Drowsiness Detection and Alert System for Driving Safety

Junyan Chen, Haoxun Wang

Zewei Wang, Zihao Yi

SYDE 660

Prof. Howcroft

Table of Contents

1. Introduction

Nowadays, drowsy driving has become a global major cause of traffic accidents, which presents a concerning threat to our daily lives. According to the National Highway Traffic Safety Administration (NHTSA)[1], in 2017 there were about 91,000 police-reported crashes involving drowsy drivers in the US, resulting in nearly 800 fatalities and around 5,000 injuries. The Centers for Disease Control and Prevention (CDC)[2] also reports that approximately 1 in 25 adult drivers have fallen asleep at the wheel in the past 30 days. We have noticed that maintaining driver alertness in the driving environment is now becoming a more and more critical issue.

With such a growing prevalence of drowsy driving, we declare the necessity for the development of effective solutions to prevent drowsy related accidents. Coping with the risk of accidents caused by driver drowsiness is more than essential for enhancing road safety and protecting our lives.

To talk about the broader context of this issue, we could never fix our sight only on the personal risk but to the level of public health concern. Traffic accidents caused by drowsy driving may cause economic impacts including medical costs, loss of productivity, and legal expenses, which also place a heavy burden on the emergency services and healthcare systems. Despite the viability of an enormous amount of existing driving assistance technologies, the issue of drowsy driving continues to be highlighting the urgent requirement for more effective and accessible solutions.

However, due to the recent robust advancements of AI&ML, we could have access to new possibilities to develop more sophisticated drowsiness detection systems. These uprising technologies include analyzing facial expressions, eye movements, and other physiological indicators to determine a driver's status of drowsiness accurately. We notice that it is possible for us to design systems that can operate effectively across different driving conditions by leveraging these innovations.

To address this issue, we need to take in action a multifaceted approach which involves collaboration among AI&ML specialists, automotive mechatronic engineers, policy makers, and public health officials. With the contribution of public awareness campaigns, strict regulations, and incentives for the adoption of safety technologies into both new and existing vehicles, we could help to ensure a broader impact of this initiative.

In a nutshell, the issue of drowsy driving has posed a significant risk to road safety and public health which is definitely worth concerning. Also, the increasing number of vehicles on the road and the limitation of traditional detection methods promote the urgency of advantaged solutions leveraging AI&ML. It is possible for us to create a safer driving environment and mitigate the risks caused by driver fatigue with our attention on real-time monitoring and intervention.

2. Project Scope & Objectives

Project Objectives

This project we designed will be able to solve the issue we mentioned in the needs assessment appropriately. As the research previously done, drowsy driving is dangerous and common in daily commuting. There is a chance for each driver to suffer from it. Though the result caused by drowsy driving is fatal, a lot of drivers choose to give it a shot even when they are aware of the fact that they are drowsy driving. Not even mention those situations when the drivers are not aware that they are drowsy[3]. Therefore, a detection-warning system is urgently needed.

Our goal in this project is to design a useful system that warns the driver when drowsiness is detected. The basic theory uses a trained AI model to process the taken picture of the driver's face and judge if the driver is drowsy. If the judgment is successful, which means the driver is drowsy, the alarm system will work dynamically based on the level of drowsiness to warn the driver, so that the driver can be active to focus on the road for a certain period to avoid accidents.

By the final presentation, we aim to complete the design of the whole alarming and driver status judgment system that includes a detection camera, an audio alarm, a vibration alarm, and a visual alarm. Deliver a medium fidelity prototype that can be tested by real-world captured simulation pictures to perform the judging procedure and alarming to warn the driver, and make sure it is within an acceptable percentage of accuracy.

Project Scope

To narrow down our scope, our set target audience is 7 seats and under automobile drivers. Specifically, we decided to focus on the detection-warning system for only the status of drowsy instead of driver distraction, because drowsiness is more fatal and has the most occurrence in daily driving, and also distraction can be very hard to detect and define. The current alarm systems are based on the performance of the driver like having a camera on the dashboard or A-pillar to detect abnormal head positions like nodding. Our project can detect drowsiness by monitoring the driver's eyes and mouth and it is going to be able to fulfill that blank in the market and make it safer to drive.

The pre-existing work that our project will be built upon is the training and testing dataset of drowsiness detection, the definition of drowsiness in driving conditions, specific methodologies and benchmarks in previous studies to be performed in the testing session, and all the hardware parts including but not limited to LEDs, speakers and vibration motors.

Since this project's timeframe is limited to 3 months, we are facing an obstacle of having not enough time. We need to try to keep up with our schedule and adjust our timeline dynamically by making time-efficient decisions. Additionally, communication issues due to unclear descriptions in meetings and low-frequency communication can lead to unawareness of potential problems. These two issues can be mitigated by scheduling a high meeting frequency with a short meeting time to focus on one subject in each meeting. For technical issues, we might face the problem of unexpected additional machine learning training time when optimizing the algorithm, or experience a tough hardware testing cycle at the end of the project. To address this, a parallel testing procedure of both software algorithm and hardware performance can allow the team to be flexible to different upcoming situations.

Roles and Responsibilities

All team members have contributed evenly to the project from the very beginning, from the team formation and brainstorming to the Final report.

Our team members consist of different specializations, which enables us to include various range of techniques into the project. In our team, the main responsibilities of Haoxun and Zihao are to develop the hardware including designing the receiving and executing the warning signals in different situations, and also in charge of the simulation and hardware testing procedure. Zewei is pursuing a specialization in AI and machine learning, thus his responsibility is to search for proper datasets as well as the training and testing of facial expression recognition algorithms.

Our last member Junyan has experience related to human factor fields. Therefore, the design of the user testing and all related human elements in the prototyping procedure will be his field of expertise, the scoring of the alarms for instance. In this way, all members will have an even contribution towards the project at the end and will be able to fulfill their pursued specializations.

3.Designed Solution

Design Concepts

Throughout our design process, many ideas came to our mind. Among all the ideas, we integrated them into 2 major promising design concepts.

The first concept is to develop a wearable device like a pair of eyeglasses. The main idea of these eyeglasses is to track down where the driver is looking, at the same time using an eye-tracking algorithm to determine whether the driver's line of sight indicates drowsiness.

In this concept, there is a small-scaled camera embedded into the right leg of the eyeglasses, which is used to capture the main viewing space the driver's eyes are facing. There is also a wi-fi communication module integrated on the same leg. On the opposite side is where the chip, the button battery, and the alarm speaker are located. Both legs are thickened and strengthened to withstand the extra weight of the device. Moreover, the nose pads are redesigned to keep the driver comfortable.

To perform the eye-tracking algorithm, an additional camera will be installed on the dashboard in front of the driver to focus on their eyeballs. The information and data will be transmitted through the wi-fi module and processed by the chip, and eventually, the chip determines whether it is necessary to trigger the buzzer alarm.

