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Research Article

An Improved Deep Learning-Based Technique for Driver Detection and Driver Assistance in Electric Vehicles with Better Performance

Gunapriya Balan,[1] **Singaravelan Arumugam**,[2] **Suresh Muthusamy**,[3] **Hitesh Panchal**,[4] **Hossam Kotb**,[5] **Mohit Bajaj**,[6] **Sherif S. M. Ghoneim**,[7] **and Kitmo**[8]

[1]*Department of Electrical and Electronics Engineering, New Horizon College of Engineering (Autonomous), Bangalore, Karnataka, India*
[2]*Department of Electrical and Electronics Engineering, Nitte Meenakshi Institute of Technology, Bengaluru, Karnataka, India*
[3]*Department of Electronics and Communication Engineering, Kongu Engineering College (Autonomous), Perundurai, Erode, Tamil Nadu, India*
[4]*Department of Mechanical Engineering, Government Engineering College, Patan, Gujarat, India*
[5]*Department of Electrical Power and Machines, Faculty of Engineering, Alexandria University, Alexandria, Egypt*
[6]*Department of Electrical Engineering, Graphic Era (Deemed to be University), Dehradun 248002, India*
[7]*Electrical Engineering Department, College of Engineering, Taif University, P.O. Box 11099, Taif 21944, Saudi Arabia*
[8]*Department of Renewable Energy, National Advanced School of Engineering, The University of Maroua, Maroua, Cameroon*

Correspondence should be addressed to Kitmo; kitmobahn@gmail.com

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Technology for electric vehicles (EVs) is a developing subject that offers numerous advantages, such as reduced operating costs. Since the goal of EVs has always been to have long-lasting batteries, any new hardware might drastically diminish battery life. Errors are common among human beings. Because of that, accidents and fatalities may occur due to drivers' different behaviors such as sports style and moderation. To advance driver safety, security, and comfort, Advanced Driver Assistance Systems (ADAS) must be personalized. Modern cars have ADAS that relieves the driver of some of the tasks they perform while driving. As a part of this research, a driver identification system based on a deep driver classification model (deep neural network as DNN) with feature reduction techniques (random forest as RF and principal component analysis as PCA) is implemented to help automate and aid in crucial jobs such as the brake system in an efficient manner. Using task models, we simulate a low-cost driver assisted scheme in real time, where various scenarios are explored and the schedulability of tasks is established before implementing them in EV. The new driver assistance scheme has several advantages over the existing options. It lowers the risk of an accident and ensures driver safety. The proposed model (RF-DNN) achieved 97.05% of accuracy and the PCA-DNN model achieved 95.55% of accuracy, whereas the artificial neural network as ANN with PCA and RF achieved nearly 92% of accuracy.

1. Introduction

Electric vehicles (EVs) have the advantage of lower operating costs and environmental protection due to the lack of greenhouse gas emissions. Modern research, on the other hand, has focused on making EVs comfortable with self-driving capabilities. Self-parking and crash prevention are examples of autonomous features already in use [1, 2]. EV research and development has not slowed down, but it is now much more focused on autonomic driving. The researchers introduced the driving assistance systems to improve road safety and minimized the crash risk, which is caused by driver mistakes called drug usage, drunk driving, and fatigue [3–5]. Driver identification products come in a variety of forms. Knowing the identity of the driver ensures the safety of the vehicle and allows for personalization according to the driver's preferences, improving the comfort and efficiency of using the vehicle. In the case of EV, this efficiency can also be exploited in terms of more reliable estimates of the range reached and projections of energy consumption. It has been shown that humans play a major role in dealing with human and machine systems, i.e., vehicles [6]. As a result, it is suggested that human behavior while driving should be investigated in depth to improve vehicle performance. In automated vehicles or advanced driving assistance systems (ADAS), driving behaviors have been carefully studied to improve system performance [7]. These studies can be building models of driving behavior and classification of behavior, etc. Several important patterns of driving behavior based on different theories of human behavior have been developed [8], focusing on different aspects of the task and providing intuitive knowledge about these behaviors. Some methods of classifying driving behavior have been proposed [9, 10], and the specific driving behavior can be applied in ADAS system design and traffic system differentiation.

The behavior of the driver that can affect the safety of driving and fuel consumption has been studied in recent years. Drivers with different behaviors tend to drive a car in different ways, which results in different fuel consumption. Specifically, drivers who prefer to drive in a sporty style may require the car to respond quickly to driving requirements, leading to higher fuel consumption. On the contrary, moderate drivers prefer to drive the vehicle moderately, and the car does not require a quick response to driving requirements, which saves fuel to some extent. For power-driven EVs, the driver's behavior can also be a vital factor in fuel consumption. Therefore, it is suggested to study the different behaviors of the driver and the power distribution between the engine and the battery in all types of electric vehicles accordingly.

Driving behavior expresses the psychological activities of drivers after receiving environmental stimulation [11]. In recent years, studies on the analysis of driving behavior have appeared constantly, mainly including the generation of driving behavior and the classification of driving style. In the areas related to the generation of driving behavior, the methods of qualitative and quantitative analysis have been widely used to reveal the factors that can cause and change driving behaviors [12], [13]. The classification of driving behavior is closely related to driving people and cars in self-driving vehicles [14], [15]. Machine learning methods [16] and deep learning algorithms [17] have been proposed to effectively identify different driving behaviors. Studies on this behavior related to energy management require even more effort. The mechanism for generating driving behavior and the reasonable classification methods is useful for formulating a more efficient strategy with better adaptability. A deep learning technique called residual convolutional neural network is developed to identify the driver behavior using the publicly available dataset [18]. However, none of the research studies focused on both driver identification and driver assistance model for better safety protection and avoiding the collision of vehicles.

In this research work, the driver is identified using a DNN (deep driver classification model) in real time. Another focus is on developing the ADAS system by using the intelligent technique. By using the proposed methodology, the risk of accidents can be controlled, and driver behavior is monitored and aided them. The strong potential of the proposed technique is illustrated with existing techniques using the experimental results.

The paper is organized as follows: In Section 2, a list of existing techniques that were used in the above topic are mentioned. Section 3 discusses how the data were gathered and how the most important attributes were chosen and categorized. Section 4 provides the examples of common experiment findings. Section 5 gives conclusion with a few ideas.

2. Related Works

In this section, the study of existing techniques based on driver behavior identification with driver assistance models is presented. Initially, the driver identification systems using various studies are given.

Reference [19] suggests the use of artificial neural networks (ANNs) to forecast the daily charging profile of EVs for improving the battery life and individual fleets, as user habits are one of the most important issues regarding EV charges. Specifically, they use historical data to predict electricity demand and better coordinate tasks.

For antitheft in automobiles, researchers [20] proposed a driver identification system. A classification method like K-nearest neighbour (KNN) or a decision tree is used to find out how long the driver should be on the road. The owner of the stolen car will be notified if the documentation score is less than a threshold set in the model. Even though the antitheft scheme was well outlined by the authors, no technological implementation of the system was made.

To classify drivers, Ref. [21] suggests using a window-based support vector machine. Researchers have found links between categorization accuracy and different data sources (such as just mobile phone sensors, just automobile sensor data, and a combination of both car and mobile phone sensor data). The combined data yielded the highest accuracy rating (86.67%).

Using GPS data and deep learning, Ref. [22] proposed a driver identification system. An auto-encoder as a special regularizer is introduced to combine the unsupervised and supervised feature learning by developing an Auto-encoder Regularized Network (ARNet) in this work. The suggested ARNet model was compared to various current models (CONet, NoPoolCNN, CNN, Pre-training, IRNN, StackedIRNN, TripGBDT, and GBDT), and ARNet came out on top in terms of accuracy (78.3 percent).

The use of driver assistance technologies is commonplace to make roads safer and prevent collisions. Many possibilities are highlighted in a global status report on road

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safety that must be addressed to ensure the safety of everyone on the road. Each element of the situations was tied to the surrounding conditions, the driver's circumstances, and the vehicle's circumstances as well.

