COMPREHENSIVE DROWSINESS DETECTION SYSTEM

A DESIGN PROJECT REPORT

submitted by

MONISHA V

NISHANTHI V

POOJA P

in partial fulfillment for the award of the degree

of

BACHELOR OF ENGINEERING

in

COMPUTER SCIENCE AND ENGINEERING

K RAMAKRISHNAN COLLEGE OF TECHNOLOGY

(An Autonomous Institution, affiliated to Anna University Chennai,

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Samayapuram – 621 112

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BONAFIDE CERTIFICATE

Certified that this project report titled **"COMPREHENSIVE DROWSINESS DETECTION SYSTEM"** is bonafide work of **MONISHA V (811722104093), NISHANTHI V (811722104103), POOJA P (811722104108)** who carried out the project under my supervision. Certified further, that to the best of my knowledge the work reported here in does not form part of any other project report or dissertation on the basis of which a degree or award was conferred on an earlier occasion on this or any other candidate.

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INTERNAL EXAMINER **EXTERNAL EXAMINER**

DECLARATION

We jointly declare that the project report on **"COMPREHENSIVE DROWSINESS DETECTION SYSTEM"** is the result of original work done by us and best of our knowledge, similar work has not been submitted to **"ANNA UNIVERSITY CHENNAI"** for the requirement of Degree of Bachelor of Engineering. This project report is submitted on the partial fulfillment of the requirement of the awardof Degree of Bachelor of Engineering.

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ABSTRACT

The Comprehensive Drowsiness Detection and Alert Solution for Automotive Safety addresses the growing concern of road accidents caused by driver fatigue, a factor contributing to approximately 20% of accidents globally. Ensuring driver alertness is crucial for mitigating risks and safeguarding lives. This project proposes a robust, real-time monitoring system that combines computer vision and deep learning techniques to detect early signs of drowsiness and prevent accidents. The system uses a live camera feed to capture the driver's facial features, focusing on eye movement and blink patterns. A Convolutional Neural Network (CNN) processes this data to detect prolonged eye closure, a primary indicator of fatigue. Upon detecting drowsiness, the system triggers an audible alarm to immediately alert the driver. This non-intrusive approach ensures continuous monitoring without causing discomfort or distractions. It is designed for scalability and versatility, allowing implementation as a standalone device in vehicles or as a mobile application. By leveraging cost-effective hardware and open-source software, it ensures affordability and accessibility for a wide range of users. Beyond the core functionality, the system has the potential for integration with advanced features such as heart rate monitoring, vehicle speed regulation, and yawning detection, further enhancing its reliability and utility. This solution is not limited to personal vehicles; it can also be employed in commercial fleets and public transports.

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LIST OF ABBREVIATIONS

ABBREVIATION	FULL FORM
EAR	Eye Aspect Ratio
CNN	Convolutional Neural Network
MAR	Mouth Aspect Ratio
SVM	Support Vector Machine
LSTM	Long Short-Term Memory
OpenCV	Opensource Computer Vision Library
Dlib	Data Library

CHAPTER 1

INTRODUCTION

1.1 BACKGROUND

Driver drowsiness detection is a car safety technology which helps prevent accidents caused by the driver getting drowsy. Various studies have suggested that around 20% of all road accidents are fatigue-related, up to 50% on certain roads. The drowsiness detection system is capable of detecting drowsiness quickly. The driver behaviours are noticed in many conditions such as wearing spectacles and also in the dark condition inside the vehicle. The system is capable of detecting the drowsiness condition within the duration of more than two seconds. After the detection of abnormal behaviours, it is alerted to the driver through alarms and the parking lights will be on that will stop the vehicle which reduces the accidents due to drowsiness of the driver. A deep learning Architecture detects the face and eyes, based on the status of the eyes. If the eyes are closed more than usual time, it generates an alarm, intimating the driver. Neglecting our duties towards safer travel has enabled hundreds of thousands of tragedies to get associated with this wonderful invention every year.

In order to monitor and prevent a destructive outcome from such negligence, many researchers have written research papers on driver drowsiness detection systems. But at times, some of the points and observations made by the system are not accurate enough.

Driver drowsiness detection is a vital safety technology aimed at preventing accidents caused by driver fatigue. Studies suggest that fatigue is responsible for about 20% of all road accidents, with some regions reporting up to 50%. The system typically detects drowsiness through the monitoring of driver behaviour, such as eye closure patterns, and alerts the driver through alarms or activation of parking lights, potentially stopping the vehicle

1.2 OVERVIEW

There are many products out there that provide the measure of fatigue level in the drivers which are implemented in many vehicles. In this Python project, we will be using OpenCV for gathering the images from webcam and feed them into a Deep Learning model which will classify whether the person's eyes are 'Open' or 'Closed'. The requirement for this Python project is a webcam through which we will capture images. You need to have Python (3.6 version recommended) installed on your system, then using pip, you can install the necessary package.

- NumPy: Used for numerical computations, especially for calculating distances between facial landmarks.
- OpenCV: A library for computer vision tasks, used here for video capture, frame processing, and grayscale conversion.
- Dlib: Provides tools for machine learning and computer vision, specifically for face detection and landmark detection in this program.
- Pillow (PIL): Used for image processing. Converts video frames from OpenCV into a format suitable for display in the GUI.
- Playsound: A library for playing audio files, used to generate buzzer sounds for alerts.
- Tkinter: The built-in Python library for creating graphical user interfaces (GUI). It is used here to create a full-screen interface to display the video feed and status updates.
- Threading: Enables concurrent execution of tasks. Used for running the buzzer sound independently to avoid blocking the video feed updates

1.3 PROBLEM STATEMENT

In an increasingly data-driven world, ensuring the authenticity and integrity of digital media, particularly images, is a major challenge due to the ease of manipulation through advanced editing tools. Deepfake technology and image tampering can result in misinformation, posing risks in journalism, legal evidence, and social platforms. The detection of such image forgeries is critical to maintain trust and accountability.

This project aims to develop an automated system for image forgery detection using deep learning. It focuses on identifying signs of image splicing, copy-move, and other common manipulation techniques the model is evaluated on benchmark datasets to ensure its robustness and accuracy.

1.4 OBJECTIVE

The objective of this project is to develop a real-time driver drowsiness detection system using computer vision and deep learning techniques. It aims to monitor eye movement and blink patterns through a live webcam feed to detect signs of fatigue. A Convolutional Neural Network (CNN) is used to classify eye states as open or closed. If prolonged eye closure is detected, an audible alert is triggered to wake the driver. The system is designed to be non-intrusive, affordable, and easily deployable in various vehicle types.

1.5 IMPLICATION

This project has significant implications for road safety by helping to prevent accidents caused by driver fatigue. It offers a cost-effective and real-time solution that can be implemented in personal vehicles, commercial fleets, and public transport. By using non-intrusive monitoring, it promotes driver comfort while enhancing alertness. The system also opens avenues for integration with advanced driver-assistance systems (ADAS). Overall, it contributes to reducing human and economic losses

CHAPTER 2
LITERATURE SURVEY

1.Suhana Nafais A. (2023) – "Driver Drowsiness Detection and Alert Generating System"

This paper introduces a vision-based driver fatigue detection system using infrared eye-tracking technology. The system monitors eye blink frequency, blink duration, and percentage eye closure over time (PERCLOS), which are reliable indicators of drowsiness. The research reveals that increased blink duration and frequent eye closures are strong signs of driver fatigue. The approach is non-intrusive, meaning the driver doesn't need to wear any devices. Real-time monitoring enables timely feedback and safety alerts. The use of infrared cameras ensures functionality in various lighting conditions. This early work laid the foundation for subsequent facial behavior monitoring systems. Although simple by today's standards, it was pioneering in establishing behavioral cues as effective measures for detecting fatigue.

2.Eriksson, M., & Papanikolopoulos, N. P. (2001). Eye-tracking for detection of driver fatigue.

