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Original Article

Smart ADAS for EVs: A Deep Learning Approach to Driver Detection and Safety Enhancement

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Abstract *- Electric Vehicle (EV) technology is an emerging field with several benefits, including lower running costs. Long-lasting batteries have always been the aim of EVs; thus, any additional hardware might significantly shorten battery life. Humans frequently make mistakes. As a result, driving habits like moderation and sports style may cause collisions and fatalities. Driver identification has emerged as a research hotspot in the fields of intelligent transportation and modern car development, and it is crucial to achieving personalized services for drivers and road traffic safety for electric vehicles. An enhanced deep learning-based method for identifying and supporting drivers in Better-performing electric vehicles was presented in this study. This method produces better results by utilizing a special real-world dataset that represents a variety of driving situations. ADAS is designed to increase vehicle efficiency and safety with features including autonomous braking, adaptive cruise control, and lane-keeping assistance. Thus, data-driven object recognition and localization methods are expected to be used in sophisticated driver assistance systems and self-driving automobiles. Specifically, deep neural networks demonstrated exceptional performance in object detection and classification from photos, frequently attaining superhuman levels of efficiency. The suggested ADAS model obtained 97.6% accuracy, 96.9% precision, 98.8% recall, and 99.3% sensitivity.*

Keywords *- Electric Vehicles, Deep Learning, Detecting Driver, battery life, Data-driven, Advanced Driver Assistance Systems (ADAS).*

1. Introduction

The absence of greenhouse gas emissions from Electric Vehicles (EVs) results in reduced operating costs and environmental preservation. Contrarily, current research has concentrated on ensuring that EVs are comfortable with their self-driving capabilities [1]. The energy management and car-following control strategies are then learnt by a deep Q-network, which offers multi-objective hybrid powertrain control while keeping the next vehicle a safe distance away [2]. It is unavoidable that microgrid components like distributed energy resources and EVs will malfunction. EVs feature energy conversion chains and a number of electrical components. A Fault Diagnosis (FD) approach must be used in order to extend their lifespans [3]. However, new technologies like edge computing, Connected Vehicles (CV), and transportation electrification have prompted engineers, researchers, and legislators to work harder to address energy and environmental issues related to transportation [4]. Longer battery life can be achieved with enhanced and flexible deep learning-based velocity predictions control EMS by making optimal use of both the battery and supercapacitor, which is necessary to improve Battery-supercapacitor HEV's EMS performance [5]. Important elements that might impact driving safety are the choices and actions of drivers.

A deep Convolutional Neural Network (CNN)-based system for identifying driving actions is created in order to comprehend driver behaviours [6]. In order to jointly improve the driving process and the energy management of the powertrain over short time horizons, the high-level solution is utilised by a low-level forecasting controller based on a DNN model, which concurrently optimises the powertrain energy management and the driving cycle across brief time horizons at the low level [7].

In order to demonstrate the features and benefits of each sophisticated deep-learning-based intrusion detection technique, this study examines ten typical techniques [8]. However, there is no fair and quantitative study comparing the horizontal performance of deep learning-based detection methods. [9]. Furthermore, an "anchor (baseline) based" approach was suggested and found to be successful in removing the dataset's uneven distribution [10]. Determining the potential driving distance and charging time can be aided by an accurate SOC estimate. An EV battery's state of charge can be predicted using two primary techniques. The first is using simulation to anticipate the SOC based on vehicle dynamics [11]. Therefore, integrating driving behaviour into EMS is necessary to lower the amount of gasoline used and prolong the lifespan of power sources. This study suggests an EMS for a three-power FCHEV that is based on driving behaviour recognition and adaptive Deep Reinforcement Learning (DRL) [12].

1.1. Research Gap

Although a proposed deep learning-based driver identification system performs well, with high accuracy, precision, recall, and sensitivity, significant research gaps remain unexplored. First, energy-efficient deployment in electric vehicles is crucial, as additional computational or hardware needs might have a negative influence on battery life and overall system performance. Second, while the model was trained on a real-world dataset, its capacity to generalize across different driving situations, weather conditions, and cultural driving patterns has not been properly investigated. Third, dynamic elements such as fatigue, stress, and emotional state influence human driving behavior, but these are not explicitly addressed in the current method. Finally, the robustness of the model in uncommon but safety-critical edge cases, such as abrupt obstacles, sensor failures, or extreme environmental conditions, has not yet been thoroughly examined. These issues include real-time processing, latency, and compliance with safety standards, which are all related to the smooth integration with advanced driver assistance systems.

