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An Expert System for Driver's Drowsiness Detection

A Thesis

Submitted to the Department of Computer Science\ College of Sciences\ University of Diyala in a Partial Fulfillment of the Requirements for the Degree of Master in Computer Science

By

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بِسْمِ ٱللَّهِ ٱلرَّحْمَٰنِ ٱلرَّحِيمِ

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صَدَقَ ٱللَّهُ العَظِيم

سورة يوسف

الآية (٧٦)

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ALI AMER

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Abstract

One of the reasons for road accidents is the driver's drowsiness which leads to a considerable number of car crashes, injuries, lots of fatalities, and significant economic losses. Driver's drowsiness is represented as a state which varies between sleep and wakefulness, that decreases cognitive skills and impacts the capability of performing the task of driving. This serious issue needs to develop an effective vigilance monitoring system capable of decreasing accidents by alerting the driver under various bad driving situations. For detecting drowsiness, vehicle-based methods (such as estimating the level of drowsiness depending on the movements of the steering wheel), behavioral-based methods (detecting the driver visual features using various resources such as facial expressions, eye movements, head movements, etc.), and physiologic-based methods (detecting the earlier stages of driver's drowsiness depending on physiological signals) can be utilized.

This thesis is focused on the designing and implementation of a driver assistance system which includes a driver's monitoring and alarming by using behavioral-based method (eye movements detection method) and physiologic-based method (intrusive acquisition method, called Electrooculography (EOG) signals). In the method of detecting eye movements (Closed/Opened), the Local Binary Pattern (LBP) is used in which the descriptors are utilized to represent eye images to extract the tissue features of different persons in the driving car to see if the driver is in a drowsy state or not and this occurs after recording the driver's video and detection the eye of the driver. To extract the features in this way the image of the eyes is divided into small regions through the LBP and sequenced into a single feature vector, where this method is used to determine the similarity features in the training group and to classify the eye image. While in the used physiologic-based method, an embedded system based on ATmega2560

microcontroller on the Arduino board has been used to implement the EOG signal acquisition circuit. The developed system used several measurements to extract the features from EOG signals which makes it very sensitive to detect the driver's drowsiness. Furthermore, K Nearest Neighbors classifier (KNN) and Support Vector Machine (SVM) are used to give good accuracy. This system creates a low-cost device capable of quickly alerting the driver to ensure their safety. The experimental results show the efficiency and reliability of the proposed driver assistance system. The results indicate that the system has a high accuracy rate comparing with the other existing methods where the accuracy rate of KNN and SVM using EOG signal dataset (90% training and 10% testing) are 95% and 99.9% respectively, and the accuracy rate of KNN and SVM using eye detection dataset (90% training and 10% testing) are 98% and 100% respectively.

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List of Abbreviations

Abbreviation	Description
ECG	Electrocardiogram
EEG	Electroencephalogram
EMD	Empirical Mode Decomposition
EMG	Electromyography
EOG	Electrooculogram
SWM	Steering Wheel Movement
SDLP	Standard Deviation Of Lane Position
SD	Standard Definition
HD	High Definition
RGB	Red/Green/Blue
IDE	Integrated Development Environment
LBP	Local Binary Pattern
SVM	Support Vector Machine
KNN	K Nearest Neighbors

Chapter One

General Introduction

CHAPTER ONE

GENERAL INTRODUCTION

1.1 Introduction

At daily life, driving is a significant activity and with the passage of time, the number of vehicles is continued to increase leading to increasing road accidents. These accidents produce a state of disquiet to the individuals over the world, affect the main life component which is the human, and exhaust the material resources. Therefore, the proposals and solutions should be found to decrease the traffic accidents or at least determine the reasons and decrease the passive-effects and identify the core issues that lead to the traffic accidents occurrence, such as driver's drowsiness, road problems, vehicle breakdown, and etc. [1].

Regarding the government information released via the Statistics Central Bureau of the Ministry of Planning, the government of Iraq witnessed after "2003" a considerable increase in the number of vehicles reach to 5.8 million vehicles distributed among the provinces. Within the past ten years, more than sixty-six thousand traffic accidents have occurred in Iraq conducting 22,952 of dead people and 79545 of injured people. The Report on traffic accidents released via the Statistics Central Bureau presented that the collisions registered the highest ratio through the year "2015" [2]. Figure (1.1) shows the ratios for different types of traffic accidents for the year "2015", and also illustrates the high ratio of accidents is occurred by the drivers [3].

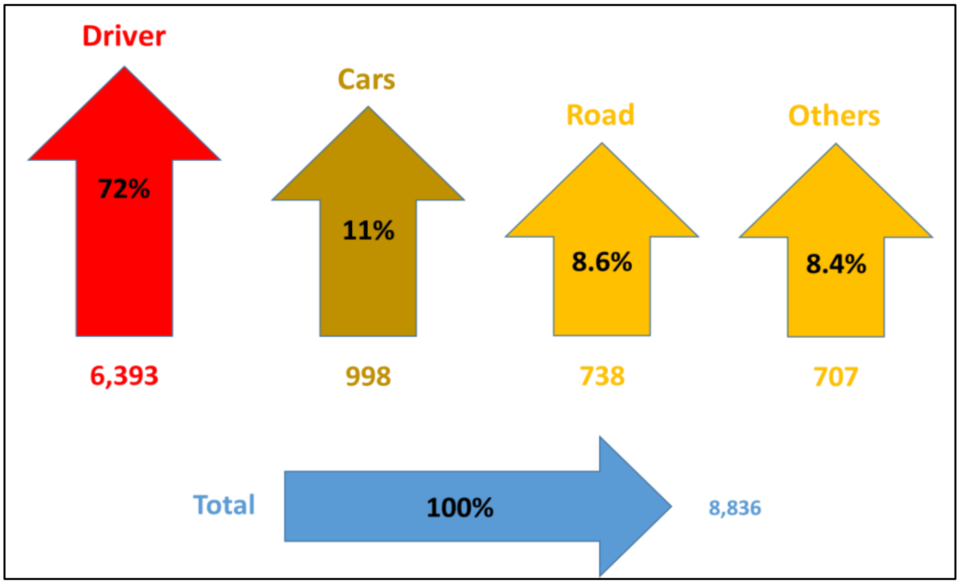
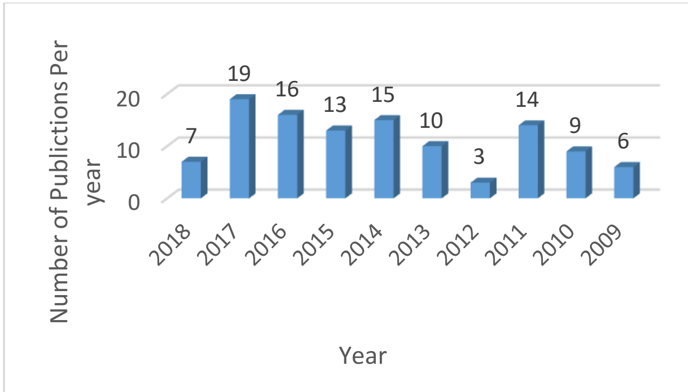


Figure (1.1): The ratios for different types of traffic accidents [3].

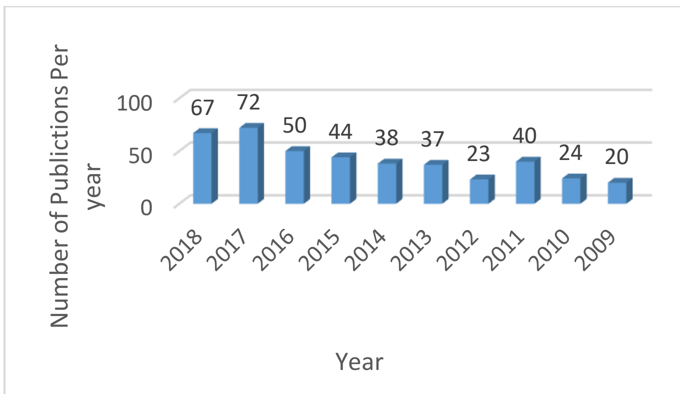
Drowsiness indicates to the near sleeping, an intense willing for sleeping, or sleeping of unusual long times. The persons in a particular status like driving a car should stay alert. On the contrary, dangerous accidents may happen [4]. In order to avoid these accidents, driver assistance systems are required which are capable of detecting driver drowsiness and sending an alert.

1.2 Related Works

Considerable researchers have exhausted a lot of effort in studying the driver's features in particular situations to design systems capable of detecting typical drowsiness signs. Figure (1.2) demonstrates the number of publications in the area of driver drowsiness detection system at the websites of "IEEE Explore", and "Science Direct" for the last ten years [3].



(a)



(b)

Figure (1.2): The publications distribution data for the years 2009-2018 have been retrieved from the websites (a) "IEEE Explore"; (b) "Science Direct" [3].

Regarding the physiological measures, the systems utilized in data gaining to detect sleep stage are depending on the generation of the signals of the electrocardiogram (ECG), the electrooculogram (EOG), the electromyography (EMG), and the electroencephalogram (EEG). It is very difficult to perform a device that alerts the drivers when falling asleep utilizing EMG and EEG signals due to a large number of electrodes that have to be located on the driver's skin [5]. EOG is the most commonly utilized physiological signal in automatic detection of sleep stages.

Hu Shuyan and Zheng Gangtie, 2009 [6] presented to perform the drowsiness prediction by employing Support Vector Machine (SVM) with eyelid related parameters extracted from EOG data collected in a driving simulator provided by EU Project SENSATION. The dataset is firstly divided into three incremental drowsiness levels, and then a paired t-test is done to identify how the parameters are associated with drivers' sleepy condition. With all the features, a SVM drowsiness detection model is constructed. The validation results show that up to 86.67% of the trials accurately detect when the subject is 'sleepy'. 16.67% of the trials which are supposed to be 'alert' are wrongly detected as 'sleepy'/ 'very sleepy'.

Mandalapu Sarada Devi et al., 2011 [7] presented a vision-based real-time driver drowsiness detection system for safety driving. The system localizes and tracks the eyes of a driver in order to detect drowsiness. Skin color model is used for face detection and after that eyes are detected by using Circular Hough transform, and then eye state is estimated (whether opened or closed) by using developed distance logic. This designed system detected face as well as eyes with an accuracy of 80%. Sometimes because of dark background the system may not be able to detect the face hence system produce some error in eye detection and gives false alarm of fatigue detection. During tracking, the system is able to decide if the eyes are open or closed. When the eyes have been closed too long, drowsiness is detected and warning signal is issued.

Wei Zhang et al., 2012 [8] presented a nonintrusive drowsiness recognition method using eye-tracking and image processing. A robust eye detection algorithm is introduced to address the problems caused by changes in illumination and driver posture. Six measures are calculated with the percentage of eyelid closure, maximum closure duration, blink frequency, the average opening level of the eyes,

opening velocity of the eyes, and closing velocity of the eyes. These measures are combined using Fisher's linear discriminant functions using a stepwise method to reduce the correlations and extract an independent index. Results with six participants in driving simulator experiments demonstrate the feasibility of this video-based drowsiness recognition method that provided 86% accuracy.

Nantakrit Yodpijit et al., 2015 [9] proposed a low-cost blinking detection system is built with simple modules and acceptable performance by measuring the EOG signal from one low-pass filter. Results from the preliminary experiments suggest that the blinking detection system can work just fine under controlled conditions such as in a laboratory. However, this blinking detection system has some technical issues that need to be resolved such as; an automatic blinking detection system, the instability of the signal, the use of electrodes, etc. There are several limitations to using this blinking detection system. Examples are; firstly, the decision parameter needs to be adjusted by the users, secondly, the electrode wires are no longer needed for the further development of the blinking detection system. In this system, the accuracy rate has not been computed, also, there are several points that should be provided, like installing this system in a driving simulator and/or a real vehicle, and testing as an in-vehicle warning system to protect drowsy drivers.

Zheren Ma et al., 2016 [10] presented a wearable drowsiness detection system. This system measures the EOG signal; transmits the signal to a smartphone wirelessly, and could alarm the driver based on a prediction algorithm that can estimate 0.5-second-ahead EOG signal behavior. This system is compact, comfortable, and cost-effective. The 0.5-second ahead estimation capability provides the critical time for a driver to correct the behavior and ultimately saves lives. In this system, the accuracy rate has not been computed.

Jinan Deeb et al. 2017 [11] proposed an empirical mode decomposition (EMD) method as a signal decomposition tool. This kind of method is useful for the analysis of natural and non-stationary processes. Some parameters are calculated for each intrinsic mode function. EMD is proved to be adaptive and highly efficient in the analysis of such signals and the proposed parameters provided significant differences between normal and sleepy status and developed an algorithm enabling reliable analyses of routine EOG measurements. Generally, the algorithm offered a successful option to attain knowledge of human sleepiness and fatigue. As perspective, the results could be used for the implementation of a real drowsiness detection system. This system should work on merging hardware and software, miniaturization, and installation on a person during driving.

Rateb Jabbar et al., 2018 [12] presents an approach towards real-time drowsiness detection. This approach is based on a deep learning method that can be implemented on Android applications with high accuracy. The main contribution of this work is the compression of the heavy baseline model to a lightweight model. Moreover, the minimal network structure is designed based on facial landmark key point detection to recognize whether the driver is drowsy. According to the experimental results, the size of the used model is small while having an accuracy rate of 81%.

Shaibal Barua et al., 2019 [13] proposed an automatic sleepiness classification scheme designed using data from 30 drivers who repeatedly drove in a high-fidelity driving simulator, both in alert and in sleep-deprived conditions. Driver sleepiness classification was performed using four separate classifiers: k-nearest neighbours (KNN), support vector machines (SVM), case-based reasoning, and random forest, where physiological signals and contextual information based on electroencephalography (EEG) and EOG electrodes were used as sleepiness

indicators. The subjective Karolinska sleepiness scale (KSS) was used as a target value. An extensive evaluation of multiclass and binary classifications was carried out using 10-fold cross-validation and leave-one-out validation. With 10-fold cross-validation, the SVM (when 80% training and 20% testing) showed better performance than the other classifiers (79% accuracy for multiclass and 93% accuracy for binary classification).

Ameen Aliu Bamidele et al. 2019 [14] proposed a behavioral driver drowsiness detection system based on tracking the face and eye state of the driver. In this system, the National Tsing Hua University (NTHU) Computer Vision Lab's driver drowsiness detection video dataset was utilized. Several video and image processing operations were performed on the videos so as to detect the drivers' eye state. From the eye states, three important drowsiness features were extracted: percentage of eyelid closure, blink frequency, and maximum closure duration of the eyes. These features were then fed as inputs into several machine learning models for drowsiness classification. Models from KNN, SVM, Logistic Regression, and Artificial Neural Networks (ANN) machine learning algorithms have experimented. The obtained result shows that the best models were a KNN model when k = 31 and an ANN model that used an Adadelta optimizer with 3 hidden layer network. The KNN model obtained an accuracy of 72.25%, while the ANN model obtained an accuracy of 71.61%.

1.3 Problem Statement

In recent years, various systems for developing effective driver assistance systems have been proposed. Most of these systems are depending on physiological measures and the main advantage of these measures is that the

physiological signals begin to alteration in earlier stages of drowsiness, that provide the earlier detection for the driver's drowsiness with maximum accuracy. While, the main disadvantage of these measures is that the physiological signals are commonly gained utilizing intrusive approaches and though several methods have been found to gain these signals utilizing non-intrusive approaches, losing the quality of signals is yet considerable [15]. Also, these systems may depend on behavioral measures used to detect the visual features of drivers utilizing a camera. Visual features sources involve eye movements, facial expressions, and head movements. The main advantage of these visual-based systems is that they can be obtained non-intrusively. But, the conditions of sunlight and light may make the task complicated. Additionally, with the partially automated driving, potentially the drivers look away from the road, and that required extra cameras or a bigger head box for providing accurate imagery to the face [16]. In this thesis, a driver assistance system is designed and implemented which includes a driver's monitoring and alarming by using intrusive and non-intrusive acquisition methods.

1.4 Aim of Thesis

The aim of this thesis is to create an accurate and low-cost system capable of quickly alerting the drivers from the drossiness to ensure their safety. The developed system is based on utilizing two methods; behavioral based method (detecting the driver visual features using eye movements (closed or opened)), and physiological based method (detecting the earlier stages of driver's drowsiness depending on EOG signals).

1.5 Outlines of Thesis

In additional to chapter one, this thesis contains four chapters:

Chapter Two: Theoretical Background

This chapter gives the background and review of some techniques especially the techniques based EOG and the techniques based detecting the driver visual features using eye movements، local binary pattern, Viola-Jones, and machine learning.

Chapter Three: The proposed system

This chapter describes the proposed system with their design and implementations.

Chapter Four: Experimental Results and Discussion

This chapter explains the results that have been gotten from the proposed system.

Chapter Five: Conclusion and Suggestion for Future works

This chapter covers the conclusions observed from the system, and the applications in which the system can may be also used for. Finally, the future work is recommended for the proposed system.

Chapter Two

Theoretical Background

CHAPTER TWO

THEORETICAL BACKGROUND

2.1 Introduction

The driving is a complicated job which requires mental awareness and physical resources. The need for complete mental awareness gives it a risky job since people have limited ability to become mindful to a long time. The Lacking of awareness and drowsiness are capable of causing earnest considerable injuries and losing the life of drivers and travelers. There are lots of causes which lead to road accidents like the condition of roads, the condition of the vehicle, weather, drivers' skills, drivers' drowsiness, and etc. The drowsiness state is usually indicated as sleepiness, in which the persons/drivers have the tendency to fall asleep. So, when the onboard system, that is capable of monitoring the status of drivers' drowsiness and producing an altering if the symptom of low attention is detected, it will give considerable support to the safety of transportation [17]. Several methods depended on recording the movements of head; monitoring the steering wheel and tracing other variables have been improved to this purpose for having sufficient knowledge about the status of driver's awareness.

2.2 Driver Drowsiness Detection Methods

There are several methods to detect and measure driver drowsiness (or sleepiness). They are generally grouped into three categories: physiological-based, vehicle-based, and behavioral-based [3].

2.2.1 Physiological-based Methods

Physiological methods offer an objective, precise way to measure sleepiness. They are based upon the fact that physiological signals start to change in earlier stages of drowsiness, which could allow a potential driver drowsiness detection system a little bit of extra time to alert a drowsy driver in a timely manner and thereby prevent many road accidents. The reliability and accuracy of driver drowsiness detection by using physiological signals is very high compared to other methods. However, the intrusive nature of measuring physiological signals remains an issue that prevents their use in real-world scenarios. Due to the technological progress in recent years, it is possible that some of the problems caused by these methods will be overcome in the future [18]. The idea of being able to detect drowsiness at an early stage with very few false positives has motivated many researchers to experiment with various electrophysiological signals of the human body, such as electrocardiogram (ECG), electroencephalogram (EEG), and electrooculogram (EOG). They are briefly defined and explained below [19].