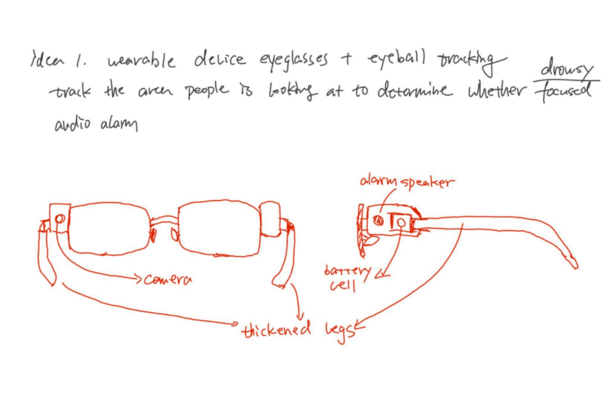


Figure 3.1 Sketch of Wearable Device

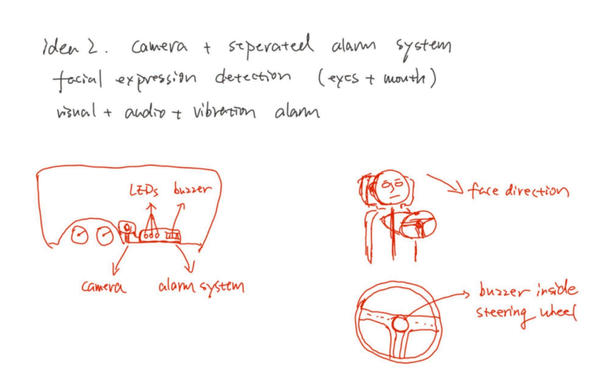


Figure 3.2 Sketch of Multi Alarm System

Our second design concept is focusing on facial expression detection with a multiple-alarm system. The idea is to use a fixed-angled camera to capture the facial expressions of the driver by a detection algorithm. Then the system decides which alarm will be set off to alert the driver of its drowsiness.

The alarm system consists of three main parts, which are three LEDs for visual alarm, a buzzer for audio alarm, and a vibration motor for tactile alarm. All system components are installed on the dashboard except for the vibration motor which is integrated inside the steering wheel. The LEDs and the buzzer along with the chip are integrated into a small box attached to the dashboard, while the camera is set beside them.

Decision Process

		Design 1 (Wearable Eyeglasses)		Design 2 (Multi Alarm System)	
Requirements	Weightings	Rating	Score	Rating	Score
System Response Time (ms)	0.25	100.00	25.00	80.00	20.00
Training Dataset Accessibility (n)	0.20	80.00	16.00	100.00	20.00
Hardware Components Accessibility (n)	0.20	60.00	12.00	100.00	20.00
Total Cost (CA$)	0.15	80.00	12.00	100.00	15.00
System Complexity (Number of Parts)	0.10	80.00	8.00	100.00	10.00

Timeline Alignment (Month)	0.05	60.00	3.00	100.00	5.00
Energy Consumption (Kilowatt-Hour)	0.05	100.00	5.00	80.00	4.00
Weight (g)	0.05	100.00	5.00	60.00	3.00
Total Score	1		81		94

Table 3.1 Computational Decision Matrix

At the beginning of our design process, we compared two approaches to our project. One is to develop this module based on wearable eye-tracking glasses, and the other one is to build a multi-alarm system module. To make a rational decision on which plan to proceed, we did a quantified comparison of them based on the weighted requirements of our expected product. Overall, there were 8 requirements we selected from our previous research on user needs and engineering requirements on the QFD chart. Refer to the Computational Decision Matrix, we are providing detailed reasons why we are performing the comparison here.

- System Response Time (ms): The System Response Time, measured in milliseconds, is the metric related to the quality of the product the most. In the scenario of detecting the driver's drowsiness, the quicker we can detect the driver's drowsiness, the higher the performance level of our product can be shown, this metric was weighted 0.25, which has the highest weighting. Since the eye-tracking glasses could track the gaze and view of the driver, it is more efficient for the AI model to detect drowsiness successfully. Therefore eye-tracking glasses win over alarm modules in this race.
- Training Dataset Accessibility (n): Training Dataset Accessibility, measured in the number of accessible datasets, is the metric we use to quantify how easy it is to obtain the training data sets, with a weighting of 0.20. Throughout our exploration under the sea of related datasets online, we discovered that most similar training datasets were pictures captured with the camera built around the dashboard. Such a fact supports the alarm modules to win this time.
- Hardware Components Accessibility (n): Hardware Components Accessibility, measured in the number of parts that need to be manually made, is the metric we use to decide if we have accessibility to the parts of the hardware, with a weighting of 0.20. We realized the eye-tracking glasses are too customized and it is difficult for us to build them directly from raw materials with high technologies like 3D printing. By comparison, the alarm module seems more accessible for us because all parts can be purchased directly. The alarm module won this time.
- Total Cost (CA$): Total Cost, measured in Canadian dollars, is the metric we used to assess our financial ability over the project, with a weighting of 0.15. If the total cost is too high, it would not only be a burden for us but also our potential users of the product. Though the eye-tracking glasses were designed to be hand-made mostly, the expected cost of building them is still higher than assembling the alarm module. Therefore, the alarm module won again by its cheaper price.

- System Complexity (Number of Parts): System Complexity, measured by the number of parts, is the metric we used to find out the feasibility of our design, with a weighting of 0.10. The number of parts for processing the signals was about the same, however, the eye-tracking glasses require more parts because they need an extra camera and brackets to support it on the face. Under such a condition, the alarm module appears to be a more feasible plan with fewer parts. Here the alarm module won over the eye-tracking glasses.
- Timeline Alignment (Month): Timeline Alignment, measured by months, is one of the important metrics we have to consider since this project is just a students' in-semester project, which has to be accomplished within 3 months. The weighting of this metric is 0.05. The eye-tracking glasses appear to be requiring more time to complete, no matter the aspect of manufacturing or testing. Therefore the alarm module won again due to it taking less time to complete.
- Energy Consumption (Kilowatt-Hour): Energy Consumption, measured by Kilowatt-Hour, is the metric we use to quantify the energy our product consumes at work, with a weighting of 0.05. Under the condition of the product running ordinarily, we are seeking higher energy efficiency due to the consideration of the product's feasibility and sustainability. Here the eye-tracking glasses have higher energy efficiency due to less energy output. Eye-tracking glasses won over alarm modules in the competition.
- Weight (g): Weight, measured in grams, is the metric for how heavy the product is, with a weighting of 0.05. Since the product is designed to be used in the vehicle, even on the face, the lighter the product is, the better the user experience can be achieved. Since the eye-tracking device is going to be built with lightweight materials, and the size has to be compact to adapt to a human's face it is going to be lighter than the alarm module. In this race, the eye-tracking glasses won.

In our overall decision process, we used a weighting and scoring method which is very similar to the Computational Decision Matrix. As shown in the chart, the final winner of the competition is the alarm module, which has great advantages in Training Dataset Accessibility, Hardware Components Accessibility, Total Cost, System Complexity, and Timeline Alignment. Therefore, we chose to process Design 2, the alarm module.

