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Abnormal Driving Behavior Detection: A Machine and Deep Learning Based Hybrid Model

Md. Ashraf Uddin[1,3] · Nibir Hossain[2] · Asif Ahamed[2] · Md Manowarul Islam[2] · Ansam Khraisat[3] · Ammar Alazab[4] · Md. Khabir Uddin Ahamed[5] · Md. Alamin Talukder[6]

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Abstract

Car accidents remain a leading cause of unintentional fatalities, with many incidents stemming from driver behaviors that impact vehicle control, such as steering, braking, accelerating, and gear shifting. Activities like searching for items, using mobile devices, or listening to the radio can distract drivers visually, audibly, and physically, posing significant risks to road safety. While various methods have been developed to detect such distractions, their effectiveness often falls short in real-world applications. This paper introduces a novel approach that combines machine learning (ML) and deep learning (DL) techniques to identify both safe and risky driving behaviors. Six ML classifiers were evaluated on real-world data to distinguish between driving behaviors such as aggressive, fatigued, and normal driving, with the Random Forest classifier demonstrating superior performance. Additionally, a specialized deep-learning baseline model was developed using ResNet50 and EfficientNetB6 to classify driving-related images into distinct categories. The hybrid model integrates ML for analyzing tabular data and DL for image recognition, achieving a classification accuracy of 99.3% on the UAH-Drive dataset. Deep learning experiments further revealed that the Base Model outperformed other models, achieving accuracies of 99.32% on the UAH-Drive dataset and 99.87% on the SFD3 dataset. This research presents a robust hybrid ML-DL framework for detecting abnormal driving behaviors, addressing shortcomings of existing techniques in real-world conditions, and offering valuable insights for improving road safety and reducing accidents.

Keywords Driver behavior · Efficient data processing · Machine learning · Classification · Deep learning

1 Introduction

Road safety remains a critical global concern, with aggressive driving behavior identified as a significant contributor to traffic accidents and crashes. Timely detection and mitigation of such behaviors are imperative to reducing these incidents and improving overall road safety [17]. Factors such as rush hours, mental stress, and retaliatory driving often exacerbate aggressive driving tendencies, posing severe risks to drivers and pedestrians alike [35]. The growing vehicular density on roads has further heightened concerns over traffic congestion and accident rates, prompting governments worldwide to prioritize initiatives aimed at curbing road-related fatalities and enhancing safety measures. One of the primary causes of road accidents is driver inattention or distraction, which can often be attributed to human behavior and decision-making within the driving environment [20]. Human driving behavior is inherently complex, influenced by a myriad of factors that interact dynamically in real-world scenarios. The advent of smartphones and mobile devices equipped with sensors has introduced a cost-effective alternative to traditional instrumented vehicles for monitoring driving behavior [29]. While these smartphone-based sensing applications offer flexibility and the potential for widespread crowdsourced data collection, their precision often falls short compared to more sophisticated instrumented systems.

A notable advancement in this domain is the development of datasets like the UAH-Drive dataset, which evaluates various driving parameters and classifies driving styles into normal or atypical categories. This dataset provides a diverse and rich resource for analyzing driving behaviors in real-world scenarios, making it invaluable for research on driver distraction and aggressive behavior [26, 28]. Talebloo et al. [30] use GPS data from smartphones to detect aggressive driving behaviors by analyzing 3-minute intervals, employing GRU and LSTM models to capture temporal patterns,

Extended author information available on the last page of the article with a good F1 score indicating strong performance. Chawan et al. [9] focus on detecting driver distraction using CNN architectures like VGG-16 and Inception, applied to the SFD3 dataset from Kaggle. Their model, implemented with Keras and TensorFlow, achieved a cross-entropy loss of 0.899 on the validation set, demonstrating effective distraction classification. Simultaneously, the field of deep learning, particularly in computer vision, has witnessed significant progress, enabling more accurate detection of distracted driving. Deep learning models have revolutionized tasks such as image classification, recognition, cyberbullying identification outperforming traditional machine learning methods [31–33] in terms of accuracy. However, despite their impressive capabilities, these models often face challenges in real-time deployment on embedded systems due to their high computational demands.

In this study, we propose a novel hybrid model that integrates machine learning and deep learning (DL) approaches to detect abnormal driving behaviors effectively. The uniqueness of our approach lies in its ability to incorporate both driver pose information and environmental cues extracted from images within a unified DL framework. While prior research has predominantly focused on either image-based or tabular data, this singular approach may overlook critical real-world scenarios. By combining these data modalities, our holistic framework aims to establish a more robust system for detecting driver distractions.

The proposed model emphasizes the immediate classification of erratic driving behaviors using machine learning techniques, providing timely notifications in a structured format, such as CSV files. Designed for enhanced performance in semi-autonomous vehicles, this hybrid approach leverages the strengths of both machine learning and deep learning methods. Our objective is to identify the most effective model combination to achieve optimal performance, ultimately contributing to the development of safer road systems.

The primary contributions of this research are:

- Proposing a Hybrid Model that synergizes machine learning and deep learning, utilizing both CSV files (ML) and image data (DL), to bridge the existing research gap.
- Implementing and fine-tuning the models, with a particular focus on hyperparameter tuning in both ML and DL. Our results indicate that the modified CNN model outperforms several existing models in this domain with minimized loss.

The structure of this paper is as follows: Section 2 presents a review of related literature. Section 3 details the architecture and materials used in this study. In Section 4, we present the results of our experiments and compare them with the counterpart results. Finally, Section 6 summarizes the paper and outlines potential future research directions.

2 Related Works

Romera et al. [26] introduced the UAH-DriveSet, a publicly available dataset designed for analyzing driving behavior, which includes data from six drivers displaying normal, tired, and aggressive behaviors across different road types. The dataset features over 500 minutes of naturalistic driving data, including raw and processed sensor data, semantic information, and video recordings. The DriveSafe program, used in the dataset, effectively detects driving behavior patterns with high accuracy for both highway and secondary road scenarios. Ghandour et al. [11] proposed four machine-learning classification techniques to identify driving behaviors (aggressive, tired, and normal) using real measurement data, focusing on lane identification and traffic flow. Their results showed that while all classifiers performed well, the gradient-boosting method outperformed others in accuracy and effectiveness, especially with imbalanced data. Nikolaos et al. [21] developed a platform integrating machine learning and deep learning algorithms to analyze vehicle data streams and assess drivers' eco-friendly behavior, demonstrating no overfitting or underfitting in their models. Meanwhile, Xie et al. [14] developed a movement-based driving behavior classification system using accelerometers, gyroscopes, and GPS, achieving an F1 score of 70.47%, with the highest score of 75.38% for the behavior of slowing down. Hajijb et al. [23] introduced a bi-level machine learning approach to classify drivers' engagement in optional tasks, with high accuracy for identifying task engagement (99.8% with Decision Tree) and task type classification (82.2% with Random Forest). These studies highlight the effectiveness of machine learning algorithms in various driving behavior and driver recognition applications. Lattanzi et al. [15] developed an AI system using in-vehicle sensor data to identify safe and dangerous driving behaviors, with both SVM and FNN classifiers achieving over 90% accuracy and no significant performance difference. Feng et al. [10] used machine learning to detect driver distraction based on photos, employing multiple classifiers to predict distracted driving behaviors. These studies highlight the application of machine learning algorithms in analyzing and identifying various aspects of driving behavior, such as safety and distraction. The study also discusses the contributions and limitations of other relevant studies in a tabular format as shown in Table 1.

Alkinani et al. [7] introduced a Stacked-LSTM Recurrent Neural Network technique to classify driving behaviors (normal, aggressive, and drowsy) using smartphone sensor data, achieving an F1-score of 91% and outperforming baseline methods. Yan et al. [34] proposed a vision-based

Table 1 Existing Author, Key Models, Contributions and Research gaps

Authors	Key Models	Contributions	Drawbacks
Ghandour et al. [11]	LR,GB,RF,NN	Four ML order algorithms are applied and examined by creators to identify various driving behaviors.	Among the four models,GB performs better than other and has an accuracy 67%.So it is not more efficient.
Nikolaos et al. [21]	SVM,RF,LR, MLP, RNN	They analyzed driving behavior using machine and deep learning methods for a continuous stream of vehicle data.	They worked with small data.
Romera et al. [26]	Null	Examined the UAH-DriveSet, a freely accessible dataset that empowers inside and out driving examination by offering a sizable measure of information got by their driving observing application DriveSafe.	The time required to process data and produce results is considerable.
Talebloo et al. [30]	GRU, LSTM	They Using deep learning to detect aggressive driving behavior.	High implementation complexity and cost of calculation.
Yan et al. [34]	R*CNN,GMM	Authors used Deep Convolutional Neural Networks to detect driving behavior.	Used small size image dataset which include six different types of behavior.
Xie et al. [14]	RF	The authors Using a machine learning model to Classify Maneuver-based Driving Behavior.	Does not perform well for Lane change and Turning.
Chawan et al. [9]	CNN,VGG-16 VGG-19	Authors used a variety of Convolutional Neural Network (CNN) models for classifying distracted drivers.	They worked with only five type of behabvior.
Hu et al. [13]	BPNN,SVM,SR,SdsAEs,RBF kernel	The authors using a deep learning approach for detecting abnormal driving with normalized driving behavior data.	Limited driving behavior data.
Saleh et al. [27]	LSTM	The authors utilizing LSTM Recurrent Neural Networks for driving behavior classification based on sensor data fusion.	There are limited GPS data.
Elassad et al. [2]	SVM,BL,EL,DT,IB,CL,NF	Authors are doing a thorough literature study and providing a conceptual framework for driving behavior analysis by employing machine learning techniques.	When used on unbalanced data sets, has very little success.
Oikawa et al. [22]	HMM,LSTM,OS-ELM	Authors propose a Online Sequential Extreme Learning Machine for Fast Semi-Supervised Anomaly Detection of Driver Behavior.	Higher compute complexity.
Ahangari et al. [6]	BN	Authors propose a model for predicting distracted driving Using machine learning.	Provide lower accuracy(67%) so it is not suitable.
Feng et al. [10]	Sofrmax,NB,DT, 2-Layer NN	The authors used deep learning and machine learning approach for detecting abnormal driving.	Did not use hybrid model.

approach for driver behavior recognition using CNN and a Gaussian Mixture Model to extract skin-like regions, achieving a mean Average Precision of 97.76% on the Southeast University Driving-pose Dataset. Hu et al. [13] developed a deep learning model utilizing a stacked denoising autoencoder to identify anomalous driving behaviors, achieving superior performance in anomaly detection. These studies demonstrate the effectiveness of advanced machine learning and deep learning techniques in driving behavior analysis and anomaly detection. Qin et al. [24] introduced the D-HCNN model, which uses only 0.76M parameters and incorporates dropout, batch normalization, and feature mapping, achieving accuracy rates of 95.59% on the AUCD2 dataset and 99.87% on the SFD3 dataset, outperforming many existing methods. Moukafih et al. [18] developed an LSTM-FCN model for classifying aggressive driving patterns from smartphone data, achieving a 95.88% F-measure score for a 5-minute window on the UAH-DriveSet dataset. Hossain et al. [12] proposed a CNN-based approach to detect distracted drivers and their causes (e.g., talking, sleeping, eating) using facial and hand cues, with the MobileNetV2 model achieving the best performance. These studies showcase the effectiveness of deep learning techniques in detecting and classifying various driving behaviors, including distraction and aggression. Abbas et al. [1] proposed a deep learning architecture using the Openpose package for distraction detection, generating face skeletons from input images and achieving 98% accuracy on the State Farm Distracted Driver Detection dataset, outperforming existing Residual Networks. Alotaibi et al. [8] developed a framework for recognizing distracted driving postures using a dashboard camera, combining deep learning techniques like the inception module, residual block, and hierarchical recurrent neural network. Their method successfully identified various distracted driving behaviors, including texting, phone use, and engaging with passengers. Both studies highlight the effectiveness of advanced deep-learning models in detecting and classifying distracted driving behaviors.