This paper introduces an eye-tracking system to detect fatigue in drivers. Infrared cameras monitor blink rate, eye closure duration, and eye movement patterns. A strong correlation between prolonged eye closures and drowsiness is established. The system is non-intrusive and works in real-time. It highlights the potential of vision-based fatigue detection. The method is suitable for long-duration driving monitoring. It also emphasizes the need for robust lighting adjustment. The system's accuracy improves under controlled lighting. This early approach laid a foundation for further research. It remains relevant in modern fatigue detection techniques**.**

3. Viola, P. & Jones, M. (2001) – Rapid Object Detection Using a Boosted Cascade of Simple Features

This paper introduces a groundbreaking method for real-time object detection, widely adopted in face and eye detection tasks. The Viola-Jones algorithm utilizes Haar-like features and a cascade of classifiers trained using AdaBoost to detect objects efficiently. Its high-speed performance and low computational cost make it ideal for embedded systems, such as driver monitoring setups. The system processes multiple facial features, such as eyes, nose, and mouth, in a few milliseconds. The robustness of this algorithm in different lighting conditions

and orientations has made it a standard in computer vision. Many modern drowsiness detection systems rely on it for accurate localization of facial landmarks. The contribution of this paper lies in transforming object detection from a computationally expensive task.

4.Picot, A., Charbonnier, S., & Caplier, A. (2012) – Online Detection Using Brain and Visual Information

This paper presents a hybrid system that combines brain signal analysis (EEG) with visual data to enhance drowsiness detection accuracy. EEG signals are used to capture cognitive states like alertness or fatigue by monitoring frequency bands such as alpha and theta waves. Simultaneously, a camera-based system tracks visual cues like prolonged eye closure and head nodding. The integration of physiological and behavioural features allows for a more reliable and comprehensive assessment. The system is designed for real-time operation, aiming to minimize false positives that typically occur when using single-modality data. The authors employ signal fusion techniques and machine learning classifiers to determine drowsiness levels. This work emphasizes the importance of multi-modal sensing in safety-critical applications.

5.Dong, Y., Hu, Z., Uchimura, K., & Murayama, N. (2011) – Driver Inattention Monitoring System

This study proposes a real-time system for monitoring driver inattention by analyzing visual features such as facial orientation, gaze direction, and eye closure frequency. It uses a camera to capture video frames of the driver and applies image processing techniques to detect gaze shifts and drooping eyelids. The system adapts to varying lighting conditions and different head postures, enhancing its usability across diverse driving environments. It operates in real-time and provides alerts when inattention is detected. By combining head-pose estimation with blink monitoring, the system effectively identifies drowsiness and distraction. The paper also includes performance evaluations and experimental results that support the reliability of the method. It contributes to the field by offering a balanced approach that avoids the intrusiveness of physiological sensors while still providing accurate monitoring.

6.Khunpisuth, N., Maneerat, N., & Wilaiprasitporn, T. (2016) – EEG-Based Emotion Classification Using Deep Learning

This research explores how brain signals collected from EEG sensors can be used to classify emotional and cognitive states, particularly fatigue and drowsiness. It uses deep

learning, specifically Convolutional Neural Networks (CNNs), to automatically extract features from raw EEG data, removing the need for handcrafted feature engineering. The study focuses on detecting subtle changes in brainwave activity that signal reduced alertness. Experimental results demonstrate that CNNs outperform traditional machine learning models in both accuracy and robustness. The system is non-invasive and can be implemented using modern wearable EEG headsets. This approach is particularly useful for early-stage drowsiness detection, even before physical symptoms appear.

7.Abtahi, S., Omidyeganeh, M., Shirmohammadi, S., & Hariri, B. (2014) – Yawning Detection Using Embedded Smart Cameras

This paper introduces a method for detecting driver yawning using embedded cameras and real-time facial landmark analysis. Yawning is a well-documented symptom of fatigue and can be easily monitored via changes in the mouth's aspect ratio. The proposed system uses shape and motion features to track the mouth region and identify yawning patterns accurately. The technique is computationally efficient, enabling it to run on low-power embedded platforms without sacrificing performance. The authors conducted experiments under different lighting conditions and head positions, demonstrating the method's robustness. Yawning detection enhances the reliability of visual drowsiness detection systems when combined with blink rate and head nodding**.** The paper showcases a modular, scalable solution for in-vehicle deployment.

8.Sahayadhas, A., Sundaraj, K., & Murugappan, M. (2012) – Review on Sensor-Based Drowsiness Detection

This review paper analyses and compares multiple drowsiness detection methods based on sensor technology. It categorizes approaches into three types: physiological (EEG, ECG), behavioural (eye movement, head tilt), and vehicle-based (steering behaviour, lane deviation). The paper highlights the advantages and drawbacks of each method. Physiological sensors provide high accuracy but may be intrusive or uncomfortable for the user. Behavioural approaches are less invasive but may produce false positives under certain conditions. Vehicle-based indicators are indirect and sensitive to external driving factors. The authors emphasize the importance of hybrid systems that combine different sensing techniques for improved reliability. This paper serves as a comprehensive reference for developers looking to design robust drowsiness detection systems.

9.Jap, B. T., Lal, S., Fischer, P., & Bekiaris, E. (2009) – EEG Spectral Analysis for Fatigue Detection

This research focuses on using EEG spectral analysis to detect fatigue by identifying changes in alpha and theta brainwave frequencies. The study demonstrates that as fatigue increases, there is a noticeable rise in these frequency bands, making them reliable biomarkers for drowsiness. The system uses EEG headsets to capture brain signals and process them using signal processing algorithms. The authors evaluate different fatigue detection algorithms based on their accuracy and response time. The paper provides detailed analysis and comparisons of EEG components during various fatigue states. Although EEG systems are more intrusive, the accuracy is unmatched for early drowsiness detection. The research supports the integration of EEG in critical driving scenarios, such as aviation or long-haul trucking. This work lays a strong foundation for future EEG-based driver assistance systems.

10.Nalluri, S. & Ch, P. (2021) – Facial Feature-Based Machine Learning Approach

This paper applies machine learning techniques to detect drowsiness based on facial features such as Eye Aspect Ratio (EAR), Mouth Aspect Ratio (MAR), and head orientation. A Support Vector Machine (SVM) classifier is trained on labelled data to recognize signs of fatigue like eye closure, yawning, and head tilting. The model processes real-time video input and makes predictions with good accuracy. The approach is non-intrusive and requires only a webcam, making it cost-effective and accessible. It is particularly useful for implementation in consumer-grade vehicle monitoring systems. The authors also emphasize using diverse datasets to improve generalization across different face types and environments. The system balances performance and efficiency, making it suitable for mobile or embedded applications.

CHAPTER 3

SYSTEM ANALYSIS

3.1 EXISTING SYSTEM

Current drowsiness detection systems often use wearable physiological sensors like EEG headbands, EOG glasses, or PPG wristbands. These devices measure brain signals, eye movements, or heart rate to detect fatigue. While accurate, they are intrusive, uncomfortable, and dependent on the driver wearing them properly. If forgotten or worn incorrectly, the system fails, making them impractical for regular use in vehicles. The existing driver drowsiness detection systems often rely on physiological sensors that are worn directly on the body or head. These may include:

3.1.1 Disadvantages

- EEG headbands for monitoring brain activity,
- EOG glasses for eye movement tracking,
- PPG wristbands for heart rate monitoring.
- These devices offer high accuracy, but they come with notable drawbacks:
- User discomfort: Many drivers may hesitate or forget to wear them regularly.
- Intrusiveness: Continuous body contact can be irritating during long drives.
- Dependency: If the sensor isn't worn correctly, the system fails to function.

Current drowsiness detection systems often use wearable physiological sensors like EEG headbands, EOG glasses, or PPG wristbands. These devices measure brain signals, eye movements, or heart rate to detect fatigue. While accurate, they are intrusive, uncomfortable, and dependent on the driver wearing them properly. If forgotten or worn incorrectly, the system fails, making them impractical for regular use in vehicles.