As an example, major legislative activities include ensuring proper speed and vehicle conditions, road status, traffic, and driver states, such as fatigue and intoxication. Similar measurements were found to be the most important drivers of road safety in another study [23] based on UK safety data. It was divided into three categories: driver skills, travel conditions, and policy options that may arise because of these factors. Road safety is affected by the leading factors such as weather conditions, road surface conditions, and lighting conditions that are suggested by the author in Ref. [24]. Reference [25] thoroughly studied the key components, technologies, and challenges of EV. Their study mentioned all types of EVs. They collected a large amount of useful data on EVs but did not analyze the difficulties of technological development of EVs in the data.

It was shown that using the traditional machine learning (ML) approaches such as KNN, random forest, and extra trees on numerous datasets with varied time frames resulted in a high cross-validation score [26]. Two types of features such as driver-related patterns and driving pattern-related components have been distinguished in this work. Data from 38 drivers were collected [27] using smartphones and classified into four to five categories. The completed trip data yielded 137 unique statistical features. A thorough investigation was conducted without regard to the specifics of the local road network, driver profile, or traffic flow. Using the random forest practice, the authors were able to achieve an accuracy rate of 82.3%.

Regarding the thermal management of batteries, Park et al. [28] proposed the use of ANN to improve the thermal management system and reduce total energy consumption. The proposal helps to keep the battery temperature within an acceptable range. In Ref. [29], a compact heater is proposed, based on resonant switched capacitors (RSC) which are powered by the onboard battery, which allows an easy implementation, capable of increasing up to 2.67°C/min. with high yield (96.4%). Vasant et al. [30] examined the daily use of EVs and stated that the proper operation of charging stations during the day as well as the proper control and management of the charging of this infrastructure can lead to a wider deployment of EVs.

Zhang et al. [31] presented a method for regulating the torque demand of EVs with single pedal driving for eco-driving. By integrating the binary dragonfly algorithm with an adaptive neuro-fuzzy inference system, the behavior of the driver is identified. To consume less energy, torque demand is generated by the whale optimization algorithm. However, the method did not focus on the driver assistance model and only focused on the torque demand of EVs. Al-Wreikat et al. [32] intended to reduce the high energy consumption in EV vehicles by considering the driving behavior, trip distance, road grade, traffic condition, and ambient temperature. Real-time data of the United Kingdom for nearly four years data are used for work. According to the operation limits, the behavior of the driver is identified as moderate, passive, and aggressive, where the average vehicle speed is also considered for traffic conditions. Liu et al., [17] used the fuzzy logic method to determine the different driver behavior because they considered it the foundation for high energy consumption in EVs. An energy management strategy is developed by using the instantaneous optimization method called equivalent consumption minimization strategy (ECMS) for reducing high consumption. In addition, the road condition is also considered in this work to minimize vehicle energy consumption.

All these existing techniques either focused on driver identification behavior or how to address the theft of cars. Some of the techniques focused on road safety and preventing the collision by using the behavior of the driver, road status, and speed of the vehicle. In addition, they focused on battery power management, and none of the existing works focused on developing a driver assistance scheme as well as behavior identification of drivers. The study by Al-Wreikat et al., [32] proves that driver behavior also leads to specific energy consumption, where it must be essential to identify the behavior of the driver, which is the main motivation of this projected scheme. This motivates the authors to develop this research study.

3. Proposed System

In this research study, two different types of the proposed method are developed RF and PCA. Initially, driver identification is carried out by using the DNN method and the second work is based on the driver assistance method. The authors used a Google Colaboratory cloud computer to train and test all ML and deep learning tests [33]. This specialized system has a dual-core 2.3 GHz Intel Xeon CPU with a 56 MB L3 cache and 13.3 GB RAM. To accelerate the calculation of computationally expensive, the training uses the RAM memory of 17.1 GB with Tesla P100 GPU. Figure 1 provides the overall block diagram of the proposed model.

3.1. Driver Identification

3.1.1. Dataset Description. We used the Ocslab driving dataset [34] from South Korea in 2015 to validate and appraise our models. A sampling rate of 1 Hz was used to extract 51 different OBD-II signals from the car's ECU. 10 different drivers took turns driving the automobile around a 46-kilometer course for a total of 23 hours, and this resulted in 94380 records overall. A city route, a motorway, and a parking space requiring cautious driving were all used in the experiment.

3.1.2. Data Preprocessing. It is imperative that we thoroughly prepare all the features in our classification model before introducing them to the model. Nearly all state-of-the-art models have a preprocessing mechanism in place to ensure that these features can guide the model and make categorization easier. As a result, we begin by standardizing the CAN-bus data. Before using standard machine learning methods/deep learning models on these type of data,

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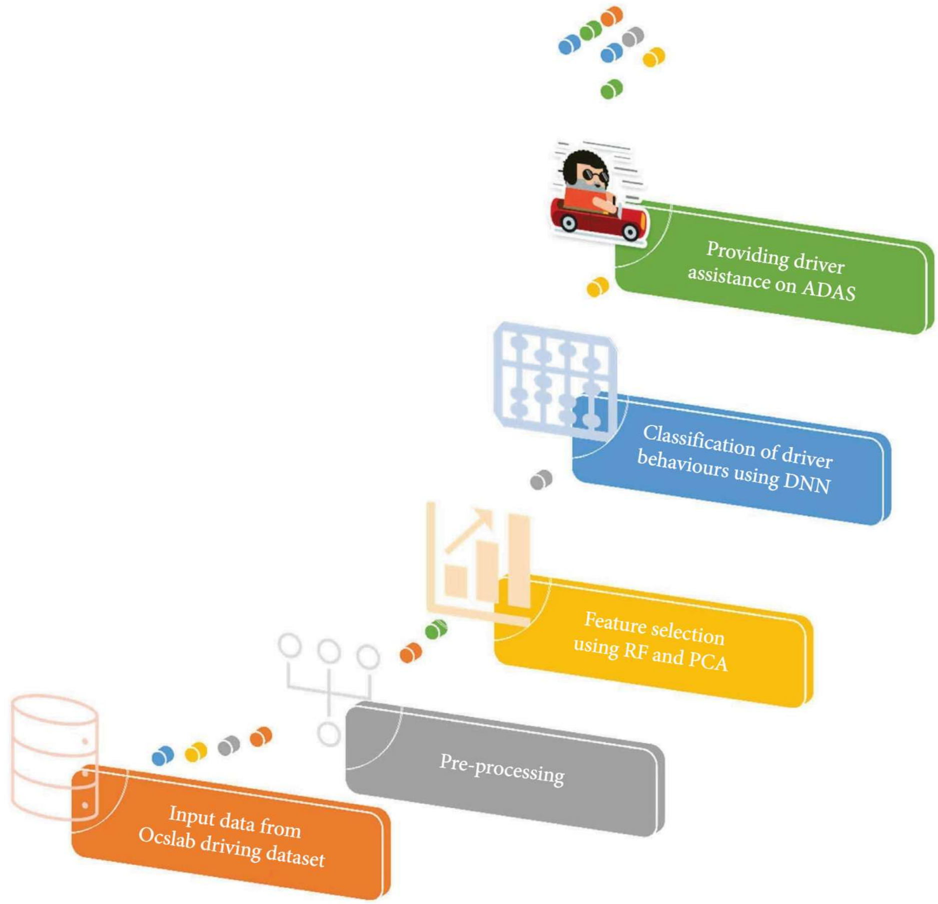

Figure 1: Block diagram of the proposed model.

normalization is considered as a part of preprocessing. To normalize the data, min-max is the most common method and creates new values to maintain the ratio and general distribution in the source data. By normalizing our features, we mean to converting them to numbers between 0 and 1, so that their various scales can be combined. Equation (1) defines the normalization of a single distinct feature $X(t)$:

$$X(t) = \frac{X(t) - X^{\min}}{X^{\max} - X^{\min}}, \tag{1}$$

which represents the feature's minimum and maximum values of CAN-bus data as $X_{\min}$ and $X_{\min}(t)$, respectively. All OBD-II features from CAN-bus data were normalized using this equation before being loaded into the model.

