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Prediction of safety in Autonomous Vehicles using Modified Deep CNN-BiLSTM with attention mechanism

Sophiya Bartalwar[1], Dr. Vijayalaxmi Biradar[2]

[1]Research Scholar, Department of Electronics and Telecommunication Engineering, Kalinga University, Raipur, India.

[2]Professor, Department of Electronics and Telecommunication Engineering, Kalinga University, Raipur, India.

Corresponding Author Mail ID: sophiyabartalwar75@gmail.com

Abstract:

In the present world, the usages of autonomous cars are getting higher because of the emerging technology. These autonomous cars give freedom to the person those who are not able to drive. It can able to control the CO2 gas emission, avoid traffic and accidents and there are no attention issues like human in autonomous cars. However, the autonomous cars are not perfect because sometimes the autonomous cars face some issues while analysing the different human hand gesture, climatic conditions and road sign. To overcome this problem the proposed model use improved search ability based GA (Genetic Algorithm) in feature selection to attain the best features from the dataset and to predict the drivers behaviour and car mechanism the modified deep CNN (Convolutional Neural Network) –BiLSTM (Bidirectional Long Short Term Memory) algorithm with attention mechanism (AM) is used. While analysing the performance of the proposed model with metrics such as precision, recall, and F1 that is obtained, the overall accuracy of 96% thereby significantly enhances the safety prediction in autonomous vehicles.

Keywords: Autonomous Cars, Improved Search Ability Genetic Algorithm, CNN- BiLSTM, Attention Mechanism.

1. Introduction

The transportation department of US reported nearly 6,734,000 numbers of accidents related to motor vehicle in the year of 2018. Overall 36,560 fatalities and 2.71 million were injured because of these accidents. In the year 2019 and 2020 the count of injuries and death also increased. Due to wrong prediction of other drivers and driver related issues nearly 33% and 80 – 94% of accidents were happened in US in the beginning of 2015. The report states that human driver related error are the main reason for accidents [1]. In recent years, the AVs (Autonomous Vehicles) have been getting popular among people. In the recent market Level 2 systems were introduced as an example of the human achievements. By controlling both lateral and longitude motion of the vehicle the level 2 systems are required to increase driving comfort and safety [2]. In complex scenarios, the vehicles ability to attain the environment information is extreme than the human drivers due to the vehicle perception technology development. An efficient way to enhance the driving safety and driving effectively of vehicles is the current auxiliary driving system. Many methods have been approached for the perception of driving environment namely fine grained fusion methods, Bayesian filtering method and fast occupancy grid filtering method [3]. Both hardware and software architecture were available in AV. The imperative information for the software module was provided by the sensors and it is one of the hardware elements. According to trajectory comfort and safety to the actuator, the control commands were generated by software module of AV. The deceleration, steering and acceleration of AV hardware activities were control by the actuator. The trajectory control layer, perception layer and planning layer are inbuilt in an AV software architecture [4].

The data collection, manual observation and physical inspection where usually involve in the traditional techniques for driver behaviour and vehicle mechanism such as data logging, video monitoring, visual inspection, driver interview, on-road testing and diagnostic testing. Data Logging is helpful to detect the vehicle location [5], speed, braking pattern and acceleration are analysed to evaluate the driver behaviour by these data loggers which was installed in vehicle to record the driver‘s behaviour [6]. The compliance with traffic rules, distractions and aggressive driving of drivers was captured by the video camera installed along roadways or in vehicles [7]. To identify any marks of malfunction, wear or damage in vehicle components such as suspension system, brakes, engine and tires are visually inspected by the technicians. While operating the vehicle, the issues faced by the drivers, their habits and experience related information gathered from drivers through interviews. Evaluate the driver behaviour, vehicle’s handling and performance in real world condition by conducting the road trails and driving test for drivers [8]. To identify any problems or fault in the performance of vehicles are analysed by the equipment or diagnostic tools for vehicle’s sensors and on board computer systems. To ensure the efficiency and safety of vehicle operation these traditional techniques provide better understanding of driver behaviour and vehicle mechanism. To improvise the accuracy and efficiency of predict the driver behaviour and vehicle mechanism, the AI integrated sensors and systems are also used increasingly because of the technology advancement [9].

The effect of new technology on car following behaviour was considered by many researches in the recent years because of the internet of vehicles development. The velocity and distance information are precisely observer by the drivers are anticipated by most of the models [10]. With their own perception drivers can observe the distance of the object but in reality drivers cannot precisely observe the velocity or distance. Based on the real data, it is also an important technology to analyse the following car model [11]. Based on ANN (Artificial Neural Network) established the elderly drivers car-following model and the experienced drivers have important impact on the constancy of car following fleet that shows in the simulation results. There are some existing methods to improve the car-following model such as NN, LSTM and data-driven methods [12]. The accident free driving future is the main objective for automated vehicles. There are six levels of autonomy ranging from 0 to 5 in theoretical form of self-driving cars technology. While driving ADS (Advanced Driving Systems) and ADAS (Advanced Driving Assistance Systems) are recommended to reduce the human errors because of its capability in order to detect possibly dangerous driving situations [13].

Even though there are different studies which discussed about car mechanism prediction and driver health in autonomous vehicle separately, there are limited studies which incorporated both these aspects together. Thus the proposed study utilises these two mechanisms by incorporating Modified Deep CNN-BiLSTM with attention mechanism (AM) for detecting the emergency centre. The dataset of vehicle (car) mechanism and driver health dataset was collected from open platform [14]. To convert the missing values into null values the dataset undergone pre-processing process. The improved search ability based GA was used for feature selection.

1.1. Motivation

The usages of autonomous cars are getting higher because of the technological advancements. It is helpful to the people those who are unable to drive the car by themselves, specifically elder people and people with disabilities. These autonomous vehicles give freedom to them. However, the autonomous vehicles struggle a lot with insufficient knowledge of human gestures and it leads to accidents. Therefore to address these faults some existing systems were used to train the model such as DL [15], ANN, CNN. However, the existing models were lacked in terms of feature selection and training, it decreases the efficiency of the existing models. Therefore to solve this problem the proposed method use the modified Deep CNN-BiLSTM with attention mechanism (AM) and improved search ability based genetic algorithm for analysis the best features from data set to detect the drivers safety by assume the behaviour of the drivers and car mechanisms.

1.2. Research Contribution

The main objective of the proposed model as follows:

- To select the important features using improved search ability based genetic algorithm
- To predict the condition of driver health using Modified Deep CNN-BiLSTM with AM
- To assess the model performance by utilising different metrics such as improve accuracy and reduce the loss.

1.3. Paper Organization

The following paper is partitioned into four sections. Section II includes the existing model with different algorithm. Section III reflects the complete methodology of the entire study with their parallel algorithms. Section IV reflects overall results and analysis of the proposed model. Section V reflects the conclusion, limitation and the future work of the proposed model.

2. Literature Review

The automated vehicles have been the rapid developed sector. Correspondingly, the suggested research [16] stated that on the autonomous system HMS (Health Monitoring System) was an important component that has been useful for diagnosis and fault detection. During the vehicle movement, the prognosis system has been allowed safer decisions and predictive maintenance. The health monitoring system based on hierarchical component along with prognosis, fault detection and diagnosis using DBN (Dynamic Bayesian Network) with residue generation, the knowledge based and model based detection combination, prognosis and diagnosis approaches. The CARLA simulator and the autonomous vehicle platform CaRINA II along with different ML (Machine Learning) and sensor dataset has been used to evaluate the Dynamic Bayesian Network. Even some variables of the model has high rate of missing data for both experimental and stimulated results attained the positive performance with DBN. The considered study [15] established the identification of driven vehicles with CAV (Connected and Automated Vehicles) to human- and it has based on trajectory data. By discussing to the demonstrating ideology of the traditional car following technique, the research has been established the data driven car following technique with

CNN-BiLSTM with attention mechanism. The NGSIM (Next Generation Simulation) data has been selected for trained the model. The comparative analysis of trajectory prediction the CNN-BiLSTM, LSTM and GRU (Gated Recurrent Unit) were selected. The higher accuracy level has attained by the CNN-BiLSTM with AM. The limitation of the considered research that the DL (Deep Learning) networks have not strong interpretation ability then it has been difficult to identify which data features were important.

