M. Tech. 3^{rd} Semester Practical Training Report

On

Driver Drowsiness Detection System Using Deep Learning

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DECLARATION

I hereby declare that the M. Tech. 3rd Semester **Major-Project** report entitled **Driver Drowsiness Detection System Using Deep Learning** which is being submitted to the National Institute of Technology Karnataka Surathkal, in partial fulfilment of the requirements for the award of the Degree of **Master of Technology in Computer Science and Engineering** in the department of **Computer Science and Engineering**, is a bonafide report of the work carried out by me. The material contained in this report has not been submitted to any University or Institution for the award of any degree.

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CERTIFICATE

This is to certify that the M. Tech. 3rd Semester **Major-Project** report entitled **Driver Drowsiness Detection System Using Deep Learning** submitted by **Saurabh Kumar Singh**, (Roll Number: 222CS029) as the record of the work carried out by him, is accepted as the M. Tech. 3rd Semester Major-Project report submission in partial fulfilment of the requirements for the award of degree of **Master of Technology in Computer Science and Engineering** in the Department of **Computer Science and Engineering**.

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Abstract

Driver drowsiness stands as a significant global contributor to road accidents, posing substantial risks to both drivers and pedestrians. In response to this critical issue, this study delves into the potential of utilizing deep learning techniques, specifically a convolutional neural network (CNN), for effective driver drowsiness detection. The research entails the meticulous collection and preprocessing of a diverse dataset, encompassing images capturing drivers in various states of alertness and drowsiness. This dataset undergoes careful processing to ensure consistency and quality. The chosen CNN is specifically selected for its efficacy in handling image-based tasks. The project systematically explores the CNN's capacity to learn and recognize visual cues associated with drowsiness through comprehensive model training and evaluation. Rigorous assessments, using appropriate metrics, showcase the model's competence in accurately discriminating between alert and drowsy states. Furthermore, the study contemplates the real-time implementation of the drowsiness detection algorithm, offering the potential for timely interventions to prevent accidents. In conclusion, this research significantly contributes to ongoing efforts aimed at enhancing road safety by addressing the crucial challenge of driver drowsiness through the application of deep learning techniques, thereby providing a promising avenue for the improvement of transportation safety.

Keywords: Deep Learning, Convolutional Neural Networks (CNN), Road Safety, Fatigue Detection, Image Processing, Feature Extraction, Alertness Detection, Machine Learning, Traffic Safety

Contents

List of Figures

List of Tables

1 Introduction

In the dynamic landscape of contemporary transportation, the escalating issue of driver drowsiness poses a critical threat to road safety, evidenced by the extensive repercussions of accidents, injuries, and fatalities associated with fatigued driving. This concern is accentuated amid the evolving coexistence of human-driven vehicles and the introduction of self-driving technology, necessitating proactive measures to uphold road safety standards. Acknowledging the gravity of this challenge, the project endeavors to play a pivotal role in augmenting road safety by developing an innovative solution for driver drowsiness detection. Through a combination of advanced technologies such as deep learning and artificial intelligence, the project seeks to create a sophisticated Advanced Driver Assistance System (ADAS)Magán López et al. [2022] capable of accurately identifying drowsy states in drivers, ultimately striving to mitigate accidents arising from impaired alertness through timely interventions.

The approach is rooted in the integration of cutting-edge technologies, specifically leveraging advancements in deep learning, image processing, and artificial intelligence. The project seeks to design an Advanced Driver Assistance System (ADAS)Magán López et al. [2022] capable of identifying drowsy states in drivers, with the ultimate goal of mitigating the potential for accidents caused by impaired alertness through timely interventions. The methodology adopted involves a systematic exploration of existing research, methodologies, and technologies in the realm of driver drowsiness detection. A key focus is placed on utilizing visual cues, eye movement patterns to discern subtle signs of drowsiness in drivers. This approach reflects a commitment to pushing the boundaries of innovation in the quest for safer roads, where technology serves as a vigilant ally in safeguarding the well-being of drivers, passengers, and pedestrians alike. As the project unfolds, it will not only contribute to the scientific understanding of drowsiness detection but also offer practical solutions that have the potential to revolutionize the landscape of road safety in the face of evolving transportation dynamics.

