Communications on Applied Nonlinear Analysis
ISSN: 1074-133X
Vol 32 No. 9s (2025)

# CNN-Powered Driver Fatigue Detection: Evaluating InceptionV3, VGG19, and ResNet50V2

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***Article History:***

***Received: 12-01-2025***

***Revised: 15-02-2025***

***Accepted: 01-03-2025***

**Abstract:**
**Introduction**: Two major factors leading to traffic accidents are driver fatigue and distraction. The World Health Organization (WHO) reports that 7% of fatal and severe traffic accidents are caused by sleepy driving. Advances in machine learning, artificial intelligence, and neural networks have paved new avenues for real-time sleepiness detection, providing practical ways that mitigate the number of mishaps

**Objectives**: The primary objective of this research is : to develop a new, real-time system for detecting driver drowsiness. The technology evaluates facial expressions and detects indicators of exhaustion using deep learning algorithms, which eventually improves road safety by reducing drowsiness-related accidents.

**Methods**: The proposed strategy uses facial cues, such as the eyes, lips, head, and pupil, to detect driver fatigue. The MediaPipe method, which is renowned for its great accuracy and resilience, is used to extract these properties. The InceptionV3, VGG19, and ResNet50V2 deep learning neural networks were assessed using a dataset captured in real time at NTHU. The drivers in the dataset show varying degrees of tiredness under different settings. To evaluate the models' efficacy, performance criteria like accuracy, recall, precision, and F1-score were applied.

**Results**: In detecting fatigue, all three convolutional neural networks performed admirably. The ResNet50V2 model performed more effectively than the other two, with an overall accuracy of 98.51%. This suggests that it can distinguish between fatigue and non-fatigue states with greater accuracy.

**Conclusions**: The efficacy of deep learning models in real-time fatigue detection has been proven by the research. More specifically, the ResNet50V2 model exhibits remarkable accuracy, making it a viable option for reducing accidents caused by drowsy driving. To improve road safety, future work can entail more system optimization and practical implementation.

**Keywords**: Fatigue, Convolutional neural network, Pupil, Nodding, ResNet0V2, InceptionV3, VGG19

## 1. Introduction

The NHTSA reports that in 2022, 1.9% of all fatal accidents were caused by sleep-deprived drivers. According to projections made by the National Safety Council (NSC), there would be 100,000 crashes involving intoxicated drivers in 2023, with 71,000 injuries and 15,550 fatalities. Fatigue-related micro sleeps while driving dramatically raise the possibility of catastrophic collisions. Several companies, including Tesla, Mercedes-Benz, and Volvo, have developed driver-alert navigation systems with automated steering, lane departure warnings, automated braking, adaptive cruise control, and other functions.[1] Technologies such as Eyesight and Samsung have been created that use facial feature analysis to track drivers' concentration. Nevertheless, these advancements are frequently restricted to expensive cars and exclusive technology.

Several companies, including Tesla, Mercedes-Benz, and Volvo, have developed driver-alert navigation systems with automated steering, lane departure warnings, automated braking, adaptive cruise control, and other functions.[2] [19] By utilizing embedded devices, mobile phones, or dashboard-mounted cameras, sophisticated computer vision systems driven by deep learning algorithms and cost-effective camera configurations might improve driver behavior detection.[3] One important topic of research is how to improve vehicle safety through technology developments. There is no established technique for determining a motorist's present degree of drowsiness, despite the fact that driver weariness is frequently the cause of auto accidents. Changes in breathing rate, pulse rate, eye movements, yawning, and brain activity are examples of physical indications of exhaustion. Three main areas of research are commonly used to analyze driver fatigue: 1) biological signal-based approaches utilizing sensors; 2) vehicle behavior-based methods; and 3) image processing methods employing computer vision to analyze changes in face features, which are important markers of sleepiness. Since Convolutional Neural Networks (CNN) have high computational efficiency and performance, we have opted for our recent deep learning research on drowsiness detection [4-6]. This model selection guarantees great accuracy during the testing, training, and assessment stages while saving time. There are five distinct scenarios in the NTHU and real-time DDD video collection. In the video, each shot is labelled as either "fatigue" or "not fatigue."

