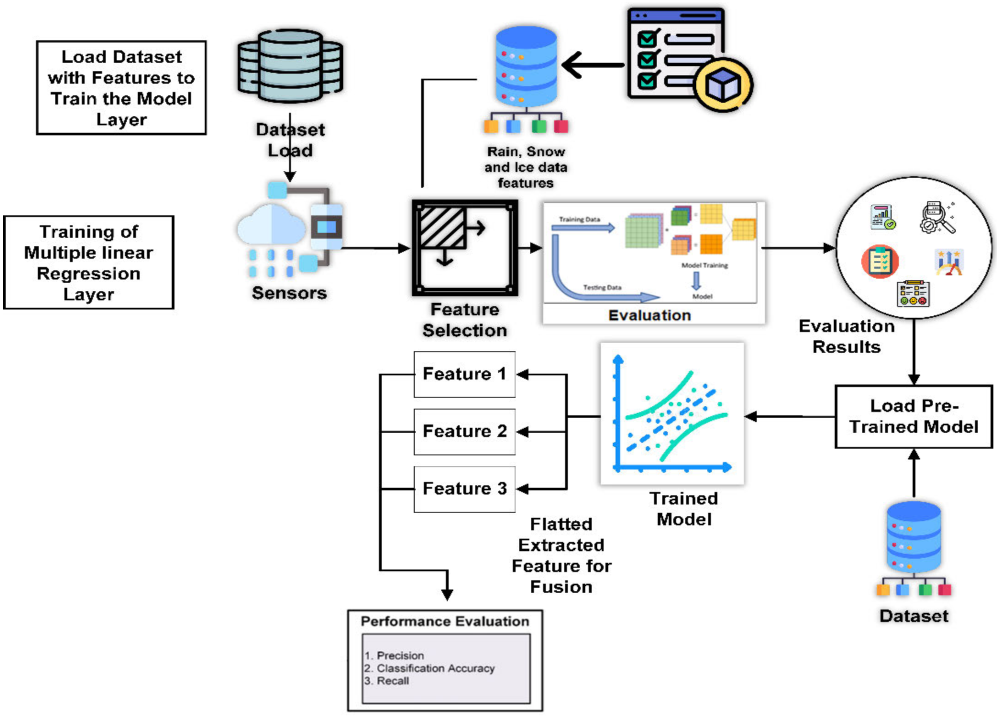


FIGURE 4. Proposed LR-based model implementation.

