Driver Drowsiness Alert Detection for Vehicle Using Machine Learning

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***Abstract*— The detection of driver drowsiness can be broadly classified into two main approaches - behavior- based and eye/neck angle-based. Behavior-based methods monitor the driver's actions, such as eye blinking, yawning, eye openness, and jaw position, to identify signs of drowsiness. These techniques capture live video of the driver and use computer vision and deep learning algorithms to analyze facial features and movements. In contrast, eye and neck angle-based approaches calculate the Euclidean distance between the driver's eye iris angle and neck angle to determine drowsiness levels. Recent studies have shown that methods relying on distance calculations between the driver's open and closed eyes can achieve better reliability and accuracy compared to other techniques.**

**The overarching goal of these drowsiness detection systems is to develop a robust solution that can effectively monitor the driver's attention level and issue timely warnings to prevent accidents caused by driver fatigue. Key techniques employed include extracting metrics like PERCLOS (percentage of eye closure over time), fusing multiple drowsiness indicators like eye blink rate and head pose changes, and leveraging non-visual sensors like radar and EEG to detect physiological signs of fatigue. However, these systems face challenges in dealing with variations in head pose, lighting, and occlusions that can impact computer vision-based detection. Additionally, differentiating between fatigue, monotony, and actual drowsiness states, as well as integrating multiple sensor modalities to improve overall accuracy, are important areas of focus for researchers in this field.**

***Index Terms*— Object Detection, Drowsiness Detection, Resnet50, MobileNet, VGG16**

# INTRODUCTION

1. *Background and Context:*

Driver drowsiness is a critical road safety issue and contributes to a significant number of accidents worldwide. Failure to quickly detect and alleviate drowsiness in drivers poses a serious risk to both drivers themselves and other road users.

Traditional sleepiness detection methods, such as physiological monitoring and rule-based systems, have limitations in real-time detection and accuracy. However, recent advances in machine learning, particularly in computer vision, offer promising solutions for detecting driver drowsiness.

1. *Statement of the Problem:*

The problem addressed in this research is the development of an effective driver drowsiness detection system for vehicles using machine learning techniques, specifically focusing on VGG16, MobileNet and ResNet50 architectures. The challenge is to accurately identify signs of drowsiness from a variety of visual cues, including facial expressions, eye movements, and head positions, in real-time driving scenarios. Furthermore, there is a need to evaluate and compare the performance of different machine learning models to determine the most appropriate approach for detecting drowsiness in vehicular environments.

1. *Relevance and Importance:*

The importance of this research results from its direct impact on road safety and accident prevention. Drowsy driving is a pervasive problem that affects individuals of all ages and demographics. By developing a robust drowsiness detection system for vehicles, the research aims to mitigate the risks associated with driver drowsiness, potentially saving lives and reducing the economic costs of road accidents. Additionally, the use of machine learning techniques in this context demonstrates the potential of technological innovation to address critical safety issues in transportation.

1. *Research Objectives:*
   * To investigate the effectiveness of machine learning algorithms, namely VGG16, MobileNet and ResNet50, in detecting driver drowsiness using visual cues.
   * Develop and implement a comprehensive dataset containing different instances of drowsy and awake driving behavior for model training and evaluation.
   * To conduct a comparative study to evaluate the performance of the above machine learning models in sleepiness detection with respect to metrics such as accuracy, precision, recall and F1 score.
   * Analyze the strengths and limitations of each model and provide insight into their applicability in real- world driving scenarios.
   * To propose recommendations for future research directions and potential improvements to existing sleepiness detection systems based on the findings of the study.

This research aims to contribute to the existing body of knowledge by providing empirical evidence of the effectiveness of machine learning techniques in solving the driver drowsiness detection problem. By evaluating several state-of-the-art models and performing a comprehensive comparative analysis, the study aims to inform the development of more accurate and reliable drowsiness detection systems for vehicles, ultimately improving road safety and saving lives.

