Novel Crash Prevention Framework for C-V2X using Deep Learning

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***Abstract*—Crash Risk (CR) prediction is essential for Intelligent Transport Systems(ITS), particularly for vehicular users' safety. The rapid development in multivariate deep learning techniques and the emergence of Vehicle to Everything (V2X) communication make it possible to predict CR in smart cities more quickly and precisely. Currently, CRs are predicted using Time-To-Collide, which depends on various interaction data of two conflicting entities. We inspect several factors affecting the CR, like speed, acceleration, Deceleration Rate to Avoid Crashes (DRAC), and Post Encroachment Time (PET). We develop a multivariate LSTM and RNN-ATT model to predict crashes that may occur within the next three seconds based on the past seven seconds of vehicle data. It is simulated on high-density roads of the Ahmedabad city map generated using the Open Street Map. The proposed framework coupling SUMO as traffic simulator and NS-3 as network simulator results in an optimal prediction horizon of 3s with a Root Mean Squared Error of 0.0611. The finding of this paper indicates the promising performance of the proposed framework and LSTM model with an accuracy of 88.20% to deploy in the Indian ITS for real-time crash prevention.**

***Index Terms*—Crash Risk Prediction, Collision Prevention, SUMO, ns-3, multivariate-LSTM, RNN-ATT**

I. INTRODUCTION

Every year around 1.3 lakhs deaths are caused by hazardous road crashes in India [1]. Road safety is a high priority for Indian transportation. Connected Vehicle Environment(CVE) advancement is considered a boon for road users. Many pieces of literature have shown that CVE data greatly improve road safety by identifying hazardous road crashes [2]- [3]. Researchers have been working on Proactive Traffic Safety Management (PTSM). It is a method to prevent crashes and take active countermeasures based on crash risk prediction in real time using uni-variate long short-term memory (LSTMs), and Multi-Layer Perceptron models [4]- [6]. Past studies have been conducted on crash detection [7] and crash severity and evaluated safety-related anomalies based on different thresholds of time-to-collide (TTC). TTC is a well-known surrogate safety measure (SSM) to assess crash potential, which has been employed as a threshold for collision detection [8]. Systems like forward collision warning systems, lane changing warning systems, and advanced driving assistance systems (ADAS) have been developed to continuously measure the SSMs using in-vehicle distance sensors like radar and lidar. These solutions have limitations when there is a Non-Line of Sight (NLOS). Some of the in-vehicle systems collect hazardous crash information and transmit warnings to the adjacent vehicles through Vehicle to Vehicle (V2V) and Vehicle to Infrastructure (V2I) [9]. In addition, studies have been conducted to enhance road safety using fuzzy logic approaches and extreme value theory approaches [10]– [11].

From the viewpoint of Indian traffic, passengers with heavy vehicles are better subjects for implementing advanced autonomous solutions for accidental risk prediction and enhancing road safety. Hence, encouraging partial CVE in India would be the first step towards PTSM where all the heavy vehicles communicate directly on the road, typically equipped with 3rd Generation Partnership Project (3GPP) Cellular Vehicle-to-Everything (C-V2X) standard transmission capabilities [12]. The 3GPP standard was released in 2017(Rel. 14), replacing the WiFi-based IEEE 802.11p standard for vehicle communication. Using C-V2X LTE (Long-Term Evolution) PC5 communication can save more fatalities and severe injuries than using IEEE 802.11p (DSRC), according to a study [13] that compares these two. It is because C-V2X communication is more reliable and enables the omnidirectional sharing of safety messages and vehicle information, such as speed and location, using a V2V connection. In [26], they have introduced open-source analytical models for C-V2X mode 4. It is for reliability, and various transmission errors in C-V2X mode 4 are developed and validated for a wide range of transmission parameters and traffic densities.