Design Description

To design and describe clearly and efficiently, we divided our whole system into two major parts: the software which consists of an AI model, an algorithm, and a scoring system to determine the output, the hardware system which includes the camera, the LED alarm, the buzzer and the vibration motor along with the control chip.

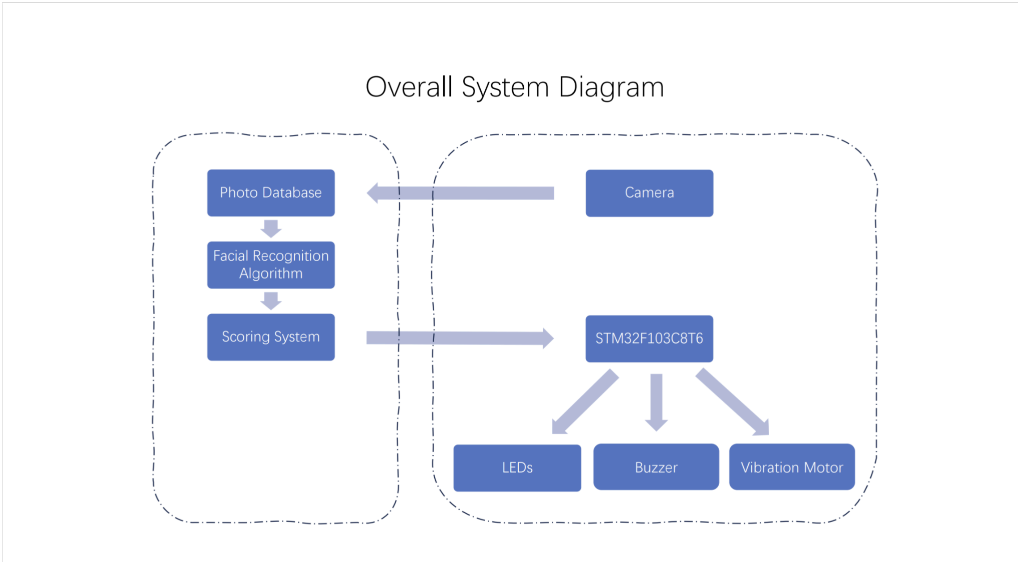


Figure 3.3 Overall System Diagram

Figure 3.3 indicates the overall system flow. The camera used is an off-shelf dash cam designed for cars, with a resolution of 1080p and 30 FPS frame. The video footage then will be transferred to the photo database and combined in 20 pictures a pack by selecting corresponding frames from the recorded video. The facial recognition model performs its duty to recognize whether the driver is drowsy and outputs the results to the scoring system to determine the level of danger. The scoring system's decisions are based on the principles of human factors. On the average level, a person blinks 10-20 times[4] per minute and each blink lasts for 0.1-0.4 seconds[4], the interval between blinks is 0.5 seconds, accounting for approximately 13% of the time. While yawning lasts for 3-5 seconds[4]. Among our research, most fatigue monitoring studies skip determining whether the eyes are blinking, instead they directly use the proportion of time that the eyes are closed, in which the values used is 60-80%[5][6][7]. It is recommended to apply a 20 fps[8] and group the frames into 5-second[5] intervals, which means 100 frames per group. If 60% of the frames show the eyes closed or yawning or a combination of them, a Level 1(Yellow) alarm is triggered, and if 80% of the frames show the eyes closed or yawning or a combination of them, a Level 2 (Red) alarm is triggered. And these will be finally transmitted to the STM32 controller to execute the final alarms.

In the software part of this project, we first set our mind on searching for a pre-trained model to be used as a function of detecting the facial fatigue of the driver. Among all the models we researched, we selected “driver drowsiness using Keras" on Kaggle [9] and reproduced it in JupyterLab[Appendix A&B]. In this model, two different functions are introduced to determine both the yawning condition of the face and the status of the driver's eyes. By outputting 4 labels (open, closed, yawn, no_yawn), the model presents the fatigue status of the driver with acceptable accuracy.

	precision	recall	f1-score	support
yawn	0.87	0.76	0.81	63
no_yawn	0.79	0.89	0.84	74
Closed	1.00	0.97	0.98	215
Open	0.97	0.99	0.98	226
accuracy			0.94	578
macro avg	0.91	0.90	0.90	578
weighted avg	0.95	0.94	0.94	578

Figure 3.4 Accuracy table of the pre-trained model

After the completion of the single input model, we realized that we must update our software system from single input to a multiple input version to further enhance the calculating logic of the algorithm. So we implemented an algorithm to intake 20 pictures as a unit and take a record of the output of each picture given by the model. In the final step, we concluded the process with a rating system, commenting on the level of alarm that should be triggered due to the proportions of certain labels of the pictures determined by the pre-trained model[10][11].

In the alarming system of the design, the circuit that connects all the execution parts with the control chip is planned to be as compact as possible. Only essential parts will be used to keep the overall dimension low. Figure 3.5 is the circuit diagram of the alarming control system.

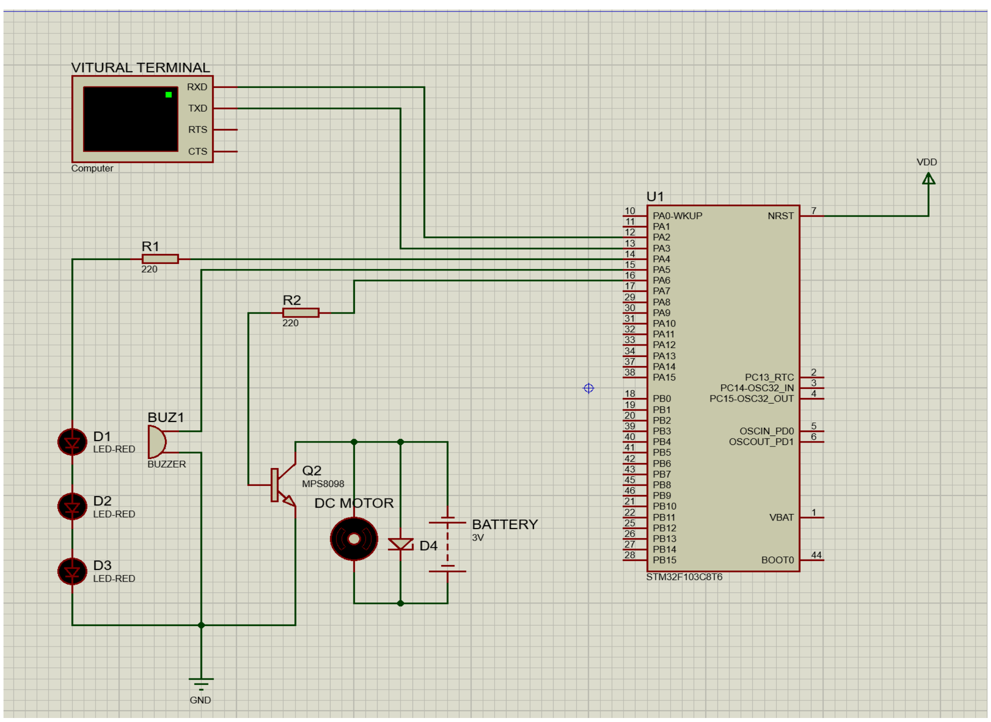


Figure 3.5 Circuit Diagram of Alarming System

The control chip is an STM32F103C8T6 series microcontroller. The core is ARM Cortex-M3 and the chip works under a 3.3V/5V voltage. The USART communication port on the chip will be responsible for communicating with algorithms to receive commands.