The main contributions of the Paper are as follows:

- Given that EVs frequently have distinctive features like silent operation and variable energy efficiency that might be enhanced by more sophisticated Advanced Driver Assistance Systems (ADAS), this could help to improve driver safety and vehicle control in EVs.
- The approach may improve the EV's performance in real time by utilising deep learning techniques, which would optimise energy consumption and the driving experience as a whole.
- Real-time processing of data from several sensors may be made possible by the deep learning technique, which could result in faster and more precise decision-making in automotive systems.
- Because EVs have special features (such as variable battery levels and regenerative braking), the approach might be modified to maximise these aspects in tandem with driver behaviour, guaranteeing improved performance.

The Paper is organised as follows: Section 1 introduces the topic and explains the need for this endeavour. Section 2 contains the related works. The Paper's suggested methodology is presented in Section 3. The results and discussion are in Section 4. Lastly, the conclusion is included in Section 5.

2. Related Works

Guo et al. (2020) [13]. As far as we are aware, no prior effort has been undertaken to use machine learning aided by physics to identify EV cyberattacks that take into account different driving conditions. We gather both device-level (such as the motor drive's current and voltage) and vehicle-level signals to represent the fleeting physical features of EVs.

Estrada et al. (2023) [14]. Pollutant emissions are mainly characterised in this work using Convolutional Neural Networks (CNN), which provide great precision for both current and cumulative data. Exhaust temperature, torque, engine rpm, and air mass flow are examples of conventional Internal Combustion Engine (ICE) metrics that are utilised as input parameters. Due to their low complexity and speed, the suggested CNNs are kept to a minimum.

Chen et al. (2019) [15]. This study examines a Convolutional Neural Network (CNN)-based driving cycle prediction technique. In order to predict the different types of driving cycles, CNN first divides the driving cycle data into 6 categories using the k-shape clustering algorithm, which is also compared with the k-means methodology, which is commonly used for driving cycle clustering.

Xu et al. (2022) [16]. Introduces a supervised learning study on driving cycle pattern identification. Training data is shown in two dimensions. It is difficult to identify driving cycles, though. Pattern recognition is becoming more popular in a variety of applications as artificial intelligence advances.

Lang et al. (2021) [17]. Examines how AI methods have been used in motor FDD recently. Fault classification and feature extraction are the two main stages of AI-based FDD. The DNN's primary objective is to accurately estimate EV range by characterising the non-linear connection between input data and outputs.

Wang et al. (2020) [18]. The suggested approach can automatically determine the best control strategy based on visual cues. The visual data that is accessible from the onboard cameras is taken out using the most advanced object detection technique based on convolutional neural networks. In order to produce energy management strategies, a continuous DRL model uses the visual data that was identified as a state input.

Julio-Rodriguez et al. (2022) [19]. In order to apply it in autonomous driving applications, this work discusses the creation of a categorisation system that can help with enhanced awareness and precision of the situational context of cars. This work's goal is to develop a machine-learning-based approach for classifying driving environments that employs real-time energy consumption measurements and dynamic features from Inertial-Measurement-Unit (IMU) sensors rather than computer vision.

Liu et al. (2021) [20]. This area of study is examined and re-examined. Furthermore, the EMSs are categorised into three groups based on the information currently available on driving cycles, and the relevant areas of research are explained and analysed, encompassing typical driving cycles. Mehedi et al. (2021) [21]. The deep transfer learning-based IDS model for IVN described in this Paper performs better than a number of currently used models. Among the notable achievements are developing a LeNet model based on deep transfer learning, assessment of real-world data, and effective selection of attributes most appropriate for detecting counterfeit CAN signals and precisely distinguishing between normal and abnormal behaviours.

3. Proposed System

Two varieties of the suggested ADAS approach are produced in this research study. The DNN step uses the first approach to identify drivers, and the driver assistance method is the basis for the second work. All ML and deep learning tests were trained and tested by the authors using a Google Collaboratory cloud computer, a specialised server with a dual-core 2.3 GHz Intel Xeon CPU, 13.3 GB of RAM, and 56 MB L3 cache. The training takes advantage of 17.1 GB of RAM memory with a Tesla P100 GPU to speed up the computation of computationally costly calculations. The proposed model's general block diagram is shown in Figure 1.

