DRIVER DROWSINESS DETECTION SYSTEM BASED ON FACEMESH MACHINE LEARNING SOLUTION

A thesis submitted to the Department of Electronics and Communication Engineering, Hajee Mohammad Danesh Science and Technology University in partial fulfillment of the requirements for the degree of Master of Science in Electronics and Communication Engineering

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DEPARTMENT OF ELECTRONICS AND COMMUNICATION ENGINEERING
FACULTY OF POST GRADUATE STUDIES

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CERTIFICATE

This is to certify that the work entitled as **"Driver Drowsiness Detection System Based on Facemesh Machine Learning Solution"** by Jafirul Islam Jewel has been carried out under our supervision. To the best of our knowledge this work is an original one and was not submitted anywhere for a diploma or a degree.

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DECLARATION

The work entitled **"Driver Drowsiness Detection System Based on Facemesh Machine Learning Solution"** has been carried out in the Department of Electronics and Communication Engineering, at Hajee Mohammad Danesh Science and Technology University is original and conforms the regulations of this University. We understand the University's policy on plagiarism and declare that no part of this thesis has been copied from other sources or been previously submitted elsewhere for the award of any degree or diploma.

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The thesis titled “**Driver Drowsiness Detection System Based on Facemesh Machine Learning Solution**” submitted by Jafirul Islam Jewel, Student ID: 2005109 and Session 'January-June' 2022, has been accepted as satisfactory in partial fulfillment of the requirement for the degree of Master of Science in Electronics and Communication Engineering (ECE).

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Abstract

Drowsiness of drivers is a severe problem for safe driving in Bangladesh. Drowsiness and fatigue are the major contributing causes of accidents on the road. Drowsiness behind the wheel has emerged as a key contributor to car crashes in recent years, resulting in serious injuries, fatalities, and monetary losses. Statistical evidence points to the necessity for a foolproof tiredness detection system that could warn the driver in time to prevent an accident. Three types of indicators have been explored by researchers in an effort to ascertain whether a driver is sleepy: Vehicle-based indicators, behavioral indicators and physiological indicators. In this thesis, we proposed a design of a system to detect drowsiness of drivers up to an extend angle position of the head of the driver while driving, and notify them. The awakeness of the driver is also detected during driving mode. The range of the multiple angles of head position using FaceMesh machine learning solution have been shown for determining the detection drowsiness. Moreover, different positions of the face are calculated to detect the drowsiness of the driver with 97.5% accuracy in straight face position, as well as the response time of the system is calculated that is around 3 seconds. We have found out that our proposed system is less complex in design, low cost and performs better than related contemporary works.

CHAPTER 1

INTRODUCTION

1.1 Introduction

Drowsiness detection is necessary for safe driving. It is an argent issue that needs to solve. This chapter contains the background, motivation of this study, objectives of our research work and the organization of the remaining chapters.

1.2 Background

Distracted driving frequently results in traffic accidents. Based on police and hospital statistics, the National Highway Traffic Safety Administration (NHTSA) concluded that drowsy driving caused 91,000 car accidents in 2017. These accidents resulted in a total of 50,000 injuries. 697 fatalities were caused by drowsy driving in only 2019 alone. The National Highway Traffic Safety Administration (NHTSA) admits that the reported numbers are probably an underestimate of the true number of drowsy driving events, injuries, or fatalities [1]. For instance, the American Automobile Association's foundation for highway safety conducted research that indicated that each year, more than 320,000 incidents involving drowsy driving result in 6400 fatal wrecks [2]. The high incidence rates indicate that drunk driving is a serious problem that has to be addressed in order to decrease its impacts. 25% of crashes involving police reports, according to NHTSA estimates, involved a driver who was "lost in thought" or otherwise disoriented, exhausted, or tired [3]. The Bangladesh Road Transport Authority (BRTA) reports that there are 4,471,625 registered cars in Bangladesh, of which only 370,519 are designated as "Private Passenger Cars," followed by 105,896 "Microbus" and 66,219 "Jeeps" [4]. According to the Road Safety Foundation's (RSF) research, as is seen in figure 1, at least 6,284 people died and 7,468 had serious injuries in Bangladesh's 5,372 confirmed road incidents in 2021. The RSF data was used to construct and characterize this graphic. Moreover, 798 drivers and their aides lost their lives in highway accidents. During that time, 76 incidents on waterways resulted in 159 fatalities, 192 injuries, and 47 unaccounted-for individuals. Rangpur had the fewest accidents, with 443 fatalities from 398 incidences, while the Dhaka division saw the most accidents, with 1,545 fatalities from 1,344 occurrences. RSF provided a list of the top ten reasons for accidents on American highways. The causes of the rising number of traffic accidents have been identified as reckless driving, poor traffic management, the use of unsafe and slow-moving vehicles on highways, semi-skilled drivers who lack proper physical and mental fitness, arbitrary working hours, the incapacity of the Bangladesh Road Transport Authority (BRTA), a lack of awareness of traffic regulations, and extortion in the transportation industry [5]. The term "drowsiness" refers to sleepiness, which is commonly used inappropriately [6]. Even though sleepiness may only last a short while, its consequences might be serious. Because it decreases focus and attentiveness, fatigue is frequently cited as the cause of this syndrome [7]. Driving long distances while fatigued or when the driver ought to be sleeping could make one drowsy [8]. The main problem in these circumstances is the driver's loss of focus, which results in a delayed response to any on-the-road event [9]. "Driver inattention" refers to diminished attention to tasks necessary for safe driving when there is no competing activity [10]. The American Automobile Association Foundation for Traffic Safety (AAA FTS) study utilized the following five categories to categorize the degree of driver attention [11]: Unknown, worn out, preoccupied, alert, and looked but did not see. An accident would have happened if the driver had been distracted.

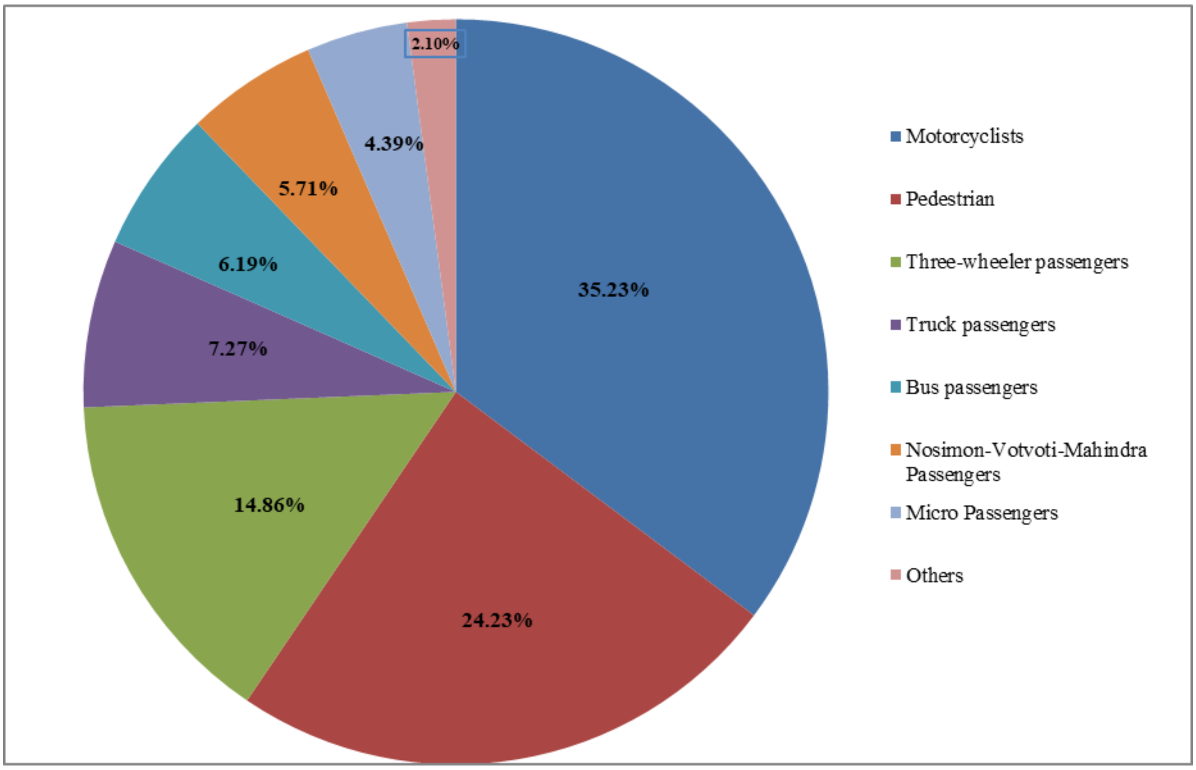

Figure 1. Annual reported in road accident of Bangladesh in 2021 [5]

Several state-of-the-art technologies are currently being used to detect driver drowsiness, the majority of which are based on driver status monitoring systems. Researchers are currently interested in learning how to identify drowsy symptoms in movies and other media by gathering important and relevant data. Because of rising living standards, more households are purchasing automobiles. Due to their numerous variable transit options, vehicles have a significant impact on transportation. They have additionally accelerated economic growth by promoting the rise of numerous sectors. Potential traffic accidents may be avoided by early detection of drowsy driving. Any possible traffic accidents may be avoided if a driver's tiredness is detected early. Several behaviors, such as frequent lane changes, periodic eye closures, and prolonged yawning, are indicative of drowsy driving [12]. One of the most important initial steps in lowering the cost of traffic accidents to society is accurately detecting weariness. In order to satisfy the demand from developing nations like Bangladesh in the future, it could be important to develop a low-cost technology for the early detection of intoxicated driving. Early identification of the condition can help to prevent accidents that are largely brought on by tiredness. The main goal is to develop a system that can accurately and effectively monitor the driver while they are on the road and can detect when the driver starts to get sleepy in real time [13]. Fortunately, it is possible to recognize the first indications of driver intoxication and warn the motorist to assist avoid any potential collisions. Several actions, including excessive yawning, frequent eye closures, and persistently drifting off the road, are signs of drowsy driving [14]. Recent years have seen a lot of research into methods for detecting driver drowsiness (DDD). Researchers have proposed a number of methods to quickly recognize these drowsiness signs in order to avoid accidents. These measures, according to Pratama et al., can be divided into four main groups: The first type of measure is image-based, in which the movements and facial expressions of the driver are captured using a camera; the second type is biological-based, in which the driver's bio-signals are captured by special sensors attached to the driver's body; the third type is vehicle-based, in which the movement and behavior of the vehicle are tracked; and the fourth type is hybrid-based, in which two or more types of measures are combined [15]. According to the literature, Ramzan et al. provided complete research of the current DDD methodology in 2019 as well as a thorough review of the frequently used categorization strategies in this industry. The DDD techniques were categorized into the following three categories by Ramzan et al. Behavioral, physiological, and vehicular parameters-based methods [16]. Sikander and Anwar gave a thorough summary of the most recent advancements in the field of driver fatigue detection. The DDD techniques were categorized into five types based on the obtained tiredness aspects in this review: physical features, vehicular features, biological features, subjective reporting, and hybrid features [17]. The effect of fatigue on driving performance as well as currently available commercial devices for fatigue detection were also looked at. Dong et al. also offered an overview of driver inattention monitoring technologies. Inattention can be brought on by distraction and fatigue

[18]. Dong et al. divided the detection measure into five categories, similar to Sikander and Anwar [17]. In their review, Dong et al. put out the notion of driver inattention and how it affects driving performance. They provided a thorough examination of past inattention detection research and talked about some of the associated commercial products. In essence, the term that is commonly used is "drowsiness," but "fatigue" is also used. Despite their distinctions, fatigue and sleepiness are used synonymously, as demonstrated by Beirness et al. in. Fatigue is described as "the unwillingness to continue an activity as a result of physical or mental strain or a prolonged length of completing the same work." However, the desire to sleep is what makes someone weary or drowsy. A strong biological desire to sleep is the main contributor to drowsiness [19].

1.3 Signs and Symptoms of Drowsiness

Numerous factors, including medications, long workdays, sleep problems, insufficient or poor-quality sleep, and extended periods of awake time, might make you drowsy [19]. Drivers do not suddenly become fatigued without displaying specific indications. These markers include, for instance [9]:

- Difficulty possession eyes open;
- Yawning;
- Frequent blinking;
- Difficulty concentrating;
- Swerving out of the lane and delayed reaction to traffic;
- Nodding;
- Indefensible differences in speed.

For assessing levels of sleepiness, a precise measurement scale is required. Two commonly used scales are the five-level Wierwille and Ellsworth Drowsiness Scale (WEDS) and the Karolinska Sleepiness Measure (KSS) [20, 21]. According to Shahid et al. [22], KSS is "a scale that analyzes the subjective levels of drowsiness at a certain time of the day." The KSS is a nine-point scale that assesses the verbal complaints of tiredness made by drivers [23]. The nine KSS scores are summarized in Table 1. The WEDS results for the five levels are listed in Table 2. According to Saito et al. [24], level one can be distinguished by quick eye movement and steady blink rates. At stage two, there is slow eye movement. The driver can touch his face, yawn, and blink slowly at level three. In stage four, the driver is seen moving pointlessly, yawning constantly, blinking excessively, and inhaling deeply. The eyes are nearly closed and the head nods at the sixth level. This scale is also widely used because these levels are determined by assessing the driver's facial expressions.

Table 1. Karolinska sleepiness scale (KSS)

Scale	Verbal Description
1	Extremely alert
2	Very alert
3	Alert
4	Fairly alert
5	Neither attentive nor drowsy
6	Some symbols of drowsiness
7	Sleepy, but making little effort to stay awake
8	Sleepy, but making effort to stay awake
9	Very sleepy, great exertion to retain alert

Table 2. Wierwille and Ellsworth drowsiness scale (WEDS)

Levels	Verbal Description
1	Not drowsy
2	Slightly drowsy
3	Discreetly drowsy
4	Meaningfully drowsy
5	Very drowsy

1.4 Drowsiness Detection Measures

There are four common ways to implement driver drowsiness detection (DDD) systems. Both biological and image-based measures can be observed in the drivers themselves. The third measurement, frequently referred to as a vehicle-based measurement, is acquired from the actual vehicle. The fourth factor considered is the hybrid measure, which incorporates at least two of the measures previously mentioned.

(i) Image-based Measures:

- Eye-based method
- Mouth-based method
- Head-based method

(ii) Biological-based Measures:

- Brain signal-based method
- Respiratory signal-based method
- Heart signal-based method
- Skin signal-based method
- Eye signal-based method
- Muscles signal-based method

(iii) Vehicle-based Measures:

- Steering wheel-based method
- Lane deviation-based method

(iv) Hybrid-based Measures:

- Vehicle and Image-based method
- Biological and Image-based method
- Vehicle and Biological-based method
- Vehicle, Image and Biological-based method

1.5 Driver Drowsiness Detection System's General Block Diagram and Data Flow

Figure 2 depicts a general block architecture and data flow for a driver drowsiness detection system, which may employ any of the four measures. The desired features are then retrieved from the signals once the data has been first collected using an appropriate sensing device. Then, certain systems might use feature transformation or dimensionality reduction. The next step is to select the characteristics that most accurately predict tiredness. The next stage is to develop a model utilizing machine learning (ML) or deep learning during the training phase to classify the driver's status. If the driver is drowsy, the alarm will go off.

