DRIVER DROWSINESS DETECTION USING DEEP LEARNING

A DESIGN PROJECT REPORT

submitted by

SHAM JOSEPHRAJ W

SESHANTH B

YOGESH WARAN T K

in partial fulfilment 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, Approved by AICTE, New Delhi)

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(AUTONOMOUS)

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BONAFIDE CERTIFICATE

Certified that this project report titled **"DRIVER DROWSINESS DETECTION USING DEEP LEARNING"** is bonafide work of **SHAM JOSEPHRAJ W (811722104140), SESHANTH B (811722104137), YOGESHWARAN T K (811722104189)** 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.

SIGNATURE	**SIGNATURE**
Dr A Delphin Carolina Rani M.E.,Ph.D.,	Mrs. M. Mathumathi, M.E.,
HEAD OF THE DEPARTMENT	**SUPERVISOR**
PROFESSOR	Assistant Professor
Department of CSE	Department of CSE
K Ramakrishnan College of Technology	K Ramakrishnan College of Technology
(Autonomous)	(Autonomous)
Samayapuram – 621 112	Samayapuram – 621 112

Submitted for the viva-voice examination held on ………………

INTERNAL EXAMINER **EXTERNAL EXAMINER**

DECLARATION

We jointly declare that the project report on **"DRIVER DROWSINESS DETECTION USING DEEP LEARNING"** 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 fulfilment of the requirement of the awardof Degree of Bachelor Of Engineering.

Signature

SHAM JOSEPHRAJ W

SESHANTH B

YOGESH WARAN T K

Place: Samayapuram

Date:

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ABSTRACT

Driver drowsiness is a critical factor contributing to road accidents. This research proposes a novel approach for driver drowsiness detection using deep learning techniques. A convolutional neural network (CNN) is employed to analyze facial features and monitor driver behavior in real-time. The system processes input from in-vehicle cameras, extracting relevant features such as eye closure, head movement, and facial expressions. By training the model on a diverse dataset, it learns to accurately classify the driver's alertness level. The proposed method demonstrates promising results in accurately identifying drowsy states, providing a proactive mechanism for timely intervention. This research contributes to enhancing road safety by leveraging advanced deep learning methodologies for real-time monitoring of driver drowsiness, paving the way for the integration of intelligent systems in vehicles to prevent potential accidents caused by driver fatigue. To enhance the system's adaptability, we incorporate transfer learning, enabling the model to generalize across different individuals and environmental factors.

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LIST OF ABBREVIATIONS

ABBREVATION	FULL FORM
IDE	Integrated Development Environment
CNN	Convolutional Neural Networks
RNN	Recurrent Neural Networks
SSD	Single Shot Multi Box Detector
SGD	Stochastic Gradient Descent
EAR	Eye Aspect Ratio
GPU	Graphics Processing Units
AU	Action Units
EOG	Electrooculogram

CHAPTER 1

INTRODUCTION

Drowsiness while driving tends to vehicle crashes and accidents. Many people die in car collisions every year due to fatigued driving that results from sleeping deprivation, intoxication, drug and alcohol abuse, and exposure to heator alcohol. Automobile manufacturers such as Tesla, Mercedes-Benz, and others have various features for driving assistance such as of lane deviation, emergency braking systems, variable cruise control, a Daid steering. These innovations have assisted drivers in avoiding the incidence of collisions. Samsung has investigated the attention level of a driver by reading facial characteristics and pattern.

At the same time, most of these technologies are proprietary and restricted to high-end cars. These drowsiness identification processes can be divided depending on some of the methods like based on the context of vehicle, behavioral & physiological. Multiple methods for the identification of drowsiness have been developed in the past. Based on vehicle based, drowsiness identification processes are performed for monitoring the lane switches, steering wheel spin, velocity, compressions on the accelerator pedal. These approaches include measurement of driver physiological signals, performance assessment based on vehicles, and recording behavior.

The bio-signal measurement method demonstrated the highest ability to detect driver drowsiness among these techniques: unlike the other two approaches, it relies solely on the state of the driver. Based on behavior like specific eye closure, yawn, and head posture, drowsiness identification processes need a camera. Another step based on physiological drowsiness identification processes works by monitoring the tiredness to relate between their physiological signals.

The limitation of drowsiness identification processes using the physiological method is that the diver needs to contain electrodes on their body. There is a substantial restriction based on vehicle-based drowsiness identification, such as they are prone to forces connected to drivers and vehicles, road situations.

There are many techniques stated in different literature those has some restrictions and several benefits. The aim of this research is to propose a cost- effective procedure to identify the drowsiness among divers while driving vehicles. To develop the drowsiness detector application, we have used a CNN architecture. This work can be divided into two parts based on the main contribution:(a) Convolutional neural networks to identify right drowsiness identification processes based on object detection, (b) and drowsy datasets to help the researchers for drowsiness identification method.

1.1 PURPOSE

The purpose a project focused on driver drowsiness detection using deep learning is to enhance road safety by leveraging advanced technology to monitor and mitigate the risks associated with driver fatigue. The primary objectives and purposes of such a project include the fundamental goal is to prevent accidents caused by drowsy driving, which is a significant contributor to road accidents. By detecting signs of driver drowsiness in real-time, the system aims to intervene before a potential accident occurs. Prioritize the safety and well-being of drivers by providing a proactive system that alerts them when they exhibit signs of drowsiness.

This, in turn, helps prevent accidents and reduces the likelihood of injuries or fatalities. Protect not only the drowsy driver but also other road users, pedestrians, and passengers. By minimizing the risks associated with drowsy driving, the project contributes to creating safer road environments for everyone. Data Collection in Datasets are gathered, containing images or videos of drivers exhibiting different levels of alertness and drowsiness. These datasets are used to train the deep learning models.

Feature Extraction in Deep learning models analyze various facial features, such as eye closure, head pose, blinking rate, yawning, etc., to recognize patterns associated with drowsiness. Model Training in Deep neural networks like Convolutional Neural Networks (CNNs) or Recurrent Neural Networks (RNNs) are trained on these features to learn the patterns and characteristics of drowsiness from the collected data.

