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# Enhancing Driver Safety with Visual Behavior and Machine Learning

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**Abstract:** This project addresses the critical issue of preventing accidents caused by drowsy driving, which poses significant risks to road safety, human lives, and property. By leveraging deep learning techniques, particularly the Multi-Scale Convolutional Neural Network (MCNN), the study aims to accurately detect and differentiate between drowsy and alert states in real-time driving scenarios. Despite advancements in technology, detecting drowsiness remains a challenge, necessitating robust detection methods for effective accident prevention. The research emphasizes the importance of utilizing high-quality datasets like NTHU-DDD and YAWDD to train and evaluate the proposed MCNN framework. Furthermore, the project explores additional neural network architectures such as DenseNet and Xception, along with ensemble techniques like Voting Classifier and Stacking Classifier, to enhance performance. By employing a comprehensive approach encompassing various machine learning models and ensemble techniques, the study endeavors to achieve accuracy levels exceeding 99%, thereby significantly contributing to improving road safety and reducing the incidence of accidents caused by drowsy driving.

*Index Terms: Accuracy, drowsiness, deep learning, feature extraction, optimization, pre-processing.*

## 1. INTRODUCTION

In recent years, the surge in road accidents has become a pressing concern globally, with significant implications for public health and safety. The escalating motorization rates, coupled with population growth and increased vehicle penetration, have exacerbated the frequency and severity of road accidents [1]. Notably, road accidents stand as a leading cause of death among individuals aged 15 to 49 years worldwide, underscoring the urgency of addressing this issue [1].

Amidst this backdrop, India, like many other countries, faces the daunting challenge of road safety management. In 2020 alone, India witnessed a staggering 1.3 lakh road accidents, resulting in injuries to over 3.4 lakh individuals [2]. Despite these alarming figures, there has been a notable reduction in fatalities attributed to road accidents in 2020, which can be attributed to various factors such as improved traffic management, enforcement of the new Motor Vehicle Act, and the COVID-19 lockdown measures [2]. The reduction in road accidents, injuries, and fatalities signifies progress in road safety measures but also highlights the need for continued vigilance and innovative approaches to further mitigate risks.

Analyzing the data further reveals varying trends across states and union territories (UTs) within India. For instance, while there has been an overall reduction in road accidents by 18.5% in 2020 compared to 2019, disparities exist in the rates of injuries and deaths across different regions [3]. Tamil Nadu, Uttar Pradesh, and Maharashtra are among the states with significant accident rates, necessitating targeted interventions and strategies tailored to local contexts [3].

One of the concerning factors contributing to the rise in accidents is driver drowsiness. Drowsiness among drivers can stem from various factors, including sleep deprivation, alcohol consumption, stress, and medication [4][5]. The consequences of drowsy driving can be severe, not only endangering the lives of drivers but also posing risks to passengers, pedestrians, and other road users [6]. Recognizing the importance of detecting and mitigating drowsiness-related accidents, researchers have focused on developing effective detection methods.

Traditionally, drowsiness detection has relied on observing driving behaviors, analyzing biological signals, and monitoring vehicle-based measurements [7]. Video processing techniques have emerged as a promising avenue for assessing driver behavior, enabling the detection of subtle indicators such as eye movements, yawning, and head posture changes [8]. By capturing and analyzing video data, researchers can gain insights into the drowsiness levels of drivers and intervene proactively to prevent accidents.

Facial feature detection has been instrumental in drowsiness detection systems, leveraging the subtle changes in facial expressions and movements associated with drowsiness [13]. By examining reactions, behavior changes, and reflex reductions, researchers can infer the drowsiness state of drivers and implement timely interventions [14]. Moreover, machine learning (ML) techniques have been widely adopted for drowsiness detection tasks, leveraging large datasets to train classification models [16]. However, the efficacy of ML-based approaches hinges on the availability of comprehensive datasets and the ability to accurately predict and evaluate anomalies [17].