There are 3 Red LEDs attached to the STM32 controller to warm the driver with a quick-flashing pattern of 8Hz to ensure a quality warning message received by the drowsy driver[12]. The 3 LEDs will be in series connection and to protect the LEDs as well as the controller, a 220 Ohm resistor will be connected between them.

The buzzer beside the chip is designed to work with a minimum frequency of 2200 Hz with a 75 dB volume, also performing a 50 ms long intermittent audio alarm with a 50 ms interval[13]. We choose to use an active buzzer that is frequency-fixed to 2300±500 Hz to ensure relatively stable performance. Moreover, the average noise volume in cars is about 60 dB, and 70 dB while in high-speed movement. With the research conducted by Sangjin Ko, Harsh Sanghavi, Yiqi Zhang, and Myounghoon Jeon[14], the buzzer volume suits best with a 75 dB peak volume.

The vibration motor is embedded in the center of the steering wheel so that the vibrations will be spread equally into different directions to warm the driver. In order to best accommodate the design scope and avoid influences of the environment, such as the vibrations of the car when driving, the vibration frequency threshold is set to be higher than 220 Hz. Since it was pointed out in the previously cited literature that the maximum of intrinsic frequency of most vehicles in motion is about 200 Hz, the vibration frequency of the motor in this design has to be more than 220 Hz or else it will cause resonance leading to a more chaotic feeling for the occupants, and it needs to have a significant gap in frequency[15][3].

The vibrator is the motor, which drives the eccentric wheel at the front end of the drive shaft through high rotation to produce vibration by hammering the steering wheel entity at high frequency. The vibrator is located in the center of the steering wheel's width, generating high-frequency vibrations by hammering and attenuating them sequentially to the periphery of the steering wheel, which provides the most even vibration feedback to the left and right hands of the steering wheel-holding driver.

The communication between algorithms and alarms will be using a cable attached to the SWD pins and USART pins on the STM32 controller. The USART pins (PINs PA2 and PA3) enable the STM32 to have a two-way real-time connection with computers. As soon as the algorithm detects drowsiness and gives a score to indicate which level of alarms will be set off, the command then will be sent through the cable to reach the microcontroller’s USART pins, to eventually execute the alarms.

Prototype

The overall purpose of our prototyping is to develop a medium-fidelity prototype that can demonstrate the core functions and allow us to test them, including the facial recognition algorithm, scoring system, STM32 controller, and the execution of all three types of alarms[16].

Due to the project timeline and team member's capability, we can't prototype and demonstrate all the features and functions designed. Therefore, there are a few things that our prototype will not have.

Firstly, we will not be using the off-the-shelf dashcam to capture the videos, instead using pre-captured and preassigned photosets to realize the function of the dashcam. The photosets were all captured by the camera of iPhone 14 Pro Max which has a resolution of 2688x1242, higher than the 1080p dashcam.

Secondly, purchasing and integrating the algorithms into the in-vehicle entertainment system's chip is almost possible, the device connection compatibility as well is a difficult issue to manage with our current resources. Eventually, we decided to prototype the software and hardware parts separately with no virtual port communication between them.

The algorithms will then grab the images depicting facial recognition and determine the label for each image. After analyzing a unit (20) of images, the scoring system would then generate an appropriate level of alarm for the hardware to operate.

As for the microcontroller and the alarm system, all parts are off-the-shelf and bought online. The overall structure of the alarm system prototype is the same as the one in the design description. However, to ensure a flexible prototyping and testing environment, the LEDs, buzzer, and vibration motor as well as the STM32 controller are installed on a breadboard instead of soldered on a regular PCB board.

The specific type of the microcontroller is STM32F103C8T6 which is a basic model of the STM32 family with a maximum frequency of 72 MHz and a flash memory of 64 KB. We use three GPIO pins for signal output and one GPIO pin for input signal. The control codes of the STM32 were written in C program language and downloaded to the chip in Keil 5 via an ST-Link V2, a commonly used programming and testing debugger for microcontrollers.

As mentioned above, there is no port communication in the prototype. But to simulate the transformation between the two levels of drowsiness alarms, we installed a button on the breadboard to simulate the switching of the input signal. The initial state of the prototype is the red level alarm, which triggers all three kinds of warning. When the button is pressed, the system switches to the yellow level alarm with only the vibration motor keeps working.

The three red color LEDs, the active buzzer along the vibration motor are all off-the-shelf products selected strictly by the design specifications and requirements. The LEDs have an average luminous intensity of 5000 mcd and are programmed to blink 8 times a second (8Hz). The active buzzer of the prototype has a peak frequency of 2300 ± 500 Hz and is programmed to be active for about 50 ms with an interval of 50 ms. The vibration motor's peak rotation speed is 27000 rpm which can generate a maximum of 450 Hz vibration on the steering wheel.

To test the vibration alarm's effectiveness, we built a replica of the Tesla Model S Yoke-style steering wheel with cardboard. The dimensions of the steering wheel are about 340 mm in width and 150 mm in height, with a thickness of 40 mm in the grip zone.The steering wheel is mainly made of two pieces of cardboard laminated together, sandwiched in the middle of the motor so that the high rotation of the deflection wheel can be stable to tell the hammering of the steering wheel on both sides, so that regardless of the front and back can feel the vibration, the driver in the steering wheel grip, the intensity of the vibration feedback received by the unilateral vibration of the both front and backside, and more able to play the role of a reminder.

4.Design Analysis & Testing

Software Analysis

Analysis and Modeling Techniques

We tried multiple techniques to realize our software in the project. Firstly we read and resized the images and normalized the pixels, and then we used OpenCV for facial detection. Secondly, we used regions of interest on standardized sized images to ensure a consistent input of data. Finally we used a multi-layer CNN for the image classification.

Mathematical Models

In our project, the mathematical model is mainly represented by Figure 4.1, the multi-layer CNN architecture, which includes convolutional layers, pooling layers, fully connected layers, and dropout layers. We make sure that the input image is resized and normalized and the output is a probability distribution over 4 classes. In this model, we implemented categorical cross-entropy as our loss function to measure the prediction error and the Adam optimizer for the gradient

Layer (type)	Output Shape	Param #
conv2d_16 (Conv2D)	(None, 143, 143, 256)	7,168
max_pooling2d_16 (MaxPooling2D)	(None, 71, 71, 256)	0
conv2d_17 (Conv2D)	(None, 69, 69, 128)	295,040
max_pooling2d_17 (MaxPooling2D)	(None, 34, 34, 128)	0
conv2d_18 (Conv2D)	(None, 32, 32, 64)	73,792
max_pooling2d_18 (MaxPooling2D)	(None, 16, 16, 64)	0
conv2d_19 (Conv2D)	(None, 14, 14, 32)	18,464
max_pooling2d_19 (MaxPooling2D)	(None, 7, 7, 32)	0
flatten_4 (Flatten)	(None, 1568)	0
dropout_4 (Dropout)	(None, 1568)	0
dense_8 (Dense)	(None, 64)	100,416
dense_9 (Dense)	(None, 4)	260

Total params: 495,140 (1.89 MB)
Trainable params: 495,140 (1.89 MB)
Non-trainable params: 0 (0.00 B)

Figure 4.1 Multi-layer CNN architecture

descent optimization. The important equations are involved in convolution operations, activation functions(ReLU), and the softmax function in the output layer to produce class probabilities.