1.2 PROBLEM DEFINITION

Driver drowsiness is a critical issue that poses a significant risk to road safety. The objective of this project is to develop a robust and accurate driver drowsiness detection system using deep learning techniques. The system should be capable of monitoring a driver's behavior and alerting them when signs of drowsiness are detected, thereby reducing the likelihood of accidents caused by impaired driving due to fatigue. Implement adaptive thresholds for drowsiness detection based on factors such as time of day, driving conditions, and individual driver characteristics.

Consider incorporating machine learning techniques to dynamically adjust the sensitivity of the system to reduce false alarms and enhance accuracy. Explore the integration of multiple modalities, such as facial expressions, eye movement,and physiological signals (if available), to improve the robustness of the drowsiness detection system. Investigate fusion techniques that combine information from different sources to make more informed predictions.

1.3 FEATURES

Driver drowsiness detection using deep learning, several features extracted from various data sources like images or videos are used to identify signs of drowsiness or fatigue in drivers. These features play a crucial role in training models to recognize patterns associated with drowsiness. Facial Landmarks Detection in analyzing facial landmarks such as eyes, mouth, nose, and eyebrows to track changes in expressions and movements. Eye Closure and Eye Aspect Ratio (EAR) in Monitoring eye closure and calculating the EAR to detect changes in eye openness, which is indicative of drowsiness. EAR measures the ratio of eye landmark distances and can indicate when eyes are closing.

Blink Rate and Duration in Measuring the frequency and duration of blinks to detect patterns of prolonged eye closures, which occur during drowsiness. Pupil Diameter Variation in tracking changes in pupil size, as drowsiness can cause changes in pupil dilation due to fatigue. Facial Action Units (AUs): Identifying facial action units related to drowsiness, such as drooping eyelids, mouth opening, or yawning. Head Movements and Orientation: Analyzing head position and sudden movements, as nodding or tilting of the head are common signs of drowsiness. Yawning Detection Recognizing yawning patterns, often associated with fatigue or drowsiness. Eye Gaze Tracking: Monitoring the direction and focus of the driver's gaze, identifying wandering or unfocused gazepatterns.

Physiological Signals in Integrating physiological signals like heart rate variability, EEG signals, or other biometric data for a more comprehensive understanding of the driver's state. Temporal Analysis in considering changes in the above features over time to detect gradual patterns of drowsiness. Ethical considerations, privacy compliance, and ensuring participants' informed consent are integral aspects of the project, maintaining the ethical standards.

Continuous monitoring systems are established to capture spontaneous instances of drowsiness during drivers' regular driving routines. Integration of sensor data, such as accelerometers, gyroscopes, or heart rate monitors, supplements the dataset, providing complementary information about the driver's physiological state. Real-time processing capabilities are pivotal for issuing timely alerts or warnings to drowsy drivers. Therefore, the system is optimized for efficient computation and processing to enable swift decision making and intervention. The project also emphasizes model interpretability, aiming to create transparent systems that provide insights into decision-making processes, ensuring user trust and understanding.

Continuous improvement and refinement of the system through periodic model updates, dataset enhancements, and advancements in deep learning techniques are integral components of the project, aiming to achieve superior accuracy, reliability, and adaptability in real-world driving environments. Ultimately, the project features are intricately designed to create a comprehensive and effective driver drowsiness detection system, contributing significantly to road safety by preventing accidents caused by drowsy driving incidents.

1.4 MODULE DESCRIPTION

1.4.1 DATA GATHERING

Driver drowsiness detection using deep learning requires diverse and comprehensive datasets for effective model training. Gathering relevant data involves capturing various instances of drivers displaying different levels of alertness and drowsiness. Video Recordings in recording videos of drivers in different driving scenarios and conditions. These videos should capture a wide range of facial expressions, eye movements, head poses, and other relevant features that indicate drowsiness.

Cameras installed within vehicles or specific setups for recording driver behavior are used. Diverse Driver Profiles in collecting data from a diverse set of drivers, including individuals of different ages, genders, ethnicities, and with varying driving experiences. This diversity helps in creating a robust and inclusive model that can generalize well across different demographics. Annotation and Labeling in Annotating the collected videos or images to label instances of drowsiness and alertness. Human annotators can mark specific time intervals or frames where a driver displays signs of drowsiness, such as yawning, closed eyes, head nodding, etc.

Simulated Data in Generating synthetic data to supplement real-world data. Simulated data can help in augmenting the dataset and introducing variability in driving conditions, lighting, weather, and other factors that affect driver behavior. Ethical Considerations and Privacy in ensuring compliance with ethical standards and privacy regulations when collecting data from individuals. Obtaining informed consent and anonymizing sensitive information is crucial to protect the privacy of the drivers involved in data collection. Continuous Monitoring in Setting up systems for continuous monitoring of drivers during their regular driving routines to capture natural and unscripted instances of drowsiness.

In-the-wild Data Collection in Capturing data from real-world driving scenarios to ensure the model is trained on a diverse range of situations and environments, including highways, urban roads, different times of day, and varying traffic conditions. Sensor Data Integration in Incorporating data from additional sensors, such as accelerometers, gyroscopes, heart rate monitors, or EEG sensors, to gather complementary information about the driver's physiological state. Dataset Balance and Representation: Ensuring a balanced representation of drowsy and alert states in the dataset to prevent biases and ensure the model can accurately distinguish between the two states.

Data gathering for driver drowsiness detection involves the meticulous collection of various instances portraying different levels of alertness and drowsiness in drivers. The process typically begins by setting up recording systems, such as cameras or sensors, within vehicles to capture real-time video footage or images of drivers during their driving activities. These recordings encompass diverse driving scenarios, including highways, urban roads, varying weather conditions, and different times of day. The collected data sources include facial expressions, eye movements, blinking patterns, head poses, and potentially additional physiological signals like heart rate or EEG data.

Human annotators meticulously label these datasets, marking specific instances or time intervals where drowsiness-related behaviors are observed, such as yawning, closed eyes, or head nodding. Ethical considerations and privacy concerns are paramount during data collection. Simulated data generation is employed to complement real-world datasets, simulating diverse driving conditions, lighting variations, and driver behaviors that might not be readily captured in real-life scenarios. This augmented data helps in enhancing the dataset's diversity and generalization capability for training robust deep learning models. Continuous monitoring systems are established to capture spontaneous instances of drowsiness during drivers' regular driving routines. This approach ensures the collection of unscripted and natural occurrences of drowsiness, contributing to a more comprehensive understanding of the phenomenon.