The proposed study overcomes limitations in earlier research by combining machine learning and deep learning techniques to handle varied data formats, such as tabular and image inputs, resulting in a more effective and adaptable hybrid framework. Using real-world datasets like UAH-DriveSet and SFD3, it demonstrates strong real-world applicability while delivering exceptional performance, with deep learning achieving 99.87% accuracy and machine learning reaching 99.32%. Moreover, the research enhances real-time usability by optimizing model architectures (e.g., ResNet50, EfficientNetB6) and fine-tuning hyperparameters to lower computational requirements.

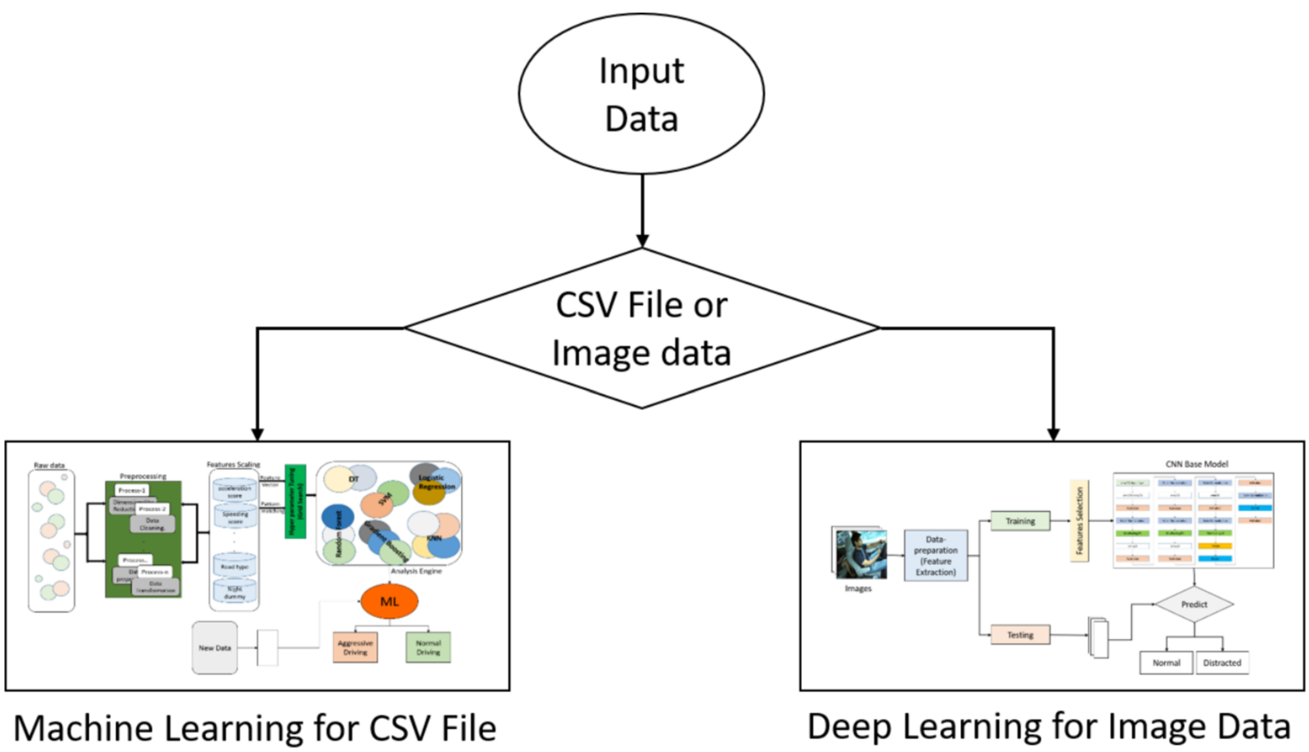


Fig. 1 Overview of Our Developed Hybrid Model

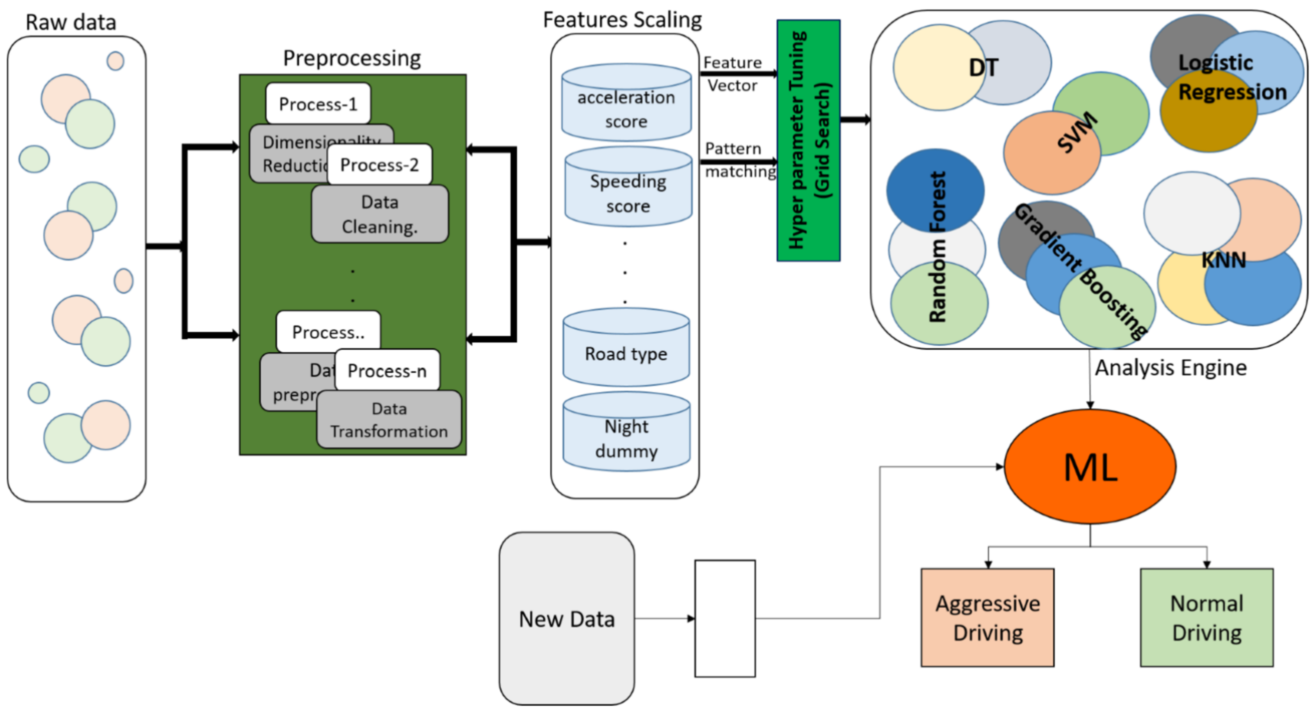


Fig. 2 Overview of Our Developed Method for ML

3 Methodology

In this section, we presented a hybrid model that integrates various deep learning and machine learning models. Driver distraction datasets might be image data and tabular data. Machine Learning algorithms perform well for tabular data [4, 5] while deep learning model performs well for image data [3]. Therefore, we build a hybrid strategy to combine machine learning and deep learning models. Figure 1 shows that the model sends the tabular data to the machine learning and image data to the deep learning model. The deep learning model consists of a CNN, ResNet50, EfficienNet and ML classifiers including Logistic Regression, Random Forest, KNN, Decision Tree, Gradient Boosting and SVM.

We train the machine learning model using the UAH-Drive dataset [26]. We use several ML models, including RF, RB, LR, SVM, DT, and KNN using UAH-DriveSet. Figure 2 provides more information about the models we utilized.

3.1 Dataset Description and Analysis

UAH-Drive Dataset The UAH-Drive Dataset was captured using the smartphone software Drive Safe, which logs and recognizes driving movements and deduces behaviors from them. Drive Safe uses all the smartphone's available sensors, including the camera, GPS, and inertial sensors, as well as its internet access. In (Table 2), the test bed is displayed. There were six separate users, each of varying ages, driving various kinds of automobiles, including an electric car.

The most crucial features: Car speed, Acceleration score, Turning rating, Class regular, Avenue kind, Day night and Braking score are considered in this experiment. Car speed, acceleration rating, class everyday, street kind, and cargo are examples of features that relate to a motive force's pastime. To the contrary, the motive force's actions are at once described by means of the throttle role, guidance wheel attitude, and brake pedal pressure. The class fashions listen on traits that display a robust hyperlink with our meant categorization set. The model is run using two units of information: "lane detection," which had a set of 214,151 pattern factors, and "visitors status," which has a set of 46,542 sample points similar to the highway class.

Table 2 List of Drivers and vehicles that performed in the test [26]

Driver	Genre	Age range	Vehicle	Fuel type
D1	Male	40-50	Audi Q5 (2014)	Diesel
D2	Male	20-30	Mercedes B180	Diesel
D3	Male	20-30	Citroen C4 (2015)	Diesel
D4	Female	30-40	Kia Picanto (2004)	Gasoline
D5	Male	30-40	Opel Astra (2007)	Gasoline
D6	Male	40-50	Citroen C-Zero	Electric

Fig. 3 Class of Images [12]

Image Dataset(SFD3) We got two publicly available image datasets (SFD3), each of which contains one safe driving action and nine distracted driving actions. The State Farm Distracted Driver Detection dataset, which was collected using a dashboard camera. The participants simulated 10 different driving movements in the car while it was being towed by a truck to simulate the driving environment. Each category has about 2000 pictures: (1) adjusting radio, (2) drinking, (3) doing cosmetics or hair, (4) reaching behind, (5) using phone on left or right, (6) safe driving, (8) conversing with passenger, (8) texting, and (9) texting on left or (10)right shown in Fig. 3.

The dataset consists of 79728 unlabeled images for testing and 22424 training images (about 2000 images in each category). 26 subjects (13 males and 13 females) with various racial backgrounds and skin tones from Asia and Africa make up the dataset. Each image has a resolution of 640 by 480 pixels.

