Driver Drowsiness Detection

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Abstract: This article outlines the development of a driver sleepiness detecting ADAS (advanced driving assistance system). The system's objective is to alert drivers about their fatigue in order to reduce the risk of accidents. the capacity to recognise fatigue in a driving situation. The process must be unobtrusive and make sure the driver is not bothered by notifications and awake. Our method for tackling this open challenge makes use of image sequences that last 60 s and are taken in a way that makes it possible to view the subject's face. Two different strategies are devised, each focusing on reducing false positives, to determine whether the driver exhibits signs of fatigue or not. The first method employs recurrent and convolutional neural networks.

Keywords: This article contains the keywords convolutional neural networks, recurrent neural networks, fuzzy logic, computer vision, ADAS, and drowsiness.

I.INTRODUCTION

Drowsiness is defined as "the propensity to fall asleep." Non-Rapid Eye Movement (NREM) sleep, while fully awake, and The three phases of rapid eye movement (REM) sleep comprise the time between being awake and going to sleep. NREM and REM sleep cycles occur during the course of sleep. Deep yet dreamless sleep is a hallmark of NREM sleep[1,2]. Autonomic physiological activity is seen to be incredibly low during this sleep stage. The majority of sleep—between 75 and 80 percent—takes place in NREM. NREM sleep is also referred to as slow-wave sleep. All of the remaining 20 to 25 percent consists of REM sleep. NREM I signals the start of a sleep episode, which can last 1 to 7 minutes and takes up 2 to 5% of the overall sleep period What is commonly perceived as weariness is actually a Sleep Onset (SO)[3] transition from being awake to sleeping. One of the primary factors contributing to significant road fatalities has been identified as driver weariness, which results in sleepiness.

II.VARIOUS DROWSINESS DETECTION TECHNIQUES

Researchers employ three different strategies, as seen in fig. 1, to identify sleepiness. I) Image processing-based methods II) Artificial neural network-based techniques III) Electroencephalography-based methods.

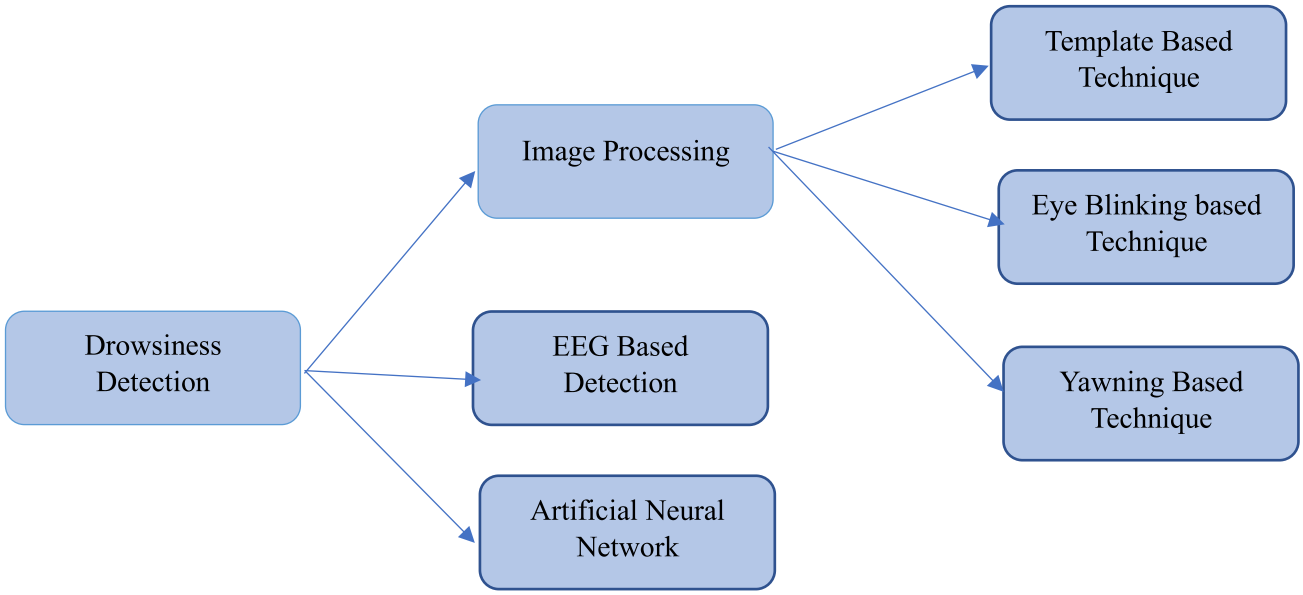

Fig 1: Various Methods for Detecting Drowsiness.

A. Techniques Based on Image Processing

Drivers' faces are processed using image processing techniques so that its states may be determined. using the driver's state of wakefulness or sleep may be seen on the facial picture. The same photos may be used to characterise the level of driver tiredness since the driver's eyelids are closed in the photograph if the driver is sleeping or nodding off. Additionally, various signs of sleepiness can be seen from the facial picture. These methods may be divided into three subgroups.