1.4.2 DATA PREPROCESSING

Driver drowsiness detection using deep learning requires diverse and comprehensive datasets for effective model training. Gathering relevant data involves capturing various instances of drivers displaying different levels of alertness and drowsiness. Video Recordings in recording videos of drivers in different driving scenarios and conditions. These videos should capture a wide range of facial expressions, eye movements, head poses, and other relevant features that indicate drowsiness. Cameras installed within vehicles or specific setups for recording driver behavior are used. Human annotators can mark specific time intervals or frames where a driver displays signs of drowsiness, such as yawning, closed eyes, head nodding, etc.

Data preprocessing in driver drowsiness detection involves cleaning, normalization, and feature extraction from images or videos capturing facial expressions, eye movements, and head poses. It includes resizing images to a consistent resolution, converting color images to grayscale, and normalizing pixel values for improved convergence during training. Feature extraction techniques focus on facial landmarks, eye closure, blinking rates, and head movements, while also handling temporal sequences and augmenting data for variability.

Furthermore, careful annotation of the dataset is imperative, marking regions of interest like eyes and facial features. Feature extraction techniques, such as convolutional layers, may be employed to capture relevant patterns. Lastly, data splitting into training, validation, and testing sets is essential for model evaluation.

By employing meticulous data preprocessing, the deep learning model can effectively learn and generalize from the dataset, contributing to the accuracy and reliability of driver drowsiness detection systems.

CHAPTER 2

LITERATURE SURVEY

2.1 TITLE : Miros crash investigation and reconstruction

AUTHORS: Z. Ahmad Noor Syukri, M. Siti Atiqah, L. Fauziana

YEAR: 2021

Pillared by three research centers that cover three main aspects of road safety—roads, vehicles and human issues—MIROS' crash investigation operation is under the responsibility of the Vehicle Safety and Biomechanics Research Centre (VSB). Under the center, the management of the operation is organised by a unit known as the Crash Reconstruction Unit (CRU). The primary purpose of MIROS' crash investigation is to identify in detail as many factors as possible that contribute to crashes and the resulting injuries to occupants, particularly factors that have not been previously identified. This process is expected to lead to the development of countermeasures that will help to reduce the human and economic impact of road crashes on Malaysian society.

2.2 TITLE : Drowsy driver detection system using eye blink patterns

AUTHORS: T. Danisman, I. M. Bilasco, C. Djeraba**.**

YEAR: 2022

This paper presents an automatic drowsy driver monitoring and accident prevention system that is based on monitoring the changes in the eye blink duration. Our proposed method detects visual changes in eye locations using the proposed horizontal symmetry feature of the eyes. Our new method detects eye blinks via a standard webcam in real-time at 110fps for a 320×240 resolution. Experimental results in the JZU eye-blink database showed that the proposed system detects eye blinks with a 94% accuracy with a 1% false positive rate.

2.3 TITLE : Vision based drowsiness detection for realistic driving

AUTHORS: I. Garcia, S. Bronte, L. Bergasa

YEAR: 2022

This paper presents a non-intrusive approach for drowsiness detection, based on computer vision. It is installed in a car and it is able to work under real operation conditions. An IR camera is placed in front of the driver, in the dashboard, in order to detect his face and obtain drowsiness clues from their eyes closure. It works in a robust and automatic way, without prior calibration. The second stage performs pupil position detection and characterization, combining it with an adaptive lighting filtering to make the system capable of dealing with outdoor illumination conditions. In order to evaluate this system, an outdoor database was generated, consisting of several experiments carried out during more than 25 driving hours. A study about the performance of this proposal, showing results from this testbench, is presented.

2.4 TITLE : A drowsy driver detection system

AUTHORS: R. Grace, V. E. Byrne, D. M. Bierman

YEAR: 2023

Drowsiness and fatigue are one of the main causes leading to road accidents. They can be prevented by taking effort to get enough sleep before driving, drink coffee or energy drink, or have a rest when the signs of drowsiness occur. The popular drowsiness detection method uses complex methods, such as EEG and ECG. This method has high accuracy for its measurement but it need to use contact measurement and it has many limitations on driver fatigue and drowsiness monitor [18]. Thus, it is not comfortable to be used in real time driving. This paper proposes a way to detect the drowsiness signs among drivers by measuring the eye closing rate and yawning.

CHAPTER 3
SYSTEM ANALYSIS

3.1 EXISTING SYSTEM

These systems predominantly employ Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), or hybrid architectures to extract meaningful features from drivers' facial expressions, eye movements, blinking rates, head poses, and occasionally, physiological signals. Diverse datasets comprising images or videos capturing drivers in various driving scenarios, lighting conditions, and environmental settings are pivotal for training models to differentiate between alert and drowsy states. Facial landmark detection, eye closure analysis, blink frequency measurement, and head movement tracking are among the core techniques used for feature extraction.

Performance evaluation metrics such as accuracy, precision, recall, F1- score, and area under the curve (AUC) often demonstrate commendable classification accuracy, typically surpassing 85-90%. However, challenges persist in ensuring the robustness and generalization capabilities of these models across different individuals and diverse driving conditions. Variability in drowsiness responses among drivers, limited availability of comprehensive and annotated datasets, and the need for model adaptability to varying lighting and environmental conditions are significant hurdles.

Real-time processing requirements for timely alerts and addressing privacy concerns associated with continuous driver monitoring further complicate the deployment of these systems in real-world settings. Research gaps highlight the necessity for standardized datasets encompassing diverse driving scenarios and populations, along with exploration into multimodal approaches integrating visual and physiological signals to enhance detection accuracy.

3.2 PROPOSED SYSTEM

Driver drowsiness detection via deep learning has garnered extensive attention in enhancing road safety by mitigating accidents caused by driver fatigue. Literature in this domain predominantly explores various deep learning architectures such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and hybrid models, aiming to detect signs of drowsiness from facial expressions, eye movements, blinking rates, head poses, and physiological signals. Numerous studies leverage diverse datasets capturing drivers in different driving scenarios, lighting conditions, and environments. These datasets serve as training resources to distinguish between alert and drowsy states, with evaluation metrics like accuracy, precision, recall, F1-score, and area under the curve (AUC) showcasing considerable classification performance, often surpassing 85-90%.