3.1.1 Examples from the UAH-Drive Dataset

To enhance understanding of the practical application of the experiment, we provide examples of real data from the UAH-Drive dataset [26]. These examples illustrate the diversity of driving behaviors (normal, aggressive, and tired) captured in the dataset and how they are represented through key features. In the following Table 3, we present examples of real data from the dataset to illustrate its practical application in this study.

3.2 Proposed Model

The overview of our developed model in which a distracted driver can be identified by their unusual behavior, as seen in Fig. 4 and the developed model procedure is shown in Fig. 5. The dataset underwent preprocessing steps including normalization, augmentation, and outlier removal so that the model can be trained using the images with different driving positions, such as eating, texting, and conversing with others. A pre-trained convolutional model built from different CNN-based deep learning architectures has been used to identify the driver's distracted driving behavior. Besides, we also utilized six ML models and integrated with the DL model as well.

3.2.1 Construction of Machine Learning Models

In the proposed hybrid model, machine learning (ML) algorithms were employed not only for performance benchmarking but also to process tabular data effectively. The following steps outline the contributions to constructing the ML models:

- Feature Engineering: Key driving parameters such as speed, acceleration, braking scores, and turning ratings were extracted from the UAH-Drive dataset. These features were chosen based on their strong correlation with driving behavior categories (normal, aggressive, tired).
- Feature Selection: A recursive feature elimination (RFE) approach was utilized to identify the most impactful features, ensuring the ML models focused on parameters critical to classification accuracy.
- Classifier Selection: Six ML classifiers-Random Forest, Gradient Boosting, Logistic Regression, Support Vector Machine, K-Nearest Neighbor, and Decision Tree-were chosen for their diverse strengths in handling tabular data.
- Hyperparameter Tuning: Grid search techniques were applied to optimize key parameters for each classifier, such as the number of estimators for Random Forest and learning rates for Gradient Boosting. This optimization improved model accuracy and robustness.
- Integration in Hybrid Framework: The ML models were designed to complement the deep learning components by providing predictions based on tabular data. This ensured that insights from structured data were incorporated alongside image-based analysis from the DL models.

3.2.2 Integration of Machine Learning and Deep Learning Models

In the proposed hybrid model, the integration of machine learning (ML) and deep learning (DL) models is designed to

Table 3 Some examples of real data from UAH-Drive dataset

Parameters	Example 1: Normal	Example 2: Aggressive	Example 3: Tired
Speed	50 km/h	120 km/h	40 km/h
Acceleration	0.3 m/s2	3.2 m/s2	0.1m/s2
Steering Angle	5∘	25∘	15∘
Braking Force	Low	High	Moderate
Road Type	Urban	Highway	Suburban
Time of Day	Morning	Night	Late Night

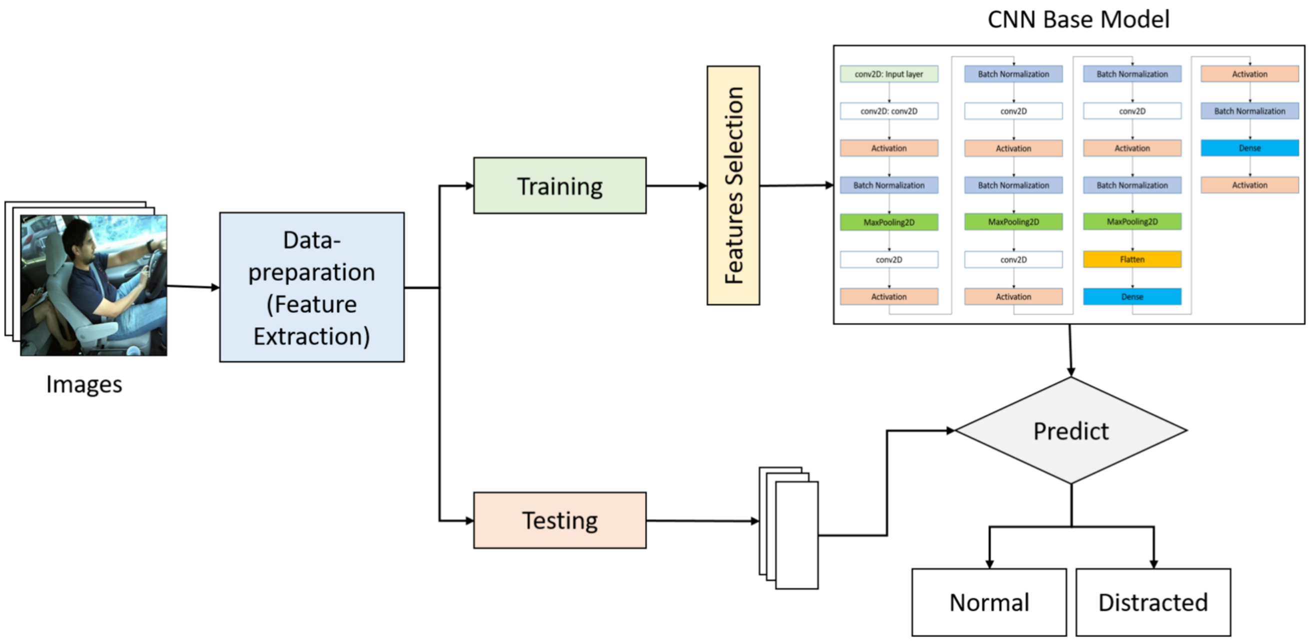


Fig. 4 Overview of Our Developed Method for DL [12]

leverage the strengths of each approach, enabling a comprehensive analysis of driving behavior.

The ML models process tabular data from structured datasets such as UAH-Drive, extracting insights from features like speed, braking patterns, and acceleration. Simultaneously, DL models analyze image data from datasets like SFD3 to detect visual distractions and driving postures.

The hybridization occurs in the decision-making layer, where outputs from the ML and DL models are combined to provide a unified prediction. Specifically:

- ML outputs, such as classification probabilities, are transformed into feature vectors.

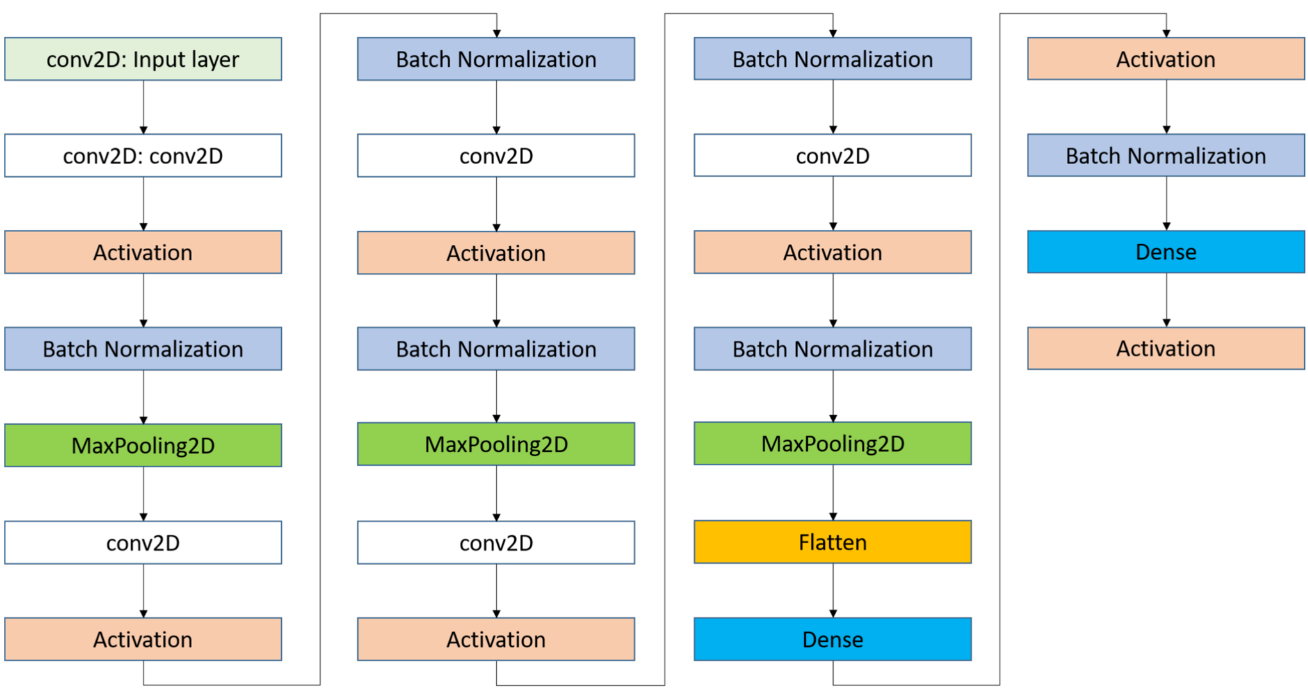


Fig. 5 Overview of Our Developed Model Procedure

- These feature vectors are concatenated with the features extracted by the DL model's final layer.
- The combined feature vector is processed by a meta-classifier (e.g., Random Forest or a fully connected neural network) to produce the final prediction.

This integration ensures that the model benefits from both structured data (capturing numerical patterns) and image-based information (capturing visual cues), resulting in enhanced accuracy and robustness. Additionally, this approach allows the hybrid model to address scenarios where either data type alone might provide incomplete information.

3.2.3 Pseudo-Code of CNN Model for Image Classification

The pseudo-code of our proposed architecture is represented in Algorithm 1.

Algorithm 1 CNN Model for Identifying Driving Behaviors.

Input: Image dataset D with labels L, input image size ($224 \times 224 \times 3$)
Output: Predicted driving behavior class C

Step 1: Import necessary libraries (e.g., TensorFlow, Keras).
Step 2: Initialize model:
a. Create sequential CNN model.
b. Add convolutional layers:
- Convolutional layer with 32 filters, 3×3 kernel, ReLU activation.
- Max-pooling layer with 2×2 pool size.
- Dropout layer (rate: 0.2).
c. Add more layers as needed:
- Repeat convolutional and pooling layers (e.g., 64, 128 filters).
- Use Batch Normalization after convolutional layers for stability.
d. Flatten the output of the final pooling layer.
e. Add dense (fully connected) layers:
- Dense layer with 256 units, ReLU activation.
- Dropout layer (rate: 0.5).
f. Add output layer:
- Dense layer with N units (number of classes), softmax activation.

Step 3: Compile the model:
- Loss function: Categorical cross-entropy.
- Optimizer: Adam (learning rate 0.001).
- Metrics: Accuracy.

Step 4: Train the model:
- Split dataset D into training, validation, and testing sets.
- Augment training images (rotation, flipping, scaling).
- Train the model using the training set (e.g., 20 epochs, batch size 32).

Step 5: Evaluate the model:
- Use the validation set for performance monitoring.
- Calculate metrics (accuracy, precision, recall, F1-score).

Step 6: Predict driving behavior class C:
- Input an image to the trained model.
- Output the predicted class with the highest probability.