- ***a. Electrocardiogram (ECG)*** records the electrical activity of a human heart. This system can very precisely tell which state the human body is in by detecting minute changes in the behavior of the heart, such as an increase or decrease of heart rate. Variability of a heart rate can be described using Heart Rate Variability measure (HRV), in which the low (LF) and high (HF) frequencies of the heartbeat are described. HRV is a measure of the beat-to-beat (R-R intervals) changes in the heart rate. When a subject is awake, the heart rate is much closer to the HF. The ECG can clearly show that when a subject starts going into a drowsy state, the heart rate starts slowing down and heading towards the LF band [20].
- ***b. Electroencephalogram (EEG)*** records the electrical activity of a human brain. It is the most reliable and most commonly used signal that can

precisely describe a human's alertness level. The EEG signal is highly complex and has various frequency bands. Frequency bands that can be measured to determine if a subject is drowsy are; delta band which corresponds to sleep activity; theta band which is related to drowsiness; and beta band which corresponds to alertness. A decrease in the power changes in the alpha frequency band and an increase in the theta frequency band indicate drowsiness. The frequencies measured using this method are very prone to errors and require very specific conditions for being measured properly [21]. Moreover, in order to measure them, sensing devices would have to make physical contact with the subject. Clearly, in a real-world driving scenario, having electrodes attached to the driver’s head, beyond their huge inconvenience, would hinder their driving capabilities and potentially increase the chances of an accident happening [15].

c. ***Electrooculogram (EOG)*** records the electrical potential difference between the cornea and the retina of a human eye. It is shown that this difference determines the behavior of the eye, which can be used to monitor drivers’ alertness levels. This method is highly invasive since it requires direct contact with a subject, usually in the following manner: a disposable electrode is placed on the outer corner of each eye and a third electrode at the center of the forehead for reference. The associated methodology is relatively simple: if a slower eye movement is detected, compared to the regular eye movement of a subject in the awake stage, the conclusion is that the subject is becoming drowsy [22].

2.2.2 Vehicle-Based Methods

The drowsy-driving crashes are often based on subjective evidence, such as police crash reports and driver’s self-reports following the event [23]. Evidence

gathered from the reports suggests that the typical drivers' and vehicles' behavior during these events usually exhibit characteristics such as; the higher speed with little or no braking, a vehicle leaves the roadway, the crashes occur on a high-speed road, the driver does not attempt to avoid crashing, the driver is alone in the vehicle. All of these characteristics noted suggest that a vehicle involved in an accident driven by a drowsy driver creates specific driving patterns that can be measured and used for the detection of a potential drowsy driving situation [24]. The two most commonly used vehicle-based measures for driver drowsiness detection are the steering wheel movement (SWM) and the standard deviation of lane position (SDLP). SWM methods rely on measuring the steering wheel angle using an angle sensor mounted on the steering column, which allows for the detection of even the slightest steering wheel position changes. While, the core idea behind SDLP methods is to monitor the car's relative position within its lane with an externally-mounted camera [25].

2.2.3 Behavioral-Based Methods

The behavioral-based methods are deemed as either unreliable or very intrusive for real-world applications, thus leading towards exploiting a different type of methodology, based upon non-invasive observation of a driver's external state. These methods are based on detecting specific behavioral clues exhibited by a driver while in a drowsy state. A typical focus is on facial expressions that might express characteristics such as rapid, constant blinking, nodding or swinging of the head, or frequent yawning. These are all tell-tale signs that a person might be sleep-deprived and/or feeling drowsy [26]. Typically, systems based on this methodology use a video camera for image acquisition and rely on a combination of computer vision and machine learning techniques to detect events of interest, measure them, and make a decision on whether the driver may be drowsy or not. If

the sequence of captured images and measured parameters (e.g., the pattern of nodding or time-lapsed in “closed eye state”) suggests that the driver is drowsy, an action such as sounding an audible alarm might be warranted [27].

Behavioral methods are considered cost-effective and non-invasive but lead to significant technical challenges. In addition to the challenges associated with the underlying computer vision, machine learning, and image processing algorithms, the resulting systems are required to perform in real-time and to exhibit robustness when faced with bumpy roads, lighting changes, dirty lenses, improperly mounted cameras, and many other real-world less-than-ideal driving situations [27].

a. ***Head or eye position:*** When a driver is drowsy, some of the muscles in the body begin to relax, leading to nodding. This nodding behavior is what researchers are trying to detect. Research exploiting this feature has started just recently. Detecting head or eye position is a complex computer vision problem which might require stereoscopic vision or 3D vision cameras [28].
b. ***Yawning:*** Frequent yawning is a behavioral feature that tells that the body is fatigued or falling into a more relaxed state, leading towards sleepiness. Detecting yawning can serve as a preemptive measure to alert the driver. It should be noted, however, that yawning does not always occur before the driver goes into a drowsy state. Therefore, it cannot be used as a stand-alone feature; it needs to be backed up with additional indicators of sleepiness [29]. The conventional method for yawn detection included chin strap, mechanical assembly for jaw movement detection. But as technology advances the method of approach also gets updated. The non-intrusive methods have gained importance as they are harmless and can be easily incorporated in any scenario. One of the non-intrusive methods includes the use of the camera. The use of a camera can be done to capture the image of the person and then processing on it, as optical flow and color predicates to

robustly track a person’s head and facial features. Here, the processing would be the extraction of the region of interest and finally detecting the state of mouth [26].

c. ***Eye state:*** The human eye is known to be one of the significant features of the human face. The characteristics extracted by studying the eye movement, texture, and gaze have attracted much attention for potential use in expressing person needs, mental processes, and emotional states. The fact that the human eye is constantly moving is indeed the principle for the development of robust nonintrusive eye detection and tracking methods. Besides, research in eye characteristics utilization, and particularly the pupil features exploitation, is currently taking place at a breathtaking pace [30]. At any given time, the eye can roughly be categorized into one of three states: wide open, partially open, or closed. The last two can be used as indicators that a driver is experiencing sleepiness. If the eyes stay in these two states for a prolonged period of time, it can be concluded that the driver is experiencing abnormal behavior. An eye-state detection system must be able to reliably detect and distinguish these different states of the eyes [31]. Detecting the state of the eyes has been the main focus of this thesis for determining if a driver is drowsy or not. Typically, the feature extraction process is followed by training and the use of machine learning algorithms of various capabilities, strengths, and weaknesses.

d. ***Multiple Facial Actions:*** The multiple facial features can be utilized, including state and position of the eyebrow, lip and jaw-dropping combined with eye blinking for detecting the driver's drowsiness [32].

2.3 Digital Video

Digital video is made of pixels, where a pixel can be regarded as a small dot on a television screen. There are many pixels in one frame of video and many frames (a series of still images) within one-second, commonly 50 or 60 fps for consumer video, and 70-90 fps for computer displays. Figure (2.1) shows that the video is composed of a series of still images and each image is composed of individual lines of data, also, there is special timing information, called vertical sync, which is used to indicate when a new image is starting. Each still image is also composed of scan lines, lines of data that occur sequentially one after another down the display. Additional timing information, called horizontal sync, is used to indicate when a new scan line is starting. The vertical and horizontal sync information is usually transferred in one of three ways: firstly, separate horizontal and vertical sync signals, secondly, separate composite sync signal, and thirdly, composite sync signal embedded within the video signal. The composite sync signal is a combination of both vertical and horizontal sync [33].

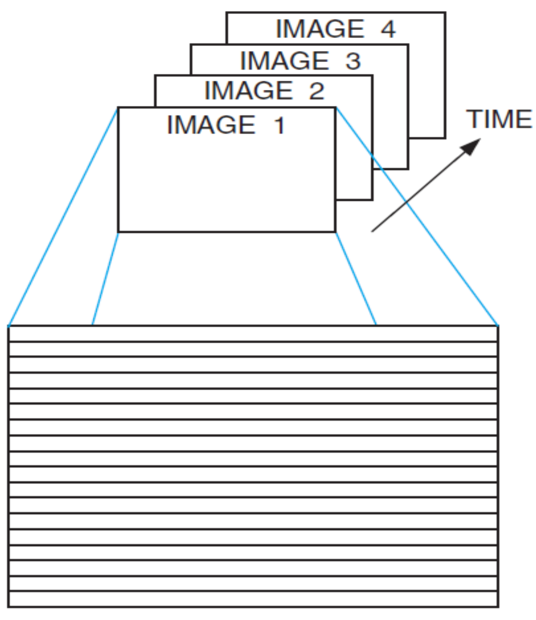


Figure (2.1): Video Timing [33].

There are various video resolutions such as standard definition (SD), high definition (HD) with 720p, or HD with 1080p. Figure (2.2) shows the number of pixels for these different resolutions that can be seen the same video frame for a 1080p TV is represented by a little over two million pixels compared to only about 300,000 pixels for standard definition. No wonder HD looks so good [34].

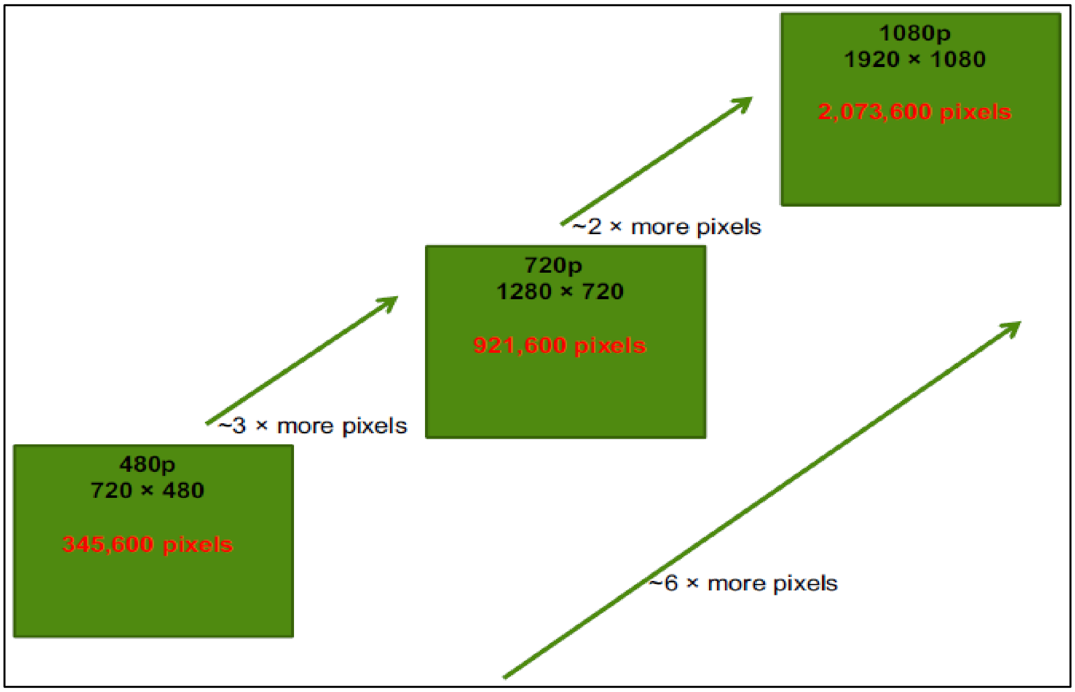


Figure (2.2): Increasing number of pixels in each frame of video [34].

The number of pixels makes a huge difference, for example, when Apple created the new 'retina' display on the iPhone 4 it proved extremely popular with consumers. The iPhone 4 had a resolution of 940×640 pixels compared to the old iPhone 3, which had a resolution of 320×480. So Apple found a way to increase the number of pixels on the same size screen by a factor of four [34].

2.3.1 Video Color Spaces

There are several conventions or “color spaces” used to construct pixels. The broadcast industry originally used black-and-white images, so a video signal contained only luminance (or brightness) information. Later, color information was added to provide for color television and movies. This was known as chrominance information. The color space formats associated with this is known as YCrCb, where Y is the luminance information, Cr and Cb are the chrominance information. Cr tends to contain more reddish hue color information, while Cb tends to contain more bluish hue color information, as shown in Figure (2.3), each is usually represented as a 10-bit value. One advantage of this system is that image processing and video bandwidth can be reduced by separating the luminance and chrominance. This is because our eyes are much more sensitive to intensity, or brightness than to color. So a higher resolution can be used for luminance and less resolution for chrominance. There are several formats used; Firstly, 4: 4: 4 YCrCb each set of four pixels is composed of four Y (luminance) and four Cr and four Cb (chrominance) samples; Secondly, 4: 2: 2 YCrCb each set of four pixels is composed of four Y (luminance) and two Cr and two Cb (chrominance) samples; Thirdly, 4: 2: 0 YCrCb each set of four pixels is composed of four Y (luminance) and one Cr and one Cb (chrominance) samples. Most broadcast systems and video signals use the 4:2:2 YCrCb format, where the luminance is sampled at twice the rate of each Cr and Cb chrominance. Each pixel, therefore, requires an average of 20 bits to represent, as compared to 30 bits for 4:4:4 YCrCb [35].

(a) Cr Image. (b) Y Image. (c) Cb Image.

Figure (2.3): Y, Cr, and Cb images [35].

An alternate system was developed for computer systems and displays. There was no legacy of black and white to maintain compatibility with, and transmission bandwidth was not a concern, as the display is just a short cable connection to the computer. This is known as the RGB format, for red/green/blue, as shown in Figure (2.4). Each pixel is composed of these three primary colors and requires 30 bits to represent. Most televisions, flat screens, and monitors use RGB video, whereas nearly all broadcast signals use 4:2:2 YCrCb video [35].

(a) Red Image. (b) Green Image. (c) Blue Image.

Figure (2.4): R, G, and B images [35].

These two color spaces can be mapped to each other as follows [35]:

$$Y = 0.299 \cdot \mathrm{R} + 0.587 \cdot \mathrm{G} + 0.114 \cdot \mathrm{B} \tag{2.1}$$

$$Cr = 0.498 \cdot \mathrm{R} + 0.330 \cdot \mathrm{G} + 0.498 \cdot \mathrm{B} + 128 \tag{2.2}$$

$$Cb = 0.168 \cdot \mathrm{R} + 0.417 \cdot \mathrm{G} + 0.081 \cdot \mathrm{B} + 128 \tag{2.3}$$

And;

$$R = Y + 1.397 \cdot (Cr - 128) \tag{2.4}$$

$$G = Y - 0.711 \cdot (Cr - 128) - 0.343 \cdot (Cb - 128) \tag{2.5}$$

$$B = Y + 1.765 \cdot (Cb - 128) \tag{2.6}$$

2.3.2 Gray level Transformation

A color pixel has an RGB count; this count is ranged on a scale of 0 to 255. In the application of behavior-based methods, when competing directly with this RGB value, the processing time for such an algorithm will be very high. Therefore, the calculations or the transformations on the gray level values of pixels should be performed. So there's a need of converting the color image to the gray image; a gray image constitutes only black and white variations. So, the color image is converted into gray by the following equation:

$$Grayscale = 0.3 * R + 0.59 * G + 0.11 * B \tag{2.7}$$

The gray level values represent those values of a gray image pixel which are ranged from 0 to 255; where 0 resembles black and 255 white. These variations of the values play an important role in the segmentation or for differentiating between the pixels [26].

2.4 Statistical Parameters

Statistics is the science of data. It involves collecting, classifying, summarizing, organizing, analyzing, and interpreting numerical information. Statistics are used in several different disciplines to make decisions and draw

conclusions based on data. These parameters include Signal energy, signal power, Peak amplitude, RMS value, Mean value, variance, standard deviation, Kurtosis, Crest factor, K factor, and Skewness. In this section, we will cover the main concepts underlying how parametric statistics are used [36] [37]:

a. ***Signal energy:*** This statistical parameter is given in the following equation:

$$Energy = \sum_{i=1}^{n} Signal_i^2 \tag{2.8}$$

b. ***Signal power:*** This statistical parameter is given in the following equation:

$$Power = \frac{1}{n}\sum_{i=1}^{n} Signal_i^2 \tag{2.9}$$

c. ***Peak amplitude:*** This statistical parameter is given in the following equation:

$$Peak\ amplitude = Max|Signal_i| \tag{2.10}$$

d. ***RMS value:*** This value is related to the energy of the signal, and calculated in the following way:

$$RMS\ value = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(Signal_i)^2} \tag{2.11}$$

e. ***Mean value:*** It is defined as measuring the arithmetic average value of signal, and it has simple algorithmic formula as following:

$$Mean\ value = \frac{1}{n}\sum_{i=1}^{n} Signal_i \tag{2.12}$$

f. ***Variance:*** It is measuring dispersal and diffusional of data. The variance is defined as the mean quadratic deviation of the variate from its mean value and it is denoted by:

$$Variance = \sigma^2 = var(Signal_i) \tag{2.13}$$

g. ***Standard deviation:*** It is one of the types of measuring dispersal and diffusional of data. It is helpful to evaluate the variability of calculated

statistical such that it is defined as a square root of the variance and denoted by:

$$Standard\ deviation = \sqrt{\sigma^2} \tag{2.14}$$

h. ***Kurtosis:*** It is defined as the fourth statistical moment, which is shown as follows:

$$Kurtosis = \frac{\frac{1}{n}\sum_{i=1}^{n}(Signal_i - \overline{Signal})^4}{RMS^4} \tag{2.15}$$

i. ***Crest factor and K factor:*** These parameters are given in the following equations:

$$Crest\ factor = \frac{Max|Signal_i|}{RMS} \tag{2.16}$$

$$K\ factor = Peak\ amplitude \times RMS\ =\ Crest\ factor \times RMS^2 \tag{2.17}$$

j. ***Skewness:*** It is the statistical moment of the third order, normalized by the standard deviation to the third power.

$$Skewness = \frac{\frac{1}{n}\sum_{i=1}^{n}(Signal_i - \overline{Signal})^3}{Standard\ deviation^3} \tag{2.18}$$

2.5 Viola-Jones Face Detection

The algorithm of Viola-Jones face detection is one of object detection algorithms that used mostly in face detection and recognition in the applications need machine learning . This algorithm deals with structures in images, shapes, edges, face feature, templet matching, statistical analysis, and Boosting algorithm (AdaBoost) for detection face. Haar features are used for face feature using integral image with three types; edge features, linear features and central features (bi-adjacency matrices, tri-adjacency, and quadra-adjacency matrices, respectively), and AdaBoost algorithm is used for two types of classifiers weak and strong classifiers and it is aggregate for reinforcing the detection as shown in Figure (2.5),

where, the white area represents the eigenvalues (features) while the black area subtracted. The AdaBoost algorithm used as feature selection and classifier training (weak classifiers) then aggregate these weak classifiers to be strong classifiers. The total sample result from Haar features is weighted for used in classification in each training of the global classification. These weights will send to lower classification for additional training and at all find the final decision. Using of Ada-Boost classifier is useful for elimination some unnecessary features and control training data [38].