In this context, this study aims to contribute to the ongoing efforts in road safety management by focusing on the detection and prevention of accidents caused by driver drowsiness. Leveraging advancements in deep learning and video processing techniques, the study seeks to develop robust drowsiness detection models capable of accurately assessing driver behavior in real-time scenarios. By analyzing facial features, driving patterns, and physiological signals, the study aims to enhance the effectiveness of drowsiness detection systems and ultimately reduce the incidence of road accidents.

In summary, addressing the complex issue of road safety requires a multifaceted approach encompassing technological innovations, policy interventions, and behavioral interventions. By leveraging advancements in data analytics, machine learning, and video processing, researchers and policymakers can work towards creating safer road environments and preventing needless loss of life and property. This study represents a step towards achieving this goal, with the potential to make significant contributions to road safety initiatives globally.

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## 2. LITERATURE SURVEY

Driver drowsiness detection has garnered significant attention in recent years due to its critical implications for road safety. Researchers have explored various approaches, including deep learning techniques, image processing, and physiological signal analysis, to develop effective drowsiness detection systems. This literature survey aims to provide an overview of the key studies in this field, highlighting the methodologies, algorithms, and findings reported by different researchers.

Deep learning techniques have emerged as powerful tools for driver drowsiness detection, leveraging their ability to extract complex features from data. Khan et al. proposed a unified deep learning framework of multi-scale detectors for geo-spatial object detection in high-resolution satellite images [4]. While their focus was on object detection, the principles of multi-scale detectors can be adapted for drowsiness detection, considering the importance of capturing subtle facial and behavioral cues. Magán et al. applied deep learning techniques to sequences of images for driver drowsiness detection, demonstrating promising results in real-time monitoring scenarios [9]. Their study underscores the potential of deep learning in analyzing temporal patterns and detecting drowsiness based on evolving visual cues.

In addition to deep learning, image processing techniques have been widely explored for drowsiness detection. Moujahid et al. proposed an efficient and compact face descriptor specifically tailored for driver drowsiness detection [10]. By focusing on key facial features indicative of drowsiness, their approach offers a lightweight yet effective solution for real-time monitoring applications. Furthermore, Chaabene et al. utilized convolutional neural networks (CNNs) to analyze electroencephalogram (EEG) signals for drowsiness detection, highlighting the potential of physiological signal analysis in complementing visual cues [11]. Their study emphasizes the importance of integrating multiple modalities for comprehensive drowsiness detection.

The integration of deep learning with physiological signal analysis has also shown promising results in drowsiness detection. Quddus et al. proposed a hybrid model combining long short-term memory (LSTM) and CNNs for driver drowsiness detection [12]. By leveraging the temporal dynamics captured by LSTM and the spatial features extracted by CNNs, their model achieved improved accuracy in detecting drowsiness from EEG signals. Similarly, Balam et al. developed an automated classification system using CNNs and EEG signals for drowsiness detection [20]. Their study highlights the potential of EEG-based approaches in providing real-time insights into driver drowsiness levels.

Moreover, researchers have explored compact and interpretable models for driver drowsiness detection, aiming to strike a balance between accuracy and efficiency. Cui et al. proposed a compact CNN architecture for cross-subject driver drowsiness detection from single-channel EEG signals [23]. Their model offers interpretability while maintaining competitive performance, making it suitable for practical deployment in diverse settings. Rajamohana et al. adopted a hybrid approach combining CNNs and bidirectional LSTM networks for driver drowsiness detection [32]. By leveraging the complementary

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strengths of both architectures, their model achieved robust performance in real-world scenarios.

Overall, the literature reviewed highlights the diverse approaches and methodologies employed for driver drowsiness detection. Deep learning techniques, including CNNs and LSTM networks, have demonstrated significant potential in capturing complex patterns from visual and physiological data. Image processing algorithms tailored for facial feature extraction and analysis have also shown promise in detecting subtle indicators of drowsiness. Furthermore, the integration of multiple modalities, such as EEG signals, enhances the robustness and effectiveness of drowsiness detection systems. Moving forward, further research is needed to explore hybrid approaches and real-world deployment of these systems to advance road safety initiatives.