4 Results and Discussion

4.1 Performance Evaluation Metrices

The proposed methodology is evaluated using Eqs. 1, 2, 3 and 4 for accuracy, precision, recall, and F1-score, respectively.

$$\text{Accuracy} = \frac{\text{True Positives} + \text{True Negatives}}{\text{True Positives} + \text{True Negatives} + \text{False Positives} + \text{False Negatives}} \tag{1}$$

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}} \tag{2}$$

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}} \tag{3}$$

$$\text{F1 Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4}$$

The letters "N" and "P" in the equations below stand for the total samples of the negative and positive classes, respectively. The proposed paradigm uses P to denote malignant and N to denote non-cancerous. The letters TP, FN, FP, and TN are used to denote True Positive, False Negative, False Positive, and True Negative, respectively.

We divided into 30 percentage for testing and 70 percentage for training the machine learning and deep learning model. The performance of the classifiers was assessed using the following common set of assessment indicators due to the unbalanced data set:

Accuracy: To compare the four various categorization models, this common assessment metric is employed. In general, accuracy refers to how often predictions are correct and either in favor of or against the occurrence throughout all instances of the event.

Precision: Out of all forecasts made in favor of the event, this metric is used to identify the successful predictions.

Recall: From all actual occurrences of the event, this metric is used to identify the successful forecasts.

F1-score: The accuracy and review measures are weighted together to give the F1- score.

ROC curve: The ROC bend considers a compromise between the genuine positive rate (the extent of right per-

Table 4 Comparison of Model Performance Before and After Tuning

Model	Accuracy (Before Tuning)	Accuracy (After Tuning)	Key Improvements
Logistic Regression	88.6%	92.3%	Regularization parameter tuning
Random Forest	93.2%	99.3%	Optimized number of trees
Support Vector Machine	91.1%	96.7%	Kernel and gamma optimization
Gradient Boosting	94.2%	98.7%	Learning rate and estimators fine-tuned
K-Nearest Neighbors	86.7%	89.4%	Optimized neighbor count

ceptions to all perceptions) and the misleading positive rate (the extent of wrong perceptions to all perceptions).

4.2 Machine Learning-based Performance Results

Plots are utilized to illustrate the results, along with the numerical results obtained from the employed assessment metrics. This section includes result of the top three models (RF, SVM, GB).

Table 4 presents the comparison of the models' performance before and after hyperparameter tuning. The improvements observed highlight the importance of fine-tuning model parameters to achieve optimal accuracy.

4.2.1 Performance Results on Logistic Regression

The provided table represents the confusion matrix and classification performance of a logistic regression model. Table 5 and Fig. 6 provide an overview of the model's predictions and performance metrics.

The table is divided into two sections. The upper section presents the confusion matrix, which shows the counts of true positive (1171), false positive (81), false negative (139), and true negative (1609) predictions. The rows represent the true class labels (Normal and Abnormal), while the columns represent the predicted class labels (Normal and Abnormal).

Table 5 Confusion matrices and classification performance of Logistic Regression

True class	Normal	Predicted class Abormal
Normal	1171	81
Abnormal	139	1609
Parameter		
precision	0.95	
Recall	0.92	
F1 score	0.94	
Support	1748	
Accuracy	0.93	

4.2.2 Performance results on Random Forest

The results for RF are shown in Fig. 7 .The performance of many parameters before and after tuning is shown in this figure. Unexpectedly, performance increases for all parameters after adjusting (hyperparameter grid search). The confusion matrix for RF is shown in Fig. 8.

4.2.3 Performance results on SVM

The models, C: 1000, gamma: 0.01, and portion: rbf SVC(C=1000, gamma=0.01) are trained and tested. Figure and shows the outcomes in Fig. 9.

We achieve better performance from SVM after hyper parameter optimization.

4.2.4 Performance results on Gradient Boosting

We obtain the best accuracy results for number of estimators = 500 and learning rate = 0.05 in this algorithm. The F1-Socre, F-beta, accuracy, precision-recall, and AUC are shown in Fig. 10.

Confusion matrix and classification performance of GB is presented in (Table 6). Figure 11 shows the confusion matrix of GB.

4.2.5 Performance Results on K-NN

Figure 12 shows accuracy, F1-Socre, F-beta, accuracy review, and AUC of the KNN model. They are displayed in Fig. 13. Figure 14 displays the confusion matrix of KNN.

4.2.6 Performance Results on Decision Tree

The decision tree in the above graph (Fig. 15) orders a particular occasion in view of its reasonableness for the best

Fig. 6 Overview of Logistic Regression Performance

Fig. 7 Overview of Random Forest performance

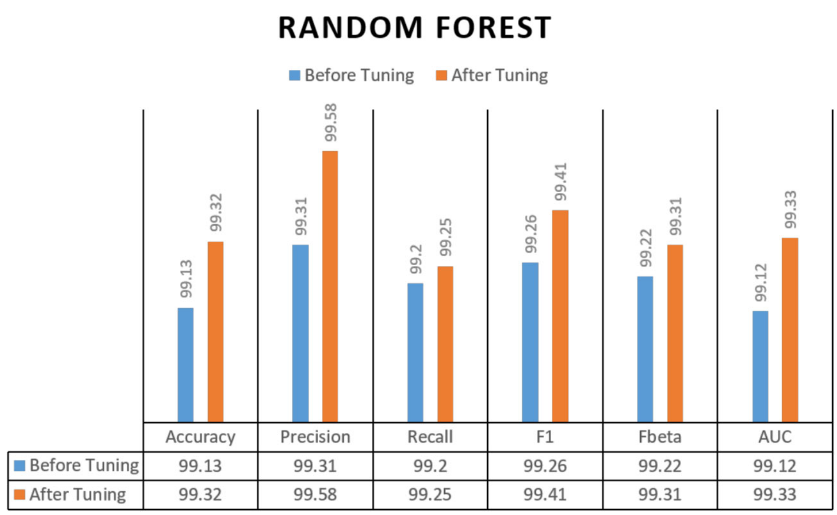
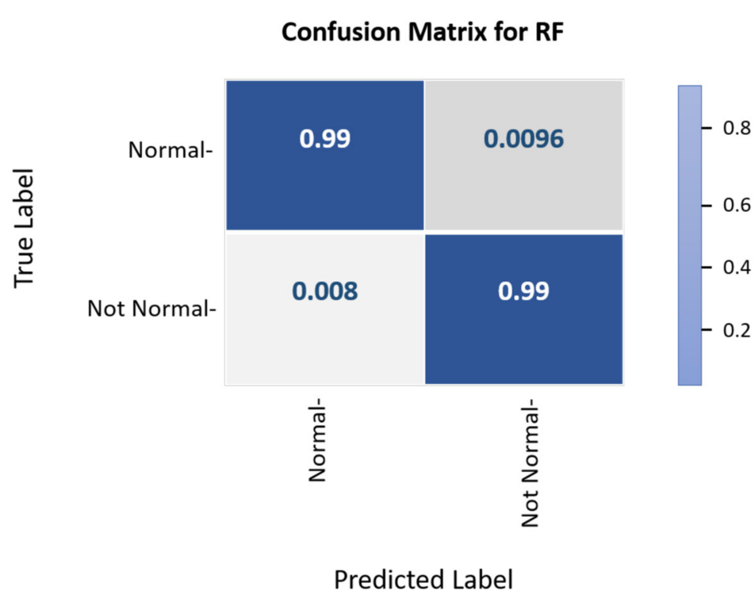


Fig. 8 Confusion Matrix for RF



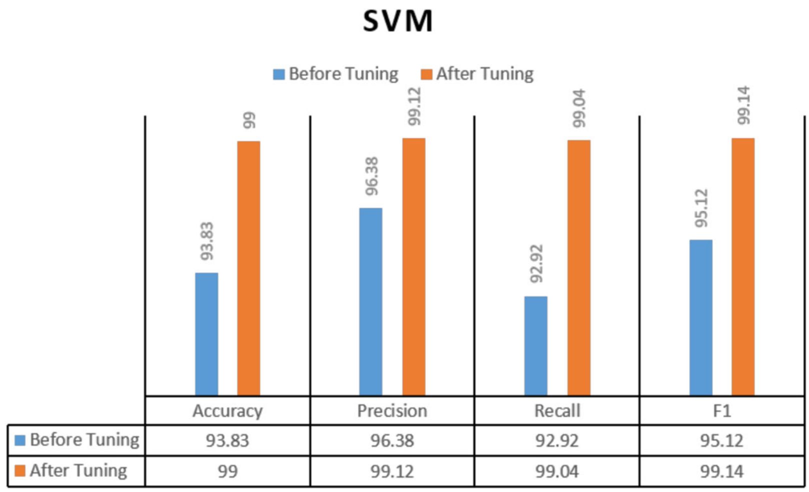


Fig. 9 Overview of SVM performance

result and returns the grouping related with the particular leaf. (In this example, a Yes or No). DT have gotten acclaim for their capacity to order DB actually by separating the informational index into more modest, more homogeneous gatherings and can forestall overfitting by pruning. All of these metrics-accuracy, F1-Socre, F-beta, accuracy review, and AUC-display outstanding depictions of the results. (Figure 16) shows them in an illustration. The performance of DT matrix confusion is assessed while attempting to distinguish between normal and deviant driving behavior using only the retrieved variables from the dataset. The outcomes that were offered in compliance are shown in (Fig. 17).

4.3 Deep Learning-based Performance Results

Each image has been downsized to 224*224 pixels prior to training. We used a device with the following specifications to perform the calculation: Intel(R) Core(TM) i5-8300H CPU running at 2.30GHz, 8 gigabytes of RAM, and a GTX 1050ti GPU. Even while training accuracy is improving, validation accuracy varied a little.

4.3.1 Base Model

We have constructed the various image classification Neural Network methods using the sample of 22424 images that were divided in an 80:20 ratio. In the beginning, we categorized the number of images into the following categories: (1) adjusting the radio, (2) drinking, (3) doing makeup or hair, (4) reaching behind, (5) using phone on left or right, (6) safe driving, (8) talking to passenger, (8) texting, and (9)

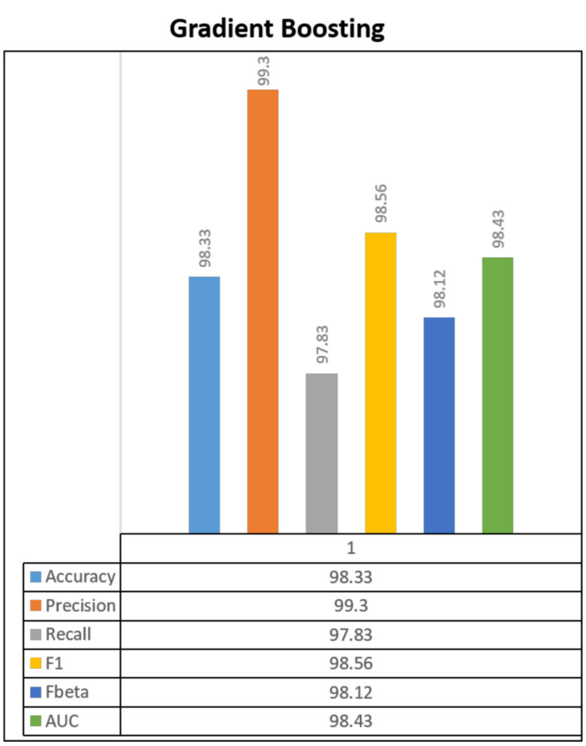


Fig. 10 Overview of Gradient Boosting performance

Table 6 Confusion matrices and classification performance of Gradient Boosting

True class	Normal	Predicted class Abormal
Normal	1242	10
Abnormal	35	1713
Parameter		
precision	0.99	
Recall	0.98	
F1 score	0.99	
Support	1748	
Accuracy	0.98	