The time series analysis component of our data is considered in the second preprocessing stage. Even when the number of classes is increased to a certain level, the 51 feature values in a single second are insufficient to provide enough information to allow the model to determine the identity of the driver. As previously said, driving is a continuous and protracted activity, which necessitates aspects that describe the driver's profile more precisely. For the CAN-bus data, most of the current references have relied on sliding window segmentation, as previously described. Our research segmented our data using an overlapping sliding window segmentation with a 1-minute frame and a 6-second step size.

3.1.3. Feature Reduction. Feature extraction and dimension reduction for ML models are the emphasis of the first development part. To identify the driver's behaviors, the existing machine learning and deep learning show good performance. However, the prediction classification accuracy is less when a greater number of features are used for the final prediction process. To avoid irrelevant and unwanted data, feature selection is important before the input is fed into the classifiers. Therefore, various feature selection or reduction techniques are introduced, where in this research work, random forest (RF) and principal component analysis (PCA) are used for the feature reduction process.

The correlation-based feature assessment of our data using RF was our first feature reduction system. We can see from the findings that the tree-based classifiers are the most effective for our dataset. The RF feature significance evaluation is therefore a logical starting point for feature reduction. The process of evaluating the weight and relevance of a particular feature on a classification to rank the various features by standing is known as feature importance evaluation, as shown in Figure 2. By considering the RF, the

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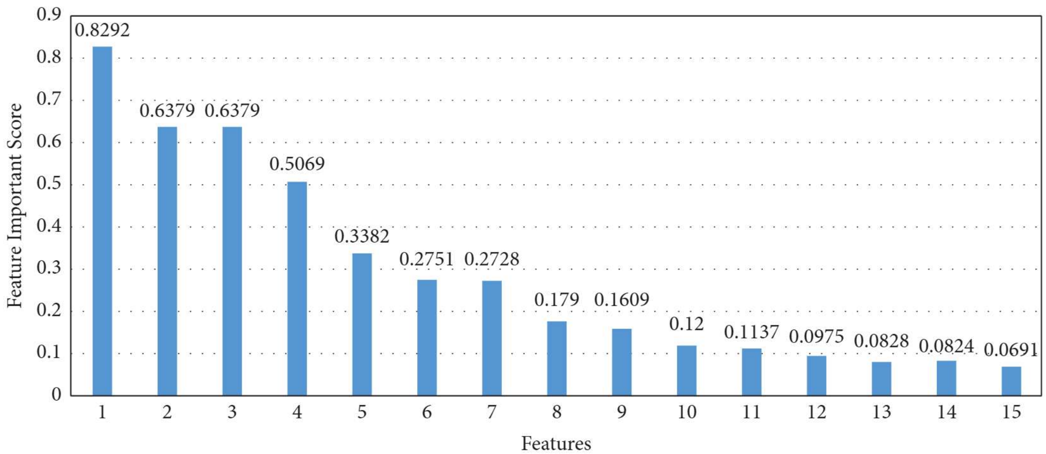

Figure 2: RF feature importance evaluation.

position criterion utilized in the split point selection narrows down the field. Using the RF feature importance evaluation, we have generated a list of the 15 most essential qualities for an electric vehicle is considered, which is presented in Table 1:

This strategy assisted in reducing the number of features, allowing our classifiers to place a stronger emphasis on the most important ones. We experimented with the three different numbers of critical features to see how they affected the accuracy of our models. As a result of our feature reduction technique, we found that 81.06 percent of the importance of the total features was expressed by using our 10 most critical features, while 87.5 percent was expressed by using our 15 most critical features, and 90.74 percent was expressed by using our 20 most critical features. Prediction among the important features related to identifying the driver's class (A to J respectively) is tested, and the results are given in Figure 3 for the activation of air compressor vs. intake air pressure, Figure 4 for accelerator pedal value vs. intake air pressure, and Figure 5 with torque of friction vs. intake air pressure. The results from Figures 3 to 5 show that the features chosen are having the best prediction of driver class.

Additionally, a statistical process called PCA [35] was performed to help minimize the size of the dataset by extracting features of driver behavior (i.e., the information of the accelerator position, driving time, same driver, different driver, random driver, total distance driven, and brake pedal pressure are the major features considered for the driver behavior identification) and reducing dimensionality. By selecting and condensing key pieces of information from the data, PCA can create new features that make data interpretation simple and straightforward for users. PCA was utilized to extract 15 components with a 99.99 percent expression rate from 51 signals in our case. After experimenting with other combinations of components, we settled on this number. However, to improve the results, the authors investigate methods based on deep learning, which will be the focus of the next section of our research.

Table 1: Selected features.

S.no	Features
1	Motor energy conversion ratio
2	On board charge
3	Off board charge
4	Torque of friction
5	Intake air pressure
6	Activation of air conditioner
7	Vehicle speed
8	Master hydrolic pressure
9	Accelerator pedal value
10	Temperature range of electric motor
11	Conversion ratio
12	Wheel velocity rear left hand
13	Wheel velocity front left-hand
14	Wheel velocity rear right-hand
15	Wheel velocity front right-hand

3.1.4. Deep Driver Classification. Because it is impacted by biological neural network properties, we use an ANN method as the computational model for our suggested method. It is possible to create an ANN that feeds information from one node to the next without generating a cycle using a feed forward neural network (FFN). There are three or more layers in our model: an input layer, one or more hidden layers, and an output layer, each of which has many neurons. We call this a multilayer perceptron (MLP). A hyperparameter feature selection technique is used to pick the number of hidden layers. With neurons in each layer fully linked, data are translated forward from one layer to the next. The mathematical definition of MLP is O: $\mathbb{R}^m \times \mathbb{R}^n$, where m is the size of the input vector $x = x_1, x_2, \ldots, x_{m-1}, x_m$ and n is the size of the output vector $O(x)$ correspondingly. Equation (2) describes the MLP expression as

$$h_i(x) = f\left(w_i^T + b_i\right), \tag{2}$$

where h_i: $\mathbb{R}^{d_i - 1} \longrightarrow \mathbb{R}^{d_i}$, f: $\mathbb{R} \longrightarrow \mathbb{R}$, $w_i \in \mathbb{R}^{d \times d_i - 1}$, $b \in \mathbb{R}^{d_i}$ signifies the size of the input, f is the nonlinear activation purpose, It can be either a sigmoid (values between 0 and 1)

