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# A Review on Drowsiness Detection using Raspberry Pi and Recent Advancements in Physiological Techniques

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*Abstract* - The purpose of this paper is to review the various Drowsiness Detection techniques that make use of Raspberry Pi for processing. Driver drowsiness detection stands as a field where a plethora of researchers from medical professionals to computer scientists have proven their mettle. As we are witnessing an era of rapid technological advancements with the likes of Artificial Intelligence & Internet-of-Things on the rise, the researchers are shifting their focus from conventional processing systems to Microcontrollers and Microprocessors like the Raspberry Pi. While outlining the different techniques evolved using these processors and a method speed up their performance, some recent advancements that exploit different Machine learning and Deep-Learning techniques to accurate Physiological detection have also been mentioned. A comparative note has been presented in the end categorising the techniques and keeping driver convenience and detection accuracies in the view. The work also highlights why the country of India needs such safety mechanisms based on the report of the respective ministry.

*Index Terms* - Eye- blink sensor, Haar Cascades & Eye Aspect Ratio, FPS rate of Cameras on Raspberry Pi 4, Physiological Detection (EEG, ECG, EOG), Machine-learning models for Physiological techniques, Deep-learning model for Physiological techniques

## INTRODUCTION

The effect of drowsiness (sleepiness) while driving a vehicle can be hazardous. Most commonly such phenomenon is noted in four-wheeler Light motor vehicles (LMVs) and Heavy motor vehicles (HMVs). The report published by Ministry of Road Transport and Highways, Govt. of India entitled “Road Accidents in India-2019” (The Transport Research Wing of the Ministry of Road Transport and Highways, 2020) has tried to reflect the causes for various Driver-responsible accidents. Also, it tells how Indian traffic system stands at par with other countries in the list.

According to the report (The Transport Research Wing of the Ministry of Road Transport and Highways, 2020) a total of 151,113 people had lost their lives in 480,652 road accidents across India in 2019, an average of 414 a day or 17 an hour. India continued to have the most road fatalities in the world, followed by China, a distant second at 63,093 deaths in 2,12,846 road accidents in 2019, the report revealed. The United States of America (USA) reported 2,211,439 road accidents and witnessed 37,461 deaths in 2019. This report reveals why the necessity of developing proactive warning and safety systems is so important to make transport much safer.

From the report presented above, we wish to analyse the accidents in correlation with driver drowsiness which forms a small yet significant percentage of all the accidents. Hence, what can be clearly attributed to Driver drowsiness is the Category of “Drunken driving/Consumption of Alcohol & Drug” as it is known that consumption of alcohol does cause lethargy or confusion after a period; hence drowsiness can be clearly associated with it. The following facts can be summarised from the table:

3.5% of the total accidents (amounting to 3053) occurred on National Highways under N.H.A.I. and 4.4% of the total fatalities (amounting to 1550) were involved in this.

3.4% of the total accidents (amounting to 1321) occurred on National Highways under State P.W.D. and 4.3% of the total fatalities (amounting to 584) were involved in this.

6.9% of the total accidents (amounting to 748) occurred on National Highways under other Departments and 5.1% of the total fatalities (amounting to 242) were involved in this.

Thus, a total of 5122 accidents had spun forth and caused nearly 2376 fatalities. These many accidents can be clearly attributed to drinking and its consequence lethargy or drowsiness. But the category of “Lane Indiscipline” does have percentage inclusion in Driver drowsiness. While necessities do cause people to take wrong lanes intentionally; but at the same it may be unintentional and out of the control of the driver as one of the major consequences of drowsiness is the deviation of the vehicle from the intended path as stated by (Mounika, Saddam Hussian, & Venkateshwara Kiran, 2019).Thus, it is possible that vehicle is travelling on a two-way traffic situation and the driver falls asleep. Consequently, the vehicle moves uncontrolled towards opposite lane and violates traffic rule thus.

With the need for drowsiness detection being highlighted, it is time to look for potential techniques for Drowsiness Detection. The following section presents how the Raspberry Pi board can be utilised for the same. Also, some recent advancements in Physiological detection are outlined following it, so that a wholesome idea on detection can be delivered to the reader.

