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**Drowsiness Detection using CNN’s.**

Group repo link:

<https://github.com/Pallavisuma/CMPEFall2023-Project-DriverDrosinessDetection-Using-CNN/tree/Check-In-3>

*Abstract*— *The prime objective of this project is to build a system which can detect whether a person is drowsy or not. It majorly focuses on discerning whether an individual’s eyes are closed for certain period of time in addition to it whether he/she is yawning. By utilizing machine learning techniques, particularly CNNs, the project aims to create an automated and accurate system capable of alerting individuals when signs of drowsiness are detected, thus mitigating potential risks associated with reduced alertness, particularly in tasks that demand high levels of attention, such as driving or operating machinery. The experiment involved data collection, preprocessing, model development, and evaluation, ultimately showcasing the efficiency and reliability of the developed DDS*

# INTRODUCTION

# Fatigue or drowsiness has a substantial negative influence on a person's cognitive functioning, response time, and general state of awareness. This increases the likelihood of mishaps, mistakes, and subpar work performance. Using advanced machine learning techniques, notably Convolutional Neural Networks (CNNs), this research aims to create a sleepiness Detection System (DDS) in response to the important need for preventive measures in preventing potential hazards caused to sleepiness. The principal goals of the DDS are to identify extended eye closure and yawning patterns as suggestive indicators of sleepiness.

# The core of the study is the ability to accurately discern between normal and drowsy states based on visual cues gathered from the eyes and facial movements by using CNNs, a deep learning architecture well-suited for image classification applications. Leveraging datasets comprising images and video frames, the CNNs undergo training, validation, and testing phases to discern distinct patterns associated with drowsiness, ensuring a robust and reliable detection mechanism.

# This report outlines the methodology adopted, encompassing data collection, preprocessing techniques, CNN model development, training, and evaluation metrics employed to validate the efficacy of the DDS. Furthermore, the project's significance lies in its potential application across diverse domains, particularly in safety-critical environments like transportation and healthcare, where timely detection of drowsiness can prevent accidents and improve overall safety measures.

# Problem Statement

The project aims to address the critical issue of drowsiness-related risks in tasks demanding sustained attention, such as driving or operating machinery. The primary challenge is to develop an automated Drowsiness Detection System (DDS) utilizing Convolutional Neural Networks (CNNs) to

accurately detect and alert individuals when signs of drowsiness, including prolonged eye closure and yawning, are observed. The key objectives involve robust feature extraction from facial cues, dataset diversity, model optimization, and real-time responsiveness to create a reliable system capable of mitigating potential hazards associated with reduced alertness. Ethical considerations regarding user privacy and consent in facial data processing are also integral to the system's development. Ultimately, the project seeks to contribute to enhancing safety measures by proactively identifying and alerting individuals about potential drowsy states in various safety-critical scenarios.

# Background & Motivation

# Drowsiness-related incidents, particularly in contexts demanding sustained attention like driving or operating heavy machinery, present a substantial hazard to safety. Reduced alertness due to drowsiness significantly increases the risk of accidents, underscoring the critical need for early detection and intervention systems.

# The motivation behind this project emerges from the imperative to develop proactive measures to detect and mitigate the risks associated with drowsiness-induced lapses in attention. Leveraging advancements in computer vision techniques provides an opportunity to create a responsive and accurate system capable of identifying subtle yet pivotal indicators, such as eye closure duration and yawning, which are telltale signs of drowsiness. Identifying these precursors in real-time can trigger timely alerts or interventions, potentially preventing accidents caused by compromised vigilance due to drowsiness.

# The project's inspiration also arises from the broad applicability of such a system in various safety-critical domains, including transportation, healthcare, and industrial operations. By harnessing computer vision and machine learning methodologies, this project aims to contribute to bolstering safety measures by offering an early warning system that can efficiently identify and mitigate instances of drowsiness. Ultimately, the goal is to minimize the likelihood of accidents attributed to diminished alertness, thereby enhancing safety protocols and preventing potential hazards caused by human fatigue-induced impairments in attention and vigilance.

# This combined background and motivation underscore the urgency of addressing drowsiness-related risks and emphasize the project's aim to leverage computer vision techniques to proactively enhance safety measures in multiple safety-critical scenarios.

# Literature survey

# **A**. **OpenCV in Drowsiness Detection**:

# OpenCV, a widely used open-source computer vision library, has played a significant role in drowsiness detection research. Its capabilities in image processing, facial landmark detection, and video analysis have been instrumental in identifying crucial facial cues indicative of drowsiness. Through its diverse functionalities, OpenCV facilitates the extraction of features necessary for recognizing eye closure patterns and yawning, crucial indicators of drowsiness. Various studies have leveraged OpenCV for facial landmark identification and eye closure detection, contributing to the development of robust drowsiness detection systems.