Similarly, the existing research [17] implemented the risk prediction model from the UK based vehicles dataset from the year of 2017 to 2018. The leading factors for traffic crashes has been analysed by the research. To identify the severity of accidents under a given feature set input, the research run the dataset with different algorithm based on the leading features in the dataset. The accuracy of Logistic Regression (LR), DT (Decision Tree) classifier and RF (Random Forest) were compared. The better accuracy level has been attained by the RF technique. To collect the dynamic data from driver the trained RF model has implemented on Ardunio the IoT (Internet of Things) based server. Compute the risk of driving the research utilise the biological conditions of driver and weather conditions and organise various sensors which occasionally sense the situations. The application has given notifications and alerts, if the driving risk has been more than some threshold.

The emerging technique of the active field has been driver identification technology and customize the advanced driver assistance systems integrated into prevent auto theft, intelligent vehicles, ride hailing services safety and provide security. The considered research [18] implemented the driver embedding's namely DriverRep a deep learning architecture to extract the latent representations that associated with each individual. The specific driving characteristics of drivers have been represent by the embedding's. Utilise the architecture of stacked encoder has been presented the fully unsupervised triplet loss that has selected the samples of triplet from unsupervised manner data and that has been extracted the embedding's. The residual blocks of the encoder have been made by the dilated casual convolutions. The top of the embedding's of obtained driver the research leverage the SVM classification accuracy to identify the performance of driver task. The better accuracy level has obtained by the DriverRep.

Likewise, the existing research [19] implemented the prediction model for driver drowsiness during driving. The accuracy of prediction and detection drowsiness has been improved by the participation and the driving time data. The optimized conditions to induce the drowsiness nearly 21 contributors have driven a car simulator for 110 minutes. The behavioural and physiological indicators were measured the behaviour from recorded driving such as steering wheel angle, position on the lane, speed, and time to lane crossing and eyelid and head movements, heart rate, respiration rate and variability. Through the TOR (Trained Observer Rating) the different combinations of collected information has been tested against the driver's real state from the video recordings. To identify the required time to reach a particular level of drowsiness and to predict the drowsiness degree by using two ANN (Artificial Neural Network) models. The behavioural indicators and additional information attained the average performance in both prediction and detection.

Correspondingly, the considered research [20] implemented the prediction model for eye movement during the driving. The research applied both feedforward NN and mixed effect of LR (Logistic Regression) between the eye movement descriptors and hazard reports from the 20 recorded driving clips of 32 females. In each video, all subjects has been reported at least one major collision vulnerability. In both vertical and horizontal dimensions, the vulnerable situations have been predicted by smaller gaze dispersion, longer fixations and fewer blinks. The LR achieved the better accuracies and feedforward NN outperformed. The depression, together with the highest ROC area returned by the pupil, saccadic magnitude, and fixation length. The LR and feedforward NN attained 70% of accuracy. Similarly, the suggested research [21] implemented the hybrid approach diagnosis system and fault detection. To separate the unsafe and safe domain the SVM (Support Vector Machine) has been selected to train the boundary curve. The normality of the residuals probability distribution has been checked by the Jarque-Bera test. The limitations of the research were fault isolation to indicate the lateral state or longitudinal deviation.

Several techniques were available to identify the fault in autonoums vehicles. The considered research [22] demonstrated the SGD (Stochastic Gradient Descent) classifier with pipeline sensor data fusion architecture. The challenges in the autonomous vehicle environment has been overcome by the SGD classifier by the isolation, signal diagonis and detection. The better accuracy level attained by the SDG classifiers. Correspondingly, the existing research [23] implemented the LCD (Lane Changing Decision) model which has been combined the DAE (Deep AutoEncoder) network with XGBoost (Extreme Gradient Boosting) technique. The Basyesian parameter optimization has been adopted by the XGBoost technique to address the autonomous LC decision making process of nonlinear and multi-parametric problem. The average performance achieved by theLCD with XGBoost technique. The limitations of the research has been not adaptable for more complex traffic environment. Likewise, the previling research [24] recommended the SSO-DLFER (Squirrel Search Optimization with Deep Learning Enabled Facial Emotion Recognition) method for identify the face emotions of drivers. The emotion recognition and face detection has been the two main process followed by the recommended technique. The GRU model and the larger feature extractor NASNet (Neural Architectural Search) has been applied in the SSO-DLFER technique for emotion recognition. The average performance accurracy attained by the SSO-DLFER technique.

Similarly, the piviling research [25] implemented the D2RL (Dense Deep Reinforcement Learning) techiqur to execute the adversarial manoeuvre drom the background agents from real driving data. The information in the training data has been densified by the approach by reconnect the critical ones and removing non-safety critical ones. The NN has been enabled by the D2RL to achieve the traditional deep-reinforcement learning approaches. The average performance accuracy has been achieved by D2RL. Likewise, the existing research [26] demonstrated the HIADB (Human Driver Inattentive Aggressive Driving Behavior) technique for the identification of DFD (Driver Fatigue Drowsiness) and DD (Driver Distraction). The HIADB attained the better accuracy level by utilising the other DL techniques were Q-learning and deep reinforcement learning. Correspondingly, the considered research [27] implemented the LLDNet (Lightweight Lane Detection) technique to identify the road conditions and adverse weather. To achiever the better outcomes the feature maps has been refined by the integration of the designed architecture were spatial attention and channel attention. The LLDNet attained the better performance level. The limitations of the research has to improve lane identification on defected and unstructured roads.

Similarly, the priviling research [28] recommended the combination of mixture density layer with dilated convolutional networks. Based on the probability the research combined different existing cluster to attained the better accuracy. The dilated convolutional network achieved the average performance accuracy. Likewise, the suggested research [29] demonstrated the TMMOE (Temporal Multi-task Mixture Of Experts) for the identification of driver intension and vehicle trajectory. A fully connected layer, a shared layer and an expert layer has been used in the technique. Each layer processes different steps which includes temporal features extraction, sequence temporal dependence filtration, integrate and export the results of prediction. The better accuracy level attained by the TMMOE.

Accordingly, AVs are depend on data that are vulnerable to anomalies caused by cyber attacks, fault and unsafety. To overcome this issue, the conventional study [30] has examined modified CNN with safety pilt model deployment dataset for anomaly perdiction in autonomus vehicle sue to sestiveness in sensor data. And the model has achieved accuracy of 99.40 % in anomaly detection. The existing study [31] has deployed vehicle –pedestrian Detection based CNN approach to resolve the issue among autonomous vehicle and pedestrian.the model has also attain the accuracy of 81.98% over thn other CNN models hence the stud has shoenthe significant improvement in safety detection between AVs and pedestriasan. The main challenges in autonmous vehicle commercialization is safety and taffic monitoring consequent that, the prevailing study [32] has evaluated the real time traffic monitoring system with hybrid CNN architecture and designed the AlexDarkNet. Hebnce the model has potential to track real time taffic monitoring with better accuracy.

2.1. Problem Identification:

Some of the problem identified from existing approach are discussed in the respective section.

- The limitation of the considered research that the DL (Deep Learning) networks has not strong interpretation ability then it has been difficult to identify which data features were important [15].
- The limitations of the research was fault isolation to indicate the lateral state or longitudinal deviation [21].
- The limitations of the research has been not adaptable for more complex traffic environment [23].