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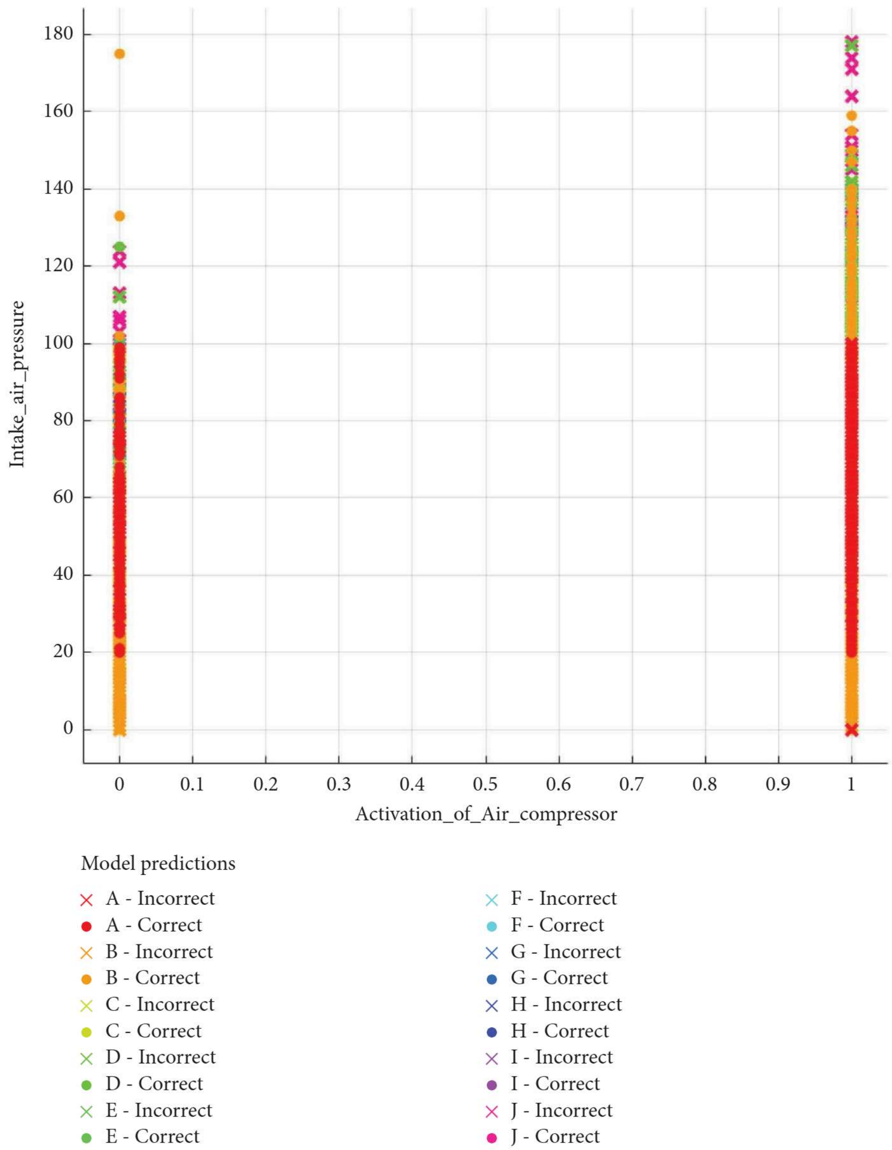

Figure 3: Model prediction with features activation of air compressor vs. intake air pressure.

or a tangent function (values between 1 and 0). Sigmoid, tangent, and softmax activation function mathematical formulas are represented as

$$\text{sigmoid} = \frac{1}{1 + e^{-x}}, \tag{3}$$

$$\text{tangent} = \frac{e^{2x} - 1}{e^{2x} + 1}, \tag{4}$$

$$\text{softmax}(x_i) = \frac{e^{x_i}}{\sum_{j=1}^{n} e^{x_j}}, \tag{5}$$

where x defines an input. The softmax function is the nonlinear activation function in our MLP model for the multiclass classification issue. Here, the research study uses the softmax function to get a more accurate estimate by seeing how likely each class is and then picking the one with the highest probability.

The multiclass logistic regression model is the same as a three-layer MLP with a softmax function in the output layer. MLP can be formulated as follows for many hidden layers, which is described as

$$H(x) = H_l(H_{l-1}(H_{l-2}(\ldots H_l(x)))). \tag{6}$$

It is common to refer to this method of stacking hidden layers as DNN. Figure 6 depicts the DNN architecture, which has one hidden layer. It takes the input $x = x_1, x_2, \ldots, x_{m-1}, x_m$ and output $o = o_1, o_2, \ldots, o_{c-1}, o_c$. However, hidden layers along with its units are not shown in Figure 6.

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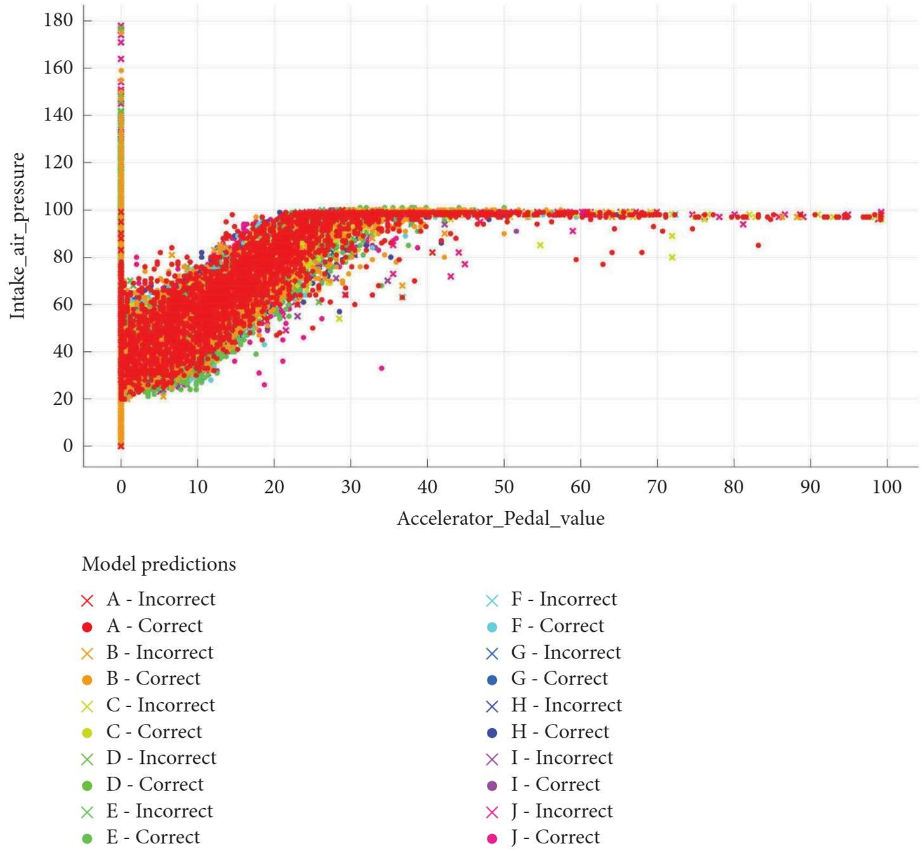

Figure 4: Model prediction with features accelerator pedal value vs. intake air pressure.

Every single hidden layer uses ReLU's nonlinear activation function to assist the alleviation of the state of vanishing and error gradient issues. We use DNNs as a more progressive model than the standard FFN. While other nonlinear activation functions take longer to train, ReLU is faster and allows for more hidden layers to be used in the MLP model. The hidden layers determine the neural network's depth while the maximum number of neurons determines the network's width.

3.2. Driver Assistance. Figure 7 depicts the architecture of intelligent ADAS. There are sensors in the car as well as on the driver that provide data that are fed into the system. The inputs are gathered and recombined based on the situation. Context aware reasoning receives the obtained input data and assimilates it according to its context. Prior to an event occurring, the contextual inputs are matched to the context representation and domain knowledge of the control subsystem to trigger safety alerts, to take safe action through driver vehicle interface (DVI), and to register the action taken in a database. Figure 7 shows the context aware DAS for safety warnings' architectural layout.

Inputs are taken [36] from sensors, radars, and lidar to create an XML document, which is then parsed by a SAX parser for various context-aware situations. When certain XML elements in a context are present, alarms or warnings are generated. They are delivered to the scenario as a set of parsed XML elements and then shown as a set of car simulation processing details.

To generate alerts and warnings, logical conditions and various rules are defined by invoking the control systems such as lane departure warning (LDW), collision avoidance system, adaptive cruise control (ACC), driver drowsy detection system, parking assistance and automotive night visions system using the context reasoning engine.

Depending on the context, driver vehicle interface provides the GUI of a single, 2-way, or 4-way road scenario and produces alerts and warnings for the driver when the control subsystems are invoked in the day or night mode. The system's performance is depicted visually by using a line graph in the GUI.

The context database keeps track of past alarms, cautions, and messages, so it can respond appropriately in the future. Let us say new circumstances arise, and we want to know how to react in advance.

