A Minor Project Report

on

Driver Fatigueness Detection Using a Hybrid CNN-LSTM Approach with D-Lib Based Facial Analysis

submitted in partial fulfillment of the requirements for the award of degree of

BACHELOR OF TECHNOLOGY

in

COMPUTER SCIENCE & ENGINEERING

by

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CERTIFICATE OF APPROVAL

This project work (**23C11**) entitled " **Driver Fatigueness detection using a hybrid CNN-LSTM approach with D-lib based Facial Analysis** " by K.Kalyan yadav, Registration No. 23211A05D0 , K.Tejas Kumar, Registration No. 23211A05F4 , K.Manoj Kumar, Registration No. 23211A05F9, L.Vishnu Nayak , Registration No. 23211A05G2 under the supervision of **Mrs.G.Ramani** in the Department of Computer Science and Engineering, B V Raju Institute of Technology, Narsapur, is hereby submitted for the partial fulfillment of completing Minor Project during II B.Tech II Semester (2024 - 2025 EVEN). This report has been accepted by Research Domain Computational Intelligence and forwarded to the Controller of Examination, B V Raju Institute of Technology, also submitted to Department Special Lab " Artificial Intelligence Machine Learning" for the further procedures.

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DECLARATION

We, the members of Research Group domain **Computational Intelligence**, declare that this report titled: **Driver Fatigueness detection using a hybrid CNN-LSTM approach with D-lib based Facial Analysis.** is our original work and has been submitted in whole or in parts for International conference or journal **NMITCON 2025-International conference**. All sources of information used in this report have been acknowledged and referenced respectively.

This project was undertaken as a requirement for the completion of our **II B.Tech II Sem Minor project** in Department of **Computer Science and Engineering** at **B V Raju Institute of Technology**, Narsapur. The project was carried out between 23-Dec-2024 and 26-April-2025. During this time, we as a team were responsible for the process model selection, development of the micro document and designing of the project.

Our study combines physiological inputs and facial traits to provide a real-time method for detecting driver weariness. It employs a hybrid deep learning methodology that combines facial analysis based on Dlib with CNN-LSTM models. In addition to triggering timely alarms, a four-level classification aids in determining the degree of exhaustion. The objective is to increase road safety by accurately and quickly detecting driver fatigue.

We would like to express our gratitude to our project supervisor **Mrs.G.Ramani** for his guidance and support throughout this project. We would also like to thank our Department Head Dr.CH.Madhu babu and Domain Incharge **Dr.Ch.Rajya Lakshmi** for his help and efforts.

We declare that this report represents Our own work, and any assistance received from others has been acknowledged and appropriately referenced.

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Finally, we would like to thank our family and friends for their continuous support and encouragement throughout the project. We acknowledge the contributions of everyone who supported us in the creation of this project report.

Thank you all for your assistance and support.

The experience of working on this project will surely enrich our technical knowledge and also give us hands on experience of working on a project and help develop our team's skill set to a great extent.

ABSTRACT

Driver fatigue significantly impairs reaction times and vehicle control, making it a critical factor in the occurrence and severity of traffic accidents. In order to increase accuracy and responsiveness, this study proposes a real-time driver fatigue detection system that combines facial landmark analysis with physiological signals (EEG,EMG,HRV, and skin conductance). The system detects signs of stress, strain, and weariness by analyzing physiological data from wearable sensors using a CNN-LSTM model. At the same time, a Dlib-based facial landmark detection algorithm analyzes the driver's head posture, eye closure, and yawning to determine how sleepy they are. A four-state classification (00, 01, 10, 11) is created by integrating the binary outputs from both models (0 = normal, 1 = tired/drowsy).To avert any collisions, the system uses this combination to assess the driver's level of weariness and instantly (within three to five seconds) activate an alert system. Compared to single-sensor techniques, our multi-modal approach greatly improves accuracy, guaranteeing prompt intervention and lowering the chance of accidents. The device provides a workable way to increase road safety and may be installed in both personal and commercial cars..

Keywords: Road safety, CNN-LSTM, EEG, EMG, HRV, skin conductance, D-lib, facial landmark detection, fatigue detection, and real-time driver monitoring

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LIST OF ACRONYMS AND ABBREVIATIONS

CNN Convolutional Neural Network

LSTM Long Short-Term Memory

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CHAPTER - 1

1. INTRODUCTION

Driver fatigue is one of the primary factors contributing to traffic accidents that cause fatalities and major injuries worldwide. Studies show that fatigue impairs cognitive function, reaction speeds, and decision-making ability, which raises the likelihood of crashes. Traditional fatigue detection systems rely on subjective self-evaluation or vehicle-based measures, such as steering patterns and lane departures. However, these methods are imprecise in real time and cannot detect early signs of fatigue.[**?**].

1.1. Background

One of the main causes of traffic accidents that frequently result in serious injuries or fatalities is driver fatigue. Conventional methods for identifying driver fatigue depend on:

signs based on the vehicle (such as lane deviations and steering tendencies)

subjective evaluations of oneself

Tracking facial features

These methods, however, are frequently imprecise, sluggish to react, and insensitive to the first indications of mental or physical depletion. Furthermore, in real-world scenarios, such as dim lighting or occlusions like masks or sunglasses, systems that only use visual cues or physiological signals frequently falter.

1.2. Motivation

The necessity to develop a fatigue detection system that overcomes the shortcomings of current approaches in terms of accuracy, speed, and dependability is what drives the project. The following are important factors in selecting this project:

1. Improving Road Safety: By detecting weariness before it becomes a risk, accidents can be decreased.

2. Combining Modalities: By combining face analysis (eye closure, yawning, head posture) with

physiological data (EEG, EMG, HRV, and skin conductance), detection accuracy can be increased.

3. Real-time Performance: To provide prompt notifications (within 3–5 seconds) so that drivers can take remedial action.

4. Real-World Implementation: To provide a system that works for both private and business automobiles with an eye towards practical implementation.

5. Filling in the Gaps: To solve issues like false positives, subpar performance under occlusion or changing lighting, and the incapacity of visual-only systems to identify mental weariness.

1.3. Objectives

1) Data augmentation techniques are used during training to increase the data's resistance to variations in illumination and facial expressions.
2) CNN is used for effective image classification in order to improve the drowsiness detection system's accuracy.
3) The system's identification capabilities can be enhanced by including an infrared camera and attention procedures. fatigue. 4) Setting up a system to alert nearby gadgets in the event that the driver is unconscious.

1.4. Problem statement

Driver fatigue is one of the primary factors contributing to traffic accidents that cause fatalities and major injuries globally. The majority of conventional fatigue detection systems rely on physiological sensors or face analysis, which may not be precise or dependable in real-world driving scenarios. To address this problem, we propose a real-time multi-modal fatigue detection system that includes:

1. A CNN+LSTM model to recognise signs of fatigue and stress from physiological sensor data (skin conductance, EEG, EMG, and HRV).

2. Using Dlib, facial landmark analysis is used to identify abnormalities and fatigue.

3. A fusion model that combines physiological and facial data to improve accuracy and response speed, offering a binary weariness classification (00, 01, 10, 11) for real-time driver alerting. This gadget aims to reduce the likelihood of collisions and encourage safer driving conditions by providing early fatigue alarms within three to five seconds .

1.5. Scope of Project

This project aims to design and implement a real-time driver fatigue detection system that utilizes a hybrid deep learning approach. The scope extends across several dimensions, covering both technical development and real-world applications.

1. Multi-Modal Detection System: The system integrates physiological sensor data (like EEG, EMG, HRV, and skin conductance) with facial behavior analysis (such as eye closure rate, yawning, and head tilt) using a CNN-LSTM model and Dlib-based facial landmark analysis. This dual approach improves reliability in detecting both physical and mental signs of fatigue.

2. Real-Time Monitoring and Alerting: The system is designed to operate in real time, capable of issuing alerts within 3–5 seconds after detecting signs of fatigue. This feature ensures that the driver receives a timely warning to prevent accidents.

3. Classification of Fatigue Levels: The model classifies the driver's state into four categories—normal, mildly fatigued, drowsy, and severely fatigued—using a binary combination model (00, 01, 10, 11). This enables graduated responses based on the severity of the condition.

4. Practical Integration: The proposed solution can be embedded into vehicle monitoring systems in both personal and commercial vehicles. It supports future expansion into edge computing for on-device analysis, which would further reduce response time and increase portability.

