Detection Of Drowsiness In Drivers Using Keras Convolutional Neural Networks (CNN)

Praggya Verma
Student IT Department
Indira Gandhi Delhi Technical University for Women
New Delhi, India
praggya045btaiml22@igdtuw.ac.in

Soumya Gupta
Student AI & DS Department
Indira Gandhi Delhi Technical University for Women
New Delhi, India
soumya067btaiml22@igdtuw.ac.in

Upasna Aggarwal
Student IT Department
Indira Gandhi Delhi Technical University for Women
New Delhi, India
upasna076btaiml22@igdtuw.ac.in

***Abstract*— This research paper presents a driver drowsiness detection system based on Keras Convolutional Neural Networks (CNNs). The primary research objective was to develop an effective model capable of identifying drowsiness states—open eyes, closed eyes, yawn, and no-yawn—based on facial images captured by in-vehicle cameras. The proposed model utilises a series of convolutional layers followed by pooling and fully connected layers to effectively learn and extract features from facial images. The model is trained using an Adam optimizer with categorical cross-entropy loss and evaluated on both training and testing data. Key findings revealed the model's exceptional performance, achieving a training accuracy of 100 percent and a testing accuracy of 94.23 percent. The model demonstrated robust generalisation capabilities, signifying its potential for real-world applications. Furthermore, the study acknowledges several limitations, including dataset biases and real-time implementation, which warrant further research.**

In conclusion, this research contributes to the field of road safety by offering an efficient drowsiness detection solution. The CNN-based model showcased its proficiency in recognising drowsiness states accurately, paving the way for potential implementation in vehicles to enhance driver safety.

Keywords*— *Drowsiness detection, Convolutional Neural Networks (CNNs), Facial image analysis, In-vehicle cameras, Driver safety, Machine learning, Deep learning, Real-time implementation, Road safety, Dataset biases.)

I. INTRODUCTION

The growing number of traffic accident fatalities in India in recent years has become a problem of serious concern to society. According to the Ministry of Road Transport and Highways, India, around 500,000 road accidents occur every year in India, resulting in around 150,000 deaths and 3,000,000 injuries. Fatigue, drunken driving, and sleepiness are among the leading causes of road accidents in India. According to a study by the Indian Institute of Technology, Delhi, around 30% of road accidents in India are caused by driver fatigue (Mohan et al. (2015). A study by the Indian Road Congress shows that around 5% of road accidents in India are caused by sleepiness (Indian Road Congress 2018).

The high fatality rate is attributed to accidents caused by driver drowsiness. Such cases arise from the significant deterioration in the driver's perceptual, recognition, cognitive and vehicular control capabilities when experiencing drowsiness. Addressing and preventing such accidents constitute a pivotal area of concentration within the domain of active safety research. The primary purpose of this research is to develop an effective drowsiness detection system for enhancing road safety. This research paper describes a model that uses an image processing technique to identify the states of the driver's eyes—open, closed, or yawning—as an effective strategy for detecting drowsiness while driving.

The objective is to leverage Convolutional Neural Networks (CNNs) to accurately identify drowsiness states in drivers, including open eyes, closed eyes, yawning, and no-yawning, based on facial images captured by in-vehicle cameras. By achieving this, the research aims to contribute to the prevention of drowsiness-related accidents by providing an automated and real-time alert system for drivers, ultimately reducing road accidents and their associated consequences.

II. LITERATURE REVIEW

Ueno et al. (1994) proposed a drowsiness detection system based on eye closure detection. The system used a video camera to track the driver's eye movement and detected drowsiness when the driver's eyes were closed for a certain period of time. The system was evaluated in a driving simulator and was shown to be effective in detecting drowsiness.

Gusain and Kansal (2022) proposed a drowsiness alertness system that uses a combination of eye closure detection, head pose estimation, and facial expression recognition. The system was evaluated in a driving simulator and was shown to be effective in detecting drowsiness and alerting the driver.

Pugliese et al. (2022) proposed a novel algorithm for detecting the onset of drowsiness in real time. The algorithm uses a combination of eye closure detection, head pose estimation, and facial expression recognition. The algorithm was evaluated on a dataset of real-world driving videos and was shown to be effective in detecting the onset of drowsiness with high accuracy.