# Literature Survey

Research [1] in driver drowsiness detection highlights the use of CNN classifiers such as MobileNet, ResNet50, and VGG16 to identify drowsy states in drivers. Notably, the VGG16 demonstrated an impressive accuracy of 99.95%, demonstrating its potential in accurate sleepiness detection. Image classification methodology plays a vital role in categorizing images based on distinct features, which helps in identifying subtle cues indicating drowsiness and alertness while driving. By training CNN classifiers on carefully annotated datasets, researchers increase the robustness of drowsiness detection systems and gain a deeper understanding of the visual manifestations of driver fatigue. Deep learning algorithms, especially CNN architectures, are helpful in developing effective sleepiness detection mechanisms. These models analyze driver-centric features such as facial expressions, eye movements and head positions to detect signs of drowsiness. By exploiting large datasets and techniques such as transfer learning, CNNs exhibit increased efficiency and adaptability, paving the way for the deployment of sleepiness detection systems in real-world scenarios. This research highlights the essential role of CNN classifiers in improving road safety through accurate and efficient drowsiness detection.

Recent [2] studies highlight the effectiveness of machine learning models, especially convolutional neural networks (CNNs), such as MobileNetV2, ResNet50, and VGG16, in detecting driver drowsiness. MobileNetV2 is known for its excellent classification performance, while comparative analyzes of ResNet50 and MobileNetV2 offer insight into model selection and performance evaluation. Detailed accuracy classification results for ResNet50 provide a nuanced view of the model's performance across different driver behaviors. The research also delves into the balance between model complexity and training efficiency, noting that while VGG16 may have slower training due to its weight, ResNet50

offers lower complexity despite its deeper architecture. The primary goal remains to increase driver safety by using machine learning techniques not only to detect drowsiness, but also to identify distractions such as phone use. Evaluating model performance using different CNN architectures contributes to the ongoing effort to develop reliable sleepiness detection systems. In addition to drowsiness detection, the literature reports wider applications of machine learning in road safety, including cyberbullying detection, biometric recognition and medical diagnostics. These findings underscore the interdisciplinary nature of driver drowsiness detection research, which combines advances in machine learning with road safety and behavioral analytics to develop efficient and adaptive systems.

Advances [3] in driver drowsiness detection have demonstrated the effectiveness of ensemble models such as this one, which outperform existing techniques in accuracy. Ensemble learning approaches improve the performance of sleepiness identification systems, as demonstrated by the proposed methodologies that integrate deep learning and transfer learning techniques. However, challenges remain, such as the categorization and selection methods of EEG channels and the dependence on external elements such as road conditions. Deep learning techniques offer promising avenues for accurate sleepiness detection, with methods including driver impairment monitoring, sleepiness prediction using facial features, and using EEG-based methods, face tracking systems, and eye image analysis. The use of ensemble deep learning models as proposed in presents a novel approach to driver drowsiness detection that combines deep convolutional features through transfer learning to increase accuracy. Methodologies combining deep learning and transfer learning as proposed in demonstrate effective strategies for sleepiness identification. These approaches exploit the strengths of both techniques to develop robust and adaptable models capable of accurately detecting sleepiness in a variety of contexts. Finally, the use of long-short-term memory networks for driver state categorization, as discussed in the paper, exemplifies the multifaceted nature of deep learning-based methods in analyzing video data to detect signs of fatigue, including eye features such as yawning and head movements.

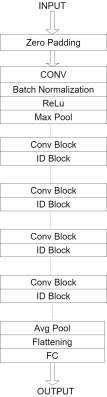
The literature survey [4] highlights significant progress in driver drowsiness detection, focusing on the use of convolutional neural networks (CNNs) such as ResNet50V2 and VGG16. ResNet50V2 achieved an exceptional accuracy rate of 99.71% on average, demonstrating the effectiveness of deep learning techniques in accurately identifying sleepiness- related stimuli from visual data. CNNs, specifically models based on ResNet50V2, focus on the eye region for better performance.