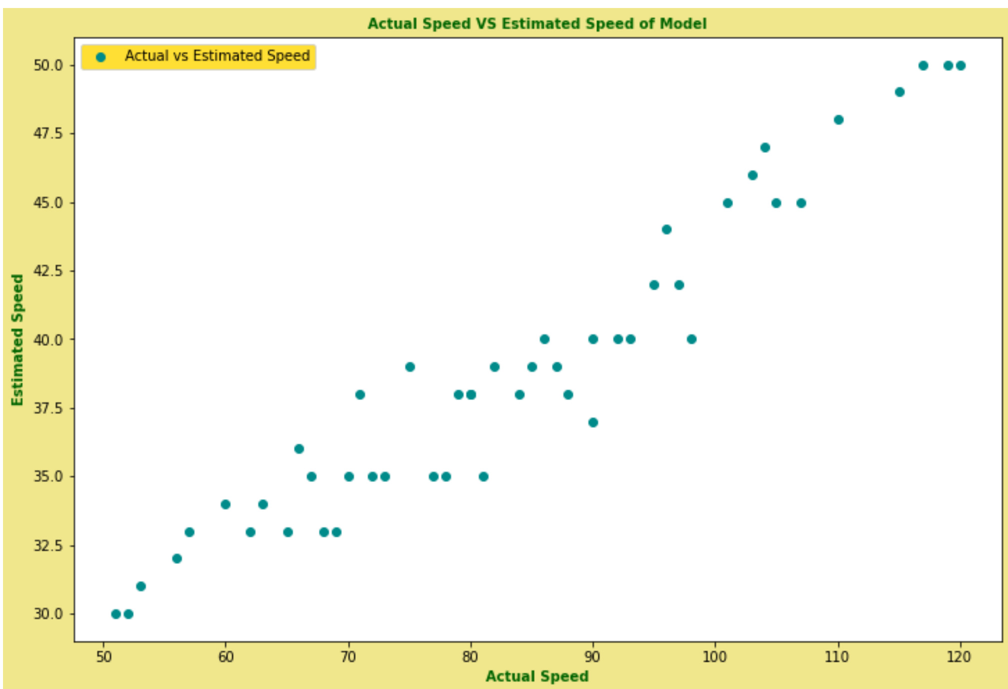


FIGURE 5. Actual speed and estimated speed using linear regression.

K. SPEED ESTIMATION USING LINEAR REGRESSION

In this section, we will describe the results of my experiment using Python development. We use Linear Regression (LR) to calculate the estimated speed for the vehicle using various parameters. For this, we used 1800 dataset examples. The LR is used for finding the relationship between variables. The

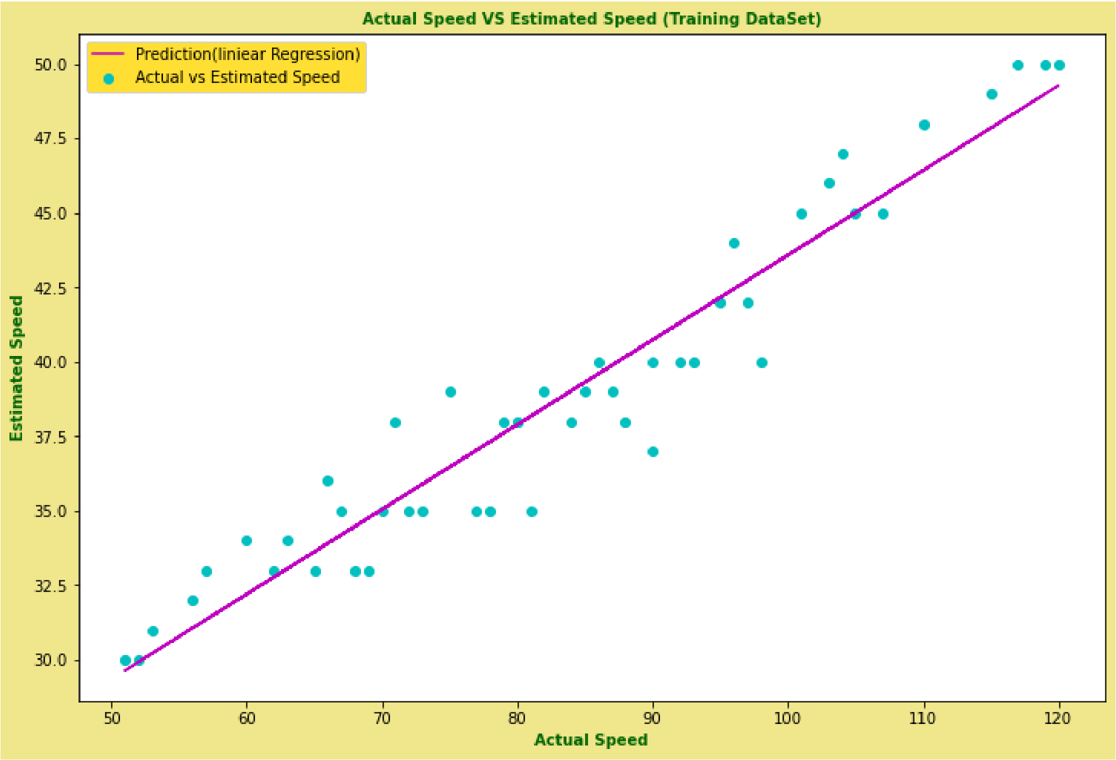


FIGURE 6. Linear regression graph for training dataset.