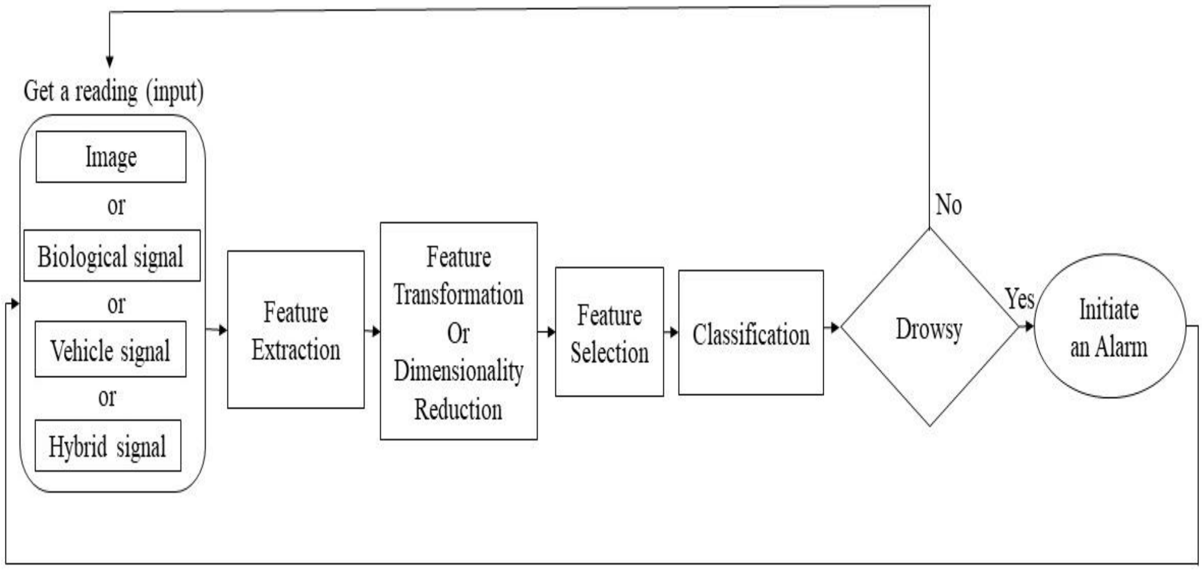

Figure 2. General block diagram and data flow of driver drowsiness detection systems

1.6 Motivation

A driver's level of weariness can be ascertained using a number of factors that drowsiness detection devices can identify. Data based on behavior, physiological measurements, and vehicle-based data can all be used in the detection process. The movements of a person's eye, face, and head can be captured on camera and stored as behavioral information. Electrocardiogram (ECG) heart rate, electrooculogram (EOG), electroencephalogram (EEG), and other analogous tests are examples of physiological measures. The movement of the steering wheel, the car's speed, its braking technique, and the lane position's deviation can all provide information about the vehicle. Two methods for gathering data for analysis include electrophysical measurements and questionnaires. However, if technology measurements are too intrusive and hinder the driver's ability to drive safely, it is frequently impossible or impracticable to obtain meaningful input from a driver while they are really driving. Usually, this is the case. Specialized tools are needed to assess vehicles, but they could be prohibitively expensive. Behavioral measurements, on the other hand, involve very little technology, are reasonably priced, and do not in any way obstruct the driver's ability to do their driving tasks. Due to all the benefits associated with them, we have decided to use behavioral measurements as the foundation for the suggested detection system that will be discussed in this study. This article describes a technique for tiredness detection that makes use of ambient cues, hand gestures, head movements, and facial traits. There are several signs of weariness, including frequent head nodding, frequent yawning, frequent blinking, and frequent yawning. Many different commercial goods have adapted this attribute, and even the percentage of eyelids that are closed for a given amount of time can be a useful indicator of tiredness. In more recent studies, researchers have used a variety of facial cues, such as a drooping jaw, an increase in both the inner and outer brows, movement of the lips when yawning, and head movement, to detect driver weariness. These hand-crafted elements can be seen on some of the earlier manufactured goods. However, manual approaches have a number of shortcomings, particularly when the driver is wearing sunglasses and the lighting is varying. When used repeatedly, these kinds of real-world circumstances cause the detection to be extremely inconsistent. In order to recognize specific face features, people began using machine learning techniques, which helped to lessen the problem.

Drowsy driving has been implicated in a significant number of accidents and fatalities in recent years. According to the American Automobile Association's foundation for highway safety, there are more than 320,000 drowsy driving incidents and 6400 fatal crashes per year. It is estimated that accidents caused by fatigued driving cost society $109 billion a year [2]. Many different automakers utilize a variety of different drowsy driver detecting systems to make sure their vehicles are perfect. Systems for detecting drowsiness have been developed by companies like Bosch, BMW, and Audi, and they are highly effective and trustworthy. Among these systems are the driver alert and driver attentiveness warning systems. Despite this, there is clearly potential for improvement.

1.7 Objectives

To detect the drowsiness of driver, this study develops a system to achieve the following objectives.

- We have been able to recognize the driver's head position while driving up to an extended angle utilizing the FaceMesh algorithm by building a sleepiness detector that is both economical and efficient.
- In contrast to other technologies, the driver's waking is also detected while operating a vehicle with minimal power and a short response time.
- We develop a simpler and cheaper drowsiness detecting technique.

1.8 Thesis Outline

The rest of the thesis is organized as follows:

- Chapter 1: Introduction. In this chapter the current situation of accident, necessity to detect the drowsiness means the problem statement and our contribution added.
- Chapter 2: Literature review. Related recent work on this problem are added in this chapter. The techniques, related result and analysis are also added.
- Chapter 3: Methods and Materials. This section discusses the proposed methodology with the experimental setup and related algorithms.
- Chapter 4: Result and Discussion. The experiment perform by our methodology are describe with real life analysis with necessary figure, diagram and tables.
- Chapter 5: Conclusion and Future work. This section describes the ending part of our work. It is a short summary of our overall work. Future work related to our model are also added at the end of this section. This section clearly represents what we actually do in this study.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

In this section, we will divide the drowsiness detection measure into different categories and discuss the literature review accordingly. Also, the comparison among the literature are shows in several tables. Already there are many studies on this problem. Different researcher tries to solve this problem in a different way. Some of them focus the hardware setup, some of them focus the algorithmic contribution of the work.

2.2 Image-Based Measures

Some drowsiness symbols are noticeable and can be recorded by cameras or pictorial sensors. They embrace the driver's facemask expressions and movements, especially the head actions. The literature denotes to these symbols as visual [25] or image-based measures [26]. Our work mentions to them as image-based procedures to highlight that these procedures usually lead to futures extracted from images or videos. Image-based DDD systems can be largely categorized into three techniques, based on whether actions of the mouth, head, or eyes are observed. Table 3 lists some of the image-based measures.

Table 3. Some of the image-based measures

Features	Description
Blink frequency [27]	The number of times an eye closes over a specific period of time.
Maximum closure duration of the eyes [27]	The maximum time the eye was closed.
Percentage of eyelid closure (PERCLOS) [28]	The percentage of time (per minute) in which the eye is 80% closed or more.
Eye aspect ratio (EAR) [29]	The EAR value drops down to zero when the eye is closed. On the other hand, it remains approximately constant when the eye is open. Thus, The EAR detects the eye closure at that time.
Yawning frequency [30]	The number of times the mouth opens over a specific period of time.
Head pose [31]	The figure describes the driver's head movements and it is determined by counting the video segments that show large deviation of three Euler angles of head poses from their regular positions.

Now, we discuss some image-based exposure systems that have been presented over the past aera. Table 4 provides a summary of those systems.

1. Drowsiness detection using eye features

- Real-time driver drowsiness detection using eye aspect ratio

Major et al. [32] established a sleepiness detection technique based on eye shapes observed by video streams using a simple web camera. The method tracks the blinking period using the EAR matric. The proportion between the eye's height and width is considered to estimate the EAR value. A high EAR value indicates that the eye is open, while a low value indicates that the eye is closed. The planned method contains of three main parts: eye detection, EAR calculation and blink classification and real time drowsiness detection. A trial was showed to generate an exercise database. After obtaining the images from the wed camera, the EAR values were calculated and stored for each frame. Then, a specific number of successive values were used as input for the machine learning algorithms. Drowsiness is distinguished if the blink period is longer, compared to a standard blink. Three classification approaches were employed: multilayer perception, random forest (RF) and SVM. The experimental result in the succeeding method accuracy 94.9%.

- Eyelid closure analysis

Khan et al. [33] showed a real-time driver sleepiness detection system based on eyelid closure. The system was implemented on hardware that used investigation videos to detect whether the driver's eyes were open or closed. The system started by detecting the face of driver. Then, using a protracted Sobel operator, the eyes were contained and filtered to notice the eyelid's curvature. After that, the curvature's concavity was slowed based on the measured concavity rate, the eyelid was classified as open or closed. If the eyes were deemed closed for a confident period, a sound alarm is originated. The system uses three datasets: the first dataset contained simple images with a homogenous background; the second dataset included a complex benchmark image and the third one used to real-time investigation videos which contains the accuracy of 95%.

- Driver drowsiness detection with CNN

Hashemi et al. [34] planned a real-time driver drowsiness detection system based on the area of eye closure and use of the convolutional neural network (CNN). The networks were familiarized for eye closure classification: transfer learning in TL-VGG16, transfer fully designed neural network (FD-NN) and transfer learning in L-VGG19 with extra design layers. The authors used the ZJU gallery dataset, in addition to 4157 new images. The experimental result in the following network accuracy 95%.

2. Driver drowsiness detection using multiple features

- Facial features analysis

You et al. proposed a real-time algorithm for driver fatigue detection using facial motion information entropy [35]. The algorithm has four components in total. First, a face positioning module, where the author upgraded the YOLOv3-tiny CNN capture the facial regions in the collected video frames under a variety of challenging settings. The features vector extraction module is the second one. In this module, the Dlib Toolkit, landmarks from the face and coordinates from the facial regions were used to create a face feature triangle geometric area. The third module comprises collecting the centroid for each frame and the face feature vectors, which provide details about each face feature triangle area.to ascertain the condition of driver, this vector is employed as an indicator. A sliding window is created in the fourth module, the tiredness judgment module, to collect the entropy of the facial motion information. The SVM classifier then uses this data to compare it to a judgement threshold in order to determine the driver's level of weariness. Using the open-source dataset YawDD, the authors tested their suggested technique and obtained an accuracy of 94.32%.

- Facial, hand and behavioral features analysis

Dua et al. [36] utilize the NTHUDD public dataset to propose an architecture that detects driver drowsiness. This architecture encompasses of four deep learning models: AlexNet, VGG-FaceNet, FlowImageNet and ResNet. The models are used to extract four different types of features: facial expression, head gesture, hand gesture and behavioral features, such as head eyes or mouth movements. While the AlexNet model accounts for diverse environmental and background situations, the VGG-FaceNet detects and extracts facial traits. In constant, FlowImageNet is used to extract head gestures and behavioral features, while ResNet is used for hand gestures. Using RCB videos of the drivers as an input and SoftMax classifier. The proposed system contains 85% accuracy.

- Facial and head movement features analysis

Wijnands et al. [37] described a new driver drowsiness detection method, based on activity prediction, through depth-wise separable 3D CNN using real-time video and used be academic NTHUDDD dataset. This approach has the benefit of intuitively deciding on the key features rather than pre-specifying a list of features. Eyelid closure, mouth position, frowning, raising of the outer brow, creases on the nose, and lifting of the chin are a few characteristics. Therefore, if enough data labels are provided, it will be able to capture these traits. Driving during the day and night was one of the various lighting and face-wear conditions used in the experiments. Subjects also operated a vehicle while donning eyeglasses, sunglasses, and without any. The proposed approach by Wijnands et al. produced an overall accuracy of 73.9%.

- Eye and mouth analysis

Celecia et al. [38] proposed a low cost, portable, robust and accurate driver drowsiness detection device that used an ultraviolet illuminator and camera to record images. The device's processing model incorporates features gleaned from the individuals' eyes and tongues, and it was executed over a Raspberry Pi 3 Model B. The characteristics include PERCLOS, average mouth opening time, and average eye closing duration. The training procedure made use of the 300-W dataset. Through the use of a series of regression tree techniques, the authors established the state of each feature. The states of the three features were then combined as input into a Mamdani fuzzy inference system, which predicted the driving state. The device produces a final output that indicates the degree of drowsiness by labeling the state as "Low-Normal," "Medium-Drowsy," or "High-Severe." As a consequence, the study produced a 95.5% accurate DDD device that is resilient to various ambient illumination situations.

- Eye state analysis and yawning

Alioua et al. [39] proposed a non-intrusive and robust system that notices drowsiness in real-time to decrease traffic accidents. Alioua et al. [39] proposed a non-intrusive and robust system that detects drowsiness in real-time to reduce traffic accidents. Based on a close-eyes and open-mouth detection algorithm, the device recognizes tiredness. In this work, a webcam was used to gather a collection of photos. The system begins by using an SVM face detector to extract the face region from the video frames, according to the authors. Then, the localization of the mouth and eye regions within the face is carried out. In order to determine whether the extracted eye is open, the circular Hough transform is used to locate the iris, a colored muscle curtain close to the front of the eye. In order to gauge the degree of mouth opening, it is also applied over the mouth area. The technology determines whether or not the driver is sleepy based on the combination of their mouth and eye states. The outcomes demonstrated the reliability of this technology, which has a 94% accuracy rate.

- Eye Closeness

Khunpisuth et al. [40] conducted a study with ten volunteers for detecting the sleepiness driver. The frequency of head tilting and eye blinking was observed throughout the investigation and was connected to the drivers' level of tiredness. The Raspberry Pi Camera and Raspberry Pi 3 Model B were used to create an embedded device for drowsiness detection that gathered image data, assessed sleepiness levels, and alerted the driver. The suggested gadget first used the Haar cascade classifier to recognize an upright face, a level head, and flashing eyes. Additionally, geometric rotation is utilized to determine the angle and rotate the image to an upright position in order to identify precisely if the head position is not upright. Secondly, template matching is used to detect whether the eyes are open or closed. In order to determine whether the eyes are open or closed, template matching is also used. Thirdly, the frequency of head tilting and eye blinking is used to determine the degree of tiredness. The system rates the level of drowsiness on a scale from 0 to 100. A loud, audible warning is activated by the system to inform the driver if the sleepiness level hits 100. Due to its sensitivity to background light and the skin tone of the person, this method does have some drawbacks. Finally, the system's accuracy resulted in a precision of 99.59%.

