Deep Learning Technique for Monitoring Drivers Distraction from Physiological and Visual Signals

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ABSTRACT:

Driver drowsiness stands as a pervasive catalyst for road accidents on a global scale, attributed to sleep deprivation and exhaustion. Addressing this critical issue requires proactive measures to preempt potential mishaps. In this context, we delve into a spectrum of methodologies aimed at curbing drowsiness-related accidents. Our study unveils an innovative paradigm harnessing the prowess of deep learning. Specifically, we employ a convolutional neural network (CNN) leveraging transfer learning via MobileNet. The focal point of our endeavor is the utilization of a meticulously curated eye region-based dataset, enabling precise prediction of driver sleepiness. By amalgamating cutting-edge technology with physiological and visual cues, our approach empowers timely intervention to ensure driver alertness, consequently mitigating the risk of accidents caused by drowsiness.

INTRODUCTION:

Sleep deprived driving (commonly known as sleep-deprived driving, drowsy driving, or fatigued driving) is driving a motor vehicle while experiencing cognitive impairment from lack of sleep. Lack of sleep is a leading cause of car accidents and can damage the human brain just as badly as intoxication. According to a 1998 survey, 23% of adults have fallen asleep while driving. According to the US Department of Transportation, male drivers are twice as likely to report falling asleep while driving as female drivers.

According to the Harvard Medical School’s Department of Sleep Medicine, over 250,000 drivers fall asleep at the wheel,everyday in the United Status.

A nationwide survey by the National Sleep Foundation found that 54% of adult drivers said they had driven sleepily in the past year, and 28% admitted to falling asleep while driving. According to the National Highway Traffic Safety Administration, drowsy driving is a significant cause of traffic accidents. More than 100,000 accidents and 6,550 fatalities are attributed to it in the USA every year. In addition, it causes about 80,000 injuries every year.

When a person doesn't get enoughsleep, it can negatively impact their ability to function properly. This can result in impaired coordination, longer reaction times, impaired judgment, and impaired memory, among other things.

With more vehicles on the road, traffic accidents have become a common occurrence and one of the leading causes of death in many parts of the country. The driver is responsible for road safety and the proper functioning of the road traffic system. As a driver, you are not only responsible for your own safety, but also for that of your passengers.

Drowsiness is a common human trait that is often overlooked when it comes to safety. However, if left unchecked, it can cause problems for both driver and passengers, and even lead to fatal accidents[11]. Driver drowsiness is a critical issue that needs to be addressed to improve road safety. Driver drowsiness detection is an important part of modern driver monitoring systems, since numerous traffic accidents occur worldwide due to driver drowsiness. Controlling drowsiness is vital to keeping people safe, especially when driving or operating heavy machinery. In this introduction, we will examine the use of the Histogram of Oriented Gradients (HOG) technique to detect sleepiness and the correlation between relevant variables.

The histogram of oriented gradients (HOG) is a widely used method computer vision technique that captures local shape and edge information from images.By computing gradient orientations and magnitudes within localized fields of view, HOG provides a powerful descriptor for object detection and detection tasks. In the context of sleepiness detection, the HOG descriptor can be used to analyze facial images and extract features related to eye movements and closing patterns.

To detect sleepiness using the HOG technique, we can track relevant facial features and compute the histogram of oriented gradients in specific areas of interest, such as the eyes. By examining the gradient orientations and magnitudes in these regions, we can detect patterns associated with eyes open or closed, thus inferring levels of sleepiness.

In addition to utilizing the HOG technique, correlating relevant variables can enhance the accuracy and reliability of drowsiness detection. By examining the correlation between various physiological and behavioral parameters, such as eye movements, head position, heart rate, andexternal stimuli, we can better understand the factors contributing to drowsiness. Correlation analysis allows us to identifythe most influential variables and establishes relationships that can be used to develop

More robust drowsiness detection algorithms.