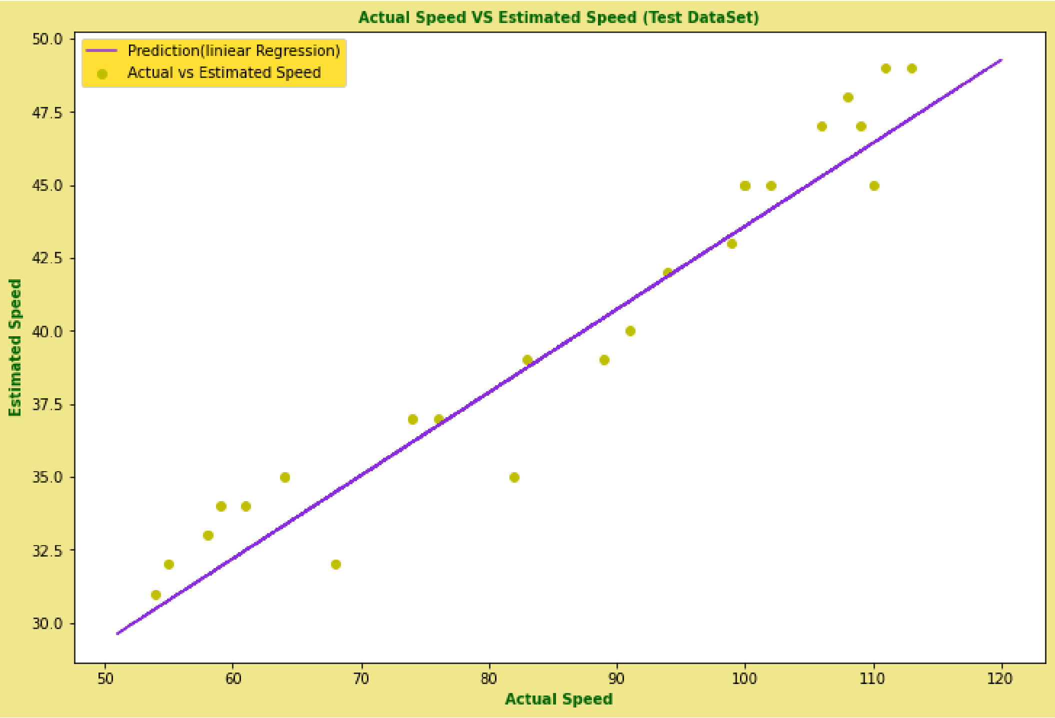


FIGURE 7. Linear regression graph for test dataset.

dependent variables need to be estimated, and independent variables are used for calculation. In our data, the dependent variable is est_{speed}, calculated using different variables. These variables are $curvetype$, $road\_condition$, $road\_width$, $curvewidth$, $weather\_cond$, $vhc - mass$, $speed$, $disf\_curve$. By using these variables, we calculate the safe speed for the vehicles. With the regression model, we are trying to find the estimated speed using the Linear Regression relationship represented in Equation 6.

$$\mathrm{Y_{estimated}} = \mathrm{mX_{actual}} + \mathrm{mX_{c_{type}}} + \mathrm{mX_{r_{condition}}} + \mathrm{mX_{road\_curve}} + \mathrm{mX_{curve_{width}}} + \mathrm{mX_{weather\_cond}} + \mathrm{mX_{vhc\_mass}} + \mathrm{mX_{disf\_curve}} + \mathrm{C} \tag{6}$$

$Y_{estimated}$ is the output variable depending upon different input ($X_{1,2,3.....n}$) and m is the magnitude of input values, and C is the equation constant. The actual speed and its estimated speed are shown in Figure 5.

Figure 6 highlights the actual speed and the estimated speed for different scenarios. Figure 6 also indicates that the estimated rate is mostly less than the actual speed. Our proposed model notified vehicle OBU to reduce the speed.

According to the calculated speed in this scenario. If the actual rate exceeds the estimated speed, the proposed system ignores it and sends no notification or warning.

Figure 7 shows the relationship between actual speed and estimated speed. The graph shows a linear relationship between actual speed and predicted speed. It also highlights that most value lies near our Linear Regression line. In Figure 7, the actual speed is independent, and the estimated speed is a dependent variable. The relationship between these variables is positive. The best-fit line is our regression line that fits the data into the best possible connection.