- Eye and mouth analysis

Zhoa et al. [41] proposed a fully automated driver fatigue detection algorithm. An information technology business called Biteda donated the driving photos collection that is used in this investigation. With the help of the feature points, the area of interest (ROI) may be recovered utilizing this algorithm's face detection and feature point localization, which uses a multitask cascaded CNN architecture. Additionally, a brand-new CNN algorithm known as eye and mouth CNN (EM-CNN) was suggested. The ROI is used by the EM-CNN algorithm to identify the mouth and eye states. The degree of mouth opening as well as PERCLOS were both used as detecting parameters. The final outcomes revealed an accuracy 93.62%.

- Eye and mouth analysis

Deng et al. [42] proposed DriCare and real-time driver drowsiness detection system. The visuals from video streams are used by this system to determine the level of somnolence.

Multiple CNNs-kernelized correlation filters, a new face-tracking technique for video, were introduced by the authors. They also used 68 critical spots on the driver's face to pinpoint important areas, such as the eyes and lips. In order to determine the driver's level of intoxication, the authors calculated the ratio of closed-eye frames to total frames, the duration of continuous eye closure, the frequency of blinking, and the number of yawns per minute. Finally, if the DriCare system detects that the driver is drowsy, it warns them. On the CelebA and YawDD datasets, the system was tested. The system displayed a 92% accuracy rate.

- Eye, mouth and head analysis

Using a series of video frame sequences, Ed-Doughmi et al. [43] demonstrated a method to analyze and forecast fatigue based on a recursive neural network (RNN). To identify weariness, the scientists developed a repeating neural network design dubbed multi-layer, model-based 3D convolutional networks [44], which is based on an RNN model. The NTHUDDD dataset films were used to extract the subjects' drowsy behaviors, including yawning, eye closing, and head nodding. A 97.3% accuracy rate was attained.

- Eye, mouth, head and scene analysis

Yu et al. [45] presented a condition-adaptive representation learning framework for DDD, based on a 3D-deep CNN using the NTHUDDD public dataset. The framework included four models: the learning of spatiotemporal representations, the comprehension of scene conditions, the feature fusion model, and the model for drowsiness detection. First, characteristics that describe movements and appearances in the movie were simultaneously extracted using spatio-temporal representation learning. After that, numerous driving scenarios were represented and drivers were categorized using scene condition understanding. Along with others, these illnesses can cause changes to the head, lips, and eyes on the face. The feature fusion model then merges two features to produce an adaptive representation for driving situations. Using the condition-adaptive representation from the prior model, the sleepiness detection model then determines the drivers' alertness status. The correctness of the framework was 76.2%.

3. Drowsiness detection based-on yawning in thermal image analysis

Using long-range infrared thermal imaging, Knapik et al. [46] introduced a unique method for yawning detection-based driver fatigue detection. For this study, a customized own dataset was produced. The system operates using the steps below. Images from a thermal video are first obtained. Then, three cascading detection modules are used to detect the yawn, corner of the eyes, and face area. Information regarding other face regions' relative temperatures is used to detect the yawn reaction because the mouth area can often be difficult to detect in thermal imaging due to the temperature difference in that location. The writers therefore employed the corners of the eyes as a sign of yawning. To identify yawning, cold and hot thermal voxel sum techniques were applied. Finally, when exhaustion is identified, an alarm is started depending on the outcomes of the suggested algorithm and the presumptive limits. The system demonstrated accuracy rates of 71% for cold voxels and 87% for hot voxels.

4. Drowsiness detection using respiration in thermal imaging

Kiashari et al. [47] introduced a non-intrusive system that distinguish drowsiness using facial thermal imaging to investigate the driver’s respiration signal. They used a driving simulator to perform their study, which involved thirty participants. The driver's thermal images were recorded by a thermal camera. The inspiration-to-expiration duration ratio and standard deviation of the respiration rate were derived from the collected thermal data and utilized as input features to train the support vector machine (SVM) and k-nearest neighbor classifiers. Drowsiness was recognized by both classifiers. 90% of the framework was accurate.

Table 4. Image-based drowsiness detection systems

Image-Based Parameters	Extracted Features	Classification Method	Description	Dataset	Accuracy
Eye [32]	EAR value	RF, SVM and multilayer perceptron	Traced eye blinking period in video stream, as a pointer of sleepiness consuming the EAR. The SVM presented greatest performance.	Prepared their own dataset	94.9%
Eye [33]	Eyelid's curvature	Classification based on the period of eye closure	The system assessed whether an eye is open or closed based on the concavity of the eyelid's curvatures. Then, it noticed sleepiness based on the eye closure.	Benchmark	95%
Eye [34]	Eye closure	TL-VGG19, TL-VGG16 and FD-NN	Used a real-time method based on CNN to determined where the eyes closed. Three networks FD-NN, TL-VGG19 and TL-VGG16 were introduced for the categorization of eye closure.	ZJU gallery	95%
Facial features [35]	Face feature vectors	SVM	Used facial sign information entropy, extracted from real-time videos. The algorithm delimited four segments.	YawDD	94.32%

Facial, Hand, Behavioral (eye, mouth, or head movements) [36]	Head posture, hand posture, facial expression and behavioral features	SoftMax classifier	This system provided an architecture that extracts four different kinds of features using four deep learning models.	NTHUDDD	85%
Head movements and Facial expression [37]	Eye closure, mouth position, chin or brow raises, frowning and nose wrinkles	3D CNN	Based on activity prediction DDD was performed through a depth-wise separable 3D CNN.	NTHUDDD	73.9%
Eye and Mouth [38]	Average mouth opening time, eye closing duration and PERCLOS	Mamdani fuzzy inference system	The extracted parameters are strongminded through a cascade of regression tree algorithm. Then the driver state guesstimates through a Mamdani fuzzy inference system.	300-W	95,5%
Eye and Mouth [39]	Mouth openness and eye closure for a duration of time	Circular Hough convert	The circular Hough transform method is applied to check the aperture is open or iris is observed.	Own dataset	94%

Eye and Head [40]	Eye blinking and head tilting frequency	Guide corresponding to sense the eyes and scheming the frequency of head sloping and eye alternating level	Drowsiness level determined by calculating the frequency of head tilting and eye blinking on scale of 0-100.	Own dataset	99.59%
Eye and Mouth [41]	Mouth opening grade and PERCLOS	Mouth and eye CNN	Applied expression exposure and feature points position, using multi-task cascaded CNNs architecture and EM-CN to perceive the mouth and eye state from the ROI	Driving image dataset	93.62%
Eye and Mouth [42]	Continuous-time of eye closure, blinking rate and number of yawns in 1-min, proportion of the number of closed-eye frames to the total number of frames in 1-min	Multiple CNNs-kernelized correlation filters method	Multiple CNNs-kernelized correlation filters method is used for extracting and face tracking the image-based parameters. If found drowsy, the driver is warned.	CelebA and YawDD	92%

Eye, Head and Mouth [43]	Eye closure, yawning and nodding	3D CN	Based on an RNN model used a repetitive neural network architecture called multi-layered 3D CN network.	NTHUDDD	97.3%
Eye, Head, Mouth and scene conditions [45]	Facial changes in eye, mouth, and head, light condition of driving and exhausting glasses	3D-deep CNN	The framework delimited four models to predictable the driver's alertness position, consuming the condition-adaptive representation.	NTHUDDD	76.2%
Mouth [46]	Yawning	Hot and cold voxels	A technique for detecting drowsiness based on the detection of yawning with thermal imaging. We use the cold and hot voxels to find yawning.	Own dataset	87%
Respiration (using thermal camera) [47]	The mean of respiration rate and ordinary eccentricity	SVM and KNN	Analyzed the driver's respiration using face thermal imaging and connected it to sleepiness.	New thermal image dataset	90%

2.3 Biological-Based measures

Many biological signals have been used to distinguish the driver's sleepiness, such as EEG, ECG, EMG and EOC which is accomplished brain activity, heart rate, breathing rate, pulse rate and body temperature indicators. These signals are composed through electrodes in interaction with the coating of the human body. EEG is extensively recognized as a good pointer of the evolution between alertness and sleep, as well as between the dissimilar sleep phases. It is frequently mentioned to as the gold standard. The most frequently used biological procedures in literature are listed in Table 5.

Table 5. Some biological-based measures

Biological signals	Description
Electroencephalography (EEG) [48]	A monitoring technique that records the electrical activity of the brain from the scalp is known as an EEG signal. It is a representation of the surface layer in the brain beneath the scalp's tiny activity. These signals are divided into five categorized based on their frequency ranges (0.1- 100 Hz): delta, theta, alfa, beta and gamma.
Electrocardiography (ECG) [49]	Electrodes positioned on the skin are used to collect ECG data, which indicate the electrical activity of the heart, including heart rate and rhythm.
Photoplethysmography (PPG) [50]	Blood volume variations can be detected using PPG signals. A pulse oximeter is used to measures these signals at the skin's surface. It is frequently used to measured heart rate.
Heart rate variability (HRV) [51]	The changes in the cardiac cycle, including heartbeats, are observed using HRV signal.
Electrooculography (EOG) [52]	EOG signals are used to monitor and documents eye movements as well as the cornea-retinal standing potential which exists between the front and back to the human eye.
Electromyography (EMG) [53]	The electric impulses that are generated collectively when muscle moves are known as EMG signal.

This section will cover some of the systems that detect drowsiness using the driver's biological changes. A summary of these systems is shown in Table 6.

1. Drowsiness detection using EEG signals

- EEG signal analysis using KPCA

In [54], the kernel principal component analysis (KPCA) algorithm was employed to extract nonlinear features from the complexity parameters of EEG and improved the simplification presentation of an HMM. The result displayed that both complexity parameters meaningfully reduced as the mental fatigue level improved and the classification accuracy reached 84%.

- EEG features with LTSM

Budak et al. [55] projected an EEG-based sleepiness detection method that contains of three essential building blocks. In the first block, the instantaneous frequency and spectral entropy features are taken out of the EEG spectrogram images. To determine the energy distribution and zero-crossing distribution properties, the raw EEG signals are also examined. The second block is the direct extraction of detailed features from the EEG spectrogram pictures using pre-trained AlexNet and VGG16 models. For the third block, a configurable Q-factor wavelet transform is used to separate the EEG signals into corresponding sub-bands. The acquired sub-bands spectrogram pictures and statistical features, such as the mean and standard deviation of the sub-bands instantaneous frequencies, are subsequently calculated by the authors. The collected feature groups are sent to an LSTM network classifier once the three blocks have been processed. The MIT/BIH polysomnographic EEG dataset was used to train and assess the technique [56]. The accuracy was 94.31% as a consequence.

- Using wavelet packet transform with EEG

A new tiredness detection approach that uses wavelet packet transform to extract the time domain features from a single channel EEG signal was proposed by Phanikrishna et al. [57]. The Fpz-Cz channel dataset, a pre-recorded dataset accessible on the National Institute of Health [58], provided the data used for this study. There was also use of the simulated virtual driving driver (SVDD) dataset from [59]. The EEG signal was divided into five sub-bands: delta, theta, alpha, beta, and gamma. The values of nine features labeled from F1 to F9 were calculated using the Higuchi fractal dimension [60], mobility [61], and complexity characteristics of the EEG signal, as well as the EEG sub-bands, retrieved in the previous stage. The PComb values for each feature were then calculated using Wilkinson's metanalysis [63] approach after applying the Mann-Whitney U test [62]. For the last stage, the features with the lowest PComb values were chosen. In this work, eleven classifiers were examined.

Extra trees, one of the eleven classifiers, had the best performance, with an accuracy of 94.4% for the Fpz-Cz channel and 85.3% for the SVDD dataset.

- EEG signal analysis using EMD and trained neural network

Kaur et al. [64] presented a technique to detect driver sleepiness, based on EEG signal analysis, using empirical mode decomposition (EMD) and trained ANN. Silver surface electrodes were applied to the subject's scalp by Kaur and Singh in order to collect the EEG signals. Along with the EEG features, they have also used a video camera to deliver a sleepiness label. They created their own dataset as a result. Using a MATLAB program, sleepiness positions in the EEG data were then classified as awake or sleepy. The intrinsic mode functions (IMFs) were then extracted from the labeled EEG data using the EMD approach. Finally, the IMFs were fed into the ANN during training. 15% of the samples were utilized for testing, 15% for validation, and 70% were used for training. The final results of the classification revealed an accuracy of 88.22%.

- Adaptive Hermite decomposition and ELM

Taran et al. [65] presented a DDD method, based on an adaptive Hermite decomposition for EEG signals. In general, Hermite functions aid in the analysis of complicated and nonstationary signals. For their study, the authors consulted the MIT/BIH polysomnographic database. First quartile, median, range, and energy were the statistical measurements of Hermite coefficients from which the features were extracted. These features were then tested and classified using the extreme learning machine (ELM), KNN, decision tree, least-squares SVM, naive Bayes, and ANN classifiers. The ELM classifier gained the highest accuracy, which was 92.28%.

- EEG signal analysis

Lin et al. [66] recognized a linear regression model to estimate the drowsiness level from the independent component analysis (ICA) of 33-channel EEG signals and cloud estimate the drowsiness level with 87% accuracy. They then realized a real-time embedded EEG-based driver drowsiness estimate system in [67], which adopted only four channels of EEG.

- Smartwatch-based wearable EEG system

Li et al. [68] proposed a driver drowsiness detection system based on EEG signals. For drowsiness identification, the proposed system uses an SVM-based posterior probabilistic model to divide drowsiness states into three groups (alert, drowsy, and early warning). This approach differs slightly from existing EEG-based detection systems that produce discrete sleepiness labels that categorize the driver's status as alert or drowsy. Therefore, the SVM-based posterior probabilistic model translates the driver's level of drowsiness to a number between 0 and 1, providing a continuous measure for tiredness, as opposed to utilizing discrete labels to identify the driver's level of drowsiness. The Bluetooth-enabled EEG and commercial smartwatch used in this study's fully wearable EEG system allowed for in-the-moment data analysis. This system presented different accuracies for each perceived state. It obtained a 91.92% accuracy for the drowsy case, 91.25% for the alert case, and 83.78% for the early warning case.