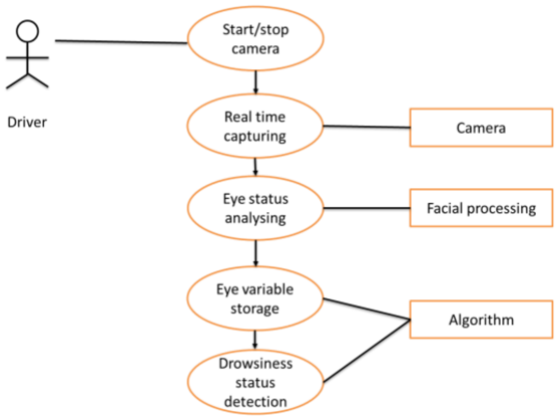

Figure 1: Operational diagram for driver drowsiness system Prasath et al. [2022]

In pursuit of precision and effectiveness, the project embraces the power of machine learning, particularly deploying sophisticated deep learning techniques. By harnessing these advanced technologies, the project aspires to achieve not only high accuracy but also heightened sensitivity in detecting the early stages of drowsiness. This multifaceted approach reflects a commitment to pushing the boundaries of innovation in the quest for safer roads, where technology serves as a vigilant ally in safeguarding the well-being of drivers, passengers, and pedestrians alike.

2 Motivation

- **Accident Prevention:** The primary objective of the drowsiness detection system is to contribute to accident prevention in both passenger and commercial vehicles.

- **Early Symptom Detection:** The system is designed to identify the early symptoms of drowsiness, allowing for intervention before the driver completely loses attentiveness.

- **Timely Warnings:** By detecting signs of drowsiness in the early stages, the system provides timely warnings to the driver, alerting them that their capability to operate the vehicle safely may be compromised.

- **Enhancing Driver Safety:** The overarching goal is to enhance driver safety by proactively addressing drowsiness, thus reducing the risk of accidents on the road.

3 Research Gap

Offline Training Phase:

- Training the model to distinguish between facial features in drowsy and alert states.
- Focus on understanding and categorizing visual cues indicative of driver drowsiness during the training phase.

Real-Time Monitoring Phase:

- The transition to real-time monitoring is a crucial aspect of the research gap.
- Continuous tracking of the driver's face in real-time to predict their current status.
- The need for a system that can dynamically assess and interpret facial features during live operation.

Alarm Trigger Mechanism:

- The challenge lies in implementing a reliable alarm mechanism.
- Identifying the optimal criteria for triggering an alarm based on real-time predictions.
- Ensuring that the system can accurately detect and respond to the evolving drowsiness status of the driver.

4 PROBLEM STATEMENT AND OBJECTIVES

4.1 PROBLEM STATEMENT

Design and develop novel architecture for Driver Drowsiness detection using Deep Learning.

4.2 OBJECTIVES

- **Design and develop deep learning techniques to detect driver drowsiness, enhancing road safety through indicators like eye closure.**

- **This study will create mobile-based applications for real-time drowsiness detection, eliminating the need for external hardware.**

5 Literature Survey

Meda et al. [2021] propose a drowsiness detection system that uses machine learning and computer vision to analyze the driver's facial features, with a specific focus on symptoms of drowsiness like eye closure and yawning. They plan to compare multiple machine learning models to find the most effective one for real-time drowsiness detection.

The ultimate goal is to develop a system that can alert drivers as soon as it detects signs of drowsiness, helping to prevent accidents. This approach could potentially save many lives that might otherwise be lost to sleep-related driving accidents. Key methods and techniques discussed in the paper include K-Nearest Neighbours (KNN), Logistic Regression, Decision Tree Classifier, Naive Bayes Classifier, Long Short-Term Memory (LSTM), and Convolutional Neural Network (CNN).

Magán López et al. [2022] references various research studies mainly focused on driver fatigue and drowsiness detection, providing a comprehensive review on methods used in the field.