3. Proposed Methodology:

There are some traditional methods to analyse the drivers behaviour and car mechanism but it consume more time and manual power. To overcome these issue AI (Artifical Intelligence) techniques were introduced in autonomus vehicle due to some security issues the proposed methodology included the Improved search ability based GA for feature selection and Modified Deep CNN-BiLSTM with attention mechanism for data classification to predict whether the journey is safety or unsafety. The figure.1. shows the working model of the proposed method.

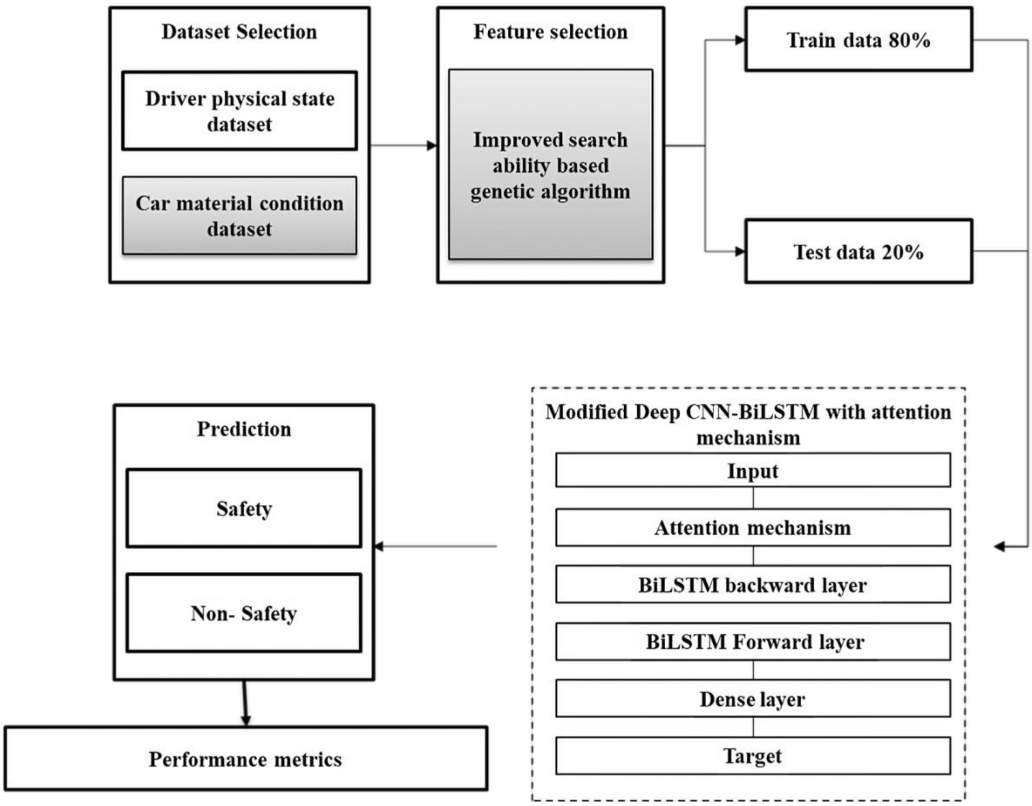

Figure.1. Block diagram of the Proposed Study

The figure.1. shows the entire process, initially the dataset are collected from the open source platform [14] for dataset selecion. The dataset includes driver physical state and car material condition dataset and the missing values of the dataset are converted in the null values in the pre-processing. Secondly, the dataset get in to the feature selection process, the proposed method used Improved search ability based genetic algorithm for select the best columns in overall dataset and the proposed method used this genetic algorithm for its less time consumption and easy cross over characteristics. The feature selection process used for train (80%) and test (20%) the dataset. Thirdly, the processed dataset get in to the Deep learning classification model, here integrated CNN and BiLSTM is used that is Modified Deep CNN-BiLSTM with attention mechanism. After that it will predict the safety and non-safety of both car mechanism and health of drivers.

3.1. Data Description:

The dataset is retrived from the kaggle website. The link of the data was given below for the reference [14].

3.2. Pre-processing:

The process of the step is to correct the inaccurate data or missing valuse in the dataset and convert them into null values. The pre-processing is an important process in both ML (Machine Learning) and DL (Deep

Learning). This process was included for data splitting, improve the data quality, dimensionality reduction, and improve the performance of model.

3.3. Feature Selection - Improved Search Ability Based Genetic Algorithm:
The feature selection also a significant phase in the procedure. It is used to identify the most relevent columns from the dataset for the specific model which means to select the best columns in overall dataset. Due to this process, the accuracy of the model will improve because it will only choose the relevent data and omit the irrelevent data. The advantages of feature selection are improve accuracy, reduce training time and decreases over fitting. The genetic algorithm is one of the important algorithm and used to solve complex problem. It generates high quality solutions by evolutionary generational cycle. But the drawbak of genetic algorithm are it is not applicable for simple problem, there is no assurance in the quality of problems final solution and it will generate computational challenges because of its repitative calculation and it will provide all the features without analyse which one is needed. To overcome this issues the proposed method used Improved Search Ability Based Genetic Algorithm because this algorithm provide only suitable features after analysis.

3.4 Flow chart of the proposed model

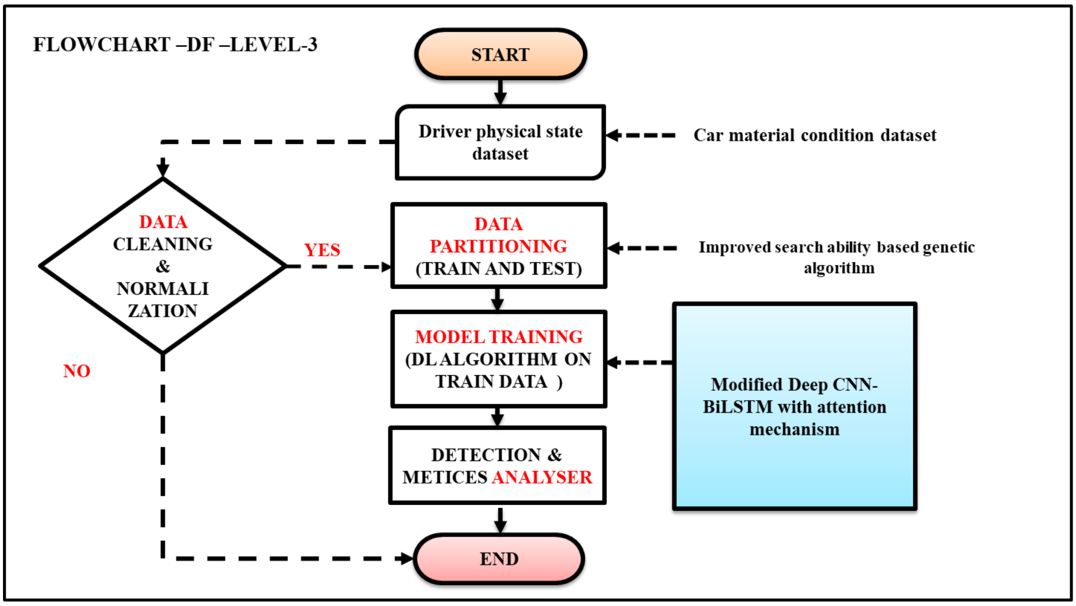

Figure.2. Proposed model flow chart

Figure 2 depicts the flow of the proposed study,the goal of the process is to analysethe driver physical state dataset. The dataset includes a huge count of gathered data from the driver regarding their physical state.the data examine for the data cleaning and normalization process to extract noise, handle missing values and scale the data to make sure stability and speed up the data processing. Following that the data is splited into training data and testing data, in which training data used to train the modeland testing data established to examine model performance. To select the important features using improved search ability based genetic algorithm follow that a modified deep CNN-BiLSTM with AM is applied on the training data, CNN extracts the spatial features from the data, BiLSTM captures temporal dependendies and sequential pattern in the data. Attenn mechanissm allow models to focus on the relevant features within complex driving environments, these mechanisms ccontribute to afer and more reliable autonomous driving systems. Hence the integration of CNN based BiLSTM with AM representsa robs framework for enhancing the safety predictions in autonomous vehicles.