- Wearable ECG/PPG sensors

Lee et al. [69] examined driver’s drowsiness by tracking the different patterns of HRV signals. These signals are acquired using PPG or wearable ECG sensors. The authors claim that because wearable sensors are more susceptible to little motions, they tend to produce more noise in signals. Thus, the scientists investigated three types of recurrence plots (RPs), obtained from the heartbeats' R-R intervals, in order to categorize the noisy HRV signals as drowsy or not (RRI). These RPs are the binary recurrence plot (Bin-RP), continuous recurrence plot (Cont-RP), and thresholder recurrence plot (ReLU-RP), which is learned by using an improved rectified linear unit (ReLU) function to filter Cont-RP. Each recurrence plot is utilized as an input feature to a CNN. The study, conducted in a simulation environment, showed that DDD’s most reliable and distinct pattern was the ReLU-RP (using either the ECG sensor or the PPG sensor). ReLU-RP CNN could differentiate between awake and drowsy states better than the other alternatives. PPG signals gave 64% accuracy. On the other hand, ECG signals gave 70% accuracy.

2. Drowsiness detection using ECG, PPG, and HRV signals

- PPG bio signals and multimodal head support

Koh et al. [70] proposed a method for DDD by employing the high frequency (HF), low frequency (LF), and low to high frequency (LF/HF) values of the PPG signals measured from sensors mounted on fingers and earlobes. The researches included 20 subjects aged, between the early twenties and late forties. The authors used a driving simulator equipped with two PPG sensors. A sensor was placed to touch the user’s earlobe, and the other was placed on the finger. The collected PPG signals were analyzed using Telescan and KITECH programs to design an algorithm to classify the driver's drowsiness state. The classification relied on the changes in the extracted LF and HF values. The standard drowsy state criteria were specified by a reduction in LF and LF/HF values and growth in HF value. In contrast, other cases will specify an awake driver.

- HRV anomaly analysis

Based on the idea that variations in alertness levels have an impact on the autonomic nervous system and HRV, Fujiwara et al. [71] created a method that employs HRV anomaly analysis to detect drowsiness. This effect is shown by the HRV in the RRI variation of the ECG trace. The ECG's height peak is known as the R wave, and the RRI refers to the space between two successive R waves. Fujiwara et al. tracked alterations in eight HRV parameters using an anomaly detection technique known as the multivariate statistical process control method. These structures include the mean of RRI (MeanNN), standard deviation of RRI (SDNN), root means square of the difference of adjacent RRI (RMSSD), total power (which is the variance of RRI) (TP), number of pairs of adjacent RRI spaced by 50 ms or more (NN50), LF, HF, and LF/HF. The proposed algorithm displayed an accuracy of 92%.

3. Drowsiness detection using EMG signals

- Hypovigilance detection using higher-order spectra

Sahayadhas et al. [72] introduced a system that uses ECG and EMG signals to identify low alertness, which is brought on by sleepiness and inattention. Through a series of inquiries sent to the driver via text messages or phone calls, inattention was managed. Contrarily, drowsiness was reduced by enabling the subjects to operate a vehicle continuously for two hours while playing a simulator game in a safe laboratory setting. With the use of single-use Ag-AgCl electrodes, the ECG and EMG data were captured. In order to reduce noise and artifacts, the physiological signals obtained from the tests were first pre-processed. After that, a number of higher-order spectral features were recovered, including the bispectrum, which is the second-order moment's Fourier transform. Other features were extracted from the bispectrum, including the first-order spectral moment of the amplitudes of the diagonal elements in the bispectrum, the sum of the logarithmic amplitudes of the bispectrum (H1), the sum of the logarithmic amplitudes of the diagonal elements in the bispectrum (H2), and more (H3). Additionally, the data gathered from the two signals were combined using principal component analysis to improve the results' accuracy. Following that, linear discriminant analysis, quadratic discriminant analysis, and KNN classifiers were used to train and categorize the collected features. The H3 feature from the ECG signal with the KNN classifier demonstrated an overall accuracy of 96.75% for the bispectral features. Moreover, the linear discriminant analysis classifier was able to accurately classify the H2 feature from the EMG signal with a 92.31% accuracy rate. The KNN classifier produced results with a maximum accuracy of 97.06% for the fused features.

4. Drowsiness detection using respiratory signals analysis

- Drowsiness detection using respiratory signals analysis

Drowsiness-related information can be obtained from respiratory signals. In reality, the signals obtained can be used to determine the driver's level of tiredness by monitoring changes in the diaphragm, belly, and rib cage during the respiratory process. Guede-Fernández et al. proposed a novel algorithm for driver drowsiness detection utilizing respiratory signal variations [73]. To provide the greatest tracking quality of the respiratory signals, three respiratory inductive plethysmography band sensors were utilized in this work. Twenty people participated in the study, which involved 36 tests in a simulator cabin to gather the data. For the suggested technique to identify changes in the driver's alertness status, the respiratory rate variability (RRV) must be examined. In order to guarantee the respiratory signals' quality level, a different technique was adopted. The thoracic effort-derived sleepiness index algorithm was created by combining those two techniques in order to minimize detection errors. The system's accuracy was 90.3%.

5. Drowsiness detection using EOG signals analysis

- EOG signal analysis

Hu et al. [74] worked an SVM to achieve drowsiness estimate with 11 eyelid-related features extracted from EOG. These eyelid features included blink duration, blink duration 50_50, amplitude, lid closure speed, peak closing velocity, lid-opening speed, peak opening velocity, delay of eyelid reopening, duration at 80%, closing time and opening time. It was reported that the drowsiness detection accuracy was 86% for "sleepy".

6. Drowsiness detection with a combination of various biological signals

- DDD using EEG, EOG, and ECG signals with fuzzy wavelet packet-based feature extraction algorithm

In order to identify the driver's condition of tiredness, Khushaba et al. [75] devised a feature extraction approach for obtaining the most pertinent features. The goal of the proposed fuzzy mutual information-based wavelet packet is to optimize the amount of data related to drowsiness derived from EEG, EOG, and ECG signals by transforming the feature extraction approach. These findings were used to categorize the driver's level of tiredness into the following categories: alert (class 1), somewhat drowsy (class 2), moderately drowsy (class 3), significantly drowsy (class 4), and severely drowsy (class 5). (Class-5). 31 volunteers who used a virtual driving test scenario provided the dataset. Using majority vote, the video data were rated and tagged. Then, the characteristics including EEG features from the temporal, frontal, and occipital channels as well as the eyeblink rate, blood pressure, and heart rate were extracted using the new fuzzy mutual information-based wavelet packet transform approach. Following that, these features were dimensionally reduced utilizing linear discriminant analysis based on spectral regression [76] and kernel-based spectral regression [77] techniques. Then, training was carried out utilizing the linear discriminant analysis, linear SVM, kernel SVM, and KNN classifiers. The final findings demonstrated that the suggested strategy had a 95% accuracy rate.

- A method based on EEG and ECG signals

To improve the performance of detection, Awais et al. [78] presented a DDD technique that combines ECG and EEG information. Using data from 22 individuals in a simulator-based driving environment, the scientists determined the difference between alert and drowsy states. A number of features were gathered from the EEG and ECG signals used in this investigation. Frequency domain absolute and relative powers, time-domain statistical and complexity metrics, and other properties were taken out of the EEG signals. On the other hand, the HR and HRV features were among the features retrieved from the ECG signals. Following feature extraction, only significant features were chosen using a paired t-test. An SVM classifier is then provided with the combined set of features. The outcomes demonstrated that combining the characteristics from both signals worked better than the features from just one type of signal. Additionally, it demonstrated how fewer electrodes might be used when combining EEG and ECG features. The accuracy obtained with a single EEG and ECG electrode was 80.90%.

Table 6. Biological-based drowsiness detection system

Biological Parameters	Sensors	Extracted Features	Classification Method	Description	Dataset	Accuracy
EEG [54]	EEG sensors	Nonlinear	KPCA algorithm	Complexity decreases as fatigue increases.	HMM	84%
Brain activity [55]	EEG headband and smartwatch	Comparative EEG power ratio	SVM-based posterior probabilistic model	A real-time system used an SVM-based posterior probabilistic model to notice and categorize drowsiness into three stages.	Own dataset	91.92%
EEG [57]	EEG sensors	The first quartile, median, range and energy of the Hermite coefficient	KNN, SVM, ELM and naïve Bayes	Recognition was based on an adaptive Hermite decomposition for EEG signals.	MIT/BIH polysomnographic dataset	92.28%
Brain activity [64]	EEG sensors	IMF of the EEG signal	ANN	By applying the EMD method, detection was performed based on the extraction of the IMFs from the EEG signal.	Own dataset	88.2%

EEG [65]	EEG sensors	F1-F9, extracted from Higuchi fractal dimension	Extra trees classifier	To extract the time domain features from a single channel EEG signal by employed wavelet packet transform.	Fpz-Cz channel and SVDD	95.82%
EEG [66]	EEG sensors	Linear regression model	ICA, FFT, LRM and correlation analysis	Estimate drowsy level	Own dataset	87%
EEG signals and EEG spectrogram images [68]	EEG sensors	Zero-crossing and energy distribution of the raw signals, in-depth features of the EEG spectrogram	LSTM network	It used pre-trained Alexnet and VGG16 models to extract in-depth features from the EEG spectrogram images and apply EEG-based drowsiness detection method	MIT/BIH polysomnograp hic dataset	94.31%
Heart rate [69]	PPG	Frequency measurements extracted from PPG signals	HF, LF and HF/LF	Obtained from measurements on fingers and earlobes by analyzing the changes in PPG signals frequency measurements.	Own dataset	88.8%
HVR [70]	ECG electrodes	SDNN, TP, NN50, MeanNN, HF, LF and LF/HF	Multivariate statistical process control	Based on HVR analysis detection was performed. Eight HVR features were mentioned to detect the changes in HVR.	Own dataset	92%

Blood volume and heart rate changes [71]	PPG and ECG	Bin-RP, Cont-RP and ReLU -RP patterns provide this feature	CNN	To track the different patterns in HVR signals in a simulation environment and used CNN based on wearable ECG/PPG sensors.	Own dataset	71%
EEG and EEG [72]	Ag-Agcl electrodes	Features extracted from the bispectrum of the signals of the signals H1, H2 and H3	KNN classifier, quadratic discriminant and linear discriminant analysis	Detects hypovigilance using EEG and EMG signals. First pre-posed meeting physiological signals and then multiple higher-order spectral structures were takeout to be classified.	Own dataset	97%
Respiration [73]	Three respiratory inductive plethysmography	Excellence of the respiratory signals and RRV	Thoracic effort-derived drowsiness	It united the quality level of the respiratory signals and the study of the RRV to sense the changes of the driver awareness status.	Own dataset	90.3%
EOG [74]	EOG sensors	11 eyelid-related features	SVM	To achieve drowsiness, estimate with 11 eyelid-related structures extracted from EOG.	Own dataset	86%

ECG, EOG, EEG [75]	ECE, EOG and EEG electrodes	ECE, EOG and EEG features are correspondingly blood pressure and heart rate, eyeblink rate and temporal, frontal and occipital changes	Linear SVM, kernel SVM and KNN	The fuzzy mutual information-based wavelet packet transform method extracted the features. Four classifiers were applied.	Own dataset	95%
EEG and ECG [78]	Enobio-20 channel device	ECG signals HR and HRV's LF, HF and LF/HF ratio, EEG signals time-domain statistical descriptors, complexity and time domain measures	SVM	To notice drowsiness, EEG and ECG features are collected. After extracting the features, a paired t-test was only used to select the important features.	Own dataset	80.9%

2.4 Vehicular-Based measures

This technique depends on tracing and investigating driving patterns. Every driver procedure an exclusive driving pattern. Thus, the driving shape of a sleepy driver can be easily notable from those of an alert driver. Zhong et al. [79] accomplished a contained energy examination of the steering-wheel angle dynamics and vehicle pursuing to perceive driver fatigue and found a trend of localized energy rise with driving time. According to Pratama et al. [25], vehicular-based events are the least examined methods, due to the difficulty of exactly determining drowsy driving state structures. Thus, many researchers combine this measure with images-based or biological measures. The two most common perceived vehicle-based measures, used to classify driver drowsiness, are steering wheel angle (SWA) and lane departure. Below, we signify some examples of vehicle-based driver drowsiness detection systems that use these measures, A summary of these system is shown in Table 7.

- Entropy features from SWA time series

This method applies online fatigue detection using SWA data. Data were gathered via a sensor installed on the steering wheel for 14.68 hours while actual driving occurred. In order to extract the approximation entropy characteristics from a SWAs time series data, Li et al. [80] suggested a technique that makes use of a fixed sliding window. Then, using an adaptive piecewise linear fitting with a particular deviation, the approximation entropy features series are linearized. The system then determines the driver's level of awareness by computing the warping distance between the linear feature series. A specially created binary decision classifier is then used to determine the alertness state, either "drowsy" or "awake." The system's accuracy in the experiments was found to be 84.85% for true "drowsy state" detections and 78.01% for true "awake state" detections.

- SWA tracking of sleepiness

McDonald et al. [81] suggested using SWA data and the RF algorithm to analyze lane departure. The scientists contrasted their strategy with another PERCLOS-based image-based sleepiness measure. The comparison revealed that the SWA measure's accuracy was higher, reaching 79% and able to predict tiredness by six seconds. The PERCLOS approach only managed to reach accuracy of 55% at the same time. A dataset (72 participants) from a study at the National Advanced Driving Simulator at the University of Iowa was used to evaluate the algorithm [82]. The tiredness associated to lane departure was retrieved from the raw simulator data using the modified observer assessment of drowsiness scale. Following leaving the lane, readings were obtained every minute. With regard to the PERCLOS measurement, the features were taken from a movie and recorded using the FaceLab eye detection program. The RF method was also trained using a randomly chosen feature using a series of decision trees.

- Selection of steering wheel features based on ANFIS

A non-invasive DDD system based on steering wheel data was reported by Arefnezhad et al. [83]. The system's goal was to improve classification accuracy through the use of feature selection techniques. The suggested technique of selection made use of wrapper feature selection algorithms, filters, and adaptive neuro-fuzzy inference systems (ANFIS). A new dataset was produced as a result of the study, which involved 39 bus drivers in a simulated driving environment. The steering wheel data were used to derive 36 features. Four various filter indices received these features. To choose the most crucial traits, the fuzzy system was given the output of each filter. The selected features are then classified using an SVM classifier, which also specifies the state of the drivers. Finally, the accuracy of the classifier is used to adjust the ANFIS's parameters using the particle swarm optimization technique. The final results revealed a 98.12% accuracy rate.

- Using wavelet transform and a neural network, measure laterality

A model for detecting driver tiredness based on lateral distance was put forth by Ma et al. [84]. By combining lane curvature, location, and the curvature derivative, one may determine the lateral distance. With a video camera mounted on the front bumper of the car, those three raw features were collected utilizing the transportable instrumentation package system [85]. Additionally, this system records live video in order to record the driver's head and face motions. The ground truth for the data from the car was the driver's visual data. To extract lane-related signals in the frequency and temporal domain, TRW's simulator was fed the recorded automobile data.