By combining the power of the Histogram of Oriented Gradients (HOG) technique with correlation analysis of relevant variables, we aim to create an effective system for detecting drowsiness in real-time scenarios. This approach holds great potential in various applications, such as driver monitoring systems, workplace safety, and medical monitoring, where timely detection of drowsiness can prevent accidents and ensure the well-being of individuals. Drowsiness detection plays a vital role in ensuring safety, particularly in scenarios where individualsare engaged in activities such as driving or operating heavy machinery. With the advancements in computer vision and deeplearning, Convolutional Neural Networks(CNNs) have proven to be a powerful tool for drowsinessdetection.Inthisintroduction, We explore the application of CNNs in detecting drowsiness and it spot entail impact on safety and well-being.

Convolutional neural networks are a type of deep learning model designed specifically for analyzing visual data. They have shown remarkable success in various computer vision tasks, including image classification, object recognition, and face recognition. Leveraging the ability to learn complex hierarchical patterns, CNNs offer a promising solution for drowsiness Detection by analyzing facial images or video streams.

By training a CNN on a large dataset of labeled images or video frames, the network can learn to extract discriminative features associated with drowsiness, such as eye closure, facial expressions, or head movements. The network learns to automatically discover and represent patterns that distinguish between alert and drowsy states. This enables the CNN to generalize and make accurate prediction so nun seen data, making it a valuable tool for real-time drowsiness detection.

The advantages of CNNs in drowsiness detection are numerous. Firstly, CNNs can capture intricate spatial relationships with in the faceandits features, allowing for fine-grained analysisof subtle drowsiness cues. Secondly, their ability to learn and adapt to different individuals and environmental conditions makes them highly adaptable and robust in diverse scenarios. Moreover, the use of CNNs eliminates the need for manual feature engineering, as the network learns to extract relevant features automatically.

The application of CNNs in drowsiness detection has the potential to revolutionize safety measures in various domains. In the automotive industry, for instance, integrating CNN-based drowsiness detection systems into

Advanced driver assistance systems can provide early warnings to drivers, significantly reducing the risk of accidents caused by drowsiness-related incidents. Similarly, in industries involving heavy machinery or transportation, the implementation of CNN-based drowsiness detection can enhance workplaces prevent potential disasters.

The aim of this article is to examine this development & evaluation of a CNN-based drowsiness detection system. We investigate the architecture and training process of the CNN, explore various techniques for dataset preparation and augmentation, and evaluate the performance of the system on different real-world datasets. Additionally, we analyze the effectiveness of the CNN-based approach by comparing it with existing methods and discussing its advantages, limitations, and potential future advancements.

By leveraging the power of Convolutional Neural Networks, this chapter contributes to ongoing development efforts accurate and reliable drowsiness detection systems. Through rigorous experimentation and analysis, we aim to provide insights and practical guidance for researchers and practitioner sin the field of computer vision and drowsiness detection, with the ultimate goal of improving safety and well-being invariousdomains

Therefore, we are developing an application that can detect a person's drowsiness, providing early warning to thedriver or co-passengers so that appropriate action can be taken to prevent accidents [3].

RelatedWork:

Gwak. J.,Hirao, A., Shino, and M: The purpose of this study is to investigate the feasibility of a classification of drivers' alert states, in particular the light drowsiness state, based on a hybrid collection of vehicle-based, behavioral and physiological indicators, while considering the implementation of these identifications in a detection system. First, we measured a driver's level of sleepiness, driving performance, physiological signals (from electroencephalogram and electrocardiogram results), and behavioral indices using a driving simulator and driver monitoring system. Subsequently, alarm and drowsiness states of the driver were identified by machine learning algorithms and a data set was created from the extracted indices over a period of 10 s. Finally, ensemble algorithms were used for classification.