5. Robustness to Real-World Challenges: Unlike traditional systems, this project addresses key real-world issues such as poor lighting, facial occlusion, and sensor noise. It uses data augmentation and normalization techniques to enhance model robustness.

6. Data-Driven Development: The system leverages publicly available datasets like NTHU-DDD for facial features and SEED-VIG for physiological data, ensuring a broad training base and support for diverse use cases.

7. Extensibility and Future Research: The architecture supports future developments such as the integration of infrared cameras, attention mechanisms, or wearable technologies for continuous monitoring, making it a scalable foundation for advanced driver-assistance systems (ADAS).

CHAPTER - 2

2. LITERATURE SURVEY

Due to its crucial role in minimizing traffic accidents, the detection of driver sleepiness has been the subject of much research. Numerous approaches have been investigated, such as deep learning models, computer vision-based algorithms, and physiological signal analysis. EEG-based detection, which measures brain activity to ascertain fatigue levels, is among the most accurate physiological methods. A deep neural network model was created in a study that can accurately identify tiredness by analysing EEG signals. The requirement for intrusive electrodes, which might not be feasible for real-world applications, is a major drawback of this approach (1). By using Graph Convolutional Networks (GCNs), which improve the capacity to model spatial and temporal correlations in EEG data, another study enhanced EEG-based detection, increasing the effectiveness and adaptability of drowsiness detection (2).

Researchers have developed multi-modal techniques that integrate several physiological information in order to get around the drawbacks of single-modality systems. A Multi- Modality Attention Network (MMA-Net) that combines photoplethysmography (PPG), electrodermal activity (EDA), and electroencephalogram (EEG) signals was proposed in a study. By using an attention mechanism to concentrate on the most pertinent tiredness indicators, our model increases accuracy and robustness. According to the findings, the multi-modality strategy performed noticeably better than conventional singlesignal detection techniques (3). Another study presented a CNN-LSTM-based model that detects driver weariness in real time by fusing physiological data with behavioural imagebased indicators. This approach performed better under dynamic driving conditions, which makes it more useful for deployment in the real world (4).

The non-intrusive nature of facial analysis tools has also led to their widespread adoption. The significance of monitoring head motions, eye blink rates, and yawning frequency was emphasised in a study that examined many facial landmarkbased sleepiness detection techniques. These techniques are now much more accurate thanks to recent developments in machine learning, which increases their dependability for practical application (5). The Eye Aspect Ratio (EAR), which continually measures eye openness to infer tiredness, was used in another study to propose a real-time detection system. Although this approach is computationally efficient, accuracy may be impacted by issues with head movements, partial facial occlusions, and illumination (6). Drowsiness detection has been further enhanced using deep learning-based methods, which increase prediction accuracy and automate feature extraction. In order to improve realtime driver sleepiness detection, a study presented Vigil-Eye, an AI-based system that uses convolutional neural networks (CNNs) with attention mechanisms. This model outperformed traditional machine learning methods in identifying behaviours associated with weariness, exhibiting great precision (7). Similarly, another study used Dlib's pre-trained facial landmark detector, which maps important facial locations to analyse eye and mouth movements, to construct a drowsiness detection system. When evaluated on publicly available datasets, the system demonstrated a remarkable recognition accuracy of 96.71. However, because of changes in lighting and facial angles, its performance was marginally worse in real-time scenarios (8).

Despite the fact that these research have significantly advanced the identification of driver drowsiness, a number of obstacles still exist. The reliability of many visionbased models in practical applications is diminished by their inability to handle different lighting situations. Accurate identification can also be impacted by head motions, occlusions such glasses or masks, and individual variations in facial anatomy. Another issue is computational efficiency because certain deep learning models have large processing power requirements, which restricts their application in low-resource settings. Furthermore, a lot of current systems are trained on homogeneous and tiny datasets, which limits their ability to generalise across a variety of populations. To increase the overall efficacy of sleepiness detection systems, future research should concentrate on incorporating multimodal sensor fusion techniques, improving real-time processing capabilities, and expanding dataset diversity.

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3. DESIGN SPECIFICATION

The design specification of a Tri-level segmented CNN involves identifying the requirements and functionalities of the system to be developed. In this section of the report we complete this very task by developing different diagrams.

The design of the proposed Driver Fatigue Detection System is structured to enable accurate, real-time monitoring of driver alertness using a combination of physiological sensors and facial landmark analysis.

We understand all these requirements better by developing the following diagrams of our system:

- Use Case Diagram
- Data Flow Diagram
- Class Diagram
- Sequence Diagram
- Activity Diagram
- State Chart Diagram

3.1. Use Case Diagram

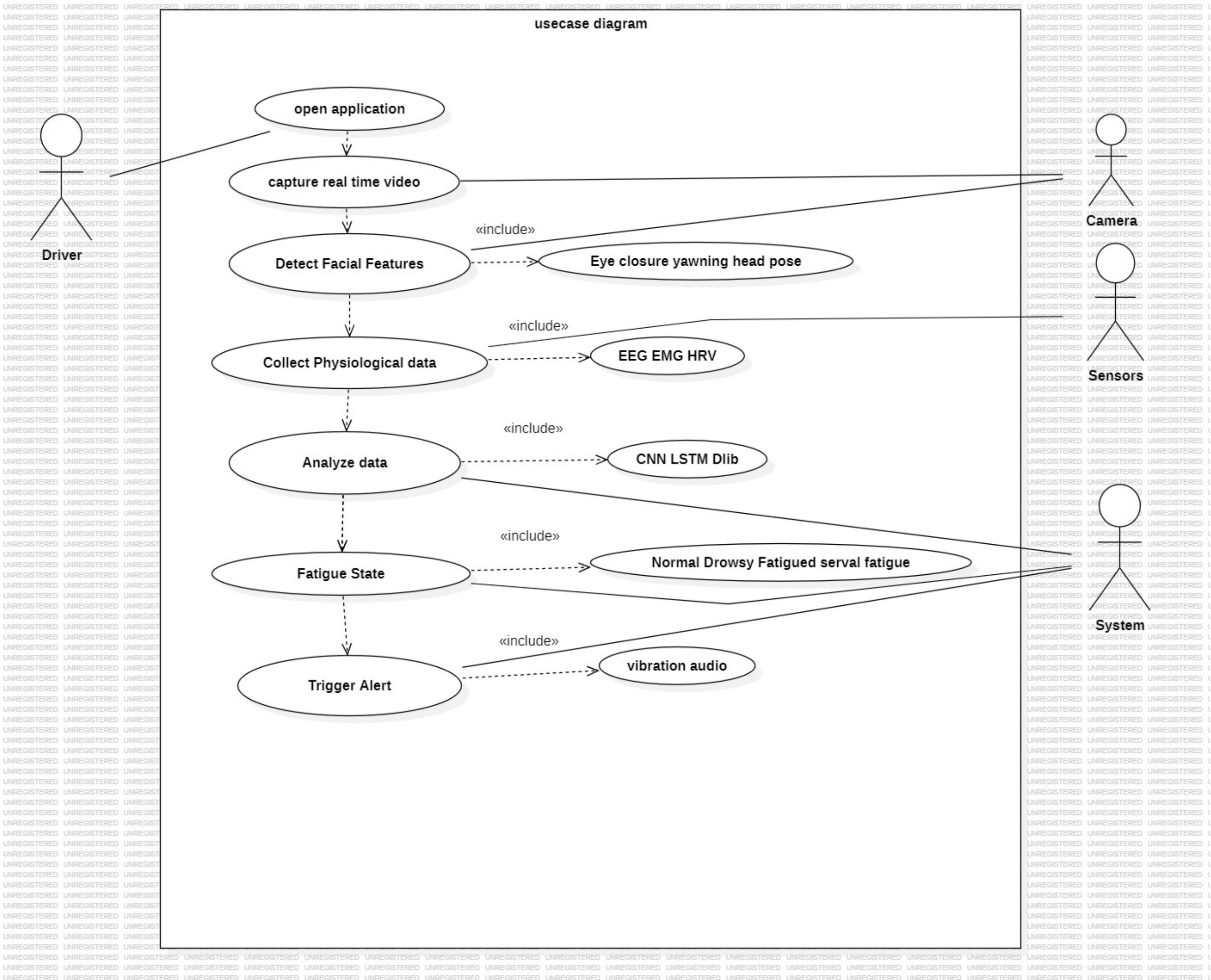

Figure 3.1: Use Case Diagram of Driver Fatigue ness Detection.