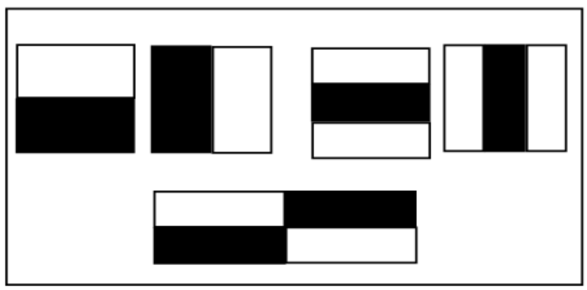


Figure (2.5) Haar Features Classification (bi, tri, and quadra adjacency Matrices) [38].

2.6 Local Binary Pattern (LBP)

Local Binary Pattern (LBP) is an easy and highly effective texture operator that works on labeling the image pixels via applying a threshold to the neighborhood of every pixel and considering the outcome as a binary number. This texture operator has been first developed in 1994 and it was found to be an efficient operator for texture classification. For improving the performance of detection, the LBP can be combined with the descriptor of oriented gradients histograms, and this combination of LBP with histogram (LBPH) is capable of representing the face images in a simple data vector. Also, it can be used in the tasks of face recognition. There are four parameters used in LBPH [39];

a. The radius parameter (commonly set to 1) which is utilized for building the circular LBP and representing the radius around the central pixel.
b. The Neighbors parameter (commonly set to 8) which represents the number of sample points for building the circular LBP. When including more sample points, the computational cost will increase.
c. Grid X and Grid Y (each one commonly set to 8) which represent the number of cells in the horizontal and vertical directions, respectively. When the number of cells is increased, the grid becomes finer, and the obtained feature vector takes high dimensionality.

For the purpose of training the algorithm, a dataset of the images is required, with an identifier for each image. Therefore, the algorithm needs to utilize this information for recognizing the input images and giving the outputs [39].

The first computational step in LBPH works on creating an intermediate image which depicted the original image in a preferable manner, via highlighting the characteristics of the facial. Here, the algorithm utilizes the sliding window concept, depending on the radius and Neighbors parameters. Figure (2.6) includes small steps to explain the operation of LBP [40];

d. Input the grayscale image.
e. Obtain a region (a window of 3×3 pixels or 3×3 matrix with 0~255 pixels' intensity) from the input image.
f. Select the matrix central value to be utilized as a threshold. This threshold will be utilized to find the new values from the eight neighbors.
g. Obtain the matrix of new binary values for the neighbors of the threshold by setting "zero" to the values which are less than the threshold, and setting "one" to the values which are higher or equal to the threshold.

h. Concatenate every binary value from every location from the matrix line by line into a new binary value (for example; 10001101).

i. Transform this value of binary to the value of decimal and set it to the central value of the matrix, in fact, it is a pixel from the original image.

j. Obtain a new image that includes preferable characteristics of the original image.

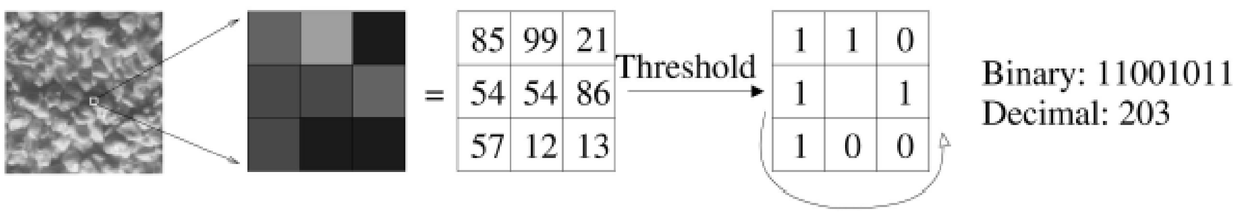


Figure (2.6): The basic operation of LBP [40].

The procedure of LBP can be developed to utilize various numbers of Neighbors and radius; It is named Circular LBP. This is accomplished via utilizing the bilinear interpolation. When several points of the data are between the pixels, it utilizes the values from the four closest (2×2) pixels for estimating the value of the new point of data. Figure (2.7) explains this process [40].

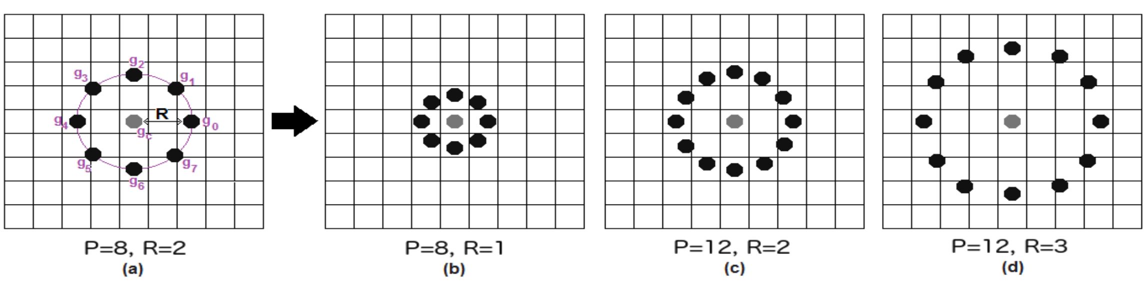


Figure (2.7): The procedure of Circular LBP [40].

To extract the histograms for the image obtained from LBP, the parameters "Grid X and Grid Y" can be utilized for dividing the image into multi-grids. Each histogram for each grid from the grayscale image will include 256 locations representing the occurrences of every pixel intensity. After that, the concatenation of each histogram is required for creating a bigger and new histogram ($8 \times 8 \times 256 = 16.384$ positions). The last histogram refers to the features for the original image [41].

In order to perform the process of recognition, here, the algorithm is already trained. Every created histogram is utilized for representing every image in the training dataset. Therefore, for the input image, the steps of LBPH are implemented again to this new image and create a histogram that refers to the image. Therefore, for finding the image which matches the input image, a comparison of two histograms are required to return the image with the nearest histogram. There are different methods can be utilized for comparing the histograms such as chi-square, Euclidean distance, absolute value, etc. The output of this algorithm is the identifier of the image with the nearest histogram [41].

2.7 Machine Learning Algorithms

Machine learning is one of the branches of artificial intelligence that are interested in providing the necessary algorithm, applications, and frameworks that make computers able to learning by achieving more precise prediction and valuable results from the analysis the input data. The role of Machine learning is two folds: First, in training the efficient algorithm is used to the optimization

problem as well as to store and process own hug data. Second, the model is learned for one time. The representation and algorithmic solution for inference needs to be effective [42].

Machine learning algorithms can be in general subdivided into three main categories, namely, supervised learning, unsupervised learning, and semi-supervised learning, as shown in Figure (2.8). All of these methods require data on which particular classes or patterns can be learned. These data are commonly referred to as training data. The first type, supervised learning, is referring to the case where the number of classes that have to be learned and the assignment of training cases to these classes, the so-called labeling, are known. This type of machine learning algorithm aims to identify patterns in terms of constellations of features that can be used to differentiate the different classes in the training dataset. The obtained classifier can be then applied to new data with unknown class labels. The second type, unsupervised learning, refers to the case where neither classes nor the assignment of training data to those classes is known. These algorithms aim to identify patterns or clusters in the training data that deviate from random noise and are correspondingly unlikely to occur by chance. The third type, semi-supervised learning, is a combination of supervised and unsupervised methods. Full assignment of all training data to their corresponding class labels may be difficult in some cases. Class labels of the training data may be unknown or the effort required to obtain an accurate class assignment for all the data is too high. A solution can be to combine a small amount of labeled data with a large amount of unlabeled data. The combination of labeled and unlabeled data can often provide an improvement in learning accuracy, as compared to unsupervised learning and to supervised learning, with a limited number of training data [43].

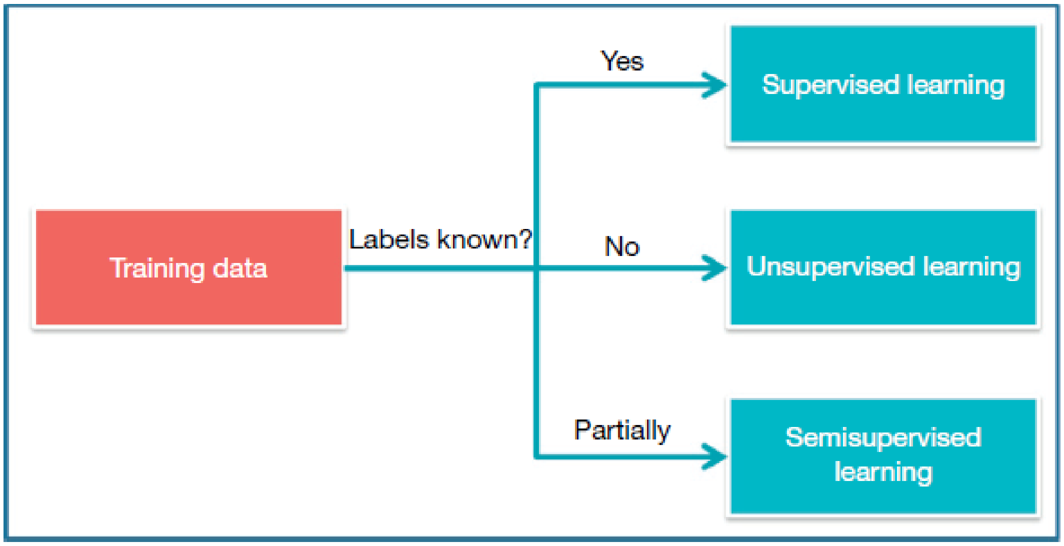


Figure (2.8): Schematic overview of different machine learning approaches [43].

2.7.1 Support Vector Machine (SVM)

The support vector machine (SVM) is a supervised machine learning algorithm that is the most popular classifier. The main goal of this supervised method is to find a function in a multidimensional space that is able to separate training data with known class labels. For example, suppose we have a training set of cases with two known class labels and two available measurements per case. The idea behind the support vector machine classification is that these measurements can be regarded as a two-dimensional space. Each case is then represented by a data point in this space. For the two-dimensional case, a line can be now drawn to separate between the training cases while minimizing misclassifications. More precisely, there is an infinite number of lines that can provide an equally good separation between the data, as shown in Figure (2.9) [43].

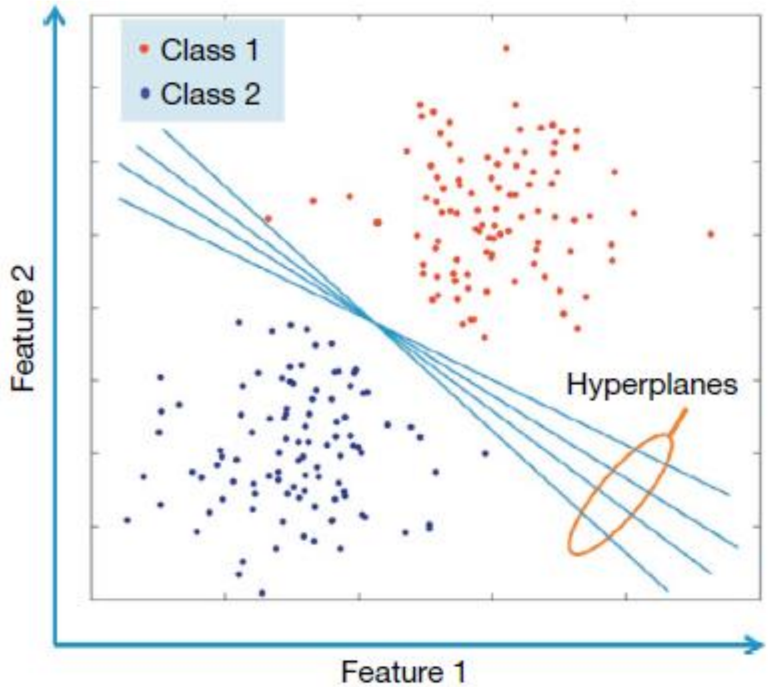


Figure (2.9): Numerous hyperplanes to provide an equally good separation between the two classes [43].

A reasonable assumption behind support vector machine classification is that the best line is the one maximizing the margin between the two classes. Correspondingly, one chooses the line with a maximum distance to the closest data points from each of the two classes. After computing such as the separation line, new cases can be automatically assigned to any of the two-class labels depending on their location relative to the line. This idea can be now extended to any higher-dimensional space with the line becoming a plane in the three-dimensional case and a hyperplane for more than three dimensions. The closest data points of both classes to the hyperplane are called support vectors, as they define the margin and correspondingly the location and orientation of the hyperplane. Figure (2.10) illustrates the concept of support vectors and margin maximization [44].

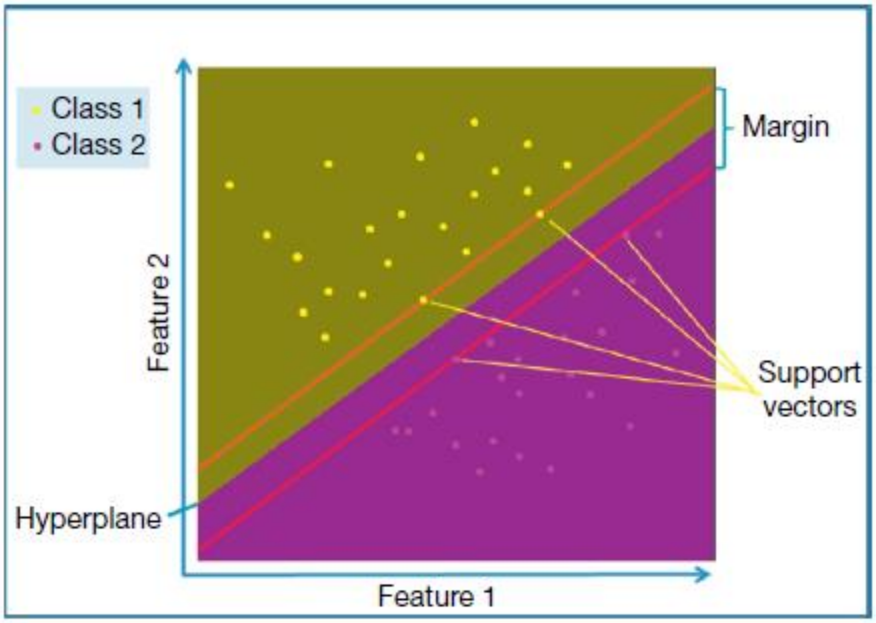


Figure (2.10): The concept of support vectors and margin maximization [44].

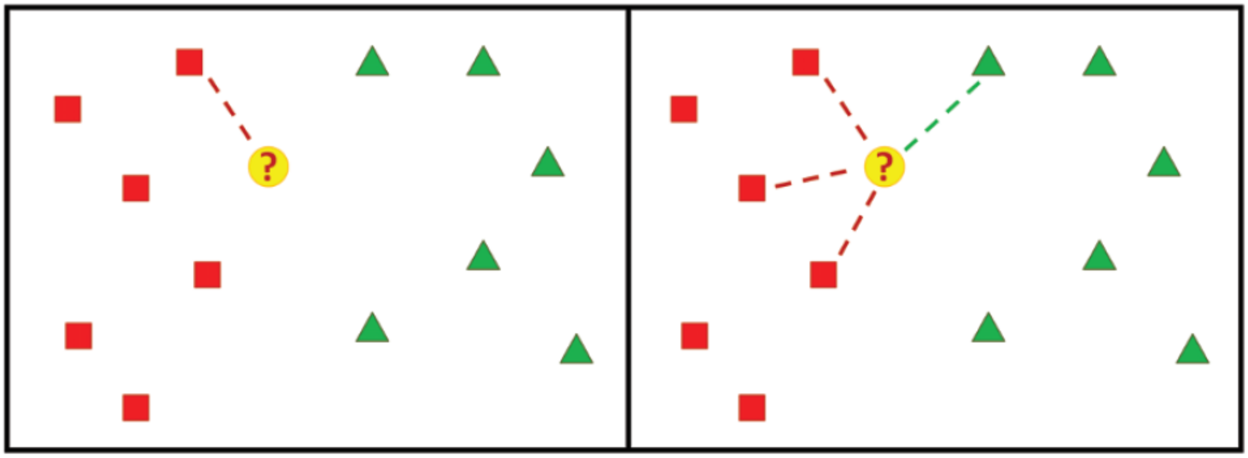
This approach can be easily extended to nonlinear separating hyperplanes such as radial basis and polynomial functions. Since its introduction, many extensions and modifications of the original approach such as support vector regression and relevance vector machine have been suggested. A further advantage of this the approach is that it provides a weight for each feature indicating how much the feature contributes to the between-class separation. Correspondingly, the support vector machine can be also used as an integrated feature reduction technique [44].

2.7.2 K Nearest Neighbors (KNN)

KNN classifier is a case-based machine learning algorithm that is depending on a function of similarity or distance for different pairs of observation like the function of Euclidean distance. This classifier is applied to considerable applications due to its efficiency, easy to implement and non-parametric

characteristics. The KNN method tries to classify an unknown sample based on the known classification of its neighbors. Let us suppose that a set of samples with known classification is available, the so-called training set. Intuitively, each sample should be classified similarly to its surrounding samples. Therefore, if the classification of a sample is unknown, then it could be predicted by considering the classification of its nearest neighbor samples. Given an unknown sample and a training set, all the distances between the unknown sample and all the samples in the training set can be computed. The distance with the smallest value corresponds to the sample in the training set closest to the unknown sample. Therefore, the unknown sample may be classified based on the classification of this nearest neighbor. However, in general, this classification rule can be weak, because it is based on one known sample only. It can be accurate if the unknown sample is surrounded by several known samples having the same classification. Instead, if the surrounding samples have different classifications, as for example when the unknown sample is located amongst samples belonging to two different classes (and hence with different classifications), then the accuracy of the classification may decrease. In order to increase the level of accuracy, then, all the surrounding samples should be considered and the unknown sample should then be classified accordingly. In general, the classification rule based on this idea simply assigns to any unclassified sample the class containing most of its k nearest neighbors. If only one sample in the training set is used for the classification, then the 1-NN rule is applied. Figure (2.11) shows the KNN decision rule for $k = 1$ and $k = 4$ for a set of samples divided into 2 classes. In Figure (2.11), (a), an unknown sample is classified by using only one known sample; in Figure (2.11), (b), more than one known sample is used. In the last case, the parameter k is set to 4, so that the closest four samples are considered for classifying the unknown one. Three of

them belong to the same class, whereas only one belongs to the other class. In both cases, the unknown sample is classified as belonging to the class on the left [45].