However, persisting challenges include the variability in individual responses to drowsiness, limited availability of annotated datasets encompassing diverse driving conditions, and ensuring model robustness across varying environmental settings and lighting conditions. Real-time processing demands and privacy concerns associated with continuous driver monitoring pose significant hurdles in practical deployment. Research gaps highlight the need for standardized datasets representing various driving scenarios and populations, along with exploration into multimodal approaches integrating visual and physiological signals to enhance detection accuracy.

Additionally, there's a focus on improving real-time processing capabilities, model interpretability, and addressing privacy concerns for practical deployment. The existing literature demonstrates the potential of deep learning-based driver drowsiness detection systems in reducing drowsy driving- related accidents and enhancing road safety. However, continual advancements in deep learning techniques, dataset curation, and addressing challenges in deployment are imperative for further improving accuracy and reliability in real- world scenarios. Overall, these studies underscore the significance of employing advanced technology to prevent accidents caused by driver drowsiness, aiming to create safer roadways for all. Identified research gaps underscore the need for standardized datasets that encompass diverse driving scenarios and populations.

Additionally, researchers are exploring multimodal approaches that integrate visual and physiological signals to enhance detection accuracy. There's a concerted effort towards improving real-time processing capabilities, model interpretability, and addressing privacy concerns to facilitate the practical deployment of these systems. The existing literature signifies the potential of deep learning-based driver drowsiness detection systems in reducing accidents caused by drowsy driving, ultimately contributing to enhanced road safety. However, continual advancements in deep learning methodologies, dataset curation, and addressing deployment challenges are crucial to further improving the accuracy and reliability of these systems in real-world driving conditions. In essence, these studies collectively emphasize the pivotal role of leveraging sophisticated technological solutions to prevent accidents arising from driver drowsiness, ultimately striving to create safer roadways and improve overall driving safety for individuals worldwide.

CHAPTER 4

MODULES

4.1 ALGORITHM

It perceives that drowsiness detection is an object detection task. We use images from incoming video streams. From several techniques of deep learning, we use Mobile Nets, a lightweight convolutional neural network architecture, along with the Single Shot Multi box Detector (SSD) system that is on top of the Mobile Net architecture to experiment.

4.1.1 CONVOLUTIONAL NEURAL NETWORK (CNN)

The suggested system for detecting driver drowsiness is used in the Convolutional Neural Network (CNN). The pre-processing for CNN is much meager compared to others classification algorithms. CNN is a mathematical technique that usually consists of three kinds of pooling, convolution, and fully connected layers. The first two pooling layers are convolution handle extraction of features, and the third one is a completely connected layer, maps the characteristics extracted, such as classification, into the final output. In CNN, which consists of a set of logical operations, such as convolution, a technical method of linear motion, the convolution layer plays a key role.

In image data, two-dimensional arrays of pixel values are processed, andat each image location, a small parameter grid called the kernel and function extractor for optimization is added, making CNN"s highly effective for image processing since a feature can appear anywhere in the image. Extracted functionality will get more complex hierarchically and gradually as one layer feeds the output into the next layer. The way parameters such, as kernels are optimized is called planning. This can be achieved by a back propagation and gradient descent optimization algorithm to minimize the discrepancy.

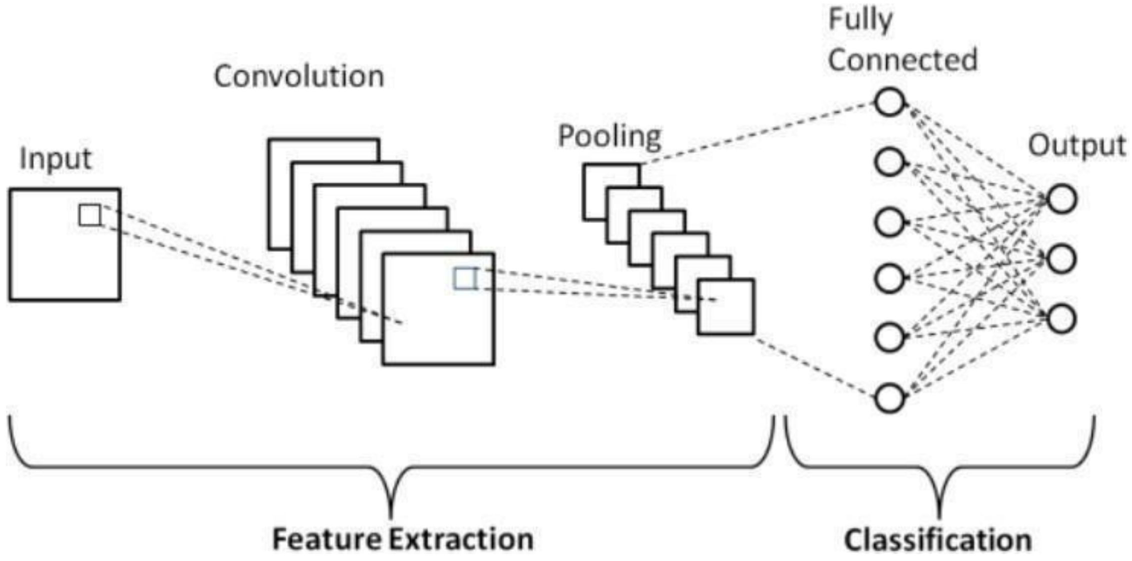

Fig 4.1 CNN Architecture

4.1.2 SINGLE SHOT MULTIBOX DETECTOR (SSD)

For our task, we use Mobile Nets a lightweight convolutional neural network architecture, along with the Single Shot Multi box Detector (SSD) system that is on top of the Mobile Net architecture. There are two types of algorithms used to detect typical objects. To define regions where objects can be found, RCNN and Faster RCNN algorithms use a two-step approach to identify objects only in certain regions.