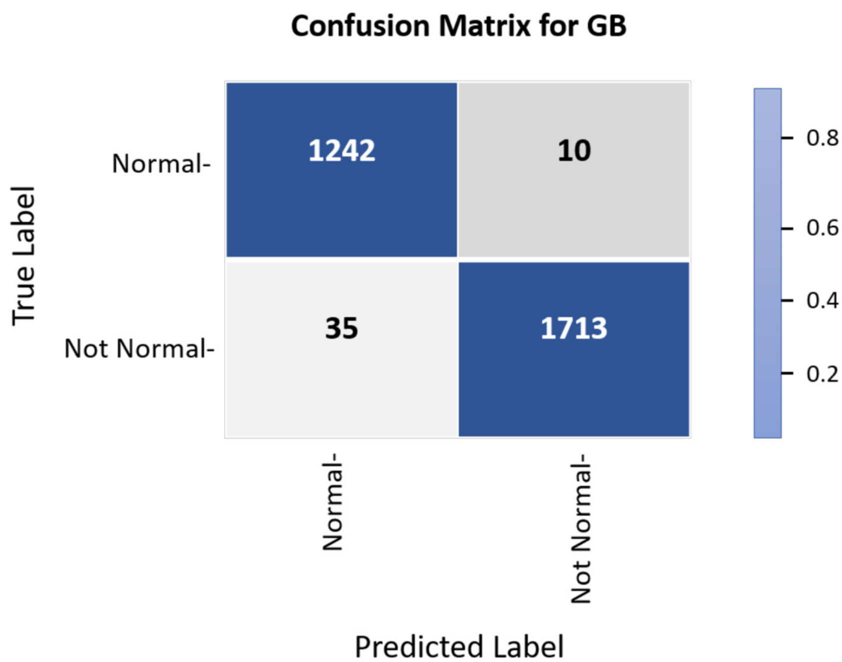


Fig. 11 Confusion Matrix of GB

texting on left or (10)right. The number of images that are categorized by subject and displayed in Figs. 18 and 19. For this model, we used the sequential procedure described in the preceding section.

Six blocks of 25 layers each in 2D convolution made up this model. ReLu layer first, then MaxPooling layer with a pool size of 2*2, follow in the block. After these six convolutional blocks, the final block uses two dense layers and a dropout layer with a dropout value of 0.5, a learning rate of 0.01, and a momentum value of 0.9. As epochs passed, the training accuracy increased to 99.87 %, whereas the validation accuracy decreased to 99.31%. Losses for training and validation are 0.0050 and 0.0264, respectively. Figures 20 and 21 provide graphic descriptions.

The following step is to gather all of the predictions made by the neutral network model once it has been trained and create a confusion matrix. The model's confusion points are depicted in Fig. 22's confusion matrix, which also identifies which classes the model correctly predicts and which classes it mistakenly predicts.

4.3.2 ResNet50

The version has been altered by means of the addition of three dense layers on the top. Using residual networks, which

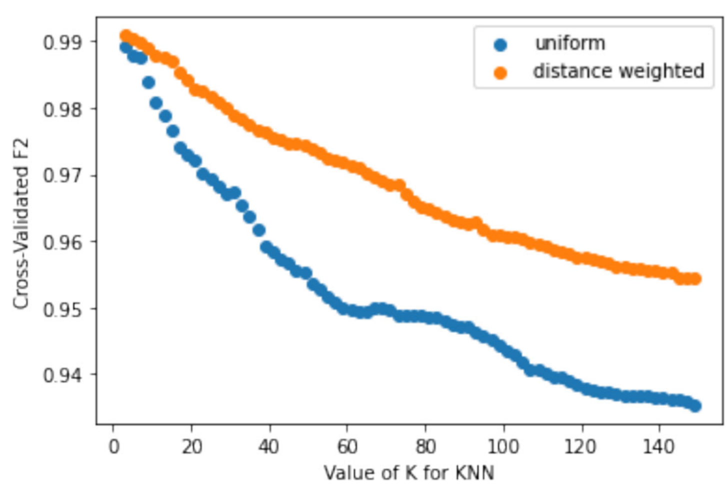


Fig. 12 Clustering of K-NN

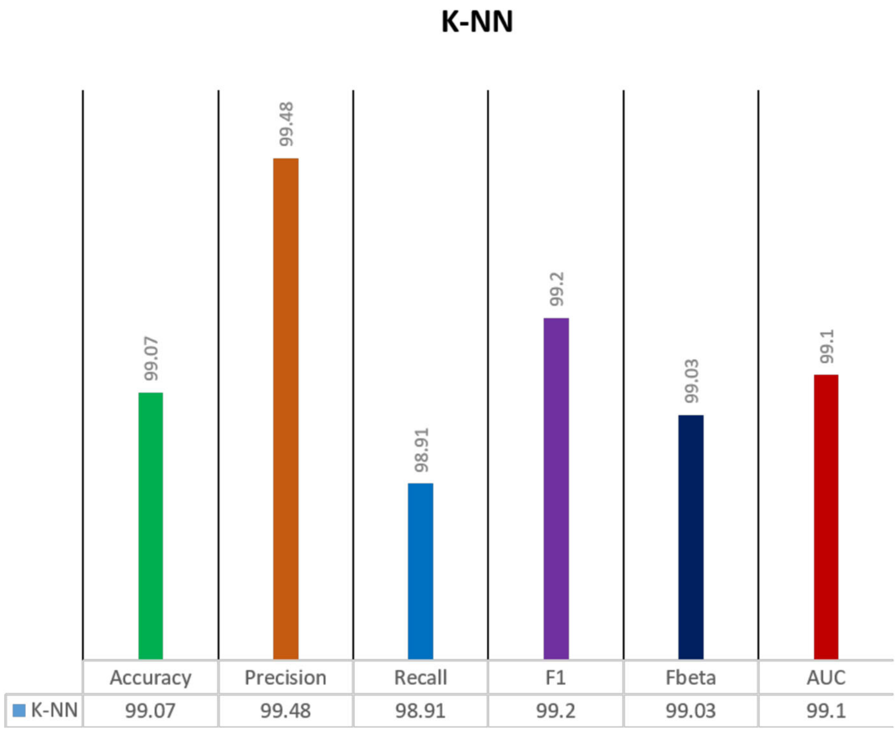


Fig. 13 Overview of K-NN performance

do now not require ongoing relearning of the snap shots, effects in excessive accuracy of 99.72% and losses of 0.0110, as shown in Figs. 23 and 24. with the exception of a few abnormalities, the loss therapy shows a consistent drop. The facts set has been well-trained, and versions are infrequent.

The training accuracy has now reached 99.72%, whilst the validation accuracy is 99.24% after epochs. The validation loss is 0.0293, and the training loss is 0.0110. The visible depiction is proven in Figs. 24 and 23. The accuracy grows as time and epoch growth, even as the loss decreases.

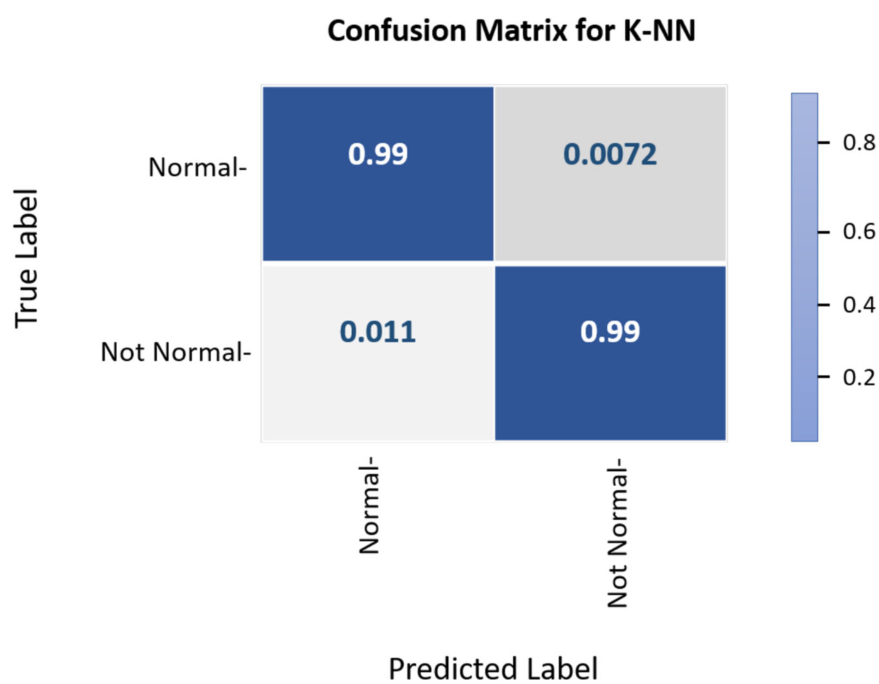


Fig. 14 Confusion Matrix for K-NN

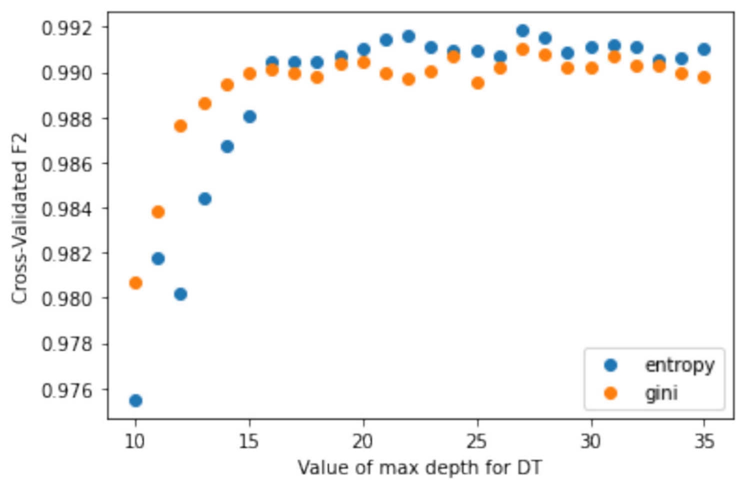


Fig. 15 Classification of DT

4.3.3 EfficienNetB6

After utilizing a base model, we load the pre-trained EfficientNetB6 model with the imagNet Dataset, and after that, we utilize the EfficientNet pre-trained model, which allows us to employ model scaling to increase accuracy and performance. The accuracy history and loss history for the EfficienNetB6 architecture model are shown in graphs in Fig. 25. The training and validation accuracy increase in diverse ways as the epoch number rises. Regarding the loss history, training loss drops off gradually while validation loss stays within certain bounds.