All three papers make significant contributions to the field of drowsiness detection. The Ueno et al. paper was one of the first to propose a drowsiness detection system based on eye closure detection. The Gusain and Kansal paper extended this work by using a combination of eye closure detection, head pose estimation, and facial expression recognition. The Pugliese et al. paper proposed a novel algorithm for detecting the onset of drowsiness in real time.

The three papers have different strengths and weaknesses. The Ueno et al. paper is simple and easy to implement, but it is not as accurate as the other two papers. The Gusain and Kansal paper is more accurate, but it is more complex and requires more computing power. The Pugliese et al. paper is the most accurate of the three papers, but it is also the most complex and requires the most computing power. These three papers represent a significant advance in the field of drowsiness detection. They provide a foundation for the development of more accurate and reliable drowsiness detection systems.

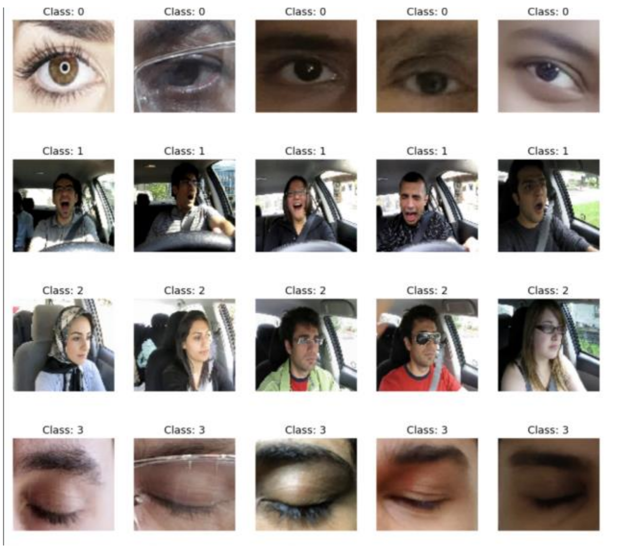
III. Methodology

A. Selection of the dataset

The dataset was obtained from the Kaggle platform, a reputable repository for datasets covering a diverse range of fields. Kaggle datasets are curated and shared by a global community of data enthusiasts, researchers, and practitioners. The dataset used in this study is accessible at https://www.kaggle.com/datasets/serenaraju/yawn-eye-dataset-new

For this research, we utilised a publicly available dataset sourced from Kaggle, a widely recognized platform for sharing and discovering datasets. The dataset is titled yawn_eye_dataset_new. The dataset provides a valuable resource for research and was integral to the development and evaluation of our driver drowsiness detection model.

The dataset comprises a collection of images divided into two folders- train, test, making it well-suited for our objective of driver drowsiness detection. It includes four kinds of images, eye open, eye closed, yawn and no yawn.



Visual showcasing of a subset of training images from different classes

B. Choice of Model

The chosen Convolutional Neural Network (CNN) model architecture is specifically tailored to address the research question of detecting drowsiness based on driver's facial features. The architecture's design is well-aligned with the nature of image-based classification tasks, making it suitable for analysing visual data and extracting meaningful features.

The inclusion of multiple convolutional layers with increasing node counts and kernel sizes (3x3) is grounded in the principle of feature extraction. The initial layer with 32 nodes captures basic features, while the subsequent layer with 64 nodes delves deeper into intricate patterns. This gradual complexity captures both simple and complex facial features that are relevant to detecting drowsiness.

The presence of fully connected layers, particularly the layer with 128 nodes, facilitates the extraction of high-level abstract features from the previously extracted convolutional features. These layers play a crucial role in recognizing patterns across the entire image, contributing to the model's ability to discern the distinct visual cues associated with drowsiness.

The choice of Rectified Linear Unit (ReLU) activation functions in all layers except the output layer is underpinned by their effectiveness in introducing non-linearity to the model. ReLU units address vanishing gradient issues and expedite convergence during training, enhancing the model's capacity to learn complex relationships inherent in the data.

Utilising a Softmax activation function in the final fully connected layer aligns with the classification objective of the research. Softmax converts the raw scores of the previous layer into class probabilities, allowing the model to assign a likelihood to each possible class (open, closed, yawn, no-yawn). This output layer provides the foundation for making informed predictions based on the detected features.