Algorithms such as SSD and YOLO use a completely evolutionary method, on the other hand, through which the network will locate all items in a picture via the Conv Net in one pass. Usually, the algorithms for the region proposal have slightly better precision but are slower to run, whereas single-shot algorithms are more powerful and have satisfying precision.

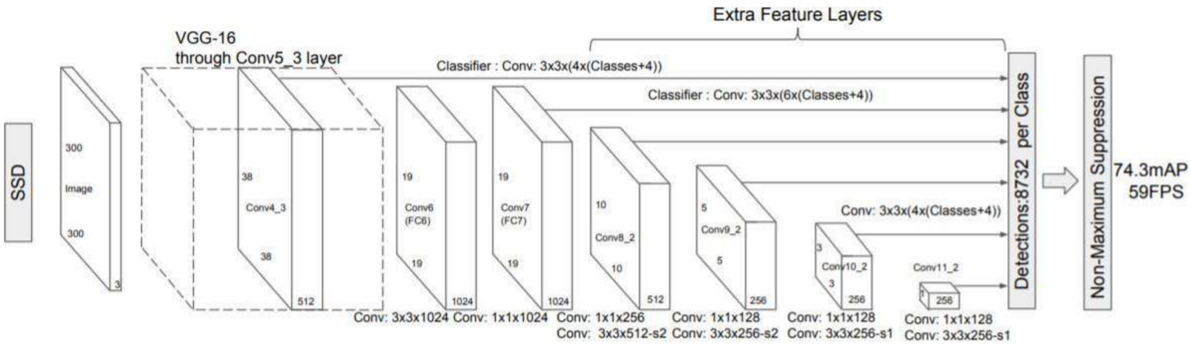

Fig 4.2 SSD Architecture

The SSD has two elements, a backbone model and an SSD head. The Backbone model is usually a pre-trained image classification network as a feature extractor. This network is educated on ImageNet such as Res Net which excludes the entirely connected classification layer. Therefore, we have a deep neural network that can infer semantic meaning from the input image while preserving the spatial structure in the image at a lower resolution. We will clarify the later feature and feature map. The SSD head is only one or more evolutionary layers attached to this backbone, and the outputs are represented as the bounding boxes and object groups in the final layer activation spatial role. There are some important parameters in SSD.

The SSD uses a grid (see Fig. 4.2) to divide the image rather than a sliding window, and each cell of the grid needs to detect the objects in that picture region. Object identification involves simply predicting the class and location of the object within the sector. We admire it as the context class if no object is present,and the location is ignored. Each grid cell is output to the position and the form of the entity it carries.

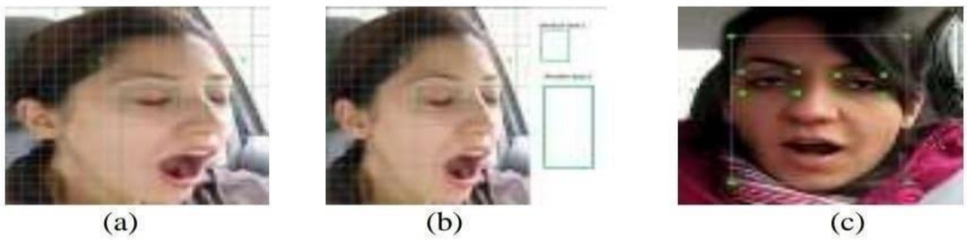

Fig. 4.3 (a) Grid View (b) Anchor Boxes (c) Higher and Lower Anchor Boxes

If many objects of different shapes exist in one grid cell, the anchor box (see Fig. 4.3(b)) and the responsive area are considered. There may be separate anchor boxes in the SSD for each grid cell. These anchor boxes are predefined, and each of them is responsible for the size and shape of a grid cell. The face in Fig. 4.3(c), for example, has the big anchor box while the eyes correspond to thesmall box. In training, the SSD framework utilizes a mapping step to align the correct anchor box with the bounding box inside an image of each ground truth entity. The anchor boxes with a greater degree of overlap with an object are ultimately responsible for estimating the class of that object and its position.

This property is used for preparing the network for detecting objects and their locations. In reality, an aspect ratio and a zoom level describe any anchor box. The objects are not always square those could be narrower, broader, or in varying degrees. With predefined aspect ratios, the SSD architecture requires the anchor boxes to account for this. The parameter ratios are used to determine the various aspect ratios of the anchor boxes at each scale level associated with each grid cell. It is not needed to have the same size as the grid cell for the anchorboxes. Inside the cell, we may select smaller or larger objects.

The zoom parameter is used to determine how much for each grid cell the anchor boxes need to be scaled up or down. The receptive field is defined as the area that a specific CNN function looks at in the input space. We have used "feature" and "activation" here and treat them at the corresponding position as the linear combination of the previous layer. Features on different layers reflect different area sizes in the input picture due to the convolution operation. The scale defined by a function grows bigger while going deeper. We begin with the bottom layer (5x5) in this example below and then add a convolution resulting in the middle layer (3x3), where one attribute represents a 3x3 area of the input layer. And then, add the middle layer convolution and get the upper layer (2x2) where each attribute on the input image corresponds to a 7x7 area. This type of green and orange 2D array is often referred to as feature maps that correspond to a group of features generated in a sliding window fashion by applying the same feature extractor at different input map locations.

The features in the same map of characteristics have the same receptive area and aim at different positions with the same pattern. The core concept of the SSD architecture helps to detect objects at varying scales and output a closer bounding box. As in the ResNet34 backbone outputs an input image function map of 256 7x7. The easiest solution is to define a 4x4 grid to add a convolution to thisfunction map and transform it to 4x4. In reality, this method will function to somedegree as the concept of YOLO. The additional step taken by SSD is to attach more convolutional layers to the map of the backbone feature and generate an object detection result for each of these convolution layers. Because earlier layerswith a smaller receptive field will reflect smaller objects, earlier layer predictionshelp with the smaller object.