(a) (b)

Figure (2.11): KNN, (a) The 1-NN decision rule: the point, is assigned to the class on the left; (b) the k-NN decision rule, with k = 4: the point, is assigned to the class on the left as well [45].

The distance function plays a crucial role in the success of the classification. Indeed, the most desirable distance function is the one for which a smaller distance among samples implies a greater likelihood for samples to belong to the same class. The choice of this function may not be trivial. Another important factor is the choice of the value for the parameter k. This is the main parameter of the method since it represents the number of nearest neighbors considered for classifying an unknown sample. Usually, it is fixed beforehand, but selecting an appropriate value for k may not be trivial. If k is too large, classes with a great number of classified samples can overwhelm small ones and the results will be biased. On the other hand, if k is too small, the advantage of using many samples in the training set is not exploited. Usually, the k value is optimized by trials on the training and validation sets. Moreover, assigning a classification on the basis of the majority of the k “votes’’ of the nearest neighbors could not be accurate in some

particular cases. For example, if the nearest neighbors vary widely in their distance, then an unknown sample may be classified considering samples that are located far from it. Therefore, a more sophisticated approach could be to weight the vote of each sample by its distance, so that the closest samples have more importance during the classification [46]. Generally, at the study identification of the optimum k number is done by experiments and the Euclidean Distance calculations method was used as a distance calculation method. The Euclidean calculation method is given as follows [47]:

$$d(x_i, x_j) = \left(\sum_{s=1}^{p} (x_{is}, x_{js})^2\right)^2 \quad (2.19)$$

Where x_i and x_j are two different points, and need distance calculation process in between.

2.8 Arduino Mega Microcontroller Board

This microcontroller was found on a development board produced by Arduino systems. At the present time, lots of universities, and a considerable number of persons who do not have knowledge in electronics are working on these types of devices, for the ease to the projects of musical, artistic and botanical among others, since its domain is highly varied, ranging from sensors, robotics, audio, action, and navigation to monitoring systems. Instances contain; an accelerometer which converts Arduino to a pitch mouse (TiltMouse), the optical tachometer, and the game of ping pong programmed with Arduino (Arduino Pong), etc. [48]. Arduino holds fifty-four input / output digital pins, fourteen from them is utilized as PWM outputs), four H/W serial ports, sixteen analog inputs, sixteen MHz crystal oscillator, a USB connection, a button for restart, a power jack, and

ICSP header. This device includes many things required for supporting the micro-controller; it can be connected to a computer by using a USB cable or powered it via a battery or AC-to-DC adapter for getting started. Arduino Mega (2560) is compatible with most shields designed for the Arduino Diecimila or Duemilanove [49].

Arduino utilizes the shields for interfacing various modules such as; motor drivers, GPS, wireless communication such as XBee shield, etcetera. The utilized shields are circuit boards equipped with whole important parts needed for constituting a module. The utilization of these shields works on simplifying the interface of different modules with the micro-controller. Figure (2.12) depicts a simple Arduino mega 2560 board and some of Arduino shields. The board designed to be able for sensing the surroundings via receipting input from various sensors and can impact its environments via controlling motors, lights and another actuator [50].

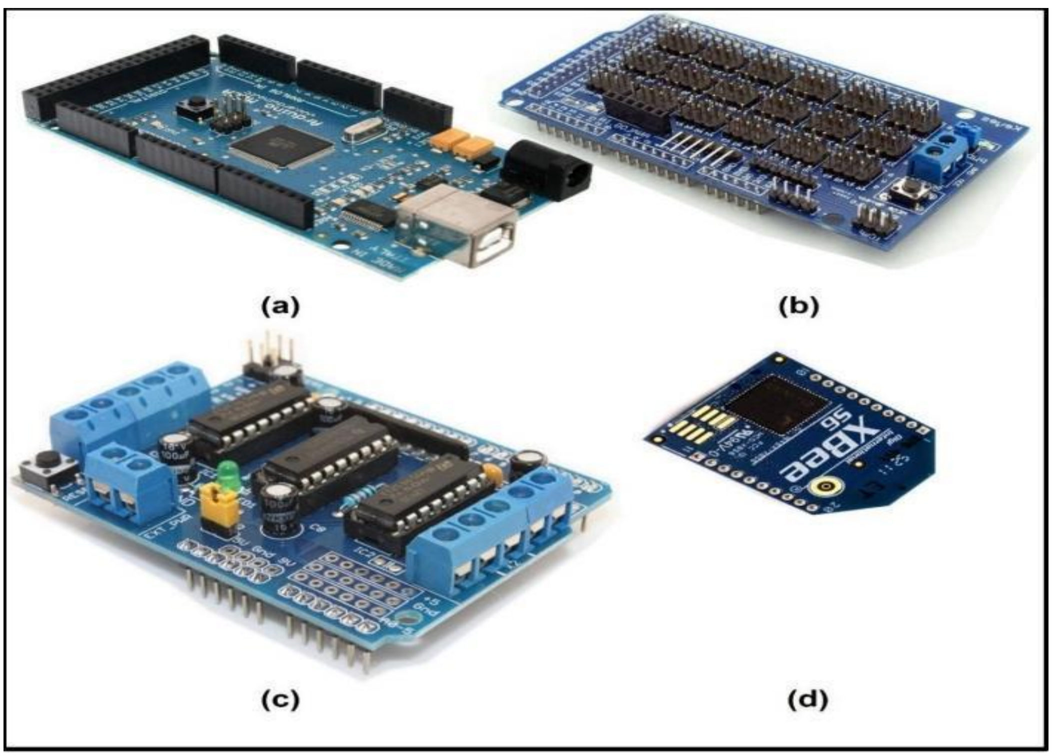


Figure (2.12): Microcontroller boards: (a) Arduino ATmega 2560, (b) Sensor shield, (c) Motor shield, (d) XBee shield [50].

The micro-controller (on the board) is programmed utilizing the programming language of Arduino, it can be programmed with the Arduino software. The software consists of a standard programming language compiler, bootloader, and integrated development environment (IDE). For programming Arduino, C++ programming language has been used. The IDE for Arduino is an application of cross-platform written in java. It involves an editor for the code with characteristics like auto-indentation, brace matching, and syntax highlighting, in addition to ability to compile and upload programs onto the board. Bootloader works on simplifying the process of the uploading programs to the on-chip flash memory removing the requirement for an external programmer [50].

Chapter Three

The Proposed System

CHAPTER THREE

THE PROPOSED SYSTEM

3.1 Introduction

This chapter relates to the design and implementation of the proposed an expert system for driver's drowsiness detection analyses. The description of the planning of the designed system includes details of each stage that have been implemented in relation to the applicable system. Each of the implementation steps is shown in detail using algorithm and/or diagrams.

3.2 Design of the Proposed System

The framework of the proposed system consists of two main parts: The first part is the hardware which includes the main component required for acquiring the EOG signals and main component detection the eyes region. The second part is software which includes two methods; behavioral based method (detecting the driver visual features using eye movements (closed or opened)), and physiological based method (detecting the earlier stages of driver's drowsiness based on EOG signals).

3.2.1 Hardware Component

The hardware containing the main component required to obtain EOG signals and detection of the main component in the eyes region.

The eye is one of the sense organs which is complex to analyse. In the proposed system, the EOG signal analysis for detecting sleepy behaviour is used. EOG is the measurement of the possible difference between cornea and retina. The design of the device is based on the EOG using Arduino board on atmage256 with the biological signal sensor AD8232 and programming the system using Arduino IDE. As it is known that the AD8232 sensor is used for heart rate monitoring, with frequency bandwidth range from 0.5-100 Hz. The EOG signal has a narrow band with a range from 0.5-10 Hz, this makes the extraction of EOG signal more difficult. Programmable filters have been designed in Arduino to fit the Ad8232 sensor signal with the EOG signal. High-quality signals are obtained, free from distortions and noise. Based on these obtained signals, the driver is alarming when the predicted EOG signal exceeding a pre-identified threshold. Generally, the minimum time of a driver response after alarming is 0.15 second. In the proposed system, the 0.5 second represents the critical time for correcting the driver's behaviour and preventing accidents.

The electrodes positions specify the obtained signal quality. So, it is very necessary to identify an appropriate facial area for placing the electrodes. In the proposed system, three electrodes were utilized. Several experiments were done for determining the optimal positions of electrodes. Based on these experiments, it was found that the positions for electrodes which give the obvious blink signals are below and above the eye, which main the vertical EOG channel and the reference behind the ear. Figure (3.1) (a) shows the location of the electrodes, and Figure (3.1) (b) shows the designed hardware device.

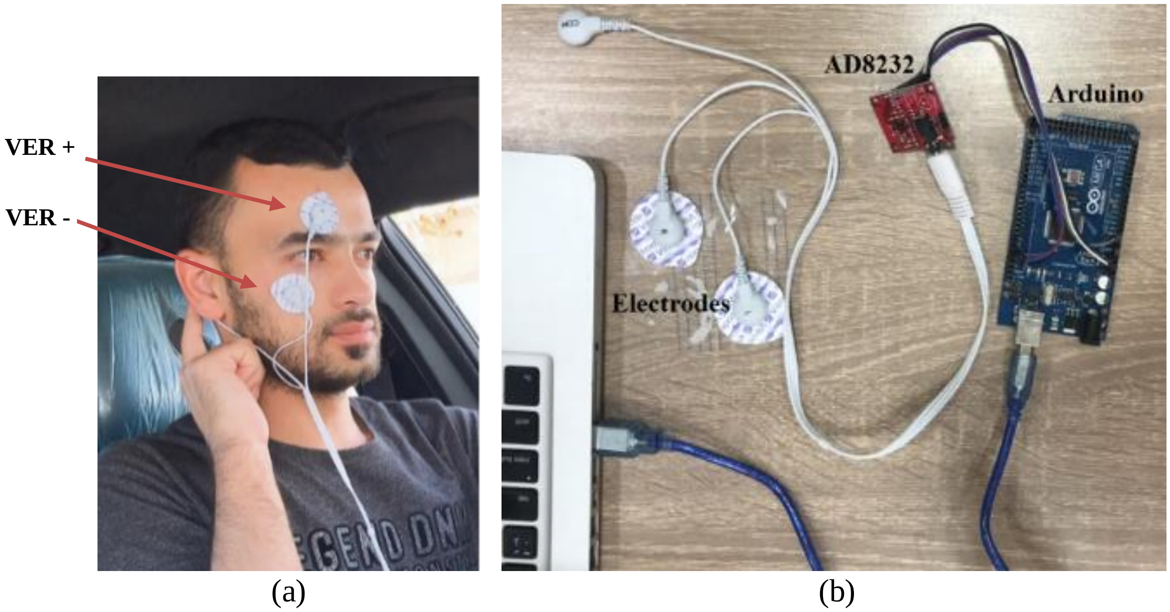


Figure (3.1): (a) The Electrodes positions around the eye, (b) The designed hardware device.

Arduino receives the acquired signal derived from the sensor, which handles the operations of (amplification, filtering, and shifting). The received signal filtered to fit the EOG signal by designing a one-pole RC programmable filter on Arduino.

After software component is implemented to make the decision to whether the signal was a drowsy signal or a normal blink, an external headset is connected to alert the driver to avoid accidents. Figure (3.2) presents the system model which is based on EOG signals to alert the drowsy driver.

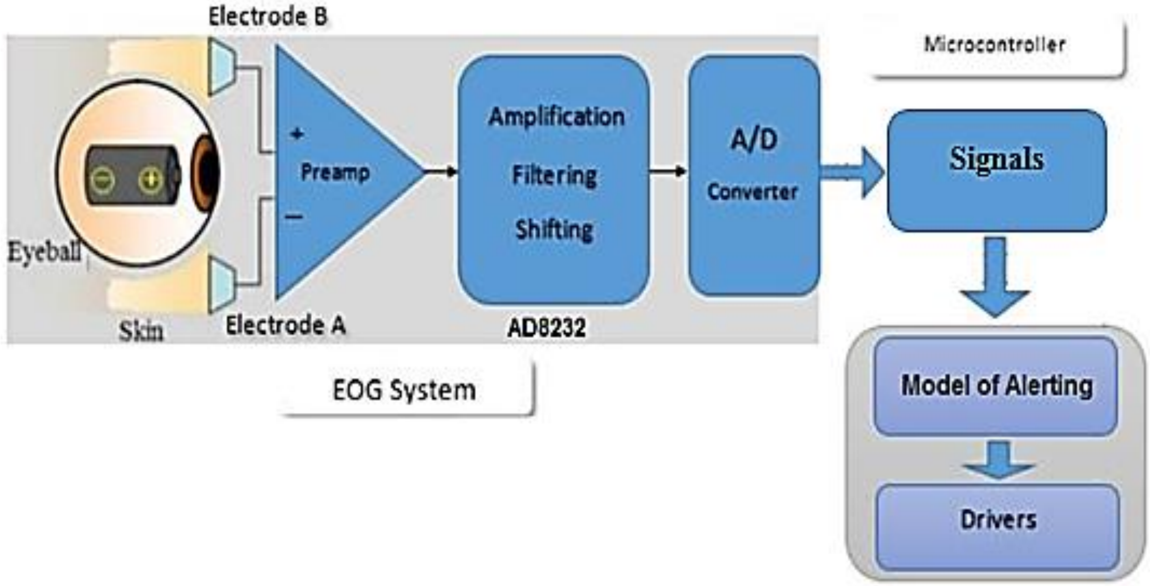


Figure (3.2): The system model of EOG signals to alert the drowsy driver.

3.2.2 Software Component

The software includes two proposed methods; behavioral-based method, and physiological based method.

I. Physiological Based Method

This proposed method includes several processes;

A. Feature Extraction

After acquiring the EOG signals, several measurements (based on some statistical parameters) are implemented on these signals for extracting eleven features. These measurements are Signal energy, signal power, Peak amplitude, RMS value, Mean value, variance, standard deviation, Kurtosis, Crest factor, K

factor, and Skewness. Each measurement represents a column of features extracted from the EOG signals.

After extracting the features, it is noticeable that the values of these eleven features have different values. Therefore, these values should be unified by using feature normalization.

B. Feature Normalization

In order to make these measured features takes the correct weight, the normalization process is applied in which firstly the mean value and the standard deviation of each column of extracted features (features 1, …, features 11) are computed, and then each element X_i in these columns are subtracted from the mean and divided on the standard deviation, and this process is explained in equation (3.1). Then, the normalization process is applied.

$$X_n = \frac{X_i - Mean}{Standerd\ deviation} \tag{3.1}$$

C. Classification of EOG signal

After the normalization process of the features extraction, these features are now ready for the classification process, to see if the person is in a drowsy state or not. Where it was used two methods of classification, the first utilized method is K Nearest Neighbours (KNN) and the second method is support vector machine (SVM).

1. K Nearest Neighbours (KNN)

The representative classifier based on "K" distance is utilized for classifying the normalized EOG data. KNN is a supervised learning method in which the new instance is classified depending on the closest samples of training available in the feature space. The new instance is mapped to the class that is very common among

the K neighbors with no model for the test dataset. In this method, weighted KNN is used and the distance is calculated utilizing Euclidean distance. Additionally, the number of neighbours K is 7. Algorithm (3.1) presents the steps of KNN classifier.

Algorithm (3.1) KNN classifier
Input: Normalized Feature **Output**: Class Label
Begin **Step 1:** Find Number of Record "N" (Normalized Feature) **Step 2:** Split dataset into a Training dataset (70% of the dataset) and Test dataset (30% of the dataset) Tr=0.7*N, Ts=0.3*N **Step 3:** For i=1 to Tr **Step 4:** Sv=select Record (1 to N) **Step 5:** Trst(i)= (Normalized [s] feature) **Step 6:** Cltr= classlable(s) **Step 7:** Next **Step 8:** For i=1 to Ts **Step 9:** Tsst(i)= Normalized (st) **Step 10:** Clts= classlabel(st) **Step 11:** For i=1 to Ts **Step 12:** Find Number of Record "N" (Normalized Feature) **Step 13:** For i=1 to N **Step 14:** Find Euclidean distance (feature vector test (1 to N), Normalize feature vector (i, 1 to N) **Step16:** Next **Step17:** Sort Euclidean distance (1 to N) to obtain Sort Vector (Euclidean distance (1 to N))

Step18: class lable new =ReArange(Class lable)

Step19: K=select K value

Step20: Specify the Prototype label

Step21: If Clts(i)== Prototype label

Ts(i)=1;

Else Ts(i)=0;

End

2. **Support Vector Machine (SVM)**

In order to test the EOG data, the features of eyelid movements required for SVM training are extracted and validated. Here, the first step is to distinguish the eye-blinks from EOG data. To prevent the loss of any flicker, leading to only one case from two potential cases for the driver. There are two-class labels have been identified: One for indicating the normal case and two to the drowsy case after calculating the accuracy of each feature of this signal. Algorithm (3.2) presents the steps of SVM classifier.

Algorithm (3.2) SVM classifier

Input: Normalized Feature
Output: Class label

Begin

Step 1: Find Number of Record "N" (Normalized Feature)

Step 2: Split dataset into a Training dataset (70% of the dataset) and Test dataset (30% of the dataset) Tr=0.7*N, Ts=0.3*N

Step 3: For i=1 to Tr

Step 4: Sv=select Record (1 to N)

Step 5: Trst(i)= (Normalized [s] feature)

Step 6: Cltr= classlable(s)

Step 7: Next

Step 8: For i=1 to Ts

Step 9: Tsst(i)= Normalized (st)

Step 10: Clts= classlabel(st)

Step 11: Specify the Prototype label

Step 12: If Clts(i)== Prototype label

Ts(i)=1;

Else Ts(i)=0;

End

II. Behavioral Based Method

At this method, the driver's eye will be determined through a short video that is recorded with duration of five minutes to see if the driver is drowsy or not. In order to do the process of eye detection, several processes are needed;

A. Extract Frames

The camera that is installed in front of the driver is used for recording video. The driver's cases are recorded and the video sequences contain sequences created inside a controlled surroundings (static lighting) and another captured in a real car (variable lighting). So that a video of at least five minutes is recorded in the normal and abnormal state, this video dividing into frames and each recorded video has 30 f/s in each case. Only one image is taken of each the five frames.