3.2. Data Flow Diagram

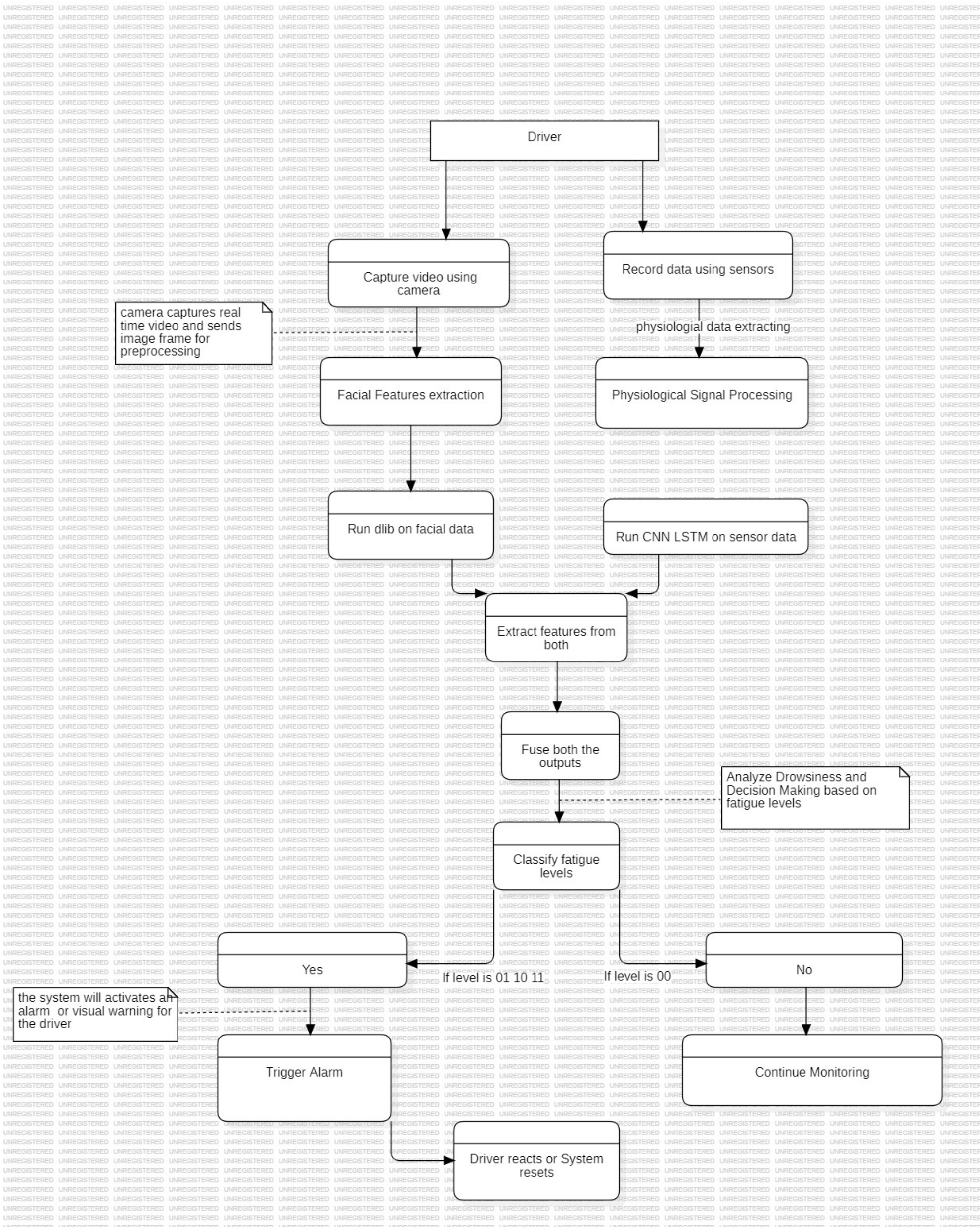

Figure 3.2: Data Flow Diagram of Driver Fatigue ness Detection.

3.3. Class Diagram

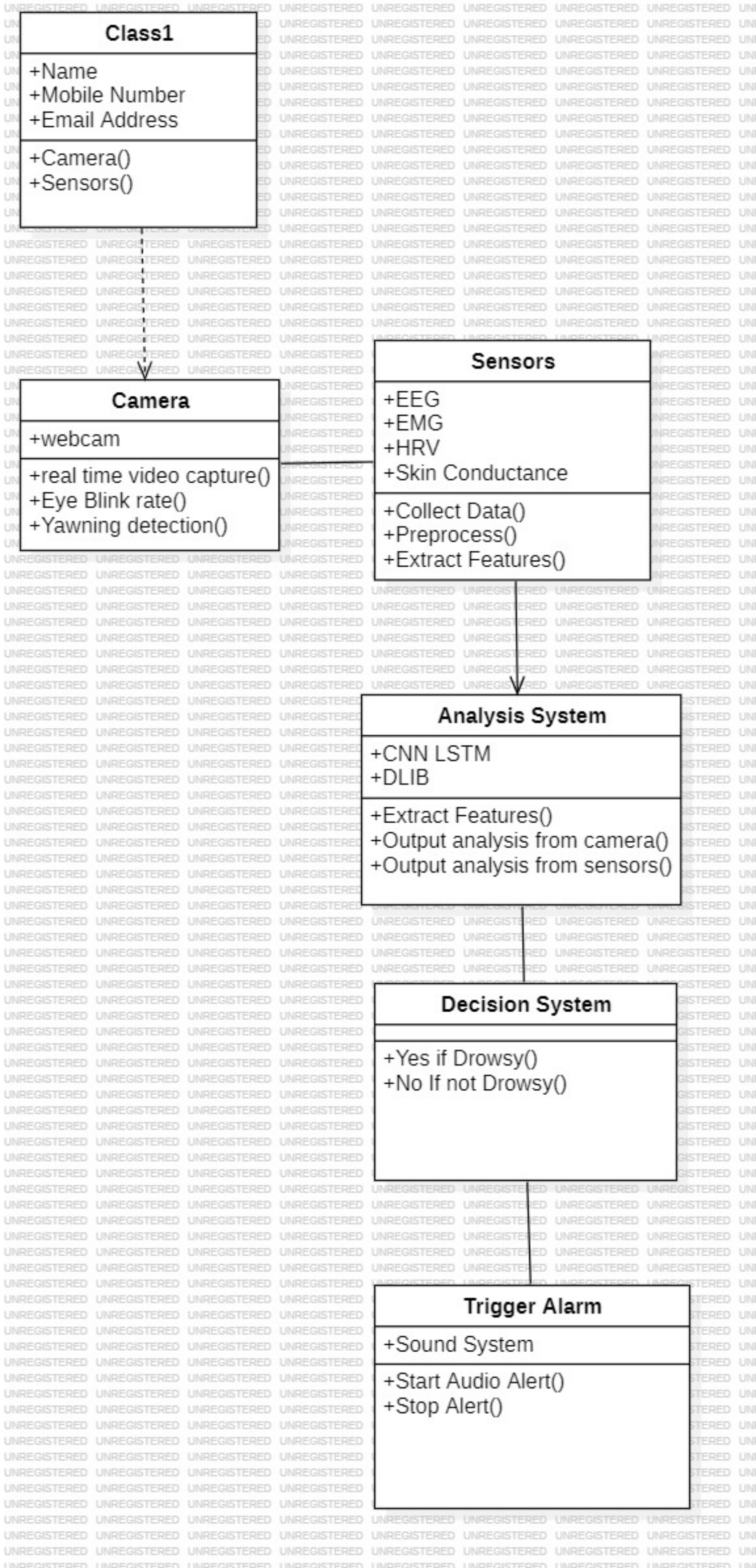

Figure 3.3: Class Diagram of Driver Fatigue ness Detection.