Results and Interpretation

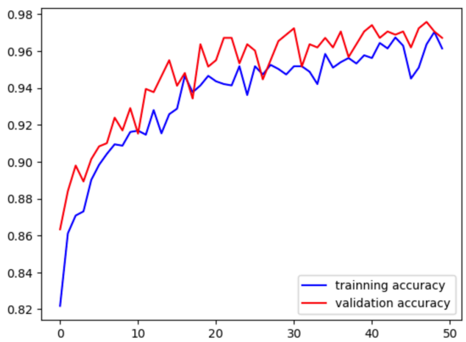
We measured the results from analysis and modeling by accuracy, precision, recall, and F1-score. Figure 4.2 shows the predicted classes of the model. The metrics used could help to interpret the performance of the model in correctly classifying the images into their respective categories.

```
predicted_classes
```

```
array([3, 3, 2, 3, 1, 3, 3, 2, 1, 2, 3, 3, 3, 2, 2, 2, 3, 0, 0, 3, 3, 3,
       2, 1, 1, 3, 2, 2, 3, 2, 3, 2, 3, 2, 0, 3, 3, 2, 1, 3, 3, 3, 2, 3,
       2, 2, 3, 3, 2, 3, 3, 1, 2, 1, 3, 3, 2, 2, 2, 0, 3, 3, 1, 2, 2, 3,
       2, 3, 2, 2, 1, 3, 3, 3, 2, 0, 1, 3, 3, 3, 2, 1, 3, 2, 2, 2, 2, 1,
       3, 3, 2, 3, 3, 3, 1, 0, 3, 1, 3, 3, 3, 1, 3, 0, 2, 3, 2, 1, 2, 2,
       1, 1, 2, 1, 1, 3, 3, 3, 2, 2, 3, 3, 3, 1, 1, 2, 3, 3, 2, 0, 3, 3,
       0, 3, 1, 3, 3, 3, 2, 1, 2, 2, 2, 1, 3, 3, 3, 3, 2, 1, 3, 3, 3, 3,
       3, 0, 0, 1, 3, 1, 3, 2, 2, 1, 2, 3, 3, 2, 3, 2, 3, 1, 2, 0, 3, 3,
       2, 2, 0, 2, 3, 1, 2, 1, 3, 2, 3, 1, 2, 0, 1, 3, 2, 2, 3, 3, 3, 0,
       3, 2, 3, 0, 2, 0, 0, 1, 2, 3, 2, 0, 3, 1, 2, 2, 2, 2, 1, 3, 1, 1,
       1, 0, 2, 3, 3, 3, 3, 0, 1, 2, 0, 0, 3, 3, 1, 3, 3, 0, 3, 3, 0, 0,
       0, 1, 3, 3, 3, 3, 3, 2, 3, 3, 2, 3, 2, 0, 2, 2, 2, 0, 3, 3, 2, 2,
       3, 2, 2, 0, 2, 3, 2, 2, 2, 3, 3, 3, 3, 3, 0, 1, 0, 3, 3, 3, 3, 2,
       2, 1, 2, 2, 2, 3, 2, 0, 2, 2, 1, 3, 2, 3, 1, 3, 3, 1, 3, 3, 0, 3,
       3, 2, 2, 2, 1, 1, 1, 3, 3, 3, 3, 1, 3, 1, 3, 2, 2, 0, 3, 3, 3, 2,
       3, 3, 2, 3, 3, 3, 3, 2, 1, 3, 2, 2, 2, 1, 2, 1, 3, 3, 2, 3, 2, 2,
       2, 2, 3, 2, 0, 2, 1, 0, 2, 2, 2, 1, 3, 2, 3, 3, 3, 2, 2, 2, 2, 2,
       2, 3, 1, 3, 3, 1, 3, 1, 3, 2, 2, 1, 0, 2, 2, 3, 2, 1, 3, 2, 3, 3,
       3, 1, 0, 3, 0, 2, 3, 2, 2, 3, 0, 3, 3, 2, 3, 3, 1, 2, 1, 3, 2, 1,
       1, 3, 2, 2, 3, 1, 3, 2, 2, 2, 3, 2, 0, 2, 0, 1, 3, 2, 1, 3, 2, 3,
       3, 3, 2, 2, 3, 2, 0, 1, 2, 2, 2, 2, 2, 0, 2, 3, 3, 2, 1, 3, 2, 2,
       2, 2, 3, 3, 0, 0, 1, 3, 3, 3, 2, 2, 2, 1, 2, 2, 1, 2, 0, 2, 3, 2,
       2, 2, 2, 3, 2, 3, 3, 2, 3, 2, 3, 2, 3, 1, 1, 2, 2, 3, 2, 2, 1, 0,
       1, 3, 0, 0, 3, 2, 2, 0, 3, 2, 3, 2, 3, 3, 3, 3, 3, 2, 0, 3, 2, 3,
       2, 2, 3, 2, 2, 2, 3, 3, 2, 1, 2, 1, 3, 3, 1, 0, 3, 3, 3, 2, 2, 0,
       3, 2, 2, 2, 3, 2, 2, 3, 2, 2, 1, 3, 2, 2, 3, 3, 2, 3, 2, 3, 2, 2,
       3, 2, 2, 3, 2, 2])
```

Figure 4.2 Predicted Classes

Figure 4.3 & 4.4 show the training and validation loss and accuracy which provide insights into the model's learning process.



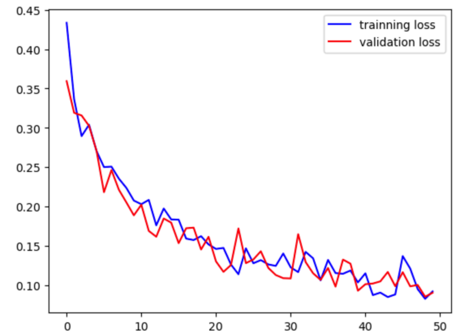


Figure 4.3 Training and validation accuracy

Figure 4.4 Training and validation loss

Optimization of Models

Model optimization includes learning rate, batch size, number of epochs, and the CNN architecture. We could apply extra data augmentation methods to increase the diversity of the training set, and thus we could improve the model's robustness and generalizability. Also, the model included dropout layers to prevent the overfitting by randomly omitting certain neurons during the training process.