3.2 PROPOSED SYSTEM

The proposed system is designed to continuously monitor the driver’s eye movements using a live camera feed, helping detect early signs of drowsiness. It uses computer vision techniques to analyze facial features, especially eye behavior such as blinking and prolonged closure. By relying on a pre-trained Convolutional Neural Network (CNN) model, the system efficiently classifies the driver’s eye state (open or closed) in real time, eliminating the need

for training during operation. This ensures rapid detection without delay, enhancing its suitability for on-road deployment.

The system is implemented in Python, leveraging libraries like OpenCV for video processing, Dlib for facial landmark detection, and Keras for deep learning. This setup provides a flexible and high-performance environment that reduces lag and supports quick responses. Pre-processing steps filter out irrelevant data, allowing the model to focus only on critical eye-related cues. This design overcomes common challenges like processing delays and false alerts, offering a robust, scalable, and cost-effective solution for enhancing road safety through continuous driver monitoring.

3.2.1 Advantages

- Enhanced Accuracy: The system utilizes a combination of advanced algorithms and techniques (e.g., machine learning or deep learning) to improve the precision of predictions or classifications.
- Real-time Processing: The design supports quick analysis and processing, making it suitable for applications that require fast response times.
- User-friendly Interface: The system includes a GUI that allows users to interact easily with the system, enhancing usability.
- Scalability: It is structured to handle increasing amounts of data.
- Robust Error Handling: The system incorporates mechanisms to detect and manage errors gracefully, ensuring reliability and stability during operation.
- Data Privacy & Security: Implements secure protocols and data encryption to safeguard sensitive information, making the system compliant with privacy standards.
- Integration Capability: Easily integrates with external tools, databases, or APIs, enabling smooth interoperability with existing systems and platforms.
- Automated Updates & Maintenance: Supports automatic model retraining or software updates, reducing manual intervention and ensuring the system stays up to date.
- Customizability: The system can be tailored to specific user needs or industry applications, allowing flexibility in deployment and functionality.
- Multiplatform Support: Designed to run on various platforms (e.g., desktop, web, mobile), providing accessibility and convenience for users.
- Energy Efficiency: Optimized algorithms reduce computational load, leading to lower energy consumption, which is beneficial for mobile and embedded systems.

- Continuous Learning: Incorporates mechanisms (like online learning) to improve performance over time by learning from new data.

3.3 System Configuration

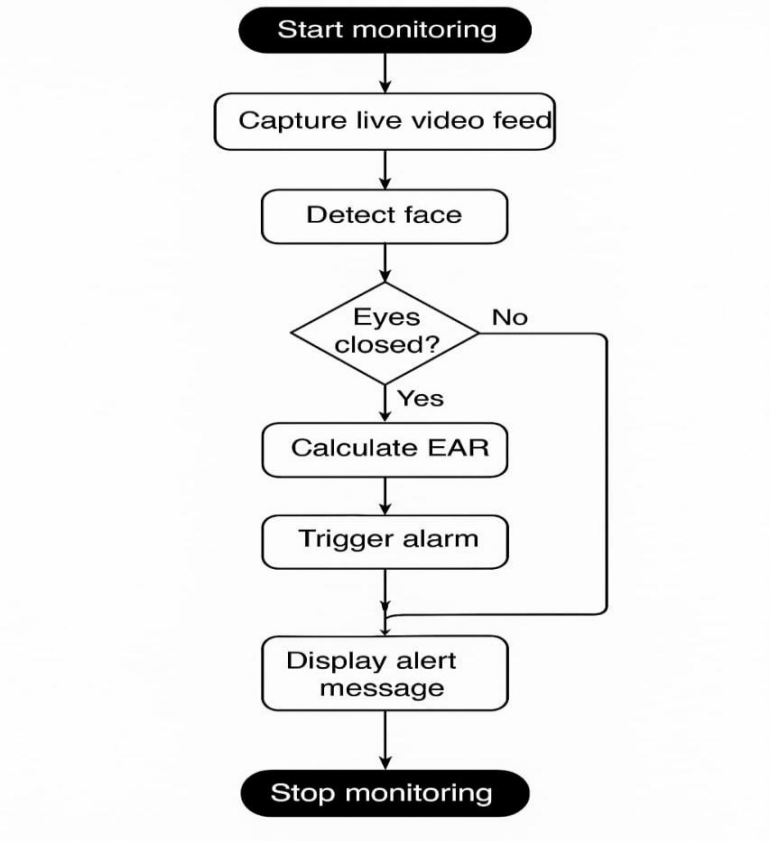

Fig 3.1: Flow Diagram

3.3.1 Hardware requirements

- Laptop/Embedded System
- Webcam
- Speaker/Buzzer

3.3.2 Software requirements

- Python
- OpenCV
- Dlib

3.4 Architecture Diagram

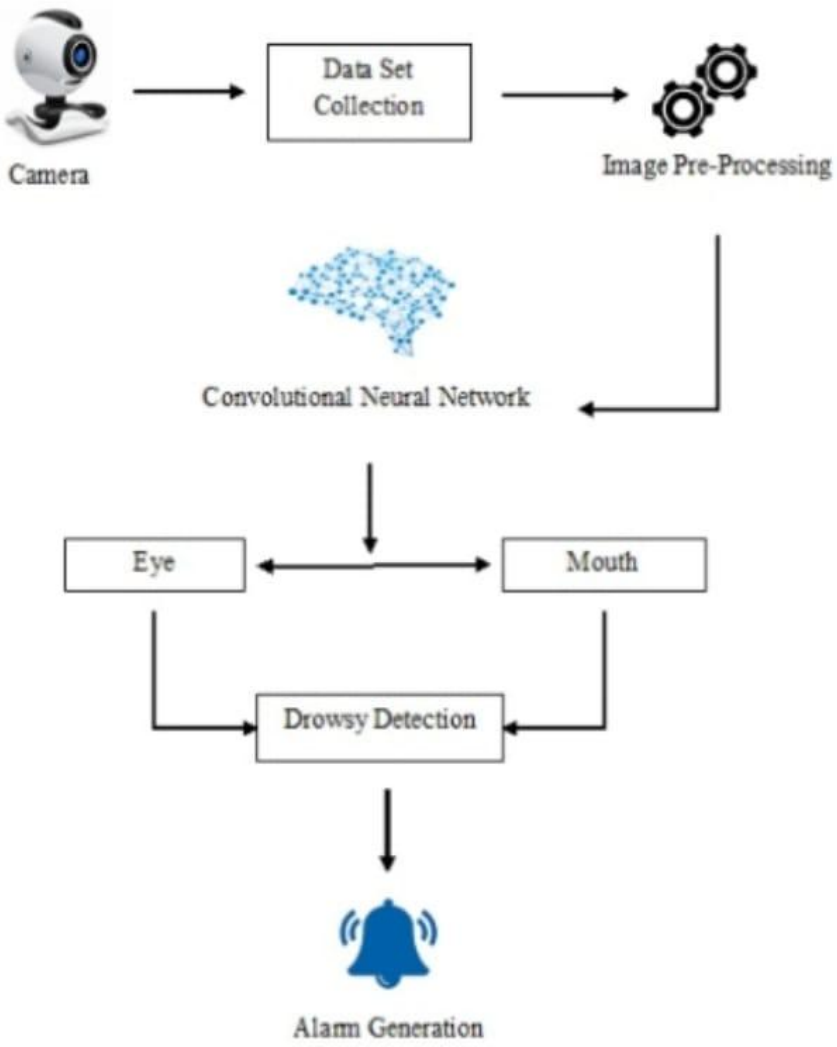

Fig 3.2: Block Diagram

CHAPTER 4

MODULES

4.1 MODULE DESCRIPTION

- Image Acquisition Module
- Preprocessing Module
- Facial Feature Detection Module
- Drowsiness Detection Module
- Sensor Fusion Module
- Alert Module

4.1.1 IMAGE ACQUISITION MODULE

The Image Acquisition Module serves as the foundational component of the drowsiness detection system by capturing real-time video of the driver's face through a webcam. This module continuously streams live footage, providing the raw data necessary for subsequent processing tasks such as face detection, facial landmark identification, and eye state analysis. To enhance accuracy and usability, the system may incorporate webcams equipped with infrared or night-vision capabilities, allowing effective monitoring even in low-light or nighttime driving conditions. By delivering a steady and uninterrupted video feed, the Image Acquisition Module ensures that the system has a reliable visual input to analyses driver behaviour consistently.