## 2. Objectives

Developing a real-time driver fatigue detection system that enhances road safety by averting fatigue-related accidents is the primary objective of the research. Driver alertness is ensured by early identification of drowsy driving, which is a significant risk factor for traffic accidents.[7] With an emphasis on crucial characteristics including eye closure duration, blink rate, yawning frequency, head motions, and pupil detection, this system uses deep learning techniques to scan facial expressions and identify early indicators of exhaustion. These indications offer trustworthy clues about the driver's level of awareness.

MediaPipe, a robust structure renowned for its remarkable accuracy in identifying face landmarks, is used by the system to achieve great precision in feature extraction. Using deep learning models like InceptionV3, VGG19, and ResNet50V2, the study seeks to determine the best architecture for classifying drowsiness. The models are tested and trained on a dataset with a variety of driving conditions to ensure the system works well in a range of real-world situations.

The real-time deployment of the detecting system, which enables ongoing observation and prompt driver feedback, is a crucial component of this study. The technology actively analyzes facial features while processing video data frame by frame. The device immediately notifies the driver to take corrective action when it detects indicators of weariness, such as an alarm or vibration in the seat. The system is also made to work in a variety of situations, such as during the day and at night, in different lighting situations, and whether drivers are wearing sunglasses, night glasses, or other eyewear.

The ultimate goal of this research is to develop a sturdy, flexible, and extremely accurate fatigue detection system that may be deployed in contemporary vehicles. It helps to improve road safety and minimize fatalities caused by drowsy driving and reducing accident risks.

## 3. Methods

The proposed method adheres to the phases illustrated in figure 1: collecting data (video), pre-processing snapshots from the videos, creating a dataset, extracting features, training the CNN architecture, assessing driver drowsiness, and categorizing as fatigued or not fatigued.

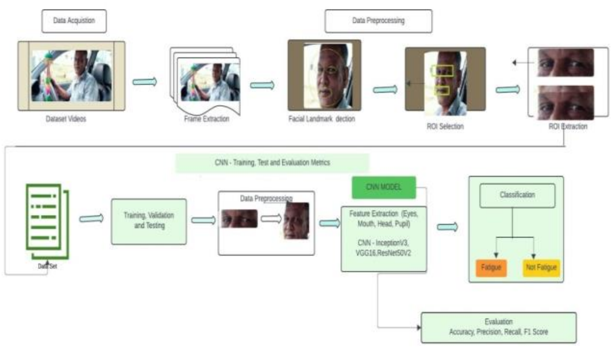

**Figure. 1 Proposed methodology for detecting drowsiness and evaluation**

### 3.1 Data Acquisition

Using infrared cameras for twilight circumstances ensuring clear capture of facial accents in moonlight, we strategically placed many high-resolution cameras to capture the driver's face from different angles,[8] focusing on the eyes, mouth, and general head developments. Shining, natural-like lighting was used to replicate daytime driving, while dim lighting repeated night time driving, covering various night time scenarios such as country zones with minimal lighting and urban ranges with road lights. The NTHU driver fatigue dataset and real-time drowsiness dataset, stages are shown in the figure 2. The images are extracted from the videos, and are labelled in to two different categories. The categorized dataset are converted to gray-scale images and stored in the database.