Interpretation of Optimization

Our primary goal is to accurately detect and classify the different states of drowsiness from facial images. We have to ensure that the model not only replies accurately on training data but also on unfamiliar data. As discussed with Professor Howcroft, we have limitations on providing two binary outputs which are more precise on facial detection. Further refining of the model should be implemented to achieve the balance between accuracy and practicality to ensure that the system meets the intention for the performance standards.

Hardware Analysis

Analysis and Modeling Techniques

The overall process of the analysis and modeling of the alarming system is based on software circuit simulation and real world debugging. The STM32CubeMX was used to set up basic parameters of the microcontroller and generate the HAL Library.

Then we translate the design specification of the vibration frequency generated by the DC motor to the rotation speed to select the specific model of the motor. As we know,

$$F_{motor} \geq 220\ Hz$$

$$F_{motor} = RPM_{motor} / 60\ seconds$$

$$\Rightarrow RPM_{min} \geq 220\ HZ \times 60\ seconds = 13200\ rpm$$

Therefore, to satisfy the design specifications and maintain a sufficient gap to accommodate with different automobile vibration environment, we choose a DC vibration motor with a minimum RPM of 13800.

After writing the codes of the chip and the hex file was generated, we used Proteus 8 as the simulator to perform a preliminary analysis of the circuit design and operation status. Figure 4.5 shows the circuit design of the prototype.

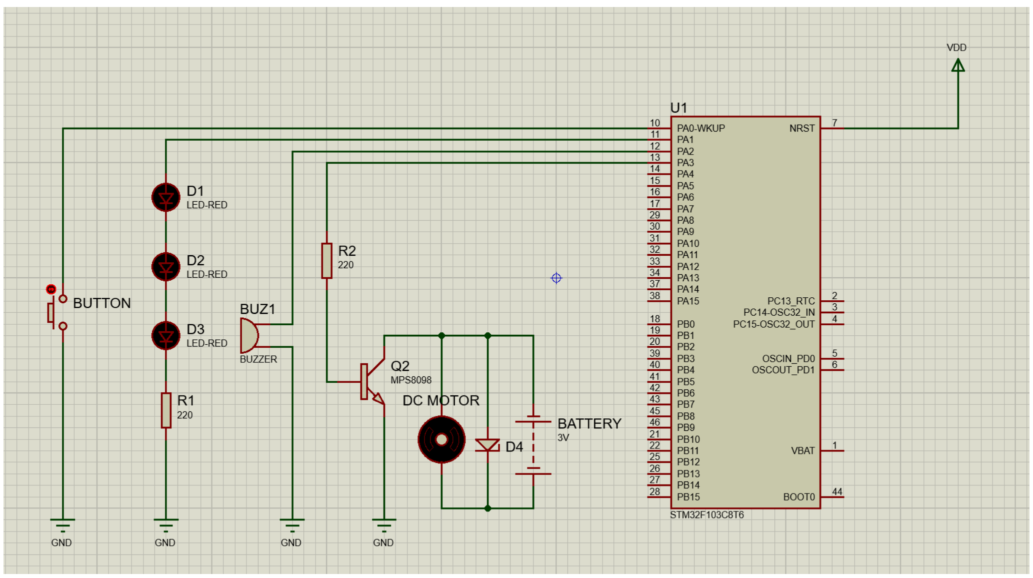


Figure 4.5 Prototype Circuit Design

The simulation in Proteus turned out to be the same as our expectation, in which the LEDs, buzzer and DC motor all worked as designed. This result indicates that the code of the STM32 microcontroller is correct and is able to perform our designated functions. Moreover, the selection of electronic parts including the LEDs, the buzzer, the DC motor and all resistors, diodes, button and battery are suitable for our circuit.

These promising results and firm background of the simulations enables us to proceed with real world testing of the alarming system.

Software Testing

As mentioned before, the prototype is separated into two parts, software with algorithms and scoring system, hardware with alarming systems. Therefore, the testing of the prototype will also be split into two different ways and protocols.

Testing procedures and participant

We aim to test for viability of the model and the accuracy under different levels of alarms.

We plan to take pictures of group members for testing purposes.

Environment

The model should be very open to different environments, especially a variety of the strength of light. The training set of images were mostly taken in an lightful ambient environment, in our test we will try to make ambient light more dim to test for accuracy.

Model

20 images/unit, test for accuracy and viability for different levels of alarms, test multiple times to see if the accuracy is consistent. And we could also test for the response time of this model.

Equipment

iPhone XSMax(7-megapixel) for image taking, MacBook Pro 13-inch, 2018(Intel, 4 thunderbolt 3 port) for model processing

Datasets used

The dataset used in the testing is totally the images of our group members, taken by an iPhone XSMax.

Test Results

It would be better to discuss the test results in 3 separate parts.

1. Condition of No Alarm:

   In this unit we input 18 no_yawn images and 2 yawn images, the output level is 0 for 10/10 times.

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 170ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 43ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 44ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 43ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 43ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 41ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 46ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 47ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 47ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 42ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 42ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 44ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 35ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 42ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 45ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 42ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 42ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 43ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 41ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 42ms/step
Unit 1: NO ALARMS (abc)
```

Figure 4.6 Test results for No Alarm

2. Condition of Level 2 Alarm (RED):

   In this unit we input 1 no_yawn images and 19 yawn images, the output level is 2 for 10/10 times.

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 42ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 46ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 42ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 42ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 43ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 43ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 41ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 48ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 41ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 45ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 40ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 41ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 42ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 41ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 34ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 42ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 44ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 42ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 43ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 42ms/step
Unit 2: Level 2: LED, BUZZING, and VIBRATING (ABC)
```

Figure 4.7 Test results for Level 2 Alarm

3. Condition of Level 1 Alarm (YELLOW):

   In this unit we input 3 no_yawn images, 6 yawn images and 11 closed images, the output level is 1 for 10/10 times.