Figure 7 indicates the relationship between the actual and predicted speed for the test dataset. The linear regression line shows that most data lie around the prediction line. The positive relationship and most predicated speed value best fit the prediction line.

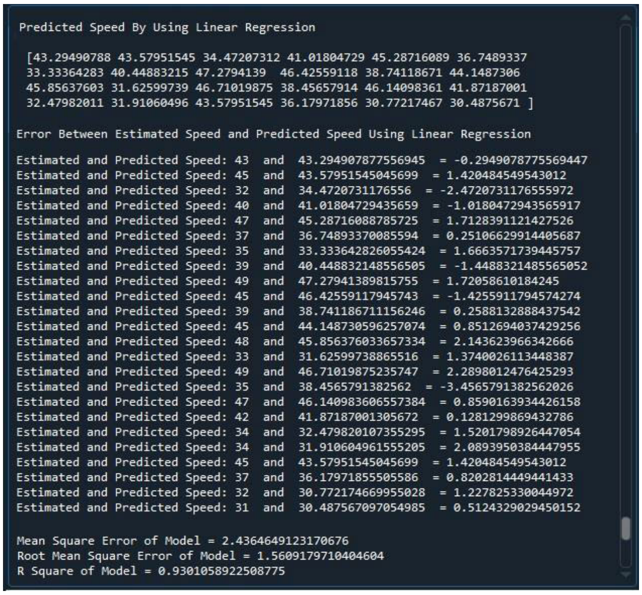
L. MEAN SQUARE ERROR (MSE)

The Mean Square Error is the difference of the average between actual results and predicted results for the output. The Mean Square Error tells us how the regression line best fits the dataset value. It is estimated by finding the data point's distance from the regression line and taking its square. Mathematically, MSE for our proposed model is calculated using the formula shown in Equation 7.

$$\mathrm{MSE} = \frac{1}{\mathrm{n}} \sum_{\mathrm{i=1}}^{\mathrm{n}} ((\mathrm{Actual} - \mathrm{Speed}) - (\mathrm{Predicted} - \mathrm{Speed}))^2 \tag{7}$$

Linear Regression calculates the predicted speed, and MSE is used to find the error between the actual and estimated values. Figure 8 indicates the importance of error computed using the MSE formula. First, it shows the estimated speed value and calculates the MSE from our

Actual and predicted values. The Root Mean Square Error for our proposed model is 2.436. The small value of RMSE indicates that the error value is minimal, and our model predicts accurately. Our proposed system calculated the predicted speed efficiently using different input variables. The proposed system achieved the MSE of 2.45 and R^2 of 0.93 for the experiment. The MSE of 2.45 indicated that the actual and predicted value difference is very low, and our model perfectly predicts the estimated speed. The R^2 Near one indicates that our model best fits the training data and correctly predicts the output. Table 13 provides the results in numbers or metrics for the results achieved.



```
Predicted Speed By Using Linear Regression

 [43.29490788 43.57951545 34.47207312 41.01804729 45.28716089 36.7489337
 33.33364283 40.44883215 47.2794139  46.42559118 38.74118671 44.1487306
 45.85637603 31.62599739 46.71019875 38.45657914 46.14098361 41.87187001
 32.47982011 31.91060496 43.57951545 36.17971856 30.77217467 30.4875671 ]

Error Between Estimated Speed and Predicted Speed Using Linear Regression

Estimated and Predicted Speed: 43  and  43.294907877556945  = -0.2949078775569447
Estimated and Predicted Speed: 45  and  43.57951545045699  = 1.420484549543012
Estimated and Predicted Speed: 32  and  34.4720731176556  = -2.4720731176555972
Estimated and Predicted Speed: 40  and  41.01804729435659  = -1.0180472943565917
Estimated and Predicted Speed: 47  and  45.28716088785725  = 1.7128391121427526
Estimated and Predicted Speed: 37  and  36.74893370085594  = 0.25106629914405687
Estimated and Predicted Speed: 35  and  33.333642826055424  = 1.6663571739445757
Estimated and Predicted Speed: 39  and  40.448832148556505  = -1.4488321485565052
Estimated and Predicted Speed: 49  and  47.27941389815755  = 1.72058610184245
Estimated and Predicted Speed: 45  and  46.42559117945743  = -1.4255911794574274
Estimated and Predicted Speed: 39  and  38.741186711156246  = 0.2588132888437542
Estimated and Predicted Speed: 45  and  44.148730596257074  = 0.8512694037429256
Estimated and Predicted Speed: 48  and  45.856376033657334  = 2.143623966342666
Estimated and Predicted Speed: 33  and  31.62599738865516  = 1.3740026113448387
Estimated and Predicted Speed: 49  and  46.71019875235747  = 2.2898012476425293
Estimated and Predicted Speed: 35  and  38.4565791382562  = -3.4565791382562026
Estimated and Predicted Speed: 47  and  46.140983606557384  = 0.859016393442615
Estimated and Predicted Speed: 42  and  41.87187001305672  = 0.1281299869432786
Estimated and Predicted Speed: 34  and  32.479820107355295  = 1.5201798926447054
Estimated and Predicted Speed: 34  and  31.910604961555205  = 2.0893950384447955
Estimated and Predicted Speed: 45  and  43.57951545045699  = 1.420484549543012
Estimated and Predicted Speed: 37  and  36.17971855505586  = 0.8202814449441433
Estimated and Predicted Speed: 32  and  30.772174669955028  = 1.227825330044972
Estimated and Predicted Speed: 31  and  30.487567097054985  = 0.5124329029450152

Mean Square Error of Model = 2.4364649123170676
Root Mean Square Error of Model = 1.5609179710404604
R Square of Model = 0.9301058922508775
```