The paper first introduces research related to examining steering wheel behavior as it pertains to fatiguing. It cites a research by Krajewski et al. [2009] which was presented at the International Driving Symposium on Human Factors in Driver Assessment, Training and Vehicle Design. Next, it brings up a study by Chai et al. [2019] that proposed drowsiness monitoring methods which use real-life driving data, particularly steering and lane data.

The paper further presents a study by Mcdonald et al. [2012] which developed a system to detect drowsiness-related lane departures by using steering wheel angle in real time. The work of Samiee et al. [2014] was also reviewed, where a data fusion system was created to detect driver drowsiness, with an emphasis on creating a model with robustness against signal loss. The research of Yang et al. [2009] in the detection of driver fatigue caused by sleep deprivation was also discussed. The paper cites studies that focused on PERCLOS (Percentage of Eye Closure) based fatigue monitoring technologies, multi-feature eye detection method for fatigue, and depth video-based two-stream convolutional neural networks for driver fatigue detection were also highlighted in the literature review.

The referenced studies show a clear trend of utilizing diverse data inputs, like steering behavior, lane data, PERCLOS, and video feeds, and applying various processing methods to detect signs of drowsiness or fatigue in drivers. This provides a thorough understanding of the strategies used in the field for fatigue detection.

Prasath et al. [2022] underscores the imperative of addressing the critical issues of driver drowsiness and fatigue, both acknowledged as significant contributors to road accidents. The paper accentuates the urgent necessity to develop proactive mechanisms that effectively mitigate these risks, particularly within the context of ongoing human-driven transportation.

A pivotal concern outlined in the paper is the interconnection between extended durations of continuous driving and the emergence of fatigue and drowsiness. This link serves as a backdrop, reinforcing the urgency to devise strategies that preemptively counteract these perilous states.

To combat this challenge, the paper introduces an image processing-based approach tailored for driver drowsiness detection. Central to this methodology is the formulation of an algorithm meticulously designed to detect key indicators of drowsiness: eye closure and yawning ratios. By prioritizing these visual cues, the algorithm endeavors to detect the early signs of drowsiness, potentially enabling timely alerts to drivers when symptoms manifest. The overarching aim is to curtail accidents by proactively notifying drivers of their compromised alertness, thereby fostering safer driving practices.

To underscore the magnitude of the issue, the paper cites pertinent statistics b11 [2020] from the "Ministry of Road Transport And Highways" in India for the year 2019. The recorded count of 15,231 accidents attributed to drowsy drivers serves as a stark reminder of the urgency to address this challenge. The problem acutely affects drivers, particularly those engaged in continuous long-haul journeys, such as truck drivers who navigate extended periods, notably during nighttime hours.

Firman Ridwan et al.Ridwan and Hung [2023] delves into the pivotal issue of driver drowsiness, emerging as notable contributors in the field, emphasizing the critical need for technological interventions. Acknowledging yawning as a pertinent indicator of driver fatigue, the study underscores the indispensability of technology in monitoring and evaluating drivers' attention levels throughout their journeys.

In the technological solutions landscape, Firman Ridwan et al.'s Ridwan and Hung [2023] work stands out, advocating for advancements in artificial intelligence and deep learning. The current study builds upon this foundation, introducing a high-precision artificial intelligence model developed through deep learning. Trained on an extensive YawDD: Yawning DetectionAbtahi et al. [2020] and COCO17 dataset featuring images of yawning and blinking individuals, the model seamlessly integrates into a mobile application designed for widespread use. A distinctive aspect of this approach is the emphasis on mobile applications, distinguishing it from previous research that predominantly focused on hardware-based solutions like webcams and smartwatches.

The model's commendable accuracy, ranging from 62-87%, is contingent on factors such as camera stream frames and device performance. Rigorous evaluation, including unit testing, integration testing, and user acceptance testing, consistently demonstrates the application's effectiveness in detecting driver drowsiness. User acceptance testing, as evaluated through the System Usability Scale questionnaire, underscores Firman Ridwan et al.'s commitment to user-friendly technology, showcasing the perceived ease of use, effectiveness, and overall satisfaction with the application. The proposed system, in line with the collective efforts of researchers like Firman Ridwan et al.Ridwan and Hung [2023], aims to significantly enhance road safety by reducing accidents through the timely identification of drowsy drivers, employing state-of-the-art technologies like deep learning within mobile applications.