Table 7. Vehicle-based drowsiness detection system

Vehicle Parameters	Extracted Features	Classification Method	Description	Dataset	Accuracy
Steering wheel [80]	SWA	Binary decision classifier	Use SWA data and a specially designed classifier for determining the alertness state.	Prepared their own dataset	84.85%
Steering wheel [81]	SWA	RF	SWA input data was used to compare with PERCLOS. With an arbitrarily chosen features, a sequence of detection was used to qualified the RF algorithm.	Own dataset	79%
Steering wheel [83]	Steering wheel velocity and SWA	SVM, ANFIS, PSO	Data from the steering wheel was used for detection. The system's selection process made use of ANFIS	Own dataset	98.12%
Lateral distance [84]	Relevant to the lateral distance and lane trajectory, derived from the time and wavelet domains and statistical features	Neural network and SVM	Based on lateral distance, drowsiness detection is counting. It gathers information on the driver's head and face movements to serve as the basic for the vehicle data.	Own dataset	90%

2.5 Hybrid-Based Measures

A hybrid driver drowsiness detection system employs a combination of image, biological and vehicle-based measures to extract drowsiness features, with the aim of producing a more robust, accurate and reliable driver drowsiness detection system. Below we represent some of the recently proposed hybrid driver drowsiness detection systems and Table 8 shows a list of those systems.

- EEG signal’s spectral, head movement and blink analysis

In order to substitute cameras and intrusive sensors in DDD systems, Mehreen et al. [86] retrieved the drivers' behavioral and biological features using a light, non-invasive wearing headband. A headband featuring an accelerometer, gyroscope, and EEG electrodes is used by the planned DDD system to collect a variety of signals. With the aid of 50 participants and a driving simulator, the dataset was gathered in both drowsy and awake states. The authors used the characteristics obtained from the head movement analysis, eye blinking, and spectral data to create a feature vector in order to improve robustness and obtain more accurate findings. The feature vector over several classifiers was then subjected to the backward feature selection approach. The greatest performance came from the linear SVM, which had an accuracy of 86.5% when fed the entire feature vector.

- Driver drowsiness detection using collaborative ML and hybrid perception

Gwak et al. [87] looked into the viability of developing a detection system for early drowsiness based on a combination of physiological, behavioral, and vehicle-based measures. In total, sixteen people took part in this investigation. The measured data and movies allowed for the extraction of a total of 80 features. The study was divided into three primary sections. Using a driving simulator and monitoring system, the drivers' physiological signals, driving performance, and behavioral sleepiness signs were recorded in the first section. The classification process was then carried out using two separate methods: RF classifier and majority voting, employing logistic regression, SVM, and KNN. Sequential backward feature selection was used in the majority vote scenario, followed by classification. The number of estimators and characteristics utilized, on the other hand, was improved in the case of RF to achieve higher classification performance. Finally, the algorithms' performance was assessed. This study focused on distinguishing between alert and slightly drowsy and alert and moderately drowsy states, using Zilberg's criteria [88] to categorize the various levels of drowsiness. With an accuracy rate of 82.4% for alert vs. mildly drowsy cases, the data indicated that the RF classifier produced the best results. For the situation of alert vs. moderately drowsy, majority voting fared best, with an accuracy of 95.4%.

- Driver support system based on image and vehicle-based feature analysis

A driving assistance system with a dual control architecture was presented by Saito et al. Based on the condition of the eyelids, the steering wheel, and lane departure, this system efficiently detects driver drowsiness and, if necessary, assumes control of the vehicle. In the event of a lane departure, the assistance system starts to partially control the car. The device allows the driver the opportunity to steer and center the vehicle in the lane. The system implies that the driver is incapable of operating the car or is sleeping if they do not take control of it within a predetermined amount of time. As a result, the system will take over and park the vehicle. This study had 20 participants. The majority of the data were gathered when the suggested help system was in operation. Through a series of mathematical procedures and predetermined methods from the study hypothesis, the driving status was ascertained. The study's findings demonstrated that when the required driving conditions were met, taking control of the vehicle could be done with up to 100% accuracy.

- DDD using image, biological and vehicle-based features fusion analysis

By using the same data that is used to define tiredness, De Naurois et al. [89] looked into the possibility of forecasting when a certain degree of drowsiness is attained. They also looked into whether adding further information, such participant data and driving time, would increase the accuracy of detection and prediction. 21 participants drove a car simulator for 110 minutes while being subjected to drowsiness-inducing circumstances. The researchers assessed biological, behavioral, and driving-related aspects of sleepiness. A few examples of these characteristics are heart rate and variability, respiration rate, blink frequency and length, PERCLOS, head and eyelid movements, time to lane crossing, position on the lane, speed, and SWA. Two ANN-based models were created, one for detecting the level of tiredness and the other for estimating the amount of time required to reach a particular level of drowsiness. Each model was run once per minute. Throughout this investigation, many feature combinations were evaluated. The models also demonstrated the ability to forecast the amount of time needed to reach a certain level of tiredness and detect drowsiness levels (with a mean square error of 0.22). (With a mean square error of 4.18 min).

- Yawning, blinking, and a pulse-based approach based on blood volume

Driving behavior indicators include yawning, blinking, and changes in heart rate. This finding led Zhang et al. [90] to develop a DDD system that makes use of the camera on a smartphone as a non-contact optical sensor. Blink and yawn signals are extracted from image sequences that the system has recorded and used as raw data. The extended-PPG signals that were collected from the image sequence also make it possible to extract the blood volume pulse without coming into close touch with the subject. The blood volume pulse, yawning, and blinking signals are simultaneously retrieved from smartphone footage using a multichannel second-order blind identification. The blinking duration and frequency, HRV, and yawning frequency are then calculated from the combined signals. In the event that any of the estimated parameters exhibits a particular value, sleepiness will be proclaimed, and a phone alarm will sound. The system displayed various sensitivity values that may reach 94%.

Table 8. Hybrid-based drowsiness detection system

Sensors	Hybrid Parameters	Extracted Features	Classification Method	Description	Dataset	Accuracy
Accelerometer, headband, gyroscope and equipment with EEG electrodes [86]	Behavioral and biological-based features	Head movement position, magnitude and superior power study and eyeblink shape investigation.	Backward feature selection method over various classifiers	Used a headband with three wearable sensors that is non-invasive. This system integrates the features obtained from spectral data, eye blinking and head movement analysis. Following a feature selection block, multiple categorization techniques are used to features. The most effective SVM was linear.	Prepared their own dataset	92%
Driving monitoring and simulator system [87]	Behavioral, biological and image-based features	80 features were extracted: PERCLOS, SWA, LF/HF, etc.	RF, SVM, KNN and logistic regression	Slightly and moderately drowsy were used to describe the driver levels of tiredness.	Own dataset	97.1%
Image-generating computers, automatic gearbox and control loaded steering system [24]	Vehicle and image- based feature	Eyelid opening degree, steering angle, driver's input torque, latera position, yaw angle, speed.	Specified schemes for the study hypothesis and a series of mathematical operation	A system that supports the driver in the event that sleepiness is found to stop lane departure. It provides the driver with a set amount of time to operate the vehicle. If not, the system drives the car into parking.	Own dataset	100%

PPG sensor, faceLAB, ECG, SCANeR Studio, MP150 [89]	Vehicle, biological and image-based features	Time-to-lane crossing, position on the lane, speed, SWA, heart rate and variability, respiration rate and blink duration.	ANN	Comprised to ANN-based models. One is used to detect the drowsiness grade and other is used to estimate how long it will take them fall asleep. Test were conducted using various features combination.	Own dataset	NA
Smartphone camera [90]	Image and biological-based feature	Blood volume pulse and eye blink and yawn signals	Any detected parameters	Yawning, blinking and blood volume pulse signals were extracted use a multichannel second order blind identification method based on the extended-PPG in a smartphone.	Own dataset	Up to 94%

CHAPTER 3

METHODS AND MATERIALS

3.1 Introduction

This chapter mainly focus the experimental design and the workflow of this study. How the setup is established and how the overall system work is discussed in this chapter. The overall methodology is described with diagram, equations and description of the algorithms are added. This chapter shows a clear scenario of our work.

3.2 Proposed Design

The proposed design of the drowsiness detection system is represented in Figure 3. The functional work flow for both the drowsiness as well as yawn detection techniques are depicted in the Fig. 4. Facial input is always read in real time by the camera. The FaceMesh algorithm processes the real-time face data, and the Microcontroller and Microprocessor component performs the necessary activities. The microcontroller and microprocessor are powered by an external power supply at all times. The Media Pipe FaceMesh machine learning (ML) function is a 468-face landmarks solution that works on the CPU. The 468 facial landmarks are depicted on a map, along with their placements on the face. The filtered landmarks on the face and real-time facial position are displayed on 7" IPS monitors. The vibration of the motor is controlled by the vibrator motor circuit in response to signals received from Facemesk. The Sound Box amplifies the related audio impulses.

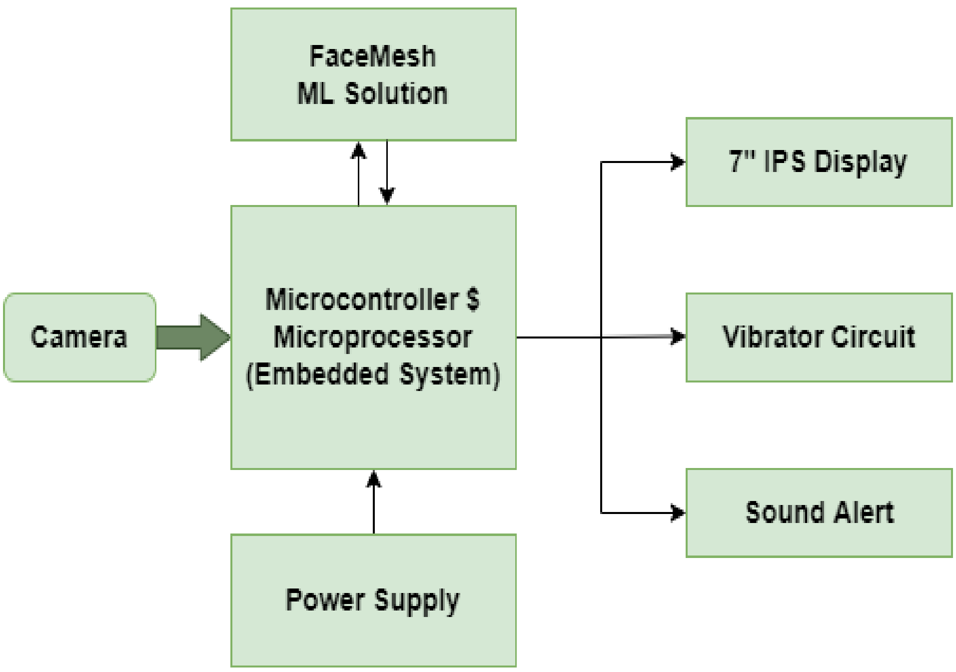

Figure 3. Proposed design of the driver drowsiness detection system

3.3 Functional Work Flow

The functional work flow for both the drowsiness as well as yawn detection techniques is depicted in Figure 4. The flowchart represents the functional work flow of our proposed system. Here, the individual thing is considered. First the eye blinks of driver and seconds the yawn of the driver. The camera is running all time to collect the real time driver's face data. A sound alert in conjunction with a seat belt vibrator is used; this will activate if drivers keep their eyes closed for at least 3 seconds.

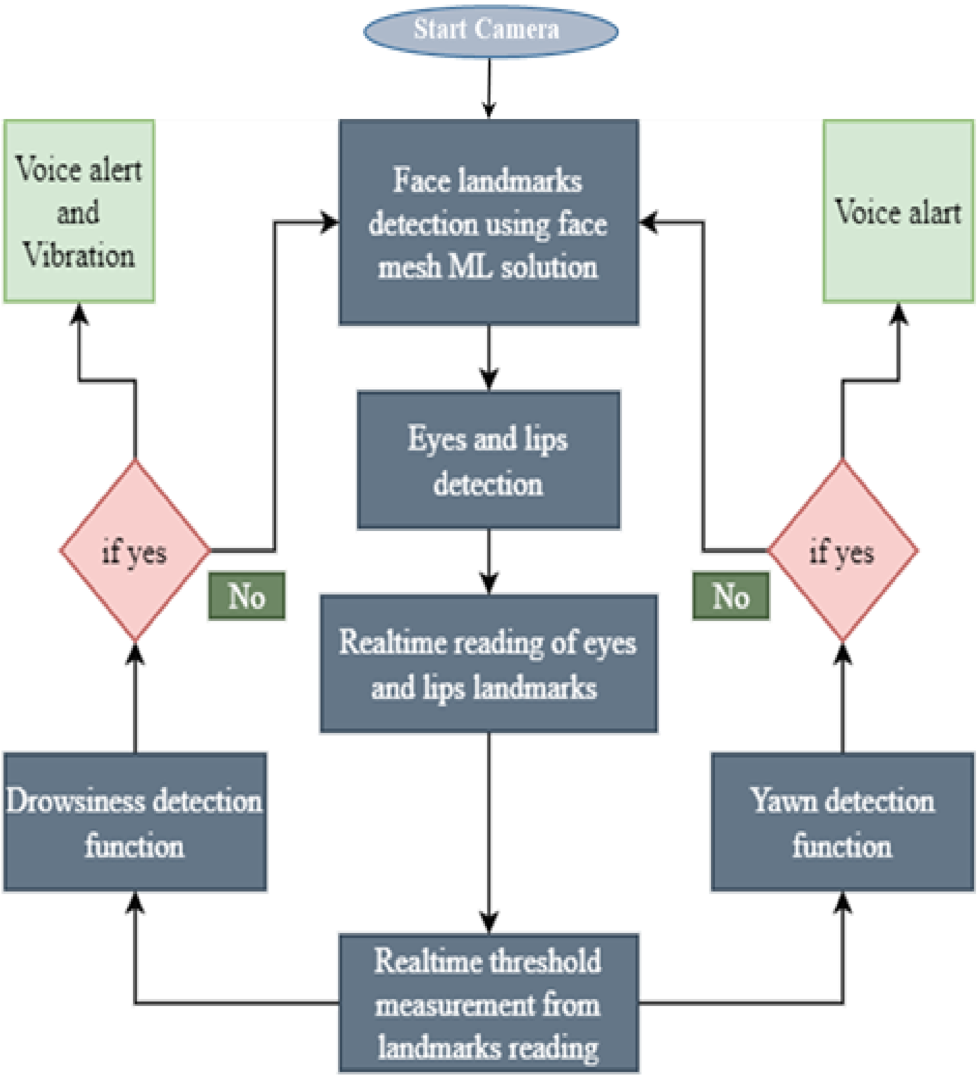

Figure 4. Functional work flow.