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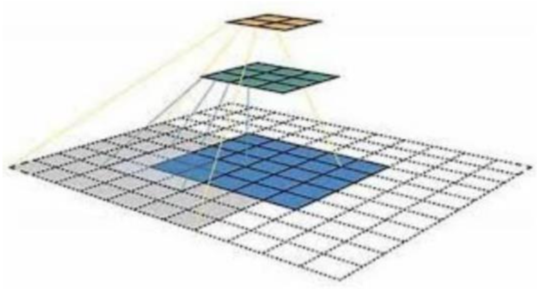

Fig.4.4 Convolutional Neural Network Feature Maps

4.1.3 MOBILENET

The architecture of Mobile Nets is designed for mobile based applications, is used for depth-wise separable convolutions, and builds lightweight deep neural networks. Except for the first layer, the Mobile Net is a separable convolution. A complete convolutional layer is the first layer. Batch normalization and Re LU non-linearity are accompanied by all the layers. The final layer, however, is a completely related layer without any non-linearity and feeds for classification to the soft max. For down sampling, stridden convolution is used for both deep convolution and the first fully evolutionary layer. The total number of layers for Mobile Net is 28, considering convolution as different layers in depth and stage. The MobileNet-SSD_v1 framework is capable of detecting multiple objects from an image. We trained it to see a human face for our drowsiness detection task to notice that the diver is yawn or no yawn and the eye open or close.

Yawn, no yawn, eye open and close were considering four separate classes. For this experiment, a regular camera is used for the incoming video stream. The technique suggested is exactly presented in. We observed that the longest length of a blink found equals 7.5 inches from the camera in the training model. From the video stream, we get an image frame, and this function is called image frames processed per second (FPS). The model would declare the driver to be drowsy if any of the driver's eyes are found close for ten consecutive frames in the incoming video stream, and an alarm will raise to wake the driver. The above approach uses only a single convolutional neural network and, thus, the total complexity of the system is much smaller. Now we need to see how well this recommended approach performs under driving environments in real life.

4.2 DATA COLLECTION

Collecting data for driver drowsiness detection using deep learning typically involves acquiring a dataset of images or videos that capture drivers in different states, including both alert and drowsy conditions. Here are the general steps for data collection:

4.2.1 DROWSINESS INDICATORS

Drowsiness indicators are observable and measurable signs that signify a decline in a person's wakefulness and alertness, often associated with the onset of drowsiness or fatigue. In the context of driver drowsiness detection using deep learning, these indicators manifest in various physiological and behavioral changes that can be visually captured. Common drowsiness indicators include but are not limited to drooping eyelids, prolonged eye closure, repeated yawning, slowed blinking rates, and changes in facial expressions. These indicators are reflective of the individual's diminishing cognitive and physical responsiveness, posing a potential risk, especially in activities that demand sustained attention, such as driving. By identifying and interpreting these indicators through advanced technologies, such as computer vision and deep learning algorithms, it becomes possible to develop automated systems capable of detecting and mitigating the risks associated with drowsy driving, thereby contributing to enhanced road safety.

4.2.2 CAMERA SETUP

Selecting an appropriate camera setup is a crucial aspect of developing an effective driver drowsiness detection system using deep learning. The choice of cameras significantly influences the quality and accuracy of the data captured, which, in turn, impacts the performance of the deep learning model. Ideally, the camera setup should provide clear and high-resolution images of the driver's face while considering practical considerations such as cost, installation ease, andreal- world deployment. Dashboard cameras, commonly known as dashcams, area popular choice for driver monitoring applications. These cameras are typically mounted on the vehicle's dashboard, facing the driver, and can capture a clear view of the driver's face and upper body.

Dashcams are widely available, cost-effective, and easy to install, making them suitable for various vehicle types. For more advanced applications, specialized eye-tracking cameras can be employed to focus specifically on the driver's eye movements and gaze direction. These cameras offer a higher level of precision in monitoring eye-related drowsiness indicators, such as blink patterns and eye closure duration. However, they may come with higher costs and installation complexities. In both cases, it's essential to ensure that the chosen camera setup provides adequate image quality under various lighting conditions, including daytime and nighttime driving. Additionally, considerations such as the camera's field of view, frame rate, and resolution should align with the requirements of the deep learning model being used.

The camera setup should be positioned to capture the driver's face without obstruction and should be securely mounted to minimize vibrations and ensure stable data capture. Ultimately, the camera setup should strike a balance between cost, practicality, and data quality.

4.2.3 DATA QUALITY CHECK

Data quality checks are an essential aspect of any machine learning project, including driver drowsiness detection using deep learning. Ensuring the reliability and accuracy of the dataset is crucial for building a robust and effectivemodel. Data quality checks involve a thorough examination of the collected data to identify and address any issues that may compromise the model's performance. This process includes verifying the correctness of labels, assessing the distribution of drowsy and alert instances, and checking for potential anomalies or inconsistencies in the dataset. It is imperative to review a representative subset of the data to confirm that drowsiness indicators are appropriately labeled and that the dataset captures a diverse range of scenarios. Addressing outliers, inaccuracies, or biases at this stage is essential for preventing the model from learning from misleading patterns. By conducting a comprehensive data quality check, developers can enhance the reliability of the dataset, ultimately leading to a more effective and trustworthy driver drowsiness detection model.

4.2.4 PERIODIC UPDATES

Periodic updates are a critical aspect of maintaining the relevance and efficacy of a driver drowsiness detection system based on deep learning. In the dynamic landscape of technology and user behavior, regularly revisiting and updating the dataset, model architecture, and algorithmic components becomes essential for staying abreast of evolving conditions and challenges. Periodic updates may involve the addition of new data samples to the training set, especially if there are changes in driving environments, vehicle technologies, or user demographics. Additionally, advancements in deep learning methodologies and algorithms should be considered to improve the model's performance and adaptability. Regularly evaluating and fine-tuning the system ensures that it remains responsive to emerging patterns and effectively addresses potential sources of error or bias that may arise over time. By embracing periodic updates, developers can uphold the system's accuracy, reliability, and generalizability, thereby contributing to its sustained effectiveness in real-world applications and enhancing overall road safety.

