

**Arab Academy for Science, Technology and Maritime Transport**

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**Advanced driver assistance system (Drowsiness detection)**

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# Report Contribution Table

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| Mohamed Ahmed Ismail | * ECG literature review * EEG literature review * ECG work * PPG work |
| Mohamed Kamel Mohamed | * PPG literature review * Abstract * Introduction * Acknowledgments |
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| Ahmed Medhat Hafez | * References * Conclusion & Future work * ECG literature review |
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# Abstract

Drowsy driving is fatal as it is most frequently associated with unfortunate mistakes. The objective is to create an advanced driving assistance system to alarm and protect the driver in case of drowsiness. Three methods can be used: vehicle-based, behavioral, and physiological measurements. All three methods are mainly non-intrusive and relatively cheap, the physiological method is crucial, primarily based on vital organs activity where drowsiness is detected throughout the driver’s HRV without using a video camera. The behavioral method monitors the EAR of the driver and acts immediately in case the driver is falling asleep. Using computer vision, the video camera inputs the video feed to a face detection algorithm to extract the face. From the extracted face, the eyes are located then EAR patterns are detected to estimate the drowsiness state.

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# List of Acronyms/Abbreviations

Circle Hough Transform

CHT 15

Correct Classification Rate

CCR 17

Electrocardiogram

ECG 10

Electroencephalogram

EEG 10

Electromyography

EMG 10

Electrooculography

EOG 10

Frames Per Second

FPS 17

Heart Rate Variability

HRV 22

Histogram of Oriented Gradients

HOG 12

National Highway Traffic Safety Administration

NHTSA 10

Non-Rapid Eye Movement

NREM 19

Otorhinolaryngology

ORL 17

Photoplethysmography

PPG 10

Power Spectral Density

PSD 20

Rapid Eye Movement

REM 19

Region of Interest

ROI 11

Support Vector Machine

SVM 12

# Introduction

Drivers can carelessly drive while feeling drowsy without looking forwards to the consequences. Unfortunately, without considering safety measures, drivers do not recognize their lack of concertation or exhaustion until it is too late. According to the National Highway Traffic Safety Administration (NHTSA), drowsy driving led to almost 91,000 accidents, more than 50,000 injuries, and 800 deaths in 2017 in the US. In addition to that, various studies estimate that drowsy driving causes up to 60,000 deadly crashes each year. However, the research implies that around 21% of deadly automotive crashes occur due to drowsiness while driving. Moreover, according to the Central Agency for Public Mobilization and Statistics, due to drowsiness and other various reasons, the number of road accidents in Egypt reaches 51,511, and the number of deaths reaches 7,101 every year. Hence, a drowsiness detection system is highly needed to protect drivers as well as pedestrians and reduce a huge number of crashes. That’s where the advanced driving assistance system comes in handy as it aims to protect the driver and reduce the huge number of crashes almost on the daily basis.

Drowsiness is the same as being sleepy, which is just another word for having a tendency to sleep. The sleep stages can be specified into REM, NREM, and awake. Where the second stage can be subdivided into:

Stage 1: Transition from being awake to falling asleep.

Stage 2: Light sleep

Stage 3: Deep sleep

There are various methods to detect driver drowsiness, the most common ones are vehicle-based, behavioral, and physiological measurements. The first method is vehicle-based which estimates a number of metrics, such as lane position deviations, steering wheel movement, and pressure on the acceleration pedal. The second method is behavioral, where a camera is used to monitor the driver’s behavior, such as eye closure, yawning, head pose, and eye blinking. The third method is physiological which detects the driver’s state using Vital organs, such as; EEG, ECG, PPG, EOG, and EMG. Using these three methods, any change that exceeds a predetermined threshold indicates a highly increased chance that the driver is fatigued. Then the driver is warned if any of these drowsiness signs are detected.

To create an effective drowsiness detection system, the benefits of each existing method can be combined into a hybrid system, but some methods can have severe limitations and drawbacks such as the vehicle-based method which are:

1. High-cost installation.
2. Hard to apply in all cars.
3. Inaccurate

# Literature Review

## Drowsiness Detection Computer Vision

### “A Method of Driver’s Eyes Closure and Yawning Detection for Drowsiness Analysis by Infrared Camera”

In this paper, the method to detect driver’s eyes closure and yawning for drowsiness analysis by an infrared camera [1].

**The Proposed Method**

The main concept is detecting the driver’s face and setting it to a ROI. Next use ROI to find targets such as eyes and mouth. This process starts from get input from an infrared 2D camera and processing by MATLAB R2015a. The flow chart has five steps:

A person smiling for the camera

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Figure 1: Input image from infrared camera

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Figure 2: Driver’s face detection and set it to ROI

1. **Input image from infrared**

Install a camera in the middle of the car’s console. Facing approximately 15 degrees to the driver’s face. The frame rate is set as 25 frames per second and the input scale is 200×200 pixels.

1. **Face detection**

The Haar-like feature is one of the methods that has the ability to detect faces. This step uses to make (ROI) for finding the driver’s face. Harr-like feature is the method classify the dominant face by determining the differential of shading rectangle and normal rectangle and comparing it with threshold and polarity.

1. **Split image to upper-half and lower-half**

This method limits the scope of detecting the driver’s eyes and mouth.

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Figure 3: Images after split two half

1. **Detecting driver’s eyes and mouth**

The driver’s image will be a little tilted, so this step will rotate the image approximately 3 degrees to the left and right.



Figure 4: Images titled after split two half

1. **Detecting eyes closure and yawning**

Using a SVM. Before training data to SVM normal images must be turned into vector data by extracting the HOG. HOG is a method that separates images into many cells and collects histogram from every single gradient and calculates the scale and vector of that cell. HOG is the vector of each pixel. There are 2 groups of data like eyes opened and eyes closed.

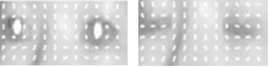


Figure 5: Eyes-opening’s HOG & Eyes-closing’s HOG

**Experiment Result**

This work has four experiments such as:

1. Face detection
2. Eyes detection
3. Mouth detection
4. Eyes closure and yawning detection

The driver would random action symptoms of driver drowsiness for example blink a lot, close driver eyes, and yawn randomly. These experiments do in low-light situations with 4 volunteers.

The program will print a green rectangle around the eyes and mouth area. When the program can detect symptoms of driver drowsiness program will print a red rectangle at the symptom area.

Graphical user interface, application

Description automatically generated

Figure 6: Output when driver is normal

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Figure 7: Output when driver is Drowsy

Table 1: Face detection accuracy

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Subject | Total frame | Correct frame | Error frame | Miss frame | Accuracy |
| 1 | 865 | 865 | 0 | 0 | 100 % |
| 2 | 1041 | 1025 | 2 | 14 | 98.46 % |
| 3 | 1047 | 1043 | 1 | 3 | 99.61 % |
| 4 | 825 | 825 | 0 | 0 | 100 % |
| Total | 3778 | 3758 | 3 | 17 | 99.47 % |

Table 2: Eyes detection accuracy

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Subject | Total frame | Correct frame | Error frame | Miss frame | Accuracy |
| 1 | 865 | 733 | 33 | 99 | 84.73 % |
| 2 | 1027 | 1004 | 16 | 7 | 97.76 % |
| 3 | 1044 | 986 | 40 | 18 | 94.44 % |
| 4 | 825 | 825 | 0 | 0 | 100 % |
| Total | 3761 | 3548 | 89 | 124 | 94.33 % |

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Subject** | **Total frame** | **Correct frame** | **Error frame** | **Miss frame** | **Accuracy** |
| 1 | 865 | 829 | 36 | 0 | 95.83 % |
| 2 | 1027 | 1016 | 11 | 0 | 98.92 % |
| 3 | 1044 | 1003 | 41 | 0 | 96.07 % |
| 4 | 825 | 816 | 9 | 0 | 98.90 % |
| Total | 3761 | 3664 | 97 | 0 | 99.80 % |

Table 3: Mouth detection accuracy

Table 4: Accuracy of eyes closure and yawning detection

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Subject | True Positive Rate (Eye) | True Negative Rate (Eye) | False Positive Rate (Mouth) | False Negative Rate (Mouth) |
| 1 | 32.4 % | 96.7 % | 51.0 % | 64.1 % |
| 2 | 92.8 % | 98.6 % | 97.4 % | 96.2 % |
| 3 | 75.4 % | 96.5 % | 77.2 % | 70.5 % |
| 4 | 99.5 % | 98.9 % | 97.7 % | 98.0 % |
| Validation | 98.0 % | 96.0 % | 92.5 % | 92.5 % |

From the experiments accuracy table found that the error of 7.5% in yawning detection is caused by the driver's mouth being open too much, so the program can’t detection are driver yawning. And the error of ROI detection that comes from the camera is set up on the side of the driver, so the camera can’t capture the full driver’s face.