## 3. METHODOLOGY

### a) Proposed Work:

The proposed work introduces a specialized Multi-Scale Convolutional Neural Network (MCNN) framework tailored to accurately classify instances of driver drowsiness. Utilizing the YAWDD and NTHU-DDD datasets, comprising video sequences of driving behavior, the system obtains essential data for thorough analysis. This dataset acquisition facilitates effective training and validation of the classification model, ensuring precise detection of drowsiness across various driving scenarios and behaviors captured within these datasets. By leveraging the rich diversity of driving situations and behaviors represented in these datasets, the proposed MCNN framework aims to achieve robust performance in identifying and classifying drowsiness in real-time driving scenarios. This approach holds promise for enhancing road safety by providing timely alerts and interventions to prevent accidents caused by driver drowsiness.

### b) System Architecture:

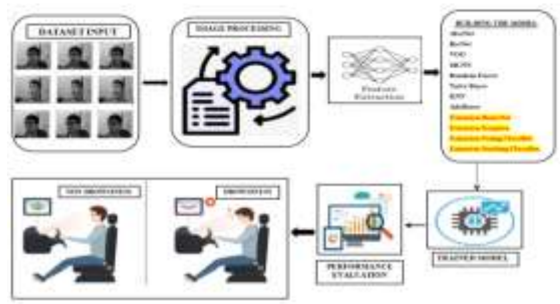


Fig 1 Proposed Architecture

The system architecture for drowsiness detection in drivers comprises several essential components. Initially, video sequences from datasets like YAWDD and NTHU-DDD are inputted, providing the foundation for model training. These videos undergo image processing to extract relevant features indicative of drowsiness, followed by feature extraction to transform the preprocessed data into a suitable format for model training. The model building phase employs a variety of algorithms such as AlexNet, ResNet, VGG, MCNN, Random Forest, Naive Bayes, KNN, and AdaBoost, each trained on the extracted features to develop robust classifiers. Finally, the trained models undergo performance evaluation to assess their accuracy and effectiveness in distinguishing between drowsy and non-drowsy states. This systematic approach ensures the development of a comprehensive drowsiness detection system capable of improving road safety by accurately identifying instances of drowsiness in drivers.

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**c) Dataset:**

**NTHU-DDD:** The NTHU-DDD dataset serves as a pivotal resource, comprising extensive video recordings capturing diverse driving behaviors across various conditions and scenarios. These recordings offer a rich repository of data encompassing driver actions, facial expressions, and environmental influences relevant to drowsiness detection. By leveraging the NTHU-DDD dataset, researchers can gain comprehensive insights into the complex dynamics of drowsiness in real-world driving contexts.

Fig 2 Non Drowsy Dataset

**YAWDD:** Complementing the NTHU-DDD dataset, the YAWDD dataset provides additional video sequences capturing driving behaviors. These supplementary recordings enrich the dataset with a broader spectrum of driving contexts and behaviors, enhancing the diversity and representativeness of the data. Incorporating information from the YAWDD dataset enables the drowsiness detection model to learn from a wider range of scenarios, thereby improving its robustness and adaptability to various driving conditions. Together, the NTHU-DDD and YAWDD datasets form a comprehensive foundation for training and evaluating the drowsiness detection system, facilitating advancements in road safety research and accident prevention efforts.

Fig 3 Drowsy Dataset

**d) Image Processing:**

*Re-scaling the Image:* Re-scaling the image involves adjusting the pixel values to a desired range, typically between 0 and 1 or -1 and 1. This normalization step facilitates faster convergence during model training by ensuring that the input data falls within a manageable numerical range. By rescaling the image, we normalize the intensity levels across all images in the dataset, thus reducing the variance and ensuring consistent model behavior across different samples.