3.5. Classification - Modified Deep CNN-BiLSTM with AM:

The proposed model incorporated the CNN and BiLSTM with AM because the data used in the experiment was in time series. Thus CNN model works better with image data but poor in time series data but the BiLSTM model is good in time series data. Though, the proposed model integrated these two algorithm to get better results. The attention mechanism was used to align the processed data in an order regarding to ites weight in the optimization layer of CNN.

The CNN includes four different layers such as CL (Convolutional Layer), PL (Pooling Layer), FCL (Fully Connected Layer) and output layer. Consider ‘x’ as the input data which contains the preprocessed data of driver health and car mechanism. In the firat layer of the network, x be the input and the output of f(x) genetate by max pooled, where it is convolved.

$$f'(x) = \mathrm{convolve}(x, \mathrm{filter1}) \quad (1)$$

$$f(x) = \mathrm{maxPool}\left(f'(x)\right) \quad (2)$$

In the next layer of the network f(x) is fed as a input, here it convolved again and the another output is generate g(x) from the max pooled. The different set of hyperparameters was involved in the first and second layers of the network but it performs the same function.

$$g'(x) = \mathrm{convolve}(f(x), \mathrm{filter2}) \quad [8]$$

$$g(x) = \mathrm{maxPool}\left(g'(x)\right) \quad (4)$$

The activation function of ReLU (Rectified Linear Unit) is fully connected with the third layer and for input g(x) is provide into the layer. Consider h(x) be the output of this layer.

$$h'(x) = g(x) * W + b \quad (5)$$

$$h(x) = \max\left(0, h'(x)\right) \quad [8]$$

To generate the output y, in the last layer h(x) is provide as input. Until the error is converged, this precised output is before utilise to optimize the network and evaluate the cost by the updation of biases and weights for the following epoch.

$$y = h(x) * W + b$$
(7)

The CNN model implementation is shown in the table 1.

Table 1. Pseudocode for CNN

Psuedocode for CNN
Step1: Gather information from four trials as $v_i \in \mathcal{R}_o\ M_o \times T_i$, M_o as channel size, T_i as time samples
Step2: Set the CNN filter weight to Model $PO_{ct_i}^{ik_o}$
Step3: Set the CNN fully connected weight to initial values U_{ip_i}, q_i i , where Pp_i is the feature size of the top convolutional layer, q_i is the size of hidden units, and j_i is the size of fully − connected layers.
Step4: For ij $<$ M_i (M_i is the convolutional layer)
Step5: convolution $Ci = ReLU \sum_{c_i,t_i}^{M_o,T_i} PO_{ct_i}^{ik_o}$
Step7 : $UU_{ii} \leftarrow$ pooling (v_i)
Step 8: iteration level in jj $=$ jj $+ 1$
Step 9: For ss $<$ F_{ci} (F_{ci} is the fully − connected layer)
Step10 Iteration level: ss $\leftarrow$ ss $+\ 1$
Step11 Back − propagate Loss (v_i, L_i), L_i as the true label

The dataset used to train the CNN model that is utilise to train the LSTM model. The model consist of three layers namely LSTM layer, embedding layer and the output layer called as a sigmoid activation function of dense layer. The unput set values of a subject consist by the tensor of ‘x’. By the given dimensions to generate the ouput tensor f(x) then x is provide into embedding layer as input. The CNN model amd embedding layer works similar.

$$f(x) = embedding\big(length(x), output - dimension\ input - length(x)\big) \quad (8)$$

In the LSTM layer, f(x) provide as a input. here the LSTM layer is covered with a bi-directional layer, the layer train the unseen unit is dissimilar to the RNN model. It used as the argument for number of unseen units present in the layer. Consider g(x) as the output of the layer.

$$lstm = LSTM(units) \quad [8]$$

$$g(x) = lstm\big(f(x)\big) \quad (10)$$

In the Dense layer with sigmoid activation function, g(x) is fed as a input. Between 0 and 1 is the values of output layer and converges. Here ‘1’ denotes the demented subjects and ‘0’ denotes non-demented subjects. The fully connected layer is the another name for dense layer and then y is the output of this layer. Till the error is not congregated the forecast output is connected with the given number of epochs.

$$z = g(x) * W + b \tag{11}$$

$$y = \frac{1}{(1 + e^{-z})} \tag{12}$$

It is evaluated on the test dataset after training the model and the pseudo code for LSTM shown in the table 2.

Table 2. Pseudocode for LSTM

Psuedocode for LSTM
Step 1: Feature ←{CSV Dataset }
Step 2: Clasess ←{Preprocessing ,Label Encoding }
Step 3: X_i ←Dataset{Feature }.values
Step 4: Y_i ←Dataset{Clasess }.values
Step 5: X_train , X_test ←TTS (X_i,Y_i,0.80,0.20)
Step 6: Batch Size ←4
Step 7: LSTM Model ←Sequential Model ([Embedding layer (X_train.length,256, X_train.column)
Step 8: LSTM Layer (256)
Step 9: Dense Layer (256,activation="CONV Model ")
Step 10: LSTM Model .compile (Loss ,optimizer)
Step 11: LSTM Model.train (train Data ,Epoches,batch Size)

The probality of potential collision is affect by the certain time segments of critical motion behavior. During other time period the avoidence, acceleration, steering and deceleration actions have more important effect on the potential for car accidents than actions within certain time interval. The prediction results and the behavior at a specific time point $\widetilde{x_t}$ will have the determined risk by larger contribution, within the time window $X_t = (x_1, x_2, \dots, x_t)$. It is used to predict the effect of motion performances at the separate time points might be vanished though, the final motion state of the car and the driver is represented by the BiLSTM output of network at time t that signifies $[\overrightarrow{h_t}, \overleftarrow{h_t}]$. To encounter the behavior of driver health and car mechanism risk, to quantify the different effects attention mechanism is used. In machine translation tasks, the attension mechanism was proposed first. To improve the understanding of drivers behavior, the different attention weights with AM can be allotted to different emotions. To quantify the different behavior of the driver and car mechanism on the various time frames of risk by the metaphor of attention mechanism.

$$p(risk_{t+\Delta t} | x_1, x_2, \dots, x_T) = p(risk | \overrightarrow{h_t}, \overleftarrow{h_t})$$
$$(\overrightarrow{h_t}, \overleftarrow{h_t}) = \text{BiLSTM}\ (x_1, x_2, \dots, x_T) \tag{13}$$

Over an entire period the motion behavior is summarize, this method varies most considerably from the basic BiLSTM and LSTM methods and ht is not approach for try to use the till the last moment of output state. But, will produce changes in the risk at specific time points that by focusing on the critical motion behavior of the drivers. The input of the attention mechanism for each moment in the motion states at

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$[h_1, h_2, \dots, h_t]$ as shown in the Eq. 14. The corresponding attention weight $[\alpha_1, \alpha_2, \dots \alpha_t]$ represent the contribution degree of each frame caluculated using Eq. 16 based on the computational approach of Bahdanau's attention. The calculation of overall attention is as follows.

$$p(risk_{t+\Delta t}|x_1, x_2, \dots, x_T) = p(risk_{t+\Delta t}|\, \overrightarrow{h_1}, \overrightarrow{h_2}, \dots, \overrightarrow{h_t}, \overleftarrow{h_2}, \dots, \overleftarrow{h_1}, \alpha_1, \alpha_2, \dots, \alpha_t)$$

$$\left(\overrightarrow{h_1}, \overleftarrow{h_1}, \dots, \overrightarrow{h_t}, \overleftarrow{h_t}\right) = \mathrm{BiLSTM}(x_1, x_2, \dots, x_T) \tag{14}$$

$$\mu_t = \tanh(W_w h_t + b_w) \tag{15}$$

$$\alpha_t = \frac{\exp(W_\mu \mu_t^T)}{\sum_t \exp(W_\mu \mu_t^T)} \tag{16}$$

$$s = \sum_t \alpha_t h_t \tag{17}$$

Here, W_w and W_μ $h_t = [\overrightarrow{h_t}, \overleftarrow{h_t}]$, are the fully connected layers weights. The all time steps of weighted sum $[h_1, h_2, \dots, h_t]$ is signifies the overall encounter process in the motion state. Each motion state of the driver in mormalized weight is denotes by α_t. The pseudo code shown isn table 3.