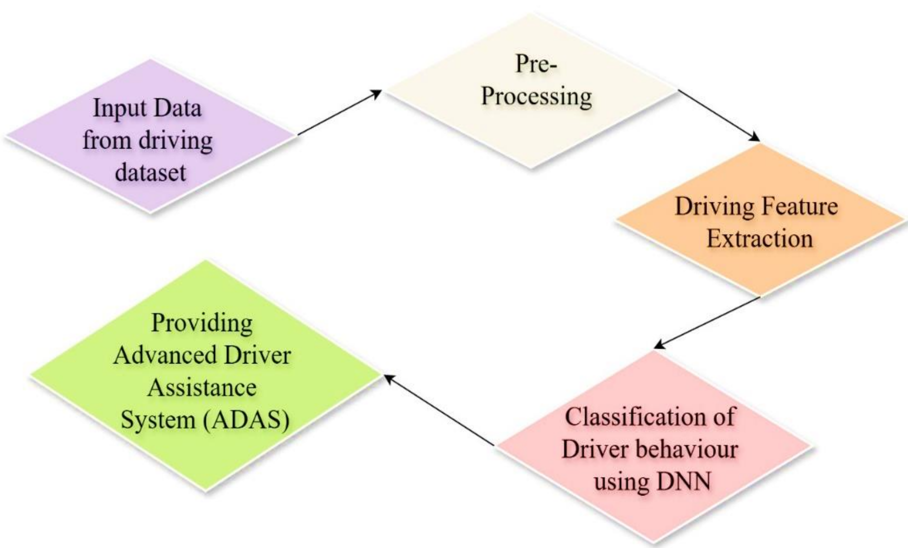


Fig. 1 Block diagram of the proposed model

3.1. Driver Identification

Scholars in the domains of intelligent transportation and vehicle engineering have conducted extensive studies on driver recognition in recent years, leading to numerous accomplishments. Accurately and promptly identifying the driver and supporting the creation of customised value-added services for drivers and traffic safety are the primary goals of the driver identification task. The researcher creates the driver identification task procedure with varying levels of granularity based on the target's requirements.

3.1.1. Dataset Description

For the validation, we utilised the 2015 Ocslab driving dataset from South Korea for our models. 51 different OBD-II signals were taken out of the car's ECU using a sampling rate of 1 Hz. For a total of 23 hours, 10 drivers alternated between operating the car around a 46-kilometre track, producing 94380 records. The experiment used a freeway, a city route, and a parking area that required careful driving.

3.1.2. Data Pre-Processing

All of the characteristics in our categorisation model must be carefully prepared before being included in the model. A pre-processing method is present in almost all state-of-the-art models to guarantee that these characteristics can guide the model and make categorisation. Therefore, we start by standardising the data from the CAN bus. Prior to using deep learning models or conventional machine learning techniques on this kind of data. Normalisation is regarded as a pre-processing step. The most popular technique for normalising data is min-max, which generates new values while preserving the ratio and overall distribution of the original data.

3.1.3. Driving Feature Extraction

The training materials must be detailed to reveal hidden aspects in the basic operating signals' time series, which will improve the recognizability of the supervisory control system that is identified by the driver. This study examines steering angle, brake pedal deflection, gas pedal deflection, and vehicle speed as driving operating signals. They were demonstrated to be a practical option for promoting style recognition in contrast to other signals that require detection by additional sensors.

Feature 0: Driving operational signals are initially compiled from a driving simulator to form a vector of rows $[\upsilon\ \gamma\ \beta\ \delta]$. For instance, the symbols υ and h stand for steering angle (rad), short-term sliding window length (60 seconds in the time domain), vehicle speed (km/h), gas pedal deflection (%), and brake pedal deflection (%), respectively.

Feature 1: The operational intensity of drivers is reflected by adopting the four time-domain elements' maximum values. Their values can be computed using time and Frequency Domain Extractions.

A transient sliding window is added to the popular time-domain extraction technique in order to control the sample size and extend the memory period of distinguishing states. Every data time step k in the driving operational signals dataset is defined as follows:

$$(\upsilon_{\max,}\gamma_{\max,}\beta_{\max,}\delta_{\max})= \max(\upsilon,\gamma,\beta,\delta_{abs})^T \quad (1)$$

Where the absolute value of $\boldsymbol{\delta}$ for each element is indicated by $\boldsymbol{\delta}abs$. Feature 2: To represent drivers' operational proficiency, the time domain, the four elements' maximum ranges are employed. The maximum range of drivers with higher operational proficiency is generally lower. It is possible to calculate their values using.

$$(\upsilon_{\text{rng},}\gamma_{\text{rng},}\beta_{\text{rng},}\delta_{\text{rng}})= \max(\upsilon,\gamma,\beta,\delta_{abs})^T - \min(\upsilon,\gamma,\beta,\delta_{abs})^T \quad (2)$$

Feature 3: Driving patterns are reflected by adopting the average values of the four time-domain elements.

$$(\upsilon_{\text{avg},}\gamma_{\text{avg},}\beta_{\text{avg},}\delta_{\text{avg}})\frac{\sum_{i=0}^{i=h}\text{n}(\upsilon,\gamma,\beta,\delta_{abs})^T}{h} \quad (3)$$

Frequency domain extraction is another popular extraction technique used to assess the degree of pre-processing behaviours. Three major characteristics are calculated here using the Discrete (fast) Fourier transform (DFT), and the recogniser will be trained using these features.