3.4. Sequence Diagram

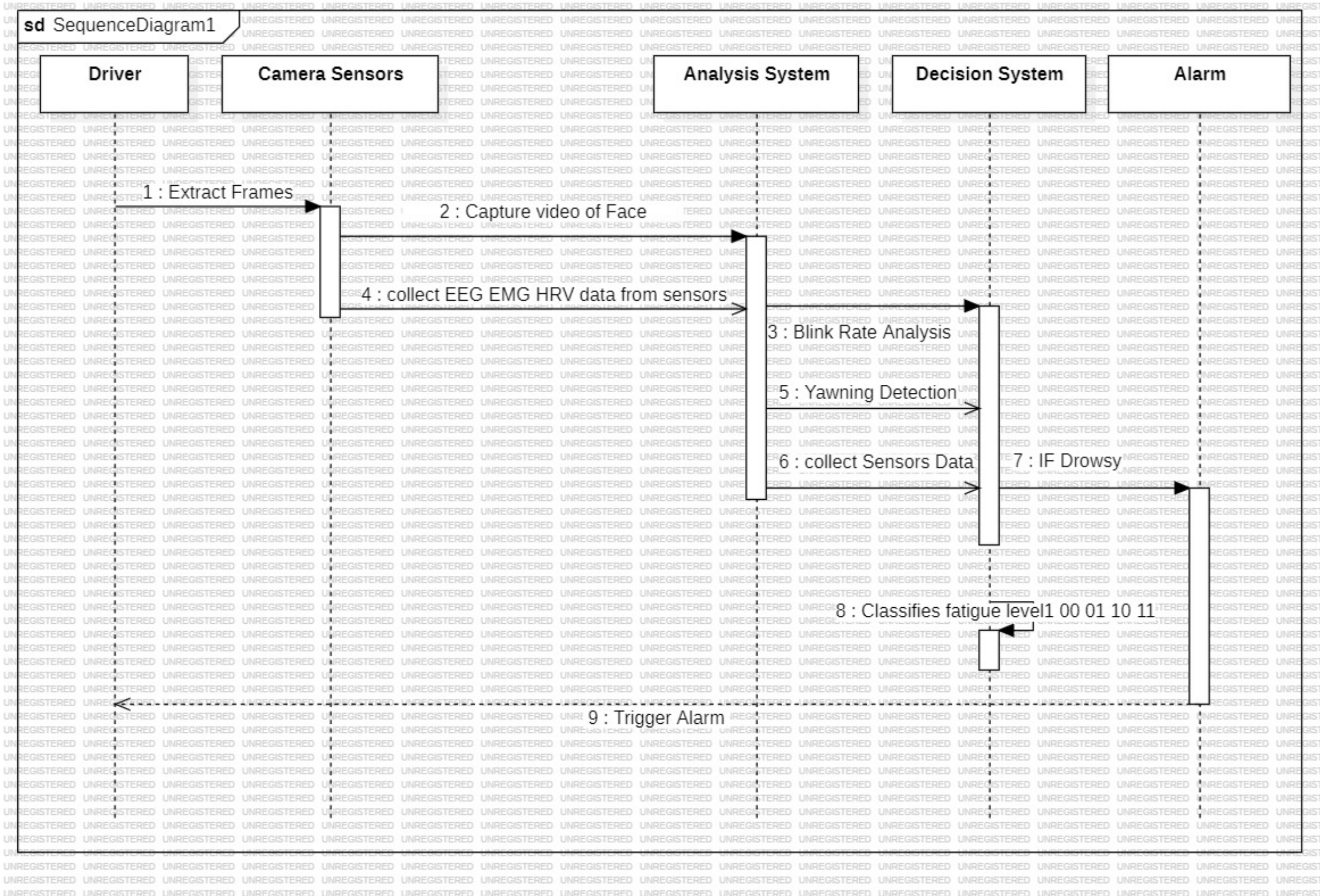

Figure 3.4: Sequence Diagram of Driver Fatigue ness Detection.

3.5. Activity Diagram

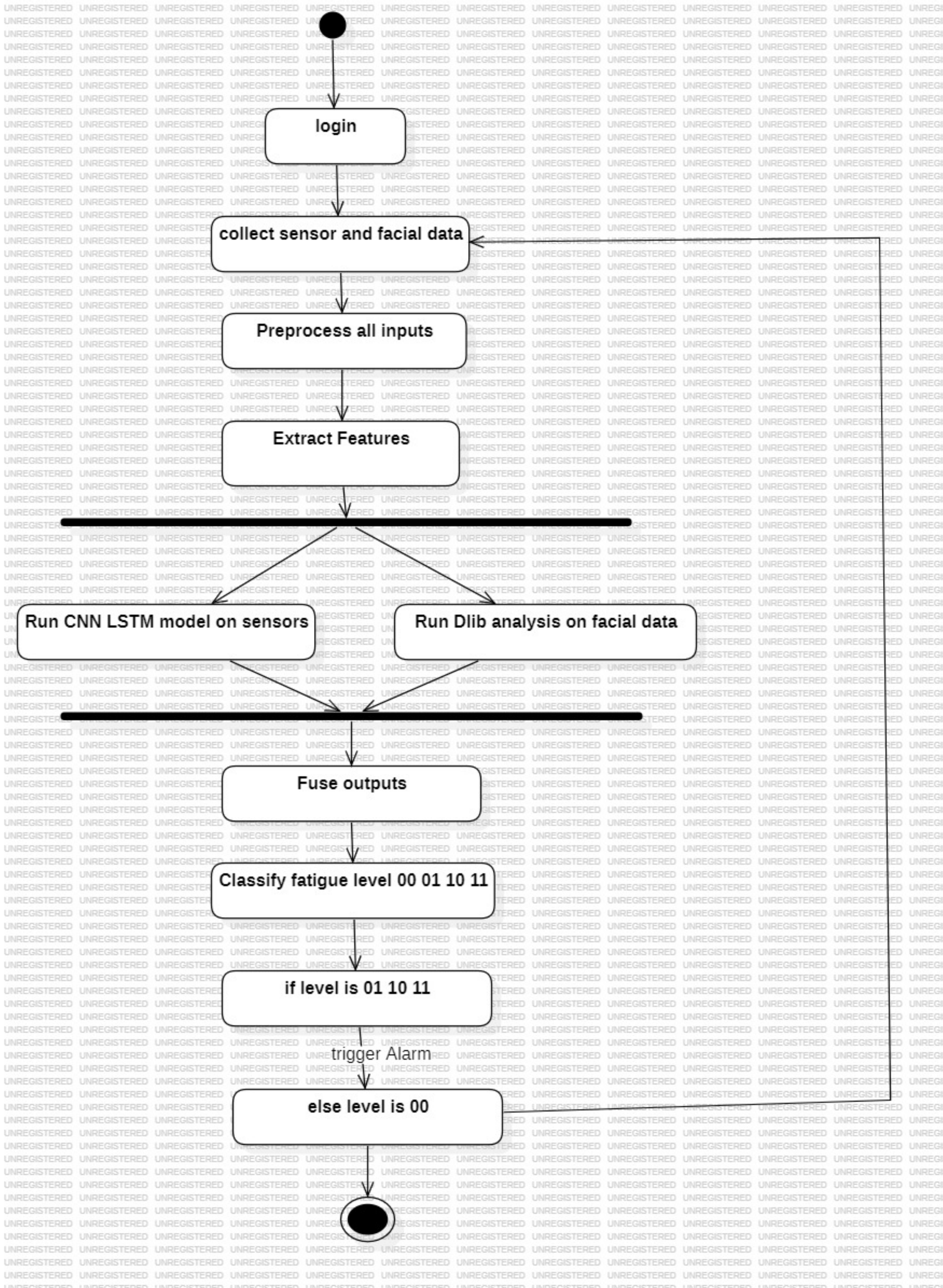

Figure 3.5: Activity Diagram of Driver Fatigue ness Detection.