### “Driver’s Fatigue and Drowsiness Detection to Reduce Traffic Accidents on Road” [2]

This paper proposes a robust and nonintrusive system for monitoring drivers’ fatigue and drowsiness in real-time. The proposed scheme begins by extracting the face from the video frame using the SVM face detector. Then CHT is applied on the eyes and mouth extracted regions. The drowsiness analysis method aims to detect micro-sleep periods by identifying the iris using a novel method to characterize the driver’s eye state.

**Driver’s Drowsiness Analysis**

1. **Iris Edge detector**

If the eye is open, viewing three main components:

**The pupil** which is the little black circle in the center of eye.

**The iris** is the circle distinguished by the eye color.

**The sclera** is the white outer area represents.

Iris edge extraction from significant intensity variations between iris and sclera. For each pixel x, a neighborhood containing n pixels at left and right of x is specified

Left (resp. Right) edge: if n or n − 1 left (resp. right) neighbors of x

provide a difference with x higher than the high threshold and if n or n − 1

right (resp. left) neighbors of x provide a difference with x lower than the low

threshold, we deduct that x is a left (resp. right) edge pixel of the iris and we

put it at 1

1. **Drowsiness detection**

Applying the CHT on this edge to obtain the iris radius from which we decide if the eye is open. Then three edge pixels are randomly chosen. and if the distance between each two pixels co-ordinates is higher than a fixed threshold, we compute the radius and the center coordinates of the candidate circle defined by these three pixels. The system stops at maximal iterations or when the edge has few pixels. Drowsiness is dependent on the microsleep periods which needs to be at least 2 seconds.

**Driver’s Fatigue Analysis**

characterized by a high yawning frequency. Because drowsiness occurs sometimes after fatigue. This step to prevent the driver before micro-sleep. Yawning is a wide-open mouth which lasts from 2 to 10 seconds. Applying CHT on mouth edge images.

A screen shot of a person's face

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Figure 8: Proposed and classic edge detectors for eye and mouth regions

Diagram

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Figure 9: Driver’s fatigue and drowsiness detection system

**Experimental Results**

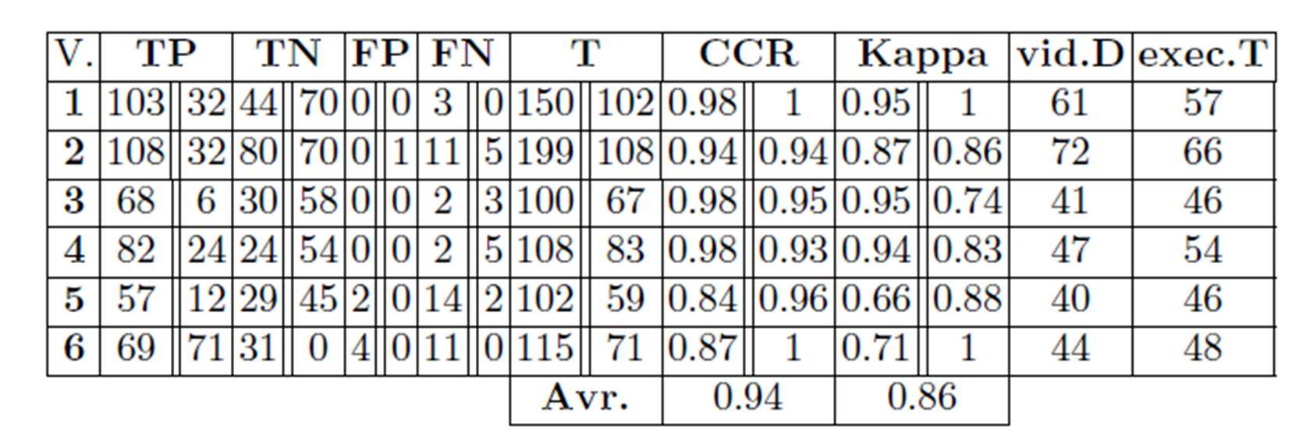
tests on 18 real video sequences of 14 different subjects in various lighting conditions to validate the proposed system. Webcam connected to a laptop by USB port. providing image of 640x480 at 30 FPS. Reducing the considered number of FPS from 30 to 2, to meet the real-time constraints. The CHT used 173 images of ORL database for evaluation. The accuracy of the first system is 90.3%. The second system presented. CCR is 94% and the average of κ is 86%. The second system uses 70 images using infra-red camera with 90% accuracy. On real images yawning detection is reduced to 81% accuracy.

Table 5: Kappa statistic interpretation

Table

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Table 6: Statistical measures of fatigue and Drowsiness detections