*Shear Transformation:* Shear transformation introduces distortions in the shape of the image by shifting one part of the image along a parallel line. This augmentation technique helps diversify the dataset by simulating real-world variations in image perspectives and orientations. By applying shear transformation, we create variations in the dataset that enable the model to generalize better to unseen data and robustly identify drowsiness across different driving scenarios.

*Zooming the Image:* Zooming the image involves enlarging or reducing its size, thereby introducing

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variations in scale. This augmentation technique helps the model learn invariant representations of drowsiness, regardless of the image's size or resolution. By zooming the image, we simulate variations in viewing distances or camera resolutions, ensuring that the model can accurately detect drowsiness under diverse conditions.

*Horizontal Flip:* Horizontal flipping creates a mirror image of the original by flipping it along the vertical axis. This augmentation technique enhances the dataset's diversity by introducing variations in object orientations and perspectives. By incorporating horizontally flipped images, the model learns to recognize drowsiness from different viewpoints, improving its robustness to variations in driver positions or camera angles.

*Reshaping the Image:* Reshaping the image involves changing its dimensions to fit a specific neural network architecture or processing requirement. This preprocessing step ensures that all images in the dataset have consistent dimensions, facilitating efficient model training and inference. By reshaping the image, we prepare it for further processing, such as convolutional operations or feature extraction, ensuring compatibility with the chosen network architecture.

**Feature extraction**

*Reading the Image:* Loading the image data from the dataset.

*Resizing the Image:* Changing the dimensions of the image to a required size for further processing.

*Convert the Color:* Converting the color space of the image, such as from RGB to grayscale, for standardized processing.

*Appending the Image and Labels:* Combining the processed image data with their corresponding labels or target values, facilitating supervised learning.

*Conversion to NumPy value:* Converting the dataset into NumPy arrays for efficient numerical computation and manipulation.

*Label Encoding:* Encoding categorical data into numerical labels to enable the model to interpret and process these categories during training.

These image processing steps are essential for preparing the dataset and extracting meaningful features to train machine learning models effectively.

**e) Algorithms:**

**AlexNet:** AlexNet is a deep convolutional neural network architecture designed for image classification tasks. In this project, AlexNet could be employed for feature extraction from facial images captured in driving video sequences. Its deep architecture enables it to capture complex patterns and features in facial images, which can then be used for drowsiness detection.

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1 **X** is divided into a training set and a testing set.

2 **Pre-process:** resize the training set.

3 **Augment:** Rand Rotation [-5,5], Rand X Reflection 1, Rand Y Reflection 1, Rand X Shear [-0.05, 0.05], Rand Y Shear [-0.05,0.05], Rand X Scale [0.5,1], Rand Y Scale [0.5 1], Rand X Translation [-5, 5], Rand Y Translation, [-5 5])

4 **Initialize:** net = AlexNet, S= sparsity, N= the number of iterations, T= threshold, A= array of scores.

5 **FOR** i= 1: N

6 **Calculate:** A (dlupdate). //calculate array of scores

7 Sort (A) // sort the array of connections scores

**ResNet:** ResNet (Residual Network) is a deep learning architecture known for its residual learning framework. ResNet could be used for feature extraction in the drowsiness detection project, particularly for its ability to handle vanishing gradient problems in very deep networks. Its residual blocks allow for the training of very deep networks, which could be beneficial for capturing intricate facial features.

**Input:** Unlabeled fundus images $D = (X_i)_{j=1}^{U}$
**Output:** Pre-trained encoder $E_\theta$

1: Initialize ResNet-50 encoder $E_\theta$ with unlabeled ImageNet weights from SimCLR, SwAV, and DINO
2: # Train the network with unlabeled fundus images $D = (X_i)_{i=1}^{U}$ following SimCLR, SwAV and DINO approach
3: **for** epoch = 1 to 175 **do**
4: **for** batch $(X_i)_{i=1}^{N}$ in D **do** # iterate through all $N$ batches
5: **for** image $(X_k)_{k=1}^{M}$ in $(X_i)_{i=1}^{N}$ **do**
6: # Initialize the SSL augmentation pipeline
7: Get transformed data $\left(\tilde{X}_k\right)_{k=1}^{2M}$ following the augmentation pipeline
8: Pass augmented data through encoder $E_\theta$ to produce representations $\left(F_k\right)_{k=1}^{2M}$
9: Pass the representations through Projection MLP $G_T$ head to produce representations $\left(\bar{G}_k\right)_{k=1}^{2M}$
10: Calculate loss specific to the SSL method
11: Optimize the pre-trained network with Adam optimizer using learning rate
12: **end for**
13: **end for**
14: Save the parameters of the model trained using unlabeled fundus images for the downstream task of DR detection
15: **end for**