The comprehensive functionality of ADAS is shown in Figure 8 that is created by following the methods outlined below.

Step 1: Gather sensor data from the lidar and radar and save it as an xml file for later use

Step 2: This is where the context acquisition fusion comes in

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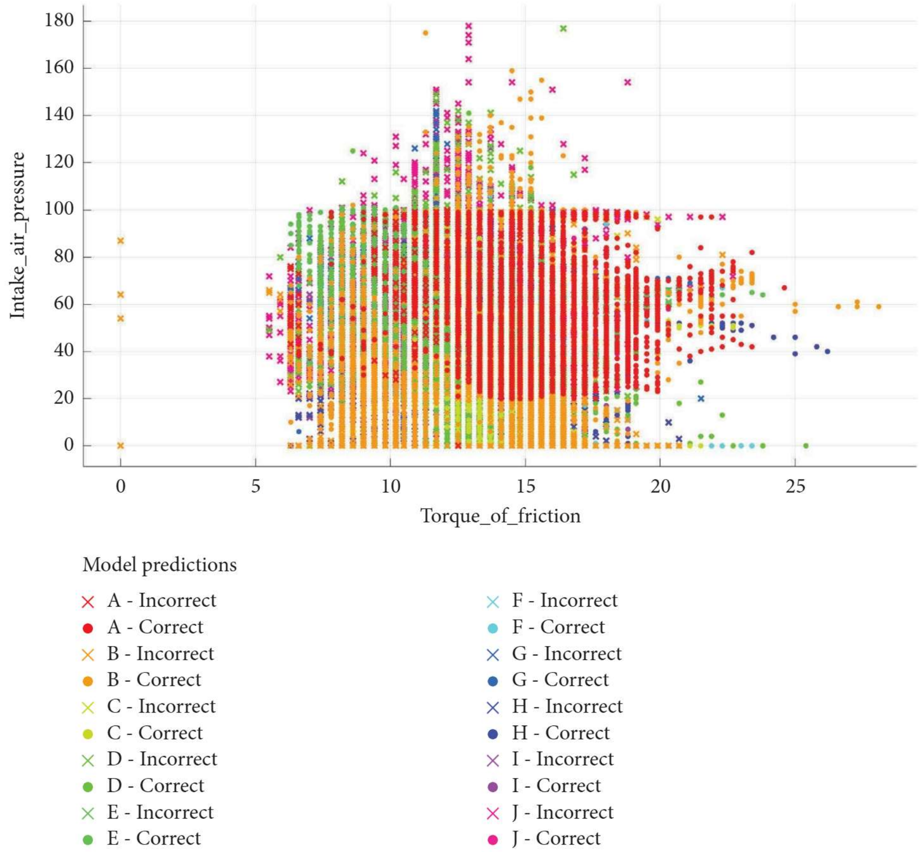

Figure 5: Model prediction with features torque of friction vs. intake air pressure.

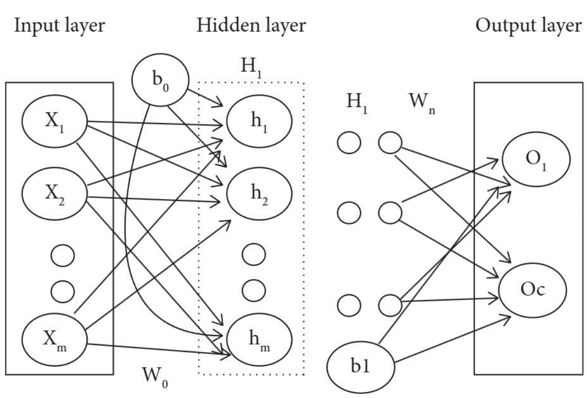

Figure 6: Construction of a deep neural network (DNN).

Steps 3: Search the context database to see if a similar circumstance has occurred before and then retrieve the required data based on the new context

Steps 4: To absorb the context, assimilate and feed the data to the context service engine in Step 5, then Step 9 is the next step

Steps 6 and 7: If the data is new, learn it, and update the database with the new information

Steps 8: A new action/service will be added to the action/service database if it is discovered

Steps 9: At this point, the context service engine queries the service/action database to see what the request is for

Step 10: The context service engine receives a response from the action/service database

Step 11: Have the context engine to carry out the activity and provide the API/agent with the inputs it needs to do so

Step 12: A human vehicle interface receives alerts and warning signals generated by the agent/API

Step 13. The action is recorded in a database of logging records

4. Results and Discussion

4.1. Performance Metrics. Our models were assessed using a variety of performance measures as well as execution time. Thus, we could assess how well and quickly our structures performed in comparison to other cutting-edge approaches. AUC, F1, and Cohen kappa scores were among the performance indicators. The k-fold cross-validation test was also utilized as an evaluation approach. While training and prediction time was the focus of the execution speed measures, the performance measures are calculated using

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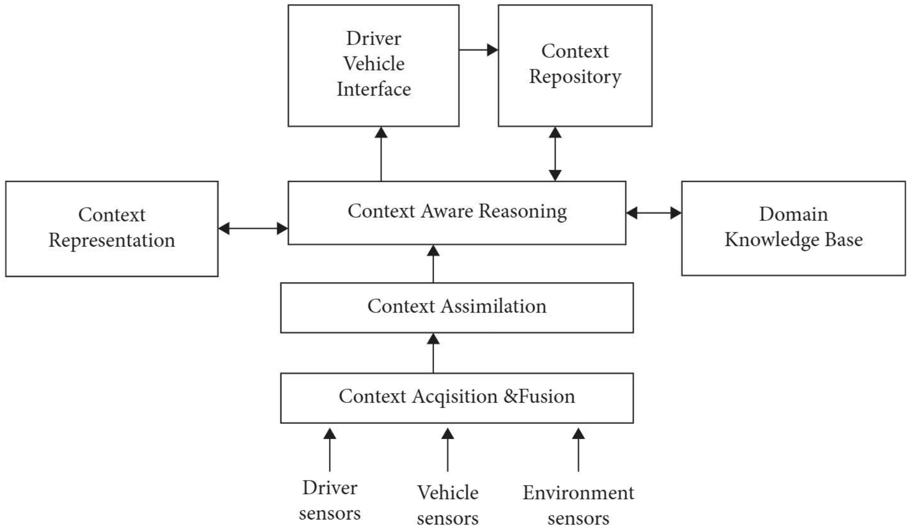

Figure 7: Architecture of intelligent ADAS.

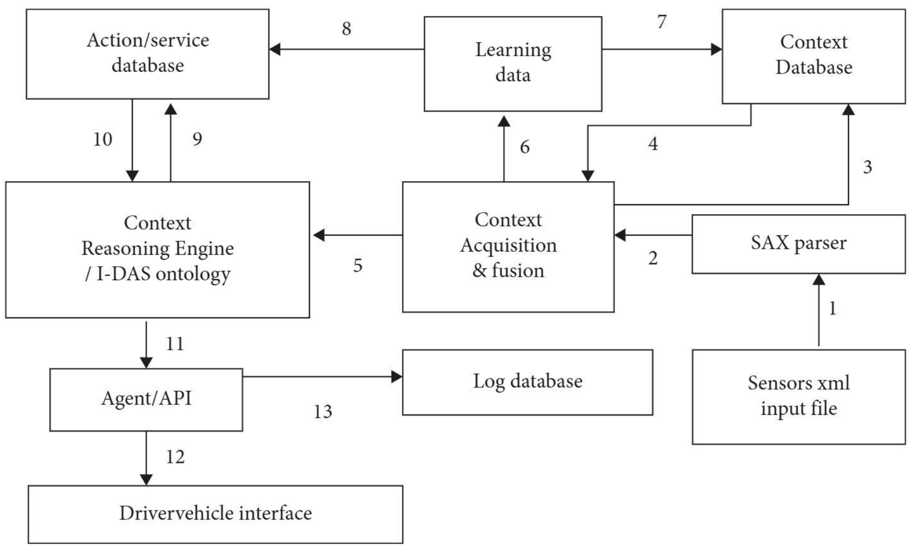

Figure 8: Functionality of intelligent ADAS.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}, \tag{7}$$

$$\text{Precision} = \frac{TP}{TP + FP}, \tag{8}$$

$$\text{Recall (True positive Rate)} = \frac{TP}{TP + FN}, \tag{9}$$

$$F1\text{Score} = \frac{2TP}{2TP + FP + FN} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}, \tag{10}$$

$$\text{Cohen Kappa Score} = \frac{\text{Accuracy} - P_{\text{random}}}{1 - P_{\text{random}}}. \tag{11}$$