4.4 Result Comparison between ML and DL Models

The Randon Forest algorithm outperformed all other classifiers, and its micro precision score reached 99.32%. The accuracy of the results the LR classifier provided was also poorer, with all of its measure scores falling below 93%. With metric scores of more than 99.07%, the GB and DT classifier gives a fair level of accuracy in compared to the KNN classifier and once again shows improvements in comparison to the results of the lane identification dataset. In terms of performance, the SVM classifier did surpass the GB and DT classifiers. The focus on micro scores is consistent with the

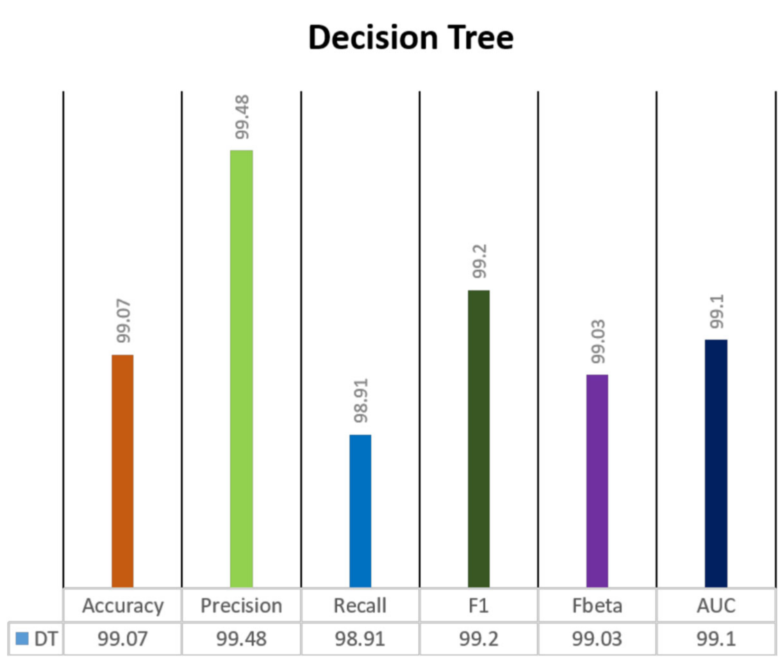


Fig. 16 Overview of DT performance

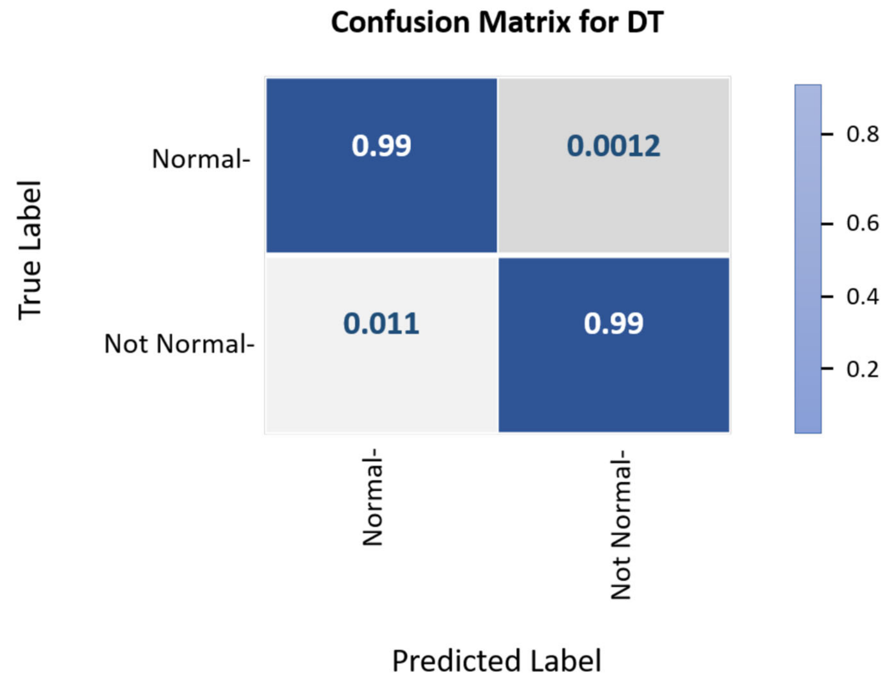


Fig. 17 Confusion Matrix for DT

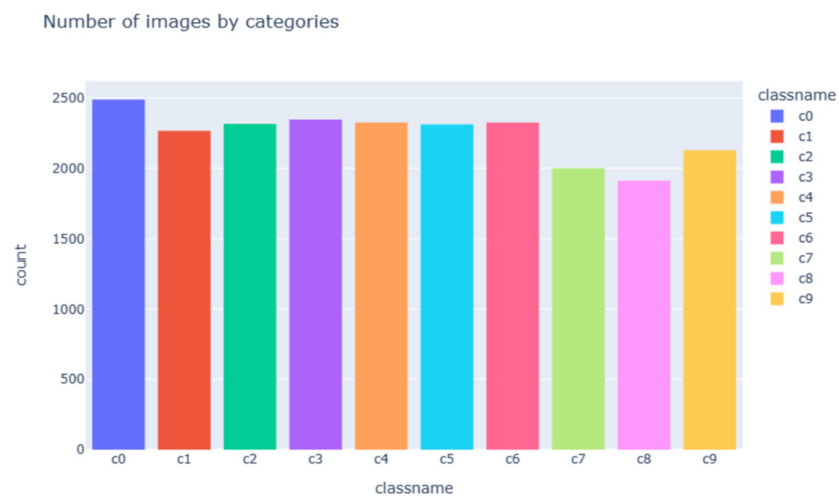


Fig. 18 Number of images by categories

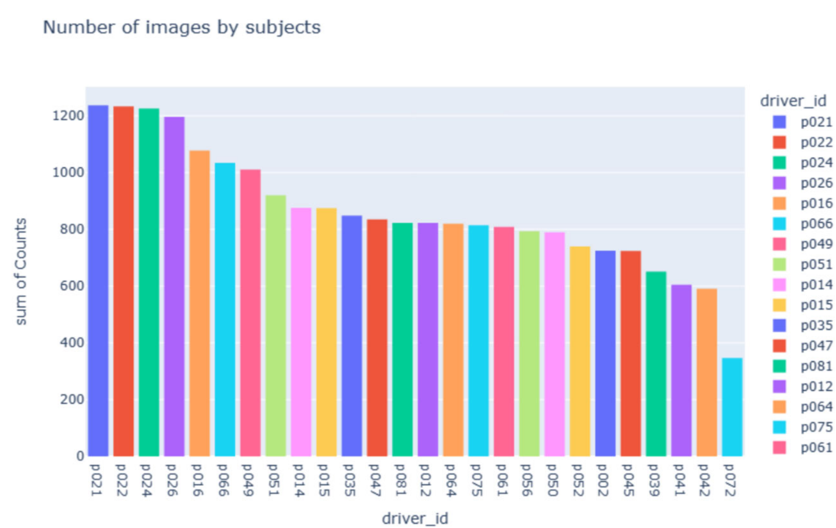


Fig. 19 Number of images by subjects

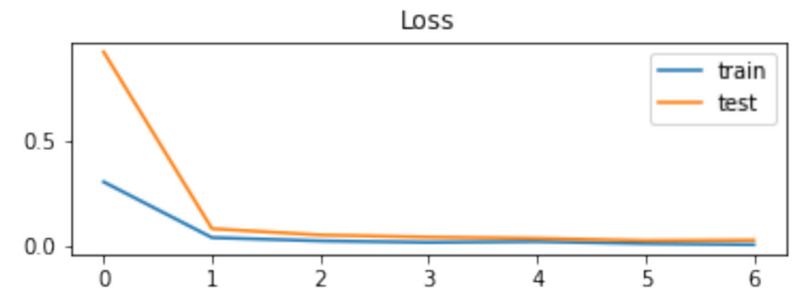


Fig. 20 Loss of Base Model

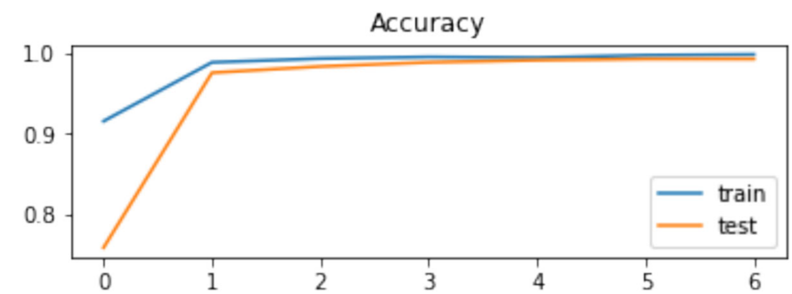


Fig. 21 Accuracy of Base Model

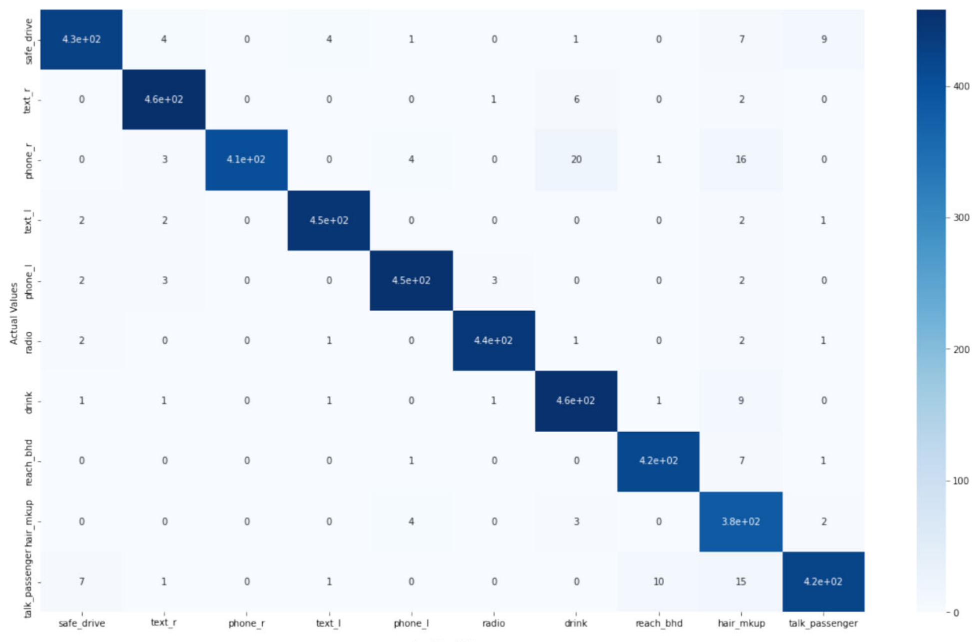


Fig. 22 Confusion Matrix of CNN Base Model

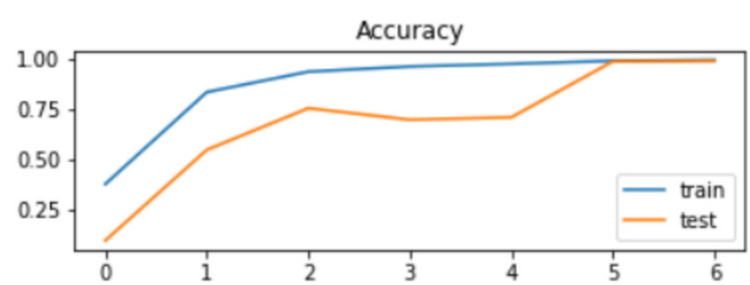


Fig. 23 Accuracy of ResNet50 Model

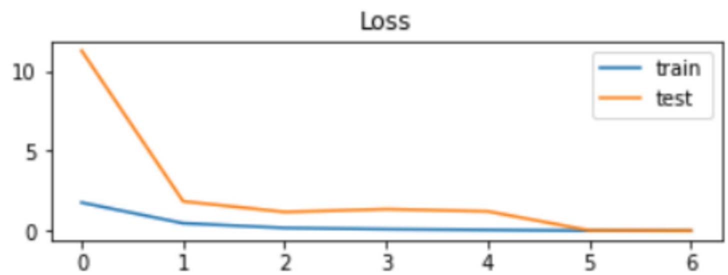


Fig. 24 Loss of ResNet50 Model

need for a metric that takes into account imbalanced datasets (Fig. 26).