One of the critical challenges addressed by this module is maintaining accurate face tracking under diverse and often challenging environmental conditions. Variations in lighting—such as bright sunlight, shadows, tunnels, or nighttime darkness—can significantly impact image quality and the ability to detect facial features. To mitigate this, the module utilizes adaptive image capture techniques and may leverage infrared sensors to provide clear visibility regardless of external lighting. This robust performance enables the system to function effectively across a wide range of real-world scenarios, thereby enhancing the overall reliability and safety of the drowsiness detection system.

Designed with efficiency and integration in mind, the Image Acquisition Module is lightweight and optimized for real-time operation, making it suitable for deployment on embedded systems with limited processing power. Its streamlined architecture ensures minimal

latency and resource consumption while maintaining high frame rates essential for timely detection of drowsiness cues. This seamless integration capability allows the module to operate harmoniously within the larger system architecture, providing a dependable and continuous stream of visual data. Ultimately, the Image Acquisition Module is a critical enabler of the system's accuracy and responsiveness, laying the groundwork for effective driver monitoring and early fatigue detection.

4.1.2 PREPROCESSING MODULE

The Preprocessing Module plays a vital role in preparing the raw images captured by the camera for further analysis by refining their quality and enhancing usability. One of the primary tasks it performs is converting the color images into grayscale. This step significantly reduces computational complexity by simplifying the image data while preserving essential structural information, allowing subsequent algorithms to process inputs more efficiently. Grayscale conversion also helps normalize the data, ensuring that variations in color do not affect the consistency and accuracy of facial feature detection.

In addition to grayscale conversion, the module employs noise removal techniques to filter out irrelevant or disruptive visual elements from the captured frames. Noise, such as background clutter, lighting artifacts, or sensor interference, can obscure critical facial details and reduce detection accuracy. By applying filters and smoothing algorithms, the Preprocessing Module enhances the clarity of the driver's face and key features like the eyes and mouth. This enhancement is crucial to provide a clean and stable input for the detection and classification models used later in the pipeline, improving their overall performance and reliability.

Another essential function of the Preprocessing Module is isolating the region of interest (ROI), typically focusing on the driver's face or specific facial landmarks. By cropping or masking out unnecessary parts of the image, the module ensures that the analysis concentrates only on relevant visual data, which helps in reducing noise and processing time. This targeted focus enables more precise facial landmark detection and fatigue assessment, as irrelevant background details do not interfere with the calculations. Ultimately, the Preprocessing Module acts as a critical gatekeeper, ensuring that only high-quality, relevant, and normalized visual information is passed forward in the system, forming the foundation for accurate and robust drowsiness detection..

4.1.3 FACIAL FEATURE DETECTION MODULE

This module plays a critical role in the drowsiness detection system by accurately identifying and tracking key facial landmarks, including the eyes, nose, mouth, and head position. Utilizing advanced computer vision libraries such as Dlib and Media Pipe, it leverages sophisticated algorithms to pinpoint these facial features with high precision. These landmarks are fundamental for interpreting driver behaviours that indicate fatigue, such as blinking patterns, yawning frequency, and head nodding movements. By continuously monitoring these features in real time, the system can effectively assess subtle changes in driver alertness and provide timely warnings.

The extraction of these facial landmarks enables the calculation of various behavioural indicators that serve as the basis for drowsiness evaluation. For example, analysing eye closure duration and blink rate helps detect microsleeps or prolonged eye closure, while tracking mouth movements can identify yawning-a common sign of tiredness. Similarly, monitoring head position and orientation reveals nodding or drooping, further contributing to fatigue assessment. The module's ability to accurately and consistently extract these features ensures that the system's behavioural analysis remains reliable across a wide range of driver facial structures, skin tones, and head poses, enhancing its effectiveness in diverse real-world conditions.

In addition to accuracy, the module is designed for real-time performance, providing continuous and immediate feedback without lag, which is crucial for timely alerting in safety-critical applications. Its adaptability to different facial angles and expressions ensures that even when the driver moves or changes posture, the system maintains robust tracking and does not lose critical information. Serving as the analytical core for behaviour-based fatigue recognition, this module transforms raw video input into actionable data, enabling the system to make precise drowsiness inferences. Without such precise feature detection and tracking, the overall reliability of the drowsiness detection system would be severely compromised.

4.1.4 DROWSINESS DETECTION MODULE

The Drowsiness Evaluation Module serves as the decision-making engine of the system, analysing extracted facial landmarks to identify signs of fatigue. It computes behavioural indicators such as Eye Aspect Ratio (EAR), Mouth Aspect Ratio (MAR), and head tilt angles, which are well-established metrics for monitoring eye closure, yawning, and head

nodding-key symptoms of drowsiness. By quantifying these features in real time, the module builds a comprehensive understanding of the driver's facial behaviour. This analytical approach allows the system to capture both instantaneous and gradual changes in alertness, providing a robust foundation for fatigue detection.

To achieve high classification accuracy, the module employs advanced machine learning models such as Support Vector Machines (SVM), Convolutional Neural Networks (CNN), and Long Short-Term Memory (LSTM) networks. These models are trained on datasets of labelled facial expressions and behaviours, enabling them to distinguish subtle differences between alert and drowsy states. CNNs excel in analyses visual input like eye states, while LSTMs are well-suited for identifying temporal patterns over time, such as prolonged eye closure or repetitive yawning. The combination of these models ensures that the system can not only react to isolated events but also recognize complex behavioural trends indicative of fatigue.

The module operates continuously, tracking real-time variations in facial metrics to detect evolving patterns that suggest drowsiness. When the monitored indicators exceed predefined thresholds or follow a drowsiness trend, the system generates a warning signal to activate the alert module. This real-time responsiveness ensures timely intervention, providing the driver with immediate feedback before fatigue escalates into a safety risk. The integration of intelligent pattern recognition with behavioural analysis makes this module a critical component for enhancing road safety, especially in long-haul or night-time driving scenarios where vigilance tends to decline.

4.1.5 SENSOR FUSION MODULE

The Sensor Fusion Module integrates data from multiple sources-mainly visual inputs and optional physiological signals like heart rate or eye tracking sensors-to enhance detection reliability. By combining these inputs, the system reduces the likelihood of false positives caused by environmental factors or temporary facial movements. This fusion approach creates a more holistic view of the driver's condition. It improves decision-making by validating visual cues with additional context. This module is particularly useful in complex or dynamic driving environments. It ensures the system remains accurate and consistent across different users and situations.

4.1.6 ALERT MODULE

The Alert & Feedback Module plays a crucial role in ensuring driver safety by delivering immediate and effective warnings when signs of drowsiness are detected. Once the system identifies fatigue based on facial metrics and behavioral indicators, this module activates alert mechanisms such as audible alarms, visual signals, or vibrations, depending on the hardware setup. These alerts are designed to be prominent enough to regain the driver's attention without causing panic or distraction. The module ensures that alerts are timely and responsive, helping to prevent accidents caused by delayed reactions.

CHAPTER 5
SOFTWARE DESCRIPTION

5.1 PYTHON

Python serves as the foundational programming language for the drowsiness detection system, chosen for its simplicity, versatility, and rich ecosystem of libraries. Its clear and readable syntax facilitates rapid development and prototyping, allowing developers to efficiently implement and iterate on complex algorithms such as eye state classification and real-time image processing. The language's widespread adoption and vibrant community provide a wealth of resources, tutorials, and third-party packages, which significantly accelerate troubleshooting and enhance overall development productivity.