Generating warning information for drivers is one of the most effective active countermeasures, as it encourages them to take good evasive actions to prevent crashes. For such effective PTSM, an optimal prediction model should be used for delivering in-vehicle warning alerts with high accuracy and reliability to reduce the number of crashes [14]. It motivates the study to develop a prevention system using multivariate deep learning models. This paper contributes towards developing an in-vehicle crash prevention framework leveraging real-time vehicle communication and an accurate crash risk prediction model. The human perception reaction time is also considered to prevent the occurrence of hazardous crashes and

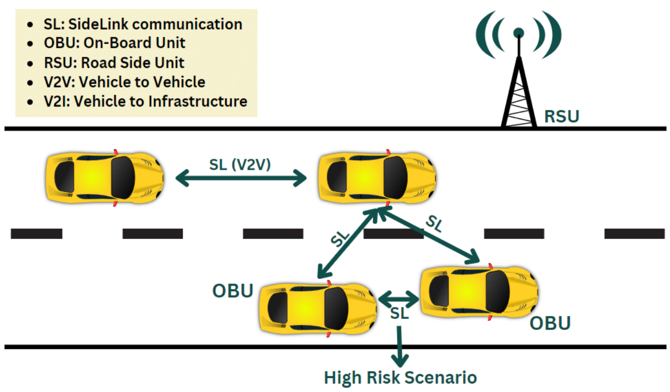

Fig. 1. 3GPP Release 14 C-V2X Sidelink network model.

increase road safety in a CVE. We have implemented different scenarios coupling SUMO and NS-3 simulators for this study. Additionally, we have attempted to create an optimized model by tuning the time scaling parameter and hyper-parameters, which impacts the model accuracy when a model is built using time series traffic data.

II. Network Model and Proposed Framework

The proposed framework is for a CVE that considers cars and heavy vehicles. All the vehicles consist of On-Board Unit (OBU) in this environment. The OBU will be connected with the neighboring OBUs leveraging the PC5 interface Sidelink communication of C-V2X. They broadcast the vehicle's position (x,y) data, acceleration, and speed for the past 7 seconds. In addition, it will be included in the Cooperative Awareness Message (CAM) of 190 bytes following the sidelink standard with a baseline distance range of 150-200m. The leveraging of direct V2V links causes a maximum of 0.02s of latency to broadcast the CAM for pre-crash sensing purposes.

The other OBU will receive the vehicle data and compute the vehicle interaction data (TTC, DRAC, PET, CRI) for the same past 7 seconds. Then the crash prediction model will predict the crash risk after 3 seconds. This computational time will be 0.2 to 0.3 seconds. If the predicted CR exceeds the threshold, the OBU will generate an In-vehicle Warning Alert, alerting the driver about the target vehicle and the high crash risk. A critical factor for traffic safety is the minimum time required for drivers to react to certain situations, called Perception Reaction Time (PRT). For example, a driver has a minimum PRT of 0.7 seconds to an alert sound while driving on the road [19]. It will give the driver two seconds to change the vehicle speed and avoid obstacles. Hence, we can prevent the crash, knowing that most hazardous collisions are due to human error. Moreover, the prevention reliability increases because both conflicting entities will perform their prediction and generate the in-vehicle warning alert. Hence, even if one OBU misses the detection, there's a probability that the other OBU can still detect it.

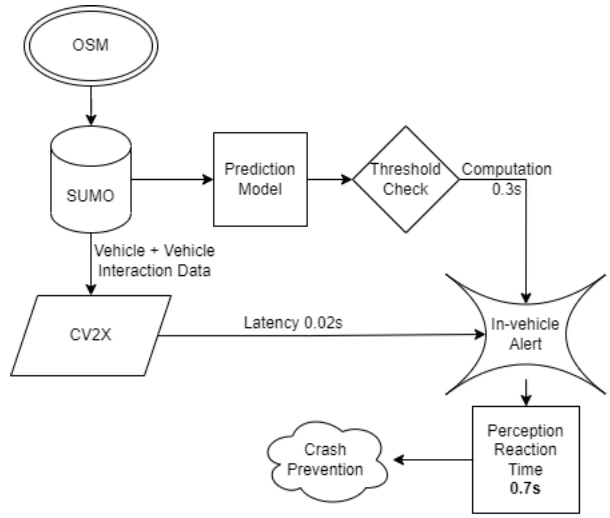

Fig. 2. Proposed framework for crash prevention.