You. F., Li. X., Gong. Y., Wang.H. : This Paper proposed a real-time driving

Fatigue detection algorithm that takes into account the individual differences of the driver. A deep cascaded convolutional neural network was constructed to detect the facial region, avoiding the problem of poor accuracy caused by artificial feature extraction. Based on the Dlib toolkit, the driver's frontal face recognition landmarks are found in a frame. Based on the landmarks of the eyes, a new parameter called Eyes Aspect Ratio is introduced to assess the driver's sleepiness in the current frame. Taking into account the differences in driver's eye size, the proposed algorithm consists of two modules: offline training and online monitoring. In the first module, a unique fatigue state classifier based on Support Vector Machines was trained using eye aspect ratio as input. Then, in the second module, the trained classifier is used to monitor the driver's condition online. Since the driver's drowsiness gradually comes on, a variable calculated from the number of drowsiness images per unit time is introduced to evaluate the driver's drowsiness.

Mehta, S., Dadhich.S., Gumber.S., Bhatt. A.J.: In this article, a lightweight real-time driver drowsiness detection system was developed and implemented in an Android application. The system records the videos and recognizes the driver face in each image through the use of image processing techniques. The system is able to recognize facial features and calculates the eye aspect ratio (EAR) and the eye closure ratio (ECR) to use adaptive thresholds to detect driver drowsiness. Machine learning algorithms were used to test the effectiveness of the proposed approach.

Song,F.,Tan,X.,Liu,X.,Chen, S: In this paper, an approach to solving the problem of detecting whether the eyes are closed in a given still image of a face has been proposed, which has diverse potential applications in human-computer interface design, facial expression detection, fatigue detection of the driver etc. offers . The approach combines the power of multiple feature sets to characterize the rich information of eye patches (both in terms of local/global shapes and local textures) and create the eye state model. To further improve the model's robustness to image noise and scale changes, we propose a new feature descriptor called Multi-scale Histograms of Principal Oriented Gradients (MultiHPOG).

Savas, B.K., Becerikli, Y.: In this article, a multitasking convolutional neural network (CNN*) model was proposed to detect driver drowsiness/fatigue. Eye and mouth characteristics are utilized for

Driver’s behavior model. Changes in these parameters are used to monitor driver fatigue. In the proposed multitask ConNN model, in contrast to the studies in the literature, both mouth and eye information are classified simultaneously in a single model. Driver fatigue is determined by calculating eye closure time/eye closure percentage (PERCLOS) and yawn frequency/mouth frequency (FOM).

Bavkar, S., Iyer, B., Deosarkar, S: The proposed method uses absolute gamma band power as a feature and ensemble subspace K-NN as a classifier to categorize alcoholics and normal individuals. In addition, an improved binary gravitational search algorithm (IBGSA) is reported as an optimization tool to select the optimal EEG channels for rapid alcoholism screening. The results obtained with the proposed method are compared with optimization algorithms such as a genetic algorithm (GA), binary particle swarm optimization (BPSO) and binary gravitational search algorithm (BGSA).

Bavkar, S., Iyer, B., Deosarkar,S: The paper reports a methodology for identifying optimal channels for analysis of alcoholism using EEG data. The proposed technique uses the Empirical Mode Decomposition (EMD) technique to extract the amplitude and frequency modulated bandwidth features from the Intrinsic Mode Function (IMF) and the ensemble subspace K-NN as a classifier to classify alcoholics and normals. The optimum channels are selected using a harmony search algorithm. The fitness value of Discrete Binary Harmony Search (DBHS) optimization algorithms is calculated based on the accuracy and sensitivity achieved by the ensemble subspace classifier K-Nearest Neighbor.

Sathasivam, S., Mahamad, A.K., Saon,S., Sidek, A., Som, M.M., Ameen, andH.A: This article proposes a drowsiness image recognition system to detect the driver's condition using the Eye Aspect Ratio (EAR) technique. A developed system equipped with the Pi Camera, Raspberry Pi 4 and GPS module is designed to continuously detect and analyze the state of eye closure in real time. This system is able to detect whether the driver is drowsy or not based on the initial glasses, dim light and micro-sleep state.