3.1.4. Classification of Driver Behavior using DNN

Deep Neural Network Model Design: The following factors can be taken into account when creating a neural network model to categorise drivers:

Features of input: Speed, acceleration, energy use, and sensor data (if available) are examples of telemetry data.

Data pre-processing: includes addressing missing data, scaling or normalising features to standardise the input, and perhaps enhancing data for training.

Model architecture: Various neural network types may be employed, contingent on the intricacy of the data:

Feedforward Neural Networks (FNN): When the features are highly structured and the task is reasonably easy.

Recurrent Neural Networks (RNN) or long short-term memory (LSTM): If there is a temporal component to the data, such as shifts in driving behaviour over time, they may be used.

Convolutional Neural Networks (CNN): When visual data is utilised, like pictures or movies captured by in-cabin cameras.

Output Layer: Usually, the last layer is made up of several nodes that represent various driver classes or categories.

The DNN's primary objective is to estimate the EV range precisely by characterising the non-linear connection between input data and output data. In the context of EV range estimates, a regression technique that minimises both instruction mistakes and errors pertaining to unknown inputs is required to estimate path loss for a variety of propagation situations.

The optimal feedforward design for path-loss prediction is found in this work by scaling the input features to guarantee that every feature makes an equal contribution to the DNN's learning process.

We obtain measurement information from the "GR Amsterdam." Figure 2 depicts the network design for a Deep Neural Network (DNN) with three hidden components. The definition of the multi-layered feedforward vectors and weights is comparable to that of the neuron model.

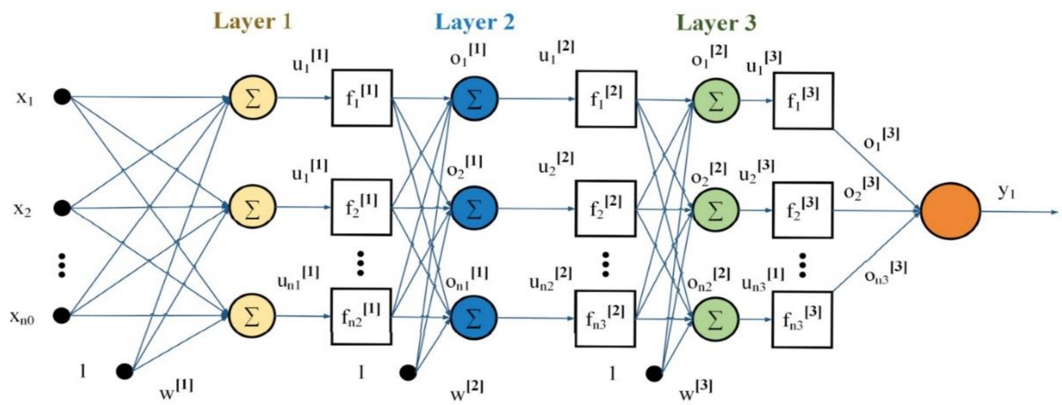


Fig. 2 Designing a deep neural network to predict EV range

An architecture with two hidden layers was chosen following comparison testing with different setups. This structure avoided overfitting and offered high prediction accuracy by striking the ideal balance between accuracy and computational economy. While deeper structures raised processing requirements without significantly improving performance, models with fewer layers demonstrated decreased accuracy.

3.1.5. Advanced Driver Assistance System (ADAS)

Electric cars with advanced driver assistance systems are the greatest option for personal transportation since they offer a safe, comfortable, and environmentally friendly substitute for traditional cars. These vehicles are an excellent option for both individuals and families due to their advanced safety features and energy-efficient technologies. They can be utilised for long-distance trips, errand running, and daily commuting. Modern driver aid technologies in electric cars make them great options for usage in public transportation systems. These cars provide a reliable and safe means of getting about cities and towns and can be utilised for bus routes, shuttle services and other public transportation choices.

By incorporating state-of-the-art safety measures and energy-efficient technologies, these cars can help reduce pollution, traffic, and other environmental consequences associated with traditional transportation systems. Furthermore, modern driver assistance technologies in electric cars make them ideal for use in commercial transportation. These vehicles can be used for delivery services, taxis, and other commercial transportation services and provide a safe, efficient, and reasonably priced way to move people and goods. The enhanced safety features of these vehicles can assist in minimising accidents and other safety dangers associated with commercial transportation, even though energy-efficient technologies can help reduce costs and increase sustainability.