A. Network Model

The network model of 3GPP Release 14 Sidelink communication is shown in Figure 2. Release 14 is considered for implementation because higher releases provide 5G-based systems, implying incompatibility and higher costs compared to 4G-based solutions for India. It plays a significant role in designing a reliable public safety network, allowing the OBUs to communicate directly in high-risk scenarios. It supports LTE-V2X to enable connected vehicular services and provide safer and more efficient transportation, accommodating many nodes (vehicles) [15].

In this study, Sidelink communication establishes direct communication between V2V over PC5 reference point. PC5 refers to a reference point where the OBU directly communicates with another OBU over the direct channel and enables proximity services [16]. In such cases, base station communication is not required. Instead, it uses a specific air interface technology called E-UTRAN (Evolution Universal Terrestrial Radio Access Network) and uses Radio Frequency for V2V communication. E-UTRAN can pre-crash sensing information transmission between OBUs with a maximum latency of 0.02s [17]- [18]. Its primary use case is for road safety. It also helps efficiently communicate vehicles in NLOS but within the baseline distance.

B. Data Collection and Preprocessing

This study uses passenger vehicles, trucks, and buses as probe vehicles. The data was collected from the SUMO simulated environment via TraCI (Traffic Client Interface). There are two types of data, i.e., vehicle data and vehicle interaction data. Vehicle data consist of position (x, y coordinates), speed (m/s), vehicle class, brake rate, and acceleration. Vehicle interaction data is the computed data between the two conflicting entities. Vehicle interaction data includes TTC (seconds), DRAC (m/s^2), PET (seconds), Time headway, and Space gapping as safety measures. Vehicle interaction data is calculated in multiple ways for following, leading, merging, and crossing situations, but post-encroachment time is for crossing situations only. DRAC is based on the required braking power to avoid a collision. In contrast, PET is the time difference between a vehicle entering the encroachment area and a conflicting vehicle leaving the same area [20]. TTC is the time before the collision happens between two conflicting entities on their trajectories if their speeds would not change. Vehicle Interaction data can also be obtained from the ADAS systems for PTSM.

$$TTC = \frac{spaceGap}{speedDifference} \tag{1}$$

$$DRAC = 0.5 \times \frac{(speedDifference)^2}{spaceGap} \tag{2}$$

$$PET = entryTime\,A - exitTime\,B \tag{3}$$

A total of 5,70,000 data samples were collected according to traffic flow characteristics with 5 features of 2750 vehicles in 3 different scenarios. Around 10,000 data samples were removed with NA values wherever a time series break was encountered. The acceleration and speed of each vehicle were collected by the traci.getAcceleration(vehID) and traci.getSpeed(vehID) TraCI APIs in SUMO, and the maximum acceleration was capped till $5m/s^2$ for heavy vehicles. For data preprocessing, features like speed, DRAC, and PET were scaled between 0 and 1, whereas acceleration was scaled between -1 and 1, considering negative acceleration values. According to [21], TTC less than or equal to 2 seconds results in hazardous events. Hence, the TTC in data is imputed between 0.01 and 2 seconds. The Crash Risk Index (CRI) is an exponential decay function of TTC defined by $y = a + b\exp(-x/c)$. CRI is an estimated crash potential of a vehicle based on the TTC. In this study, we have considered {a,b,c} = {0, 1, 1.87} as per [22]. CRI estimation from the TTC is mentioned in equation (4).

$$CRI = e^{(\frac{-TTC}{c})} \tag{4}$$

The data is divided into input and output data generated as continuous time series with two Time Scaling Parameters (TSP). TSP includes rolling time (5,7 seconds) and forecast horizon (2,3,4 seconds) with an interval timestep of 1 second. These TSPs are determined according to the characteristics of the collected data. Rolling time is a sliding window size, defined as turning a single time series into multiple time series, each ending one timestep later than the previous one. A forecast horizon is the length of time into the future for which forecasts are to be prepared. Different models are trained for a total of six datasets scenarios formed with the combinations of TSPs, as shown in Table I.