3.6. State Chart Diagram

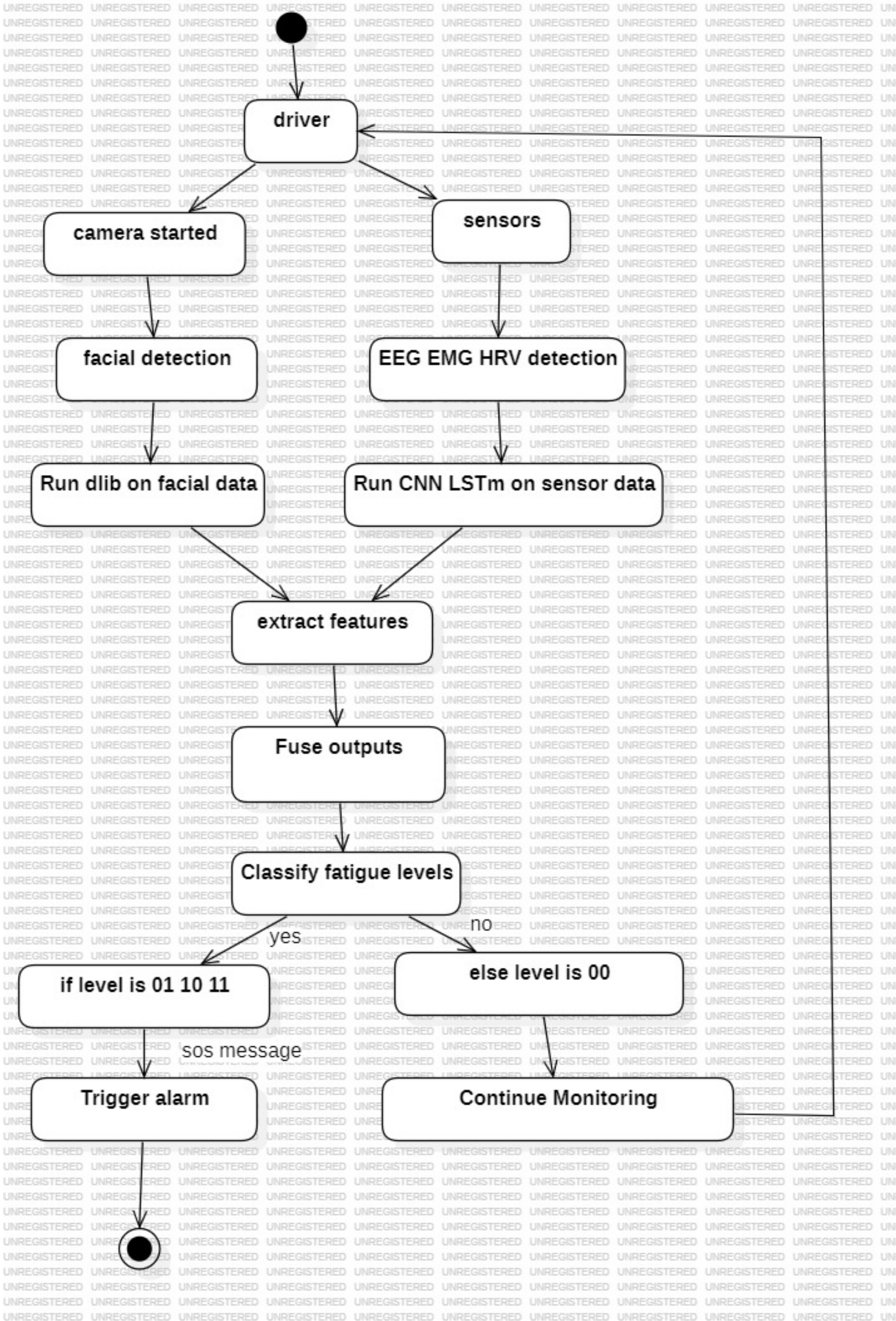

Figure 3.6: State Chart Diagram of Driver Fatigue ness Detection.

CHAPTER - 4

4. METHODOLOGY

4.1. Modules:

Our module contains several important modules that work together for effective driver fatigue detection. The facial landmark detection module analyzes real-time video using Dlib to monitor eye closure, yawning, and head posture. Simultaneously, the physiological signal processing module collects and analyzes data from sensors such as EEG, EMG, HRV, and GSR to detect internal signs of fatigue. A deep learning classification module, based on a CNN-LSTM model, processes the sensor data to identify fatigue patterns. The outputs from facial and physiological analysis are combined in a feature fusion and decision module, which classifies the driver's condition into different fatigue levels. When fatigue is detected, the alert generation module activates sound or vibration alerts. Finally, a data preprocessing module ensures all inputs are clean, normalized, and ready for accurate analysis.

4.2. Facial landmark detection:

This module is responsible for analyzing the driver's face using real-time video input. It utilizes the Dlib library with a 68-point facial landmark detector to locate key facial regions such as eyes, mouth, and jawline. The system calculates two important metrics: Eye Aspect Ratio (EAR) to monitor eye closure and blinking patterns, and Mouth Opening Ratio (MOR) to detect yawning. These metrics are highly correlated with visible signs of drowsiness. The module also considers head posture to identify nodding or tilting, which often precede sleep. All facial data is normalized to ensure accuracy across different face shapes, sizes, and positions in the frame.

4.3. physiological Signal Processing:

This module processes real-time biosignals collected from wearable sensors that track EEG (brain activity), EMG (muscle activity), HRV (heart rate variability), and skin conductance (GSR). The signals are passed through preprocessing steps to reduce noise and remove artifacts. A Butterworth Bandpass Filter is applied to clean EEG, EMG, and HRV signals, and various domain features are extracted. For EEG, features such as alpha, beta, and theta wave ratios are computed; for HRV, metrics like RMSSD and LF/HF ratio are used; for EMG, Zero Crossing Rate (ZCR) and Root Mean Square (RMS) values are calculated. These features reflect both mental and physical states of fatigue.

4.4. Deep Learning Classification:

This module employs a hybrid CNN-LSTM architecture to classify the fatigue state based on physiological data. The Convolutional Neural Network (CNN) extracts spatial features from the sensor data, identifying patterns such as brainwave fluctuations or muscle tension trends. The Long Short-Term Memory (LSTM) network captures the temporal dependencies in the sequential input, enabling the system to detect fatigue that develops over time. The model is trained using labeled datasets to distinguish between normal and fatigued conditions and provides a binary output (0 or 1) indicating the presence or absence of physiological fatigue.

4.5. Feature Fusion and Decision:

n this critical module, outputs from the facial analysis model (Dlib) and the physiological model (CNN-LSTM) are fused to create a more reliable and robust fatigue detection system. The fusion logic evaluates the binary outputs from each model and categorizes the driver's condition into one of four possible states:
00: Normal
01: Drowsy (facial signs detected)
10: Fatigued (sensor signs detected)
11: Severely Fatigued (both facial and physiological signs present)
This multi-modal classification improves detection accuracy and reduces false positives compared to single-model approaches.

4.6. Alert Generation

This module is designed to trigger immediate alerts when the driver's state is classified as drowsy, fatigued, or severely fatigued. The system issues audible alarms and/or vibrations within 3–5 seconds of detection to prompt the driver to take corrective action. In future implementations, this module could be linked to the vehicle's control systems to initiate automatic braking, lane correction, or notification to emergency services, particularly in commercial or high-risk settings.

4.7. Data Preprocessing and Feature Selection

Before classification, all incoming data must be cleaned and structured. This module handles preprocessing tasks such as normalization of facial landmarks, scaling of sensor signals, and time synchronization between data streams. Feature extraction algorithms compute relevant indicators like power spectral densities, aspect ratios, and wavelet coefficients. Dimensionality reduction techniques, such as Principal Component Analysis (PCA), are used to eliminate redundant data and improve processing speed without losing important information. By selecting only the most relevant features, this module enhances both the accuracy and efficiency of the classification models.