## POTENTIAL TECHNIQUES FOR DROWSINESS DETECTION

As already stated, Drowsiness detection is a broad field where medical researchers to computer scientists have all claimed different strategies to discover the state of a person while driving. The various detection techniques can be divided into two main categories: Physiological and Physical (or Behavioural). We focus on Physical detection techniques in this section. The Raspberry Pi's due to their compact space utilisation, delivering enough processing power, low power utilisation and wide range of sensors to interoperate, make them interesting equipment to work with. This is the reason why researchers consider them for safety systems within cars. These methods have been discussed in brief below:

### SENSOR-BASED EYE-BLINK AND DRUNKENNESS DETECTION

Through the work proposed (Mounika, Saddam Hussian, & Venkateshwara Kiran, 2019), have presented how to use an Eye-blink sensor which easily senses the blinking of eyelid and used a 3 second interval as a measure of drowsiness in the person. Also, they have incorporated a MQ3 Alcohol sensor which measures the amount of Alcohol consumption. The sensory data is received by an Arduino Uno development board which actuates a buzzer, sends SMS via the GSM module, and reports it onto the IoT cloud.


**Figure 2:MQ3 Alcohol Sensor**

**Figure 1: Eye-blink Sensor**

### COMPUTER VISION-BASED EYE-BLINK DETECTION

Coming towards Computer Vision techniques, Haar-Cascade features function as the most prominent method in detection of the faces, the eyes, the mouth as well as other facial landmarks of a person. They contain a pre-trained classifier evolved with a large set of positively classified and a large set of negatively classified offering a good range of accuracy in detection. Many researchers have tried to combine Haar-Cascades with other techniques to achieve more accurate predictions for detection of drowsiness.

#### SIMPLE AND LAYERED USE OF HAAR FEATURES

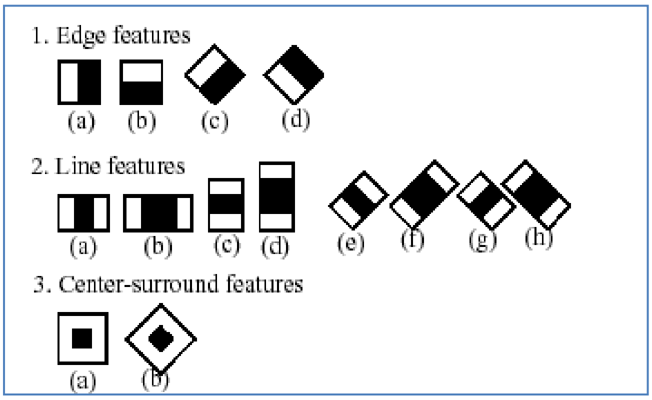


**Figure 3: Haar Cascade features**

Through the work proposed (Kulkarni, Harale, & Thakur, 2017), they have demonstrated preparing of Haar-like features from the sample of collected images of eyes. Adaptive boost has been used for training the classifier. In this each feature has a single value obtained by subtracting the sum of pixels under the white region from the sum of pixels under the black region. One classifier alone cannot give accurate predictions; hence it is a weak classifier. Together with 200 features, it becomes a strong classifier.

In the layered approach, some features are put together in the first layer, other in second layer and so on. When an image is input, the features in the first layer are calculated first, if results are positive then only move to next layer otherwise discard the image as a no face image.

### EYE-ASPECT RATIO METHOD

On the other hand, through the work proposed (Hashmi, Kusuma Priya, Surya Reddy, Vakula, & Usha, 2021) they have demonstrated using an Eye-Aspect ratio over Haar-Cascades for better detection. After the region of eyes is extracted from Haar features, the coordinates of six points (p1, p2, p3...p6) are calculated and then a value called Eye-Aspect Ratio (EAR) is calculated by the formula:

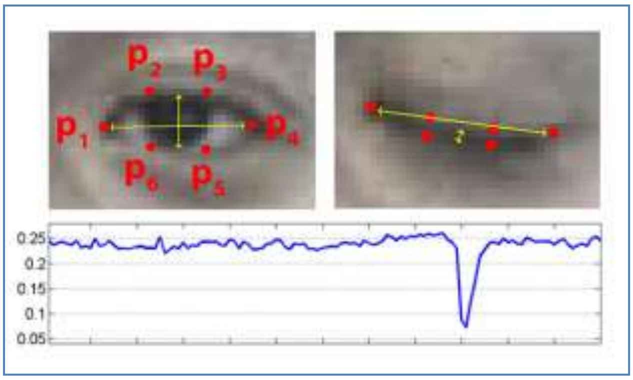


**Figure 4:Eye-Aspect Ratio Points and values in Open and Closed state**

EAR = ( || p2 - p6 || + || p3-p5|| ) / || p1 – p4 ||

This value EAR remains a constant when the eyes are open as soon as eyes start closing the value falls to zero rapidly. Hence eyeblink is reported.

### NORMALISED SUMMATION OF SQUARE OF DIFFERENCE METHOD

Also, worth mentioning is the work (Noman & Ahad, 2018), which has claimed 98% accuracy in gaze detection and eye-blink detection using Haar-Cascades combined with a Normalized Summation of Square of Difference template-matching method. The system has been developed to operate on the Android mobile phones. First, the region of interest (ROI) is determined from the convention that the face of a person can be divide into six regions. If the height of face is 'h', then location of eyes is '0.4h' from the top. This ROI image is then template-matched with values from set of values in the database to compute a square of difference of the input image from the template in the database. The normalisation makes the value more versatile for detection.

### COMPUTER VISION-BASED YAWNING DETECTION

Yawning is one of the facial features closely associated with drowsiness in a person. In their paper (Saini & Saini, 2014), they have made use of Computer vision techniques to draw contours around the mouth and sense for yawning. The yawning is determined by calculating the difference in the maximum of the points on upper half of the contour and minimum of the points on the lower half of the contour.

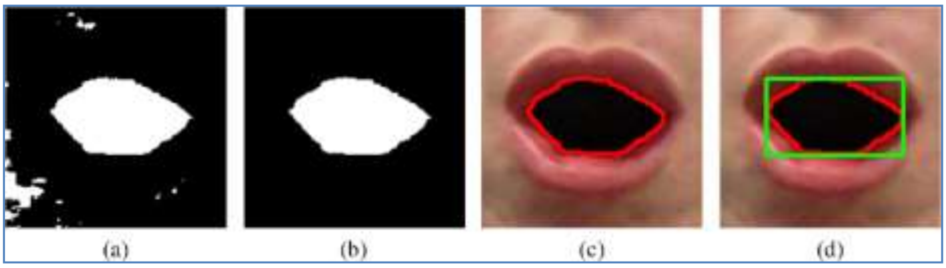


**Figure 5: Yawning detection from contours**

**Computer Vision-based Stooping and Head nodding detection**

Some researchers have focussed identifying stooping of head, a consequence of sleepiness as well as head nodding to which a person often resorts to avoid sleeping while driving.

**Detection Speed of Physical Detection Techniques**

Most of the research, which features Physical detection on the Raspberry Pi use cameras and the OpenCV Python library to capture driver images and processing of frames. The researchers do talk about increasing the accuracy but sparingly is the speed (frame rate) of detection mentioned. It is a common practice that, to scale up detection you scale up the hardware, but recent posts by Dr. Adrian Rosebrock (Rosebrock, 2021) have shown how to scale up detection even using a 5 MP Pi Camera and on USB cams. The result has been attributed to the contributions of a three-step approach:

Installing picamera[array] and importing the PiRGBArray package that allows creation of stream objects for direct access to camera frames without the requirement of additional drivers.

The use of capture() and capture_continuous() functions on the stream object with option of "bgr" format which renders images as Numpy arrays in "bgr" which is the native format OpenCV processes images. This is opposed to the conventional use of cv2.VideoStream() function that makes costly compression to JPEG format which are again decoded internally to Numpy arrays for use by OpenCV.

The use of Polling I/O rather than Blocking I/O by placing the reading of frames in an entirely separate thread than the main thread; hence main thread runs very fast and achieves the additional scale up.