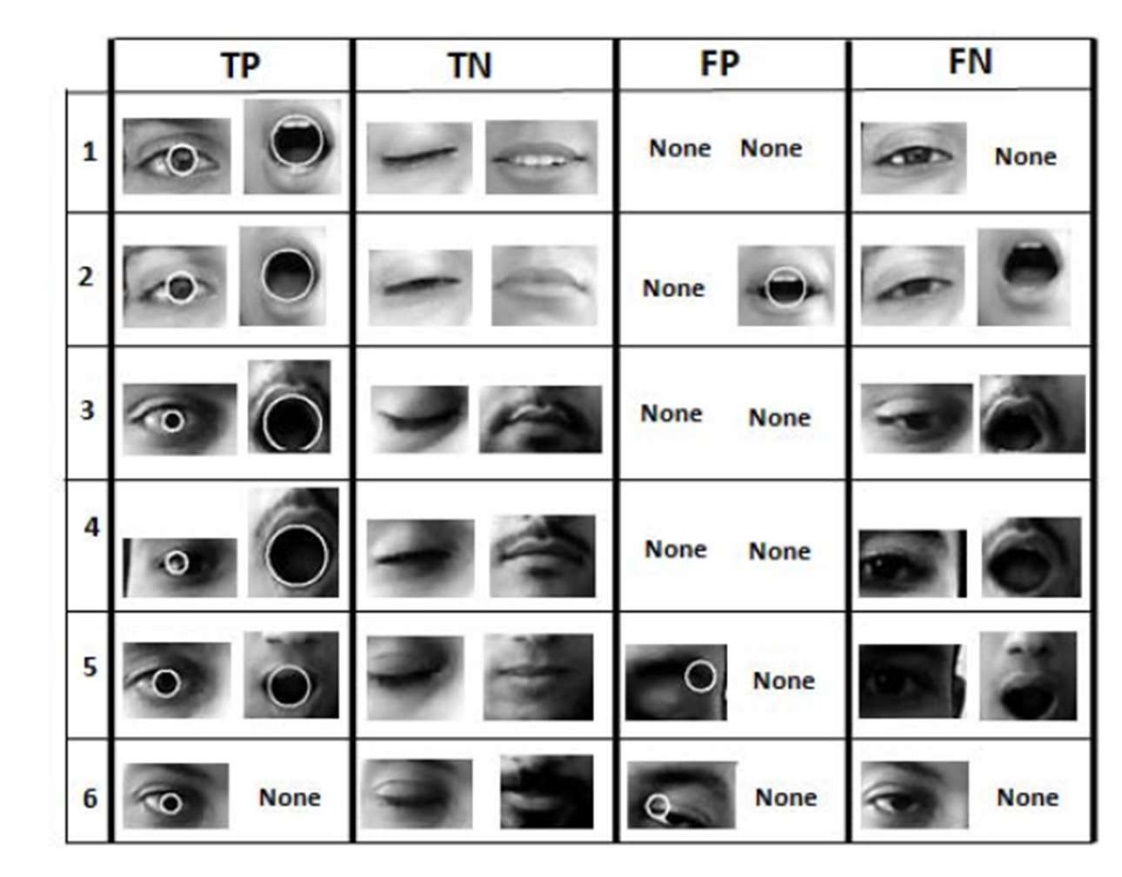


Figure 10: Results of fatigue and drowsiness detections

## Drowsiness Detection Using Vital Organs

### “On-board Drowsiness Detection using EEG: Current Status and Future Prospects.”

EEG is a relatively reliable indicator for drowsiness and fatigue monitoring. EEG is a record of the electrical activities of various brain areas where it uses surface.

Electrodes are positioned on the scalp to analyze brain electrical activity. The EEG frequency band is separated into the following frequency bands: alpha (8–13Hz), beta (13–30Hz), delta (0.5–4Hz), and gamma band (>30Hz). Low-frequency EEG bands are defined as those between 0.5 and 13 Hz, whereas high-frequency bands are defined as those above 13 Hz. There are three types of sleep: wakefulness, rapid eye movement (REM) sleep, and non-rapid eye movement (NREM) sleep. NREM sleep can be further classified into the following three stages:

Stage 1: Shift from alert to drowsy

Stage 2: Little sleep

Stage 3: Deep sleep,

Researchers in this discipline generally concentrate on Stage 1 sleep, during which a decrease in brain activity is shown with an abundance of slow EEG waves. Stage 1 sleep is when driver tiredness is perceived and explored. A drowsiness detection system can be designed by concentrating on this transitional phase and its relationship to EEG signal frequency. An example drowsiness monitoring and warning system based on EEG is shown in Figure 11



Figure 11: EEG Detection Cycle

Even while EEG is frequently used to improve drowsiness estimation, the raw data collecting method, which includes placing several electrodes on the scalp, is frequently inconvenient and a barrier to real-time onboard applications. These challenges can be overcome by determining the frequency bands and brain regions that are most useful, which will ultimately result in a reduction in the number of electrodes required for data collection. As a result, substantial research is being done in this area to identify the suitable brain regions, electrodes, and frequency bands to develop a universal EEG-based drowsiness detection device that is simple to wear.

As previously established, the delta, theta, alpha, beta, and gamma frequency bands are where the frequency domain behavior of EEG is observed.

Figure 12. shows the waveforms from these frequency bands. Typically, these bands are subjected to PSD analysis, and the absolute and relative power changes between baseline and the drowsy or early drowsy periods are compared.

Each of these five frequency bands has a different range of applications. According to studies, the participants' vigilance and performance states including weariness, drowsiness, and sleep are related to the delta, theta, alpha, and beta bands.

As a result, one of the objectives of ongoing research in this area is to determine the most informative frequency range that can aid in the quicker, more accurate, and more practical real-time use of drowsy state detection.

According to studies, the onset of sleepiness is accompanied by a rise in slow frequencies like delta, theta, and alpha (often in the frontal, parietal, and occipital locations). Faster frequencies, in particular the beta band, demonstrated a decline in activity with the onset of drowsiness in contrast to this. In addition to the frequency bands' absolute and relative power, a number of ratio indices have also been applied.

A picture containing diagram

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Figure 12: EEG Waves

**EEG detection**

The electrical activity of the brain is captured by an EEG machine. It has electrodes that, when applied to a subject's scalp, can detect brain activity. The EEG machine transfers the data to a computer or cloud server after the electrodes have recorded the brain wave patterns.

Most of these devices have analog to digital converters, amplifiers, filters, and electrodes. While wired EEG equipment must be connected directly to a computer, wireless or portable EEG machines have a battery.

An extended EEG reading is conducted using an ambulatory EEG machine. Ambulatory EEGs record for up to 72 hours, whereas typical EEG examinations record for 1-2 hours, and are frequently used to diagnose sleep abnormalities or seizure disorders.

EEG devices that enable a subject to view their brain activity in real-time are known as EEG neurofeedback machines, also referred to as EEG biofeedback machines. In this kind of EEG monitoring, the subject's brain waves are shown on a computer screen while the EEG machine is synced to a computer or cloud device.

**Measurement**

Instead of capturing ideas or emotions, EEG scanners track variations in the electrical activity the brain generates. Ionic current within and between neurons is what causes these voltage variations. The electrical signals that your brain produces naturally as it takes in and analyses information are what EEG equipment simply catches.

**Examples of the devices**



Figure 13: EEG Detection Devices

**Drawbacks of EEG**

Electroencephalogram (EEG) is the most widely accepted signal to assess the driver's state of relaxation. However, because it uses uncomfortable contact electrodes to collect data, this technology is not appropriate as a safety system for common real-life circumstances. Muse 2 is the initial approach to be implemented in the project, but it has a relatively high cost and the idea of wearing a gadget on the scalp will not be the best-suited option since this project is meant to serve different types of drivers, including truck drivers, who drive cars for long periods of time and long distances.

### “Driver fatigue and drowsiness monitoring system with embedded electrocardiogram sensor on steering wheel”

The process of electrocardiography involves creating an electrocardiogram, which is a recording of the electrical activity of the heart. It is a heart electrogram, which uses electrodes attached to the skin to create a graph of voltage over time for the electrical activity of the heart. Each cardiac cycle results in the depolarization and repolarization of the cardiac muscle, which is detected by these electrodes. Numerous cardiac disorders, including irregular heartbeat, insufficient coronary artery blood flow, and electrolyte problems, result in changes in the normal ECG pattern.

It is a rapid, risk-free, and painless test as the body is not exposed to any electricity while it is being performed. Similar to removing a sticking plaster, removing the electrodes from the skin could cause some minor discomfort. Additionally, some people may experience a moderate rash where the electrodes were placed.

Since an electrocardiogram is simple to monitor using a wearable sensor, a drowsiness detection method based on HRV, which is an R-R interval fluctuation obtained from an ECG, has been proposed. Drowsiness has an impact on HRV, which is associated with the autonomic nervous system.

Participants' individual ECG signal patterns may change with time, body posture, and physical circumstances. The P wave, PQ-segment, and QRS complex with strong R-peak, ST-segment, and T waves are represented graphically in Fig. 1 of the ECG wave. It translates the features as time intervals and voltage amplitudes (mV) (msec).

Atrial depolarization results in the production of a P wave, an isoelectric line indicating an AV delay, and what is known as a PQ-segment. Ventricular depolarization results in the generation of the QRS complex, which can occasionally be affected by bundle branch block, a delay, or obstruction of electrical impulses. Additionally, the ST segment is an isoelectric line that accompanies the PQ-segment, and ventricular repolarization results in the generation of the T wave. A higher heart rate is induced by standing and sitting than by sleeping.

Chart, line chart

Description automatically generated

Figure 14: Schematic of One Cardiac Cycle

Standing position, as opposed to sitting and lying down, has been shown to significantly decrease HRV values representing vagal activity and enhance sympathetic activity.