4.8. System Block Diagram

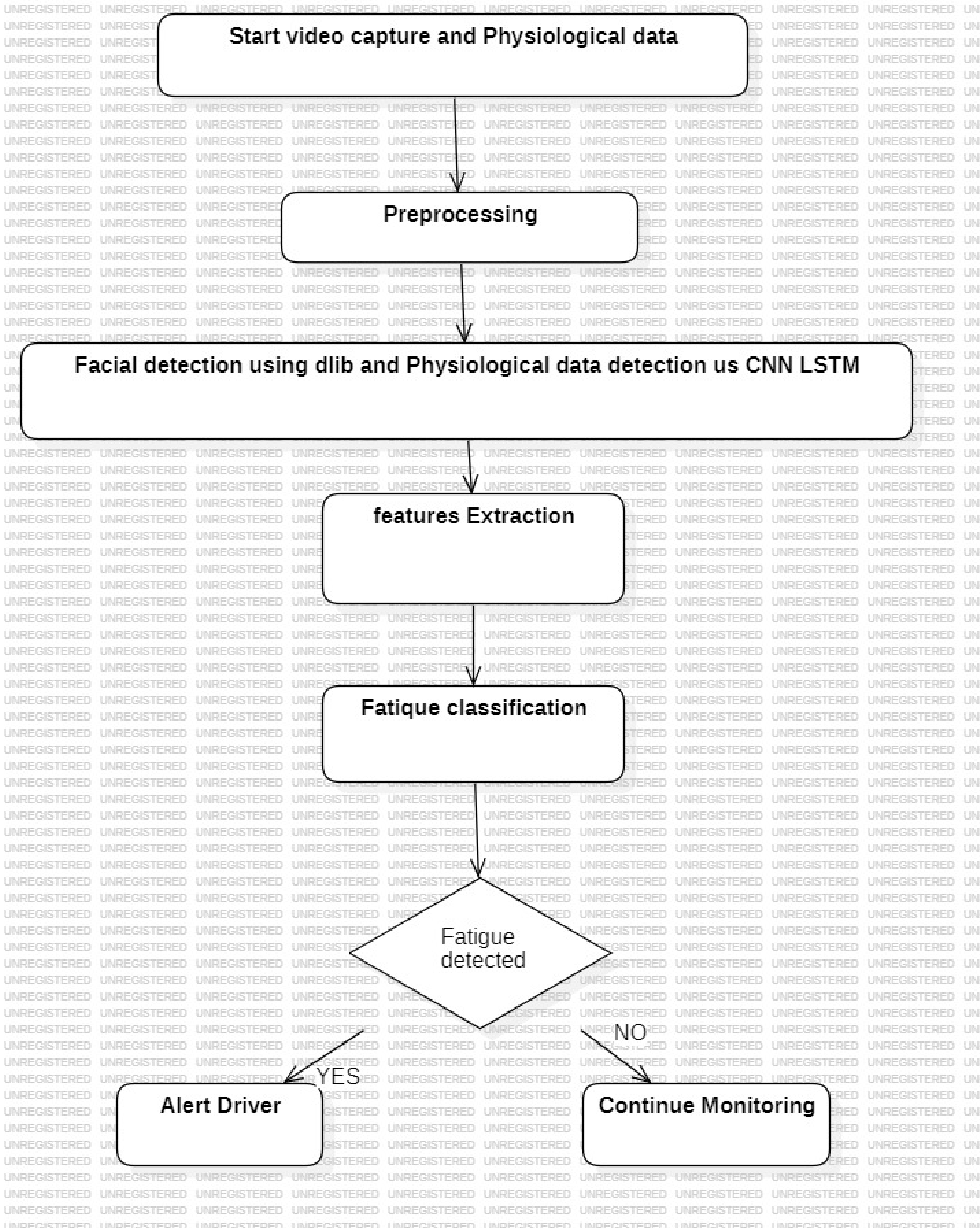

Figure 4.1: Block Diagram

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5. IMPLEMENTATION DETAILS

The fatigue detection system is implemented using Python with OpenCV and Dlib for facial landmark detection and TensorFlow for the CNN-LSTM model. It processes both facial and physiological data to classify fatigue levels. Features like eye and mouth ratios and sensor signals are analyzed to detect drowsiness. Alerts are triggered within 3–5 seconds. The system achieves high accuracy and can be deployed on devices like Raspberry Pi for real-time use.

5.1. Technology Stack

The system is primarily implemented using Python, leveraging a combination of machine learning and image processing libraries. OpenCV is used for real-time video stream processing, while Dlib is responsible for extracting 68 facial landmarks, which are essential for calculating fatigue indicators like Eye Aspect Ratio (EAR) and Mouth Opening Ratio (MOR). TensorFlow and Keras are used to build and train the CNN-LSTM models for analyzing physiological signals. Supporting libraries such as NumPy, Pandas, and Scikit-learn are employed for data manipulation, preprocessing, and feature selection. Physiological signals are captured using sensors that monitor EEG, EMG, HRV, and skin conductance.

5.2. System Architecture

The architecture of the system consists of two main input sources: a camera for facial monitoring and wearable sensors for physiological data collection. The facial data is processed using Dlib to detect eye and mouth movements, while the sensor data undergoes filtering and feature extraction. A CNN processes spatial characteristics of the physiological data, and LSTM captures temporal patterns to classify the driver's fatigue state. These outputs are combined into a four-class system (00 – normal, 01 – drowsy, 10 – fatigued, 11 – severely fatigued) which is used to trigger real-time alerts within 3 to 5 seconds of fatigue detection.

5.3. User Interface

Although the paper doesn't provide a detailed description of the UI, a practical implementation could feature a dashboard displaying a live camera feed with facial landmark overlays, fatigue status, and real-time notifications. This interface could be built using desktop GUI frameworks like Tkinter or PyQt, or web technologies such as Flask or Streamlit for remote monitoring. The alert system would also integrate sound or vibration feedback mechanisms to immediately notify the driver.

5.4. Integration

Sensor integration is handled through USB or Bluetooth connections, allowing real-time data collection. The system synchronizes facial and physiological data streams to analyze them simultaneously. Outputs from both modalities are fused using decision logic to improve detection reliability. The system is designed to be modular, making it suitable for integration into modern vehicles. Future integration with vehicle control systems (e.g., automatic braking, steering assistance) or external IoT devices (e.g., driver's smartphone or fleet management systems) is also envisioned.

5.5. Security

While not explicitly covered in the paper, implementing security measures is vital for deployment. Facial and physiological data are highly sensitive, so encryption for data in transit and at rest should be used. On-device processing is recommended to enhance privacy by avoiding unnecessary cloud transmission. Access controls, data anonymization, and user consent mechanisms would also be necessary in real-world applications, especially in commercial or shared vehicle environments.

5.6. Testing and Deployment

The system was tested using datasets such as NTHU (for facial features) and SEED-VIG (for EEG signals). Evaluation metrics include accuracy (98.5%), precision, recall, and F1-score, confirming high performance. Real-world tests validated the system's ability to detect fatigue with a response time of 3–5 seconds. For deployment, the system can be integrated into vehicles using edge computing platforms such as Raspberry Pi or NVIDIA Jetson Nano, which are capable of handling real-time deep learning inference efficiently. The model's low false positive rate and high detection speed make it practical for both personal and commercial vehicle integration.

CHAPTER - 6

6. OBSERVATIONS

6.1. Time Domain - Gannt Chart

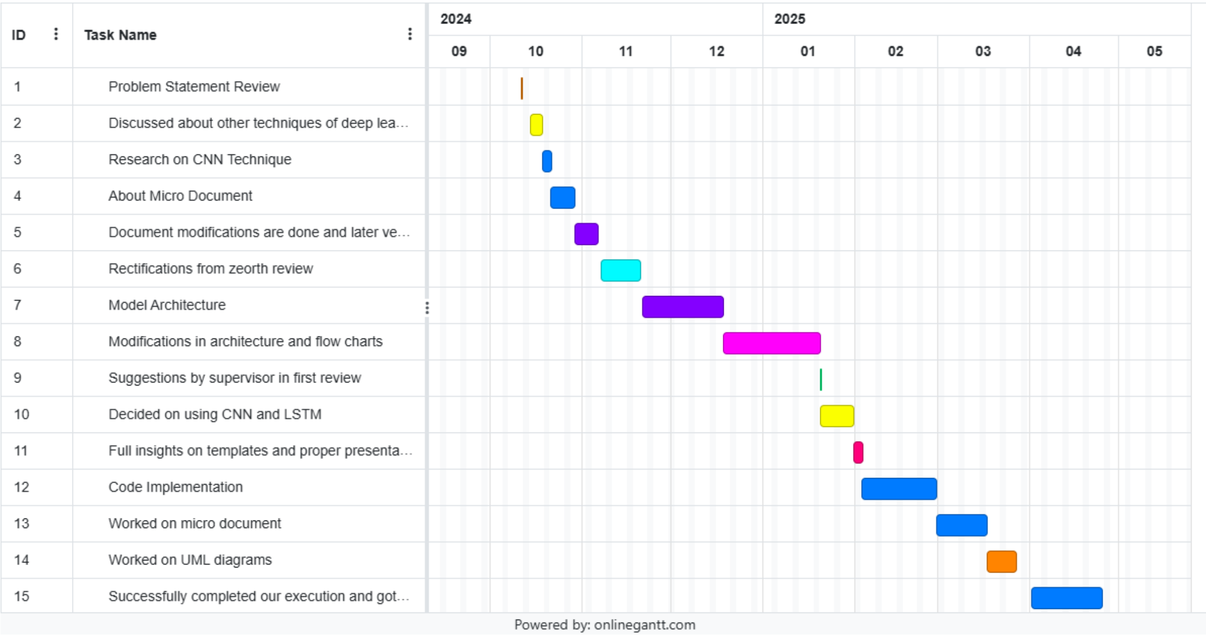

Figure 6.1: Gannt Chart.