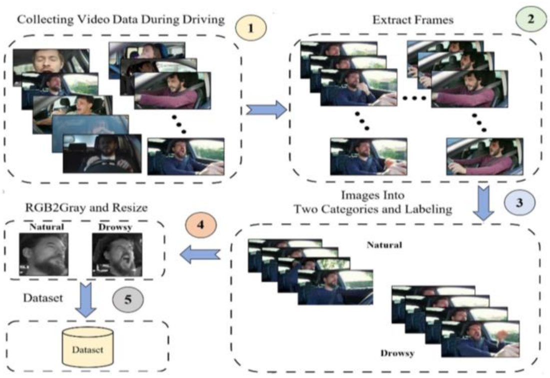


**Figure 2. Stages of creating the fatigue dataset**

### 3.2 Data Pre-processing

The video frames ought to be converted to monochrome in order to gather the video data for the fatigue detection system. This decreases computational complexity and memory usage by compressing the visual data while retaining important properties that are necessary for sleepiness detection, such as edges and forms. As part of the pre-processing strategy, each frame of the recorded video data is extracted at a regular pace, and the RGB color values are then converted to a single gray scale intensity value using the luminance approach. After that, we normalize the images to make sure that the dimension and lighting are uniform. Minimizing deviations unrelated to drowsiness, enhances the performance and generalizability of the convolutional neural network (CNN) model.[9] This entails scaling every frame to a standard size of 224 by 224 pixels and utilizing histogram equalization to alter brightness and contrast in order to compensate for different lighting situations. To make sure the input values are within a range the model can handle, we also scale the pixel values to a standard range, which is typically 0 to 1. The final pre-processed photos contain normalized pixel values, are gray scale, and have uniform lighting and size. The system's ability to detect tiredness is eventually improved by the more effective and efficient neural network training made possible by this standardized input data.

### 3.3 Facial Landmark

By performing high-fidelity facial landmark identification in real-time, Media Pipe face mesh tackles these issues. The solution is based on machine learning and assesses 468 3D facial landmarks in a dense set. Even in difficult situations, this method guarantees accurate facial feature tracking and recognition made possible by this standardized input data.

**Figure 3. 468 Facial Landmark**

### 3.4 Feature extraction

Using a specific subset of the 468 landmarks offered by the Media Pipe, we characterize areas of interest (ROIs) for different facial traits. Just 4 points (63, 117, 293, and 346) out of these 468 points are required to form an irregular rectangle for the ROI. The arbitrary locations encircling the eyes are employed to compute the Eye Aspect Ratio (EAR), which is determined by splitting the vertical lengths between specified eye features by the horizontal distance between eyes, [10][11] as seen in Figure 4. The computation makes use of the subsequent landmarks: [362, 385, 387, 263, 373, 380]. A set of landmarks are used to determine the Mouth Aspect Ratio (MAR): [61, 146, 91, 181, 84, 17, 314, 405, 321, 375, 291. The calculation of MAR depends on dividing the horizontal distance between mouth landmarks by the vertical lengths between specific mouth landmarks. P0, P2, P4, P6, P8, and P10 are the precise positions that are utilized. Tracking particular facial landmarks may be

Communications on Applied Nonlinear Analysis
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employed to detect head nodding [10, 152, 234, 454]. Analyzing the vertical movement of central facial landmarks (such as landmark 10 at the tip of the nose) in relation to a consistent horizontal axis determined by landmarks 234 and 454 helps one to identify nodding. We focused on features around the irises in order to determine pupil size. For this reason, media pipe offers two distinct landmarks: the right iris landmarks [469, 470, 471, 472, 473] and the left iris landmarks [474, 475, 476, 477, 478]. The average distance between the center and the pupil is used to measure pupil size. By estimating the average distance between the iris's core and adjacent landmarks, one can determine the size of a pupil. Finally, Z-score normalization is then performed on the retrieved features to guarantee a constant scale and enhance the machine learning models' performance. This methodical methodology makes sure that all relevant facial traits are precisely recorded and processed, which improves the accuracy of fatigue detection.