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 80ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 42ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 46ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 42ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 43ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 42ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 42ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 41ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 41ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 35ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 41ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 42ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 40ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 45ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 42ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 43ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 42ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 42ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 42ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 42ms/step
Unit 3: Level 1: VIBRATING (C)
```

Figure 4.8 Test results for Level 1 Alarm

Hardware Testing

For the testing of our alarming system, we designed and followed the following protocols and procedures.

Testing procedures and participant

The three different kinds of alarms will be tested separately to avoid unnecessary distractions. There will be 4 participants in the procedure who are not a team member of our project in the functionality testing, and testing results will be recorded by our team member who will be sitting beside the participant.

Environment

The testing environment is set to be in an automobile's passenger seat under an outdoor and clear sunny day. The automobile will remain parked but will be started and held idle in some of the tests. The breadboard with the alarms and the STM32 microcontroller will be placed on the dashboard of the passenger seat, with an average alarm-to-face distance of 55 cm. The cardboard steering wheel will be held up by the participant and have contact with the dashboard to ensure the connection to the automobile.

Equipment

The equipment and evaluating software used are a 2024 Mazda 3 hatchback as the automobile, an Apple Watch SE2 to measure the decibels of volume of the auditory alarm, the Sonic Tools SVM software on Apple iPhone 14 Pro to measure the peak frequency of the auditory alarm.

Testing Protocols

Before the actual testing started, we announced the experiment agreement to the participants, making sure that they were all aware that they ought to respond verbally when they signal the alarm. Also, they were aware that their response will be recorded by handwriting and used as the testing result of our project. All participants verbally agreed to our agreement.

The testing was run under the condition of the automobile parking in a parking lot with ignition on all the time. It was composed of 3 different steps for different hardware parts. For each participant, we conducted the same testing procedure. Once the participant indicates to be ready, we will ask the participant to imagine driving and keep observing any factors through the front windshield and rear mirrors. We will activate the parts at random time and wait for the participant's response of signal receiving. Each part was activated 5 times for each participant with different time intervals and we will expect the participant to respond verbally each time so we can mark it as success for that time. Otherwise, it was marked a failure for that time. If the user responds without the alarm being activated, it will be noted.

Other than the user side, before we invited the participants, we also measured the buzzer's auditory factors to make sure it could be heard clearly but not harmful.

Test Results

Success Times	Vibratior	Buzzer	LED	Overall
P1	5	5	5	15
P2	5	5	5	15
P3	5	5	5	15
P4	5	5	2	12
Success Rate	1	1	0.85	0.95
Comment	Vibration too strong	None	Fail due to sunlight	Overall Successful

Table 4.1 Test Results

As shown in the chart, the vibrator and buzzer passed the test with all 4 participants. The only remarkable note was 2 participants complained the vibration within the vibrator was too strong and it made them feel numb within their hands and arms, which might cause danger in driving. Other than that, everything was working as we expected. The buzzer's frequency was 2699Hz with 73 dB, we even ran the test under the condition of playing music at about 64 dB, the participants still showed perfect response rate in the auditory function.

However, the LED testing failed with the last participant. After our discussion and observation the LED was not working perfectly. Though the first 3 participants can tell the LED was up whention, in an interview with the participant, we conclude the result that when the fourth participant ran the test for LED, the sunlight directly came through the windshield and reflected on the LED bubbles, which made it hard to tell if the LED was on or not. However, our tester tried to move the module to the gauge at the driver's seat, under the same condition of the sunlight directly coming through, the module successfully got a shield from the sunlight by the board on the top of the gauge. We believe if we ran the test at the driver's seat, which is our expected location for the module, such a problem would not be a pain. Whereas, we did not proceed to the test at the driver's seat due to safety considerations.

The results from the testing give us a positive feedback to our project. It indicates that we have made a success with our project mostly. Even though some limitations exist in our testing, it directs our future work and how we can improve the module and make it more mature to fit in the actual market.

5.Limitations & Challenges

Though our prototype successfully meets our partial expectations for the final product, limitations still exist within it due to limited time and resources.

Firstly, our AI model requires some advance in results deliverables. The AI model we trained can successfully detect facial features. It reaches a satisfyingly high accuracy when returning a result if the person in the picture is yawning or not, or if the person's eyes are closed or not. However, it only returns to one label from all four possibilities. The fact is, those four labels should be grouped into 2 and each result the AI model returned should be in the form of a paired result. For example, when it returns "yawning" in our label, there are possibilities that the person's eyes are either closed or opened, which means a result in the format of "(yawning, closed)" or "(yawning, opened)" would be better. We detected this issue after our AI model was trained, but due to time constraints, we did not manage to fix this issue. To ensure our model works to our needs, we ran a test to figure out the preference of the AI model. It turns out that it always returns to "yawning" when the person in the picture is yawning, which means the assessment of yawning is potentially the primary test. Meanwhile, if the person is not yawning, the model tends to return the status of eyes either closed or opened. Therefore, we modified the scoring system to fit this feature in our AI model. In the scoring system, we abandoned the original plan of scoring yawning and eyes status separately. Instead, we see them equally and score them based on the combined score for them. This is not ideal but we increased the sensitivity of the prototype successfully and avoided it from doing nothing when the driver is actually drowsy.

Secondly, there are a few issues during our testing of the alarms that can lead to limitations. The LED alarm appears to be clear and visible during most of the testing time, but there are still chances of missing due to the occasional brightness increase caused by the sun and clouds. Therefore, under direct unshaded sunlight, the limitation of the visual alarm is it is hard for the driver to notice. In addition, the vibration of the tactile alarm generated by the DC motor seems to have a slightly excessive intensity than expected. This might cause unnecessary shock to the driver and may highly result in safety hazards. Another unexpected issue is the loud noise of the DC motor that may influence the effectiveness of the auditory alarm. The noise is not an alarm feature initially designed and is ignored which eventually can have a negative impact on our project objectives.

Last but not least, some parts of our design are not being prototyped fully which limits the precision of functionality testing. The first one is we did not use the 1080p resolution dash cam as the camera to capture pictures. Besides the AI model analyzes pictures instead of slicing frames from videos, we could only provide pictures to the AI model manually, and then the AI model returns the results. The other issue is related to soft-hard connection and communications. We tried several different methods to set up the communication port between the algorithm and the STM32 chip such as ST-Link and DAPLink, but they all failed due to compatibility issues of PC drives and STM32. Therefore, we did not have enough time to solve the issue to connect our software and hardware, but to prototype and test them separately. Such limitations alarm us that the connection between different parts of a team is so important and sufficient research with a thorough idea communication before designing and prototyping is crucial to cross-section projects.