6.2. Results and Comparitive Study

Metric	**CNN+LSTM (Sensor Data)**	**Dlib (Facial Detection)**	**Integrated Model**
Accuracy	94.2%	95.1%	98.5%
Precision	93.5%	94.7%	97.8%
Recall	92.8%	93.9%	97.2%
F1-Score	93.1%	94.3%	97.5%

Table 6.1: Performance comparison of different models.

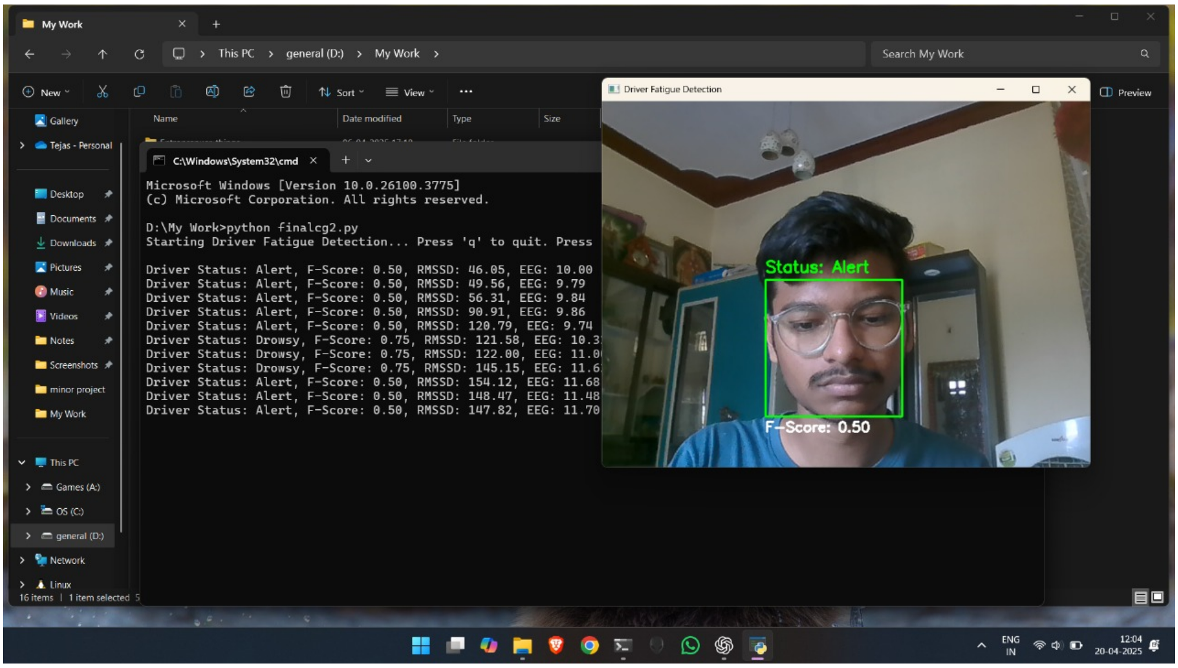

Figure 6.2: Tells Driver is alert

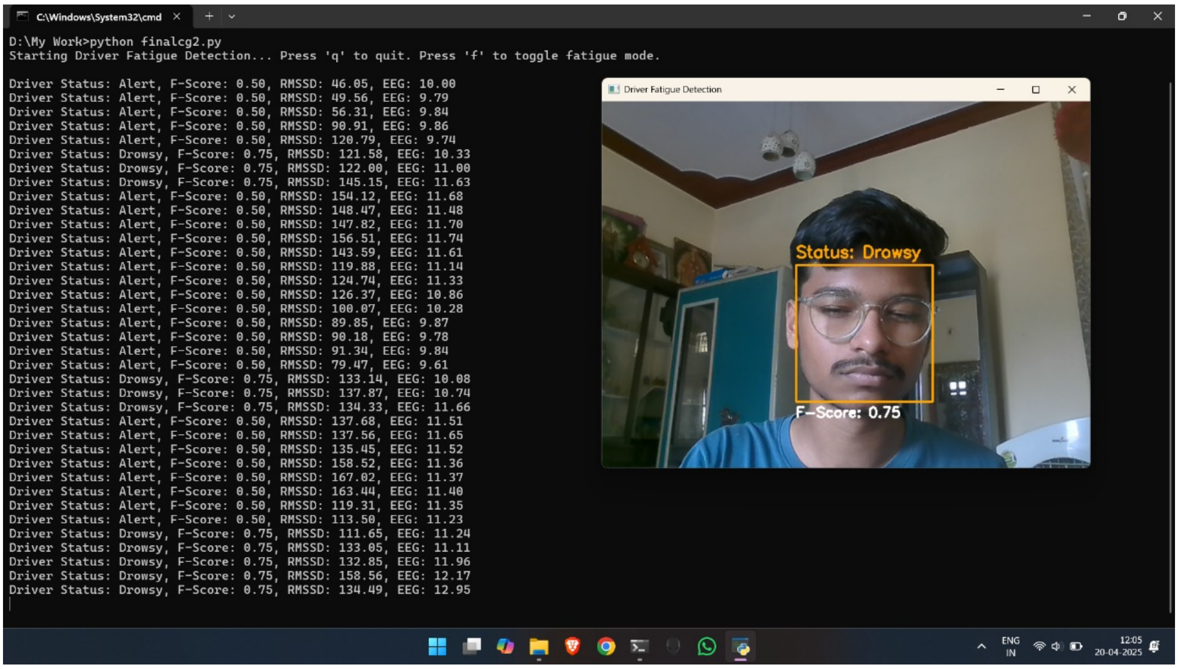

Figure 6.3: Tells Driver is Drowsy

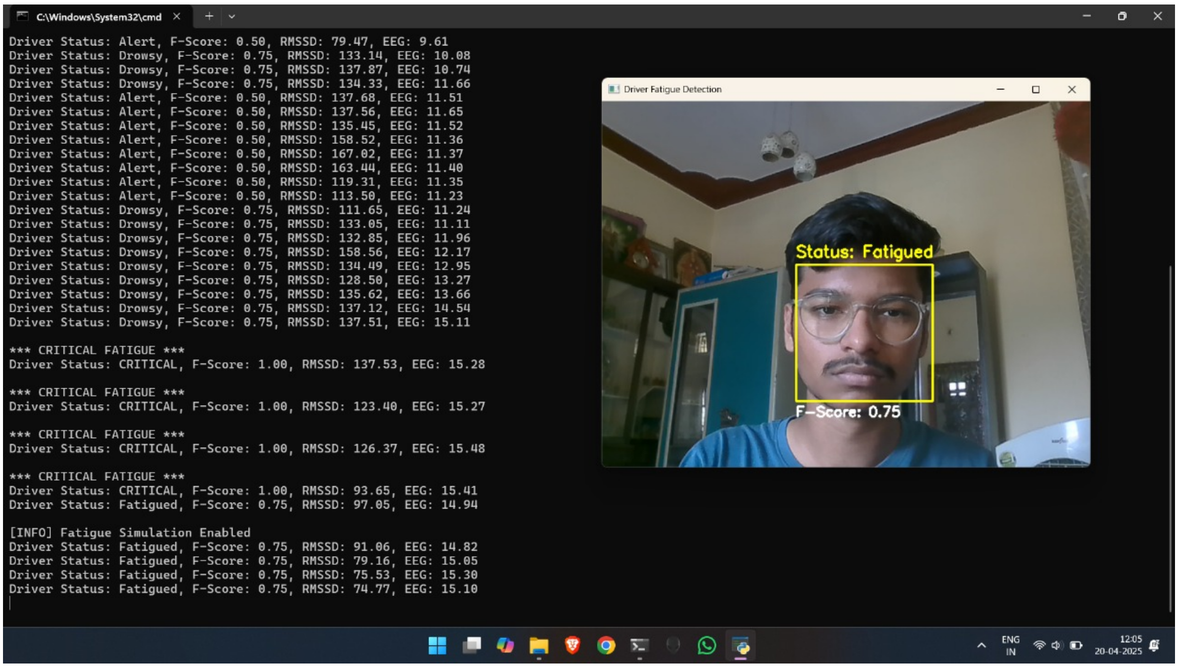

Figure 6.4: Tells Driver is Fatigue

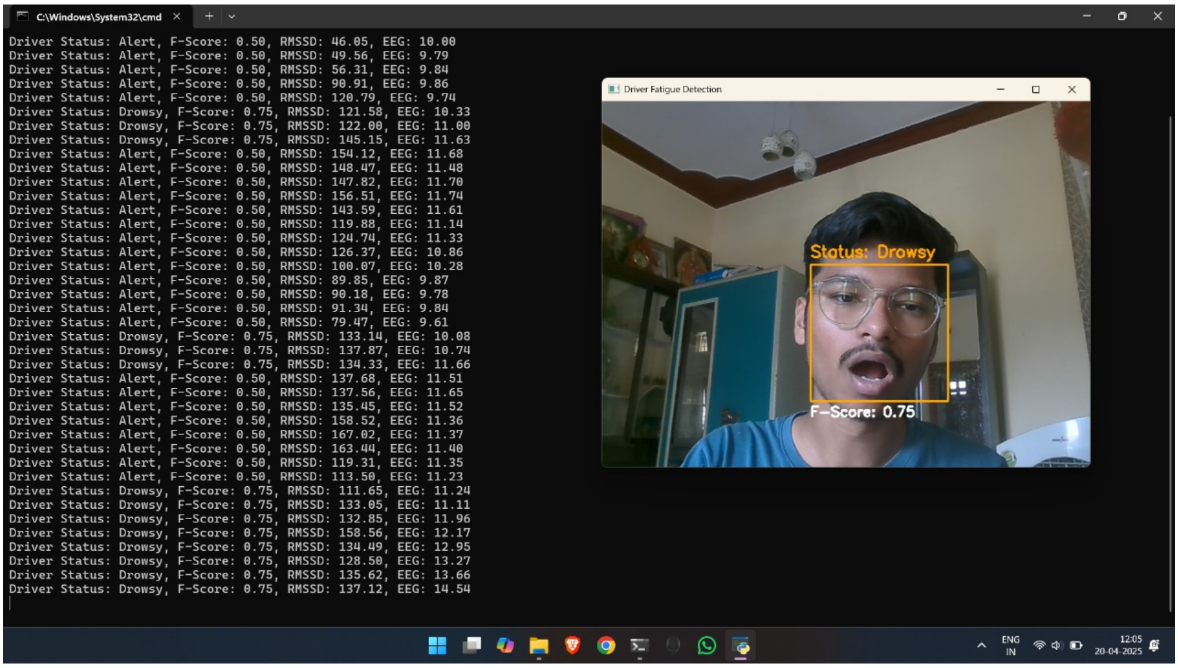

Figure 6.5: Tells Driver is Drowsy

CHAPTER - 7

7. Discussion

The proposed multi-modal fatigue detection system shows high accuracy by combining CNN-LSTM models for physiological data with Dlib-based facial analysis. However, its performance is affected by practical limitations. Issues like poor lighting, facial occlusions (e.g., masks, glasses), and natural head movements can reduce facial detection accuracy. Wearable sensors, though effective, may cause discomfort and are not ideal for long-term use. Additionally, the system's reliance on high computational resources and small, controlled datasets limits its generalization and real-time usability in real-world conditions.To address these challenges, future improvements include using infrared cameras, enhancing datasets with real-world driving data, incorporating edge computing for faster processing, and developing more user-friendly wearable sensors. Adaptive models and attention mechanisms can also improve accuracy and reduce false alerts. These enhancements will help create a more reliable and deployable fatigue detection system for everyday use.

CHAPTER - 8

8. CONCLUSION

we suggested a multi-model driver fatigue detection system in this study that combines CNN+LSTM for physiological data analysis with D-lib-based facial recognition. In order to detect symptoms of weariness and drowsiness, the system efficiently processes EEG, EMG, HRV, and skin conductance information in addition to facial landmark identification. Our combined method uses real-time feature extraction and deep learning approaches to achieve a high accuracy rate (98%). The technology ensures prompt alerts to avoid mishaps by processing input data in 3–5 seconds. By distinguishing between physical exhaustion and drowsiness, the four-state categorization model (00, 01, 10, 11) improves early warning capabilities and increases precision.

Real-time multi-model fatigue detection that combines facial and physiological information is one of the main contributions. CNN+LSTM and Dlib for deep learning-based decision making. prompt alert system to alert drivers before collisions happen. Future scope: Adding more real-world driving scenarios to the data set to improve generalization. lowering latency by integrating edge computing for on-device processing. investigating wearable sensor technologies for ongoing observation. By improving the accuracy of driver monitoring and offering prompt interventions to stop fatigue-related incidents, this technology promotes road safety.

CHAPTER - 9

9. LIMITATIONS AND FUTURE ENHANCEMENTS

9.1. Limitations

This project is highly planned and acted upon from the beginning. Nevertheless, the project had to face some of the limitations due to various factors. Different aspects of the projects such as nature of data, visualisation methods, data storage method and so on have their own limitations. Some of the limitations faced by the project are:-

1. Facial landmark detection accuracy drops in low-light or high-glare conditions, reducing system reliability during nighttime or tunnel driving.

2. Normal head movements (like mirror-checking) can be mistaken for fatigue-related behavior due to lack of context-awareness in the system.

3. Sunglasses, masks, hats, and other accessories obstruct key facial features like eyes and mouth, causing incorrect drowsiness predictions.