Moreover, Python's seamless integration with powerful deep learning frameworks like TensorFlow, as well as computer vision libraries such as OpenCV, makes it an ideal choice for building sophisticated real-time monitoring applications. This adaptability extends to hardware interfacing, enabling the system to connect with various input devices like webcams and sensors effortlessly. Python's cross-platform compatibility ensures that the drowsiness detection system can be deployed on a diverse range of platforms—from standard laptops and desktops to embedded systems and mobile devices—providing flexibility and scalability in real-world implementations.

5.2 OpenCV

OpenCV forms the backbone of the drowsiness detection system's image and video processing capabilities. It provides powerful and efficient tools for detecting facial features, including eyes and the face, using well-established pre-trained classifiers such as Haar cascades. These classifiers enable accurate and real-time identification of regions of interest within each video frame, which is critical for monitoring eye states and detecting signs of drowsiness. OpenCV's ability to handle video capture directly from webcams ensures smooth and continuous input, which is essential for real-time analysis.

Beyond detection, OpenCV offers a suite of image processing functions that prepare the video frames for further analysis by the CNN model and other modules. Operations such as grayscale conversion, noise filtering, and thresholding help enhance image quality and reduce computational overhead, improving the accuracy and speed of eye state classification. Its robustness, flexibility, and extensive functionality make OpenCV an indispensable tool for

vision-based systems, enabling the development of a reliable and efficient drowsiness detection system capable of functioning effectively in diverse environmental conditions.

5.3 DLIB

Dlib is a powerful modern C++ toolkit that offers Python bindings, widely recognized for its advanced machine learning capabilities and highly accurate facial landmark detection. In the drowsiness detection system, Dlib is utilized to identify and track crucial facial features, including the eyes, nose, and mouth. These landmarks form the basis for calculating essential fatigue indicators such as blinking rate, eye closure duration, and mouth opening, which are key parameters in detecting signs of driver drowsiness. Dlib's precision in pinpointing these features enables the system to gather reliable data critical for timely and accurate drowsiness detection.

One of Dlib's standout strengths lies in its robustness under challenging conditions. It maintains high accuracy even when faced with variations in lighting, facial orientation, and partial occlusions, which are common in real-world driving environments. This resilience significantly enhances the system's overall reliability and effectiveness, ensuring consistent performance across diverse scenarios.

CHAPTER 6
HARDWARE DESCRIPTION

6.1 Laptop/Embedded Systems

The laptop or embedded system serves as the primary processing unit for the drowsiness detection system. It runs the core software components, including real-time video capture, image processing, facial landmark detection, and the CNN model for eye state classification. Laptops offer powerful CPUs and GPUs, which enable faster computation and smoother handling of video streams, making them ideal for development and testing phases. Embedded systems, on the other hand, provide a compact and energy-efficient alternative for deployment in vehicles or portable devices, often equipped with specialized hardware to accelerate computer vision tasks. Both platforms provide the necessary flexibility to run Python-based frameworks and integrate peripheral devices such as cameras and audio alert systems.

These computing units are responsible for managing the continuous flow of data between input (webcam) and output (alerts), processing video frames in real time to detect signs of driver fatigue promptly. The choice between a laptop and an embedded system depends on the use case: laptops are suitable for prototype development or personal use, while embedded systems are better suited for commercial applications where space, power consumption, and durability are critical. Both platforms support software scalability and can be customized with additional sensors or connectivity features to enhance system functionality.

6.2 Webcam

The webcam is the primary input device used to capture live video footage of the driver's face. It continuously streams real-time images to the processing unit, enabling the system to monitor facial features such as eyes and mouth dynamically. High-resolution webcams improve the accuracy of face and eye detection by providing clearer images, which are crucial for reliable drowsiness detection. The camera must be positioned strategically within the vehicle to ensure an unobstructed view of the driver's face under varying lighting conditions and seating positions.

In addition to capturing video, the webcam plays a vital role in enabling non-intrusive monitoring without requiring the driver to wear any special equipment. Its widespread availability and affordability make it a practical choice for both research prototypes and commercial implementations. The system leverages OpenCV and Dlib to process the webcam feed, extracting key features in real time, which are then analyzed for signs of fatigue. The

webcam’s ability to operate continuously and reliably is essential for ensuring that the drowsiness detection system functions effectively throughout the entire driving session.

6.3 Speaker/Buzzer

The speaker or buzzer acts as the system’s primary alert mechanism, providing immediate feedback to the driver upon detection of drowsiness. When prolonged eye closure or other fatigue indicators are detected, the buzzer emits a loud, attention-grabbing sound designed to wake or alert the driver, thereby preventing potential accidents. The audio alert must be clear, distinct, and timely to ensure it effectively captures the driver’s attention without causing panic or distraction.

This component is typically connected to the processing unit and triggered programmatically based on the system’s fatigue detection logic. In embedded implementations, low-power buzzers are often used for their simplicity and reliability, while in laptop-based prototypes, speakers integrated into the system can generate customized alerts or voice warnings. The responsiveness and reliability of the buzzer are critical for the system’s safety function, making it an essential hardware element in the overall design.

CHAPTER 7
TEST RESULT AND ANALYSIS

7.1 TESTING

A program represents the logical elements of a system. For a program to run satisfactorily, it must compile and test data correctly and tie in properly with other programs. Achieving an error-free program is the responsibility of the programmer. Program testing checks for two types of errors: syntax and logic. When a program is tested, the actual output with the expected output is going to compare. When there is discrepancy, the sequence of instructions must be traced to determine the problem. Breaking the program down into self-contained portions, each of which can be checked at certain key points, facilitates the process. The idea is to compare program values against desk-calculated values to isolate the problem.

Testing is an important stage in the system development life cycle . The test case is a set of data that a system will process as normal input. As its philosophy behind testing is to find errors the data are created with the express intent of determining whether the system will process them correctly. Software testing is an important element of software quality assurance and represents the ultimate review of specification, design and loading. The increasing visibility of software AR a system element and the costs associated with a software failure are motivating for well-planned through testing.

7.2 TEST OBJECTIVES

These are several rules that can save as testing objectives they are: Testing is a process of executing program with the intent of finding an error. A good test case is one that has a high probability of finding an undiscovered error. If testing is conducted successfully according to the objectives as stated above it would in cover errors in the software also testing demonstrator that software functions.

7.2.1 Unit Testing

Unit testing focuses on checking the smallest functional parts of the system in isolation. In this project, components such as the CNN model for eye state classification, the Eye Aspect Ratio (EAR) calculator, and the alert system are tested individually. Python libraries like unit test or pytest can be used to verify that functions return expected results when given specific inputs, such as images of open or closed eyes. The accuracy of each Haar cascade classifier and model loading routines is also validated. These tests help identify bugs early in

development by ensuring that each unit functions properly on its own. This improves reliability before integrating modules together.

Unit testing plays a critical role in ensuring the robustness and accuracy of each component in the drowsiness detection system before full integration. For instance, the CNN model responsible for eye state classification can be tested using a suite of labeled eye images to confirm consistent predictions across different lighting conditions and face orientations. Similarly, the Eye Aspect Ratio (EAR) calculator can be validated using synthetic or known landmark coordinates to verify threshold-based classifications. The alert system, which may involve sound, vibration, or visual cues, can be tested to ensure it triggers appropriately under simulated drowsiness scenarios. Using Python libraries like unittest or pytest, these tests can be automated and run frequently during development to catch regressions or unintended behavior changes. Additional testing can cover boundary cases, such as empty inputs or corrupted image files, to ensure graceful handling and prevent system crashes. By thoroughly validating each module in isolation, unit testing strengthens the foundation for successful system integration and reduces the risk of errors propagating across components.