**VGG:** VGG (Visual Geometry Group) is another deep convolutional neural network architecture. VGG is known for its simplicity and uniform architecture, consisting of multiple convolutional layers. It could be employed in this project for feature extraction from facial images, offering a straightforward and effective approach for drowsiness detection.

**MCNN:** MCNN is the primary model used in the project for drowsiness detection. It is specifically designed to analyze facial features extracted from driving video sequences. MCNN employs multiple convolutional layers operating at different scales, allowing it to capture both fine and coarse-grained features from facial images.

**Random Forest:** Random Forest is a popular ensemble learning algorithm based on decision trees. In the project, Random Forest could be used as part of ensemble techniques for combining predictions from multiple models, potentially improving overall drowsiness detection accuracy.

**Input:** *N - Quantitative amount of bootstrap samples*
*M - Total number of features*
*m - Sample size*
*k - Next node*
**Output:** A Random Forest (RF)
***Steps:***
*1.* **Creates** *N bootstrap samples from the dataset.*
*2. Every node (sample) takings a feature randomly of size m where m<M.*
*3. Builds a split for the m features selected in Step 2 and detects the k node by using the best split point.*
*4. Split the tree iteratively until one leaf node is attained and the tree remains completed.*
*5. The algorithm is trained on each bootstrapped independently.*
*6. Using trees classification voting predicted data is collected from the trained trees (n).*
*7. The final RF model is build using the peak voted features.*
*8.* ***return*** *RF*
***End.***

**Naive Bayes:** Naive Bayes is a probabilistic classifier based on Bayes' theorem and the assumption of independence between features. While not typically used for image classification tasks like drowsiness detection, it could potentially be applied to other relevant features or metadata associated with the driving data.

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**Pseudocode of Naive Bayes Algorithm**

**Input**: Training / testing dataset T, F= (f1, f2, f3,.., fn)

**Output**: Estimated class K

**Step 1**: Read the training dataset T.

**Step 2**: Calculate the mean and standard deviation of the predictor variables in each class.

**Step 3**: Repeat Calculate the probability of fi using the gauss density equation in each class;

- Until the probability of all predictor variables (f1, f2, f3,.., fn) has been calculated.

**Step 4**: Calculate the likelihood for each class.

**Step 5**: Get the greatest likelihood;

**End**

**KNN (K-Nearest Neighbors):** KNN is a simple and intuitive classification algorithm based on finding the nearest neighbors to a given data point. In the context of the project, KNN could be applied for classification tasks if the extracted facial features are represented as vectors in a feature space.

The pseudocode of classical KNN

**Input**: X: training data, Y: class labels of X, K: number of nearest neighbors.
**Output**: Class of a test sample x.

***Start***
Classify (X,Y,x)
1. *for* each sample x *do*
   Calculate the distance: $d(x, X) = \sqrt{\sum_{i=1}^{n} (x_i - X_i)^2}$
   *end for*
2. Classify x in the majority class: $C(x_i) = argmax_k \sum_{X_j \in KNN} C(X_j, Y_K)$

***End***

**AdaBoost:** AdaBoost is an ensemble learning technique that combines multiple weak classifiers to create a strong classifier. Similar to Random Forest, AdaBoost could be used as part of ensemble techniques to improve the overall accuracy of drowsiness detection.