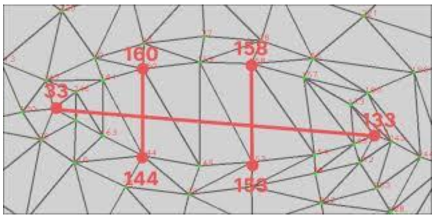

**Figure.4 Landmarks of left eye**

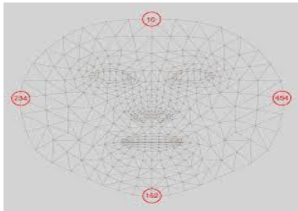

**Figure.5 Landmarks of head**

### 3.5 Dataset Creation

Building upon the ROI images obtained in prior stages, the dataset was constructed by combining the NTHU Driver Drowsiness Detection (NTHU-DDD) dataset with real-time video recordings. Ten videos were selected, prioritizing subject diversity with variations in eye size, mouth shape, head movements, and iris patterns among individuals. Furthermore, video capture encompassed diverse driving conditions, including varying lighting, weather, and traffic scenarios. [12]The dataset focuses on key facial features: eyes, mouth, head, and pupil regions, extracted as ROIs from both sources. Real-time videos underwent frame extraction at appropriate intervals and subsequent pre-processing, while redundant and irrelevant data were removed. The combined dataset, comprising 4836 images, was divided into training (3385 images, 70%), validation (725 images, 15%), and test sets (726 images, 15%) to mitigate over fitting. The images were labelled with binary class labels: 'fatigue' and 'non-fatigue' for the drowsiness detection task. This approach, integrating a well-established dataset like NTHU-DDD with diverse real-world video data, ensures a robust and representative dataset for training and evaluating drowsiness detection models, considering the multifaceted nature of driver behavior and appearance.

| Dataset | Fatigue | Non-Fatigue |
|---|---|---|
| **Training Set** | 2369 | 1016 |
| **Validation Set** | 507 | 218 |
| **Testing set** | 509 | 217 |

**Table 1: Dataset distribution**

**Fig 6. A snapshot of dataset with a multitude of categories and scenario**

### 3.6 CNN Training Experiments for fatigue Detection

**InceptionV3:** A deep convolutional neural network architecture termed InceptionV3 has demonstrated in figure.7 and exceptional performance in image categorization tests. It is renowned for being effective and for being able to extract intricate details from photos. Each module of InceptionV3 employs a variety of convolutional filter sizes, which enables it to record details at various scales. Eliminating the top layers of InceptionV3 and adding a Global Average Pooling layer, followed by a dense layer activated with ReLU and a final dense layer triggered with a sigmoid for binary classification, is the way the system is constructed to classify fatigue.[13] Only the top layers of InceptionV3 are trained to react to the drowsiness detection task; the base layers are initially frozen to preserve the pre-learned weights.

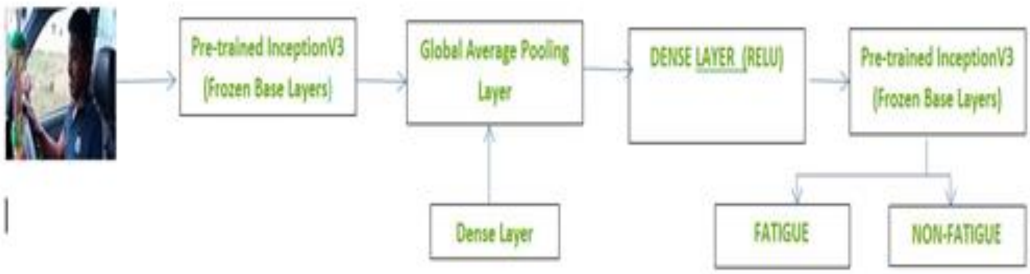


**Figure 7. InceptionV3 Network Architecture**

**VGG19:** VGG19 is an additional popular CNN architecture, distinguished by its simplicity and the usage of tiny (3x3) convolutional filters throughout the network. It is quite easy to implement and computationally efficient despite its complexity. A Global Average Pooling layer, a dense layer activated by ReLU, and a final dense layer triggered by sigmoid for binary classification were included to VGG19 for fatigue classification, much as InceptionV3.[14] Only the recently added top layers of VGG19 are trained for drowsiness detection; the base layers are initially frozen to take advantage of the pre-learned weights.