Most HRV measurements, such as SDNN and RMSSD, vary more during rest in the supine position compared to the upright position. Males were also reported to have higher HRV measurements than females.

From supine to standing, there has been observed to be a considerable increase in HR and commensurate drop-in time-domain HRV measurements. At rest, the frequency-domain variables total power (TP), low frequency (LF, ms2), normalized low frequency (LF, nu), high frequency (HF, ms2), and LF/HF measures all show a significant decrease from the supine to the sitting posture and an even greater decrease from the sitting to the standing posture.

The HRV in prone versus supine and prone versus seated postures were both examined in the same study. The study's findings showed that the HR in prone posture remained between supine and sitting posture, and substantial variations were seen in a number of HRV components.

A control system, the autonomic nervous system (ANS) is a component of the peripheral nervous system. It generally operates below the level of consciousness and regulates visceral processes. The parasympathetic nervous system and the sympathetic nervous system are the two traditional divisions of the ANS.

**Types:**

**There are three primary ECG types:**

Resting ECG: which is performed when the person comfortably lying down.

Stress or activity ECG: that is performed while on a treadmill or exercise cycle.

Ambulatory ECG: also known as a Holter monitor, connects the electrodes to a small, portable device that is worn around the waist and allows monitoring the heart for one or more days.

**Drowsiness detection using ECG**

The embedded ECG sensor interface was put through actual tests, and its performance was assessed. For a 2-hour driving test, two test volunteers (both male, ages 27 and 31), who had no heart conditions, were selected.

A subject was required to drive for two hours nonstop. The subjects were alert and moving around at the beginning, but by the end, the drivers appeared to be quite drowsy, often yawning, and breathing deeply. The time when the individuals experienced feelings of exhaustion and drowsiness while driving was monitored and used to extract three minutes of the recorded ECG signals for condition evaluation.

The test findings for a 27-year-old male person are shown in Fig. The subject's sleepy ECG signals were recorded, and the predicted HRV signals are shown on the first trace. The second trace displays the computed HRV signals as well as the ECG signals for the same subject during a period of weariness. The identical subject's ECG signals are seen in a normal state on the third trace. This study utilized the interpretation of the HRV signals in the time and frequency domains as one of the analysis techniques used to look for the indicator that indicates the activity of the ANS from the collected HRV signals to accurately monitor the subjects' health state. This shows that during tired and sleepy phases, the parasympathetic nervous system was more active than the sympathetic nervous system

A picture containing text, antenna

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Figure 15: HRV Using ECG for Normal State

Chart, line chart

Description automatically generatedChart, line chart

Description automatically generated

Figure 16: HRV Using ECG for Fatigued and Drowsy State

.**AD8232 tests and drawbacks**

For ECG and other physiological measurement applications, the AD8232 ECG sensor shown in Figure 17. is an integrated signal conditioning block. In the presence of noisy circumstances, such as those brought on by motion or the use of distant electrode implantation, it is intended to extract, amplify, and filter minor biopotential signals. An embedded microcontroller or an ultralow power analog-to-digital converter (ADC) may simply acquire the output signal according to this design.



Figure 17: AD8232 ECG Sensor

The purpose of the tests is to compare the BPM values recorded by ECG sensors and devices. The ECG instrument in use is a Philips ECG type G30. By comparing the electrocardiograph sensor output with the results of the equipment, up to 10 tests were conducted. Reading values is done simultaneously. The average error percentage across all 10x experiments was 2.39. The table 7 below shows the results of comparing the BPM readings obtained using the AD8232 ECG sensor and the BPM readings obtained using Philips ECG equipment.

Table 7: BPM Values of AD8232 Sensor

Table

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The AD8232 ECG sensor is the most commonly used ECG sensor due to its availability, low cost, and ease of use. Since the ECG sensor is a 3-lead electrode module that requires a placement on the right arm, left arm, and right leg as show in Figure 18. Therefore, the implementation of the sensor is uncomfortable for the driver due to the requirement of attaching the electrodes to the human body's skin.

Diagram

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Figure 18: Implementation AD8232 Sensor

**Capacitive electrodes implementation drawbacks**

Capacitive electrodes (CE) enable the collection of biopotentials through a dielectric layer without the need for electrolytes, by placing them on skin or clothing as shown in Figure 19., but they require front ends with extremely high input impedances.

The fully non-contacting ECG capacitive electrodes have been implemented in Ford’s car seat in 2011 as shown in Figure 19. and proved inaccurate results due to vibrations and noises as well as the implementation issues depending on each car seat model. Ford ended the ECG project since the upgradability of the product would not cope with modern life electronics such as wearable bands and smart watches which are low-cost gadgets.

**Diagram

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Figure 19: Capacitive Electrodes by Ford

### “A review on wearable photoplethysmography sensors and their potential future applications in health care”

A simple optical method called photoplethysmography (PPG) is used to determine changes in blood volume in peripheral circulation. It is an inexpensive, non-invasive technique that measures skin surface characteristics.

The method offers insightful data about our cardiovascular system. Interest in this method, which is widely used in clinical physiological testing and monitoring, has been renewed by recent advances in technology and for that reason, it is applied in the project.

**Principle:**

Low-intensity infrared (IR) light is used by PPG. When light passes through biological tissues, it is absorbed by venous and arterial blood, skin pigments, and bones. PPG sensors can detect variations in blood flow as changes in light intensity since blood more strongly absorbs light than the surrounding tissues.

The amount of blood flowing through the blood vessels is directly correlated with the voltage signal from PPG. Although this technique cannot be used to measure the amount of blood, it can detect even small variations in blood volume.

A PPG signal has several components, including variations in the volume of venous blood, which modulates the signal, changes in the volume of arterial blood, which are related to cardiac activity, a DC component that displays the optical properties of the tissues, and subtle energy changes in the body.

Place of measurement and contact force between the placement and the sensor are two important variables that influence the recordings from the PPG. Where the variations in blood flow typically happen in the arteries rather than within the veins.

PPG uses a bar or graph to represent the fluctuating blood flow as a waveform. Direct current (DC) and alternating current (AC) components compensate the waveform.

The AC component reflects fluctuations in blood flow that are related to heartbeats. The tissue structure, venous and arterial blood volumes, and optical signals that are reflected or transmitted by the tissues all affect the DC component.

With respiration, the DC component demonstrates minor variations. The DC baseline is stacked on the AC component's fundamental frequency, which fluctuates with heart rate.

**Usage:**

PPG technology is used in multiple applications such as:

* Blood oxygen saturation
* Blood pressure
* Heart rate
* Respiration
* Blood pressure and heart rate variability

Focusing on blood pressure and heart rate variability, to detect drowsiness, offer multiple wearable devices with fairly low cost.

**PPG Signal:**

Pulsatile (AC) and superimposed (DC) components form the PPG signal. The cardiac synchronous fluctuations in blood volume that result from heartbeats give the AC component. Respiration, sympathetic nervous system activity, and thermoregulation all influence the DC component.  The blood volume fluctuations driven along by heart activity and dependent on the systolic and diastolic phases are represented by the AC component. The pulse wave's systolic peak occurs at the end of the systolic phase, also known as the "rising period," which begins with a valley. Another drop at the conclusion of the diastolic period indicates the completion of the pulse wave. In the bloodstream, vascular changes can be predicted by characteristics including rise time, amplitude, and shape. As demonstrated in Figure 2, PPG can also be used to measure HRV, or fluctuations in peak-to-peak or P-P Interval heartbeat time intervals. The variance may result from a variety of variables, including the person's age, heart health, and level of physical fitness. The PPG signal is split into two distinct phases: the anacrotic (rising edge), which predominantly defines the systole, and the catacrotic (falling edge), which reflects the diastole.