Template Matching Technique: Using the Template Matching Technique, the system will inform the driver if they close their eye(s) for a predetermined amount of time. Because the template used by the driver in this method has both closed and open eyes. It is possible to teach this system to record the driver's Eyes-open and-closed template..

(i)

(ii)

Fig 2: Eyes-open and-closed template.

Because the system already has templates for both the open and closed eye states depicted in fig 2, this solution is straightforward and simple to apply. This approach has been adopted by researchers[4].

Eye Blinking Based Technique: This method measures how quickly and how long a person's eyelids stay closed to determine whether or not they are sleepy. Driving when tired is easy to spot since drowsy drivers exhibit different patterns of eye blinking and the gap between their eyelids. To determine the frequency and duration of blinking, this technology tracks the position of the irises and the health of the eyes over time[5]. This kind of gadget records footage using a remote-controlled camera, which is afterwards analysed using computer vision algorithms to localise the face, eyes, and eyelids and calculate the percentage of closure[6]. By observing a driver's eyelid closure and blink rate, one can determine whether or not they are sleepy.

Technique Based on Yawns: One sign of weariness is the want to yawn. According to legend, the yawn has a wide vertical mouth opening. When yawning, the mouth opens wider than when speaking. You can identify yawns by first observing the lips, then the face. In article [6], they describe how to recognise yawning using the speed at which the mouth opens and the size of changes in the mouth contour area (figure 3). Instead of using just one technique, some studies[1,2,3] used different vision-based image processing methods to detect driver fatigue. The result has been improved performance.

B. EEG Based Technique

EEG signals are claimed to be significantly connected to alertness, sleep, and cognition and thus serve as an ideal instrument in defining drivers' tiredness while driving because the human brain is the centre of any reaction to a specific stimulus[9,10]. The EEG spectral power (delta, theta, alpha, and beta bands), the amplitude and latency of the third and highest positive peak (P300) of Event Related Potential (ERP), and the EEG signal entropy are the characteristics that are typically employed to assess driver weariness. To find the precise location on the scalp that produces the best results in sleepiness detection, EEG data are primarily collected from several brain regions.

Fig 4: EEG data acquisition system

The scalp EEG is another common way to collect data. The experimental results of[7] indicate that electrode location is crucial for acquiring EEG data from volunteers. According to the study, the EEG alpha intensity in the central to occipital lobes may be utilised as a reliable indicator of fatigue for each participant in this experiment. After a 20-minute driving activity, [8]captured a consistent increase in alpha and theta spectral power at the occipital region with an accuracy of roughly 82.8%. 12 male volunteers between the ages of 22 and 27 have been collected for the research mentioned in [11]. This study shows a significant drop in beta band power following a 120-minute driving workout in the frontal, central, and temporal areas (p 0.05). Theta (frontal, central, and occipital) and alpha (central, occipital, parietal, and temporal) power levels also significantly rise throughout the task (p 0.05).

C. Artificial Neural Network Based Technique

The recommended system must first be used to gather and pre-process the pertinent data. The desired traits are then extracted, including PERCLOS, the maximum amount of time the eyes may be closed, and blink frequency. Several classifiers are then given the extracted features in order to assess whether the recovered characteristics belong to an awake or sleepy person. These classifiers include artificial neural networks (ANN), logistic regression, KNN, and SVM. The final findings showed that the KNN and ANN models performed the best, with accuracy rates of 72.25% and 71.61%, respectively.

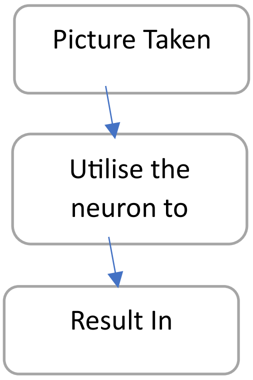

Fig 5: Operation of ANN

The goal of deep learning is to replicate the functions and principles of the human brain[12]. Since artificial neural networks (ANNs) are used in a thick, multi-layered network, the name "deep learning" is largely warranted. Deep learning employs automatic/implicit feature extraction and selection. When given a lot of unstructured data as input, deep learning models perform better and produce better results. Neural networks are effective at classifying targets and grouping information. They serve as a layer of classification and grouping for the information that is managed, processed, and stored.

III.MATERIALS AND METHODS

Determining the frame rate that the camera must deliver to the system in order to record the driver is crucial. A low frame rate might have a substantial impact on the system's performance, while a high frame rate could overload the system because to the vast amount of frames per second (FPS) that must be evaluated. To understand elements of the picture sequence that are only visible for incredibly brief periods of time, such blinks, this sector must have a frame rate that is high enough.