4.3 PREPROCESSING

Data preprocessing is a critical phase in the development of a robust deep learning model for driver drowsiness detection. Several preprocessing steps are employed to ensure that the input data is suitable for effective model training and generalization. Image normalization is a fundamental step aimed at standardizing the pixel values of images, typically by subtracting the mean and dividing by the standard deviation. This process helps mitigate variations in illumination across images. Resizing ensures that all images in the dataset have a consistent dimension, facilitating uniform input to the model. Data augmentation is another key step, involving the generation of additional training samples through random transformations such as rotation, zooming, and flipping. This not only diversifies the dataset but also improves the model's ability to handle variations in driver poses and environmental conditions. Collectively, these preprocessing techniques contribute to the creation of a well-conditioned dataset, optimizing the deep learning model's ability to recognize and generalize patterns associated with drowsiness indicators, ultimately leading to a more robust and accurate driver drowsiness detection system.

4.3.1 IMAGE NORMALIZATION

Image normalization is a crucial preprocessing step in the development of deep learning models for tasks such as driver drowsiness detection. This process involves adjusting the pixel values of images to a standardized scale, typically by subtracting the mean and dividing by the standard deviation. The primary goal of image normalization is to create consistency in the pixel intensity distribution across all images in the dataset. By normalizing images, variations in lighting conditions and color intensities are mitigated, allowing the model to focus on essential features without being sensitive to irrelevant factors. Thisstep is particularly important in computer vision tasks where consistent input characteristics contribute to the stability and convergence of the training process. In the context of driver drowsiness detection, image normalization aids in improving the model's ability to discern drowsiness indicators reliably, regardless of variations in lighting conditions or camera settings, ultimately enhancing the system's accuracy and reliability in real-world scenarios.

4.3.2 DATA AUGMENTATION

Data augmentation is a crucial preprocessing technique in the realm of deep learning for driver drowsiness detection. This process involves generating diverse training samples by applying various transformations to the existing dataset. In the context of image data, common augmentations include random rotations, horizontal flips, and changes in brightness, and zooming. The primary objective of data augmentation is to enhance the model's ability to generalize to different scenarios and variations in input data. By introducing these augmented samples during training, the model becomes more robust, learning to recognize drowsiness indicators under a broader range of conditions. This strategy is particularly beneficial when working with limited datasets, as it effectively expands the training set without requiring additional data collection efforts. Data augmentation helps mitigate over fitting, improves the model's generalization performance, and contributes to the creation of a more reliable and versatile driver drowsiness detection system capable of handling real-world variations in driver behavior and environmental conditions.

4.3.3 DATA LABELLING

Data labeling is a crucial step in the development of a supervised machine learning model for driver drowsiness detection. In this process, each instance in the dataset is assigned a corresponding label that indicates the state of the driver whether they are alert or exhibiting signs of drowsiness. For driver drowsiness detection, these labels are essential for training the model to recognize distinct patterns associated with alertness and drowsiness. The labeling process often involves human annotators who review images or video frames and categorize them based on observable indicators like eyelid closure, facial expressions, or head movements.

Accurate and consistent labeling is paramount for the model to learn effectively and generalize well to unseen data. It establishes the ground truth for the training process, allowing the model to associate specific features with the corresponding drowsiness state. However, the labeling process can be challenging due to subjective interpretations of drowsiness indicators and potential inter-annotator variability. Establishing clear guidelines and providing annotators with training can help mitigate these challenges, ensuring the quality and reliability of the labeled dataset.

4.4 MODEL ARCHITECTURE

The model architecture for driver drowsiness detection using deep learning plays a pivotal role in the system's effectiveness and performance. Typically, convolutional neural networks (CNNs) are employed due to their ability to automatically learn hierarchical features from visual data. The architecture comprises layers that extract and process features from input images, gradually forming a representation that aids in discriminating between alert and drowsy states.

A common approach involves stacking convolutional layers for feature extraction, followed by pooling layers to reduce spatial dimensions and enhance computational efficiency. The extracted features are then flattened and fed into one or more fully connected layers, which act as classifiers, making predictions based on the learned representations. Dropout layers may be incorporated to prevent over fitting by randomly dropping connections during training. The final layer often uses a soft max activation function to produce output probabilities for the two classes-alert and drowsy.

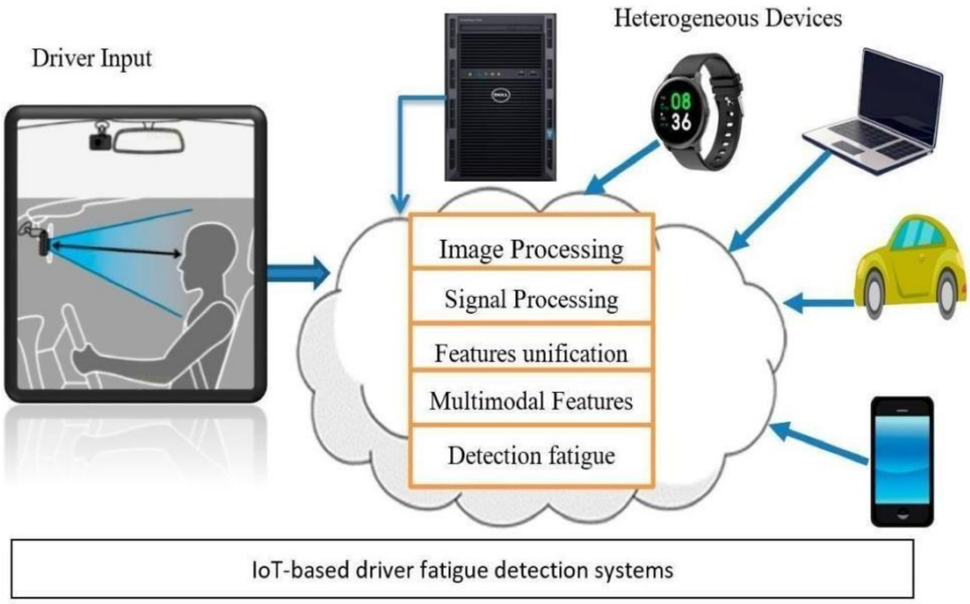

Fig 4.5 Model Architecture

Pre-trained CNN architectures, such as VGG16, ResNet, or MobileNet, can also be utilized, leveraging features learned from large-scale datasets. Fine- tuning these pre-trained models on a specific drowsiness dataset allows for effective transfer learning, particularly when the dataset is limited. The choice of architecture depends on factors like the size of the dataset, computational resources, and the desired balance between accuracy and model complexity.