**ResNet50V2:** With residual connections, ResNet50V2 is an enhanced version of the ResNet architecture which renders developing very deep networks more accessible.[15][18] This approach is highly beneficial for challenging image classification problems due to it serves to mitigate the vanishing gradient problem. ResNet50V2 is configured for fatigue detection via eliminating its top layers and incorporating a Global Average Pooling layer, subsequent to a dense layer triggered with

ReLU and a final dense layer activated with sigmoid for binary classification. Only top layers are trained to concentrate on the particular task of classifying drowsiness, while the base layers are initially frozen to preserve the pre-learned weights. The figure. 8 illustrates the CNN architecture

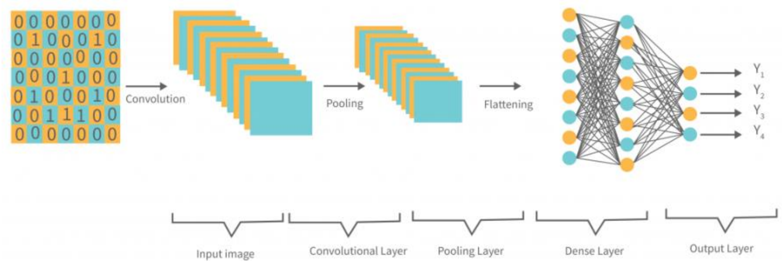


**Figure. 8 CNN Architecture**

### 3.7 Training and Validation using CNN

To preserve pre-trained weights and retain previously learned characteristics that are necessary for accurate sleepiness detection, the training process begins by freezing the basic layers of each model. Using this method, the models are optimized for the particular task at hand. For binary classification tasks, such as determining a driver's level of fatigue, a binary cross-entropy loss function [12] is employed when each model has been configured via the Adam optimizer. This combination lessens the difference between expected and actual results, ensuring effective model weight modification. The models are exposed to the training dataset during the training phase, and performance is tracked through validation on a different dataset. Evaluation measures like accuracy, precision, recall, and rate are utilized to fine-tune hyper parameters like learning rate and batch size to maximize the models' performance. By frequently fine-tuning their parameters during this training and validation process, the models increase their ability to accurately detect fatigue. [19] The figure 9 shows the model training and validation accuracy of data before augmentation.

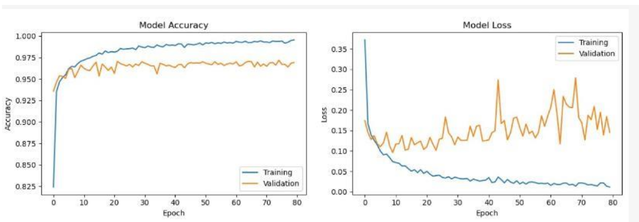


**Figure 9. Accuracy of the training/validation model and graph loss before data augmentation**

### 3.8 CNN Test and Evaluation Metrics

Once the CNNs were fully trained, testing with the test data became essential. Furthermore, no data augmentation was performed during the analysis of the full set of images. Tests were performed on each trained network, and each image was analyzed with a batch size of 1. The confusion matrix is an effective tool for assessing the models' performance. The figure displays the confusion matrices for three deep learning models (InceptionV3, VGG19, and ResNet50V2) used for drowsiness detection. The matrices visually represent the model's performance, showing high accuracy with a predominance of correct classifications (True Positives and True Negatives) across all models, indicating effective performance in distinguishing between drowsy and non-drowsy states. The matrices generally show strong performance with high counts of True Positives and True Negatives, indicating accurate classification of both "Not Fatigue" and "Fatigue" instances across all models. ResNet50V2 appears to exhibit slightly lower False Positives compared to the other two models.