The typical blink lasts 100–400 ms, hence this study employs 10 FPS, which is sufficient to identify blinks without overtaxing the system. Every time a new frame is recorded by the camera, this analysis is run on 600 frames. In order to accomplish this, the system remembers the previous 599 frames, making it possible to analyse a complete 60 s of video at any given time. 10 FPS is the rate that is employed, which is sufficient to identify blinks and prevent system overload.

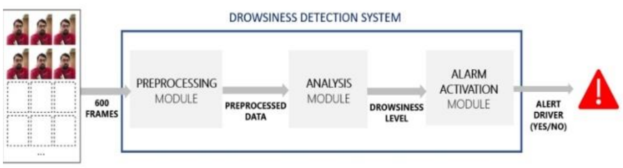

Fig 5: shows the overall system.

As seen in Fig. 5, the system gets 600 frontal pictures of the driver, or the preceding 60 seconds, captured at a frame rate of 10 frames per second (FPS) by a camera mounted on the car (for example, on the driver's dash).

Recurrent and Convolutional Neural Network

In this instance, the analysis module is a recurrent and convolutional neural network, or "recurrent CNN". This recurrent CNN is in charge of calculating a numerical output that displays the driver's estimated level of sleepiness in order to estimate the driver's level of weariness at any given time. The alarm activation module chooses whether or not to sound the associated alert after obtaining this value.

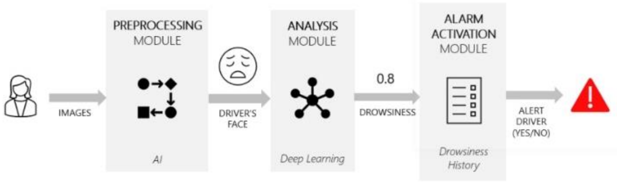

Fig 6. Alternative

Fig 6 depicts a flowchart of the system's three stages of operation, which are described in this section.

Preprocessing

We next scale the face to 64 64 pixels, which allows us to maintain the face's fine features while also drastically reducing the computing time needed to analyse each image.

A histogram equalisation is then used to alter the contrast of the image in order to remove unnecessary features. We employ ImageNet mean subtraction[14], a method that lessens the likelihood that the classification will be affected by the image's lighting, to carry out transfer learning using models that have been trained in the ImageNet domain. An illustration of the earlier processing.

IV. A REVIEW OF SLEEP DETECTION BASED ON IMAGE PROCESSING

It is suggested to employ a non-intrusive prototype computer vision system to continuously check a driver's alertness[2]. It is composed of hardware that uses an active IR illuminator to capture a driver's visuals in real-time and software that tracks specific visual behaviours that indicate a driver's level of awareness. They utilised the percentage of eye closure (PERCLOS), the length of eye closure, fixed gaze, blink frequency, and frequency of nodding. The four main modules of the system are as follows: Image gathering is the first phase, followed by pupil detection and tracking, visual preferences, and driver awareness. By using visual signals and pupil detection, they can detect tiredness. This system can automatically initialise and reinitialize as necessary and is completely independent. The system's functionality declines during the day, especially on sunny days, and it currently does not function while a driver is wearing spectacles.

Fig 8: General Architecture of Drowsiness Detection

Here, the pictures are preprocessed utilising AI (linear SVM coupled with HOG and an ensemble of regression trees) and deep learning (pre-trained CNN). The objective is to identify numerical traits that may be added to a fuzzy inference system (FIS). The driver's assessed degree of weariness is then represented by a value produced by the FIS. Based on this value, the system may then choose whether to raise an alert.

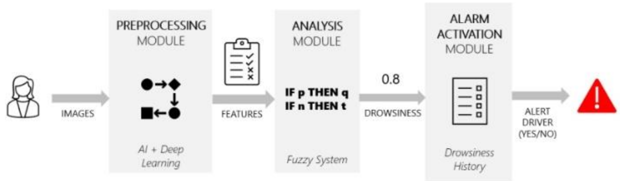

Fig 7 Fuzzy Logic

Fig 7 depicts a flowchart of the system's three stages of operation, which are delineated in this section.

V.CONCLUSION AND RESULT

This study's recommended sleepiness detection technique can reliably identify tiredness. Because it is being deployed on a distributed design, it may avoid the issues that arise when essential systems are deployed on centralised architectures. The sleepy detection process involves two detection phases: local detection via facial expression analysis and global detection via the integration of local and driving behavioural detections. For the mouth and eye classifiers, the results using CNN models are 97.3% and 98.2%, respectively. The output of the two classifiers and the information from the accelerometer in the automobile are combined to calculate the total level of fatigue. The next research will assess the driver's level of weariness using other factors including heart rate and sensor body measures.

The first recommended method uses a deep learning model to integrate a convolutional and recurrent neural network to determine how tired the driver is. The second method must first use deep learning and artificial intelligence to calculate fatigue to get the data ready for the fuzzy inference system.

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