Electric automobiles with ADAS provide a more economical and ecologically friendly alternative to traditional diesel-powered delivery trucks. With features like regenerative braking, predictive cruise control, and traffic sign recognition, these cars can reduce fuel use and speed up delivery times. ADAS-equipped electric vehicles can also be used by emergency services, providing them with a rapid and efficient means of conducting their work. Thanks to features like autonomous driving and adaptive cruise control, these cars can help emergency responders get where they need to go more quickly and safely.

3.2. Methods of Analysis

After that, we used f-measure, Area Under the Curve (AUC), accuracy, precision, recall, and other metrics to evaluate and contrast the chosen models. To ascertain correctness, the confusion matrix can first be determined in the manner described below:

$$\frac{TP+TN}{TP+FP+TN+FN} \tag{4}$$

In this study, accuracy is employed to demonstrate the actual performance of each model. In light of this, precision makes it possible to quickly and easily depict the performance of each individual outcome, facilitating comparison. Precision findings are then provided so that the user can evaluate the degree of repeatability of a model. This might inform the user that if the measurements were made in the same conditions, the same outcome would be achieved. The following is how it is depicted.

$$\frac{TP}{TP+FP} \tag{5}$$

Recall is the next metric that we have employed. This is sometimes referred to as sensitivity since it attempts to provide information on the overall quantity of relevant items chosen. It can be shown as follows: It displays the total number of relevant examples that were obtained out of all the relevant instances that could have been chosen.

$$\frac{TP}{TP+FN} \tag{6}$$

The f-measure metric is then included. This can be explained by the fact that it provides the outcomes of the precision and recall harmonic mean, where recall is calculated by dividing the number of accurate positives by the precision, where precision is the sum of accurate positives divided by the sample size. It has a maximum value of 1 and can be quantified as follows:

$$2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{7}$$

AUC is the final metric we employed in our investigation. To determine how well a model can identify actual outcomes, the AUC plots two different metrics. Two parameters are plotted on the curve: the recall and the false positive rate. The actual positive rate is another name for it. An example of how to illustrate these is as follows:

$$TRP = \frac{TP}{TP+FN} \qquad FPR = \frac{FP}{FP+TN} \tag{8}$$

The AUC curve aggregates a performance metric across all potential categorisation thresholds by plotting TPR against FPR at various thresholds. The overall architecture of the intelligent ADAS is shown in Figure 3.