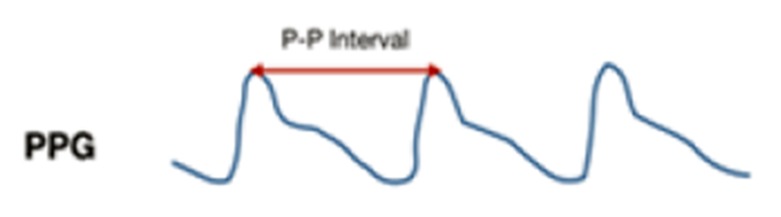


Figure 20: P-P Interval

**Devices:**

Since green light is often used to calculate the absorption of oxygen in oxyhemoglobin (oxygenated blood) and deoxyhemoglobin, IR-LEDs are typically utilized to measure the flow of blood that is more deeply concentrated in certain areas of the body, such as the muscles (blood without oxygen present). Although there are alternative LED sensors for measuring hemoglobin that have different colors, green LED is thought to be the most popular. This is simply because it can provide measures that are more accurate due to its deeper tissue penetration. To measure the strength of the light reflected from the tissue, PPG sensors further utilize a photodetector. The amount of the detected light can then be used to determine (measure) the changes in blood volume. Only a few body regions, as seen in Figure 1, are suitable for the placement of wearable PPG sensors.

Diagram

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Figure 21: PPG Sensor Implementation Positions on Human Body

However, the degree of precision varies between different measurement sites. Additionally, PPG sensors can be used to identify drowsiness, or an excessive blood flow. Although certain body parts, such the finger, earlobe, and forehead, are frequently used, researchers are also examining at other body parts as more practical options.

PPG sensor-based HR monitoring methods have a number of advantages over conventional ECG-based methods. PPG sensors, for example, require only one sensor to be implanted on the body for functioning and have simpler hardware implementation and cheaper prices. In contrast to conventional ECG recordings. For a traditional ECG-based system to function properly, at least three bioelectrodes must be positioned on various body parts, such as the right arm, left arm, and right leg. This requirement significantly limits the drivers' range of motion. Additionally, PPG sensors can perform better if they are positioned in certain anatomically accessible areas, such as the fingertip and earlobe, where the necessary PPG signals are more successfully captured.

**PPG Sensors:**

Although photoplethysmography sensors come in a variety of designs, they all detect changes in blood volume and provide comparable results. A common PPG sensor uses one or more LEDs to emit light at the tissue location. The photodiode monitors the amount of light that is reflected from tissue but is not absorbed. The most common LED colors used in scientific experiments are red and green; however, a yellow LED has also been employed in some investigations. Longer wavelength light can reach deeper into the tissue. As an illustration, infrared light penetrates the skin more deeply than green light. Infrared light, **according to the researchers, is more vulnerable to interference. As a result, for some applications, green LED with a shorter wavelength may be preferable. The movement of the PPG sensor over the tissue, skin deformation, blood flow dynamics, and ambient temperature are the usual causes of interference.**

Whereas the sensor used in the project is the MAX30102 PPG sensor and the future improvement for the existing sensor is the SEN0203 PPG sensor by DFROBOTS since it requires less implementation and comes in with an existing band but it is currently inaccessible due to the shipping constraints.

**Wristband-type PPG-based devices:**

The wristband-type PPG is recognized as the most widely used and desired device among the several PPG-based HR monitoring systems currently available. Its exceptional qualities, such as being affordable, relatively portable, and extremely comfortable for people to wear, contribute to its popularity. These devices do have some restrictions, though as the drawbacks of wrist-type PPG devices for clinical settings have been addressed in several ways, according to several research that have been conducted thus far. The idea of having a wearable device for the driver is acceptable as it can be treated as a wearable band, a seatbelt, or a smart watch to protect his life as well as the pedestrians.

**Factors affecting PPG sensor recordings.**

PPG recordings can be impacted by various circumstances. These include biological, sensory, and cardiovascular variables. Alterations of interior tissues, such as muscular movement and tissue expansion, can result from tissue modifications produced by controlled or involuntary motions. These movements will affect the receiving light, resulting in a different signal. The way that light propagates through tissue varies depending on an individual's anatomy, organ size, and the amount of fluid that tissues can hold. The displacement of the sensor is another element that can impact the signal. The sensor may move relative to its initial location as a result of physical activity and body motion. The light's path is affected by the sensor movement, which also modifies the signals. The device's pressure on the skin determines how strong the signal is received. Where this is crucial for the driver as most drivers are exposed to uneven road and continuous vibration.

## Safety Features

### “Simultaneous Face Detection and Pose Estimation Using Convolutional Neural Network Cascade”

In this paper, face detection and pose estimation combined by Multi-task CNN cascade framework to achieve real-time performance.

The proposed method

The proposed is a multi-task framework for real-time face detection and pose estimation using cascaded networks, multi-task learning, and feature fusion to improve CNN architecture.

**A. OVERALL FRAMEWORK**

The multi-task framework consists of three CNN components: Coarse-detection Network, Optimized-detection Network and Fine-detection & Pose-estimation Network. Coarse-detection Network classifies probability, Optimized-detection Network rejects false detections, and Fine-detection & Pose-estimation Network estimates pose for each detected face.

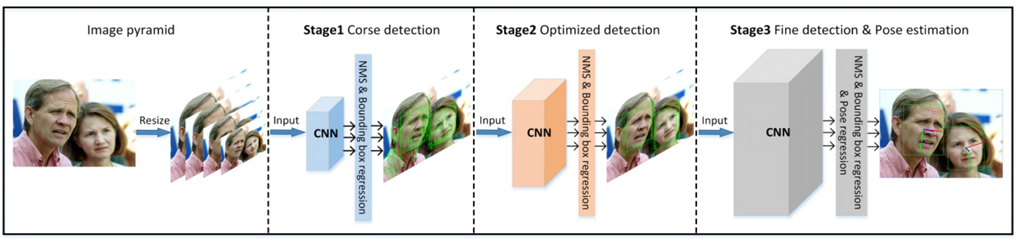


Figure 22: The CNN framework

The framework consists of three cascaded deep convolutional neural networks, optimizing the face detections of the front CNN and performing pose estimation on fine face detections.

**B. CNN ARCHITECTURES**

1. **INSPIRATION AND CONSIDERATIONS**

Cascaded convolutional neural networks have achieved reliable performance in face detection, with three networks adjusting the input image size to 10\*10, 20\*20, 40\*40. The network width and depth are determined based on the classification effect of the model to the dataset.

1. **COARSE-DETECTION NETWORK**

The Coarse-detection Network is a shallow fully convolutional network used to quickly find regions that contain exactly one face on the images. It has an input size of 10 \* 10 and gives a face vs. non-face classification probability distribution, bounding box regression offsets, and pose regression vectors for each window. In the training stage, the three variables are used as optimization targets.

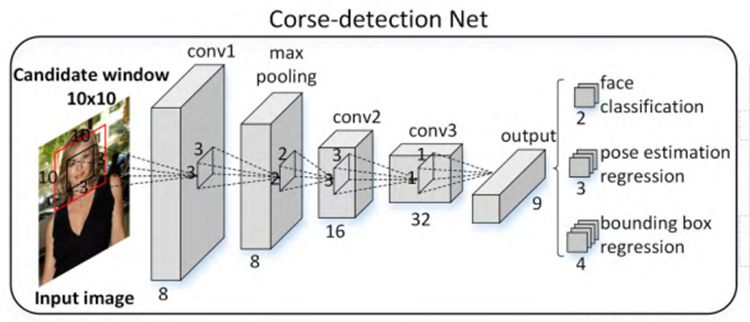


Figure 23: Corse-detection Net

1. **OPTIMIZED-DETECTION NETWORK**

The Optimized-detection Network is a CNN after Coarse detection Network that rejects false detection windows. The final layer outputs a vector containing face vs. non-face binary classification score, bounding box regression offsets, and pose regression vector.