Table 3. Pseudo Code for BiLSTM with AM

Pseudo Code 3
Input: Smart data collection $C(n_i)$ Output: Energy Hourly , Month and Daily prediction model H_o Compute behavioral features $X(k)$and risk level of encounter from $C(n_i)$ Generate the training data set Mtrain and Mtest from $X(k_i)$ For mini batch M_i in Mtrain For T_i time window data MT_i in M_i For $t_i = 1$ to T_i Using forward LSTM to encoder ht_i Using backword LSTM to encoder ht_i End For Compute Attention score αt and s_i Compute risklevel from s_i End For Training the model H_o with back propagation algorithm End For Save the prediction model H_o

Proposed modified deep CNN and BiLSTM with AM

$$c_{ii} = f_o(w_{ii} * x_{oii} + b_{ii}) \tag{18}$$

Here x_{oii} signifies the convolutional layer input. The i th output feature map denoted by c_{ii}, the weight matrix represented by w_{ii}, the dot product denoted by *, the bias vector denoted by bi and the activation function denoted by $f(\cdot)$. In CNN, the ReLU (Rectified Linear Unit) activation function is generally selected. The mathematical form of ReLU is:

$$c_{ii} = f(h_{ii}) = \max\ (0, h_{ii}) \tag{19}$$

Here the feature maps elements attained from convolutional operations is denoted by h_{ii}. Prevent overfitting by cutting down the dimensions of feature map in the pooling operation functions. One of the most pooling method is max pooling method. According to Equation [8] and (4), in feature maps it is realized by calculating the maximum value of assigned area.

$$\gamma\left(c_{ii}, c_{ii_1}\right) = \max\left(c_{ii}, c_{ii_1}\right) \tag{20}$$

$$p1_i = \gamma(c_{ii}, c_{ii} - 1) + \beta_{ii}$$

The max pooling subsampling function is denoted by $\gamma(\cdot)$. The bias is denoted by β_{ii}. The output of maxpooling layer represented by $p1_i$. The fully connected layer are fed up by pooling and convolutional operations and found the feature maps. The below equation shows the final output vector layers calculation.

$$y_{ii} = f\,(t_{ii}p_{ii} + \delta_{ii}) \tag{21}$$

The final out vector denoted by y_{ii}, the bias is denoted by δ_{ii} and the weight matrix denoted by ti.

The modified deep CNN-BiLSTM with attention mechanism provides high accuracy than compare to the existing model. Due to the improved search ability based genetic algorithm in the feature selection, it helps to analysis the data and provide best features among the dataset. The model projected modified deep CNN-BiLSTM with AM, because the CNN is good with image dataset but not in time series data but BiLSTM is good with time series data for this reason the CNN and BiLSTM was hybrid and attention mechanism is used to align the processed data in the optimization layer of CNN.

3.6 Model architecture of the modified deep CNN BiLSTM

The following figures 3, 4, and 5 representing the architecture of integrated modified deep CNN-BiLSTM with attention mechanism that aids effectively enhance the safety prediction in autonomous vehicles.

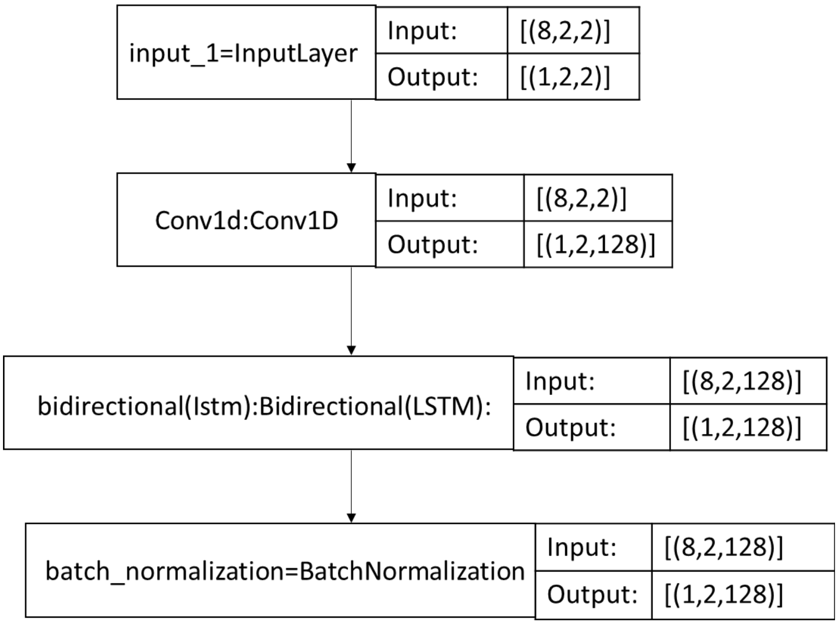

Figure.3. CNN-BiLSTM with Attention Mechanism part 1

Figure 3 illustrates the CNN based BiLSTM with attention mechanism first part. The model begins with an input layer that accepts raw data; the first part model contains multiple conventional layers structured to extract the spatial features from the input data. These layers deploy filters to create required pattern.

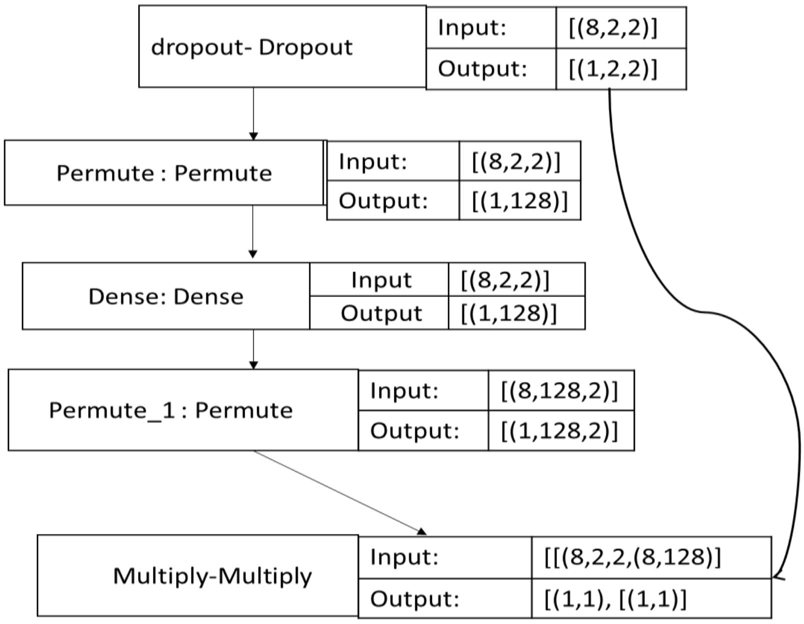

Figure.4. CNN-BiLSTM with Attention Mechanism part 2

Figure 4 demonstrates the CNN based BiLSTM with attention mechanism second part. Following the CNN layer, the output feature maps are flattened into a 1D vector this step is crucial for preparing the subsequent data for BiLSTM layer. Before that, attention mechanism is employed to process the relevant data for predictions.