B. Eye Detection

To extract the eye region of the driver, the images need to convert them into Grayscale images, and then detect the eye region using Viola-Jones Algorithm.

Figure (3.3) presents the system model which is based on detecting the eye (closed/opened) for alerting the driver.

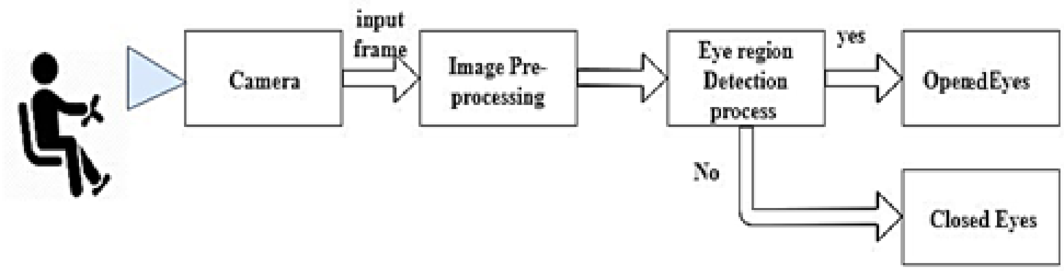


Figure (3.3): The system model of eye detection (closed/opened) for alerting the driver.

1. **Convert RGB to Grayscale Image**

The captured input images are RGB color images. In order to decrease the number of colors, a pre-processing step is required for converting the RGB color images into Grayscales.

2. **Eye Detection of Viola-Jones Algorithm**

The eye is then detected and its condition determined in a normal and abnormal state. Haar features are used for eyes feature using the integral image with three types; edge features, linear features and central features (bi-adjacency matrices, tri-adjacency, and quadra-adjacency matrices), and AdaBoost algorithm used for two types of classifier weak and strong classifier and it is aggregate for reinforcing the detection

The AdaBoost algorithm is used as feature selection and classifier training (weak classifiers) then aggregate these weak classifiers to be strong classifier. The total samples resulted from Haar features are weighted to be used in classification in each training of the global classification. These weights will send to lower classification for additional training and at all find the final decision. Using of Ada-Boost classifier useful for elimination some unnecessary features and control

training data. Algorithm (3.3) shows the steps of eye detection using Viola-Jones algorithm.

Algorithm (3.3) Viola-Jones Algorithm

Input: Image File

Output: Detected Eyes in already Detected Faces

Begin

Step 1: The coordinates for all the faces previously detected were stored. When these eyes were detected, they were first checked for their presence Inside the coordinates of the face.

Step 2: All the eyes of existing detected faces are considered for the algorithm.

Step 3: If (p1, q1) and (p2, q2) are coordinates of the face and (r1, s1) and (r2, s2) are coordinates of the eyes, (eyes are present inside the face).

Then p1< (r1 and r2 both) < p2

q1< (s1 and s2 both) < q2

Otherwise, Eyes are Discarded (lie outside the face).

Step 4: Detection of eyes.

Step 5: For the remaining eyes, compute the distance between the eyes

Step 6: If that distance satisfies, Then distance signifies that eyes are paired eyes of the face or not.

Step 7: When one eye is detected then, it is checked with other eyes for being a pair of eyes by their intermediate distance and near about same sizes. If the two detected eyes are rectangles such that their topmost, leftmost points are (x1, y1) and (x2, y2), Compute the distance between these two points.

Step 8: For all the pair of eyes: The Region of interest (ROI) is constructed for all the pair of eyes.

End

C. Feature Extraction using Local Binary Pattern (LBP)

Here, the image of eyes is spilt into regions. In every region, a mask of 3×3 is implemented to compute the binary patterns. These patterns are serialized for deriving eyes descriptors. The descriptors represent the eyes feature which is also called the texture feature. Generally, this method is utilized for grayscale eyes images. Pseudo-code (3.4) illustrates the steps of LBP.

Algorithm (3.4) Local Binary Pattern (LBP)
Input: Detected Eye Region Image **Output: Feature Vector**
Begin **Step 1:** For every pixel (x, y) in an image, I, choose P neighboring pixels at a radius R. **Step 2:** Calculate the intensity difference of the current pixel (x, y) with the P neighboring pixels. **Step 3:** Threshold the intensity difference, such that all the negative differences are assigned 0 and all the positive differences are assigned 1, forming a bit vector. **Step 4:** Convert the P-bit vector to its corresponding decimal value and replace the intensity value at (x, y) with this decimal value. Thus, the LBP descriptor for every pixel is given as: $LBP = \sum_{p=0}^{p-1} f\left(g_p - g_c\right) 2^p$, where g_c and g_p denote the intensity of the current and neighboring pixel, respectively. **Step 5:** Compute the histogram, over the cell, of the frequency of each "number" occurring This histogram can be seen as a 256-dimension feature vector. **Step 6:** Optionally normalize the histogram. **Step 7:** Concatenate (normalized) histograms of all cells.

End

D. Classification of Eye Detection

The same methods used earlier will be used in the classification process; KNN and SVM.

3.3 Implementation of The Proposed System Model

The proposed system is implemented in two cases; The first case when the system is offline and the second case when the system is online.

3.3.1 Offline Implementation

At this case, the dataset was collected for a signal using (EOG) and stored through the hardware part and then the dataset was collected to the driver's eye by recording a video clip and then the eye is detected as explained in the previous paragraphs. Each one individually and we conducted the training of the samples and testing. To find out the result we will obtain the accuracy using two methods of classification KNN, and SVM. Figure (3.4) shows the structure of offline implementation.

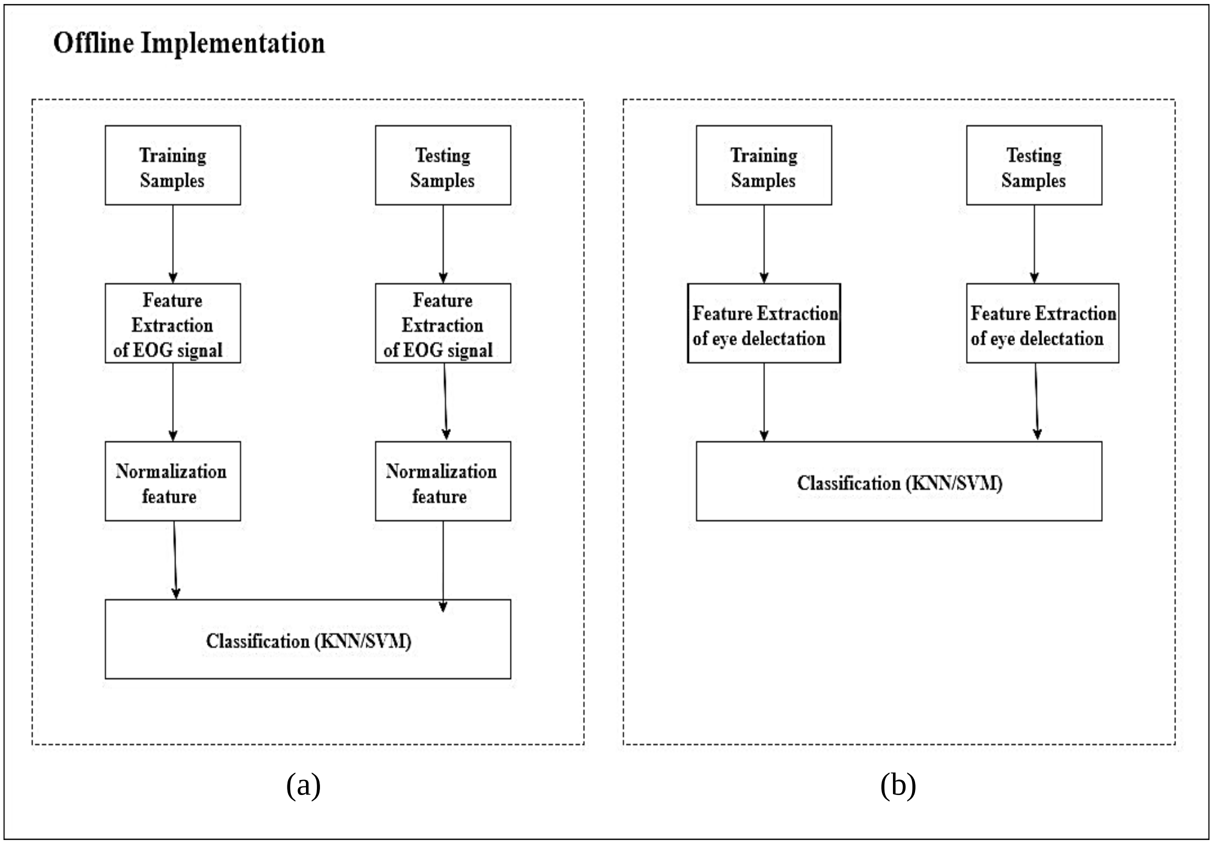


Figure (3.4) Block diagram of drowsiness detection offline implementation, (a) Physiological based method, (b) Behavioral based method.

3.3.2 Online Implementation

The model is a signal integrated with the eye detection model and data are collected directly where the signal is captured after the EOG is placed under the eye and the camera is located in front of the driver to record video duration of five minutes and then the eyes are detected. So every half minute represents a complete reading and is saved in a folder and then features are extracted for each signal and whenever picked a new signal is erased previous data and during the process of storage for these features process the normalization process for values is done, then the two models are classified by using SVM instead of KNN because it is stronger and more accurate, depending on experiments. The extracted features are eventually merged and presented to the SVM classifier, leading to only one case

from two potential cases for the driver. Two classifications were identified: 1 for normal and 2 for abnormal. The SVM classifier was trained to use six people for a database containing a total of 8,000 vectors. The parameters trained by the SVM classifier are then used for identification if the person drowsy or not. The concept of overlapping signal of fatigue windows was adopted for quickly determining the fatigue case. Figure (3.5) shows the structure of online implementation.

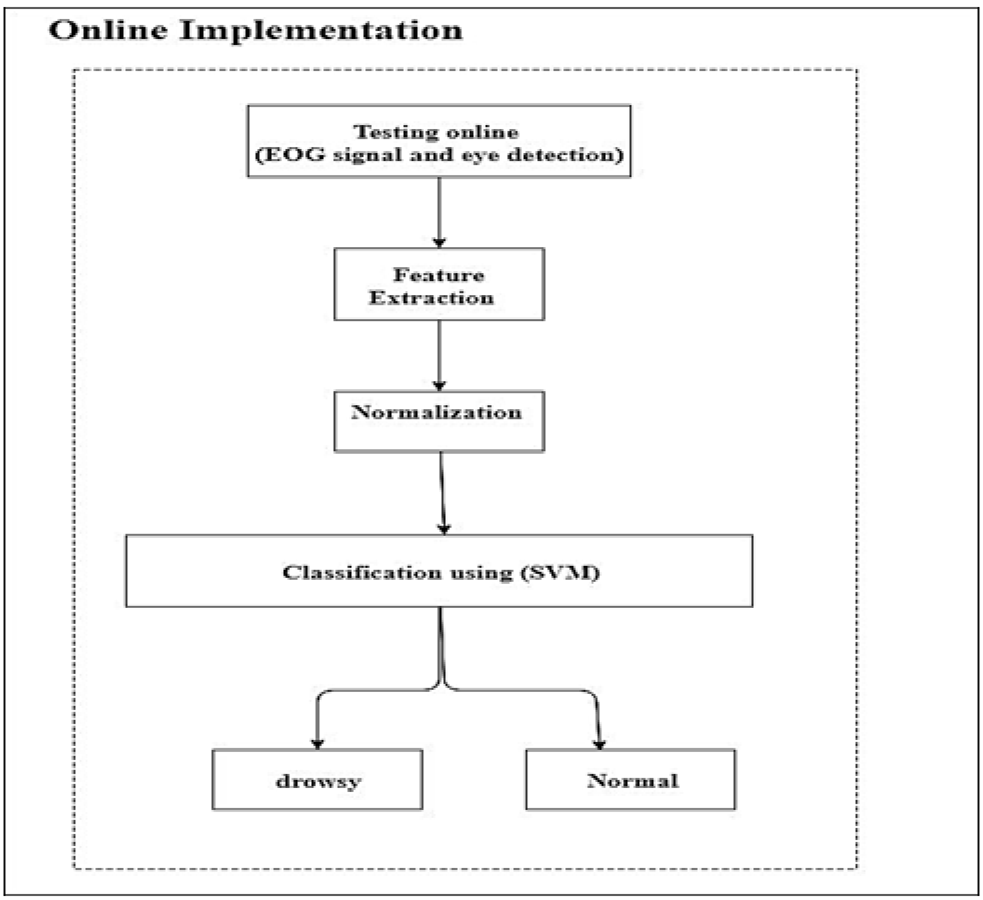


Figure (3.5): Block diagram of online implementation

Chapter Four

Experimental Results and Discussion

CHAPTER FOUR
EXPERIMENTAL RESULTS AND DISCUSSION

4.1 Introduction

This chapter contains the results of two set of features that are used to evaluate the performance of the proposed expert system for driver drowsing detection analyses system, as well as exploring the effects of the different involved system parameters on the overall system performance.

The designing and implementation of a driver assistance system which includes a driver's monitoring and alarming by using intrusive acquisition methods, called Electrooculography (EOG) signals. An embedded system based on ATmega2560 microcontroller on the Arduino board has been used to implement the EOG signal acquisition circuit. The developed system used several statistical measurements to extract the features from EOG signals which makes it very sensitive to detect the driver's drowsiness. The developed system has been established using Matlab programming language, and the tests have been conducted under the environment of the Windows-10 operating system, laptop computer processor: laptop type hp, CORE i7, Ram 4GB, CPU 1.70 GH.

4.2 Hardware Component

In the proposed system, the hardware component represents the EOG signal analysis for detecting drowsy behaviour is used.

4.2.1 EOG Signal

EOG signals acquisition system have been designed and implemented. The acquired EOG signals were processed to generate various control signals. These control signals were then used to alert the drowsy driver. Electrical potentials are generated as a result of the movement of the eyeballs within the conductive environment of the skill. The EOG signal is picked up by a Vertical (VER) channel signal acquisition system. VER is the position to measure the vertical eye movement. Additionally, an electrolytic gel based on sodium chloride must be placed on the skin because the upper layers of the skin are poor conductors of electricity. Using the gel gives a good electric conductivity, furthermore, to minimize the resources and electrodes noise. The proposed model used only one EOG channel.

Because the voltage level of physiologic signals is very weak, processes for analog signals usually need several steps of amplification, filtering, and electrical conditioning. The AD8232 is used to solve this weak which involves a fast restore function which decreases the duration of otherwise long settling tails of the high-pass filters. After an abrupt signal change that rails the amplifier (like leadoff condition), automatically, the AD8232 adjusts to a higher filter cut off. This feature permits the AD8232 to recover quickly, and thus, to take correct measurements soon after connecting the electrodes to the subject. The data of EOG signals are recorded for six persons. For each person, five minutes EOG signal was recorded in the awake situation, and five minutes for sleepiness situation. Figures (4.1) and (4.2) show the samples of two cases normal and abnormal.

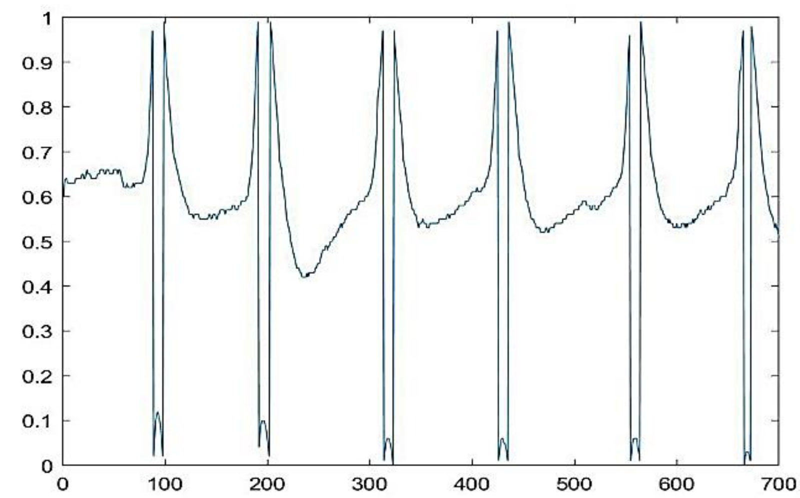


Figure (4.1): Sample of awake Dataset Signal.

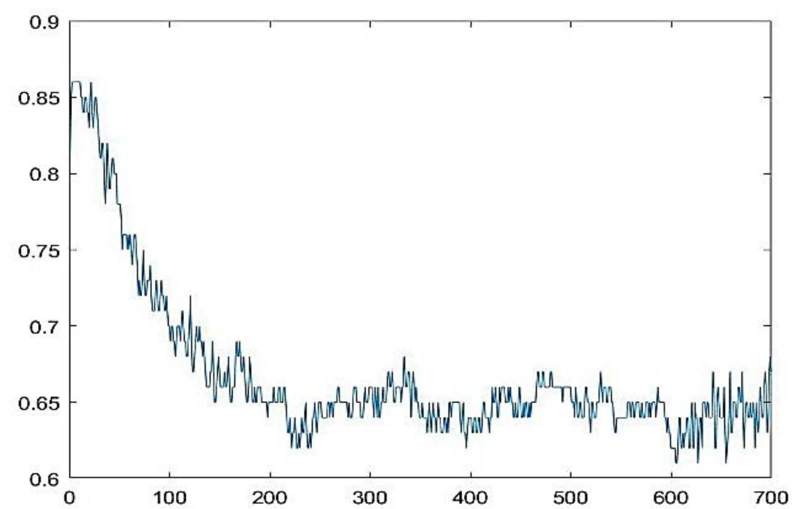


Figure (4.2): Sample of drowsy Dataset Signal.

4.3 Software Component

In the proposed system, the software component represents physiological based method and behaviour based method are used.

4.3.1 Physiological Based Method

After signal extraction process, several measurements are implemented for extracting eleven-features to the sub-signals as shown in Figure (4.3).