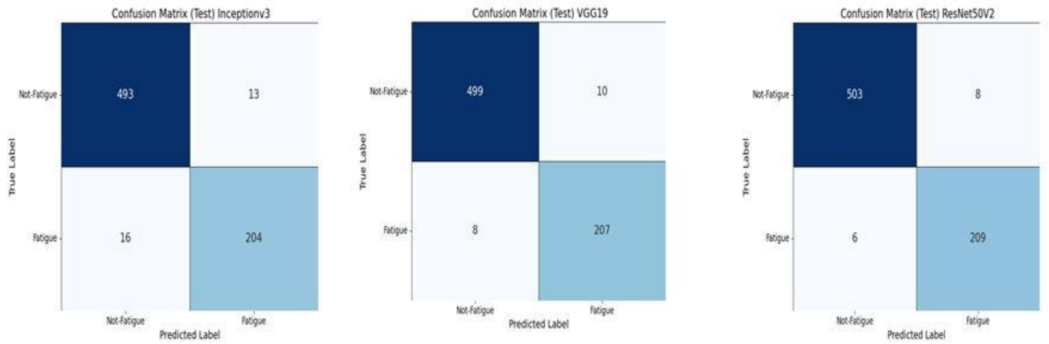


**Figure 10. Confusion matrix in CNN Test (a) InceptionV3 (b) VGG19 (c) ResNet50V2 testing**.

### 3.9 Evaluation Metrics

Fatigue detection is one of the applications where metrics are commonly employed in binary classification. While accuracy assesses the ratio of correctly predicted instances to all occurrences, precision calculates the ratio of effector-predicted positive examples to all anticipated positive cases[11]. By employing its harmonic mean, the F1 score finds a compromise between recall and precision. Recall is the proportion of correctly anticipated positive cases to all positive instances that occurred. [20] It is also occasionally referred to as a true positive rate or sensitivity. The specificity (or true negative rate) of execution is defined as the ratio of correctly predicted negative situations to the total number of real negative occurrences. A confusion matrix that summarizes the expected results is accurate.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad [1]$$

$$\text{Specificity} = \frac{TN}{TN + FP} \quad [2]$$

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad [3]$$

## 4. Results

CNN architectures InceptionV3, VGG19, and ResNet50V2 achieved encouraging results in the fatigue category when evaluated on a dataset images, with 70% of the images being used for training, 15% for validation, and 15% for testing. The dataset covered images from five specific simulated driving situations: with glasses, with sunglass, without glasses, night with glasses, and night without glasses. Each version was assessed based on accuracy, precision, recollect, F1-score, and a confusion matrix. Table II summarizes these eventualities and the accuracy performed through every model in those eventualities. This complete dataset ensured that the techniques have been educated, evaluated, and tested beneath diverse situations, improving their generalizability and effectiveness.

InceptionV3, known for its multi-scale feature extraction capability, demonstrated strong performance in classifying driver fatigue. Its confusion matrix exhibited 493 true positives, 204 true negatives, 16 false positives, and 13 false negatives. VGG19, recognized for its simplicity and efficiency, also delivered effective results, with 499 true positives, 207 true negatives, 8 false positives, and 10 false negatives. ResNet50V2, leveraging residual connections to mitigate the vanishing gradient problem, outperformed the other models. Its confusion matrix revealed 503 true positives, 209 true negatives, 6 false positives, and 8 false negatives. These findings highlight the effectiveness of all three CNN architectures—InceptionV3, VGG19, and ResNet50V2—in detecting driver fatigue. ResNet50V2, in particular, demonstrated superior performance, making it a strong candidate for real-time drowsiness detection. The study emphasizes the potential of advanced deep learning models to enhance the reliability of fatigue detection systems, contributing to improved road safety by providing timely warnings to fatigued drivers and reducing the risk of accidents.