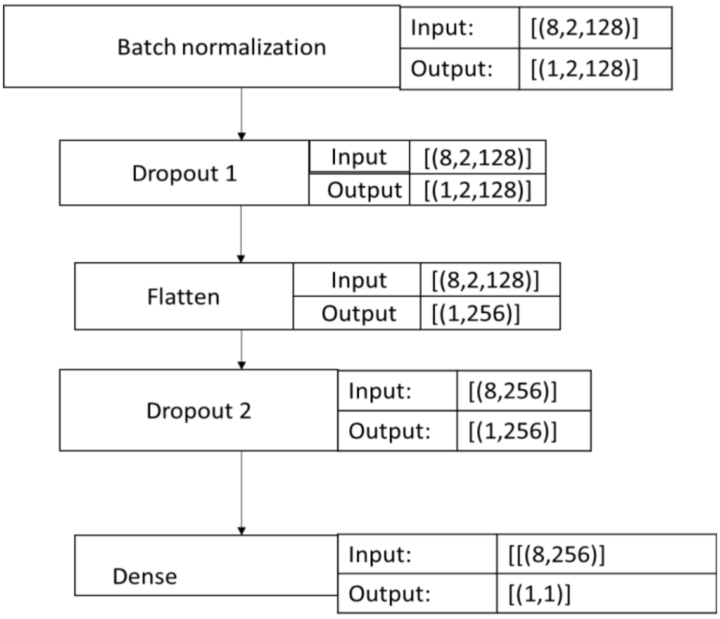

Figure.5. CNN-BiLSTM with Attention Mechanism part 3

Figure 5 specifies the CNN based BiLSTM with attention mechanism final part. . CNN extracts the spatial features from the input data, after that the featured data is flattened into a 1D array which is given as a input for the BiLSTM layer. The outcome from the attention mechanism is fed into the BiLSTM Layer where the data are processed in both front and back directions for capturing the temporal dependencies efficiently. Eventually, after processing through BiLSTM layer the output is transferred to an output layer that produced predictions based on the learned features.

4. Results and Discussion

4.1 Performance Metrics

The proposed model performance is explained in the respective section with some measurable and suitable metrics for the evaluation. The proposed model assessed through the metrics namely F1 score, precision, accuracy and recall.

4.1.1 Accuracy

Across all the classes, accuracy metric is used to provide the model measure. The

- True Negative rate represented by the Tr_N
- True Positive rate represented by the Tr_P
- False Negative rates represented by Fl_N
- False Positive rates represented by Fl_P

The overall accuracy assessed using,

$$\text{Accuracy} = (Tr\_P + Tr\_N)/(Tr\_P + Tr\_N + Fl\_P + Fl\_N) \quad (22)$$

4.1.2 Precision

The important metrics for model performance are instances and the precision is used for saving the information and given using,

$$\text{Precision} = \text{Tr\_P}/(\text{Tr\_P} + \text{Fl\_P}) \tag{23}$$

4.1.3 Recall

In the proposed model, to define the model detecting the total number of false and true incidents of the positive instances the metric is used.

$$\text{Recall} = \text{Tr\_P}/(\text{Tr\_P} + \text{Fl\_N}) \tag{24}$$

4.1.4 F1-Score

The weighted harmonic mean value of recall and precision is signifies by F1 score. It is valued with the following equation.

$$\text{F1} - \text{score} = 2 \times (\text{RC} \times \text{Pc})/(\text{Rc} + \text{Pc}) \tag{25}$$

Here, R is denoted as recall and P is denoted as precision.

4.2 Performance Analysis

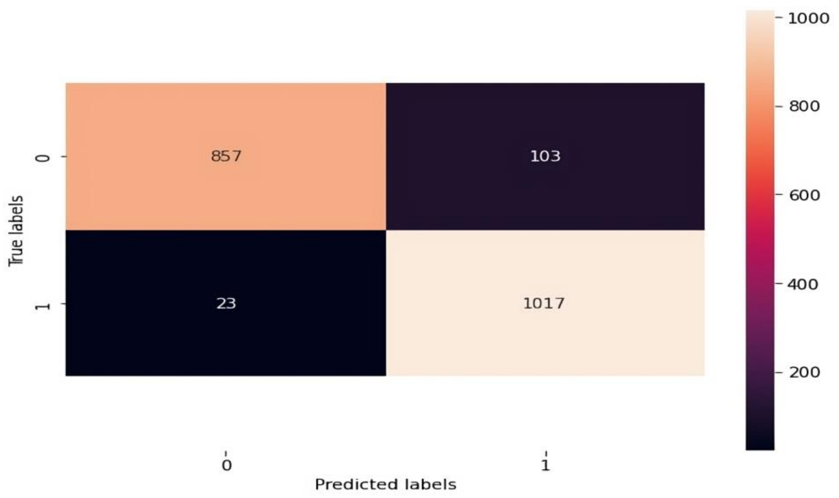

Figure.6. Confusion Metrics

Figure 6 shown the proposed model attain good True Positive (1017) and True Negative (857) values and False Positive (103) and False Negative (23). In the proposed model, the correct classification is higher than the misclassification.

Table 4. Comparative Performance Analysis of Proposed Method

Algorithm	F1 Score	Precision	Accuracy	Recall
CNN-BiLSTM	96.1	96.5	93.45	92.14
Modified Deep CNN-BiLSTM with attention mechanism	99.5	99.5	99.5	99.5

Table.4 shown the comparative performance analysis with F1 score, precision, accuracy and recall of proposed model attain high value with 99.5, 99.5, 99.5 and 99.5.

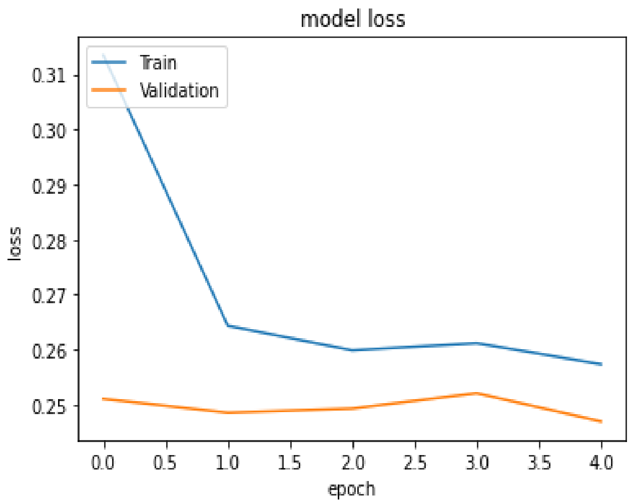

Figure.6. Line Plot of Proposed Model During Train and Validation of Dataset

The figure 6 has shown the line model loss during the train and test dataset of proposed model. The proposed model attain good results and applicable to predict the drivers health and car mechanism.

```
=================================================================
Total params: 24,643,893
Trainable params: 24,643,893
Non-trainable params: 0
_________________________________________________________________
CNN-Bilstm
CNN-Bilstm Accuracy: 92.71943332306745 %
------Classification Report------
              precision    recall  f1-score   support

           0       0.66      0.72      0.69       116
           1       0.12      0.50      0.19         4
           2       0.09      0.19      0.12       172
           3       0.91      0.80      0.85      3788
           4       0.70      0.79      0.74       316
           5       0.99      1.00      0.99      7781
           6       1.00      1.00      1.00      3862
           7       0.14      0.25      0.18       192
           8       0.00      0.00      0.00         4

    accuracy                           0.93     16235
   macro avg       0.51      0.58      0.53     16235
weighted avg       0.95      0.93      0.94     16235
```

Figure.7. Modified Deep CNN-BiLSTM with AM Accuracy

The figure.7 shown the accuracy of the CNN-BiLSTM, it includes 8 classes of classification report with the metrics of precision, recall and f1-score. The proposed model attains good results in accuracy (0.93), macro average (0.51, 0.58, and 0.53) and weighted average (0.95, 0.93 and 0.94).