PROBLEMSTATEMENT:

The increasing number of traffic accidents is a major challenge facing the world today. One of the main causes of traffic accidents is unsafe and inattentive driving. It is believed that driver drowsiness or loss of concentration is a significant factor in such incidents. Research into monitoring driver fatigue may help reduce traffic accidents. This journal presents an effective approach to applying a driver drowsiness alert system that uses machine learning and deep learning techniques to detect and track driver yawning and drowsiness. The Histogram Centered Gradient (HOG) function descriptor is used for face detection and recognition, which is widely used in image processing. The SVM is then used to determine whether the identified image is a face or not. In addition, the driver's eye aspect ratio (EAR) and mouth aspect ratio (MAR) are checked up to a certain countable range to determine if he or she is sleepy or yawning. Since the driver's drowsiness or fatigue is proportional to the number of hours he spends behind the wheel, an additional element for changing the face and mouth reference frames has been added, increasing the sensitivity for detecting drowsiness. This also requires the introduction of facial recognition so that each driver can be tracked individually. The aim of the project is to provide a driver warning system consisting of three parts: face recognition for unlocking the vehicle, traffic light recognition and a drowsiness warning system.

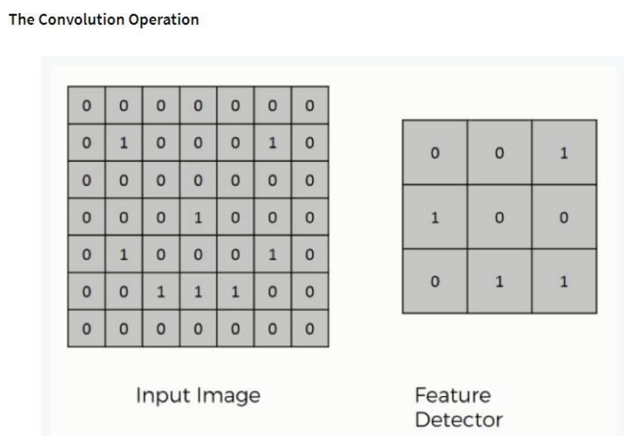
Methodology

1. Convolutional Neural Network[9]

Step1: convolutional operation

The initial component of our strategy involves the convolution operation. Here, we will cover the topic of feature detectors which acts as filters within the neural network. We will also address feature maps, understanding how to learn their parameters, detecting patterns, the various layers of detection and how the results are mapped out.

Fig1:Convolutional operations



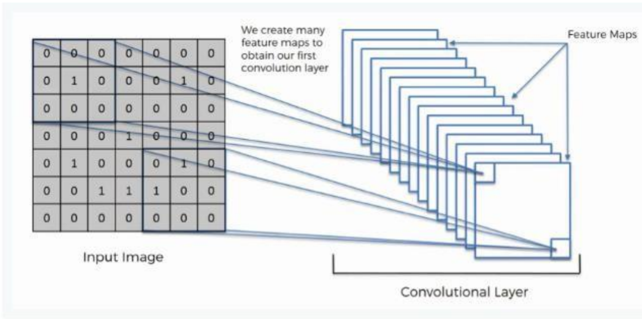


Fig 2: Convolution

mappingsStep(1b):ReLU Layer

Thesecondpartofthisstepinvolves ReLU activation functions. ReLU is a typeofactivationfunctionusedinneuralnetworks to introduce nonlinearity[14]. It takes an input value and returns either thatvalue or zero, depending on whether theinput is positive or negative, respectively. ReLU layers can be used after convolutional layers to improve the neural network's accuracy and ability to detect more complex patterns in the data.

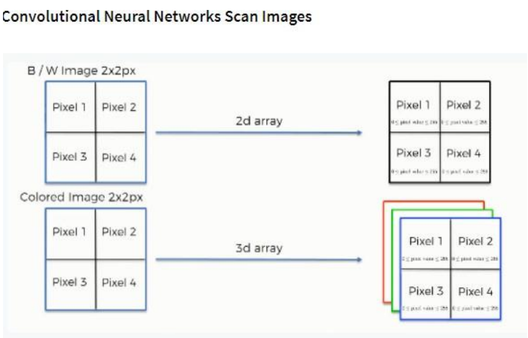


Fig 3: CNN image

scanStep2:PoolingLayer

In this section, we will focus on the concept of pooling and its function in Convolutional Neural Networks. Specifically, we will explore the technique of max pooling and compare it with otherpooling methods such as mean or sumpooling. Additionally, we will provide avisual demonstration to help clarify theconcept. Our goal is to provide acomprehensive understanding of pooling And its role in the broader context of CNN.