The results of these experiments have been tabulated below for convenience:

| **Camera connected to Raspberry Pi** | **Event** | **Blocking I/O** | **Polling I/O** | **Scale Up (%)** |
|---|---|---|---|---|
| 5 MP Pi Camera | For capturing (or reading) frames only | 15.46 fps | 226.67 fps | **1366% approx.** |
| | For capturing and displaying | 14.97 fps | 51.83 fps | **246% approx.** |
| USB Camera | For capturing (or reading) frames only | 22.00 fps | 36.09 fps | **64% approx.** |

*Table 1: Increasing FPS of Cameras in Rasp. Pi*

Hence, using this approach we can increase the detection speed of a given camera. Though the fps is seen to drop if much processing is done on the frame, it is still better than the conventional method.

## RECENT ADVANCEMENTS IN PHYSIOLOGICAL DETECTION

Physiological detection techniques have not been dealt much elaborately; some recent advancements that make use of Machine learning and Deep learning techniques for feature extraction evolved to accurate detections have only been discussed:

### EEG (ELECTRO-ENCEPHALOGRAM)

The work proposed (Zhang, et al., 2016), they have made use of Machine learning Classification technique namely the Sparse Representation Classification (SRC) which has been used in pattern recognition tasks like facial recognition in more recent times. In their paper, SRC has been used to identify the drowsiness pattern from the clean denoised wavelet of the EEG signals. The

**Figure 7: Wearable EEG cap fitted with**

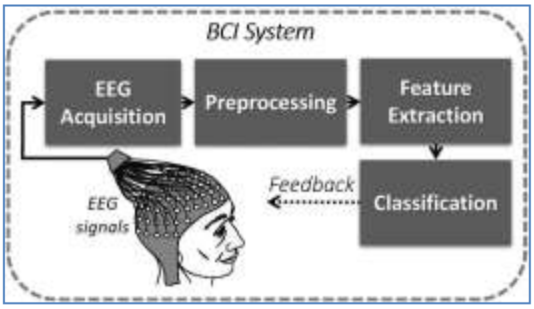


**Figure 6: Entire BCI workflow**

KVSD (k-singular value decomposition), another neural network model to down-sample irrelevant data. The technique has been reported to improve detection accuracy of EEG signals. The BCI system uses EEG caps as shown in the figure 6 and entire setup is as shown in figure 7.

### ECG (ELECTRO-CARDIOGRAM)

Recent advancements have shown that even ECG signals can provide a high degree of accuracy in drowsiness detection. ECG signals are used to measure the Heart Rate Variability (HRV). The work cited (Lee, Lee, & Shin, 2019) has shown how to combine a POLAR H7 Strap (worn on the arm) and a Microsoft Band 2 (worn on the wrist) to obtain signals and operate with different Recurrence Plots (RPs). The various Machine learning and Deep-learning models have been used to provide inferences from these RPs. It was found that the ReLU-based CNN (Convolutional Neural Network) model, a Deep-Learning architecture has found to be superior compared to SVM, KNN, LR, etc.



**Figure 8: Polar H7 Chest strap Figure 9: MS Band 2**

Also, through their research (Chui, Tsang, Chi, Ling, & Wu, 2016), they have shown how to interoperate the ECG signal with a self-designed convolutional kernel, also a Deep-Learning model to obtain 97.01% accuracy in detecting driver drowsiness.

### EOG (ELECTRO-OCULOGRAM)

Feature-extraction from EOG signals is a big problem, often a time-consuming and difficult task. But the work cited here (Zhu, et al., 2014), has shown how to do the same with the help of Convolutional Neural Network (CNN) involving 2 Convolutional layers with 8 and 4 neurons respectively. This paper tells that CNN model developed has upper hand over the manual ad-hoc feature extraction.

In the two methods mentioned earlier, only the classification task was vested upon Machine learning or deep learning models but in EOG, feature extraction is vested upon CNNs.