Author Name	**Detection Parameter**	**Observation**
Alshaqaqi et al. [2013]	PERCLOS	AI-based module for ADAS that visually monitors the driver's fatigue level by tracking facial and eye movements to measure the percentage of eye closure.
Meda et al. [2021]	Eye Closure,Yarn	ML models to detect driver drowsiness using indicators like eye closure and yarn
Magán López et al. [2022]	Drooping eyelids, Yarn	A non-intrusive Advanced Driver-Assistance System that uses AI and deep learning techniques to detect driver fatigue from sequences of images
Prasath et al. [2022]	Harr-cascade(EAR)	Use of a detection system that leverages eye closure and yawning ratios as indicators of drowsiness
Ridwan and Hung [2023]	Yarn	A feature-rich mobile application, with positive user feedback on the comprehensive feature set.

Table 1: Observation Table

Work	**Method**	**Dataset**	**Performance**
System 1Vitabile et al. [2010]	Eye region segmentation, Eye region Selection , Eye Detection, Drowsiness Calculation	Real-time video stream	Camera detection using JSPDF-402 infrared sensitive with a spectral range of 400-1000 nm and a peak at approximately 800nm
System 2 Mehta et al. [2019]	Eye Aspect Ratio (EAR), Eye Closure Ratio (ECR), Facial Landmarks	Real-time video stream	84 Percent detection accuracy
System 3 Shakeel et al. [2019]	MobileNets architecture , Single Shots Multibox Architecture (SSD)	Face detection and dataset benchmark(FD DB), Yawning while Driving (Yawdd), Closed Eye in theWild (CEW), Custom Image	Mean Average Precision (mAP) of 0.84
System 4 Tombeng et al. [2019]	OpenCV Python Library, Haar Cascade Classifier	Real-time camera video	18% of the cases fail , 27% are bad detection , 11% percent categorized as good detection, 11% fall into fast detection
System 5 Yu et al. [2019]	Single Shots Multibox Architecture (SSD) as detector	ImageNet, WIDER-FACE, 300-VW	High prediction accuracy of 97.8%.

Table 2: DROWSINESS DETECTION RESEARCH SUMMARY Ridwan and Hung [2023]

6 Design And Methodology

6.1 Dataset

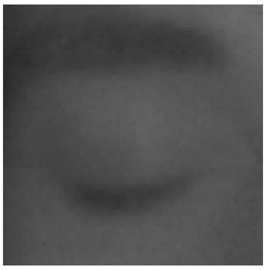

Figure 2: Eyes Closed

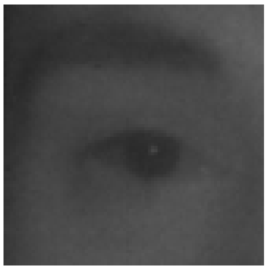

Figure 3: Eyes Opened

The MRL Eye DatasetFusek [2018] encompasses both low and high-resolution infrared images, capturing a diverse range of lighting conditions and utilizing different devices for data acquisition. With its expansive scope, the dataset provides a robust foundation for evaluating various features or training classifiers in the field. To facilitate algorithmic comparisons, the images are systematically categorized, enhancing their suitability for both training and testing purposes.

Within the dataset, annotations include distinctive properties presented in the following order: subject ID (data collected from 37 individuals), image ID (comprising 84,898 images), gender (0 for man, 1 for woman), glasses (0 for no, 1 for yes), eye state (0 for closed, 1 for open), reflections (0 for none, 1 for small, 2 for big), lighting conditions (0 for bad, 1 for good), and sensor ID (01 for RealSense, 02 for IDS, 03 for Aptina). This rich set of annotations offers a nuanced understanding of the dataset, facilitating diverse research applications and algorithmic evaluations.