The Roc-Curve graph by RF, K-NN, and DT demonstrates how well a classification model performs at every classification threshold. The True Positive Rate and False Positive Rate are plotted on this graph. The results that were supplied in compliance are shown in Fig. 27. The ROC curve illustrates the trade-off between specificity and sensitivity (or TPR) (1 - FPR). A better performance is shown by classifiers that provide curves that are closer to the top-left corner. A random classifier is anticipated to provide points that are diagonal by default (FPR = TPR).

In Deep Learning With the exception of ResNet50 and EfficientNetB6, the Base Model performance has improved, as seen by a comparison of the bar graph in Fig. 28. It also shows that, in comparison to other models, the losses of the base model are very minor. Performance improves better when there is a larger amount of training data. It illustrates that the dropout strategy is effective in reducing the possibility of overfitting.

The test accuracy is (99.87%) after the base model has been applied to the State Farm Distracted Driver data set. Here, the dataset correctness is respectable. The test accuracy for the SFD3 samples data set was higher while using ResNet50, and the result is decent (99.71%). On the other hand, we obtained 98.28% accuracy from the data set for EfficienNetB6.

The hybrid model's performance demonstrates the advantage of combining ML and DL approaches. For example, while the ML model achieves high accuracy on tabular data (99.32%) with Random Forest), the DL model excels in image-based classification (99.87%)) with the Base Model). When the outputs of both models are integrated, the hybrid system achieves an overall improved prediction accuracy compared to using either model independently.The results indicate that hybridization enables the model to capture multi-dimensional insights that would otherwise remain undetected when using ML or DL alone.

4.5 Result Comparison among Proposed ML and DL Framework with other State-of-art Works

In an effort to get some understanding and produce some conclusions, we have read a number of articles that are pertinent to our research. We have used two different kinds of datasets to conduct our research. The first one is a csv file data set for ML, and the second one is an image data set for DL. These two sets are referred to as UAH-DriveSet and SFD samples data set, respectively. We also used this data set to compare to other study articles. Figure 29 shows the performance of our suggested technique, which is for ML, together with that of Saleh et al. [27], Moukafih et al. [18], Lattanzi et al. [15], Ghandour et al. [11], and Peppes et al. [21]. Here, we can see that our performance is rather good and much

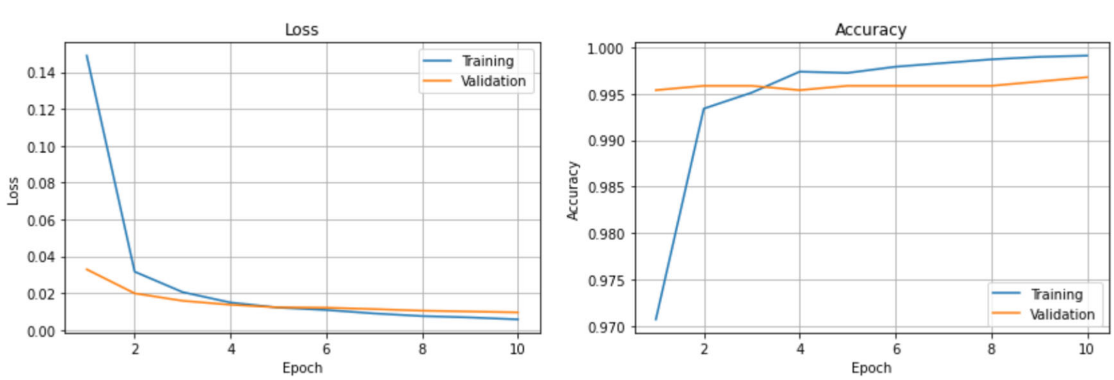
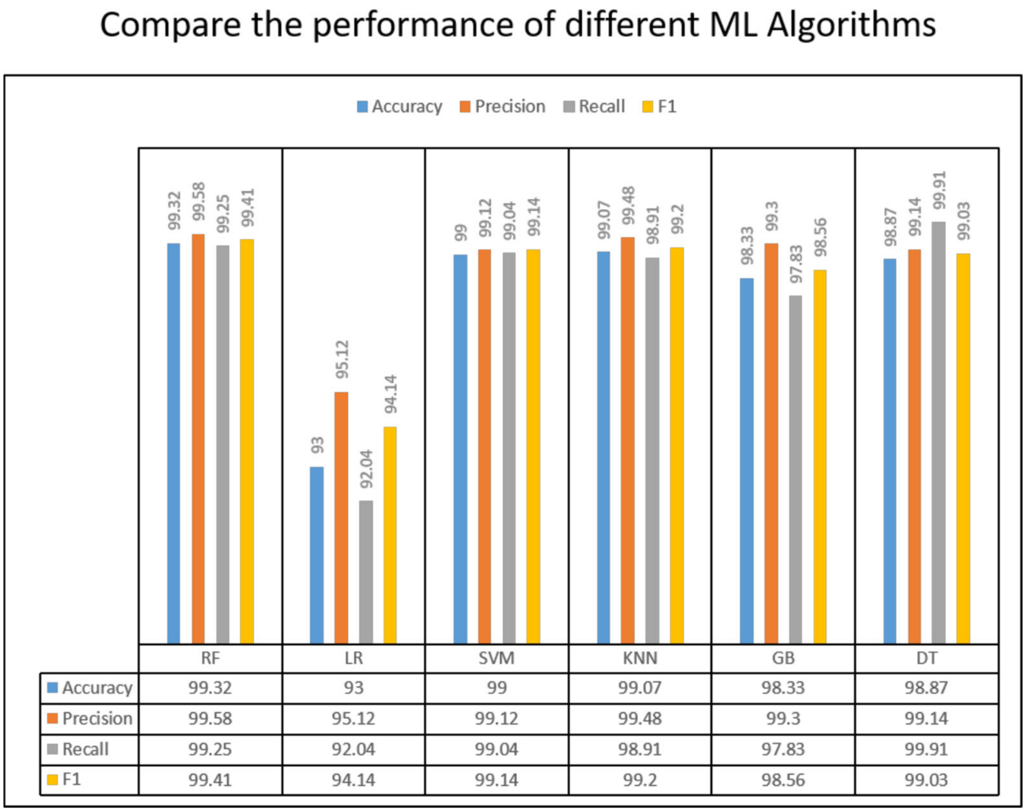


Fig. 25 Accuracy and Loss of EfficientNetB6 Model



	RF	LR	SVM	KNN	GB	DT
Accuracy	99.32	93	99	99.07	98.33	98.87
Precision	99.58	95.12	99.12	99.48	99.3	99.14
Recall	99.25	92.04	99.04	98.91	97.83	99.91
F1	99.41	94.14	99.14	99.2	98.56	99.03

Fig. 26 Result Comparison of different Machine Learning Models

better than these other works, which have an accuracy rate of 99.32 percent.

On the other hand, in DL, while using the same image data set for DL, we compare our results to those of previously published publications. Rajput et al. [25], Hossain et al. [12], Qin et al. [24], Leekha et al. [16], Nasri et al. [19], Abbas et al. [1] and our proposed method for DL performance are shown in Fig. 30. Due to the usage of a special CNN-Base model with an additional layer that helped us raise the outcome, which is 99.87 percent, this figure demonstrates that our DL model performs better than previous efforts.

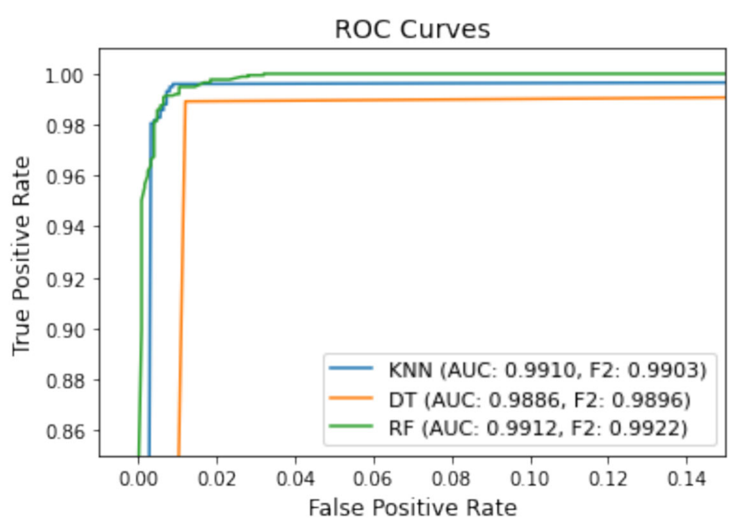
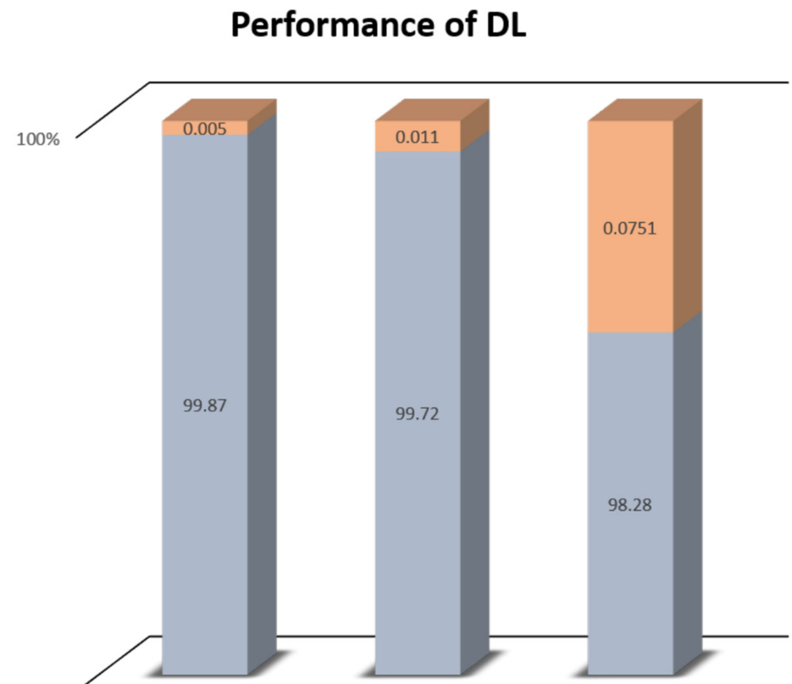