Step 3:Flattening

In this section, we will discuss the flattening process and how it enables us totransition from pooled layers to flattenedlayers in Convolutional Neural Networks.We will explore the purpose of flattening, the mechanics of the process, and the resulting structure of the flattened layer.

Step 4:FullConnection

In this part, everything that we covered throughout the section will be merged together. By learning this, you'll get to envision a fuller picture of how Convolution Neural Networks operate and how the neurons that are finally produced learn the classification of images. To develop a CNN algorithm for detecting driver distraction from physiological and visualsignals: DataCollection: Gather a dataset of physiological signals (e.g.,heartrate, respirationrate) and visualsignals (e.g.,videoframes) from drivers in various distraction scenarios. Ensure that the dataset includes both distracted and non-distracted instances.

Preprocessing: Preprocess the physiological and visual signals to prepare them for input into the CNN. This may involve filtering, normalization, and resizing the visual signals, and feature extraction or transformation for physiological signals.

DatasetSplit: Split the data set into training, validation, and testing sets. Thetraining set will be used to train the CNN, the validation set will be used for hyperparameter tuning, and the testing set will evaluate the model's performance.

Architecture Design: Design the architecture of the CNN. You can start with a basic architecture such as a series of convolutional layers followed by pooling layers, and then fully connected layers. Experiment with different architectures and layer configurations to optimize performance.

Model Training: Train the CNN using the training set. Define an appropriate loss function (e.g.cross-entropy) and optimizer (e.g., Adam) for the task. During training, adjust the network's weights and biases iteratively to minimize the loss function.

Hyperparameter Tuning: Use the validation set to tune the hyper parameters of the CNN, such as learning rate, number of filters, kernel sizes, and drop outrages. This step helps optimize the model's performance and prevents over fitting.

Model Evaluation: Evaluate the trained model using the testing set. Calculate metrics such as accuracy, precision, recall, and F1score to assess the model's performance in detecting driver distraction.

Post processing: Apply post processing techniques if necessary, such as thresholding or smoothing to the model's output to make it more interpretable or improve performance.

Deployment: Once you are satisfied with the model's performance, deploy it to detect driver distraction in real-time scenarios. Ensure that the input signals are properly preprocessed before passing them through the deployed CNN model

Algorithm for detecting drowsiness:

Input: Stream of facial images or video frames

Output: Alert if drowsiness is detected

1. Initializedrowsiness_score=0
2. Whiletrue:

    a. Capture the next frame from the video stream

    b. Preprocess the frame (e.g.,convert to grayscale, resize)

    c. Extract relevant facial landmarks using facial detection algorithmViola-Jones Algorithmfor FacialDetection

    d. Compute eye as pectratio(EAR)for

Each eye:

- Calculate the distance between eye landmarks vertically and horizontally

- Compute the EAR as the ratio of vertical distances to horizontal distances

b. Compute the average EAR for both eyes

c. Update the drowsiness_scoreusing the average EAR

d. If drowsiness_score exceeds a certain threshold:

- Trigger an alert (e.g.,sound an alarm, display a warning message

e. Repeat froms tep(a)