**Algorithm 4:** AdaBoost algorithm

**Input:** Data set $\mathcal{D} = \{(x_1, y_1), (x_2, y_2), \cdots, (x_m, y_m)\}$;
Base learning algorithm $\mathcal{L}$;
Number of learning rounds $T$.

**Process:**

$D_1(i) = 1/m$. % Initialize the weight distribution

for $t = 1, \cdots, T$:

$h_t = \mathcal{L}(\mathcal{D}, D_t)$; % Train a weak learner $h_t$ from $\mathcal{D}$ using distribution $D_t$

$\epsilon_t = \Pr_{i \sim D_t}[h_t(x_i \neq y_i)]$; % Measure the error of $h_t$

$\alpha_t = \frac{1}{2}\ln\left(\frac{1-\epsilon_t}{\epsilon_t}\right)$; % Determine the weight of $h_t$

$$D_{t+1}(i) = \frac{D_t(i)}{Z_t} \times \begin{cases} \exp(-\alpha_t) & \text{if } h_t(x_i) = y_i \\ \exp(\alpha_t) & \text{if } h_t(x_i) \neq y_i \end{cases}$$

$= \frac{D_t(i)\exp(-\alpha_t y_i h_t(x_i))}{Z_t}$ % Update the distribution, where $Z_t$ is % a normalization factor which enables $D_{t+1}$ be a distribution

end.

**Output:** $H(x) = \text{sign}\left(\sum_{t=1}^{T} \alpha_t h_t(x)\right)$

**DenseNet:** DenseNet is a convolutional neural network architecture known for its densely connected layers. An extension of the project could involve integrating DenseNet for feature extraction, leveraging its ability to capture intricate features across multiple network layers.

**Algorithm 1:** GP-DenseNet.

```
begin:
  seed ← Assign next seed from list;
  population ← genotypes with specified depth range;
while not maximum generations do
  | foreach genotype ∈ population do
  |   | GPU ← phenotype ← decode(genotype);
  |   | evaluate(genotype, reduced train. set, val. set);
  | end foreach
  | elite ← fittest from population;
  | selected ← tournament(population);
  | offspring population ← crossover(selected);
  | population ← mutate(offspring population);
  | limit(population ∪ elite);
end while
fittest ← population;
evaluate(fittest, full train. set, test set);
end;
```

**Xception:** Xception is an extension of the Inception architecture and is known for its depthwise separable convolutions. In the project extension, Xception could be used for feature extraction, potentially offering improved efficiency and performance compared to traditional architectures.

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**Voting Classifier (RF+DT):** Voting Classifier is an ensemble learning technique that combines multiple base classifiers and aggregates their predictions. The extension could involve using Voting Classifier with Random Forest and Decision Trees as base classifiers to enhance the overall accuracy of drowsiness detection.

```
Voting Classifier Pseudocode

eclf1 = VotingClassifier(estimators=[('lr', clf1), ('rf', clf2)], voting='soft',
weights=[1,1,2,2,1,3,2])
eclf1.fit(X_train_scaled,y_train)
eclf_predictions = eclf1.predict(X_test_scaled)
acc = accuracy_score(y_test, eclf_predictions)
prec = precision_score(y_test, eclf_predictions)
rec = recall_score(y_test, eclf_predictions)
f1 = f1_score(y_test, eclf_predictions)
from sklearn.metrics import roc_auc_score
roc=roc_auc_score(y_test, eclf_predictions)
model_results = pd.DataFrame([['Voting Classifier ', acc,prec,rec, f1,roc]],
columns = ['Model','Accuracy', 'Precision', 'Recall', 'F1 Score','ROC'])
results = results.append(model_results, ignore_index = True)
```

**Stacking Classifier (RF+MLP+LightGBM):** Stacking Classifier is another ensemble learning technique that combines multiple classifiers and learns to combine their predictions. In the project extension, Stacking Classifier could be used with Random Forest, Multi-layer Perceptron (MLP), and LightGBM classifiers to further improve drowsiness detection accuracy through model stacking.