Fig. 27 ROC Curves of different Machine Learning Models

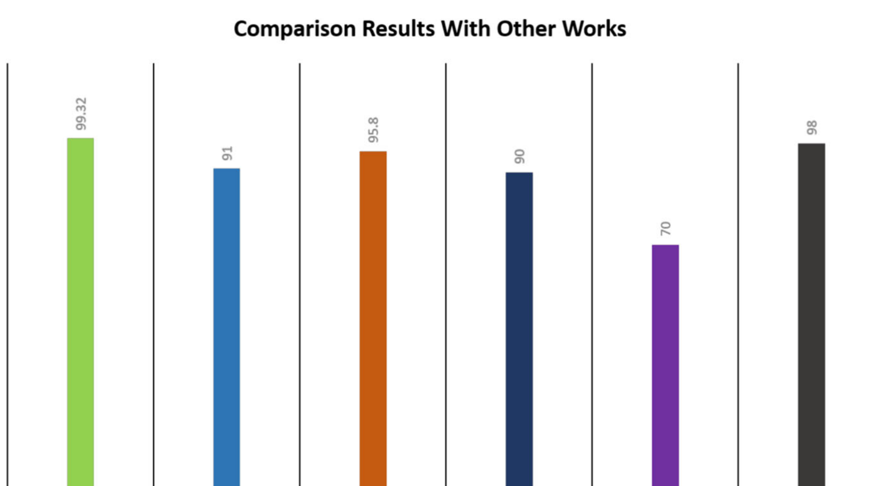


	Base Model	ResNet50	EfficienNetB6
Loss	0.005	0.011	0.0751
Accuracy	99.87	99.72	98.28

Fig. 28 Compare the performance of DL Models

5 Discussion

We suggest a Hybrid Model based on machine learning and deep learning methods for distinguishing between safe and risky driving behaviors. In this study, six machine learning techniques (Logistic Regression, Gradient Boosting, Random Forest, Support Vector Machine, K-Nearest Neighbor and Decision Tree) and three deep learning techniques (Base model, EfficienNetB6, and ResNet50) were used to identify drivers' manner of behavior and interruption situations based on actual data compared to various manners of behavior, such as forceful, tired, and normal. The machine learning algorithm is controlled by six different drivers and cars, who behave in three different ways on two different types of streets (normal, sleepy, and forceful) (engine way and optional street). The data were randomly generated to improve the



	Proposed Method	Saleh et al.	Moukafih et al.	Lattanzi e .al.	Ghandour et al.	Peppes et al.
Accuracy	99.32	91	95.8	90	70	98

Fig. 29 Compare the performance of ML Models with Others

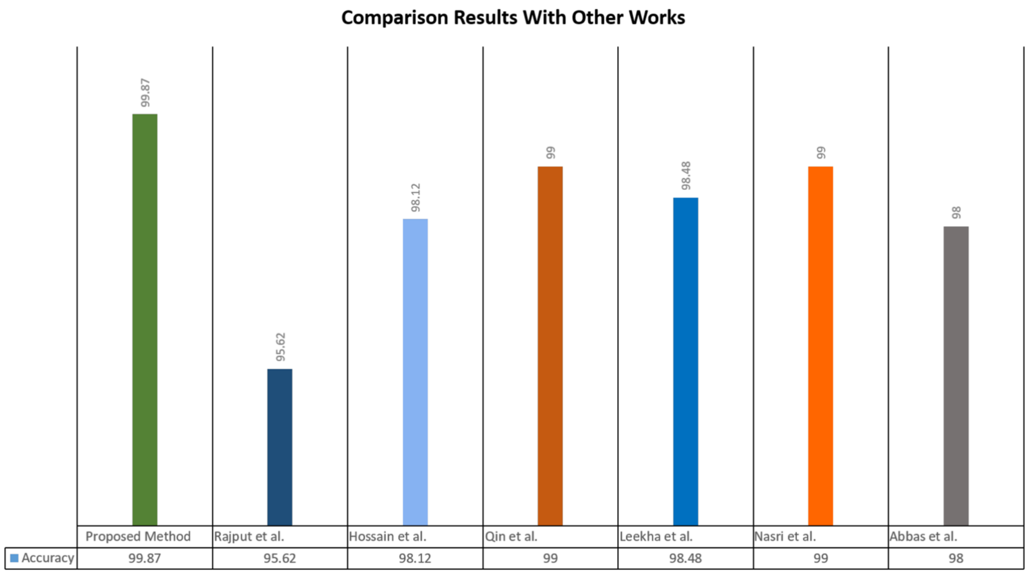


Fig. 30 Compare the performance of DL Models with Others

applicability of the tactics. We show that the Random Forest method works better than the other classifiers and has a 99.32% accuracy rate. We use a high number of epochs to calculate accuracy and loss in the deep learning training and validation data sets. Utilizing all of the data in the set for training. Each image had its resolution reduced to 224*224 pixels prior to training. Even while training accuracy has increased, validation accuracy has varied a little. There were fewer variances in validation accuracy even when training accuracy rose. The obtained results demonstrate the Base Model's superiority over the other models in use in this case and its accuracy rate of 99.87%. We will use deep learning in our upcoming projects because it offers significantly greater performance than machine learning. The construction and optimization of ML models played a pivotal role in enhancing the overall hybrid framework. By focusing on feature engineering and selection, the ML classifiers could provide accurate and interpretable results from structured data. These insights were particularly valuable for detecting patterns that might not be evident in image-based analysis. Additionally, the ability of ML models to process data with lower computational requirements made them an efficient component of the hybrid system, especially for real-time applications.

Unlike object detection models such as YOLOv5, which excel in identifying objects or behaviors as single categories, our proposed hybrid model is designed to recognize and categorize diverse driving behaviors, including compulsive, fatigue, and normal driving. This distinction is critical for applications such as driver monitoring systems, where the ability to differentiate between types of abnormal behaviors can inform targeted interventions. The advantages of our proposed model include the following:

- **Multi-Modal Data Integration:** By combining ML and DL techniques, the model effectively integrates tabular data (e.g., speed, acceleration, braking force) with image data to provide a holistic analysis of driving behaviors.
- **Behavior-Specific Insights:** The model identifies and categorizes specific behaviors, enabling more nuanced analysis compared to treating all abnormal behaviors as a single category.
- **High Accuracy Across Diverse Scenarios:** The hybrid model achieves superior accuracy by leveraging the strengths of ML for structured data and DL for unstructured image data, making it robust across varied real-world scenarios.
- **Customizability:** The proposed framework can be adapted to incorporate additional features or behavior types, making it a versatile solution for evolving research and application needs.

6 Conclusion

This study provides a novel approach for multi-modal analysis of driving behaviors, integrating machine learning and deep learning to achieve robust classification. Here We used two kinds of dataset : UHA-Drive set and SFD3 dataset. Where UHA-Drive set utilized for AI and SFD3 dataset utilized for deep learning. UAH-Drive set data were obtained from six distinct driving behaviors that were categorized into three states: usual, sleepy, and hostile. The data were randomized for improved analysis and use of the machine learning models. DT, KNN, RF, SVM, GB and LR outcomes were shown for the UAH-Drive sets. We also used three types of algorithms of deep learning for identifying driver behavior that are capable of classifying numerous photos into different groups. We have used is the CNN (Base Model) architecture, which is regarded as a superior vision model architecture with good real-time performance and a lowering filter size. Two further models that did well were ResNet50 and EfficienNetB6. Therefore, our research and database might help advance the future. This work's main contribution is a thorough examination of the data set's properties and their applicability to categorizing the driver's mental state. The results also demonstrated a clear differentiation when compared to the probabilistic strategy. As a result, our research and database might contribute to the future. The study does not offer a novel technique for big data-based driver behavior analysis. Instead, this offers an integrated platform that combines technology, big data infrastructure, and ML and DL modules for data analysis. Due to our working equipment limitations, DL does not have a very good number of epochs. In upcoming investigations, Ensemble can be applied to create a system or deliver outcomes that are both quicker and more accurate than those from current models. Updating our hardware and using the most epochs possible will aid in producing better results. This system will make use of a real-time application.

Author Contributions Md Ashraf Uddin: Conceptualization; Data curation, Writing-original draft; Visualization; Formal analysis, Supervision, Investigation. Nibir Hossain and Asif Ahamed: Data curation, Implementation, Methodology, Software, Writing- Original draft preparation; Md Manowarul Islam, Ansam Khraisat, Ammar Alazab: Conceptualization, Methodology, Formal analysis, Visualization; Md. Kabir Uddin Ahmed: Visualization, Investigation, Validation, Writing-Reviewing and Editing.; Md. Alamin Talukder: Investigation, Validation, Analysis, Visualization, Writing-Original-Draft preparation, Writing-Reviewing and Editing

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Availability of data and materials The dataset is available at: UAH-Drive http://www.robesafe.uah.es/personal/eduardo.romera/uah-driveset/#sidebar, SFD3 https://www.kaggle.com/c/state-farm-distracted-driver-detection/data

Declarations

Conflict of interest The authors have no conflicts of interest to declare that they are relevant to the content of this article.

Ethics approval Not applicable

Consent to participate Not applicable

Consent to Publish Not applicable

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Authors and Affiliations

Md. Ashraf Uddin[1,3] · **Nibir Hossain**[2] · **Asif Ahamed**[2] · **Md Manowarul Islam**[2] · **Ansam Khraisat**[3] · **Ammar Alazab**[4] · **Md. Khabir Uddin Ahamed**[5] · **Md. Alamin Talukder**[6]

✉ Ansam Khraisat
ansam.khraisat@deakin.edu.au

✉ Md. Alamin Talukder
alamin.cse@iubat.edu

Md. Ashraf Uddin
ashraf.uddin@cihe.edu.au

Nibir Hossain
nibirhossain0101@gmail.com

Asif Ahamed
shishir.ahamed2018@gmail.com

Md Manowarul Islam
manowar@cse.jnu.ac.bd

Ammar Alazab
ammar.alazab@torrens.edu.au

Md. Khabir Uddin Ahamed
khabir.cse@bsfmstu.ac.bd

1 Crown Institute of Higher Education, 116 Pacific Highway, North Sydney, NSW 2060, Australia

2 Department of Computer Science and Engineering, Jagannath University, Dhaka, Bangladesh

3 School of Information Technology, Deakin University, Waurn Ponds Campus, Geelong, Australia

4 Centre for Artificial Intelligence and Optimization, Torrens University, Adelaide, Australia

5 Department of Computer Science and Engineering, Bangamata Sheikh Fojilatunnesa Mujib Science and Technology University, Jamalpur, Bangladesh

6 Department of Computer Science and Engineering, International University of Business Agriculture and Technology, Dhaka, Bangladesh