3.4 Driver View and Device Setup

Figure 5. shows the integration of the system with the driver. The driver will sit in the driving position and the device is set in front of the driver and the alarming vibrator is integrated with the seat belt.

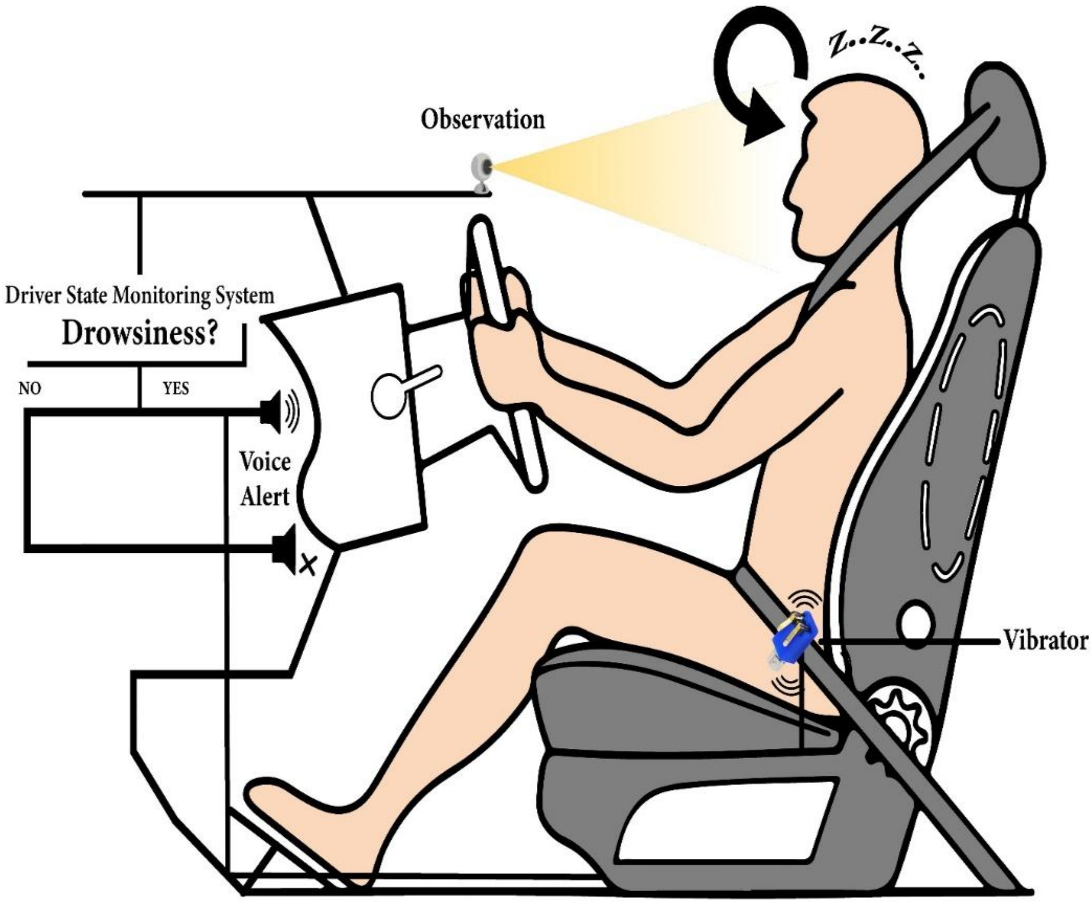

Figure 5. Driver view and device setup

3.5 Hardware Arrangement

To implement the device, we use some electronics components. All of them discussed below.

(i) Raspberry Pi 4.0
(ii) 7-inch touch screen display
(iii) Webcam
(iv) Vibrator
(v) Speaker
(vi) HDMI cable
(vii) Power cable
(viii) Wire cables

Raspberry Pi 4.0: The Raspberry Pi is a low-cost Linux computer with a set of GPIO (general purpose input/output) ports for controlling electronics in physical computing and experimenting with the Internet of Things (IoT).

7-inch touch screen display: This device is used for input and output purpose.

Webcam: A webcam is an embedded digital video camera in a personal computer. One of its primary uses is to share images online. It finds widespread application in the realms of both image capture and instant messaging.

Vibrator: A haptics driver receives input from the screen's touch sensors and then transmits impulse drive signals to the screen's vibration motors. Activating the motors causes the display to vibrate, mimicking the action of pressing a real button.

Speaker: Frequency and amplitude are the two main characteristics of speaker-produced sound. How high or low a sound is in pitch is determined by its frequency. The voice of a soprano vocalist, on the other hand, produces high-frequency sound waves, while the low-frequency sounds of a bass guitar or kick drum are produced.

HDMI cable: High-Definition Multimedia Interface is what it means to communicate video and audio at a very high resolution. It's the most used format for sending high-definition video and audio via a single connection from one device to another. A lot of

Power cable: A power cable is a type of electrical cable that consists of one or more electrical conductors encased in an outer sheath. The unit is employed in the distribution of electrical energy. Energy cables can be permanently wired into a building, buried, run overhead, or left uncovered.

Wire cables: Wires are singular conductive elements, while cables consist of multiple conductive strands bundled together. Despite this, these conductors are typically composed of copper or aluminum. Usually, the wires are exposed and coiled. However, some of the wires have a thin PVC coating.

3.6 Software

To run the setup hardware, we use an operating system and a programming language. We use:

(i) Python

(ii) Linux

Python: New data-handling classes, faster asynchronous I/O, and improvements to script compilation and garbage collection may all be found in Python 3.7. Python 3.7, the newest version of the language, has been released to the public with the goal of simplifying previously intractable problems.

Linux: Among Linux's many applications are: Server operating system for use in hosting websites, databases, files, emails, and other shared resources. Linux is perfect for use with any kind of server application because of its support for high-volume and multithreaded workloads. Personal productivity operating system designed for use on a desktop computer.

3.7 Experimental Setup

All the devices are organized to build the whole system. We connect the device using wire and the device is flexible. We can easily rearrange it and shows the setup of our experiment in Figure 6.

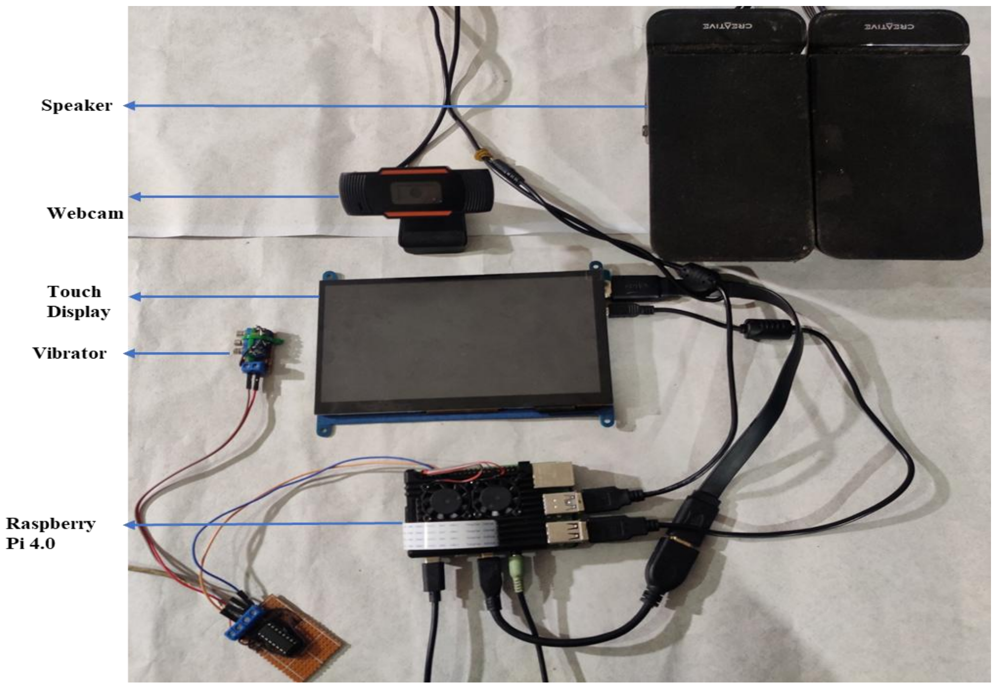

Figure 6. Experimental Setup

The Raspberry Pi is programmed with Facemesh and connected with camera, vibrator, touch-screen display and alarm by connecting wire. We use the sound-box to amplify the alarm. The vibrator is put in a position that driver can sense it and a display is integrated to the system for command purpose.

In this study, the media pipe face mesh was used. Even on using of different devices, it has 468 real-time 3D facial landmarks. The solution includes the Facial Transform which is a module that connects the dots between the estimation of facial landmark and the applications of augmented reality. It constructs a metric in 3D space and employs the facial landmark screen positions to estimate a face transform inside that space. Among the common 3D primitives present in the face transform data, a face position transformation matrix and a triangular face mesh in important. A lightweight statistical analysis approach, called procrustes analysis is employed to power the logic, which is robust, performant, and portable. On top of the ML model inference, the analysis runs on the CPU and has a small speed and memory footprint. We have used a new library named "Media Pipe". Media Pipe brings heavy AI models to embedded systems and smartphones, utilizing various model optimization techniques. Media Pipe's face mesh is a 468-face landmark solution [91]. A map of the 468 facial landmarks with their corresponding positions on Fig. 7.

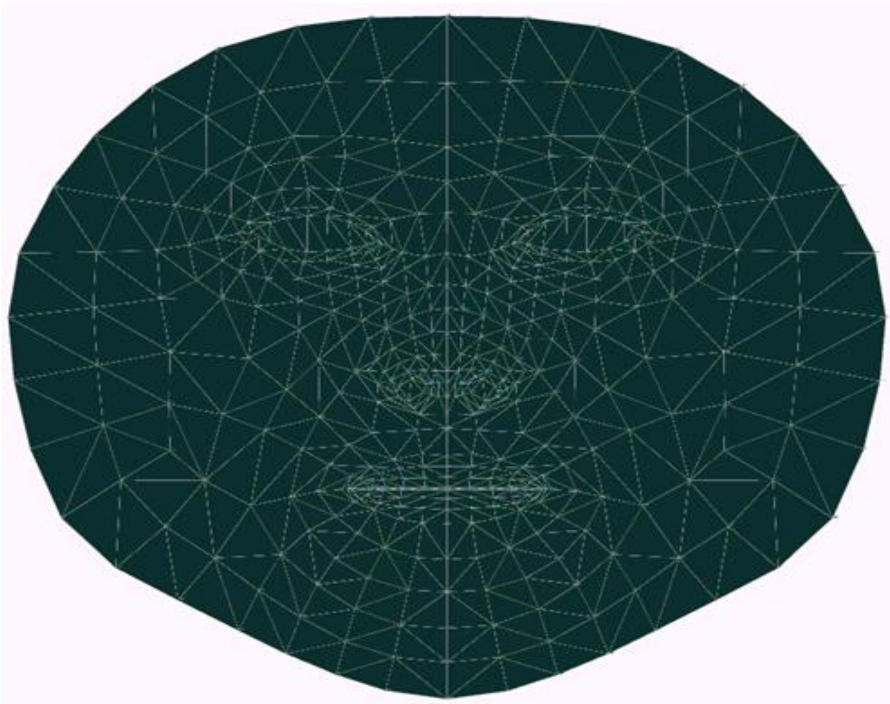

Figure 7. The numbers of the facial key points

3.8 Machine Learning Pipeline

The machine learning (ML) pipeline used in this study consists of two deep neural network models in real-time that cooperate: a detector that computes face positions on the full image and a model of 3D face landmark which acts on those locations and employs regression to prognosticate an approximation of the 3D field [92]. Correct cropping of the face significantly reduces the requirement for typical data augmentations such affine transformations, which include rotation, translation, and scale modifications. This results in less consistency in the data and more variation between data points. Additionally, it permits the network to concentrate most of its efforts on improving coordinate prediction accuracy. Additionally, facial landmarks detection-based cropping was included to our pipeline in an earlier frame, and the face detector model is only employed to delocalize the face in cases where the landmark model failed to detect its presence.

3.9 Models Used in this Study

Blaze Face detection model [93], a compact and effective face detector model that functions well on both Low-end and High-end based processors, has been utilized for face detection. It runs at a pace of 200–1000+ FPS on flagship devices. A lightweight feature extraction network built on a GPU-friendly anchor technique derived from Single Shot MultiBox Detector (SSD) and an enhanced tie resolution strategy in place of non-maximum suppression are used in the model's backend [94].

3D facial landmarks are another name for the face landmark model. The 3D landmark coordinates on synthetic rendered data are predicted by the network while simultaneously predicting 2D semantic contours on annotated real-world data via transfer learning. Along with the Face Landmark Model, it is used a model for focusing on the important facial features. This model requires more computation but predicts landmarks more accurately around the eyes, irises, and mouth. Among other things, it makes it possible for AR puppeteering and cosmetics.

The Facial Landmark Model employs a single camera to locate facial landmarks in screen coordinate space; the Horizontal and Vertical coordinates are conventional screen coordinates, while the Z coordinate is related to the Horizontal coordinate under the weak perspective projection camera model. Despite being suitable for some applications, this format does not support all augmented reality (AR) features, such as matching a virtual 3D object with a recognized face. The Face Transform module transforms a detected face into a standard 3D object by leaving the screen coordinate space and entering metric 3D space. When the landmark model can no longer detect the presence of a face, it is intended to be able to project the finished 3D scene back into screen coordinate space using a perspective viewpoint while keeping the location of the face landmarks

3.10 Facial Landmarks Detection Using Mediapipe Library

We have previously worked with face detection using the Mediapipe library alone, but there was a problem with detecting the landmarks points because they were not that clear when we were visualizing the other elements of the face, such as the major facial key points, in different angles. To deal with this problem, the only other method we have is to detect all 468 of the landmark's points.

3.11 Real-world Application of Face Mesh

Iris detection: This application can be very useful in healthcare and for simplicity in this article we will be majorly focusing on eye landmarks detection only.

Snapchat's filters: So, we have often seen a filter that acts whenever we change our facial moments so behind that pipeline there is one process that is known as detection of facial landmarks.

Drowsiness detection: This application can be very useful to detect driver drowsiness from eye blink detection and yawn detection.

CHAPTER 4

RESULT AND DISCUSSION

4.1 Introduction

Detection of drowsiness using proposed methodology is described in previous chapter. The obtained result and finding of our study are introduced in here with proper diagrams, pictures and tables.

4.2 Result Analysis

The total outcome of this experiment is organized in this chapter. The full setup is used in real-life experiment and the result are added in this chapter. The view of different head position is analyzed in this chapter to find the correctness of our proposed method. The response time is also calculated and the total workflow is discussed part by part.

After performing implementation of the proposed system in terms of experimental setup as well as real time output have been described in this section. The proposed system has been tested in terms of user angle that indicates how many angle the system cover to takes its input, and distance which measures how far the system captures input from a driver. Then the response time has been measured.