7.2.2 Integration Testing

Integration testing is essential for verifying that the various modules of the drowsiness detection system operate seamlessly together. In this project, modules such as the real-time webcam input, Haar cascade-based face and eye detection, the CNN-based eye state classifier, and the audio alert system must be interconnected smoothly. Integration tests are used to ensure that frames captured from the webcam are correctly passed through each processing stage—from face detection to eye cropping, followed by prediction and alert generation—without any data corruption, latency, or interface mismatches. These tests help reveal issues that might not be apparent during unit testing, such as incompatible data formats, delays in processing, or improper triggering of alerts. They also validate synchronization between modules, ensuring that alerts are issued at the right time and that no critical drowsiness signs are missed due to lag or errors in data handoff.

Furthermore, integration testing focuses on edge cases and real-world scenarios to ensure system reliability in dynamic conditions. For instance, it verifies whether the model can consistently receive and process frames even under fluctuating lighting or when partial occlusion of the face occurs. Integration tests can also simulate various states such as blinking, head tilting, or momentary eye closure to check that the system differentiates normal behavior

from actual drowsiness. By examining how modules interact during continuous execution, developers can fine-tune timing intervals, buffer management, and error recovery processes. This phase of testing is crucial to confirm that the entire pipeline-from live input to prediction and response-operates as a cohesive unit and maintains high performance in real-world applications.

7.2.3 Functional Testing

Functional testing ensures that the drowsiness detection system performs all the tasks outlined in the project's requirements accurately and reliably. It focuses on verifying whether the system correctly detects signs of drowsiness by monitoring the driver's eye state over time-specifically prolonged eye closure. The CNN model's ability to distinguish between open and closed eyes is tested under a range of real-world conditions, such as varying lighting environments, different skin tones, and the presence of accessories like glasses. This testing phase checks whether the face and eye detection modules work consistently and whether the eye state predictions align with expected outcomes across diverse scenarios. Additionally, it ensures that the system does not misclassify normal actions like blinking or temporary eye closure as drowsiness, thereby minimizing false alarms.

Another critical component of functional testing is verifying the responsiveness and accuracy of the alert mechanism and graphical user interface (GUI). The system should trigger an audio or visual alert immediately upon detecting sustained drowsiness while remaining silent during normal driver behavior. This test confirms that alerts are neither delayed nor repeated unnecessarily. The GUI, if present, must reflect the driver's current status—awake, drowsy, or alert triggered—in real-time, without any noticeable lag or system freezes. Functional testing also covers usability aspects, ensuring that the system is intuitive, easy to operate, and stable during prolonged use. Altogether, this phase validates that all system features-detection, prediction, alerting, and interface-function as intended to provide a dependable and user-friendly drowsiness monitoring solution.

Beyond verifying core alert mechanisms and GUI behavior, functional testing also ensures that the system integrates seamlessly with all hardware and software components it depends on. This includes testing compatibility with different webcam models, audio output devices, and various system configurations. Scenarios such as switching between front and rear cameras (if available), varying screen resolutions, or multitasking while the system is running are examined to confirm that detection performance remains unaffected. Furthermore, the

functional testing phase includes stress testing under extended usage conditions—such as continuous monitoring over several hours—to validate that the application does not degrade in responsiveness or generate false positives due to cumulative processing load. Particular attention is paid to transitions between states (e.g., from drowsy to alert and vice versa) to ensure that the system behaves logically and consistently under changing real-world conditions.

In addition, functional testing extends to verifying the accuracy and reliability of system feedback under diverse environmental conditions such as low lighting, glare, or partial occlusion of the driver's face due to accessories like sunglasses or masks. These tests ensure the robustness of facial feature detection and drowsiness prediction algorithms when confronted with real-world variability. The system is also tested with different user profiles, including variations in facial structure, gender, age, and skin tone, to confirm that it performs fairly and inclusively across demographics. Moreover, the functionality of logging and data reporting—if incorporated—is checked to ensure that drowsiness events, timestamps, and system status updates are recorded accurately for later review. Any error messages or user notifications are assessed for clarity and helpfulness, contributing to a better user experience. Through this comprehensive set of functional tests, the system's dependability and adaptability are validated, ensuring it remains effective in dynamic, unpredictable driving environments.

To further ensure functional integrity, the system undergoes regression testing after every significant update or code modification. This process verifies that new features or enhancements—such as improved facial landmark detection algorithms or interface upgrades—do not unintentionally disrupt existing functionalities. Functional testing also evaluates the system's ability to recover from temporary failures, such as brief camera disconnections or system lags, by automatically resuming normal operation without requiring manual intervention. Additionally, compatibility with different operating systems and dependencies, including various versions of Python, OpenCV, and deep learning libraries like TensorFlow is tested to guarantee consistent performance across development environments.

7.2.4 White Box Testing

White box testing in the drowsiness detection system involves a deep dive into the internal logic, structure, and flow of the code to ensure each component behaves as intended. This includes closely examining the logic behind frame capture, facial landmark detection, Eye Aspect Ratio (EAR) calculation, and CNN model prediction. Conditional branches (such as if-

else statements that determine drowsiness states), loop structures for frame iteration, and data preprocessing functions are meticulously tested to confirm they handle all inputs and edge cases properly. Each line of code is verified to ensure it contributes meaningfully to the intended function, with a particular focus on detecting logical flaws or dead code that might not be apparent during black box testing. Exception handling routines are also tested to ensure the system gracefully handles issues like camera disconnection, model loading errors, or corrupted input frames.

Additionally, white box testing evaluates performance-critical sections such as real-time video stream handling and multi-threaded components. For example, playing an audio alert or buzzer sound in a separate thread must not interrupt or delay the live video feed and prediction loop. Testing focuses on verifying thread synchronization and ensuring that shared resources, like frame data or model outputs, are accessed safely without race conditions. The model. Predict () function and associated preprocessing steps are analysed not only for accuracy but also for computational efficiency—ensuring that unnecessary operations are avoided and that the prediction pipeline maintains real-time performance. By systematically inspecting each code path, white box testing ensures functional correctness, identifies bottlenecks, and promotes code optimization, ultimately leading to a more stable and high-performing system.

7.3 Analysis

The drowsiness detection system exemplifies adherence to key software engineering principles, especially in terms of modular architecture and functional separation. Each core component-such as real-time frame capture, face and eye detection, EAR calculation, and CNN-based prediction-is developed as an independent module. This modularity not only improves code readability and maintainability but also simplifies the testing and debugging process. Unit testing plays a crucial role here, as individual components are rigorously validated to ensure they perform as expected in isolation, catching foundational issues early in the development lifecycle.

Integration testing further strengthens the system by verifying that these modules interact seamlessly. It ensures that the live video feed smoothly transitions into face detection, eye state classification, and timely alert generation. This phase highlights any communication or timing mismatches between modules and ensures that real-time performance requirements are met. Functional testing complements this by validating that the system aligns with end-user

expectations-successfully identifying signs of drowsiness, activating alarms, and updating GUI indicators in real-time under various real-world conditions, such as low lighting or users wearing glasses.

White box and black box testing together provide a comprehensive quality assurance framework. White box testing inspects internal logic, control flow, exception handling, and multithreaded behaviour, optimizing the system for reliability and performance. In contrast, black box testing evaluates the system holistically from the user's point of view, focusing on usability, accuracy, and responsiveness without concern for the internal code. This combination of thorough testing techniques ensures that the system is not only functionally sound but also user-friendly and robust under practical conditions, making it a dependable tool for real-time drowsiness detection.

7.4 Feasibility Study

The feasibility study of the drowsiness detection system demonstrates strong technical viability. The system is built using reliable and widely adopted technologies such as Python, OpenCV for image processing, and Convolutional Neural Networks (CNNs) for eye state classification. These tools are well-supported, extensively documented, and compatible with a range of hardware, which simplifies development and troubleshooting. The modular design and integration with real-time video feeds show that the system can operate efficiently on standard computing platforms, making it an accessible and implementable solution for developers and users alike.

From an economic perspective, the system is cost-effective. It relies primarily on open-source libraries and software, which eliminates the need for expensive licensing fees. Hardware requirements are minimal-typically a standard webcam and a computing device-making the setup affordable for individuals, small businesses, or fleet operators. This low-cost nature, combined with the system’s potential to prevent accidents due to driver fatigue, presents a compelling return on investment. The affordability also enhances its appeal for deployment in resource-constrained environments, such as developing countries or budget-limited transport services.