C. Crash Risk Prediction Models

The model predicts the CRI of the vehicle after the forecast horizon. It uses the past data of the specific rolling time. Multivariate datasets relating to temporal sequences are difficult to align. It requires framing all the datasets as a supervised learning problem and normalizing the input variables. The temporal data of *n* number of vehicles is converted in a 3-D matrix with a single input I_i^t at time *t* for vehicle *i* being a 2D matrix of dimension 7×5. In simple terms, input is formed with the rolling time (rt) having 5 features at every timestep as shown in equation 5. Consider speed (S), Acceleration (A), DRAC (D), PET (P), and Crash Risk Index (C) are the features of a particular vehicle *i* at that timestep. Here, our output is a single-valued variable CRI after a forecasting horizon of *fh* seconds in equation (6).

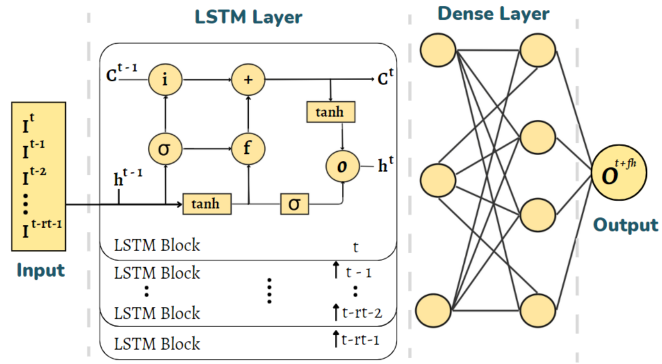

Fig. 3. LSTM prediction architecture; *i*=input gate; *f*=forget gate; *o*=output gate; I^t=Input at time t; O^{t+fh}=Output at time t+fh

TABLE I
DATA COLLECTED FROM SUMO.

Rolling Time(s)	Forecast Horizon(s)	Training data	Testing data
5	2	2,58,937	1,10,973
7	2	1,82,650	0,78,279
5	3	3,97,050	1,70,165
7	3	3,88,667	1,66,572
5	4	3,92,854	1,68,366
7	4	2,47,899	1,06,243

$$I_i^t = \begin{bmatrix} I_i^{t-1} \\ I_i^{t-2} \\ \vdots \\ I_i^{t-rt} \end{bmatrix} = \begin{bmatrix} S_i^{t-1} & A_i^{t-1} & D_i^{t-1} & P_i^{t-1} & C_i^{t-1} \\ S_i^{t-2} & A_i^{t-2} & D_i^{t-2} & P_i^{t-2} & C_i^{t-2} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ S_i^{t-rt} & A_i^{t-rt} & D_i^{t-rt} & P_i^{t-rt} & C_i^{t-rt} \end{bmatrix} \tag{5}$$

$$Output = [C^{t+fh}] \tag{6}$$

We have considered two multivariate multi-step deep learning models: LSTM and the Recurrent Neural Network-Attention model. Both models are currently well-known to capture long-term dependency and extract the time-variant features of vehicle data. In addition, these models can explicitly learn from the various features of crash risk and hazardous forecast crashes.

1) Multivariate LSTM: Multi-step LSTM layer works on a block-wise structure based on the output of the previous timestep. The model was developed by optimizing the TSPs and hyperparameters for better accuracy. Hyperparameters such as the number of hidden units(numHidden), batch size, and the number of epochs are tuned for the same. Epochs are the parameter that shows how many times the learning of training data takes place. This study attempts to minimize prediction errors by adjusting the number of hidden units in both models. The hidden layer of LSTM computes the result of processing the input value through the activation function at that unit. The number of units of the hidden layer is increased to deepen the network and improve the neural network's performance. The batch size used is 32 generally, and the number of epochs varies between 40 and 50. The Adam optimizer keeps the learning rate tuned with the training data. It is known that LSTM helps with the vanishing gradient problem in time series data.