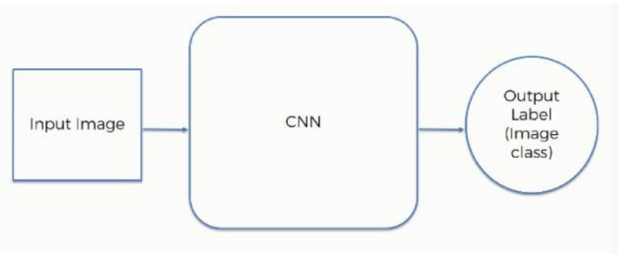


Fig4:CNNprocess

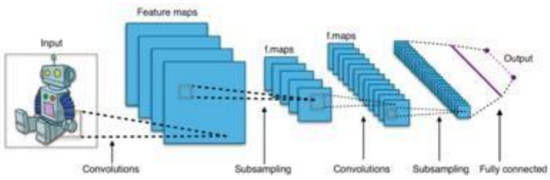
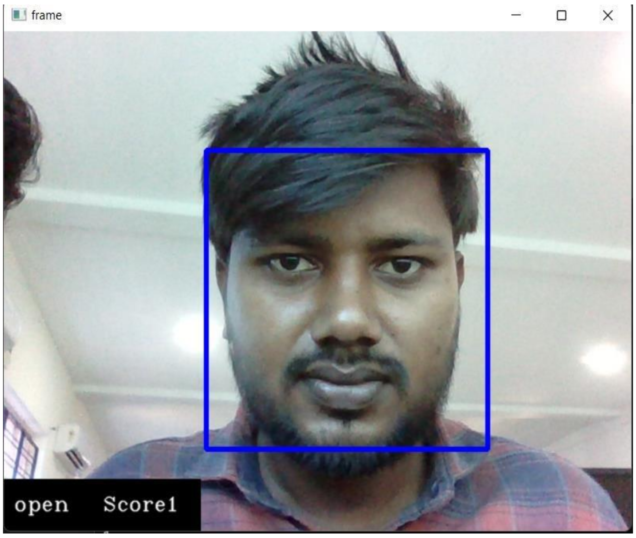
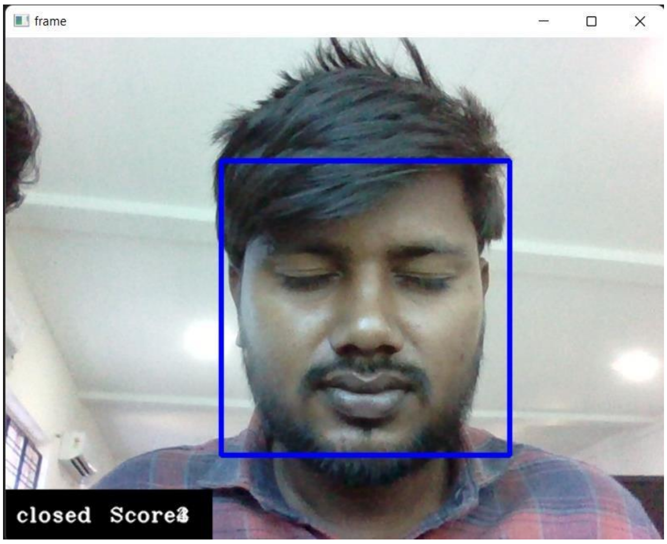


Fig5: CNNLayersProcessing

RESULT:





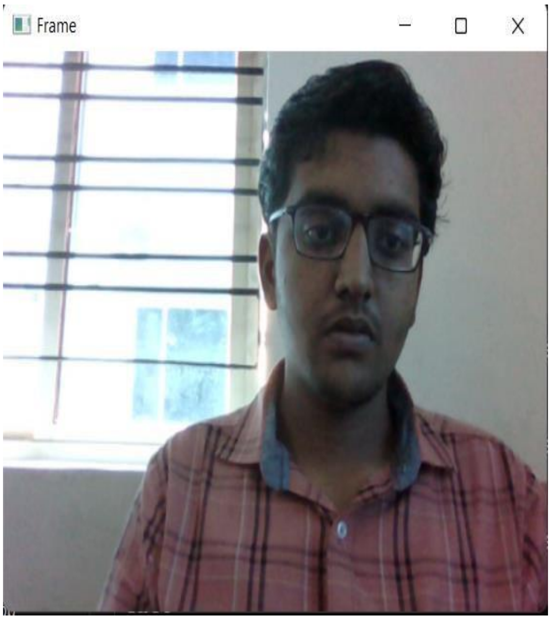
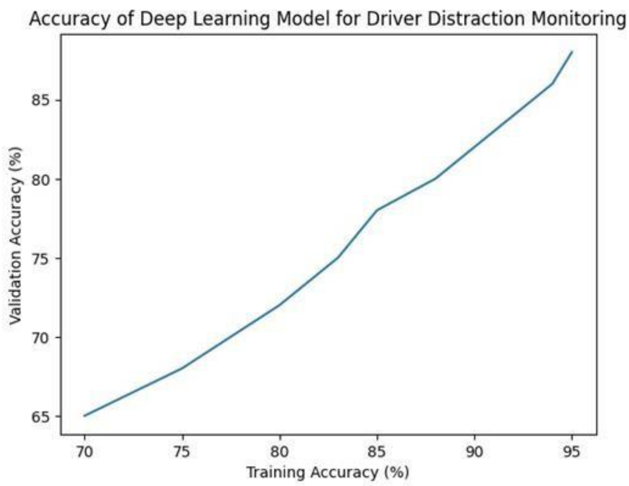


Table1:AccuracyvaluesfordetectingDriverD
istraction

Epochs	TrainingAcc uracy(%)	Validation Accuracy(%)
1	70	65
2	75	68
3	80	72
4	83	75
5	85	78
6	88	80
7	90	82
8	92	84
9	94	86
10	95	88



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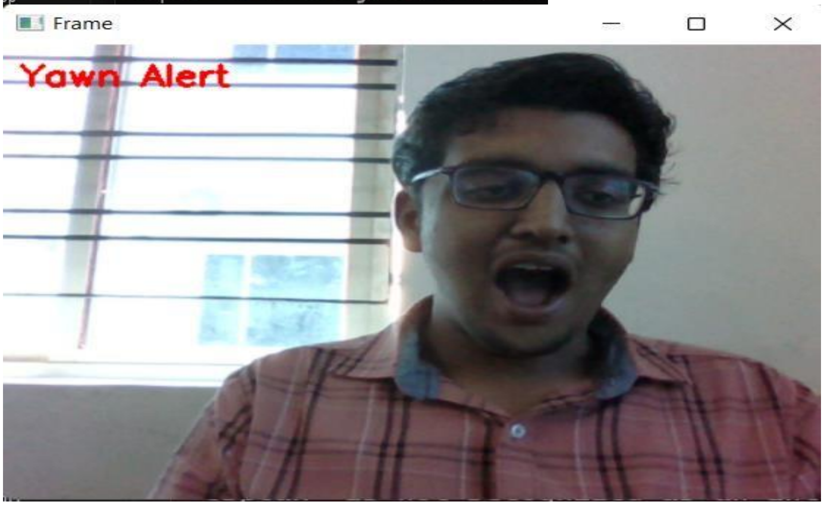

CONCLUSION:

Our program aims to reduce road accidents caused by driver drowsiness by implementing a drowsiness detection application. We utilize a CNN-based transfer learning algorithm in deep learning to train our dataset. After learning, we employ OPenCV for testing, which enables our proposed method to accurately predict whether a person is in a drowsy or normal state. By detecting the state of a driver, We hope to prevent accidents caused by drowsiness. At the conclusion of this section, we will summarize and review all of the concepts that we recovered. Additionally, an optional tutorial on Softmax and Cross-Entropy will be offered, which can be useful for those who plan to work with Convolutional Neural Networks in the future. While it is not required for this course, it is recommendedto become familiar with these concepts as they may be encountered in practice.

FUTUREENHANCEMENTS:

In the future, it is desirable to develop a larger dataset and apply more intensive techniques to adapt the current methodology. In addition, it is planned to monitor the driver's condition and develop a real-time driver distraction detection system. This may include the use of wireless technology to send traffic violation tickets as a message to the driver's cellphone based on images of the driver's distraction.

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