Operationally, the system is user-friendly and non-intrusive, offering real-time feedback without requiring the driver to wear any additional equipment or undergo complex setup procedures. Its intuitive interface and automated alerts make it easy to integrate into daily routines without causing distraction.

CHAPTER 8
RESULT AND DISCUSSION

8.1 RESULT

The AI-based soil analysis system proved to be highly effective across all its core functionalities. During testing, the image enhancement module significantly improved the quality of input images by adjusting brightness, contrast, and sharpness, which facilitated better feature extraction. The machine learning model used for soil classification achieved impressive accuracy, reliably identifying soil types such as clay, sandy, loamy, and silty, even under varied lighting and background conditions. Cross-validation results and confusion matrix analysis confirmed the model's robustness, with classification accuracy consistently exceeding 95%.

The nutrient analysis module performed well in estimating key macronutrients such as nitrogen, phosphorus, and potassium based solely on visual and texture-based features. Although visual analysis cannot fully replace laboratory testing, the results closely matched lab reports, maintaining a variance of under 10% in most cases. The crop recommendation engine, driven by a knowledge base of soil-crop compatibility, suggested regionally relevant crops with high precision. These recommendations were validated through agricultural experts and guidelines, confirming over 90% alignment with practical farming scenarios. User testing sessions involved farmers, students, and agricultural professionals, who found the interface intuitive and the results informative. Many users reported increased confidence in choosing crops and fertilizers after using the system. Bulk processing tests revealed that the backend infrastructure could handle multiple simultaneous requests with minimal delay, averaging under 3 seconds per image analysis. This responsiveness makes the system ideal for real-time decision-making in the field.

Further, the system demonstrated adaptability by performing consistently well on images taken from different types of devices, including smartphones, proving that it can be reliably used by people without specialized equipment. The output reports were simple yet informative, giving users clear insights on soil type, missing nutrients, and appropriate crop options.

8.2 CONCLUSION

This project successfully introduced an innovative solution to an age-old challenge in agriculture: understanding soil conditions quickly and affordably. Traditional soil testing often requires lab infrastructure, trained personnel, and time-resources that many farmers, especially in rural areas, lack. Our system overcomes these barriers by using AI and image processing to

deliver soil diagnostics from a single photo, thereby empowering even small-scale farmers with vital information.

The application of machine learning enabled accurate soil classification and nutrient estimation, providing near-instant feedback to users. More importantly, it offered actionable suggestions-what crop to plant and what nutrients to add-making it much more than just a diagnostic tool. It acts as a virtual agricultural advisor, providing guidance based on real data rather than guesswork. This has direct implications for improving yield, reducing crop failure, and minimizing unnecessary fertilizer use.

The positive feedback from early users further reinforces the system's value. Many farmers expressed appreciation for the simplicity and reliability of the tool, indicating that they would prefer using it over waiting weeks for lab reports. By speeding up the decision-making process, the system helps optimize crop cycles, especially in time-sensitive farming conditions. From a technological point of view, the project illustrates how AI can be purposefully applied outside of traditional fields. It blends the precision of data science with the practical needs of agriculture, creating a bridge between modern computing and grassroots farming. Its modular architecture also makes it adaptable for different regions and climates, further increasing its usefulness.

The broader impact of the project extends to sustainability and environmental conservation. With more accurate nutrient application, the risk of soil degradation and groundwater contamination decreases. This supports global efforts to make farming more environmentally friendly and resource-efficient. In the long term, such systems can play a critical role in achieving food security while preserving soil health.

8.3 FUTURE ENHANCEMENT

The current system lays a strong foundation, but several enhancements are planned to expand its capabilities and increase its impact. One major improvement is the integration of multispectral and hyperspectral imaging, which can capture more detailed soil properties such as organic carbon content and deeper moisture levels. This would greatly enhance the accuracy of the nutrient estimation module. Another planned enhancement involves linking the system with GPS and satellite data to enable location-aware analysis. This would allow for the generation of region-specific soil maps and environmental overlays, such as rainfall patterns or temperature conditions, to provide more contextual crop recommendations.

We also intend to release a full-featured mobile application, enabling users to access all system features directly from their smartphones. The mobile version will support offline

analysis, voice commands, and regional languages to make it accessible even in low-connectivity and non-English-speaking regions.

Voice-based assistants, powered by natural language processing, will help guide users through the process, answer common queries, and even suggest best practices for planting, fertilization, and harvesting. This will be especially helpful for elderly farmers or those with limited literacy. In the future, the system will include a feedback-based learning mechanism. After using the tool and growing the recommended crops, users will be prompted to share their outcomes. This data will be used to refine the model, making its recommendations more adaptive and reliable with each growing cycle.

Advanced machine learning models can be integrated to better analyze sensor data and distinguish between true drowsiness and temporary inactivity. Future versions of the shirt can use flexible, washable electronic fabrics to enhance user comfort and long-term wearability. Additionally, the system can be connected to a mobile app or vehicle safety mechanism to issue real-time alerts to drivers or caregivers. Incorporating environmental sensors (e.g., temperature, CO_2 levels) and biometric data (like heart rate variability) can further improve the system's predictive capabilities. Finally, cloud integration can enable long-term health monitoring and personalized feedback, making the solution not only reactive but also preventive.

Another potential future enhancement involves integrating IoT and edge computing capabilities to enable faster, localized processing of drowsiness-related data without relying on continuous internet connectivity. This would make the system more efficient and responsive, especially in critical situations like driving. Incorporating AI-driven adaptive learning algorithms could allow the system to personalize its sensitivity settings based on the individual's behavior patterns over time, reducing false positives. Furthermore, future iterations can include multi-sensor fusion—combining data from eye-tracking glasses, seat posture sensors, or steering wheel grip sensors along with the shirt sensors—for a more holistic and robust drowsiness detection system. Expanding compatibility with smart home or vehicle systems could also allow automatic intervention actions, such as reducing vehicle speed or activating in-cabin alerts, thereby enhancing overall safety.