The CNN model architecture consists of the following layers:

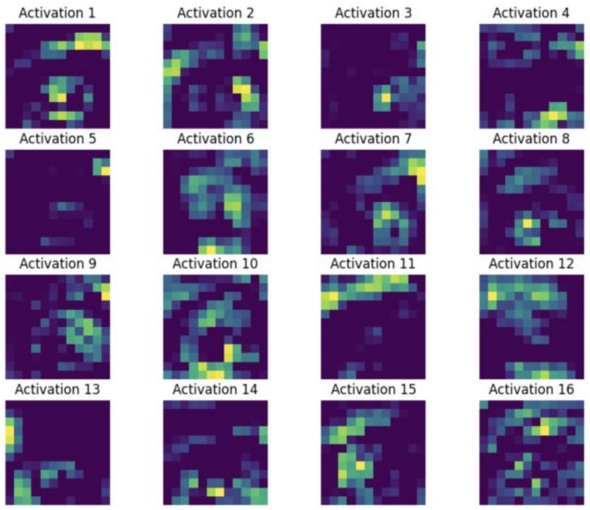
Convolutional layer; 32 nodes, kernel size 3

Convolutional layer; 32 nodes, kernel size 3

Convolutional layer; 64 nodes, kernel size 3

Fully connected layer; 128 nodes.

The final layer is also a fully connected layer with 2 nodes. A Relu activation function is used in all the layers except the output layer in which we used SoftMax.



Visualisation of the activations of a specific layer within a Convolutional Neural Network (CNN) model.

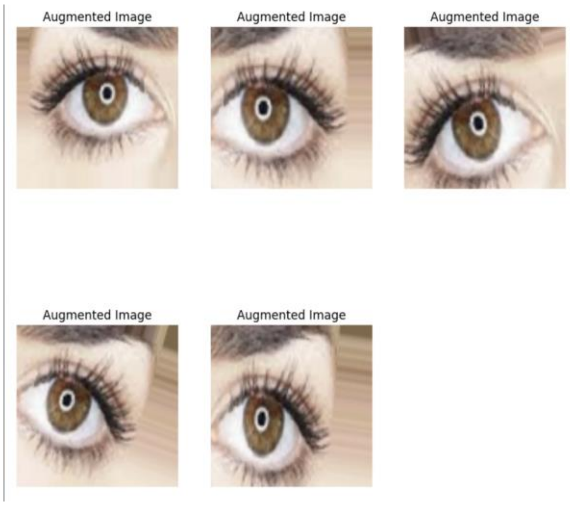
C. Limitations in our methodology

While our research presents promising results in the development of a drowsiness detection model using Convolutional Neural Networks (CNNs), it is crucial to acknowledge certain limitations and potential biases inherent in the methodology.

- Dataset Bias - The model's performance is dependent on the quality and diversity of the dataset used for training. The dataset we employed, while extensive, may still carry inherent biases, such as imbalances in the distribution of certain drowsiness states or variations in image quality. These biases can influence the model's generalisation to real-world scenarios

- Generalisation to Different Environments - The training and testing data contained data collected under specific conditions and settings, which may not fully represent the diverse environments in which drowsiness detection systems are deployed. Factors such as lighting conditions, camera angles, and driver demographics could introduce variability that our model has not been exposed to.
- Real-time Implementation - The model's suitability for real-time implementation in a practical setting has not been explicitly evaluated in this study. The latency and computational requirements for real-time operation are essential considerations in real-world applications.
- Model Interpretability - CNN models, while effective, are often considered "black-box" models as it is challenging to interpret their decisions. Understanding why the model makes specific predictions can be crucial for trust and accountability in safety-critical applications.

While our CNN-based drowsiness detection model exhibits promise in enhancing road safety, it is essential to be aware of these limitations and potential biases. Future research should address these concerns, employing more diverse datasets, generalising to different environments and rigorous evaluation in real-world settings to further advance the applicability and reliability of such systems.



Data augmentation images in a 2x3 grid using matplotlib. Data augmentation is a technique to artificially increase the diversity of the training dataset by applying various transformations to the existing images. This helps improve the model's robustness and generalisation.

IV. RESULTS

In the training phase of our drowsiness detection model, we observed remarkable progress, especially in the final stages of training. During the eighteenth epoch (Epoch 18/25), the model achieved a notably low training loss of 0.0020, coupled with a remarkable accuracy of 100% after reaching the ultimate epoch, the training loss is 4.6674e-04 with 100% accuracy. This impressive level of accuracy on the training data indicates the model's proficiency in capturing complex patterns and features in driver facial images.