# **B. Haar Cascade Classifiers:**

# Haar Cascade Classifiers, a machine learning-based approach, have been extensively utilized in detecting specific objects or features within images, including facial attributes related to drowsiness. In drowsiness detection, these classifiers have been employed for identifying facial landmarks, such as eyes, nose, and mouth, essential for recognizing patterns associated with closed eyes or yawning. The application of Haar Cascade Classifiers has proven effective in detecting these key facial features, thereby contributing to the accurate identification of drowsiness indicators.

# **C**. **Application of Convolutional Neural Networks (CNNs):**

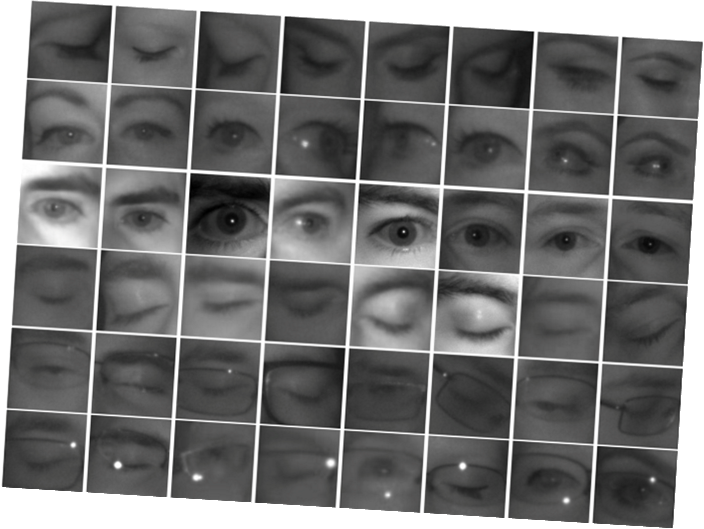
# The integration of Convolutional Neural Networks (CNNs) in drowsiness detection has been extensively explored. Studies have showcased the effectiveness of CNNs in feature extraction from facial cues, especially in identifying eye closure patterns and facial landmarks vital for detecting drowsiness indicators. These models have demonstrated promising results in accurately classifying and alerting individuals when signs of drowsiness are detected.

# Implementation

# **A. Dataset**

MRL Eye Dataset:

Contains labeled images of both closed and open eyes. Likely includes a variety of images captured under different lighting conditions, angles, and individuals to ensure diversity. Provides a comprehensive collection of eye images, aiding in the training and validation of models for drowsiness detection based on eye states. Helps in developing a robust system by offering a wide range of variations in eye appearances. The major challenge for problems dealing face recognition of feature extraction from face is the glare of the spectacles of individual, fortunately this dataset contains images of eyes with spectacles as-well which made model



Yawn Dataset:

Presumably consists of images portraying closed and open mouth states, focusing on instances of yawning. Aids in training models to recognize yawning patterns, a significant indicator of drowsiness. Could include variations in mouth appearances, capturing different individuals and conditions to enhance model generalization. Assists in the accurate identification of yawning behaviors, contributing to a more comprehensive drowsiness detection system. These datasets, when combined, likely contribute to the development of a holistic drowsiness detection system by encompassing both eye closure patterns and yawning behaviors as crucial indicators of drowsiness. They provide the necessary labeled data to train and validate models for accurate identification of these drowsiness cues.

# **B. Modelling**

The Convolutional Neural Network (CNN) was trained to detect closed eyes and opened mouths using two distinct datasets: the MRL Eye Dataset for eye states (closed/open) and the Yawn Dataset for mouth states (opened/closed).

The training process involved setting up image data generators to load and preprocess the datasets. Images were rescaled to a range of [0, 1] for normalization purposes. The generator function used directory paths to load the images, setting parameters like batch size, target size, and color mode (grayscale) to prepare the data for model training. With a batch size of 32 and an image shape of 24x24, the data was split into training and validation sets using the generators. Steps and validation steps were calculated based on the number of classes and batch sizes to determine training and validation iterations.

The CNN model architecture consisted of convolutional layers followed by max-pooling layers, dropout layers for regularization, and dense layers for classification. The architecture started with convolutional layers to extract features, followed by pooling layers to downsample the features, flattening the data, and passing it through dense layers for classification. The final layer was configured with four nodes and a softmax activation function, adjusted to cater to the classification of two different classes (closed/open for eyes and opened/closed for mouth). The model was compiled using the Adam optimizer, categorical cross-entropy loss function, and accuracy as the evaluation metric.