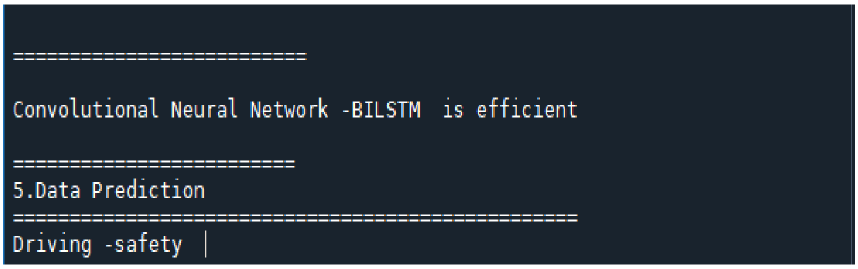

Figure.8. Prediction Outcome of Proposed Method

The figure 8 shown the prediction outcome of proposed modified deep CNN-BiLSTM model and it predicted the safety of driving with the given dataset.

4.3 Comparative Analysis

The respective section compared the proposed model with the existing model in table.1.

Table 5. The Comparative Analysis of Existing Method with Proposed Method [33]

Algorithm	F1 score	Precision	Recall
RF	98.3	98.7	97.8
KNN	98.5	98.8	98.1
DT	97.8	97.9	97.8
NB	59.1	64.5	54.9
Proposed	99.5	99.5	99.5

Table.5. has shown the precision, recall and F1 score of RF, KNN, DT, NB and proposed model for normal health condition of drivers. When compared to the existing models, proposed model attain higher value on F1 score, precision and recall are 99.5%, 99.5% and 99.5%. The pictorial representation of the above table is shown is figure.9.

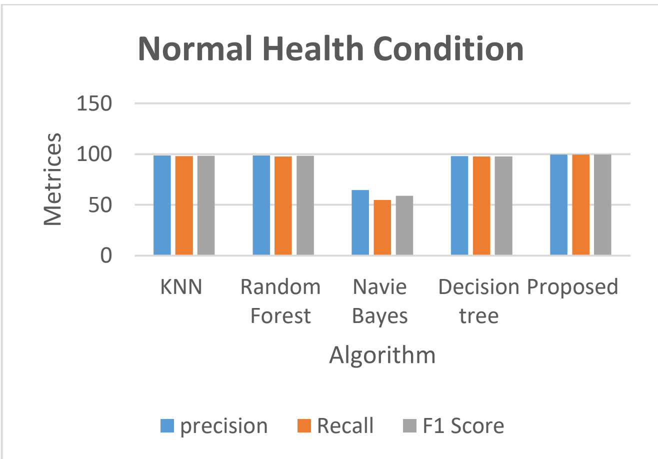

Figure 9. Performance Metrics of Normal Health Condition [33]

Table 6 The Comparative Analysis of Existing Method with Proposed Method [33]

Algorithm	precision	Recall	F1 Score
NB	64.4	54.8	59.2
RF	99	98.3	98.7
DT	98.6	98.4	98.5
KNN	99.2	98.8	99
Proposed	99.9	99.9	99.9

Table.6. has shown the precision, recall and F1 score of KNN, RF, NB, DT and proposed model for abnormal health condition of drivers. When compared to the prevailing models, proposed model attain higher value of precision, recall and F1 score with 99.9%, 99.9%, and 99.9%. The pictorial representation of the above table is shown is figure.10.

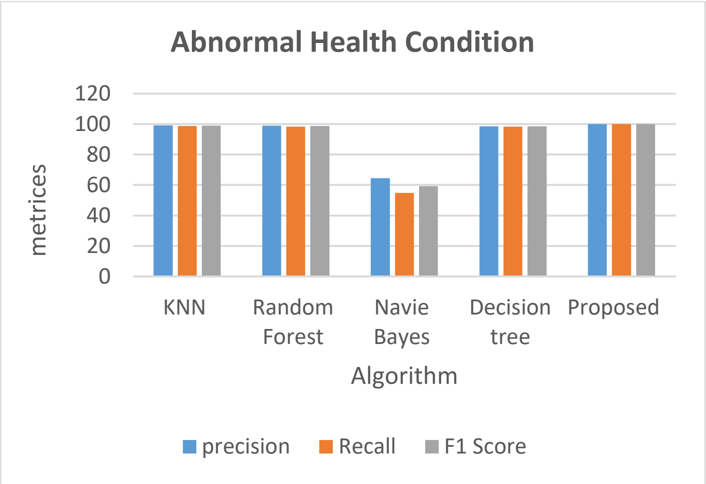

Figure10. Performance Metrics of Abnormal Health Condition [33]

Table 7. performance Metrics in Low, Medium and High Range [34]

Algorithm	Low Accuracy	Low F1 Score	Medium Accuracy	Medium F1 Score	High Accuracy	High F1 Score
Stacking	90.2	83.9	91.5	86.6	91.7	86.7
Random Forest	90.6	84.7	92.8	87.7	92.7	88.1
KNN	86.3	78.8	91.2	86.6	91.6	87.8

Proposed	99.5	99.5	99.5	99.5	99.5	99.5

Table 7 has shown the low accuracy and F1 score, medium accuracy and F1 score and high accuracy and F1 score of KNN, Random Forest, stacking and proposed model. Where the proposed model attains high accuracy and F1 score in all range (99.5, 99.5, 99.5, 99.5, 99.5 and 99.5) than compare with existing model. Its pictorial representation is shown in figure 11.

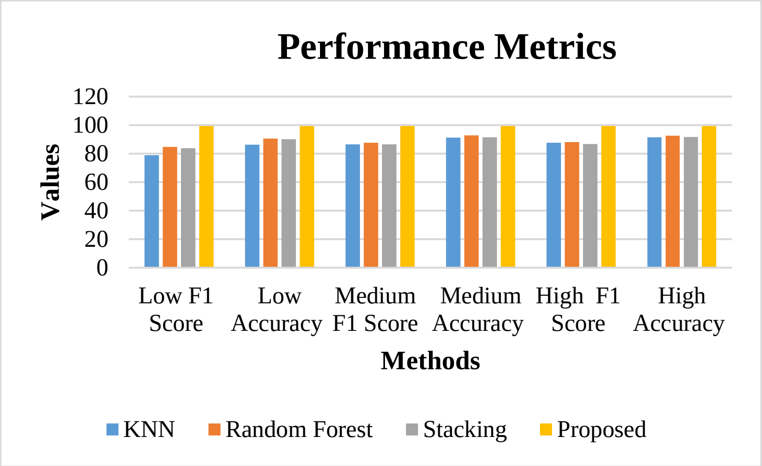

Figure 11. Pictorial Representation of Low, Medium and High Range [34]

Table.8. Performance analysis on Test MCC

Dataset	**Test MCC**
NSL-KDD	0.9724
CICIDS201	0.9965
CIRA-CIC-DoHBrw-2020	0.9975
ICS-SCADA	0.8864
Proposed SDNDDOS	0.9979

Table 8 illustrated the performance analysis of th MCC among various dataset examined for the safety prediction in autonomous vehicle and proven the proposed model dataset has high MCC as 0.9979 % that other dataset. Its pictorial representation is shown in figure 12.