4. Continuous use of wearable physiological sensors like EEG, EMG, HRV, and skin conductance is uncomfortable and impractical for daily or long-term use.

5. CNN-LSTM models used for fatigue detection require high computational power, making them difficult to deploy in real-time on embedded or low-resource devices.

6. The training datasets are often small, controlled, and lack diversity, limiting the model's ability to generalize across different drivers and driving conditions.

7. Many systems focus solely on visible signs of fatigue, overlooking mental or cognitive fatigue which can also impair driving.

8. Some current systems take 10–20 seconds to confirm and alert fatigue, which may be too late to prevent potential accidents.

9. External noise, lighting changes, or individual behavior patterns (e.g., naturally slow blinking) can trigger false alarms, reducing system credibility.

10. Single-modality systems relying only on visual cues or sensor data are unable to capture the complete range of fatigue symptoms effectively.

9.2. Future Enhancements

Future enhancements for the driver fatigueness detection can be planned to further improve its capabilities and address emerging needs. Some potential areas for enhancement include:

1. Expand the dataset with real-world driving data in diverse conditions (weather, lighting, traffic) to improve model robustness and accuracy.

2. Implement edge computing (e.g., Raspberry Pi, Jetson Nano) to enable low-latency, real-time processing directly in the vehicle.

3. Develop lightweight, flexible, and comfortable wearable sensors for physiological monitoring that are suitable for long-term driver use.

4. Integrate infrared (IR) cameras to improve face and eye detection under poor or no lighting, especially during night driving.

5. Use attention mechanisms in CNN-LSTM models to prioritize the most relevant features, improving performance and reducing unnecessary computations.

6. Enable connectivity with other vehicle systems and IoT devices to trigger proactive actions like slowing the car or notifying emergency contacts.

7. Create multi-stage alert systems that vary in intensity (sound, vibration, visuals) depending on the detected level of fatigue (mild, moderate, severe).

8. Introduce adaptive learning where the system personalizes fatigue thresholds over time based on individual driver habits and responses.

9. Add real-time feedback options for drivers to confirm or dismiss alerts, helping refine model accuracy through supervised learning.

10. Employ advanced fusion techniques (e.g., autoencoders, decision-level fusion) to more effectively combine sensor and visual data for better decision-making.

A. APPENDIX

A.1. References

References

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A.2. Project Timeline Table

Driver Fatigueness Detection: 11 october 2024 to 26 april 2023

date what discussed what actions taken

Table A.1: Project Time Line.

Date	What Discussed	What Actions Taken
11-10-2024	Problem Statement Review	Reviewed and finalized problem statement
14-10-2024	Deep learning techniques	Explored alternative methods
18-10-2024	Research on CNN	Studied CNN techniques
21-10-2024	Micro Document	Drafted initial document
29-10-2024	Document modifications	Verified by guide
07-11-2024	Zero-th review rectifications	Addressed feedback
21-11-2024	Model architecture	Designed initial structure
18-12-2024	Architecture modifications	Updated flowcharts
20-01-2025	Supervisor suggestions	Implemented changes
20-01-2025	CNN and LSTM decision	Finalized methods
31-01-2025	Presentation templates	Prepared final templates
03-02-2025	Code implementation	Started coding
28-02-2025	Micro document updates	Revised document
17-03-2025	UML diagrams	Created and refined
10-04-2025	Execution and documentation	Finalized project

A.3. Coding

https://github.com/TejasKumar-4