The bellow figure represents the different angle of the driver head position and yawn of the driver also. Figure 8 shows that when a driver is in a normal head position and his eyes are open, the LED and vibrator are off state.

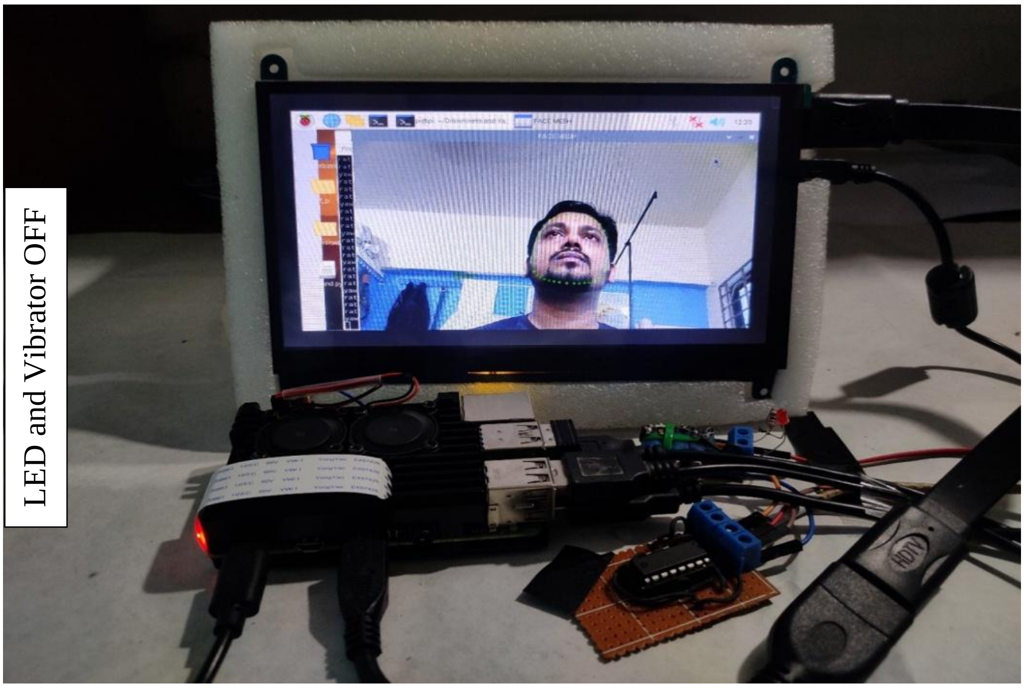

Figure 8. Normal head position of the driver

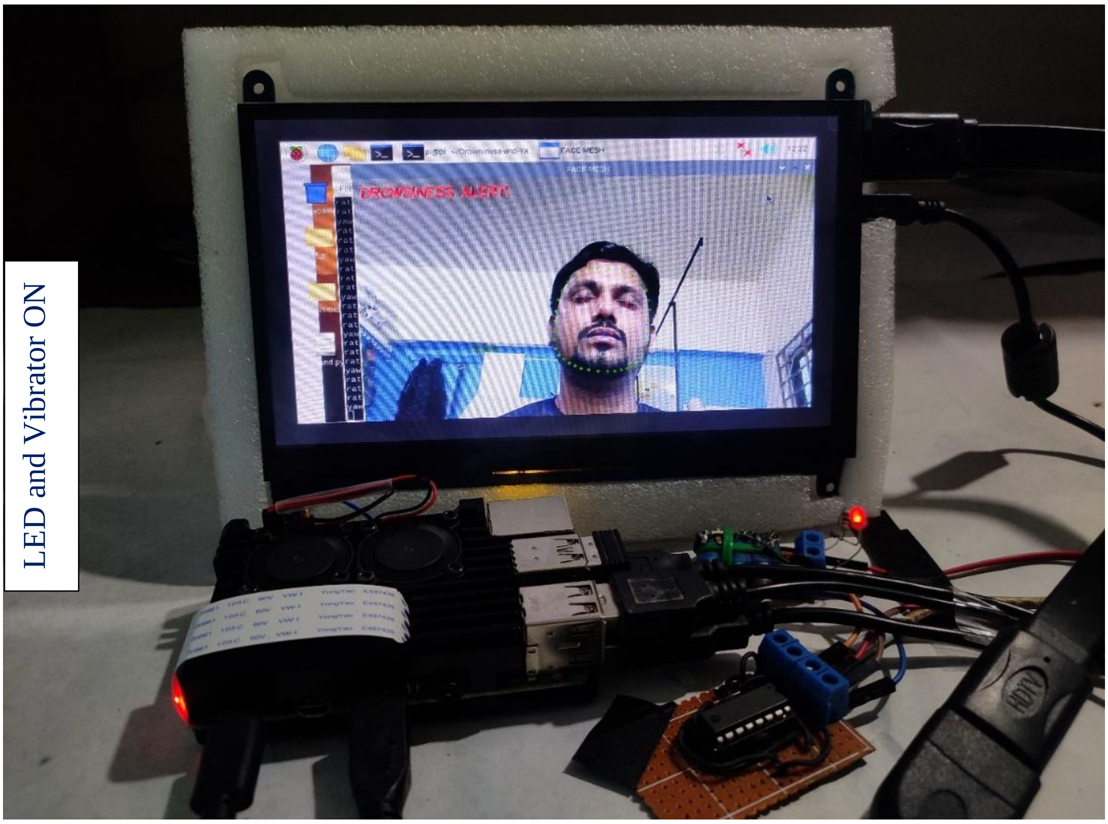

Figure 9. Drowsiness driver with normal head position

Figure 9 shows that when a driver is in drowsiness condition and his eyes are closed and also normal head position then our developed system is working and agreed to detect the drowsy state of the driver. After detecting this drowsy condition, our system alerts and vibrates the seat belt as a warning to stop the driver from drowsy and wakeup quickly.

Figure 10, 11,12 and 13 are respectively shows that when a driver is in drowsiness condition and keep his head position left-side, right side, up and down respectively then our developed system is also working and agreed to detect the drowsy state of the driver. After detecting this drowsy condition, our system alerts and vibrates the seat belt as a warning to stop the driver from drowsy and wakeup quickly.

Figure 14 shows that when a driver is in drowsiness condition with yawn then the system also perform and detect the drowsiness driver with yawn condition and give the alert sign. Since, it is an ongoing process, it will continue.

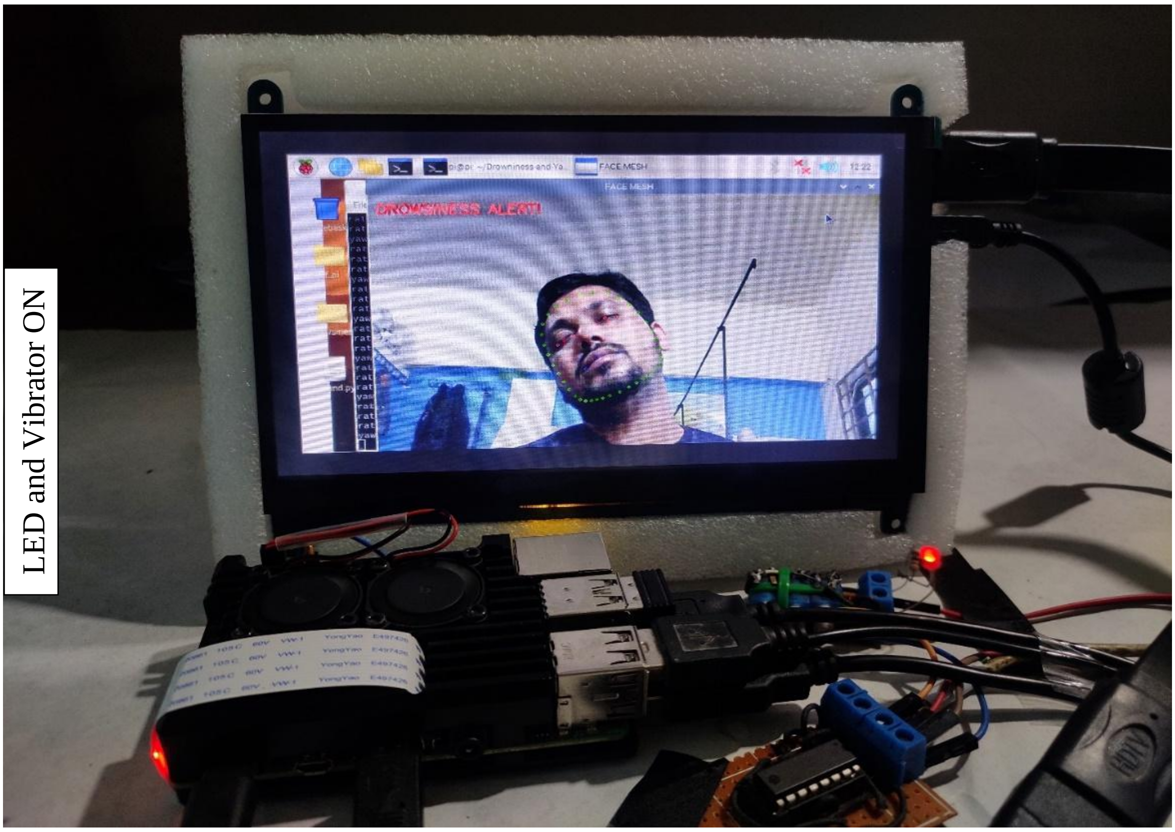

Figure 10. Drowsiness driver with left-sided head position

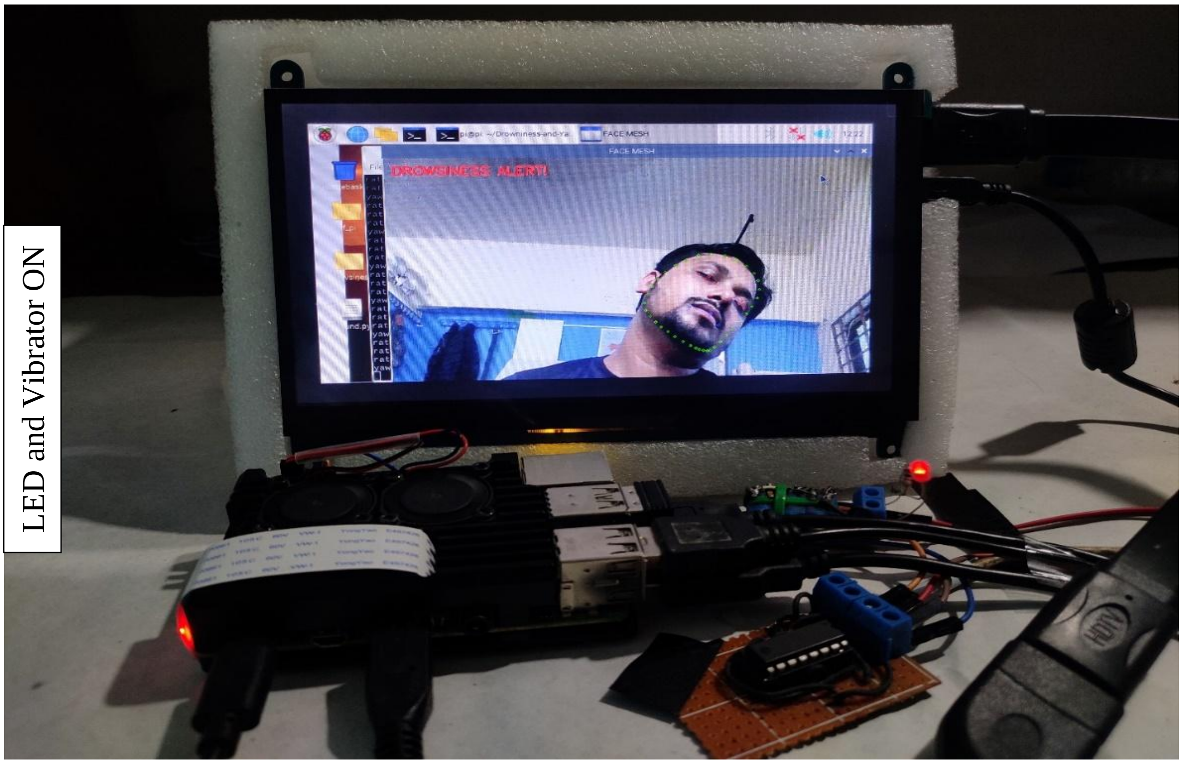

Figure 11. Drowsiness driver with right-sided head position

Figure 12. Drowsiness driver with lower-sided head position

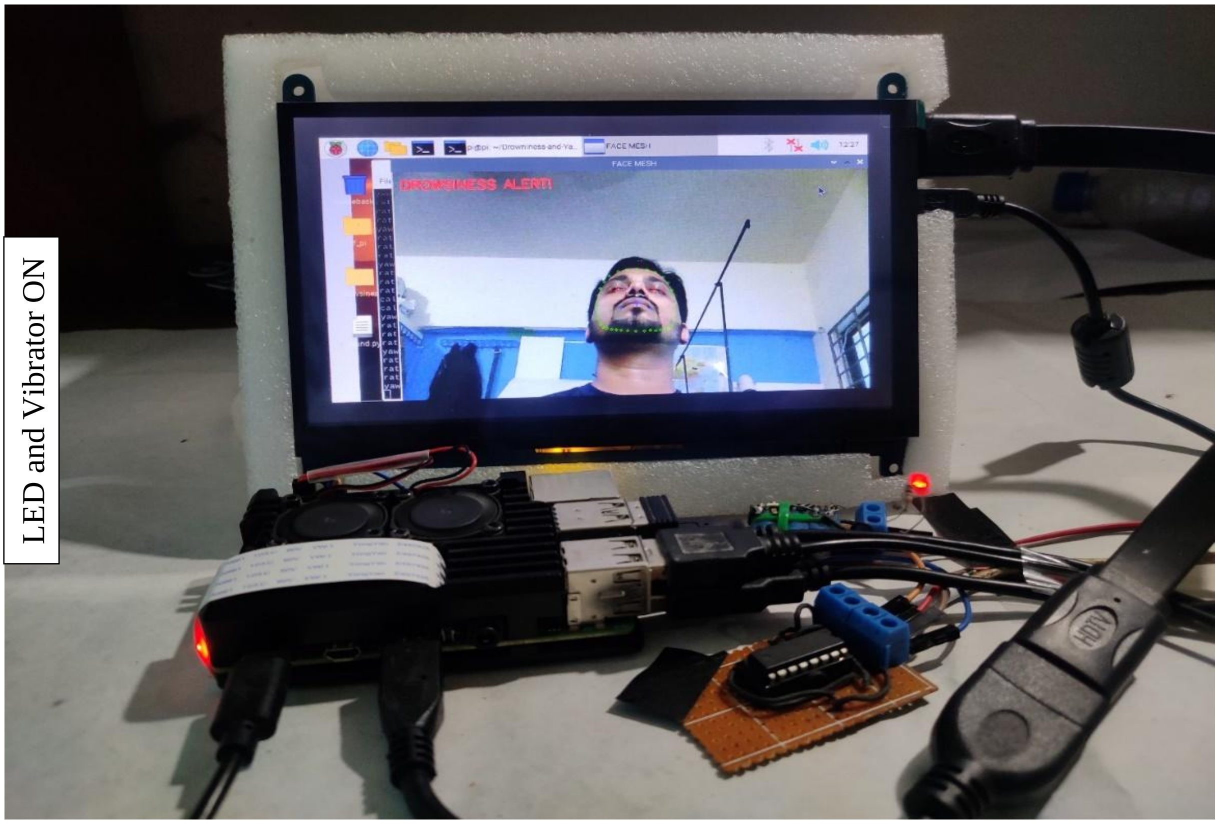

Figure 13. Drowsiness driver with upper-sided head position

Figure 14. Drowsiness driver with yawn

4.3 Head Measures

Figure 15. shows the measurement procedure of determining the maximum angle position of the driver. Both eyes of the driver were positioned with the camera at zero-degree (0^o) angle. When the driver turned his head at maximum 80^o angle to the right side, the camera could be able to accurately detect at least his left eye. On the other hand, when the driver rotated his head at maximum 80^o angle to the left side, the camera could be able to accurately detect at least his right eye. The angle cover of the device based on eyes is tabulated in Table 9.