A single block takes three inputs, such as the input of the current time step, output (h^{t-1}) of the previous unit, and the memory (C^{t-1}) of the last unit. The output state is derived through the adjustment of the input weights W, recurrent weights R, and biases b, which are indicated W = $[W_i W_f W_o]'$, $R = [R_i R_f R_o]'$, and $b = [b_i b_f b_o]'$. Here, the input gate is *i*, the forget gate *f*, and the output gate *o*. The LSTM layer is followed by a single dense layer as shown in the model architecture in Figure 3. It connects all the hidden states output from the LSTM layer and integrates them into a one-dimensional array. At last, the output layer receives neurons from the dense layer and gives the predicted crash risk index corresponding to *fh*, which is the forecasting time window.

2) Multivariate RNN-Attention: Similar to LSTM, the same hyperparameters were set for the RNN-ATT model to compare the performance. This model consisted of a Recurrent Neural Network with an Attention layer followed by a single dense layer. The RNN layer exhibits temporal dynamic behavior for sequential data. It consists of three layers, i.e., Input, Hidden, and Output. It uses its previous internal states to process the current input I_i^t, at time *t* for vehicle *i*. The output at any given time is fetched back to the network to improve. It uses the *sigmoid* activation function to determine whether a neuron is to be activated. A fully-connected RNN connects the output of all neurons to the input of all neurons and returns the entire sequence of hidden output states. The attention layer takes that sequence, selects the information that needs to be given significance to store in model memory, and decides how much attention to pay. It automatically updates its weights, passing them through *tanh* and *softmax*. The softmax activation benefits the predicted multinomial probability distribution vector called the output layer of attention. At last, the output vector is passed through a fully-connected dense layer to forecast a single-valued output, CRI of time *t+fh*.

III. Experiments

The lack of availability of a literature dataset containing vehicle and vehicle interaction data for each second in the context of Indian cities' roads and drivers made us build the dataset from scratch. Besides, performing field tests in Connected Vehicular Environments for high-density roads is challenging and expensive.

Hence, to perform a proper vehicular environment simulation, there are traffic simulators such as SUMO and PTV-VISSIM, as well as network simulators such as NS-3 and OMNET++. Researchers tend to couple these simulators to facilitate the development of such applications and prepare them for ITS. In this paper, we have coupled SUMO and NS-3 to simulate the connected vehicle environment of the C-V2X mode4 scenario and hazardous traffic situations. We have considered all 3 types of conflict situations: merging, leading, following, and overtaking. Combining situation causes junction collisions, whereas lead/follow condition causes Forward/Rear-end collisions, and overtaking causes lane-changing crashes.

TABLE II
NS-3 C-V2X Mode 4 Configuration Parameters [23].

Parameters	Values
Number of vehicles	5 to 100
Mobility	SUMO tracefile
Simulation time	50s
Channel bandwidth	10, 20 MHz
CAM message size	190 bytes
Baseline distance	150 m
Transmission power	23 dBm
Resource block per subChannel	10
Num of subChannels	5
Modulation and coding scheme	20(QPSK)
Resource reservation period	100 ms
Subchannel scheme	Adjacent

A. Simulation Scenario

A map of Ahmedabad city was extracted from OpenStreetMap for simulating traffic. The vehicles focused on in this paper are passenger vehicles, trucks, and buses because they cause more hazardous crashes compared to motorcycles, and more people are affected by them. In Ahmedabad, the driver state has randomly distributed behaviors like Impatience, Pushy, Red Light breaking, and speeding. It is because 80.5% of serious crashes are caused by human error [1]. We have extracted five features, i.e., speed, Acceleration, DRAC, PET, and TTC, of every second and every vehicle present in the simulation. The vehicles enter the simulation at a random rate. If there was a crash, the two vehicles were removed from the simulation. All the vehicles are equipped with Surrogate Safety measuring devices to compute the vehicle interaction data whenever a neighboring vehicle is close.