**A Comparative Note on Various Drowsiness Detection Techniques**

The various drowsiness detection techniques can be grouped together under three broad categories: Physical, Physiological and Vehicle-related.

| Technique | Category | Wear-able for the Part of the Body | Equipment to Carry On-board | Detection Quality (relative) | Noise Sensitivity (relative) |
|---|---|---|---|---|---|
| **EEG (Electro-Encephalogram)** | Physio-logical | Head wearable | Brain-Computer Interface (BCI) system (for EEG feature extraction) + Bluetooth module (to send data) + Processor (to process digital signals and trigger alerts) | Highest (EEG signal often referred to as Gold standard) | Distortion due to noise is significant. Hence noise reduction tech. ought to be applied |
| **ECG (Electro-cardiogram)** | Physio-logical | Chest Strap & Wrist band (optional) | Chest Strap (for cardiac signal measurement like Polar H7) + Wrist band (for PPG sensory data like MS Band 2 though optional) + Processor (for pattern classification from Recurrence plots) | High (though little lesser than EEG since HRV-Heartrate variability more susceptible to noise than Brain EEG) | Distortion due to noise is more significant here. Hence noise reduction tech. ought to be applied |
| **EOG (Electro-oculogram)** | Physio-logical | Head wearable+ Electrodes below eyes at front and back | Similar equipment as in EEG + Additional electrode wearing below eyes in front, left, right and back-head | Good (Feature extraction from EOG signal is tough and cumbersome task) | Feature extraction itself is difficult. Noise produces additional threat in detection |
| **Sensor-based Eye-Blink detection** | Physical (Behavioural) | Eye-blink Sensor (form of eyeglass) | Alcohol sensor (MQ3) + Micro-processor (Raspberry Pi) / Micro-controller (Arduino) | Good (though lower than physiological | No significant noise only false triggering a |

| | | | | | |
|---|---|---|---|---|---|
| | | | | methods since they provide the primary signs whereas physical methods are secondary) | problem. |
| **Computer Vision-based Eye-blink and Yawning detection** | Physical (Behavioural) | Not Required | Webcam or Pi Camera + Micro-processor (Raspberry Pi) / Micro-controller (Arduino)<br>Or,<br>Android phone with detection code running for the entire duration of journey | Good (detection proves to be superior to sensor based and SWM since more facial features can be combined and glance duration, PERCLOS etc can be incorporated) | No significant noise here as well.<br>False triggering can be reduced, and detection accuracy elevated up to 98%. |

*Table 2: Comparative Study of Various Detection Techniques*

## DISCUSSION AND SUMMARY

It is clear from the table above that Physiological detection techniques do hold the upper hand in drowsiness detection. But the requirement of wearables poses some problem while driving as it might get uncomfortable wearing such EEG caps or Chest Straps for long duration. Feature extraction in such techniques makes use Machine learning - Classification algorithms like the Support Vector Machine (SVM), K-NN (k-Nearest Neighbour), Random forest, Logistic Regression (LR), etc. (Lee, Lee, & Shin, 2019)or the Deep Learning model involving Convolutional Neural Network (CNN) (Lee, Lee, & Shin, 2019; Chui, Tsang, Chi, Ling, & Wu, 2016). Thus, Signal Capturing plus Feature Extraction plus Classification together yields the Detection result. Though the detection accuracies of Physiological detection (EEG, ECG, EOG) are very high, the requirement of too many wearables and additional overhead in processing or feature extraction makes the use of these very sparing amongst common public.

Thinking about the Physical (Behavioural) techniques, they do not require any wearables and their installation requirements are also minimum. The Sensor-based Eye-blink detection does require an Eye-blink sensor like eyeglasses to be worn always but CV-based techniques do not require even that instead a small Webcam or Pi Camera fixed on the dashboard or front roof is sole. The method of Polling I/O along with necessary package installations and functions have also been discussed that can speed up the performance in OpenCV. These techniques however cannot detect drowsiness too much in advance but work on secondary and visible effects like eye-blinking, glance duration or gaze detection and other facial postures of yawning, stooping, etc. Due to its low installation requirements, it is more suitable for practical applications and wide use. Nevertheless, this in any way is not an attempt to see Physiological detection techniques inferior to Physical detection techniques but it is good if researchers focus towards Physical (Computer Vision-based) techniques as they would increase the acceptance rate of such safety systems among common public as the discomfort is minimum. Later more capable systems may be incorporated evaluating the need.

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