Table 9. Angle covered by this device.

Angle (Left)	**Detection**	**Angle (Right)**	**Detection**
0^o	Yes	0^o	Yes
40^o	Yes	40^o	Yes
60^o	Yes	60^o	Yes
80^o	Yes	80^o	Yes

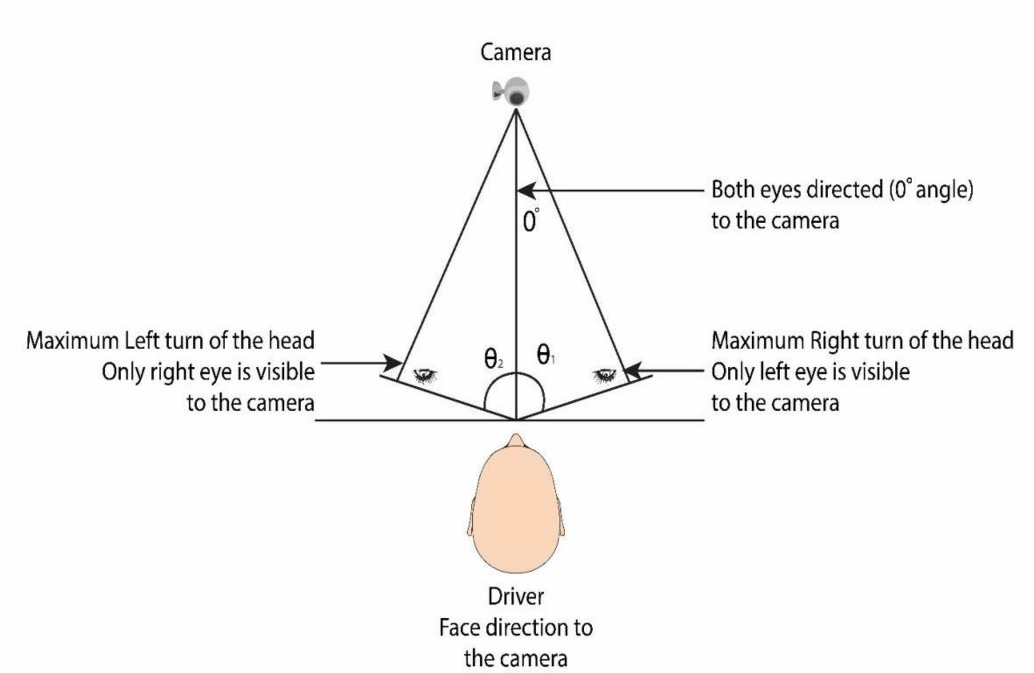

Figure 15. Measurement Procedure

We trail 20 times for each position and then calculate the mathematical average of the response time using following equation.

$$Avg = \sum_{i=1}^{n=20} \frac{T_i}{n} \tag{1}$$

After calculating the average for each position, we get the response time almost 3 seconds. Average time for each position is tabulated in Table 10.

Table 10. Response time for different head position of driver

Position	Response Time
1	3.02s
2	3.05s
3	3.02s
4	3.03s
5	3.00s
6	3.04s
7	3.02s
Average	3.02s

The average response time is 3.02 seconds. It means the alarm and vibrators are activated after detecting the drowsiness of the driver. 3.02 seconds is not a big time in real world and both the alarm and vibrator start warning together can make aware the driver about drowsiness. Driver can get back the safe mode of driving within this few time that ensure the safe drive in a vehicle. Moreover, the designed system was tested 80 times, where it showed 78 times positive feedback which indicated 97.5% accuracy of the system.

CHAPTER 5

CONCLUSION AND FUTURE WORK

This chapter this divided into two different segment, conclusion and future work. The work that are perform in this study are summarized in this chapter. The final outcome and future direction of the work that are related to our study are also discussed in here.

The proposed design of the system can find the drowsiness of driver during driving mode in a short time. FaceMesh technique is used to determine the eye and facial expression of the driver and after calculating the different face point, this system take a decision that the drowsiness is detected or not. Average 3.02 seconds response time has been achieved during several test. It is minimal and a vibrator is response quickly to aware the drive about the driving mode. Most of the components are connected by cables that give the permission to separate the parts and reassemble easily. In future, this drowsiness detection system can be implemented by a cloud-based system and proper monitoring system in integrated to observe the activities of driver. This experimentation is based on the behavioral features of a driver only, vehicle and physiological measurements are not considered because they are too pricey, intrusive and not completely efficient. Physiological measurements are intrusive and the sensors and equipment are very expensive

If we can train the model using more videos and images of the drowsiness as well as more features like body language, facial expression of drivers, which will make the system more intelligent for the re in the future if due to technology advances in the hardware field, these equipment become less costly and meddlesome, then it would be possible to incorporate theseal environment, then the system will response more quickly and provide more accuracy. with the behavioral data to obtain a more reliable and complementary result. Furthermore, using complex deep learning models on more diverse dataset would also extract additional features, thereby roviding a more satisfying result.

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APPENDIX

Appendix 1

Implementaion Code

```
from imutils.video import VideoStream

import cv2 as cv

import mediapipe as mp

from scipy.spatial import distance as dis
from threading import Thread
import time
import os
import pygame
import random
import os
import argparse
import imutils


import RPi.GPIO as GPIO

GPIO.setmode(GPIO.BCM)
GPIO.setwarnings(False)
GPIO.setup(17,GPIO.OUT)

def alarm():
    global alarm_status

    global saying

    while alarm_status:
        print('call-m')
        GPIO.output(17, True)

        print('call')
        path = '/home/pi/Drowniness-and-Yawn-Detection-with-voice-alert-using-Dlib/'
        sound_file = ['w.mp3', 'w1.mp3', 'w2.mp3', 'w3.mp3']

        pygame.mixer.init()
        volume = 1
        pygame.mixer.music.set_volume(volume)

        pygame.mixer.music.load(path + random.choice(sound_file))
        pygame.mixer.music.play()
        while pygame.mixer.music.get_busy() == True:
            continue
        # GPIO.output(17, False)
```

```
def alarm2():
    global alarm_status2
    if alarm_status2:
        print('call')
        saying = True
        path = '/home/pi/Drowniness-and-Yawn-Detection-with-voice-alert-using-Dlib/'
        sound_Y = ['m1.mp3', 'm2.mp3', 'm3.mp3']

        pygame.mixer.init()
        volume = 1
        pygame.mixer.music.set_volume(volume)
        pygame.mixer.music.load(path + random.choice(sound_Y))
        pygame.mixer.music.play()
        while pygame.mixer.music.get_busy() == True:
            continue
        saying = False


def draw_landmarks(image, outputs, land_mark, color):
    height, width = image.shape[:2]

    for face in land_mark:
        point = outputs.multi_face_landmarks[0].landmark[face]

        point_scale = ((int)(point.x * width), (int)(point.y * height))

        cv.circle(image, point_scale, 2, color, 1)


def euclidean_distance(image, top, bottom):
    height, width = image.shape[0:2]

    point1 = int(top.x * width), int(top.y * height)
    point2 = int(bottom.x * width), int(bottom.y * height)

    distance = dis.euclidean(point1, point2)
    return distance


def get_aspect_ratio(image, outputs, top_bottom, left_right):
    landmark = outputs.multi_face_landmarks[0]

    top = landmark.landmark[top_bottom[0]]
    bottom = landmark.landmark[top_bottom[1]]

    top_bottom_dis = euclidean_distance(image, top, bottom)

    left = landmark.landmark[left_right[0]]
    right = landmark.landmark[left_right[1]]
```

```
    left_right_dis = euclidean_distance(image, left, right)

    aspect_ratio = left_right_dis / top_bottom_dis

    return aspect_ratio


face_mesh = mp.solutions.face_mesh
draw_utils = mp.solutions.drawing_utils
landmark_style = draw_utils.DrawingSpec((0, 255, 0), thickness=1, circle_radius=1)
connection_style = draw_utils.DrawingSpec((0, 0, 255), thickness=1, circle_radius=1)

STATIC_IMAGE = False
MAX_NO_FACES = 1
DETECTION_CONFIDENCE = 0.5
TRACKING_CONFIDENCE = 0.5

COLOR_RED = (0, 0, 255)
COLOR_BLUE = (255, 0, 0)
COLOR_GREEN = (0, 255, 0)

LIPS = [61, 146, 91, 181, 84, 17, 314, 405, 321, 375, 291, 308, 324, 318, 402, 317, 14, 87,
178, 88, 95,
        185, 40, 39, 37, 0, 267, 269, 270, 409, 415, 310, 311, 312, 13, 82, 81, 42, 183, 78]

RIGHT_EYE = [33, 7, 163, 144, 145, 153, 154, 155, 133, 173, 157, 158, 159, 160, 161, 246]
LEFT_EYE = [362, 382, 381, 380, 374, 373, 390, 249, 263, 466, 388, 387, 386, 385, 384,
398]

LEFT_EYE_TOP_BOTTOM = [386, 374]
LEFT_EYE_LEFT_RIGHT = [263, 362]

RIGHT_EYE_TOP_BOTTOM = [159, 145]
RIGHT_EYE_LEFT_RIGHT = [133, 33]

UPPER_LOWER_LIPS = [13, 14]
LEFT_RIGHT_LIPS = [78, 308]

FACE = [10, 338, 297, 332, 284, 251, 389, 356, 454, 323, 361, 288, 397, 365, 379, 378, 400,
        377, 152, 148, 176, 149, 150, 136, 172, 58, 132, 93, 234, 127, 162, 21, 54, 103, 67, 109]

face_model = face_mesh.FaceMesh(static_image_mode=STATIC_IMAGE,
                                max_num_faces=MAX_NO_FACES,
                                min_detection_confidence=DETECTION_CONFIDENCE,
                                min_tracking_confidence=TRACKING_CONFIDENCE)

capture = cv.VideoCapture(1)

min_frame = 13  # 6
```

```
min_tolerance = 3.6  # 5.0
frame_count = 0
alarm_status = False
alarm_status2 = False
saying = False

while True:
    result, image = capture.read()
    resize = cv.resize(image, (600, 450), interpolation=cv.INTER_LINEAR)
    if result:
        image_rgb = cv.cvtColor(resize, cv.COLOR_BGR2RGB)
        outputs = face_model.process(image_rgb)

        if outputs.multi_face_landmarks:

            draw_landmarks(resize, outputs, FACE, COLOR_GREEN)

            draw_landmarks(resize, outputs, LEFT_EYE_TOP_BOTTOM, COLOR_RED)
            draw_landmarks(resize, outputs, LEFT_EYE_LEFT_RIGHT, COLOR_RED)

            ratio_left = get_aspect_ratio(resize, outputs, LEFT_EYE_TOP_BOTTOM,
LEFT_EYE_LEFT_RIGHT)
            print("ratio_left", ratio_left)

            draw_landmarks(resize, outputs, RIGHT_EYE_TOP_BOTTOM, COLOR_RED)
            draw_landmarks(resize, outputs, RIGHT_EYE_LEFT_RIGHT, COLOR_RED)

            ratio_right = get_aspect_ratio(resize, outputs, RIGHT_EYE_TOP_BOTTOM,
RIGHT_EYE_LEFT_RIGHT)
            print("ratio_R8", ratio_left)
            ratio = (ratio_left + ratio_right) / 2.0
            print("ratio", ratio)

            if ratio > min_tolerance:
                frame_count += 1

            else:
                frame_count = 0

            if frame_count > min_frame:
                if alarm_status == False:
                    alarm_status = True
                    t = Thread(target=alarm)
                    t.deamon = True
                    t.start()
                cv.putText(resize, "DROWSINESS ALERT!", (10, 30),
cv.FONT_HERSHEY_SIMPLEX, 0.7, (0, 0, 255), 2)
```

```
            else:
                alarm_status = False

            draw_landmarks(resize, outputs, UPPER_LOWER_LIPS, COLOR_BLUE)
            draw_landmarks(resize, outputs, LEFT_RIGHT_LIPS, COLOR_BLUE)

            ratio_lips = get_aspect_ratio(resize, outputs, UPPER_LOWER_LIPS,
LEFT_RIGHT_LIPS)
            if ratio_lips < 1.8:
                cv.putText(resize, "Yawn Alert", (10, 40), cv.FONT_HERSHEY_SIMPLEX, 0.7,
(0, 0, 255), 2)
                # Open his mouth
                if alarm_status2 == False:
                    alarm_status2 = True
                    t = Thread(target=alarm2)
                    t.deamon = True
                    t.start()
            else:
                alarm_status2 = False

        cv.imshow("FACE MESH", resize)
        if cv.waitKey(1) & 255 == 27:
            break

capture.release()
cv.destroyAllWindows()
```

List of Publications:

1. Jafirul Islam Jewel, Md. Mahabub Hossain, Md. Dulal Haque, "*Design and implementation of a drowsiness detection system up to extended head angle using FaceMesh machine learning solution*" International Conference on Machine intelligence and Emerging Technologies 2022 (MIET 2022), Noakhali Science and Technology University, Bangladesh, September 23-25, 2022. Proceedings will be published in the Lecture Notes of the Institute for Computer Science, Social Informatics and Telecommunications Engineering (LNICST) Series of Springer Nature, in cooperation with EAI (DBLP, EI Compendex, INSPEC, SCImage and Scopus Indexed).