A total of 3 hours of the simulation was performed with three different levels of driver states. The entire data was extracted from SUMO via Traci API for the model training, whereas NS2MobilityHelper was used for the NS-3.

For implementation purposes, we have used *ns-3* network simulator. All nodes represent passenger vehicles, trucks, and buses fully equipped with 3GPP Release 14 C-V2X standard that uses an LTE PC5 interface for V2V communications. It efficiently connects the neighboring vehicles on peer-to-peer basis and exchange vehicle data. All the nodes have the adequate configuration parameters of C-V2X Mode 4 given in

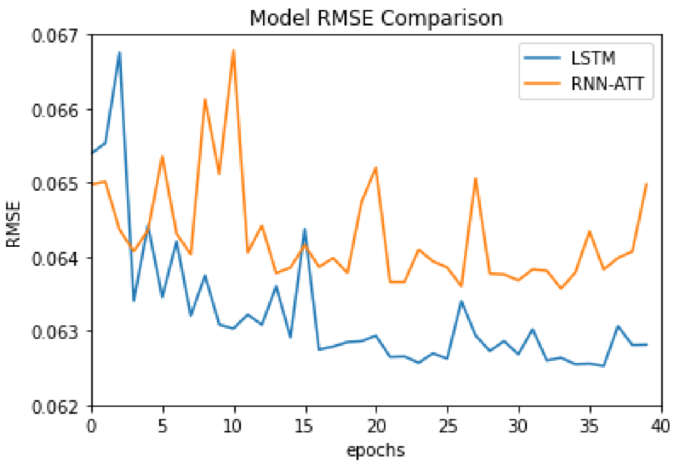

Fig. 4. LSTM and RNN-ATT validation RMSE curves.

TABLE III
PREDICTION CONFUSION MATRIX.

	LSTM		RNN-ATT	
	High Risk	**Low Risk**	**High Risk**	**Low Risk**
True	10,934	43,738	16,593	32,807
False	707	6,604	1,669	10,914

*Forcast Horizon (FH) = 3 seconds

Table 1. It does not require the support of the cellular infrastructure. Vehicles can autonomously select their sub-channels for their V2V transmissions i.e unsupervised. Cooperative Awareness Messages are exchanged between vehicles within a distance of 150m with a transmitting power of 23 dBm [24]. The trace file extracted from SUMO contains timestamps, nodes, and node data which will be simulated in this Open C-V2X Mode 4 NS-3 simulator [25]. A total of four simulations were performed with different simulation seeds, generating four datasets from SUMO. From those datasets, three were later used to train and test the model and for NS-3, and one was used for the prediction and derived the confusion matrix.

IV. RESULTS

We have constructed 18 models based on the combinations of six scenarios of TSPs and three hyperparameters to increase the reliability of CRI prediction. Table IV shows the best-performing combinations with their Root Mean Squared Error (RMSE). As computed in equation 7, RMSE gives relatively high weight to large errors because they are squared before they are averaged. This performance metric helps improve the CRI prediction when large errors are particularly undesirable. $\widehat{CRI}$ represents the predicted value, *CRI* is the actual value, and N is the total number of data samples.

$$RMSE = \sqrt{\frac{\sum(CRI - \widehat{CRI})^2}{N}} \tag{7}$$

Here, LSTM has significantly outperformed the RNN-ATT model for every forecast horizon. As the forecasting horizon increases, the probability of error increases. The prediction results for 2s are better than 3s. But 2s is a very short horizon (considering the latency and PRT) for the driver to take any active countermeasures and prevent crashes. Small forecasting horizons perform well with short rolling times, whereas 3s and 4s require 7s for better prediction. More past data leads to a better knowledge of the situation; simultaneously, a very high amount of data can lead to increased latency and packet loss in wireless communication. At the same time, RNN-ATT outperforms LSTM in terms of speed. Due to less trainable parameters compared to LSTM, computation becomes faster for RNN-ATT. But a slight change in accuracy makes a considerable difference for human life in this crucial CRI prediction. Figure 4 clearly shows a notable difference between LSTM and RNN-ATT error rates for each epoch. Hence, this study considers LSTM the best fit for implementation with a forecasting horizon of 3s.