6.Conclusion & Future Work

Conclusion

In summary, by looking at the testing results of the medium fidelity prototype, the AI algorithms and scoring system have successfully achieved the designed project objectives of identifying driver drowsiness by using facial recognition detection with a promising accuracy that reached our testing thresholds. The alarming system including visual, auditory and tactile alarm also delivers their functions as designed. Though a few issues occurred, both the user and functionality testing result shows a fully functioning multiple alarming system that can warn drowsy drivers to avoid safety hazards.

However, due to several reasons and conditions, the fully soft-hard integrated system was not completed and tested as expected in the project objectives. Therefore, we would say we have reached a preliminary success on the functions and addressed most of the identified problems described in the previous sections.

Future Works

Based on the conclusions stated above, future work is very necessary in this case. Suggestions for future work from the first limitation that the AI model is not satisfied. We still need to build the AI model with clearly grouped photos and design it to return a paired result that indicates the status of yawning and eyes. With such improvements on the AI model, we could then produce more accurate outcomes with 2 binary outputs and thus increase the sensitivity of the system. Furthermore, we could enhance the safety level of the finalized high-feasibility model.

The problem related to the alarm systems will probably be resolved by redesigning and testing the hardware parts. Visibility issues of LEDs not performing well in direct sunlight shining will be discussed and redesigned by using a RGB LED with a higher luminous intensity to ensure a clear visual warning in such conditions. The vibration motor will also be assessed since its loud noise can affect the buzzer or shock the driver. This will involve prototyping with a different type of motors, such as magnetic vibration motors.

As for the limitation regarding connection between parts, in future work, we will seek solutions to build a prototype that fulfills the hypothesis that the product takes pictures or videos by itself in real time automatically once the vehicle is on. Also, we will be working on transforming the results from the AI model into electric signals and transporting them to the hardware directly, such as using a wifi communication module or with bluetooth connection to transmit the command. In this way, the prototype can basically run by itself and fulfill the expectation of alarming the driver in drowsiness based on facial features.

Finally, improving the level of fidelity will be considered as the major task after changing the design with additional analysis and testing. The parts of the alarming system will be expected to be soldered on a PCB board with a compact design, integrated in a 3D printed container. Also, the container's dimensions, color and materials will require further design to blind in the interior, which will meet the project objectives and specifications of a user centered product.

References

[1] National Highway Traffic Safety Administration. (2017). "Drowsy Driving." NHTSA. https://www.nhtsa.gov/risky-driving/drowsy-driving#:~:text=NHTSA%20estimates%20that%20in%202017,injured%20and%20nearly%20800%20deaths.

[2] Centers for Disease Control and Prevention. (2013). "Drowsy Driving: Asleep at the Wheel." CDC. http://medbox.iiab.me/modules/en-cdc/www.cdc.gov/features/dsdrowsydriving/index.html#:~:text=An%20estimated%201%20in%2025,in%20the%20previous%2030%20days.&text=The%20National%20Highway%20Traffic%20Safety,and%20800%20deaths%20in%202013.

[3]N. Zhang, M. Fard, J. Xu, J.L. Davy, S.R. Robinson, Road safety: The influence of vibration frequency on driver drowsiness, reaction time, and driving performance, Applied Ergonomics, Volume 114, 2024, 104148, ISSN 0003-6870, https://doi.org/10.1016/j.apergo.2023.104148.

[4] C. Jia, L. Jianping, C. Changrun and C. Lixi, "A Review of Driver Fatigue Detection Based on Facial Expression Recognition," 2023 20th International Computer Conference on Wavelet Active Media Technology and Information Processing (ICCWAMTIP), Chengdu, China, 2023, pp. 1-6, doi: 10.1109/ICCWAMTIP60502.2023.10387098. https://ieeexplore.ieee.org/document/10387098.

[5] M. ShiJie and P. Lian, "DMS Fatigue Detection System For Driver In Vehicle," 2023 35th Chinese Control and Decision Conference (CCDC), Yichang, China, 2023, pp. 823-827, doi: 10.1109/CCDC58219.2023.10327447. https://ieeexplore.ieee.org/document/10327447.

[6] S. Liu, L. Yu and M. Hou, "An efficient method for driver fatigue state detection based on deep learning," 2019 2nd International Conference on Safety Produce Informatization (IICSPI), Chongqing, China, 2019, pp. 172-176, doi: 10.1109/IICSPI48186.2019.9095909. https://ieeexplore.ieee.org/document/9095909.

[7] R. Ayachi, M. Afif, Y. Said and A. Ben Abdelali, "Drivers Fatigue Detection Using EfficientDet In Advanced Driver Assistance Systems," 2021 18th International Multi-Conference on Systems, Signals & Devices (SSD), Monastir, Tunisia, 2021, pp. 738-742, doi: 10.1109/SSD52085.2021.9429294. https://ieeexplore.ieee.org/document/9429294.

[8] K. Gupta, S. Choubey, Y. N, P. William, V. T. N and C. P. Kale, "Implementation of Motorist Weariness Detection System using a Conventional Object Recognition Technique," 2023 International Conference on Intelligent Data Communication Technologies and Internet of Things (IDCIoT), Bengaluru, India, 2023, pp. 640-646, doi: 10.1109/IDCIoT56793.2023.10052783. https://ieeexplore.ieee.org/document/10052783.

[9] Aditta N. (2022). Driver Drowsiness Using Keras, Version 2. Retrieved May 31st, 2024 from https://www.kaggle.com/code/adinishad/driver-drowsiness-using-keras.

[10] J. Zhang, Y. Wu, Y. Chen, J. Wang, J. Huang and Q. Zhang, "Ubi-Fatigue: Toward Ubiquitous Fatigue Detection via Contactless Sensing," in IEEE Internet of Things Journal, vol. 9, no. 15, pp. 14103-14115, 1 Aug.1, 2022, doi: 10.1109/JIOT.2022.3146942. https://ieeexplore.ieee.org/document/9695956.

[11] I. J. Pournaki, N. Heidari, M. Gratuze, M. Y. Elsayed, H. H. Tawfik and F. Nabki, "Sensitivity Analysis of Novel PolyMUMPs-Based Ultrasonic MEMS Microphones," 2023 IEEE International Ultrasonics Symposium (IUS), Montreal, QC, Canada, 2023, pp. 1-4, doi: 10.1109/IUS51837.2023.10307089. https://ieeexplore.ieee.org/document/10307089.

[12] W. Li, T. Qiu, J. Zhang and C. Xue, "A Visual Study of Automotive Augmented Reality Head Up Display Warning Signals," 2023 4th International Conference on Intelligent Design（ICID）, Xi'an, China, 2023, pp. 156-161, doi: 10.1109/ICID60307.2023.10396762. https://ieeexplore.ieee.org/document/10396762.

[13] S. Petermeijer, F. Doubek and J. de Winter, "Driver response times to auditory, visual, and tactile take-over requests: A simulator study with 101 participants," 2017 IEEE International Conference on Systems, Man, and Cybernetics (SMC), Banff, AB, Canada, 2017, pp. 1505-1510, doi: 10.1109/SMC.2017.8122827. https://ieeexplore.ieee.org/document/8122827.

[14] Sangjin Ko, Harsh Sanghavi, Yiqi Zhang, Myounghoon Jeon, Modeling the effects of perceived intuitiveness and urgency of various auditory warnings on driver takeover performance in automated vehicles, Transportation Research Part F: Traffic Psychology and Behaviour, Volume 90, 2022, Pages 70-83, ISSN 1369-8478, https://doi.org/10.1016/j.trf.2022.08.008.

[15] Shaogan Ye, Liang Hou, Pandeng Zhang, Xiangjian Bu, Jiawei Xiang, Hesheng Tang, Jiahe Lin, Transfer path analysis and its application in low-frequency vibration reduction of steering wheel of a passenger vehicle, Applied Acoustics, Volume 157, 2020, 107021, ISSN 0003-682X, https://doi.org/10.1016/j.apacoust.2019.107021.

[16] F. S. M. Zuki and S. Sulaiman, "Investigating sensory modalities in fatigue driver warning systems," 2016 4th International Conference on User Science and Engineering (i-USEr), Melaka, Malaysia, 2016, pp. 128-132, doi: 10.1109/IUSER.2016.7857947. https://ieeexplore.ieee.org/document/7857947.

Appendix

Appendix A: the coding for the AI model of drowsiness detection

https://colab.research.google.com/drive/166F0Jb0hyyztzNZW145tSzQ6YRDSUtKY

Appendix B: the coding for the scoring algorithm and testing for one single round
https://colab.research.google.com/drive/1UqBAYqSpHoPTQgQOYUaX8uE4FVhROWo3

Appendix C: STM32 MDK Project File

https://drive.google.com/file/d/1rCwIL41TmdC6fpdsGU-apY_3BFQwEmTU/view?usp=drive_link