Prediction and target are both true in a TP (true positive) situation. There are times when a prediction is correct, but the target is incorrect. This is known as TN. When a prediction is positive, but the target is false, it is called an FP (false positive), while a prediction is negative, but the target is true is called a FN (false negative). Our performance validation technique of choice is the k-fold cross-validation test. In this test, the dataset is segmented into k folds as 5-folds and iterations are made between the training and testing portions. As we rotate through the dataset segments, we can test the model's capacity to function with previously unknown data. This test was performed to ensure that our models were reliable in terms of their performance, accuracy, and resilience. The simulation results with the confusion matrix for the 15-feature model are shown in the Figure 9. The positive predicted values (PPV) vs. false discovery rate (FDR) graph is shown in Figure 10. True positive rate (TPR) vs. false negative rate (FNR) matrix is shown in Figure 11. The A, B, C, D, E, F, G, H, I, and J in Figures 9–11 represent the ten different driver class types.

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True Class \ Predicted Class	A	B	C	D	E	F	G	H	I	J
A	6921	1	54	10			24	1		229
B	7	11241	106	889	87	57	155	302		20
C	9	1	4140	2624	32		95	198	386	15
D		1102	69	9261	66	420	149	68	245	1864
E		232	72	30	6778			1		1323
F		68		110	4	10830				
G	10	782	48	787		2	5406	224	65	168
H		734	122	1406	1			7355	223	39
I	3	236		1338			62		4206	1963
J	110	23		168	111		42	2	74	8374

Figure 9: Confusion matrix with predicted class vs. true class for 15-feature model.

True Class \ Predicted Class	A	B	C	D	E	F	G	H	I	J
A	98.0%	0.0%	1.2%	0.1%			0.4%	0.0%		1.6%
B	0.1%	78.0%	2.3%	5.3%	1.2%	0.5%	2.6%	3.7%		0.1%
C	0.1%	0.0%	89.8%	15.8%	0.5%		1.6%	2.4%	7.4%	0.1%
D		7.6%	1.5%	55.7%	0.9%	3.7%	2.5%	0.8%	4.7%	13.3%
E		1.6%	1.6%	0.2%	95.7%			0.0%		9.5%
F		0.5%		0.7%	0.1%	95.8%				
G	0.1%	5.4%	1.0%	4.7%		0.0%	91.1%	2.7%	1.3%	1.2%
H		5.1%	2.6%	8.5%	0.0%			90.2%	4.3%	0.3%
I	0.0%	1.6%		8.0%			1.0%		80.9%	14.0%
J	1.6%	0.2%		1.0%	1.6%		0.7%	0.0%	1.4%	59.8%

	A	B	C	D	E	F	G	H	I	J
PPV	98.0%	78.0%	89.8%	55.7%	95.7%	95.8%	91.1%	90.2%	80.9%	59.8%
FDR	2.0%	22.0	10.2%	44.3%	4.3%	4.2%	8.9%	9.8%	19.1%	40.2%

Figure 10: Confusion matrix with PPV vs. FDR for 15-feature model.

The receiver operating characteristic (ROC) with cross-validation results for class A and F are shown in the Figures 12 and 13.

4.2. Validation of Driver Detection and the Assistance Model. In this section, the proposed model performance for driver detection and computation time of driving assistance model

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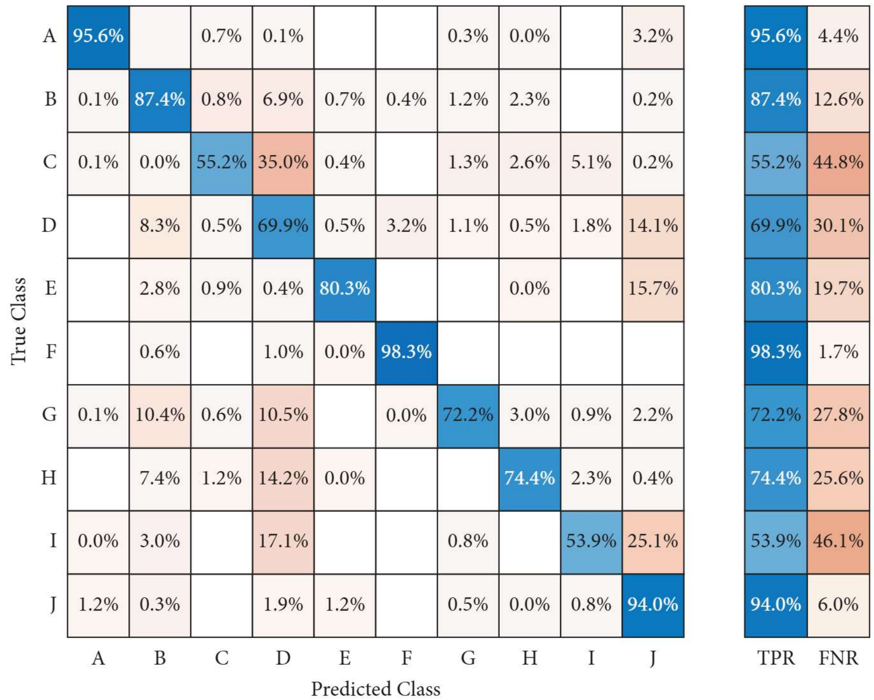

Figure 11: Confusion matrix with TPR vs. FNR for 15-feature model.

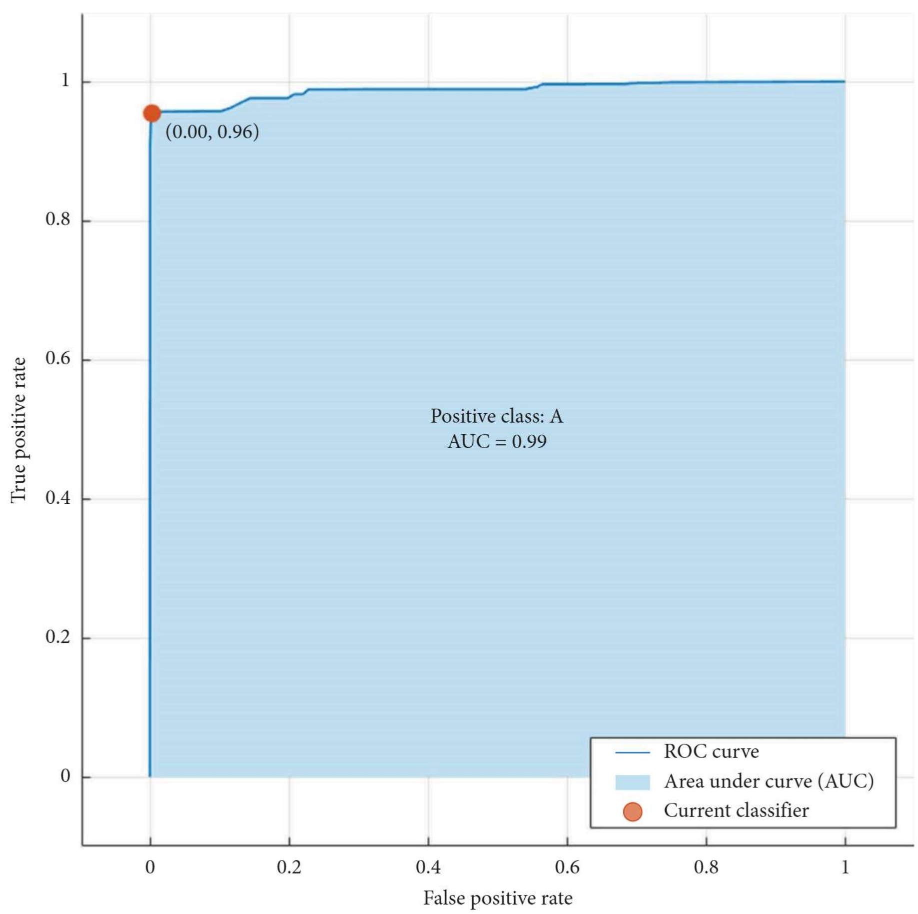

Figure 12: ROC curve for class A.