TABLE IV
MULTIVARIATE MODEL PREDICTION RESULTS.

RT	FH	Hyperparameters		RMSE	
(secs)	(secs)	*numHidden*	*Epochs*	*LSTM*	*RNN-ATT*
5	2	50	40	0.0537	0.0571
7	3	100	50	**0.0611**	0.0640
7	4	150	50	0.0670	0.0675

*RT = Rolling Time; FH = Forcast Horizon;

Leveraging C-V2X Sidelink communication is essential to increase the reliability of pre-crash sensing. Considering the maximum latency of 0.02s as per the network model, the total computation time of 0.3s, and a minimum PRT of 0.7s leaves us with an optimal choice of 3 seconds of forecast horizon to feasibly prevent the crash and take active safety measures.

Hence, both the models with *fh*=3 and *rt*=7 and *numHidden*=100 are considered for prediction on the dataset collected from SUMO. The final confusion matrix for that dataset is shown in Table III. The threshold to consider the crash risk high was set to 0.5, i.e., $CRI > 50\%$. The threshold can be tuned as per the requirement at the implementation time. Lowering the threshold will detect the accident sooner but will increase the warning alerts and false detection. Similarly, having a high threshold can increase the risk of missed detection of hazardous crashes. There were 10,983 true positives (alerting the vehicle for the high-risk scenarios) and 43,738 true negatives (when driving is safe) for the LSTM model, while 16,593 true positives and 32,807 true negatives for the RNN-ATT model from 61,983 predicted data samples.

Further comparison of the models is conducted based on some basic measures of the confusion matrix to understand their performance from different perspectives. LSTM has an accuracy of 88.2% and a precision of 93.93%, while RNN-ATT has an accuracy of 79.7% and a precision of 90.86%. Accuracy is the true detection rate of a model, i.e., predicting high risk when there is an actual high-risk scenario and vice versa. Precision and Specificity are other performance measures that show how precisely the model predicts high-

TABLE V
MODEL COMPARISON

	LSTM	RNN-ATT
Accuracy	0.8820	0.7970
Precision	0.9393	0.9086
Specificity	0.9841	0.9516
F1-score	0.7494	0.7251

risk and low-risk strategies, respectively. Specificity is a true negative rate, whereas Precision is a positive predicted value. F1-score is a combined measure of Precision and sensitivity (also called true positive rate) in a confusion matrix. LSTM has more effective predictions than RNN-ATT in terms of Accuracy, Precision, Specificity, and the F1-score shown in Table V. Hence in the case of LSTM, we can detect high and low CRI with the best accuracy and Precision of 88.2% and 93.93%, respectively.

V. CONCLUSION AND FUTURE WORK

This novel approach has considered all the aspects of a crash, i.e., knowledge of N-LOS and LOS vehicles, human error while driving, prediction with 88.2% accuracy, and the perception reaction time to prevent the detected impact. In future work, different scenarios can be considered to analyze the scalability performance of various deep learning techniques. There are some drawbacks of the LSTM model on large input sequences. As the number of vehicles increases, the computational time increases for the LSTM model at a particular second. Hence, the various models' scalability and speed need to be contemplated in the future. Such a Crash Prevention Framework for Proactive Traffic Safety Management would help to increase road safety on high-density urban roads as well as freeways and prevent heavy vehicle crashes from occurring due to human error. Other vehicular categories, along with road and weather conditions, should be considered for future work. This framework can be further developed to improve prediction accuracy and incorporate other classes of vehicles to support road safety.

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