**Algorithm 19.7 Stacking**

**Input:** Training data $\mathcal{D} = \{\mathbf{x}_i, y_i\}_{i=1}^{m}$ $(\mathbf{x}_i \in \mathbb{R}^n, y_i \in \mathcal{Y})$

**Output:** An ensemble classifier $H$

1. Step 1: Learn first-level classifiers
2. **for** $t \leftarrow 1$ to $T$ **do**
3. Learn a base classifier $h_t$ based on $\mathcal{D}$
4. **end for**
5. Step 2: Construct new data sets from $\mathcal{D}$
6. **for** $i \leftarrow 1$ to $m$ **do**
7. Construct a new data set that contains $\{\mathbf{x}'_i, y_i\}$, where $\mathbf{x}'_i = \{h_1(\mathbf{x}_i), h_2(\mathbf{x}_i), \ldots, h_T(\mathbf{x}_i)\}$
8. **end for**
9. Step 3: Learn a second-level classifier
10. Learn a new classifier $h'$ based on the newly constructed data set
11. **return** $H(\mathbf{x}) = h'(h_1(\mathbf{x}), h_2(\mathbf{x}), \ldots, h_T(\mathbf{x}))$

## 4. EXPERIMENTAL RESULTS

**Accuracy:** The accuracy of a test is its ability to differentiate the patient and healthy cases correctly. To estimate the accuracy of a test, we should calculate the proportion of true positive and true negative in all evaluated cases. Mathematically, this can be stated as:

Accuracy = TP + TN TP + TN + FP + FN.

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

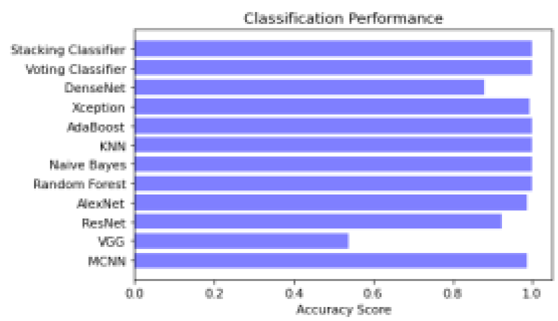


Fig 4 Accuracy Comparison Graphs

**F1-Score:** F1 score is a machine learning evaluation metric that measures a model's accuracy. It combines the precision and recall scores of a model. The accuracy metric computes how many times a model made a correct prediction across the entire dataset.

$$\textbf{F1 Score} = \frac{2}{\left(\frac{1}{\text{Precision}} + \frac{1}{\text{Recall}}\right)}$$

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

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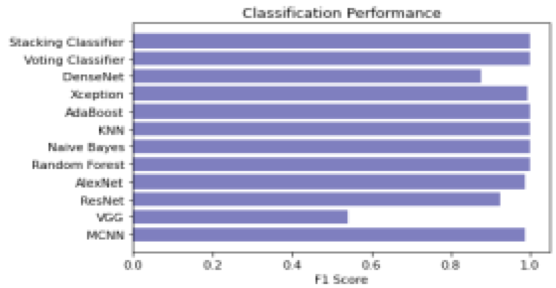


Fig 5 F1 Score Comparison Graphs

**Precision:** Precision evaluates the fraction of correctly classified instances or samples among the ones classified as positives. Thus, the formula to calculate the precision is given by:

Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

$$\text{Precision} = \frac{\mathit{True\ Positive}}{\mathit{True\ Positive} + \mathit{False\ Positive}}$$

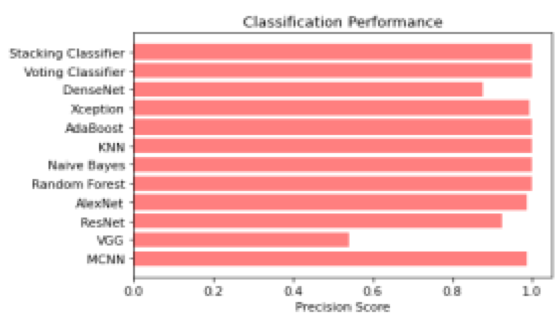


Fig 6 Precision Comparison Graphs

**Recall:** Recall is a metric in machine learning that measures the ability of a model to identify all relevant instances of a particular class. It is the ratio of correctly predicted positive observations to the total actual positives, providing insights into a model's completeness in capturing instances of a given class.