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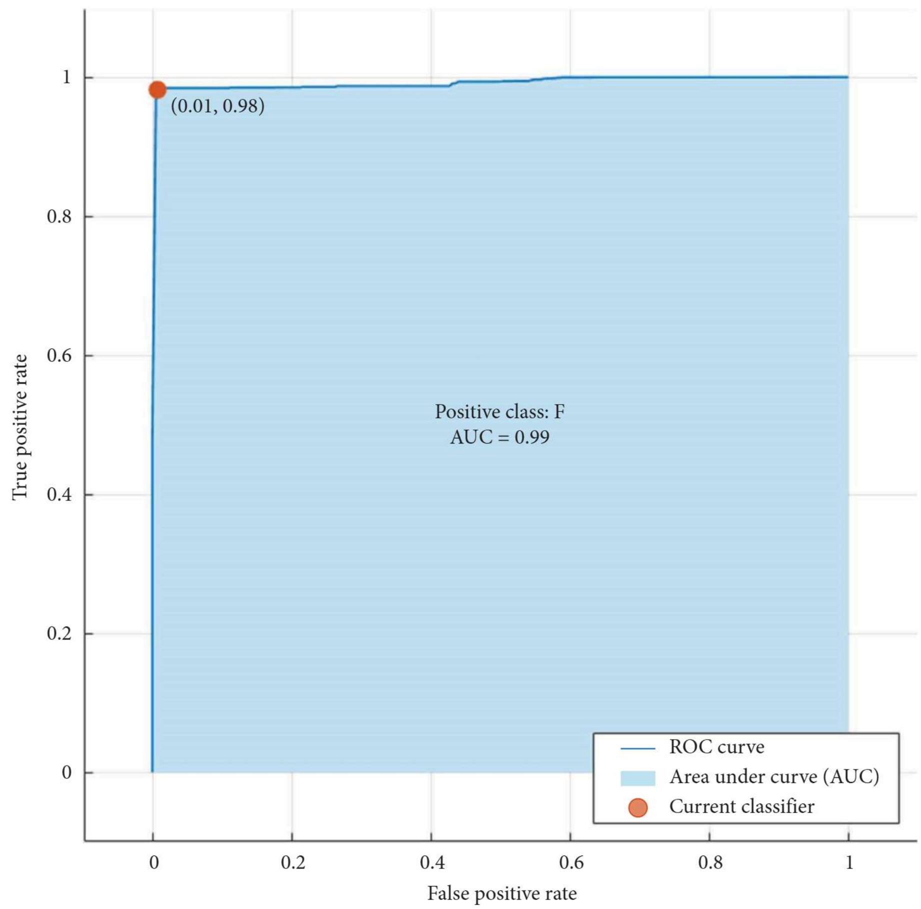

Figure 13: ROC curve for class F.

Table 2: Validation of the proposed model for 15features.

Model	Accuracy	Precision	Recall	F1-score	Cohen kappa score
PCA-ANN	**91.17**	**0.912**	**0.912**	**0.912**	**0.7809**
RF-ANN	**92.64**	**0.928**	**0.928**	**0.928**	**0.8203**
PCA-RNN	**92.64**	**0.930**	**0.926**	**0.926**	**0.8529**
RF-RNN	**94.11**	**0.943**	**0.941**	**0.941**	**0.8825**
PCA-DNN	**95.55**	**0.956**	**0.956**	**0.956**	**0.9118**
RF-DNN	**97.05**	**0.971**	**0.971**	**0.971**	**0.9472**

is validated by using different features with various parameter metrics. Table 2 shows the experimental analysis of proposed DNN model with a different feature selection model for the total number of features is 15.

The three different ML and deep learning techniques such as ANN, recurrent neural network (RNN), and the proposed DNN are tested with PCA and RF techniques and validated with different metrics. ANN [19, 28] and RNN are mostly used for driver fatigue detection techniques [37–39], and no one tested its performance on ADAS; hence, we considered these techniques for comparing with the proposed model. In addition, no existing techniques tested its

Table 3: Validation of the proposed method for computational timing analysis in Google Colab.

Model	Timing (s)
PCA-ANN	**259**
RF-ANN	**210**
PCA-RNN	**234**
RF-RNN	**205**
PCA-DNN	**197**
RF-DNN	**186**

effectiveness based on reducing the features and computational timing in Google Colab. Therefore, we implement the existing techniques and compared with the proposed model.

In the accuracy experiments, ANN achieved nearly 92% when implemented with both PCA and RF, RNN achieved nearly 94% when implemented with both PCA and RF, where the proposed DNN achieved 95.55% with PCA and 97.05% with RF. In the Cohen kappa score, ANN with PCA achieved a small value, i.e., 0.78 and the same technique achieved 0.82 with RF. The RNN achieved 0.85 with PCA and 0.88 with RF, where the proposed DNN method achieved 0.91 with PCA and 0.94 with the RF technique. When the ANN is implemented with RF, it achieved 0.92 of precision, recall, and F1-score, RNN with RF achieved 0.94

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Table 4: Validation of the proposed model for 30 features.

Model	Accuracy	Precision	Recall	F1-score	Cohen kappa score
PCA-ANN	**85.29**	**0.861**	**0.853**	**0.850**	**0.6912**
RF-ANN	**85.29**	**0.856**	**0.882**	**0.883**	**0.6996**
PCA-RNN	**86.76**	**0.873**	**0.868**	**0.865**	**0.7233**
RF-RNN	**89.70**	**0.902**	**0.897**	**0.898**	**0.7909**
PCA-DNN	**88.23**	**0.885**	**0.882**	**0.882**	**0.7597**
RF-DNN	**91.17**	**0.912**	**0.912**	**0.912**	**0.7809**

Table 5: Validation of the proposed method for computational timing analysis in Google Colab with 30 features.

Model	Timing (s)
PCA-ANN	**316**
RF-ANN	**353**
PCA-RNN	**342**
RF-RNN	**319**
PCA-DNN	**280**
RF-DNN	**263**

of precision, recall, and F1-score, and finally, the proposed DNN with RF achieved 0.97 of precision, recall, and F1-score. But these deep learning techniques achieved less performance of precision, recall, and F1-score when implemented with PCA. This proves that the RF technique improves the performance of deep learning techniques by reducing a greater number of features effectively than PCA. Table 3 shows the performance of intelligent driver assistance for computational timing.

When compared with existing techniques, the proposed method achieved less training time, i.e., 197 s for PCA and 186 s for RF. The ANN technique achieved high training time when implemented with PCA, i.e., 259 s and the same technique achieved only 210 s with RF. The RNN technique achieved 205 s of computational training time with RF and achieved 234 s of training time in Google Colab with PCA. This proves that the proposed DNN with RF achieved better performance than existing techniques. The DNN can learn by themselves and produce the output, where the training of RNN is a difficult process when compared to ANN and DNN. Table 4 provides the validated results of proposed technique for driver identification using 30 features.