FIGURE 8. Mean square error value calculation for our proposed model.

TABLE 13. Units for magnetic properties.

S.No	Metrix	Value
1	Accuracy	98.5%
2	MSE	2.45
3	R^2	0.93

Figure 9 shows the graphical representation of MSE. The green line indicates the actual speed value for our proposed models, the blue dot shows the estimated speed values for our system, and the red line between the best-fit line (blue line) and the estimated value (green dots) shows the error from the best fit.

The smaller the MSE, the closer we find the best-fit line for our data. As the data is real-time, it is very scattered, and gaining this small amount of MSE indicates that our model finds the best-fit line.

M. ROOT SQUARE ERROR (R^2)

The goodness of the proposed model Root Square is how the regression line fits over a set of observations. Finding the best-fit model is called optimization, which can be achieved by the Root Square Method. It measures the strength of the relationship between independent and dependent variables on a scale of 0 to 100. The higher value of R^2 more negligible difference between predicted and actual value. Our proposed

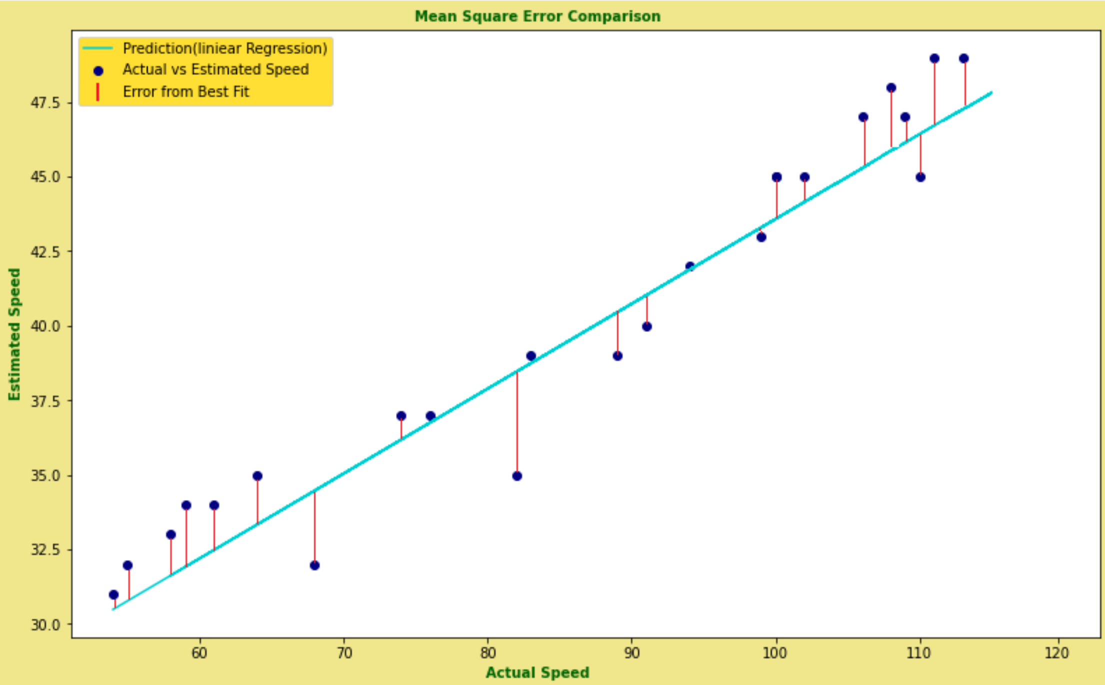


FIGURE 9. The graphical representation of mean square error.

model value is 0.93, which is closely near to 1. It means our proposed model has expected a good result. Our model best fits test data that is never random observations after training data set values.

V. CONCLUSION, LIMITATIONS, AND FUTURE WORK

A. CONCLUSION

The 2CAP Curve Crash Avoidance Protocol represents a significant advancement in Vehicular Ad-Hoc Networks (VANETs) by introducing an innovative approach to mitigate curve crashes. Our protocol focuses on providing real-time warning alerts in curved areas, enhancing safety and ultimately preserving human life. Using Vehicle-to-Infrastructure (V2I) communication and a network of sensors, our research identifies crucial factors influencing curve crashes and establishes advisory speed limits. The protocol's effectiveness lies in its ability to process vehicle-related data, calculate estimated speeds using Linear Regression, and trigger timely alerts to onboard units for speed adjustment. The proposed scheme, encompassing Information Acquisition, Processing, and Storage, offers a comprehensive solution to the challenges of curve crashes. By addressing the unique geometric characteristics of curves and leveraging intelligent control units in both Onboard Units (OBUs) and Road-side Units (RSUs), our research aims to significantly reduce personal and social damages associated with curve crashes. The anticipated impact of this novel protocol extends beyond individual safety, contributing to the broader goal of minimizing the future economic and societal costs linked to curve-related accidents.