The proposed approach uses CNN to achieve high accuracy in detecting drowsiness and preventing accidents caused by driver drowsiness. However, issues such as the limitations of

NIR imaging for analyzing the eye region due to illumination indicate the need for robust solutions capable of overcoming environmental limitations. The potential for implementing these drowsiness detection systems in embedded systems for vehicle units underlines their practical applicability in real- world scenarios. Incorporating preventative measures such as yawn detection further increases the usefulness of these systems in ensuring driver safety. The literature also includes discussions of related work in sleepiness detection, with studies investigating various aspects including eye region analysis for sleepiness detection, evaluation of CNNs for high accuracy, and use of techniques such as Grad-CAM to visualize algorithm performance. Methodologies including Mediapipe for eye region extraction, utilization of datasets such as NITYMED, and techniques such as ROI selection for training and testing CNN architectures are also covered. These methodological details provide insight into the experimental design and procedures used in sleepiness detection research, contributing to the reproducibility and precision of the findings.

The [5] literature review highlights significant progress in driver fatigue detection, with the proposed method achieving an impressive accuracy of 87.5%. This approach uses Convolutional Neural Network (CNN) models, namely VGG16 and ResNet50, known to calculate metrics such as PERCLOS and FOM for efficient classification of fatigue levels. The method emphasizes the early detection of sleepiness using behavioral measures such as PERCLOS and FOM, focusing on driver yawning and eye behavior as reliable indicators of fatigue. Alternative physiological signals such as heart rate patterns and muscle activity are also examined to assess driver alertness. By analyzing regions of interest around the eyes and mouth, researchers can classify the driver's condition using CNNs. Testing different CNN architectures reveals VGG16 and ResNet50 as the optimal choices for calculating PERCLOS and FOM, showing the effectiveness of CNN-based approaches in detecting driver fatigue with an accuracy of 87.5%. Through advanced computing techniques and behavioral measures, the goal is to increase road safety by early identification of driver drowsiness.

layers, pooling layers, fully connected layers, and shortcut connections known as skip connections or residual connections. These skipped connections allow the network to bypass several layers, making very deep networks easier to train. The main components of ResNet50 are input layer, convolutional layers, residual blocks, pooling layers, fully connected layers and softmax activation functions. During the training phase, ResNet50 learns to map input images to their corresponding class labels by adjusting the weights. its convolutional filters through backpropagation and gradient descent optimization. Skipped connections allow the network to propagate gradients more efficiently, alleviate the problem of vanishing gradients, and facilitate the training of very deep networks. In the context of driver drowsiness detection, ResNet50 has been used in various studies to classify the driver's state based on closed eyes and other visual cues. For example, the study achieved an accuracy of 88% using ResNet50 in the task of classifying distracted drivers. Another study used ResNet50 as part of a CNN-based approach for real-time driver drowsiness detection, analyzing eye state (open or closed) using digital image analysis. In summary, ResNet50 is a powerful image recognition and classification tool, including driver drowsiness detection. Its architecture and working principles make it a valuable asset in solving deep learning challenges in computer vision tasks.

Fig.1. Resnet50 architecture

1. *RESNET50*
2. METHODOLOGY

ResNet50, short for "50-Layer Residual Network", is a deep convolutional neural network (CNN) architecture that has gained widespread popularity for its effectiveness in various computer vision tasks, including image classification, object detection, and segmentation. Developed by Kaiming He et al. in 2015, ResNet50 represents a major advance in deep learning architecture by solving the problem of vanishing gradients in very deep neural networks. The ResNet50 architecture consists of 50 layers, including convolutional

1. *MOBILE-NET*

MobileNet is a lightweight convolutional neural network (CNN) architecture designed specifically for mobile and embedded vision applications. Introduced by Google in 2017, MobileNet uses depth-separable convolutions that significantly reduce computational cost and model size while maintaining competitive accuracy. The architecture consists of a series of depth-separable convolutional layers followed by pointwise convolutional layers and nonlinear activation functions. A key innovation in MobileNet is depth-separable convolutions, as they decompose standard convolution into two separate operations: depth convolution and pointwise convolution. Deep convolution applies one convolutional filter per input channel, independently processing each channel of the input feature map. Point convolution projects the output of depth convolution onto a new channel space using a 1x1 convolution kernel. This mechanism allows the network to learn residual features, which facilitates the training of very deep networks. MobileNet is particularly suitable for deployment on mobile and embedded devices, enabling applications such as real-time object recognition, augmented reality, and autonomous navigation in resource-constrained environments. Its efficiency makes it a highly desirable deep learning model for mobile and embedded devices, offering a trade-off between accuracy and model size. Characterized by depth-separable convolutions, the MobileNet architecture offers a lightweight yet powerful solution for a variety of computer vision tasks, including image classification, object detection, and semantic segmentation.