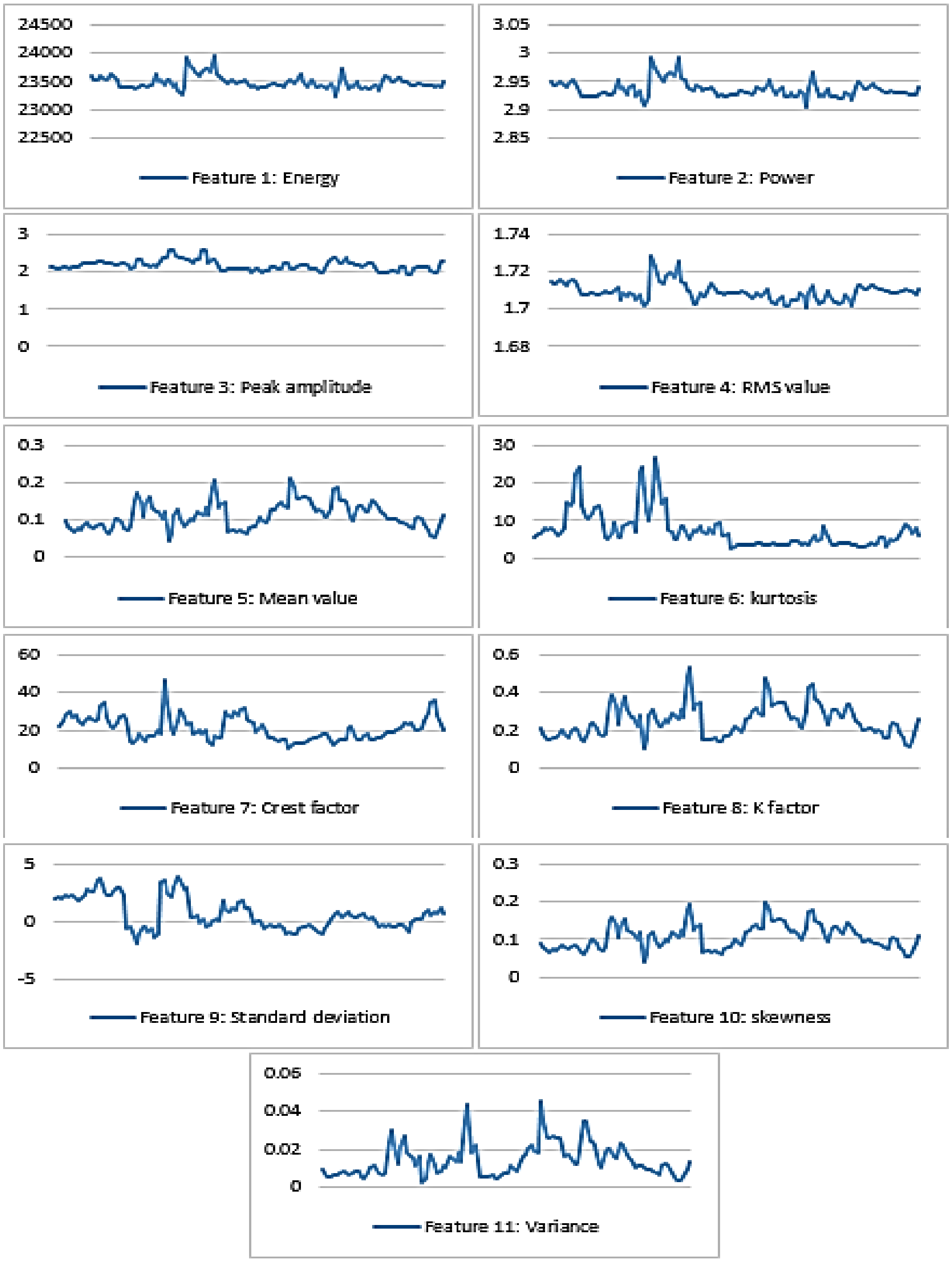


Figure (4.3): An example of the extracted features based on eleven measurements.

A. Feature Extraction of EOG Signals

The data of EOG signals are recorded for six persons. For each person, EOG signal was recorded duration of five minutes in the awake situation, and duration of five minutes for sleepiness situation. The experiments are applied minimally on five minutes to each situation owing to the normal variability of eye blinking. Accordingly, through five minutes, the number of blinks for a normal person is approximately 57 times. The time-series data is separated into segments of one overlapped minute length. Therefore, for six persons, there are twenty signals for awake and sleepiness situations, and totally, there are 120 sub-signals require to be analyzed. Several measurements are implemented for extracting eleven-features to these sub-signals as shown in Tables (4.1) and (4.2).

Table (4.1): The normal of feature extraction.

Sample	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11
person1	23603.487	2.950	2.130	1.715	0.097	5.521	21.865	0.207	0.092	2.040	0.009
	23542.343	2.943	2.120	1.713	0.085	6.319	24.949	0.180	0.080	2.148	0.007
	23539.505	2.942	2.070	1.714	0.073	6.529	28.212	0.152	0.069	2.092	0.005
	23589.457	2.949	2.080	1.716	0.070	7.961	29.646	0.146	0.066	2.301	0.005
	23568.730	2.946	2.120	1.715	0.078	7.448	27.199	0.165	0.073	2.288	0.006
	23517.020	2.940	2.120	1.713	0.076	7.754	27.852	0.161	0.072	2.321	0.006
	23574.852	2.947	2.090	1.715	0.082	7.269	25.422	0.172	0.078	2.216	0.007
	23630.958	2.954	2.130	1.716	0.092	5.991	23.207	0.195	0.087	1.951	0.008
	23581.177	2.948	2.130	1.715	0.087	6.671	24.577	0.185	0.082	2.064	0.008
	23518.938	2.940	2.120	1.713	0.078	8.119	27.332	0.164	0.073	2.366	0.006
person2	23384.789	2.923	2.240	1.708	0.085	14.912	26.250	0.191	0.080	2.919	0.007
	23395.530	2.924	2.260	1.708	0.092	13.834	24.649	0.207	0.086	2.677	0.008
	23384.157	2.923	2.260	1.707	0.087	14.709	25.866	0.197	0.082	2.624	0.008
	23388.821	2.924	2.240	1.708	0.069	22.442	32.604	0.154	0.065	3.676	0.005
	23386.271	2.923	2.240	1.709	0.064	24.417	34.973	0.143	0.060	3.842	0.004
	23380.051	2.923	2.280	1.707	0.085	13.957	26.954	0.193	0.080	2.668	0.007
	23416.087	2.927	2.280	1.708	0.102	10.917	22.261	0.234	0.097	2.424	0.010
	23447.818	2.931	2.250	1.709	0.105	10.570	21.498	0.235	0.099	2.403	0.011
	23446.298	2.931	2.250	1.709	0.094	11.846	23.946	0.211	0.089	2.652	0.009
	23414.270	2.927	2.240	1.709	0.082	13.356	27.478	0.183	0.077	3.072	0.007

person3	23418.244	2.927	2.170	1.709	0.077	13.835	28.336	0.166	0.072	3.041	0.006
	23449.878	2.931	2.180	1.710	0.083	12.135	26.294	0.181	0.078	2.321	0.007
	23629.383	2.954	2.260	1.712	0.156	5.561	14.471	0.353	0.147	-0.534	0.024
	23489.655	2.936	2.260	1.705	0.172	4.900	13.161	0.388	0.162	-0.425	0.029
	23523.109	2.940	2.210	1.708	0.148	6.420	14.952	0.327	0.139	-0.809	0.022
	23419.717	2.927	2.070	1.707	0.112	9.613	18.532	0.231	0.105	-1.846	0.012
	23520.303	2.940	2.150	1.709	0.143	5.661	14.984	0.308	0.135	-1.008	0.021
	23545.337	2.943	2.320	1.708	0.163	5.348	14.211	0.379	0.154	-0.461	0.027
	23397.147	2.925	2.320	1.705	0.134	8.631	17.304	0.311	0.126	-0.388	0.018
	23458.519	2.932	2.170	1.708	0.126	8.980	17.184	0.274	0.119	-0.843	0.016
person4	23343.368	2.918	2.170	1.704	0.124	9.467	17.438	0.270	0.117	-0.598	0.015
	23261.495	2.908	2.120	1.702	0.105	9.714	20.239	0.222	0.099	-1.423	0.011
	23389.869	2.924	2.210	1.705	0.126	6.944	17.567	0.278	0.119	-0.973	0.016
	23937.059	2.992	2.120	1.729	0.045	22.936	46.805	0.096	0.043	3.567	0.002
	23776.961	2.972	2.300	1.723	0.065	24.478	35.163	0.150	0.062	3.670	0.004
	23739.094	2.967	2.390	1.719	0.116	12.414	20.550	0.278	0.110	2.456	0.014
	23670.825	2.959	2.390	1.715	0.130	10.135	18.437	0.310	0.122	2.286	0.017
	23587.804	2.948	2.600	1.714	0.104	16.216	25.094	0.269	0.098	2.987	0.011
	23669.244	2.959	2.600	1.718	0.085	26.778	30.751	0.220	0.080	3.978	0.007
	23736.978	2.967	2.430	1.720	0.089	19.432	27.286	0.216	0.084	3.655	0.008
person5	23716.349	2.965	2.400	1.718	0.106	14.683	22.572	0.255	0.100	2.903	0.011
	23668.540	2.959	2.400	1.717	0.101	15.754	23.749	0.243	0.095	2.996	0.010
	23956.564	2.995	2.330	1.726	0.126	7.376	18.521	0.293	0.119	0.488	0.016
	23647.245	2.956	2.320	1.715	0.121	6.840	19.153	0.281	0.114	0.430	0.015
	23614.364	2.952	2.250	1.714	0.114	4.844	19.792	0.256	0.107	0.606	0.013
	23524.211	2.941	2.340	1.710	0.133	5.196	17.637	0.310	0.125	-0.050	0.018
	23489.053	2.936	2.340	1.710	0.116	8.246	20.209	0.271	0.109	0.255	0.013
	23479.820	2.935	2.600	1.703	0.188	8.391	13.814	0.489	0.177	-0.352	0.035
	23543.488	2.943	2.600	1.703	0.208	6.043	12.480	0.542	0.196	-0.284	0.043
	23509.070	2.939	2.260	1.709	0.135	5.157	16.764	0.305	0.127	0.172	0.018
person6	23471.755	2.934	2.340	1.707	0.145	7.264	16.084	0.340	0.137	0.259	0.021
	23486.298	2.936	2.340	1.707	0.149	6.823	15.719	0.348	0.140	0.153	0.022
	23486.934	2.936	2.130	1.712	0.071	8.471	30.021	0.151	0.067	1.942	0.005
	23531.701	2.941	2.020	1.714	0.072	6.748	27.908	0.146	0.068	1.141	0.005
	23449.663	2.931	2.020	1.710	0.074	6.290	27.163	0.150	0.070	0.968	0.006
	23387.099	2.923	2.110	1.708	0.070	7.789	30.189	0.147	0.066	1.202	0.005
	23419.390	2.927	2.110	1.709	0.075	6.646	27.968	0.159	0.071	1.119	0.006

	23379.750	2.922	2.100	1.708	0.067	8.817	31.245	0.141	0.063	1.658	0.005
	23394.454	2.924	2.100	1.709	0.066	9.511	31.895	0.138	0.062	1.849	0.004
	23411.569	2.926	2.090	1.709	0.080	6.191	26.052	0.168	0.076	1.252	0.006

Table (4.2): The abnormal of feature extraction.

Sample	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11
person1	23414.303	2.927	2.090	1.709	0.083	5.928	25.057	0.174	0.079	1.160	0.007
	23426.886	2.928	2.080	1.709	0.086	6.414	24.303	0.178	0.081	0.575	0.007
	23456.758	2.932	2.010	1.709	0.108	2.490	18.689	0.216	0.101	-0.125	0.012
	23459.430	2.932	2.110	1.709	0.101	3.021	20.830	0.214	0.096	0.147	0.010
	23427.962	2.928	2.110	1.709	0.092	3.416	22.815	0.195	0.087	0.168	0.009
	23436.189	2.930	1.990	1.708	0.106	3.664	18.753	0.211	0.100	-0.541	0.011
	23416.542	2.927	2.060	1.706	0.128	3.406	16.077	0.264	0.121	-0.388	0.016
	23453.382	2.932	2.060	1.707	0.130	3.353	15.831	0.268	0.123	-0.292	0.017
	23521.564	2.940	2.130	1.709	0.141	3.702	15.134	0.300	0.133	-0.464	0.020
	23493.543	2.937	2.130	1.707	0.149	3.746	14.253	0.318	0.141	-0.392	0.022
person2	23479.478	2.935	2.100	1.707	0.140	3.798	15.044	0.293	0.132	-0.264	0.019
	23558.030	2.945	2.070	1.711	0.136	3.964	15.273	0.281	0.128	-0.477	0.018
	23639.184	2.955	2.240	1.706	0.213	3.518	10.500	0.478	0.201	-1.035	0.046
	23509.924	2.939	2.240	1.704	0.189	3.649	11.862	0.423	0.178	-0.911	0.036
	23409.259	2.926	2.080	1.703	0.160	3.528	13.024	0.332	0.151	-0.975	0.026
	23467.945	2.933	2.100	1.705	0.161	4.095	13.059	0.338	0.152	-1.020	0.026
	23525.741	2.941	2.120	1.707	0.165	3.726	12.858	0.350	0.155	-0.508	0.027
	23391.720	2.924	2.170	1.702	0.162	3.314	13.385	0.352	0.153	-0.329	0.026
	23386.607	2.923	2.190	1.702	0.160	3.416	13.686	0.350	0.151	-0.410	0.026
	23428.057	2.929	2.190	1.705	0.143	3.678	15.279	0.314	0.135	-0.280	0.021
person3	23388.394	2.924	2.090	1.705	0.127	3.299	16.508	0.265	0.119	-0.450	0.016
	23377.208	2.922	2.080	1.704	0.130	4.323	15.999	0.270	0.123	-0.686	0.017
	23473.207	2.934	2.080	1.708	0.123	4.704	16.852	0.257	0.116	-0.906	0.015
	23410.689	2.926	1.980	1.707	0.112	4.617	17.752	0.221	0.105	-0.962	0.012
	23233.890	2.904	1.980	1.701	0.109	3.755	18.243	0.215	0.102	-0.517	0.012
	23505.108	2.938	2.190	1.709	0.136	4.207	16.081	0.298	0.128	-0.012	0.019
	23737.368	2.967	2.290	1.712	0.186	3.629	12.282	0.427	0.176	0.298	0.035
	23576.177	2.947	2.390	1.706	0.188	4.495	12.717	0.449	0.177	0.693	0.035
	23382.470	2.923	2.390	1.702	0.156	5.970	15.282	0.374	0.147	0.894	0.024
	23426.017	2.928	2.260	1.704	0.155	4.465	14.579	0.350	0.146	0.472	0.024
person4	23398.565	2.925	2.260	1.704	0.147	4.795	15.391	0.332	0.138	0.522	0.022

	23487.493	2.936	2.400	1.710	0.112	8.506	21.489	0.268	0.105	0.883	0.012
	23391.978	2.924	2.260	1.707	0.101	7.131	22.453	0.227	0.095	0.659	0.010
	23381.142	2.923	2.260	1.704	0.135	4.279	16.713	0.306	0.127	0.372	0.018
	23393.951	2.924	2.180	1.704	0.140	3.634	15.527	0.306	0.132	0.401	0.020
	23366.292	2.921	2.180	1.703	0.140	3.692	15.532	0.306	0.132	0.641	0.020
	23358.552	2.920	2.150	1.704	0.126	4.219	17.110	0.270	0.118	0.711	0.016
	23444.163	2.931	2.190	1.707	0.124	3.883	17.663	0.272	0.117	0.363	0.015
	23423.361	2.928	2.240	1.704	0.152	3.806	14.770	0.340	0.143	0.338	0.023
	23341.530	2.918	2.240	1.702	0.150	3.784	14.941	0.336	0.141	0.351	0.022
person5	23531.174	2.941	2.130	1.710	0.132	3.506	16.168	0.281	0.124	-0.131	0.017
	23586.679	2.948	2.010	1.713	0.122	3.456	16.455	0.246	0.115	-0.342	0.015
	23572.847	2.947	2.000	1.713	0.117	2.908	17.143	0.233	0.110	-0.155	0.014
	23489.243	2.936	1.980	1.710	0.102	2.982	19.415	0.202	0.096	-0.310	0.010
	23489.808	2.936	1.980	1.710	0.103	2.993	19.220	0.204	0.097	-0.202	0.011
	23556.440	2.945	2.020	1.713	0.106	3.526	19.105	0.214	0.100	-0.430	0.011
	23562.945	2.945	2.020	1.713	0.102	3.779	19.825	0.206	0.096	-0.316	0.010
	23513.030	2.939	2.010	1.712	0.097	3.730	20.779	0.194	0.091	-0.294	0.009
	23489.347	2.936	2.140	1.711	0.096	4.231	22.343	0.205	0.090	-0.143	0.009
	23473.810	2.934	2.140	1.711	0.091	5.742	23.562	0.194	0.086	-0.308	0.008
person6	23444.093	2.931	1.950	1.710	0.085	5.410	23.025	0.165	0.080	-0.835	0.007
	23428.076	2.929	1.950	1.709	0.081	3.092	24.188	0.157	0.076	-0.047	0.007
	23457.361	2.932	2.100	1.709	0.106	4.891	19.848	0.222	0.100	0.315	0.011
	23453.935	2.932	2.160	1.709	0.110	4.691	19.693	0.237	0.103	0.300	0.012
	23443.273	2.930	2.160	1.709	0.105	4.920	20.658	0.226	0.099	0.203	0.011
	23449.411	2.931	2.150	1.710	0.087	5.974	24.742	0.187	0.082	0.765	0.008
	23436.233	2.930	2.150	1.710	0.074	8.224	29.237	0.158	0.069	1.096	0.005
	23443.276	2.930	2.020	1.711	0.057	9.072	35.191	0.116	0.054	0.566	0.003
	23412.948	2.927	1.990	1.710	0.056	7.791	35.450	0.112	0.053	0.895	0.003
	23419.733	2.927	2.010	1.709	0.071	6.356	28.187	0.143	0.067	0.691	0.005

B. Feature Normalization

After extracting the features, it is noticeable that the values of the obtained features as shown in Tables (4.1) and (4.2) are variation values, so, there is a need to make these values convergent, and this is done by using the normalization process. Figure (4.4) shows an example of the results for this process.