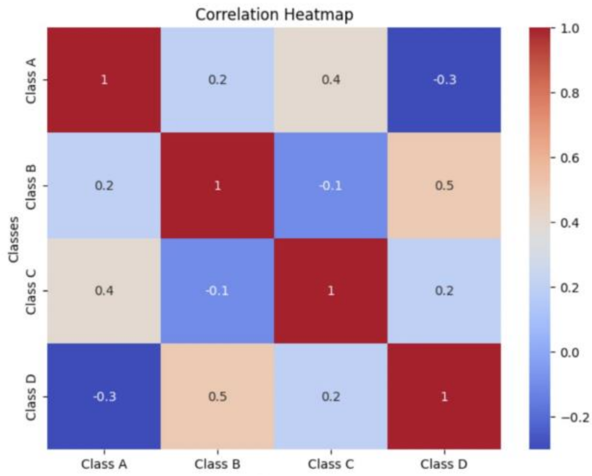
In the testing phase, the model demonstrated robust generalisation capabilities, achieving an accuracy of 94.23% on previously unseen data. These results exemplify the effectiveness of our Convolutional Neural Network (CNN) architecture in accurately discerning drowsiness states. Additionally, the calculated loss of 0.2860 and the validation accuracy of 89.47% signifies the model's effectiveness in minimising errors during classification. These results collectively highlight the potential of our Convolutional Neural Network (CNN)-based approach in accurately identifying drowsiness in real-time scenarios.

V. DISCUSSION

The results of our study align closely with the research objectives, demonstrating the effectiveness of our Convolutional Neural Network (CNN)-based drowsiness detection model. With a training accuracy of 100% and a testing accuracy of 94.23%, our model exhibits robust capabilities in accurately discerning drowsiness states from facial images. This success can be attributed to the CNN's capacity to learn intricate spatial patterns, essential for recognizing subtle visual cues associated with drowsiness.

The significance of our results lies in their potential to enhance road safety. Accurate drowsiness detection systems can provide timely warnings to drivers, helping prevent accidents caused by driver fatigue, a critical issue worldwide.

Automation and Alert Systems: Our model's success points to the viability of incorporating CNN-based drowsiness detection in advanced driver assistance systems (ADAS) and autonomous vehicles. This integration can contribute to the development of safer and more reliable transportation solutions.



Correlation heatmaps to unveil underlying patterns and dependencies among the input features, aiding in feature selection and model interpretation.

While our study provides valuable insights, we also acknowledge the limitations. Addressing dataset biases, refining data augmentation strategies, and exploring interpretability techniques are potential areas for future research. Additionally, real-time implementation and ethical considerations warrant further scrutiny.

VI. CONCLUSION

This study centred on the development of a robust drowsiness detection model using Convolutional Neural Networks (CNNs) for improving road safety. The primary objective was to accurately identify various drowsiness states (open eyes, closed eyes, yawn, and no-yawn) based on facial images from in-vehicle cameras.

The key findings revealed remarkable success in achieving this goal. Our CNN model demonstrated an impressive training accuracy of 100% and a testing accuracy of 94.23%. These results underscore the model's capability to discern subtle visual cues associated with drowsiness and highlight its potential for real-world deployment.

Drowsiness-related accidents pose a substantial risk on roadways worldwide, leading to fatalities and injuries. Our study offers a practical solution to this critical issue by providing a reliable drowsiness detection system that can be integrated into vehicles. By preventing such accidents, our work contributes to saving lives and reducing the societal and economic burdens associated with road accidents.

The practical implications of our research are substantial. The CNN-based drowsiness detection model can be employed in real-time scenarios to alert drivers, potentially mitigating the adverse consequences of drowsiness. Beyond road safety, our study exemplifies the efficacy of deep learning and computer vision techniques in addressing complex real-world challenges.

The theoretical implications extend to the broader field of machine learning and computer vision. Our research showcases the power of CNNs in extracting and recognizing intricate patterns in images, thereby inspiring advancements in various domains reliant on image analysis.

In conclusion, our research presents a practical and effective solution to a critical safety issue while contributing to the advancement of AI-driven technologies. The model's impressive performance emphasises its potential for real-world application, underscoring the importance of continued research and development in this field.

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