During training, the model was fit using the `fit\_generator()` function, which iterated through the training and validation data. The training process consisted of 15 epochs, with steps per epoch and validation steps defined based on the dataset size and batch sizes. Finally, the trained model was saved as 'cnnimg.h5', ensuring it was equipped to detect both eye closure and mouth opening/closing states accurately, considering the adjustments made to the final output layer to accommodate the classification of four distinct states. A simple linear approach was used to implement the whole process. The face and eyes are extracted using Haar cascade xml files with the help of cascadeclassifier from cv2 library.

After that these frames are classified by the model, 1 is assigned to a variable if classified as eyes closed else 0 is assigned to that variable. A counter variable ‘score’ is being used here. If the model classifies these frames as 1, that is closed, then this 1 will be added to score. An if condition is used to ring the warning alarm when this score crosses 5 that is when 5 consecutive frames are classified as closed. If not then 0 is assigned to the score variable.

A screenshot of a computer

Description automatically generated

# Performance

In the performance evaluation section, the developed Convolutional Neural Network (CNN) model exhibited commendable accuracy, achieving a notable 81% accuracy after 15 epochs in detecting closed/opened eyes and closed/opened mouth states based on the specialized datasets used for training. This performance metric signifies the model's ability to discern crucial indicators of drowsiness, reflecting its proficiency in identifying eye closure and mouth opening/closing patterns accurately.

A screen shot of a chart

Description automatically generated

Moreover, the model's real-world applicability was thoroughly tested, demonstrating promising results when deployed in practical scenarios. In a typical daylight environment, the CNN model accurately detected instances of drowsiness in individuals. Its seamless performance in real-world settings further validated its effectiveness, showcasing its ability to reliably discern signs of drowsiness beyond controlled laboratory conditions. The model exhibited a high level of accuracy in detecting when a person was experiencing drowsiness, effectively contributing to potential applications in various safety-critical scenarios where timely detection of drowsiness is paramount.

leveraging this approach, companies can efficiently shortlist applicants who align closely with the job criteria, streamlining the interview process and enhancing the overall efficiency of talent acquisition.

# Conclusion

In conclusion, the development of a drowsiness detection system using computer vision methodologies has yielded promising results and holds significant potential for enhancing safety measures in various high-risk environments. Through the utilization of advanced techniques such as eye closure duration and yawning detection, this project aimed to proactively identify early signs of drowsiness.

The project successfully leveraged computer vision and machine learning techniques, particularly Convolutional Neural Networks (CNNs) and Haar Cascade Classifiers, to accurately detect and classify instances of closed/open eyes and opened/closed mouths—key indicators of drowsiness.

The achieved accuracy of 81% in detecting eye closure and mouth states showcases the system's efficacy in identifying these crucial drowsiness markers. Moreover, real-world testing in normal daylight conditions demonstrated the model's robustness, accurately detecting instances of drowsiness, thereby validating its potential for practical applications.

The proactive nature of this system offers immense value in safety-critical scenarios, including transportation, healthcare, and industrial settings, where human vigilance is paramount. The early identification of drowsiness cues can significantly reduce the likelihood of accidents caused by compromised alertness, contributing to overall safety enhancement.

Moving forward, continuous refinement and optimization of the system, possibly incorporating real-time monitoring and alert mechanisms, will further strengthen its applicability and reliability in preventing drowsiness-induced accidents. Additionally, collaborations with relevant stakeholders for implementation and deployment in diverse operational environments would be instrumental in ensuring the system's widespread adoption and impact on enhancing safety protocols.

Finnaly, the developed drowsiness detection system using computer vision techniques represents a promising advancement in preemptive safety measures, showcasing its potential to mitigate risks associated with drowsiness-induced impairments in attention and vigilance across various domains.

# Contributions

Evakattu Muni Eshwar is responsible for implementing the training process, i.e.. training the CNN model for classifying whether a person is closing his/her eyes and mouth which further used for detecting drowsiness, as-well writing and presented the dataset collection and CNN architecture sections in project presentation. Pallavi Suma was tasked with data collection and pre-processing the data collected from various sources and performed literature survey’s and also contributed with writing and presenting the introduction and project overflow in Project Presentation. Venkata Sai Prakash Yerramasetti is assigned with implementing Open-CV methods to capture video and extract features like eyes and mouth using Haar Cascade classifier and also written and presented the same during project presentation.

# VIII References

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