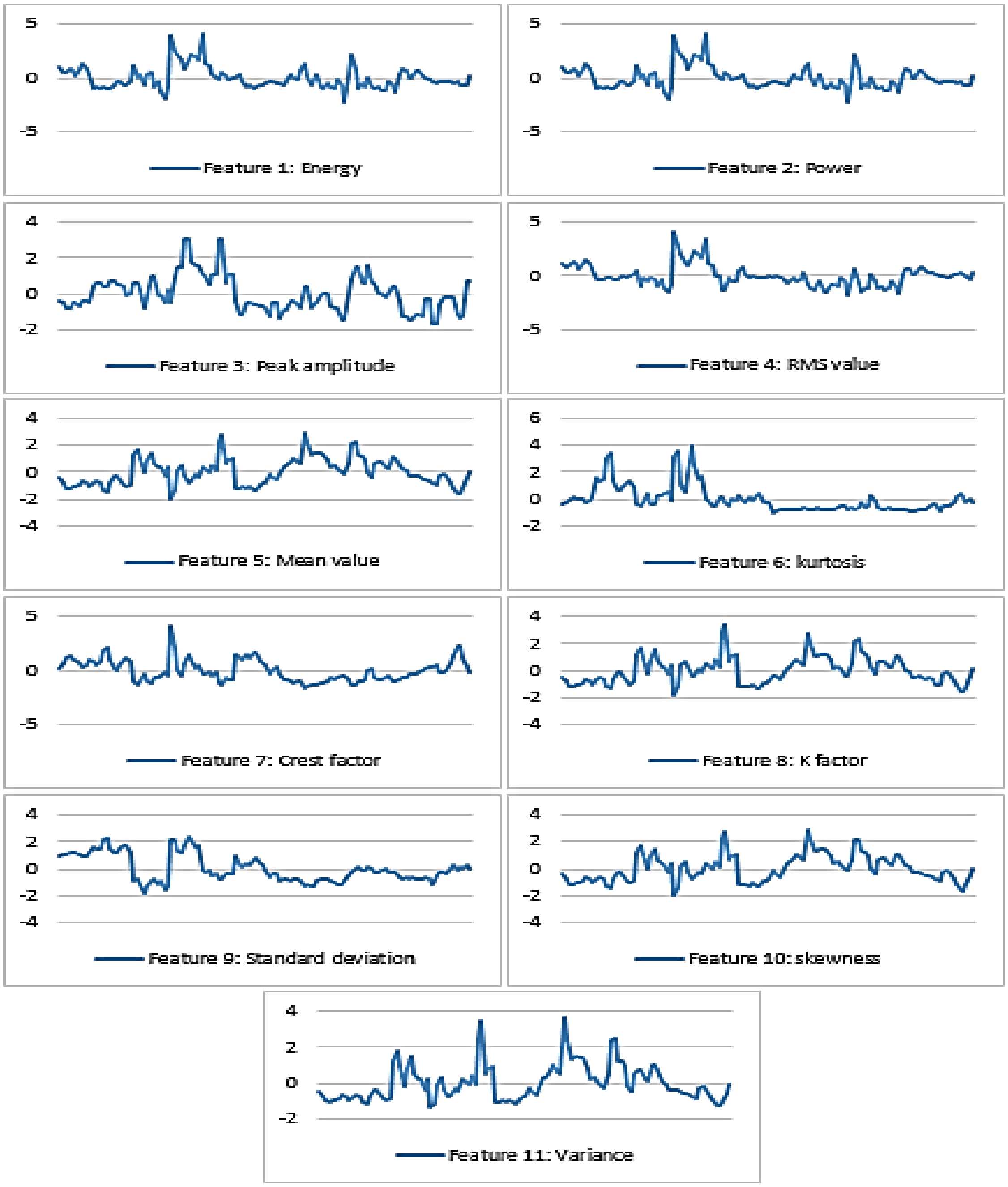


Figure (4.4): An example of the extracted features based on eleven measurements after the normalization process.

Tables (4.3) and (4.4) illustrate the extracted features after the normalization process.

Table (4.3): Feature normalization of normal signal.

Sample	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11
person1	1.004	1.004	-0.381	1.162	-0.458	-0.372	0.131	-0.492	-0.458	0.959	-0.525
	0.470	0.470	-0.454	0.832	-0.819	-0.209	0.615	-0.817	-0.819	1.038	-0.789
	0.445	0.445	-0.816	0.923	-1.155	-0.166	1.128	-1.153	-1.155	0.997	-1.003
	0.882	0.882	-0.743	1.335	-1.248	0.128	1.353	-1.224	-1.248	1.150	-1.056
	0.700	0.700	-0.454	1.105	-1.023	0.023	0.969	-0.994	-1.023	1.141	-0.922
	0.248	0.248	-0.454	0.725	-1.076	0.085	1.071	-1.040	-1.076	1.165	-0.955
	0.754	0.754	-0.671	1.110	-0.899	-0.014	0.690	-0.916	-0.899	1.087	-0.843
	1.245	1.245	-0.381	1.438	-0.622	-0.276	0.342	-0.634	-0.622	0.894	-0.649
	0.809	0.809	-0.381	1.112	-0.770	-0.137	0.557	-0.764	-0.770	0.977	-0.755
	0.265	0.265	-0.454	0.726	-1.034	0.160	0.989	-1.004	-1.034	1.197	-0.929
person2	-0.909	-0.909	0.416	-0.385	-0.809	1.553	0.820	-0.686	-0.809	1.602	-0.782
	-0.815	-0.815	0.560	-0.371	-0.624	1.332	0.568	-0.495	-0.624	1.425	-0.651
	-0.914	-0.914	0.560	-0.411	-0.750	1.511	0.759	-0.611	-0.750	1.386	-0.741
	-0.873	-0.873	0.416	-0.196	-1.291	3.097	1.817	-1.129	-1.291	2.156	-1.080
	-0.896	-0.896	0.416	-0.177	-1.426	3.502	2.189	-1.253	-1.426	2.278	-1.152
	-0.950	-0.950	0.705	-0.414	-0.830	1.357	0.930	-0.666	-0.830	1.419	-0.797
	-0.635	-0.635	0.705	-0.341	-0.313	0.734	0.193	-0.182	-0.313	1.240	-0.409
	-0.357	-0.357	0.488	-0.125	-0.248	0.663	0.073	-0.159	-0.248	1.225	-0.354
	-0.371	-0.371	0.488	-0.006	-0.559	0.924	0.458	-0.445	-0.559	1.407	-0.602
	-0.651	-0.651	0.416	-0.118	-0.919	1.234	1.012	-0.788	-0.919	1.714	-0.856
person3	-0.616	-0.616	-0.091	-0.040	-1.062	1.332	1.147	-0.983	-1.062	1.692	-0.947
	-0.339	-0.339	-0.019	0.142	-0.879	0.984	0.826	-0.810	-0.879	1.165	-0.829
	1.231	1.231	0.560	0.445	1.245	-0.364	-1.030	1.237	1.245	-0.926	1.209
	0.009	0.009	0.560	-0.947	1.696	-0.500	-1.236	1.655	1.696	-0.846	1.802
	0.301	0.301	0.198	-0.217	1.003	-0.188	-0.954	0.925	1.003	-1.127	0.913
	-0.603	-0.603	-0.816	-0.436	-0.044	0.467	-0.392	-0.210	-0.044	-1.887	-0.177
	0.277	0.277	-0.236	-0.161	0.877	-0.344	-0.949	0.709	0.877	-1.273	0.766
	0.496	0.496	0.995	-0.342	1.450	-0.408	-1.071	1.544	1.450	-0.873	1.472
	-0.800	-0.800	0.995	-0.950	0.604	0.265	-0.585	0.739	0.604	-0.819	0.463
	-0.264	-0.264	-0.091	-0.351	0.378	0.337	-0.604	0.299	0.378	-1.152	0.227
person4	-1.271	-1.271	-0.091	-1.211	0.325	0.437	-0.564	0.252	0.325	-0.973	0.173
	-1.987	-1.987	-0.454	-1.565	-0.246	0.487	-0.124	-0.319	-0.246	-1.577	-0.352
	-0.864	-0.864	0.198	-0.873	0.365	-0.081	-0.544	0.347	0.365	-1.247	0.212
	3.922	3.922	-0.454	4.167	-1.969	3.198	4.047	-1.817	-1.969	2.076	-1.390
	2.522	2.522	0.850	2.810	-1.386	3.514	2.219	-1.170	-1.386	2.152	-1.131
	2.190	2.190	1.502	1.954	0.089	1.041	-0.075	0.346	0.089	1.263	-0.055

	1.593	1.593	1.502	1.230	0.476	0.574	-0.407	0.725	0.476	1.139	0.326
	0.867	0.867	3.023	0.965	-0.279	1.820	0.638	0.244	-0.279	1.652	-0.380
	1.580	1.580	3.023	1.810	-0.831	3.986	1.526	-0.345	-0.831	2.377	-0.797
	2.172	2.172	1.792	2.281	-0.701	2.480	0.982	-0.386	-0.701	2.141	-0.706
person5	1.992	1.992	1.575	1.916	-0.200	1.506	0.242	0.075	-0.200	1.590	-0.314
	1.573	1.573	1.575	1.617	-0.353	1.726	0.427	-0.075	-0.353	1.659	-0.441
	4.093	4.093	1.068	3.476	0.365	0.008	-0.394	0.526	0.365	-0.177	0.212
	1.387	1.387	0.995	1.180	0.229	-0.102	-0.295	0.382	0.229	-0.220	0.078
	1.100	1.100	0.488	1.034	0.013	-0.511	-0.194	0.082	0.013	-0.091	-0.125
	0.311	0.311	1.140	0.053	0.564	-0.439	-0.533	0.732	0.564	-0.572	0.419
	0.003	0.003	1.140	0.041	0.074	0.186	-0.129	0.263	0.074	-0.348	-0.069
	-0.077	-0.077	3.023	-1.389	2.174	0.216	-1.133	2.859	2.174	-0.792	2.493
	0.480	0.480	3.023	-1.391	2.757	-0.265	-1.343	3.481	2.757	-0.743	3.421
	0.179	0.179	0.560	-0.099	0.626	-0.447	-0.670	0.664	0.626	-0.409	0.486
person6	-0.148	-0.148	1.140	-0.571	0.935	-0.015	-0.777	1.089	0.935	-0.345	0.834
	-0.021	-0.021	1.140	-0.520	1.033	-0.105	-0.834	1.183	1.033	-0.423	0.949
	-0.015	-0.015	-0.381	0.540	-1.226	0.232	1.412	-1.162	-1.226	0.887	-1.043
	0.376	0.376	-1.178	0.872	-1.184	-0.121	1.080	-1.220	-1.184	0.301	-1.019
	-0.341	-0.341	-1.178	0.223	-1.127	-0.215	0.963	-1.173	-1.127	0.174	-0.986
	-0.888	-0.888	-0.526	-0.219	-1.256	0.093	1.438	-1.205	-1.256	0.345	-1.061
	-0.606	-0.606	-0.526	-0.020	-1.095	-0.142	1.089	-1.066	-1.095	0.284	-0.967
	-0.953	-0.953	-0.598	-0.253	-1.334	0.303	1.604	-1.281	-1.334	0.679	-1.103
	-0.824	-0.824	-0.598	-0.129	-1.374	0.446	1.706	-1.315	-1.374	0.818	-1.125
	-0.674	-0.674	-0.671	-0.126	-0.957	-0.235	0.788	-0.965	-0.957	0.381	-0.880

Table (4.4): Feature normalization of abnormal signal.

Sample	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11
person1	-0.650	-0.650	-0.671	-0.137	-0.864	-0.289	0.632	-0.886	-0.864	0.314	-0.820
	-0.540	-0.540	-0.743	-0.063	-0.801	-0.189	0.514	-0.842	-0.801	-0.114	-0.777
	-0.279	-0.279	-1.250	-0.094	-0.165	-0.994	-0.368	-0.389	-0.165	-0.626	-0.283
	-0.256	-0.256	-0.526	0.007	-0.346	-0.885	-0.031	-0.418	-0.346	-0.427	-0.435
	-0.531	-0.531	-0.526	-0.130	-0.601	-0.804	0.280	-0.639	-0.601	-0.412	-0.634
	-0.459	-0.459	-1.395	-0.234	-0.206	-0.753	-0.358	-0.448	-0.206	-0.931	-0.319
	-0.631	-0.631	-0.888	-0.704	0.432	-0.806	-0.778	0.179	0.432	-0.819	0.281
	-0.309	-0.309	-0.888	-0.451	0.490	-0.817	-0.816	0.228	0.490	-0.749	0.341
	0.288	0.288	-0.381	-0.103	0.798	-0.745	-0.926	0.605	0.798	-0.874	0.676
	0.043	0.043	-0.381	-0.475	1.050	-0.736	-1.064	0.826	1.050	-0.822	0.969

person2	-0.080	-0.080	-0.598	-0.407	0.764	-0.726	-0.940	0.526	0.764	-0.728	0.638
	0.607	0.607	-0.816	0.266	0.647	-0.692	-0.904	0.377	0.647	-0.884	0.508
	1.317	1.317	0.416	-0.782	2.902	-0.783	-1.653	2.722	2.902	-1.292	3.666
	0.186	0.186	0.416	-1.171	2.192	-0.756	-1.440	2.070	2.192	-1.202	2.520
	-0.694	-0.694	-0.743	-1.321	1.347	-0.781	-1.257	0.991	1.347	-1.249	1.339
	-0.181	-0.181	-0.598	-0.890	1.379	-0.665	-1.252	1.056	1.379	-1.282	1.380
	0.324	0.324	-0.454	-0.526	1.497	-0.740	-1.283	1.197	1.497	-0.907	1.534
	-0.848	-0.848	-0.091	-1.505	1.417	-0.825	-1.200	1.224	1.417	-0.776	1.429
	-0.893	-0.893	0.053	-1.503	1.357	-0.804	-1.153	1.208	1.357	-0.835	1.350
	-0.530	-0.530	0.053	-0.870	0.873	-0.750	-0.903	0.773	0.873	-0.740	0.761
person3	-0.877	-0.877	-0.671	-0.897	0.388	-0.828	-0.710	0.187	0.388	-0.864	0.236
	-0.975	-0.975	-0.743	-1.037	0.487	-0.618	-0.790	0.256	0.487	-1.037	0.338
	-0.135	-0.135	-0.743	-0.194	0.296	-0.540	-0.656	0.094	0.296	-1.198	0.144
	-0.682	-0.682	-1.468	-0.503	-0.049	-0.558	-0.515	-0.333	-0.049	-1.239	-0.182
	-2.228	-2.228	-1.468	-1.829	-0.136	-0.734	-0.438	-0.404	-0.136	-0.914	-0.258
	0.144	0.144	0.053	-0.152	0.666	-0.642	-0.777	0.587	0.666	-0.543	0.529
	2.175	2.175	0.778	0.637	2.123	-0.760	-1.374	2.117	2.123	-0.316	2.416
	0.766	0.766	1.502	-0.639	2.166	-0.583	-1.305	2.381	2.166	-0.028	2.481
	-0.929	-0.929	1.502	-1.464	1.251	-0.280	-0.903	1.485	1.251	0.120	1.217
	-0.548	-0.548	0.560	-1.101	1.212	-0.589	-1.013	1.206	1.212	-0.190	1.167
person4	-0.788	-0.788	0.560	-1.160	0.974	-0.521	-0.886	0.987	0.974	-0.153	0.880
	-0.010	-0.010	1.575	0.086	-0.045	0.240	0.072	0.228	-0.045	0.111	-0.178
	-0.846	-0.846	0.560	-0.505	-0.365	-0.042	0.223	-0.254	-0.365	-0.052	-0.450
	-0.940	-0.940	0.560	-1.092	0.638	-0.627	-0.678	0.675	0.638	-0.262	0.499
	-0.828	-0.828	-0.019	-1.082	0.788	-0.759	-0.864	0.680	0.788	-0.241	0.665
	-1.070	-1.070	-0.019	-1.295	0.786	-0.747	-0.863	0.679	0.786	-0.065	0.663
	-1.138	-1.138	-0.236	-1.113	0.360	-0.639	-0.616	0.253	0.360	-0.014	0.208
	-0.389	-0.389	0.053	-0.426	0.312	-0.708	-0.529	0.270	0.312	-0.269	0.160
	-0.571	-0.571	0.416	-1.058	1.114	-0.724	-0.983	1.080	1.114	-0.288	1.047
	-1.287	-1.287	0.416	-1.658	1.064	-0.729	-0.956	1.034	1.064	-0.278	0.986
person5	0.372	0.372	-0.381	0.122	0.537	-0.786	-0.764	0.377	0.537	-0.631	0.390
	0.857	0.857	-1.250	0.699	0.259	-0.796	-0.718	-0.040	0.259	-0.785	0.107
	0.736	0.736	-1.323	0.673	0.100	-0.908	-0.610	-0.185	0.100	-0.649	-0.045
	0.005	0.005	-1.468	0.228	-0.326	-0.893	-0.254	-0.558	-0.326	-0.762	-0.419
	0.010	0.010	-1.468	0.219	-0.296	-0.891	-0.284	-0.534	-0.296	-0.683	-0.394
	0.593	0.593	-1.178	0.697	-0.217	-0.781	-0.302	-0.419	-0.217	-0.849	-0.328
	0.650	0.650	-1.178	0.796	-0.329	-0.730	-0.189	-0.512	-0.329	-0.766	-0.421
	0.213	0.213	-1.250	0.475	-0.478	-0.740	-0.040	-0.647	-0.478	-0.750	-0.540

	0.006	0.006	-0.309	0.304	-0.506	-0.637	0.206	-0.522	-0.506	-0.640	-0.562
	-0.130	-0.130	-0.309	0.241	-0.649	-0.327	0.397	-0.648	-0.649	-0.761	-0.669
person6	-0.390	-0.390	-1.685	0.079	-0.827	-0.395	0.313	-0.995	-0.827	-1.146	-0.795
	-0.530	-0.530	-1.685	-0.003	-0.945	-0.870	0.496	-1.090	-0.945	-0.569	-0.873
	-0.274	-0.274	-0.598	-0.067	-0.215	-0.501	-0.186	-0.317	-0.215	-0.304	-0.327
	-0.304	-0.304	-0.164	-0.145	-0.103	-0.543	-0.210	-0.142	-0.103	-0.316	-0.229
	-0.397	-0.397	-0.164	-0.159	-0.251	-0.496	-0.058	-0.274	-0.251	-0.386	-0.357
	-0.343	-0.343	-0.236	0.097	-0.763	-0.280	0.583	-0.737	-0.763	0.025	-0.750
	-0.459	-0.459	-0.236	0.127	-1.151	0.182	1.289	-1.079	-1.151	0.267	-1.000
	-0.397	-0.397	-1.178	0.311	-1.618	0.356	2.223	-1.580	-1.618	-0.121	-1.246
	-0.662	-0.662	-1.395	0.087	-1.655	0.093	2.264	-1.630	-1.655	0.121	-1.262
	-0.603	-0.603	-1.250	0.020	-1.215	-0.201	1.124	-1.255	-1.215	-0.029	-1.037

C. Classification of Normalized Features

After the normalization process, these features are now ready for classification. Where two methods of classification were used KNN and SVM. Accuracy is calculated for both methods after determining the percentage of training and testing. Training ratios were taken (70%, 80%, 90%) at random and the testing was taken on ratios (30%, 20%, 10%), respectively.