1. **FINE-DETECTION & POSE-ESTIMATION NETWORK**

The Fine-detection & Pose-estimation Network is the last CNN in the framework. It has fine detection windows and more accurate pose estimation due to its more complicated network structure.

**C. CNN FEATURE FUSION STRAT**

CNN features are hierarchically distributed, with lower layers containing better localization properties and deeper layers containing more complicated features. Our baseline framework only takes advantage of the complex features of deeper layers, so we reconstruct a new CNN by fusing the low, mid, and high-level layers of the last

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Figure 24: The architecture of improved CNN

**Experiment Result**

**A. Face detection results**

Comparing the face detection result against state-of-the-art methods on the Face Detection Data Set and Benchmark (FDDB) dataset, this method outperforms most of the reported algorithms. Qualitative evaluation results show it can deal with challenging cases. Comparisons of face detection with state-of-the-art methods on (a) ROC curves on FDDB with discrete scores, (b) ROC curves on FDDB with continuous scores (shown in Figure25)

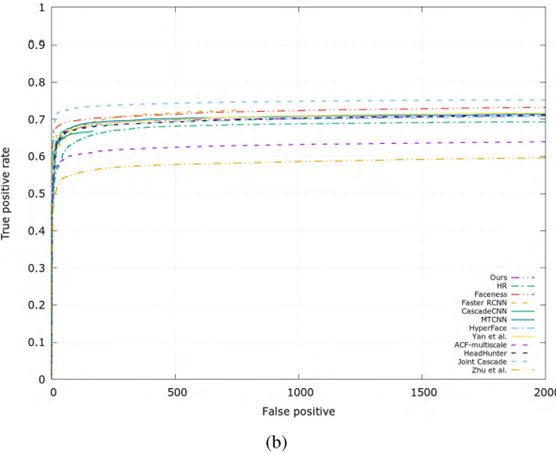
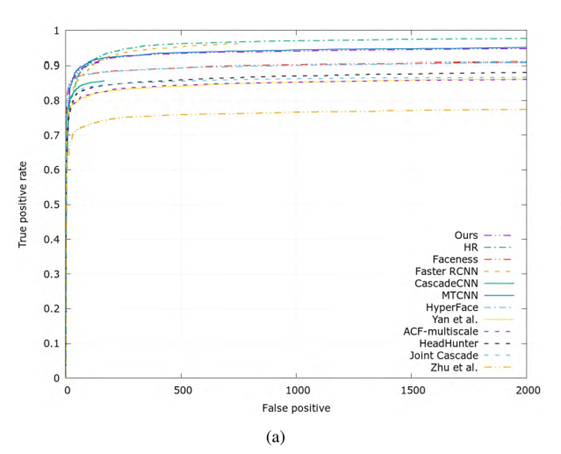


Figure 25: Comparisons of face detection

**B. Pose estimation results**

Annotated Faces in the Wild (AFW) is a popular dataset used for the evaluation of face alignment algorithms. It consists of 205 images collected from Flickr containing 468 in-the-wild faces with absolute yaw degrees up to 90. This paper presents the pose estimation performance on the AFW dataset. The method outperforms the first four methods by a large margin and is comparable with state-of-the-art methods using deep learning. However, Hyperface takes 3s to process an image and All-in-One takes 3.5s per image. The AFW processes 30 entire images per second and the speed is extremely competitive compared with other methods. Pose Estimation cumulative error distribution curves on AFW dataset. The numbers in the legend are the percentage of test faces with absolute yaw error less than or equal to 15 Degree (shown in Figure 26)..

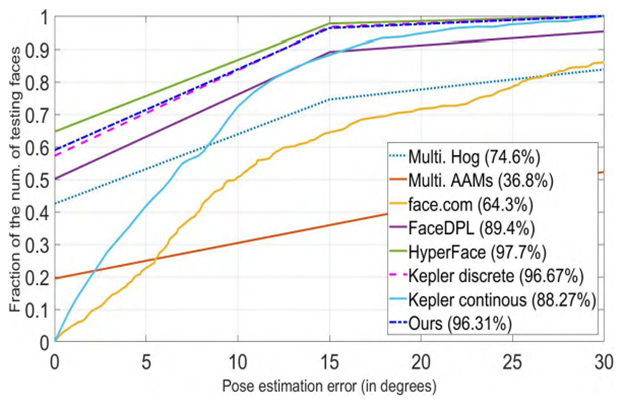


Figure 26: Pose Estimation cumulative error

**C. Ablation experiments**

Additional experiments to explore the correlation between CNN feature fusion and ablation studies to gain deeper insights.

1. **Joint training of face detection and pose estimation.**

Joint training of face detection and pose estimation promotes the performance of face detection on FDDB dataset, as evidenced by the performance of two frameworks.

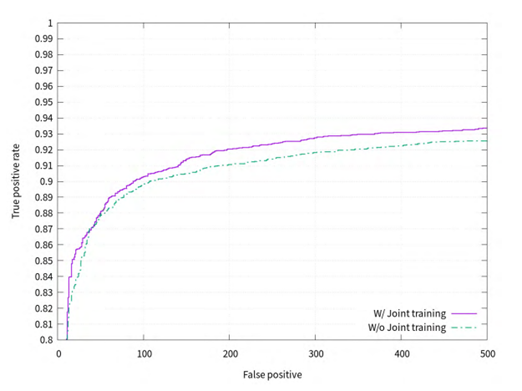


Figure 27: Comparisons of ROC curves on FDDB with and without joint training

1. **CNN feature fusion**

The Fine-detection & Pose-estimation Network was reconstructed by fusing the low, mid, and high-level layers of the last CNN.

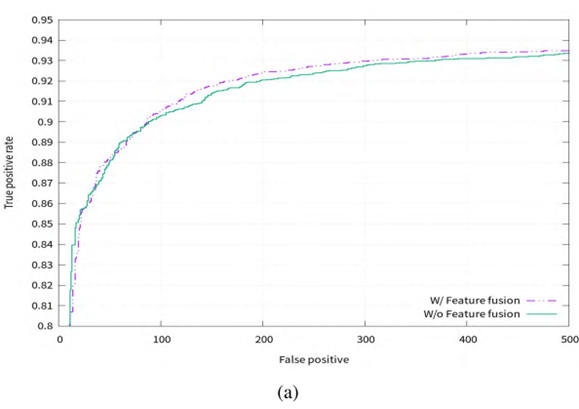


Figure 28: Comparisons of ROC curves on FDDB with and without feature fusion

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Figure 29: Comparisons of cumulative error distribution curves on AFW with and without feature fusion

The face detection tasks do not gain much by fusing intermediate layers but pose estimation task achieves a boosted performance (shown in Figure 28 & Figure 29) due to the hidden information from lower layers.

**D. Runtime efficiency**

Cascade-based methods have the advantage of runtime efficiency, combining several simple CNNs for faster face detection and better accuracy. The method achieved about 30fps for the two tasks. Compared with the methods for resolving multiple face-related tasks, this method is quite fast in computation speed. Hyperface takes 3s per image on a GTX Titan X GPU and All-in-one takes an average of 3.5s to process an image. Compared with these methods, this method achieves real-time performance for simultaneous face detection and pose estimation.

**Conclusion**

The "Simultaneous Face Detection and Pose Estimation Using Convolutional Neural Network Cascade" paper offers a highly effective method for simultaneously detecting faces and estimating their poses. However, it has some limitations, such as the need for a lot of labeled training data and high computational resources. Additionally, the method may not be robust to occlusion, meaning that if a part of the face is obscured by an object or another part of the face, the method may fail to detect or estimate its pose accurately.