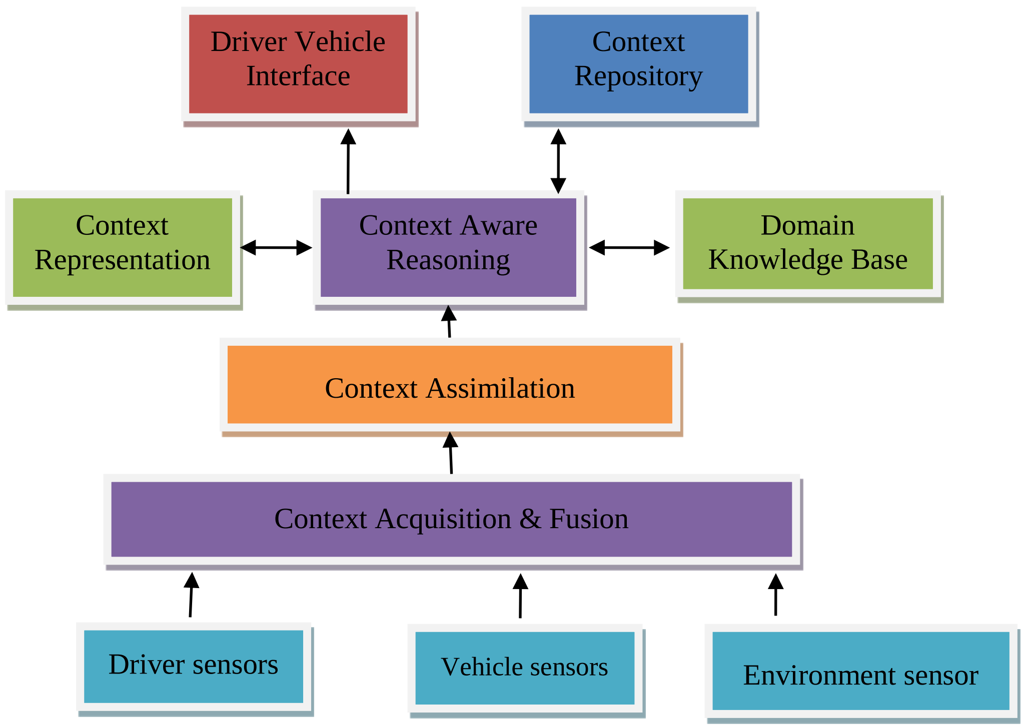


Fig. 3 Architecture of intelligent ADAS

4. Result and Discussion

Both execution time and a range of performance metrics were used to evaluate our models. We could evaluate our structures' speed and performance against other cutting-edge techniques. Performance metrics included Cohen's kappa values, F1, and AUC. Additionally, the k-fold test for cross-validation was used as an assessment technique. Performance metrics focused on training and prediction time, whereas execution speed metrics focused on speed.

4.1. Driving Operation Patterns

Three groups of observable driving signals can be distinguished [34]: 1) driving behaviour, such as steering angles and pressures on the gas and brake pedals; 2) vehicle status, such as engine speed, acceleration, and velocity; and 3) vehicle position, such as yaw angle, relative lane position, and following distance. We concentrate on driving behaviour among these driving signals in connection to the operating signals for steering angle, brake pedal, gas, and velocity. Six individuals' driving-related data are given in Table 1.

Table 1. Driving information of six subjects

Driver	Age	Time to hold a driving license (yrs.)	Annual mileage (mile)	Driving geography
A	28	9	2500	Urban
B	28	6	3500	Hybrid
C	25	8	3000	Hybrid
D	27	10	2000	Hybrid
E	27	5	6500	Motorway
F	31	2	1500	Urban

Driving operation patterns for 10-minute driving signals collected in the simulator with a 5:6 data capacity ratio and a 10Hz sample frequency are shown in Figure 4. Training is done in (a), and testing is done in (b). .6000x4 original signal data has been gathered for a single driver. The system's resiliency is verified using only testing data from Driver F. The pieces of archaic driving operating patterns are clearly intertwined. resembling a "yarn ball." Under identical road conditions, it is challenging to identify their owners.

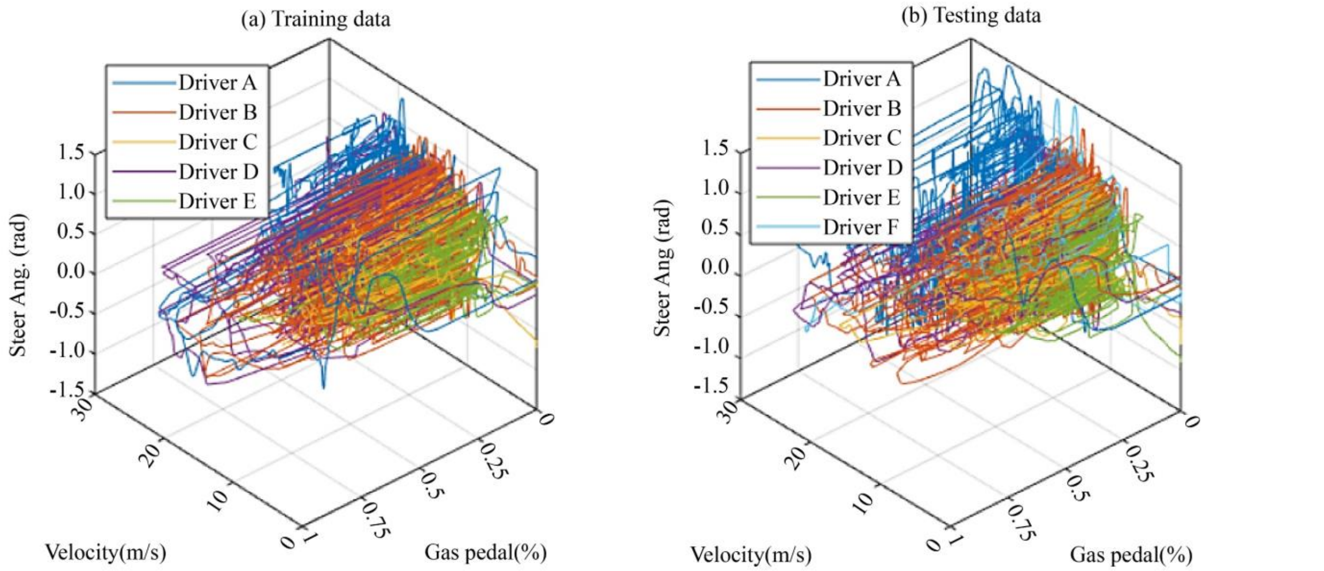
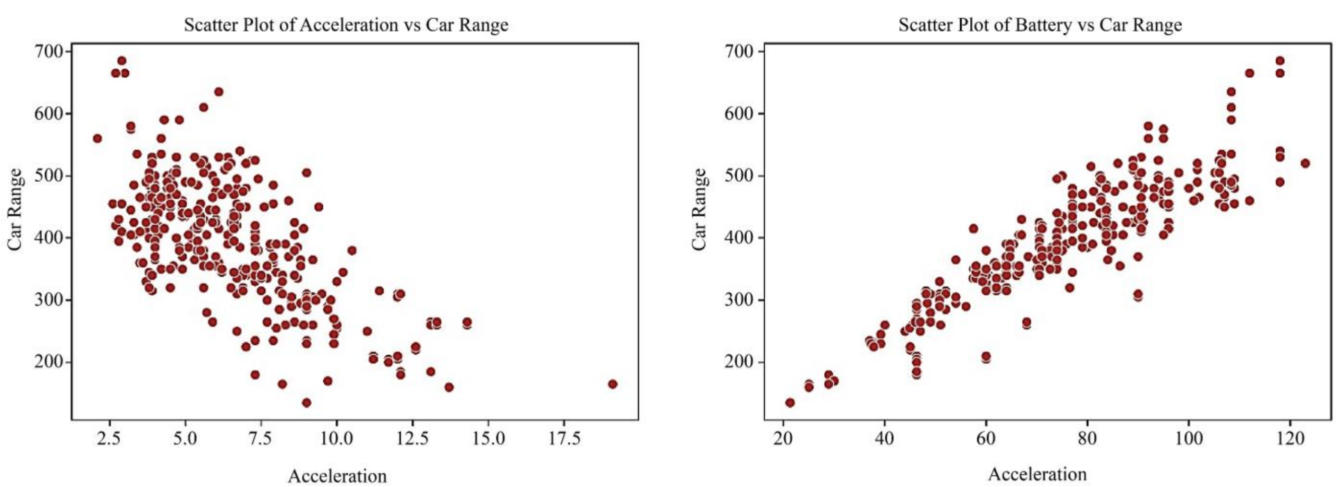