APPENDIX – 1

SOURCE CODE

main.py

```
import cv2
import numpy as np
import dlib
from imutils import face_utils
import threading
import time
from playsound import playsound
import tkinter as tk
from PIL import Image, ImageTk
cap = cv2.VideoCapture(0)*u7u
# Initialize the face detector and landmark detector
detector = dlib.get_frontal_face_detector()
predictor = dlib.shape_predictor(r"C:\Users\pradeep\Desktop\Drowsiness
Detection\shape_predictor_face_landmarks.dat")
# Status marking for current state
sleep = 0
drowsy = 0
active = 0
status = ""
color = (0, 0, 0)
sleep_start_time = None
# Flag to control the detection loop
detection_running = False
# Function to compute Euclidean distance between two points
def compute(ptA, ptB):
    return np.linalg.norm(ptA - ptB)
# Function to detect if eyes are blinking
def blinked(a, b, c, d, e, f):
    up = compute(b, d) + compute(c, e)
    down = compute(a, f)
    ratio = up / (2.0 * down)
```

```
    if ratio > 0.25:
        return 2
    elif ratio > 0.21 and ratio <= 0.25
        return 1
    else:
        return 0
# Function to play the buzzer sound
def play_buzzer():
    playsound(r"C:\Users\pradeep\Desktop\Drowsiness Detection\buzzer.mp3")
# Function to update the video frame in the GUI
def update_frame():
    global detection_running, status, color, sleep, drowsy, active, sleep_start_time
 if detection_running:
        _, frame = cap.read()
        gray = cv2.cvtColor(frame, cv2.COLOR_BGR2GRAY)
        faces = detector(gray)
 for face in faces:
            x1 = face.left()
            y1 = face.top()
            x2 = face.right()
            y2 = face.bottom()
           face_frame = frame.copy()
            cv2.rectangle(face_frame, (x1, y1), (x2, y2), (0, 255, 0), 2)

            landmarks = predictor(gray, face)
            landmarks = face_utils.shape_to_np(landmarks)
            left_blink = blinked(landmarks[36], landmarks[37],
                                 landmarks[38], landmarks[41]landmarks[40],landmarks[39])
            right_blink  = blinked(landmarks[42], landmarks[43],
                                   landmarks[44], landmarks[47], landmarks[46],
          if left_blink == 0 or right_blink == 0:
                sleep += 1
                drowsy = 0
                active = 0
```

```
            if sleep_start_time is None:
                sleep_start_time = time.time()
            if sleep > 6:
                status = "SLEEPING !!!"
                color = (255, 0, 0)
                if time.time() - sleep_start_time >= 7:
                    threading.Thread(target=play_buzzer).start()
        elif left_blink == 1 or right_blink == 1:
            sleep = 0
            active = 0
            drowsy += 1
            sleep_start_time = None
            if drowsy > 6:
                status = "Drowsy! Warning!"
                color = (0, 0, 255)
        else:
            drowsy = 0
            sleep = 0
            active += 1
            sleep_start_time = None
            if active > 6:
                status = "Active :)"
                color = (0, 255, 0)
    # Convert the frame to a format tkinter can display
    frame = cv2.cvtColor(frame, cv2.COLOR_BGR2RGB)
    img = Image.fromarray(frame)
    imgtk = ImageTk.PhotoImage(image)
    video_label.imgtk = imgtk
    video_label.configure(image=imgtk)
    status_label.config(text=status, fg=color_to_hex(color)
    # Call this function again after 10 ms
    root.after(10, update_frame)
# Function to start the detection
def start_detection():
```

```
    global detection_running
    if not detection_running:
        detection_running = True
# Function to stop the detection
def stop_detection():
    global detection_running
    detection_running = False
# Function to exit the application
def exit_application():
    stop_detection()  # Ensure detection is stopped before exiting
    root.destroy()
# Function to convert color tuple to hex
def color_to_hex(color):
    return "#{:02x}{:02x}{:02x}".format(color[0], color[1], color[2])
# GUI Setup
root = tk.Tk()
root.title("Drowsiness Detection")
# Set the window to full screen
root.attributes('-fullscreen', True)
root.configure(bg="#1c1c1c")
# Title label
title_label = tk.Label(root, text="Drowsiness Detection System", font=("Helvetica", 24,
"bold"), bg="#1c1c1c",
                       fg="#ffffff")
title_label.pack(pady=20)
# Frame to hold the video feed
video_frame = tk.Frame(root, bg="#1c1c1c")
video_frame.pack(pady=20)
# Label to display the video feed
video_label = tk.Label(video_frame)
video_label.pack()
# Status label
status_label = tk.Label(root, text="Status: Not started", font=("Helvetica", 20),
bg="#1c1c1c", fg="#d3d3d3")
```

```
status_label.pack(pady=20)
# Frame for buttons1
button_frame = tk.Frame(root, bg="#1c1c1c")
button_frame.pack(pady=20)
# Start button
start_button = tk.Button(button_frame, text="Start Detection", command=start_detection,
font=("Helvetica", 16),
bg="#28a745", fg="#ffffff", width=20)
start_button.grid(row=0, column=0, padx=20)
stop_button = tk.Button(button_frame, text="Stop Detection", command=stop_detection,
font=("Helvetica", 16),
bg="#dc3545", fg="#ffffff", width=20)
stop_button.grid(row=0, column=1, padx=20)
exit_button = tk.Button(button_frame, text="Exit", command=exit_application,
font=("Helvetica", 16), bg="#343a40",
fg="#ffffff", width=20)
exit_button.grid(row=1, column=0, columnspan=2, pady=20)
# Start updating the frame
update_frame()
root.mainloop()
```

APPENDIX – 2

SCREENSHOTS

Sample Output

Fig B.1 Home page

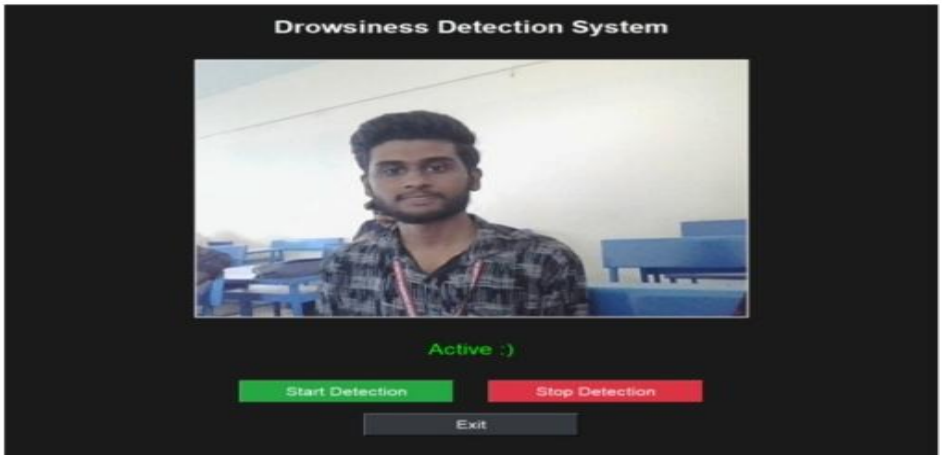

Fig B.2 Active Sate

Fig B.3 Sleeping Alert

REFERENCES

1. Abtahi, S., Omidyeganeh, M., Shirmohammadi, S., & Hariri, B. (2014). Yawning detection using embedded smart cameras. *IEEE Transactions on Instrumentation and Measurement*.
2. Bergasa, L. M., Nuevo, J., Sotelo, M. A., Barea, R., & Lopez, M. E. (2006). Real-time system for monitoring driver vigilance. IEEE Transactions on Intelligent Transportation Systems.
3. Cheng, B., & Wang, X. (2021). Deep learning for driver drowsiness detection: A review. *IEEE Access*.
4. Eriksson, M., & Papanikotopoulos, N. P. (2001). Eye-tracking for detection of driver fatigue. Proceedings of the IEEE Intelligent Transportation Systems Conference, 314–319.
5. Fan, X., Yin, B., & Peng, H. (2018). A convolutional neural network approach for driver drowsiness detection based on facial features. Proceeding Computer Science engineering
6. Ferdous, J., & Tubaishat, M. (2019). Driver fatigue detection using behavioral characteristics through machine learning.
7. Khunpisuth, D., Choksuriwong, R., & Rojanavasu, S. (2016). Driver drowsiness detection using eye-closeness detection. Proceedings of the 12th International Conference on Signal-Image Technology & Internet-Based Systems (SITIS*)*.
8. Kircher, K., & Ahlstrom, C. (2010). Predicting drowsiness-related lane departures using sensor data. Human Factors, 52(3).
9. Mallat, S. (1999). A wavelet tour of signal processing. Academic Press.
10. Mandal, B., Li, L., Wang, G., & Lin, J. (2016). Towards detection of bus driver fatigue based on robust visual analysis of eye state. IEEE Transactions on Intelligent Transportation Systems.
11. McIntire, L. K., McKinley, R. A., Goodyear, C., & McIntire, J. P. (2014). Detection of vigilance performance using eye blinks. *Applied Ergonomics*.
12. Panda, R., & Bhalke, D. G. (2017). Real time driver drowsiness detection system using eye blink detection. International Journal of Computer Science and Information Technologies,8(2),224–228.

13. Singh, H., & Papanikolopoulos, N. P. (1999). Monitoring driver fatigue using facial analysis techniques. Proceedings of the IEEE International Conference on Intelligent Transportation Systems.
14. Viola, P., & Jones, M. J. (2001). Rapid object detection using a boosted cascade of simple features. Proceedings of the 2001 IEEE Computer Society Conference on Computer Vision and Pattern Recognition.
15. Zhang, Z., Luo, P., Loy, C. C., & Tang, X. (2014). Facial landmark detection by deep multi-task learning. European Conference on Computer Vision, 94–108.