# System Component Candidates

## Eye Aspect Ratio

### Face Detection

After processing the image such that the face area is completely visible, dlib’s face detector is used to find and locate the face in the image.

### Facial Landmarks

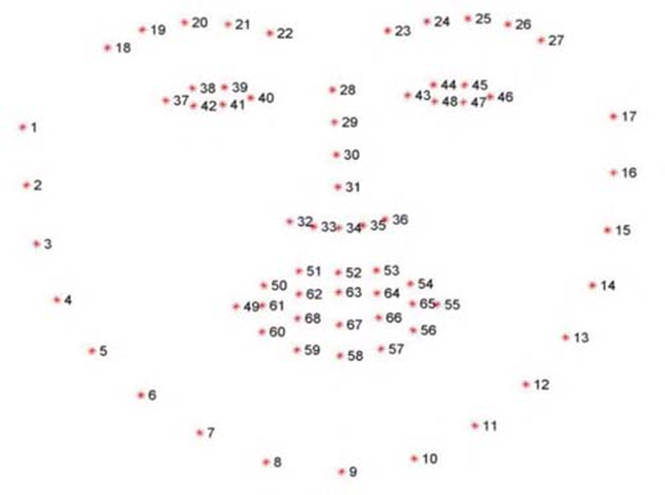
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Figure 30: Landmarks Coordinates

Facial landmark recognition used to detect drowsiness and fatigue. To detect sixty-eight facial landmarks, we used the open-source Python library d-lib. These predefined annotations help in shape prediction by recognizing various facial regions such as the eyebrows, eye, nose, and mouth region, among others (shown in Figure 22).

Table 8: Coordinates of various facial regions

|  |  |
| --- | --- |
| Region | Coordinates |
| Jaw | [0 - 17] |
| Right eyebrow | [18 - 22] |
| Left eyebrow | [23 - 27] |
| Nose | [28 -36] |
| Right eye | [37-42] |
| Left eye | [43 - 48] |
| Mouth | [49 – 68] |

### Eye Aspect Ratio (EAR)

The aspect ratio describes the relationship of an object's width to its height. The Eye Aspect Ratio is an estimate of the eye state. Each eye is represented by 6 (x,v) –coordinates (shown in Figure 23), beginning from the left comer of an eye and moving clockwise around the remaining of the points. Calculates the ratio of distances of the sum of the difference between the vertical points to twice the difference between the horizontal points. EAR is always calculated for the left and right eye separately.

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Figure 31: EAR

### Methodology

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Figure 32: Flow Chart

### Pre-processing

To capture the video, we used a wide-angle color camera attached to the car’s dashboard at an angle that can see the driver’s face. The video stream that acquired by the camera is converted into frames so that it is easy to process and detect objects. Then the system converts each frame from RGB to grayscale for easier processing.

### Data gathering

After processing the image, dlib’s face detector is used to find and locate the face in the image. The pre-trained facial landmark detector in the dlib library is used to estimate the position of 68 (x, y)-coordinates (as shown in Fig. 1) that map to facial structures on the face to locate the facial landmarks. Following the location of the coordinates, the system establishes a bounding box around the face to concentrate properly.

Going ahead, we extract the coordinates of both eyes, and encapsulate the focused region into a polygon. We then draw contours around the eyes region by joining the coordinates along the boundary for visual shape analysis by green boundary (shown in Figure33).

Subsequently, we calculated the initial Eye Aspect Ratio (EAR) of the driver as soon as the system is turned on, that is when the car is started, and a face is detected. We do so because using a single standard EAR threshold value can result in inaccurate predictions for people with certain genetic disorders or people of various nationalities.

Figure 33: The Eye Region

## ECG

### Circuitry

As part of the research on analog signal amplification and filtration, circuit concepts were chosen Jeremy Nash, who has experience designing and building circuits, suggested using a Sallen-Key filter to isolate the target frequencies. The decision to use two Sallen-Key filters in series (a Butterworth filter) to sharpen the amplitude attenuation after the corner frequency resulted from sound filtration research. The preamplifier circuit was found online and chosen because it was designed to be used with a condenser microphone, similar to the one chosen for the fetal heart monitor.

The condenser microphone signal is routed through a pre-amplifier, a low pass Butterworth filter, and then to the Arduino for digital analysis. The Arduino's 5V DC power supply will power the entire circuit. The circuit will be built on a breadboard. The circuitry is depicted in Figure 26 below.

Diagram

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Figure 34: Overview Circuit of Amplification and Filtering

### Analog Preamplification

A preamplifier is used to prepare the microphone signal for further amplifying, filtering, and processing. First, a low noise audio operational amplifier (op-amp) was chosen to determine the preamplifier.The following op-amps were chosen for their high quality characteristics and reputation for use in audio applications, as well as their low-to-medium price points to keep the device affordable: NE5532,TL072 The TL072 and NE5532 require an adequate supply voltage that can be powered by a 9V battery or by the 5V from the Arduino.That concludes the photos for the schematics:

Diagram, schematic

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Figure 35: ECG Pre-Amplifier Circuit

Diagram, schematic

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Figure 36: ECG Pre-Amplifier Circuit on Proteus

### Analog Signal Filtration

Sampling is the process of converting an analog continuous-time signal into a discrete numerical sequence that can be processed digitally. For the signal to be perfectly reconstructed, the sampling rate frequency must be at least double the highest frequency of the band-limited signal's upper limit (Dinez et al., 2002).

The Butterworth filter is the most common anti-aliasing filter used in audio applications where specific signal response is required across the circuit's bandwidth (National Instruments, 2010). This is largely because the Butterworth filter has the least amount of attenuation across its pass region, resulting in the least distortion of the signals that are passed. The Butterworth filter is a higher order filter composed of a series of cascading first or second order filters. Professor Hall confirmed the use of the Sallen-Key filter. He proposed that several Sallen-Key filters be used to improve the response's gain roll-off. With a higher gain roll-off, signals above the cut-off frequency are reduced by a greater magnitude. That concludes the photos for the schematics:

Chart

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Figure 37: Butterworth Filter

COG-type ceramic capacitors with tolerances ranging from 0.25 pF to 1% for higher values are the most precise capacitors available in the range of 0.5 pF to 47 nF. (Kugelstadt, 2012). X7R-type ceramic capacitors have a tolerance of +1% and range from 100pF to 2.2F. Tantalum electrolytic capacitors have the lowest tolerance for values greater than 2.2 F. National Semiconductor recommends that resistor values be between 1 k and 100 k, and capacitor values be between 1nF and several F.

The most important characteristic in selecting the appropriate operational amplifier used in the filter was the unity gain bandwidth. The open loop gain of the op amp should be 100 times greater than the peak gain of the filter for a maximum gain error of 1%. The maximum bandwidth required, as shown in Appendix IV, is 24 kHz. Another important parameter to consider is the slew rate, and the chosen op amp must have a slew rate greater than 3.14 V/ms. The LM741 op-amp was chosen as the op-amp for both Sallen-Key filters because it fits the given parameters and is widely available.

Diagram, schematic

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Figure 38: Butterworth Filter on Proteus

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Figure 39: Final ECG Circuit on Breadboard

## PPG

### Band design

#### Concept Generation and Selection

Concept generation began with a breakdown of the function of the device shown in Figure 32.

Diagram

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Figure 40: PPG Band Concept

First, the device is worn in the hand like a watch and is used to measure the ppg signals of the max30102 sensor, then sends those signals to a microcontroller by using i2c communication protocol to analyze those signals and identify the heartbeat. Based on the inputs, the person’s condition is determined by whether he is sleepy or not then those signals will be sent to the master microcontroller of the system by using a Bluetooth module attached to the band.

First, brainstorming sessions for the method of signal detection were held, and a main concept was chosen.