Fig. 4 Driving profiles during the designed road condition



(a) **(b)**

Fig. 5 Car Range, Data Features. Scatter plots: (a)Acceleration vs. Car Range; and (b)Battery vs. Car Range.

4.2. Deep Neural Network (DNN)

An innovative deep learning-based method for estimating EV range using actual data was presented in this study. Particularly when paired with the Adam and RMS prop optimisers, the constructed Deep Neural Network (DNN) models demonstrated remarkable performance with an amazing R2 score of 0.99. This indicates that accurate EV range forecasts are made possible by the deep learning architecture's ability to capture the intricate correlations seen in the dataset, as illustrated in Figure 5. A number of tactics were used throughout the training process to reduce the chance of overfitting. With a dropout rate of 0.3, dropout layers were added to the architecture of a Deep Neural Network (DNN). Selecting a subset of neurons randomly during each training cycle keeps the model from being unduly reliant on any neuron, promoting improved generalisation to new data.

4.3. Performance Evaluation Measures in ADAS

When evaluating the performance of the proposed ADAS, standards such as F1-score, recall, accuracy, and precision revealed that CFS selected fewer than 10% of the original features, resulting in the largest dataset reduction. A total of 825 features were chosen by RFF, while 840 features were chosen by IG and CHI. As can be shown, all of the FS techniques greatly reduced the original dataset, which included 1508 attributes. Table 2 displays the results of the recommended method.

Both the classification models' and the FS's performance will be evaluated. Three distinct ADAS, PCA, and RF algorithms are Deep learning and machine learning methodologies that are utilised to assess Recurrent Neural Networks (RNN) and the proposed DNN, and a variety of metrics are used to confirm the results. We looked at ANN and RNN for comparison with the suggested model because they are primarily utilised for driver tiredness detection methods, and their effectiveness on ADAS has not been verified. Furthermore, no methods are now in use that have evaluated their efficacy based on cutting down on Google Colab's features and processing time. As a result, we apply the current methods and contrast them with the suggested model. The comparative performance of the proposed ADAS in terms of accuracy with different features is depicted in Figure 6.