B. LIMITATIONS

The research limitations are.

- The research may be constrained by a lack of extensive real-world testing, limiting the ability to validate the effectiveness of the 2CAP protocol in diverse and complex driving scenarios.
- The proposed Curve Crash Avoidance Protocol heavily relies on sensor data from onboard units, and limitations in accurately sensing and responding to rapid environmental changes (e.g., sudden weather changes and road conditions) could impact the protocol's reliability.
- While the abstract mentions using a secure communication channel for data exchange between sensing nodes and roadside units, the specific security measures, potential vulnerabilities, and the impact of malicious attacks on the protocol's functionality are not thoroughly explored.
- The use of Linear Regression as the machine learning technique may have limitations in handling the complexity of various driving scenarios, and the model's generalization ability across diverse road conditions and driving behaviors is a potential concern.
- The abstract does not explicitly address the scalability of the proposed system, and limitations related to the scalability of the Curve Crash Avoidance Protocol in a larger vehicular network context are not discussed.

The 2CAP protocol can be applied in real-world scenarios to significantly reduce road departure crashes on curved roads. By integrating the Intelligent Curve Crash Avoidance Algorithm and utilizing multiple sensors, Global

Positioning Systems, and Global Information Systems, the protocol enhances driver safety through intelligent decision-making and notification mechanisms, ultimately preventing disastrous crashes and saving lives on curved roads in Vehicular Ad-hoc Networks.

C. FUTURE WORK

The 2CAP framework for VANET and vehicles will be investigated using Artificial Neural Network (ANN) in the future. Our plans will use a system to use real-time data that allows it to respond according to the situation, saving valued time, cost, and more critical human lives.

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