#### Detect Signals

To determine the heartbeat, the MAX30102 sensor was chosen due to a lot of data such as its tiny size 5.6mm x 3.3mm x 1.55mm, Ultra-Low Power Operation for Mobile Devices operates on a single 1.8V power supply and a separate 3.3V power supply for the internal LEDs. , Low-Power Heart-Rate Monitor, -40°C to +85°C Operating Temperature Range.A standard I2C-compatible interface is used for communication.

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Figure 41: Max30102 Sensor

#### Analyze signal

* Arduino Nano was chosen due to its small size when placed on the hand and the ease of programming it in the C language and the presence of a signal converter from analog to digital and finally because it shares with the sensor the Low power operation (5 volts) and finally because it also shares with the sensor in the presence of standard I2C-compatible interface is used for communication.
* To operate the band a battery is needed, choosing the Lipo Rechargeable Battery as it has 2.5 hours of charging time and it's able to work for 2-5 hours
* To recharge the battery, the Micro USB 5V 1A TP4056 Lithium Battery Charger Module is selected since the operating conditions are the same between the driver and the battery

#### Output data

* After analyzing those signals coming from the sensor through the controller, they are sent to the main controller in the system to take the necessary measures aimed at protecting the person who wears that band.
* Moreover, finding that the most suitable thing for sending this data is Bluetooth, specifically the UART, due to its high speed, in which its baud rate reaches 115200, and also due to the small distance between the band wearer and the main controller.
* Choosing the HC05 Bluetooth module, which is designed for wireless communication, having a range of up to <100m which depends upon transmitter and receiver, atmosphere, geographic, and urban conditions.

### Testing

Testing the band on two test subjects (male, 22 and male, 59) without any heart diseases for an hour at bedtime, the embedded ppg sensor continuously recorded the subject's biomedical signal.

The subjects were not sleepy at all at the beginning and the body movement was active whereas, at the end, the subjects appeared very sleepy, with frequent yawning and deep respiration.

The time when the subjects felt fatigued and drowsy was recorded and used to extract the recorded ECG signals for condition evaluation using an Arduino plotter.

So for the first subject, founding that at his normal state, the average heart rate is about 75 (beats/min) as shown in Figure 34.

Graphical user interface, application

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Figure 42: PPG Band Result in Normal State

The second trace shows the ppg signals for the same subject in a fatigued state and the calculated HRV and we found that the beat decreases by about 66 (beat/min) as shown in Figure 35 below.

Graphical user interface, chart, line chart

Description automatically generated

Figure 43:PPG Band Result in Fatigued State

The last trace shows the ppg signals measured when the subject was in a drowsy state and its HRV is about 55 (beat/min) as shown in Figure 36 below.

Graphical user interface, chart, line chart

Description automatically generated

Figure 44: PPG Band Result in Drowsy State

Table 9 shows the heart rate (beat/min) of the two cases that were tested, as explained previously the first subject was male at 22 years, and the second male at 59.

|  |  |  |  |
| --- | --- | --- | --- |
| Subject | Normal  BPM | Fatigued  BPM | Drowsy  BPM |
| 1 | 75 | 66 | 55 |
| 2 | 80 | 68 | 59 |

Table 9: BPM Results

Table 10 represents the data.

Table 10: BPM Data Chart

### Concept Description

The band consists of a sticker that contains the controller, Bluetooth, battery, charger, and sensor, as shown in Figure 37 below.

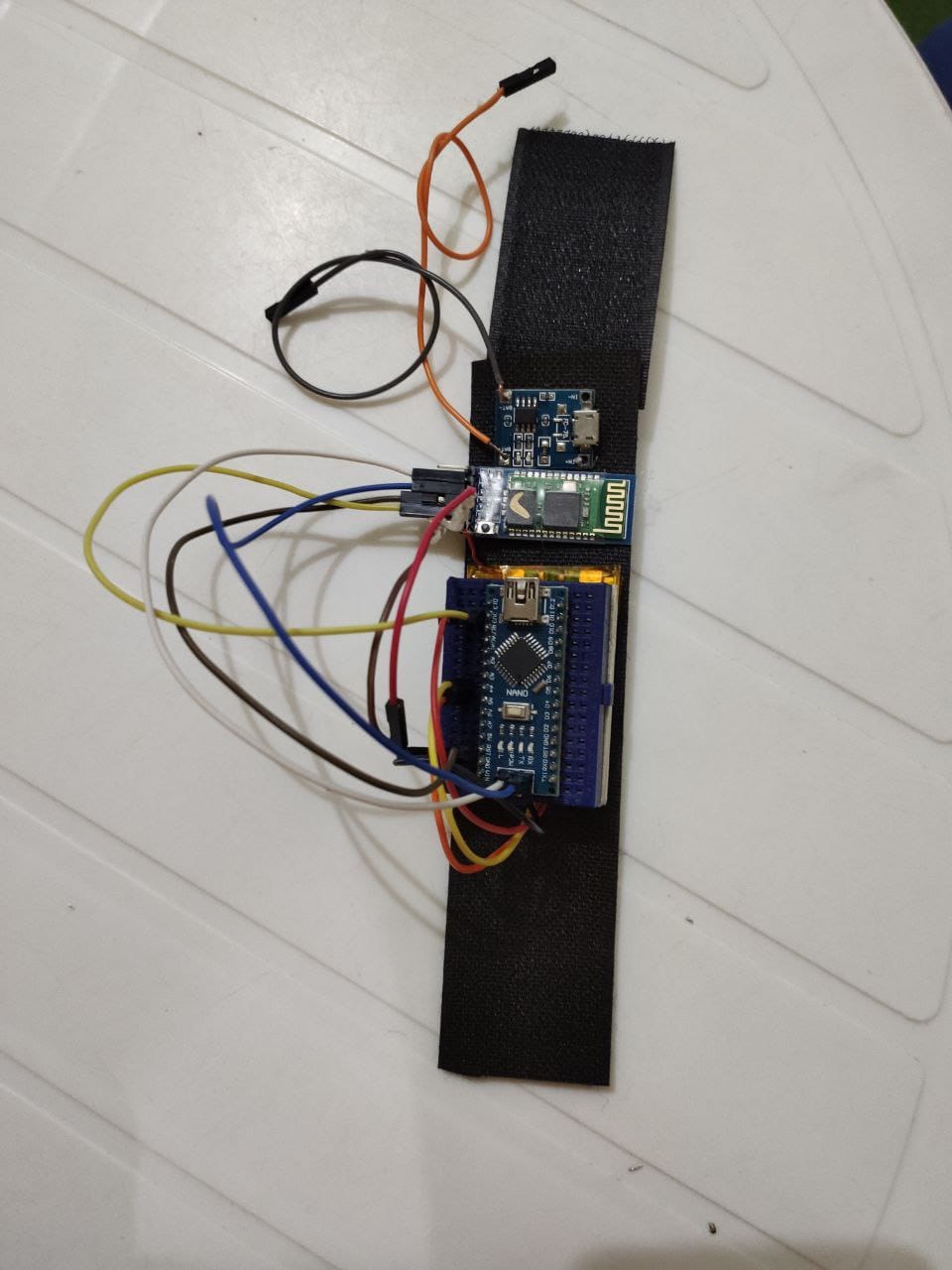


Figure 45: Our PPG Band

# Conclusion & Future Work

In a nutshell, creating a hybrid advanced driving system can reduce accidents and car crashes due to the driver’s fatigue and drowsiness. Targeting the automotive embedded systems companies, the current system can indicate the driver’s state using two methods that may need further improvements to be more accurate and implemented in vehicles.

The future work plans are modifying the current EAR code speed to be more responsive or upgrading the hardware components, looking for ECG circuit alternatives to be implemented in the car seat, and adding more features such as auto parking.

# Gantt Chart

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