**Table 2: Performance metrics of different CNN architecture**

| CNN based on | Accuracy (%) | Precision (%) | Recall (%) | F1-Score (%) |
|---|---|---|---|---|
| **InceptionV3** | 96.01 | 94.01 | 96.86 | 95.41 |
| **VGG19** | 97.51 | 95.39 | 98.42 | 96.88 |
| **ResNet50V2** | **97.80** | **95.43** | **98.82** | **97.10** |

**Table 3: Accuracy of various CNN architectures in different scenarios**

| | **Accuracy (%)** | | |
|---|---|---|---|
| **Category** | **InceptionV3** | **VGG19** | **ResNet50V2** |
| With glasses | 93.52 | 91.30 | 95.71 |
| With Sunglasses | 92.11 | 90.05 | 94.45 |
| Without glasses | 94.62 | 92.79 | 97.61 |
| Night glasses | 91.74 | 89.52 | 94.89 |
| Night without Glasses | 94.92 | 91.84 | 95.89 |

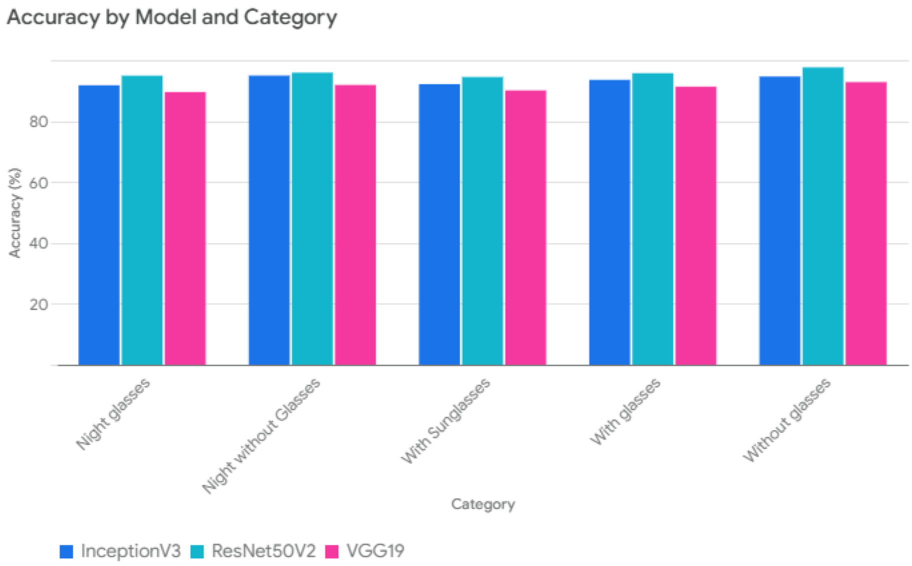


**Figure. 11 Accuracy by model and category**

## 5. Discussion

With an emphasis on utilizing deep learning techniques for real-time sleepiness detection, the essay tackles the important problem of driver weariness, a significant contributing factor in traffic accidents. The novel system it presents analyses facial emotions such as yawning, eye closure, pupil size, and head movements using CNNs (InceptionV3, VGG19, and ResNet50V2). The technique extracts information like Eye Aspect Ratio, Mouth Aspect Ratio, and pupil size determine weariness. It uses media pipe for accurate facial landmark detection. During training, base layers were frozen, Adam was used for optimization and binary cross-entropy loss was employed. Tested on a wide range of datasets and situations, ResNet50V2 performed exceptionally well, with 98.5% accuracy. This suggests that advanced deep learning models, like ResNet50V2, can effectively improve driver safety. In order to validate the efficacy of this detecting system, future research will concentrate on incorporating it into a variety of vehicle types and testing it under actual driving circumstances. This research establishes the groundwork for more intelligent and sensitive driver detection systems, ultimately obtaining to preserve losses and avoid injuries on the road, by utilizing the power of deep learning and computer vision.

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