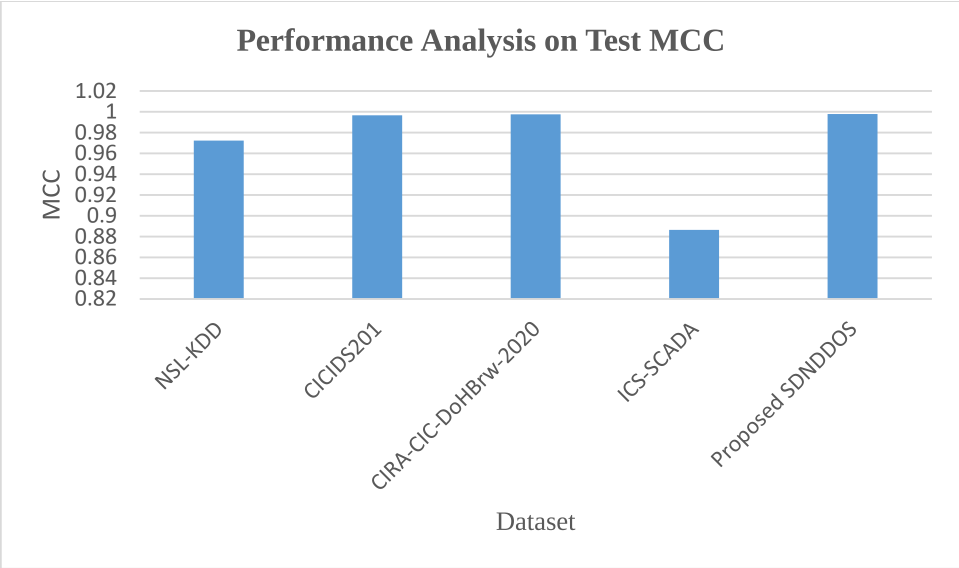

Figure 12. Performance analysis on Test MCC [35]

Table.9. Performance analysis on false positive

Dataset	**Accuracy**	**Precision**	**Recall**	**FI-Score**	**False positive**
CICIDS2019	98.70%	99.78%	98.81%	98,78%	18.50%
InSDN	98.20%	97.51%	97.93%	98.27%	18%
Slow-read-98.88%	98.88%	96.80%	95.90%	96.27%	3.65%
DDoS-attack	99.26%	99.10%	99.60%	98.17%	2.25%
Proposed SDNDDOS	99.79%	99.50%	99.80%	98.47%	1.25%

Table 9 describes the performance analysis on the metric such as False positive various dataset examined in existing studies with different dataset and proven the proposed model dataset has less false positive prediction as 1.25 % that implies the significance of the model. Its graphical representation is shown in figure 13.

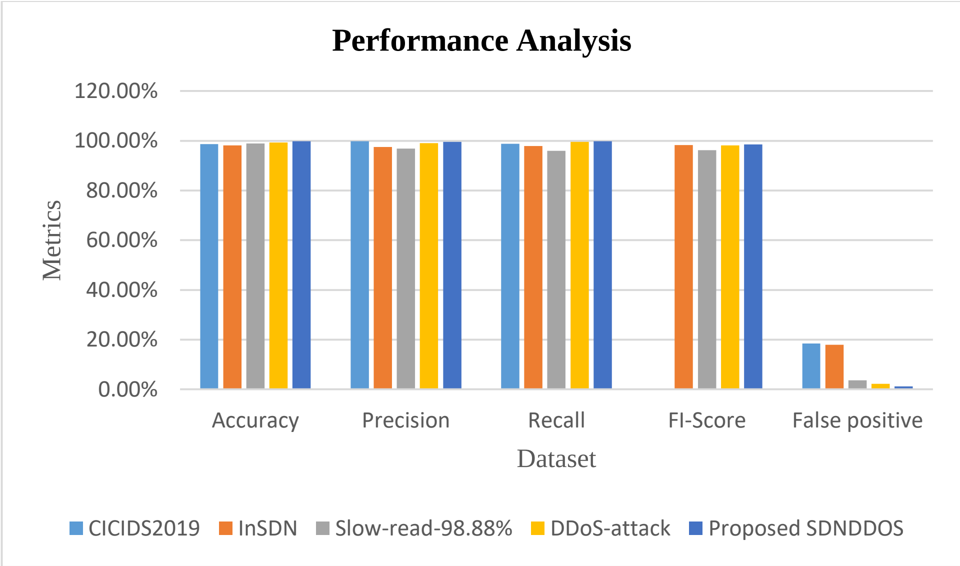

Figure.13. Performance analysis on false positive prediction [36]

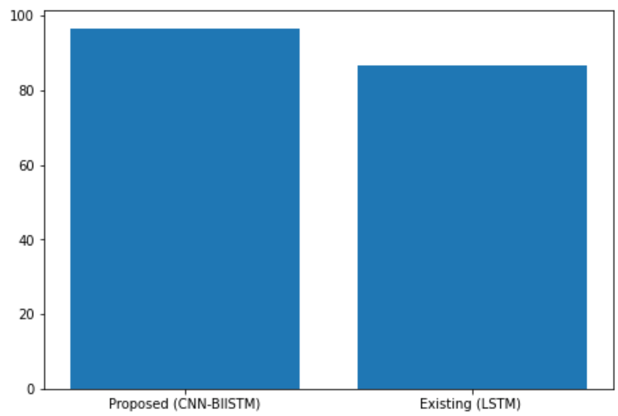

Figure 14. Comparison of Proposed Model with Existing Model

The figure 14 has shown the comparison graph of proposed model with existing mode. Here the proposed model attains higher accuracy (96%) than the existing model (85%).

5. Conclusion and Future Recommendation

Recently, advancement in technology goes high, also antonomous cars usage are getting higher in the world. It has been gave independent to the people those who are unable to drive particlualrly for senior citizens and those have disabilities. The impetus for modeling autonomous vehicle traffic stems from the neccessity of achieving a seamless and safe integration of AVs into current transportation systems. It has been avoid the emission of CO2, accidents and traffic and most importantly in autonomous cars there has no attention problems like human. Even, the autonomous vehicles are also met with an ancident because of some malfunction and drivers health. To avoid the problem some manual techniques has been used to analyse the drivers behavior while driving with dashboard camera, survey and so on. But these techniques needed more manual work and time. To overcome this drawback the proposed model has been used improved search ability genetic algorithm in feature selection to obtained the best features from the given dataset and modified deep CNN-BiLSTM with attention mechanism has been used to predict the drivers behavior and car mechanism.

The proposed model integrated the CNN and BiLSTM aumented by an attention mechanism, to enhance the prediction of safety issue in auttonomous driving car in complex driving road. By evaluating the actions of other vehicle drivers and pedestrains can effectively contribute to collision avoidance strategies hence forth improves the safety precation of autonomous vehicles. The attention mechanism permits for a more relevant understanding of crucial features from input data, enabling the study to concentrate on relevant aspects that impact decision making scenarios. Hence, has obtained the best performance research integrated the modified deep CNN and BiLSTM with AM model.
When the existing models such as KNN, Random Forest, Naive Bayes, Decision Tree and deep CNN-BiLSTM are compared with the proposed model, that has attain high performance in precision, recall and F1 with 99.5%, 99.5% , and 99.5%. In addition, MCC as 0.9979 %, and less false prediction of 1.25 % has obtained than other dataset. As a result, the overall accuracy of the proposed model was 96%. Though the model has several advantages there exist certain limitations which includes high training and testing time has been needed. In future work of the proposed work the real time data can be collected from autonomous vehicle's cameras and sensors for detection.

Declaration
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Acknowledgement: None
Data Availability: Data sharing not applicable to this article as no datasets were generated.
Ethical statement for human participant: Not applicable for this research

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