6.2 Models

Inception V3:

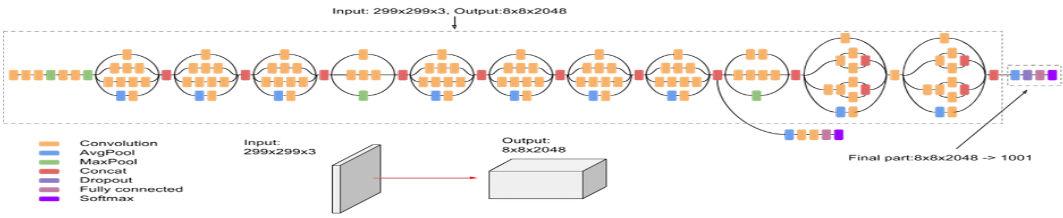

Figure 4: Architecture of Inception V3

Inception V3 is a powerful deep convolutional neural network architecture designed for image classification tasks. Comprising approximately 48 layers, this model introduces inception modules that perform parallel convolutions of different kernel sizes, including 1x1, 3x3, and 5x5 convolutions, along with pooling layers. Notably, factorization is employed to reduce computational costs. The architecture incorporates auxiliary classifiers at intermediate layers during training, contributing to enhanced gradient flow and regularization. Utilizing batch normalization for improved training, Inception V3 culminates with fully connected layers and a softmax activation for final classification. Trained on the ImageNet dataset, Inception V3 has approximately 23 million parameters.

EfficientNetB4:

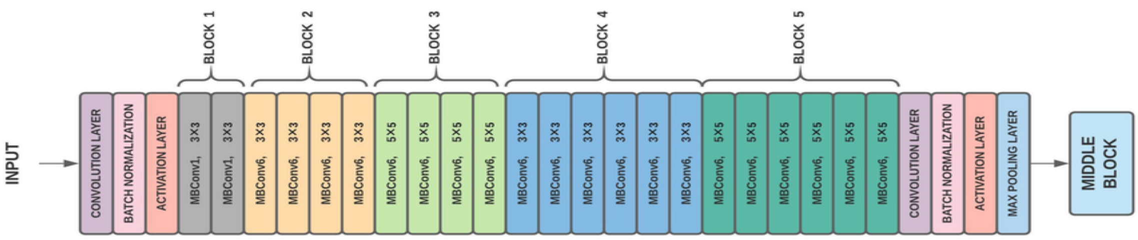

Figure 5: Architecture of EfficientNetB4

EfficientNetB4 is a convolutional neural network (CNN) architecture that belongs to the EfficientNet family, which is known for its emphasis on achieving high performance while maintaining computational efficiency.EfficientNetB4 consists of approximately

390 layers and approximately 19 million parameters. The architecture is particularly notable for its effectiveness in handling diverse computer vision tasks, including image classification and object detection. EfficientNetB4's training often involves datasets like ImageNet, and its lightweight yet powerful design makes it well-suited for resource-constrained environments.

MobileNetV2:

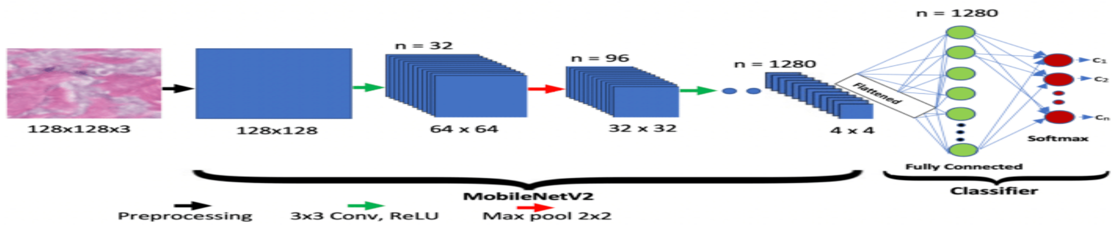

Figure 6: Architecture of MobileNetV2

MobileNetV2, an evolution of the original MobileNet architecture, stands out as a lightweight and efficient convolutional neural network designed for optimal performance on mobile and edge devices. With approximately 53 layers, MobileNetV2 introduces inverted residuals and linear bottlenecks to strike a balance between computational efficiency and model accuracy. The architecture's inverted bottleneck blocks, featuring lightweight depthwise separable convolutions, reduce computational costs while preserving valuable information flow. Notable design elements include the incorporation of skip connections for enhanced gradient flow during training and an expansion factor to control bottleneck layer dimensionality. MobileNetV2's suitability for resource-constrained environments, coupled with its versatility in tasks like image classification and object detection, has positioned it as a go-to choice for efficient neural network inference.

6.3 Proposed Architecture

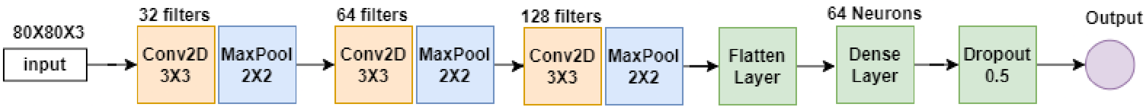

Figure 7: Architecture

Convolutional Layers:

The model starts with a convolutional layer with 32 filters and a 3x3 kernel, employing rectified linear unit (ReLU) activation. This is followed by a max-pooling layer with a 2x2 pool size for spatial downsampling. Subsequent convolutional layers with 64 and 128 filters, respectively, further capture hierarchical features in the input images, each followed by max-pooling for feature reduction.

Flatten Layer:

After the convolutional layers, a flatten layer reshapes the 2D feature maps into a 1D vector, preparing them for input into the fully connected layers. Fully Connected Layers:

The flattened features are fed into a dense layer with 64 units and ReLU activation, introducing non-linearity for enhanced representational power. To prevent overfitting, a dropout layer with a dropout rate of 0.5 is employed before the final output layer. The output layer consists of two units with softmax activation, facilitating binary classification.

Data Preprocessing and Augmentation:

The training data undergoes preprocessing and augmentation using TensorFlow's ImageDataGenerator. This includes rescaling pixel values to the range [0, 1], as well as applying various augmentation techniques such as rotation, shear, zoom, and horizontal/vertical shifts. Augmentation enhances model generalization by exposing it to diverse variations of the input images. The training data is further split into training and validation sets, with 80% used for training and 20% for validation.

Model Compilation:

The model is compiled using the Adam optimizer, categorical crossentropy loss function, and accuracy as the evaluation metric. The Adam optimizer adapts learning rates for each parameter individually, facilitating efficient training.

Training:

Training involves fitting the model to the augmented training data while validating on the separate validation set. The model aims to minimize the categorical crossentropy loss, and training progress is monitored using accuracy. Training on the provided dataset is crucial for the model to learn discriminative features for effective binary classification.

Test:

The model's performance is rigorously evaluated through a dedicated testing phase, utilizing separate images not encountered during training or validation. The testing data, preprocessed to maintain consistency with the training process, is fed into the Convolutional Neural Network (CNN) model. The model's predictive accuracy is assessed by calculating key metrics such as categorical crossentropy loss and accuracy.

6.4 Comparison

Name	**Total Parameters**	**Trainable Parameters**	**Accuracy**
InceptionV3	21934050	131266	0.83
EfficientNetB4	18706209	1032386	0.70
MobileNetV2	2995458	797474	0.81
MODEL	617730	617730	0.68

Table 3: Comparison between different architecture

The presented table provides a summary of key metrics for various pretrained neural network models, including InceptionV3, EfficientNetB4, MobileNetV2, and a custom model labeled as "MODEL." The "Total Parameters" column signifies the overall number of parameters in each model, while the "Trainable Parameters" column specifically denotes the parameters that are trainable during the fine-tuning or modification process. It is important to note that these pretrained models have undergone slight modifications, resulting in a subset of parameters being labeled as trainable.The "Accuracy" column represents the model's performance on the given task, showcasing the ability of each model to make accurate predictions.

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