When compared with 15 features, the performance of deep learning techniques achieved less performance when it is tested with 30 features. In the accuracy experiments, ANN achieved 85.29% when implemented with both PCA and RF, and RNN achieved nearly 87–89% when implemented with both PCA and RF, where the proposed DNN achieved 88.23% with PCA and 91.17% with RF. In the Cohen kappa score, ANN with PCA and RF achieved less value than other deep learning techniques, i.e., 0.69. The RNN achieved 0.72 with PCA and 0.79 with RF, where the proposed DNN method achieved 0.75 with PCA and 0.78 with the RF technique. When the ANN is implemented with RF, it

Table 6: Validation of the proposed model for 50 features.

Model	Accuracy	Precision	Recall	F1-score	Cohen kappa score
PCA-ANN	**73.56**	**0.735**	**0.735**	**0.735**	**0.3564**
RF-ANN	**75.34**	**0.753**	**0.753**	**0.753**	**0.3043**
PCA-RNN	**77.16**	**0.771**	**0.771**	**0.771**	**0.3411**
RF-RNN	**78.99**	**0.789**	**0.789**	**0.789**	**0.4266**
PCA-DNN	**78.53**	**0.785**	**0.785**	**0.785**	**0.4309**
RF-DNN	**80.36**	**0.806**	**0.804**	**0.803**	**0.4696**

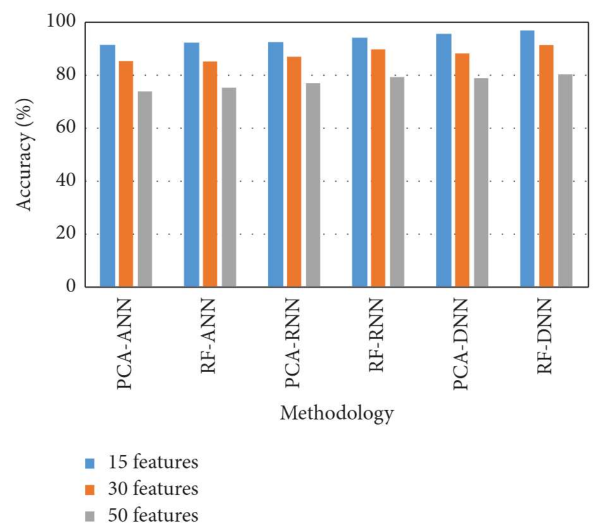

Figure 14: Graphical representation of the proposed model for driver identification in terms of accuracy with different number of features.

achieved nearly 0.85–0.88 of precision, recall, and F1-score, and RNN with RF achieved nearly 0.89-0.90 of precision, recall, and F1-score, and finally, the proposed DNN with RF achieved 0.91 of precision, recall, and F1-score. But these deep learning techniques achieved very less performance of precision, recall, and F1-score when implemented with PCA. This proves that the RF technique improves the performance of deep learning techniques effectively than PCA. Table 5 provides the performance of intelligent driver assistance for computational timing in Google Colab.

When compared with the existing techniques, the proposed method achieved less training time, i.e., 280 s for PCA and 263 s for RF. The ANN technique achieved high training time when implemented with PCA, i.e., 316 s, and the same technique achieved 353 s with RF. The reason for high training time is that the output produced by ANN does not give optimum results, and there is a hardware dependence, which influences the performance of the network. The RNN technique achieved 319 s of computational training time with RF and achieved 342 s of training time in Google Colab with PCA. This proves that the proposed DNN with RF achieved better performance than the existing techniques. However, when a greater number of features are used, the training time

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Table 7: Validated analysis of the proposed model for computational timing analysis in Google Colab with 50 features.

Model	Timing (s)
PCA-ANN	**652**
RF-ANN	**685**
PCA-RNN	**643**
RF-RNN	**620**
PCA-DNN	**611**
RF-DNN	**601**

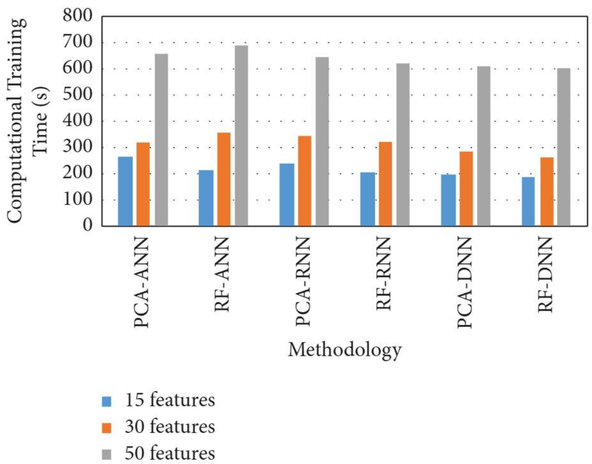

Figure 15: Graphical representation of the proposed driver assistance model for different number of features in terms of computational training time.

of all deep learning techniques also increased, which is already shown in Table 3. Finally, the deep learning techniques are tested with 50 features and the validated results are provided in Table 6, and Figure 14 shows the comparative graph of proposed model for driver identification in terms of accuracy for different number of features.

When compared with 15 and 30 features, the performance of deep learning techniques achieved very less performance when it is tested with 50 features because a greater number of features reduce the classification accuracy. In the accuracy experiments, ANN achieved 73.56% when implemented with PCA and achieved 75.34% with RF, RNN achieved 77.16% when implemented with PCA and achieved 78.99% with RF, where the proposed DNN achieved 78.53% with PCA and 80.36% with RF. But the accuracy of proposed method is less when compared with Tables 2 and 4. In the Cohen kappa score, ANN and RNN with PCA and RF achieved a lesser value than the proposed deep learning technique. The RNN achieved 0.34 with PCA and 0.42 with RF, where the proposed DNN method achieved 0.43 with PCA and 0.46 with the RF technique. When the ANN implemented with RF, it achieved 0.75 of precision, recall, and F1-score, RNN with RF achieved 0.78 of precision, recall, and F1-score, and finally, the proposed DNN with RF achieved 0.80 of precision, recall, and F1-score. But these deep learning techniques achieved very less performance of precision, recall, and F1-score when implemented with PCA, i.e., 0.73, 0.77, and 0.78 of ANN, RNN, and DNN, respectively. This proves that the RF technique improves the performance of deep learning techniques effectively than PCA. Table 7 shows the validated analysis of proposed driver assistance model for timing analysis.

When compared with the existing techniques, the proposed method achieved less training time, but it acheived high training time when tested with 15 and 30 features, i.e., 611 s for PCA and 601 s for RF. The ANN technique achieved high training time when implemented with RF, i.e., 685 s and the same technique achieved 652 s with PCA. The RNN technique achieved 620 s of computational training time with RF and achieved 643 s of training time in Google Colab with PCA. This proves that the proposed DNN with RF achieved better performance than existing techniques. Figure 15 shows the comparison analysis of driver assistance model for computational training time with different number of features.

5. Conclusion

In this paper, a unique ADAS presented an optimal driving strategy (ODS) that includes the driver behavior identification and driver assistance system. The DNN model was used to build a unique network that accomplished two tasks: the detection of drivers and the evaluation of driving behavior. In addition, the intelligent driver support system is also proposed in this study. Introducing a safety layer to a vehicle's architecture without adding new hardware or making large infrastructural changes is another benefit of our idea. The EV drive simulation model is based on literature-based EV component model information and is validated by looking at how vehicle speed and other important model parameters change over time. Diverse methods such as using EA parameters and simulation time steps discovered through parametric studies are used to reduce the computational time of the system, and it was discovered that the system's response time may be implemented practically while also providing acceptable ideal outcomes. Driver identification system performance will be improved in the future by adding additional features, such as Cepstral features combined with time-domain and frequency-domain features mentioned above. The consumption of energy can be minimized by using a developed technique as a future work.

Abbreviations

RF: Random forest
PCA: Principal component analysis
ADAS: Advanced driver assistance systems
DNN: Deep neural network
ANN: Artificial neural network
KNN: K-nearest neighbour
ARNet: Auto-encoder regularized network.

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Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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