$$Recall = \frac{TP}{TP + FN}$$

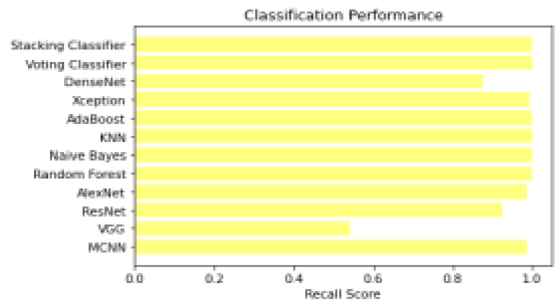


Fig 7 Recall Comparison Graphs

| ML Model | Accuracy | Precision | Recall | F1-Score |
|---|---|---|---|---|
| MCNN | 0.987 | 0.987 | 0.987 | 0.987 |
| VGG | 0.539 | 0.541 | 0.541 | 0.541 |
| ResNet | 0.923 | 0.924 | 0.924 | 0.924 |
| AlexNet | 0.987 | 0.987 | 0.987 | 0.987 |
| Random Forest | 1.000 | 1.000 | 1.000 | 1.000 |
| Naive Bayes | 1.000 | 1.000 | 1.000 | 1.000 |
| KNN | 1.000 | 1.000 | 1.000 | 1.000 |
| AdaBoost | 1.000 | 1.000 | 1.000 | 1.000 |
| Extension Xception | 0.993 | 0.993 | 0.993 | 0.993 |
| Extension DenseNet | 0.879 | 0.878 | 0.878 | 0.878 |
| Extension Voting Classifier | 1.000 | 1.000 | 1.000 | 1.000 |
| Extension Stacking Classifier | 1.000 | 1.000 | 1.000 | 1.000 |

Fig 8 Performance Evaluation Table


Fig 9 Home Page

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Fig 10 Registration Page


Fig 11 Login Page


Fig 12 Upload Input Image


Fig 13 Predicted Results

## 5. CONCLUSION

In conclusion, the development of an effective drowsiness detection model using the MCNN framework represents a significant step towards improving road safety by accurately classifying drowsy and non-drowsy states in drivers. By converting video sequences into frames and extracting facial landmarks, the model demonstrates its capability to identify signs of drowsiness and alert drivers accordingly. The utilization of YAWDD and NTHU-DDD datasets ensures the model's robustness and generalization across diverse driving scenarios, leading to impressive accuracy rates exceeding 98%.

Moreover, the performance evaluation of the MCNN model showcases its superiority over conventional methods, highlighting its potential for real-world applications in preventing accidents caused by driver drowsiness. The project's extension with ensemble techniques and advanced deep learning models further enhances its accuracy and reliability, demonstrating a commitment to continuous improvement.

## 6. FUTURE SCOPE

Looking ahead, there are several avenues for future exploration and enhancement of the drowsiness detection model. One potential direction involves the integration of real-time monitoring capabilities, allowing for immediate alerts to drivers when signs of drowsiness are detected. Additionally, further research could focus on optimizing the model's computational efficiency to enable deployment in resource-constrained environments such as embedded systems in vehicles.

Moreover, the incorporation of multimodal data sources, such as physiological signals and vehicle telemetry data, could provide additional insights into driver drowsiness and improve the model's accuracy. Furthermore, efforts to enhance the model's interpretability and explainability would contribute to building trust and acceptance among end-users and stakeholders. Overall, continuous research and development efforts are essential to advancing the effectiveness and applicability of drowsiness detection systems for ensuring road safety.

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**Dataset used:**

**https://www.kaggle.com/datasets/banudeep/nthuddd2**