Table 2. Result of classification task: No feature selection was used on the data set

ADAS	Precision	Recall	F1	AUC
67.78	0.72	0.71	0.72	0.73
57.31	0.65	0.73	0.69	0.72
70.16	0.75	0.77	0.76	0.75
68.58	0.76	0.79	0.76	0.8
65.45	0.69	0.83	0.74	0.78
66.10	0.64	0.84	0.76	0.79
65.02	0.65	0.9	0.75	0.79
67.16	0.73	0.75	0.74	0.78

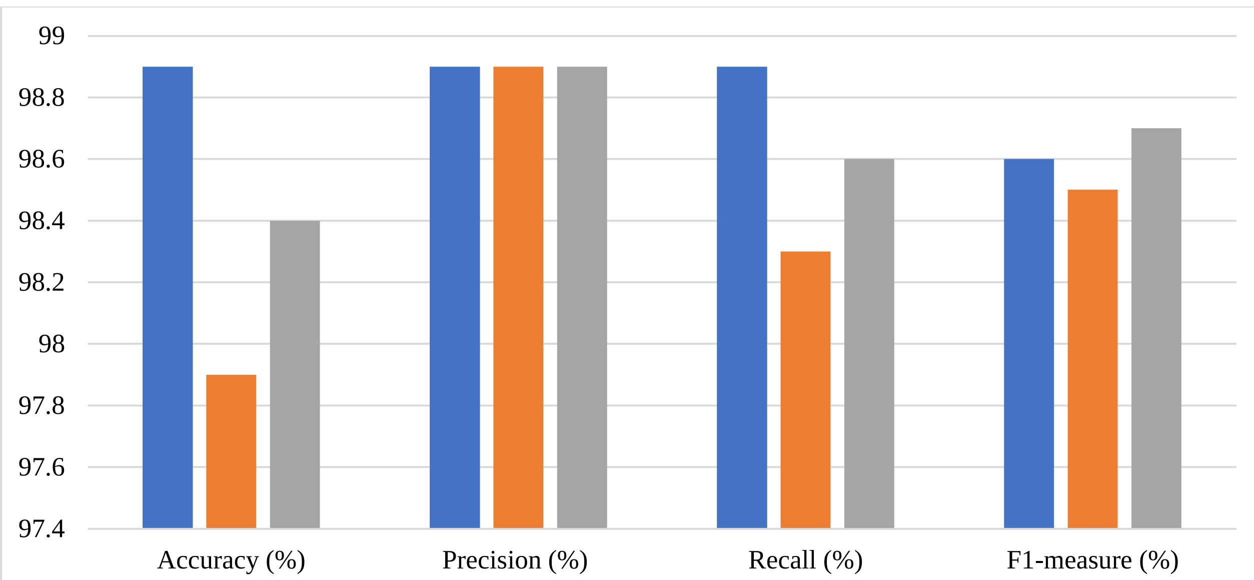


Fig. 6 Graphical representation of the proposed model for driver identification in terms of accuracy with different numbers of features

Table 3. Comparison table

Reference	Techniques	Accuracy	Precision	Recall	Sensitivity
M. Almehdhar et. al (2024) [22]	Intrusion Detection Systems (IDS)	97.2	87.0	NA	NA
Y. Xun et. al (2019) [23]	CNN and SVDD Model	92.0	95.0	92.0	92.0
A. Kavousi-Fard et. al (2020) [24]	Generative Adversarial Network (GAN)	96.0	95.5	96.0	95.6
H. C. Lin et. al (2022) [25]	In-Vehicle Network (IVN)	96.3	95.7	96.8	97.3
Proposed approach	**ADAS**	**97.6**	**96.9**	**98.8**	**99.3**

The recommended DNN performed 97.05% using RF and 95.55% using PCA in the accuracy tests, whereas ANN and RNN performed roughly 92% and 94%, respectively, when used with both PCA and RF. For ANN with PCA, the Cohen's kappa value was a pitiful 0.78. In comparison, the identical approach employing RF yielded a score of 0.82. In contrast, the suggested ADAS approach obtained 0.91 with PCA, and the 0.94 RNN achieved 0.85 with PCA and 0.88 with RF. The RNN with RF had an F1-score of 0.94, whereas the ANN with RF had a precision, recall, and an F1-score of 0.92.

5. Conclusion

An Optimal Driving Strategy (ODS) that integrates driver behaviour detection and driver assistance was described in this work using a unique ADAS. A novel network that could detect drivers and assess driving conduct was constructed using the DNN model. Furthermore, this study proposes an intelligent driver support system that uses a revolutionary deep learning approach to accurately predict an Electric Vehicle's (EV) driving range. The fact that our work relies on real-world EV data highlights its significance because it increases range prediction accuracy and user reliability, both of which reduce driving anxiety. By increasing safety and efficiency, Advanced Driver Assistance Systems (ADAS) in Electric Vehicles (EVs) can minimise traffic accidents and improve energy Management, both of which have a substantial positive environmental impact. The suggested ADAS model obtained 97.6% accuracy, 96.9% precision, 98.8% recall, and 99.3% sensitivity.

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