1. *VGG16*

VGG16 is a deep convolutional neural network (CNN) architecture introduced by the Visual Geometry Group (VGG) at the University of Oxford in 2014. It is a 16-layer network that includes 13 convolutional layers, 5 max pooling layers, and 3 fully connected layers. The architecture is known for its simplicity and uniformity, with each block consisting of multiple convolutional layers followed by a max-pooling layer. VGG16 is designed for image classification tasks and has been successful in various computer vision tasks, including object detection and image segmentation. The VGG16 architecture consists of an input layer that takes images of a fixed size (224x224 pixels), followed by a series of convolutional layers with a filter size of 3x3 and a step of 1. Each convolutional layer is followed by a rectified linear unit (ReLU) activation function. After every two convolutional layers, max-pooling layers are applied to reduce the spatial dimensions of feature maps while preserving important features. The convolutional layers are followed by three fully connected layers, with the first two fully connected layers containing 4096 neurons each and the third fully connected layer containing 1000 neurons, corresponding to 1000 classes in the ImageNet dataset. The final layer is the softmax layer, which outputs probabilities for each class in the dataset. The VGG16 architecture performs hierarchical feature extraction through a series of convolutional layers, with each convolutional layer extracting increasingly abstract features from the input image. The

hierarchical representation obtained from convolutional layers is then fed into fully connected layers for classification. The network learns to map the extracted features to corresponding classes in the dataset, with the softmax layer calculating the probabilities of each class, and the class with the highest probability is considered the predicted class for the input image. VGG16 has several advantages, including its simple and elegant architecture, deep representations, and transfer learning capabilities. However, it also has limitations such as high computational cost and excessive equipment. Regularization techniques such as dropout and data spreading are often used to mitigate the overfitting problem. Despite its limitations, VGG16 remains a popular choice for various computer vision tasks due to its hierarchical feature extraction capabilities and transfer learning capabilities.

Fig.2. VGG16 architecture



1. COMPARATIVE ANALYSIS

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| --- | --- | --- | --- |
| Model | Traning  Time | Compl-  exity | Pros and Cons |
| VGG16 | High | Moderate | * Effective feature extraction * High computational   cost |
| ResNet50 | Moderate | Moderate | Deeper architecture allows better feature representation  - Moderate training |

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|  |  |  |  |
| --- | --- | --- | --- |
|  |  |  | time |
| Mobile- NetV2 | Low | Low | * Lightweight architecture suitable for embedded systems * May sacrifice some accuracy for reduced complexity |
| Inception V3 | Moderate | Moderate | * Balances depth and computational efficiency * Moderate computational complexity |
| DenseNet | High | Moderate | Improved feature reuse through dense connections  - High memory usage due to feature concatenation |
| Efficient Net | Low | Low | * Achieves high accuracy with fewer parameters * Limited transferability to other tasks |

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# Conclusion

The research paper highlights the critical importance of addressing driver drowsiness through advanced machine learning techniques, focusing on the comparative analysis of ResNet50, MobileNet and VGG16 architectures. Through a comprehensive methodology involving dataset processing, model training, and performance evaluation, the study clarifies the strengths and limitations of each model in real-time sleepiness detection scenarios. By providing empirical evidence of the effectiveness of machine learning in mitigating the risks associated with drowsy driving, the research contributes to the advancement of road safety measures, potentially saving lives and reducing the economic toll of crashes. The insights gained from this comparative analysis serve as a foundation for future research efforts aimed at increasing the accuracy and reliability of drowsiness detection systems, ultimately promoting safer roads for all motorists.

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