The obtained accuracies from (70%, 80%, 90%) training, and (30%, 20%, 10%) testing, respectively, using KNN and SVM classifiers are shown in Table (4.5). The best obtained accuracies (when the training 90% and testing 10%) are 95% using KNN classifier and 99.9% using SVM classifier.

Table (4.5): Accuracy result of classification model.

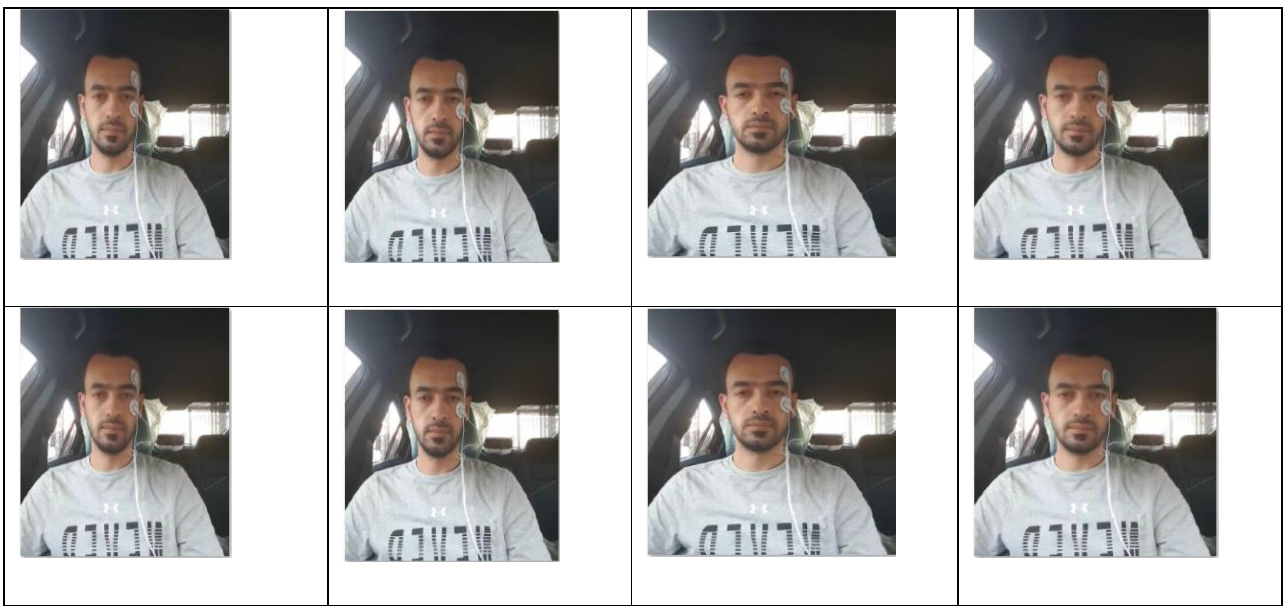
	(70% -30%)	**(80% -20%)**	**(90% -10%)**
KNN	89 %	92 %	95 %
SVM	94 %	96 %	99.9%

4.3.2 Behavioral Based Method

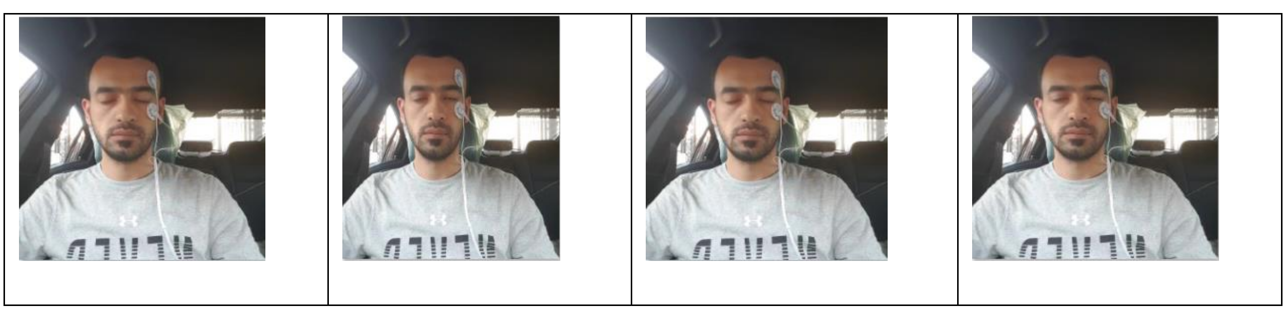
After the video acquisition process, the video is converted into frames, and then driver's eyes are detected. To extract the features, the image of eyes is divided into small regions through the LBP and sequenced into a single feature vector.

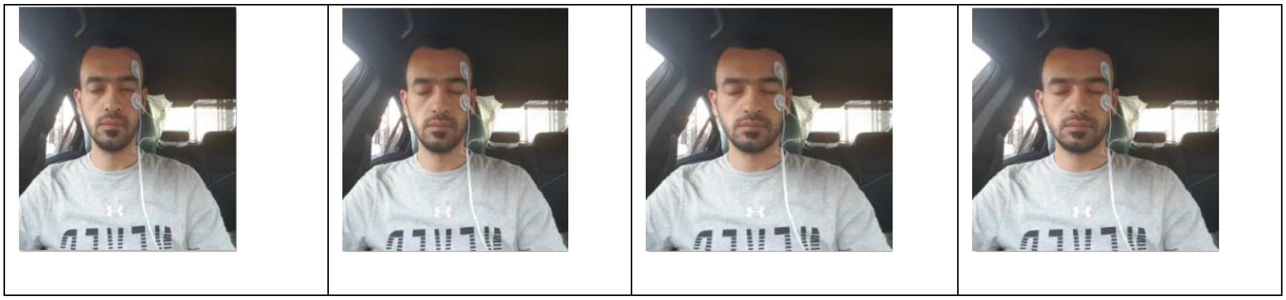
A. Extract Frame

Using the camera installed inside the car, we can get the driver image. The camera creates a video. Then, for each five frames, only one image of the person is taken in the case of normal and abnormal, as shown in Figure (4.5).



(a)



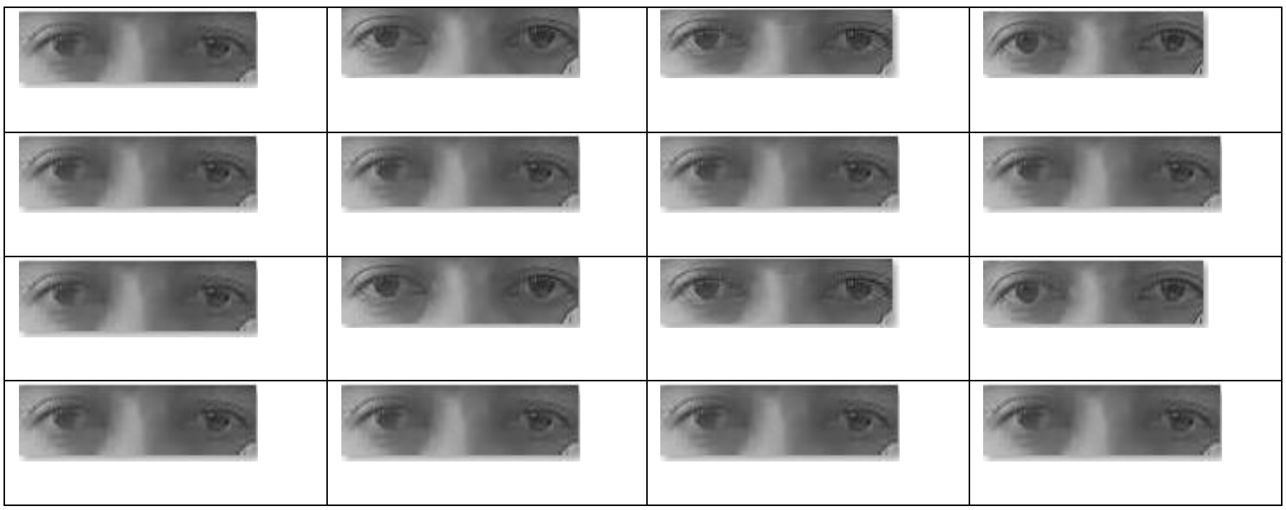


(b)

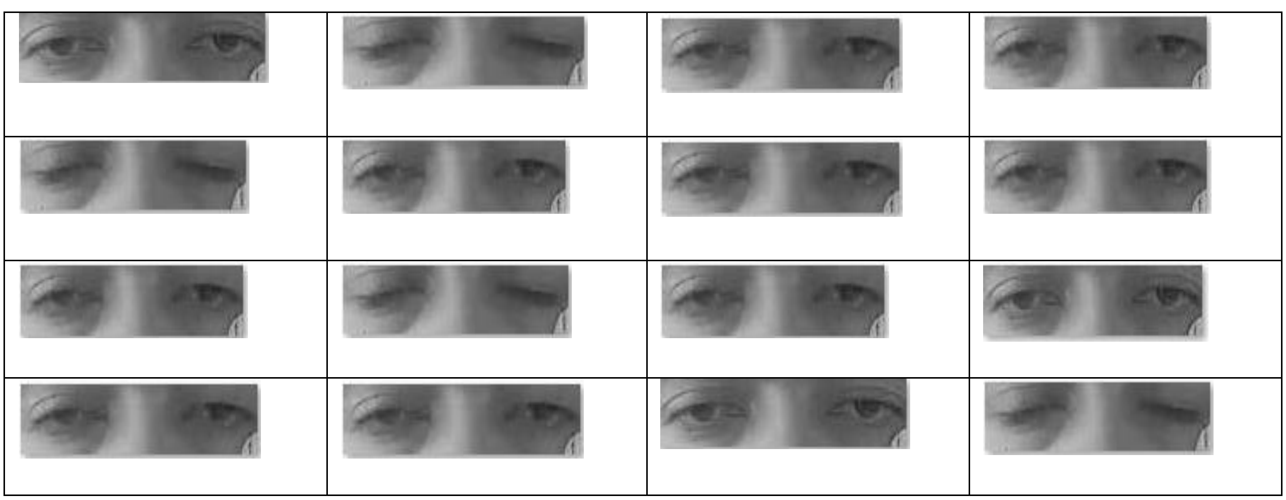
Figure (4.5): Sample of dataset for driver drowsiness, (a) Normal, (b) Abnormal.

B. Eye Detection

The eye is determined after converting the RGB image into grayscale image and also determine the state of the eye in the case of normal and abnormal, as shown in Figure (4.6) which represents the sample of eye detection for the driver.



(a)



(b)

Figure (4.6): Sample of eye detection for driver, (a) Normal, (b) Abnormal.

C. Feature extraction using LBP

The LBP algorithm was applied to the eye detection dataset used in which the eye image is divided into several regions. In each region of the eye image, a 3×3 filter is applied so that it calculated the binary patterns of each divided region of the eye image and then extracted the features to the eye in the normal and abnormal state.

D. Classification of Eye Detection

Now the features are ready for classification. Also, the same two previous methods were used KNN and SVM. The accuracy of both methods is calculated after determining the percentage of training and testing as described previously.

Table (4.6) shows the classification accuracy of both methods KNN and SVM of eye detection obtained from (70%, 80%, 90%) training and (30%, 20%, 10%) testing, respectively. The best obtained accuracies (when the training 90% and testing 10%) are 98% using KNN classifier and 100% using SVM classifier.

Table (4.6): The result of eye detection classification.

	(70% - 30%)	**(80% - 20%)**	**(90% - 10%)**
KNN	93 %	96 %	98 %
SVM	97 %	99 %	100%

The proposed system results have been compared with several previous related works, as shown in Table (4.7).

Table (4.7): Comparison with some related works.

Author/(s) name, Year, Ref.	**Drowsiness Detection Methods**	**Classification Methods**	**Accuracy**
Hu Shuyan and Zheng Gangtie, 2009, [6]	EOG Signals	SVM	86.67%
Mandalapu Sarada Devi et al., 2011, [7]	Drivers' Eye State Detection	-	80%
Wei Zhang et al., 2012, [8]	Drivers' Eye State Detection	-	86%
Rateb Jabbar et al., 2018, [12]	Facial Landmark Key Point Detection	-	81%
Shaibal Barua et al., 2019, [13]	EEG and EOG Signals	SVM	93%
Ameen Aliu Bamidele et al. 2019, [14]	Drivers' Eye State Detection	KNN and ANN	72.25% and 71.61%
The Proposed Physiological Based Method	EOG Signals	KNN and SVM	95% and 99.9%
The Proposed Behavioral Based Method	Drivers' Eye State Detection	KNN and SVM	98% and 100%

From the above comparison, we found that the proposed system is more accurate than the other related works

Chapter Five

Conclusions And Suggestion

CHAPTER FIVE

CONCLUSIONS AND SUGGESTIONS

5.1 Conclusions

In this work, a new benchmark of an expert system for driver drowsing detection analyses was generated. Several conclusions can be stated from the achieved results, which are summarized as follows:

1. The use of two methods (EOG signal and eye detection) in the detection of drowsiness adds strength to the work because we used more than one set of features to determine the driver's condition which increases the classification accuracy.
2. The statistical features are extracted from the signal and improved by overlapping signal up to 50%.
3. This system creates a low-cost device capable of quickly alerting the driver to ensure their safety. The developed system used several statistical measurements makes it very sensitive to detect the driver's drowsiness. Furthermore, KNN and SVM classifier is used in this system to give good accuracies. The obtained decision was reliable enough for the activation of the alarm.
4. The use of the Local Binary Pattern (LBP) method gives this type of features even more power because of this method more robust variable lighting conditions and noise free.

5.2 Suggestions for Future Works

Driver drowsiness is one of the leading reasons for industrial and serious car accidents, that are increasingly drawing the researcher's community's attention about the safety of road for protecting the industrial environments. Generally, the utilization of the features extracted from the eye movements for detecting driver's drowsiness is a promising method. But there are still several problems to talk over in the future works:

1. Because the driver's drowsiness is capable of leading to dangerous accidents, a highly-precision detector of drowsiness will be highly helpful as a protection tool to the driver for preventing possible risks. In another side, for ensuring the comfort of driving, also, the rate of low false alarm must be regarded as a substantial operator in the development of a device and/or a method. A heartbeat device the electromyography (EMG), and the electroencephalogram (EEG) can be used, which is also the case if a person is not in a normal state, the heartbeat can either accelerate or slow down.

2. In the proposed Behavioral based method, the LBP algorithm was used to extract the features of the eye. It would be interesting to examine other algorithms, such as Speeded Up Robust Features (SURF), and compare their performance with LBP. The investigation of other algorithms will allow us to more generalize the force field features extraction concepts and impacts.

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الملخص

أحد أسباب حوادث الطرق هو نعاس السائق الذي يؤدي إلى عدد كبير من حوادث السيارات والإصابات والوفيات والخسائر الاقتصادية الكبيرة. يتم تمثيل نعاس السائق على أنه حالة تختلف بين النوم واليقظة ، مما يقلل من المهارات المعرفية ويؤثر على القدرة في أداء مهمة القيادة. تحتاج هذه المشكلة الخطيرة إلى تطوير نظام فعال لمراقبة اليقظة قادر على تقليل الحوادث من خلال تنبيه السائق في حالات القيادة السيئة المختلفة. هنالك عدة طرق للكشف عن النعاس ، الطرق القائمة على المركبة (مثل تقدير مستوى النعاس اعتمادًا على حركات عجلة القيادة) ، الطريقة السلوكية (الكشف عن الميزات البصرية للسائق باستخدام موارد مختلفة مثل تعابير الوجه ، حركات العين ، حركات الرأس ، وما إلى ذلك) ، ويمكن استخدام الأساليب القائمة على الفسيولوجية (الكشف عن المراحل المبكرة لنعاس السائق اعتمادًا على الإشارات الفسيولوجية).

تركز هذه الرسالة على تصميم وتنفيذ نظام مساعدة السائق الذي يتضمن مراقبة السائق وتنبيهه باستخدام طريقتين، الطريقة الاولى تمثل الطريقة السلوكية وهي طريقة الكشف عن حركات العين اما الطريقة الثانية فتمثل الطريقة القائمة على الفسيولوجية التي تعتمد على إشارات EOG. في طريقة الكشف عن حركات العين (مغلقة / مفتوحة) ، يتم استخدام النمط الثنائي المحليLBP حيث يتم استخدام descriptors لتمثيل صور العين لاستخراج ميزات الأنسجة لأشخاص مختلفين في السيارة لمعرفة ما إذا كان السائق في حالة نعاس أم لا ، ويحدث هذا بعد تسجيل فيديو السائق واكتشاف عين السائق. لاستخراج الميزات بهذه الطريقة ، يتم تقسيم صورة العيون إلى مناطق صغيرة من خلال LBP وتسلسلها إلى ناقل ميزة واحد ، حيث يتم استخدام هذه الطريقة لتحديد ميزات التشابه في مجموعة التدريب وتصنيف صورة العين. أثناء استخدام الطريقة القائمة على الفسيولوجية، تم استخدام نظام مضمن يعتمد على متحكم ATmega2560 على لوحة Arduino لتنفيذ دائرة اكتساب إشارة EOG. استخدم النظام المقرح العديد من القياسات لاستخراج الميزات من إشارات EOG مما يجعلها حساسة للغاية لاكتشاف نعاس السائق. علاوة على ذلك ، تم استخدام مصنّف K Nearest Neighbours (KNN) و Support Vector Machine (SVM) في الطريقتين لإعطاء دقة جيدة. يقدم النظام المقترح جهازًا منخفض التكلفة قادرًا على تنبيه السائق بسرعة لضمان سلامته. تظهر النتائج التجريبية كفاءة وموثوقية نظام مساعدة السائق المقترح. تشير النتائج إلى أن النظام لديه معدل دقة عالية مقارنة بالطرق الأخرى حيث يكون معدل الدقة للمصنفين KNN و SVM باستخدام مجموعة بيانات إشارة EOG هو ٩٥٪ و ٩٩,٩٪ على التوالي. وعند استخدام مجموعة بيانات الكشف عن العين، فيكون معدل الدقة هو ٩٨٪ و ١٠٠٪ على التوالي.

جمهورية العراق

وزارة التعليم العالي والبحث العلمي

جامعة ديالى - كلية العلوم - قسم علوم الحاسوب

نظام خبير لاكتشاف نعاس السائق

رسالة مقدمة الى قسم علوم الحاسوب في كلية العلوم/ جامعة ديالى وهي جزء من متطلبات نيل درجة الماجستير في علوم الحاسوب

من قبل

علي عامر حياوي

بإشراف

أ. م. د. جمانة وليد

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