4.5 TRAINING

Training a deep learning model for driver drowsiness detection is a critical phase that involves optimizing the model's parameters based on the labeled dataset. During training, the model learns to recognize patterns and features that distinguish between alert and drowsy states.

The process typically begins by initializing the model's weights and biases, and then iteratively adjusting them tominimize a predefined loss function. In the context of driver drowsiness detection, a binary classification task is often employed, where the model predicts whether the driver is alert or drowsy based on visual cues.

The training dataset, consisting of labeled images or video frames, is fed into the model in batches. The model computes predictions, compares them to the ground truth labels, and calculates the loss a measure of the disparity between predicted and actual outcomes.

To minimize the loss, optimization algorithms such as stochastic gradient descent (SGD) or variants like Adam are employed. The gradients of the loss with respect to the model parameters are computed, andthe parameters are updated in the opposite direction of the gradient, gradually converging towards values that yield better predictions.

During training, it is essential to monitor the model's performance on a separate validation set to prevent over fitting when the model performs well onthe training data but fails to generalize to new, unseen data. Hyper parameters, such as learning rate and dropout rates, may be fine-tuned to achieve optimal performance.

CHAPTER 5

CONCLUSION

The conclusion section of a driver drowsiness detection project using deep learning is a critical segment where the implications and findings of the study are analyzed in-depth. It offers an opportunity to interpret the experimental results, discuss the significance of the model's performance, and explore potential areas for improvement. In this section, researchers can delve into the strengths and limitations of the proposed deep learning model. Positive aspects, such as high accuracy and robustness, can be highlighted, emphasizing how the model effectively identifies drowsiness indicators in varying conditions. Conversely, limitations, such as instances of misclassification or sensitivity to certain environmental factors, should be acknowledged and addressed. Consideration of real-world applications and the model's practical utility is vital in the discussion.

This involves reflecting on how well the model aligns with the goals of driver safety and potential integration into existing vehicle safety systems. Discussions on computational resources, deployment feasibility, and scalability may also be pertinent. Comparisons with existing methods, as well as insights into how the model performs relative to traditional techniques, contribute to the discussion's depth. Additionally, the relevance of the chosen evaluation metrics and their alignment with the specific requirements of drowsiness detection in a driving context can be explored.

5.1 FUTURE WORK

For future work in the realm of driver drowsiness detection using deep learning, several avenues can be explored to further refine and enhance the capabilities of the proposed system. Firstly, the dataset used for training and evaluation could be expanded to include a more diverse set of driving conditions, environments, and demographic factors. This would contribute to a more comprehensive understanding of the model's generalization capabilities across a broader spectrum of real-world scenarios. Additionally, the model architecture can be subjected to further optimization and fine-tuning.

The integration of multimodal data, combining visual cues with other sensor inputs such as steering behavior or physiological signals, could provide amore holistic understanding of driver state. Investigating the fusion of information from diverse sources may enhance the model's robustness and reliability. Real-time implementation and deployment of the developed system within a vehicular context represent a significant area for future exploration. Addressing the computational efficiency and latency aspects of the model to make it suitable for deployment in real-time driving scenarios would be crucial for practical applications.

APPENDIX A
SAMPLE CODING

Auto detect text files and perform LF normalization

```
* Text=auto

# Custom for Visual Studio

*.cs diff=csharp

# Standard to msysgit

*.doc diff=astextplain

*.DOC diff=astextplain

*.docx diff=astextplain

*.DOCX diff=astextplain

*.dot  diff=astextplain

*.DOT diff=astextplain

*.pdf diff=astextplain

*.PDF diff=astextplain

*.rtf diff=astextplain

*.RTF diff=astextplain
```

driverdrowsiness.py

```
from scipy.spatial import distance as dist
from imutils.video import VideoStream from
imutils import face_utils
from threading import Thread import
numpy as np
import playsound
import argparse
import imutils
import time import
dlib import cv2
def sound_alarm(path):
playsound.playsound(path) def
eye_aspect_ratio(eye):
# compute the euclidean distances between the two sets of #
vertical eye landmarks (x, y)-coordinates
A = dist.euclidean(eye[1], eye[5])
B = dist.euclidean(eye[2], eye[4])
# compute the euclidean distance between the horizontal #
eye landmark (x, y)-coordinates
C = dist.euclidean(eye[0], eye[3]) ear
= (A + B) / (2.0 * C)
return ear
ap = argparse.ArgumentParser()
ap.add_argument("-p", "--shape-predictor", default="shape_predictor_68_face_landmarks.dat",
help="path to facial landmark predictor")
ap.add_argument("-a", "--alarm", type=str, default="alarm.wav", help="path
alarm .WAV file")
ap.add_argument("-w", "--webcam", type=int, default=0,
help="index of webcam on system")
```

```
args = vars(ap.parse_args())
EYE_AR_THRESH = 0.25
EYE_AR_CONSEC_FRAMES = 48
COUNTER = 0
ALARM_ON = False
print("[INFO] loading facial landmark predictor...") detector
= dlib.get_frontal_face_detector()
predictor = dlib.shape_predictor(args["shape_predictor"])
(lStart, lEnd) = face_utils.FACIAL_LANDMARKS_IDXS["left_eye"] (rStart,
rEnd) = face_utils.FACIAL_LANDMARKS_IDXS["right_eye"] print("[INFO]
starting video stream thread...")
vs = VideoStream(src=args["webcam"]).start()
time.sleep(1.0)
while True:
frame = vs.read()
frame = imutils.resize(frame, width=450)
gray = cv2.cvtColor(frame, cv2.COLOR_BGR2GRAY) rects
= detector(gray, 0)
for rect in rects:
shape = predictor(gray, rect)
shape = face_utils.shape_to_np(shape)
leftEye = shape[lStart:lEnd]
rightEye = shape[rStart:rEnd] leftEAR =
eye_aspect_ratio(leftEye)
rightEAR = eye_aspect_ratio(rightEye) ear =
(leftEAR + rightEAR) / 2.0 leftEyeHull =
cv2.convexHull(leftEye) rightEyeHull =
cv2.convexHull(rightEye)
cv2.drawContours(frame, [leftEyeHull], -1, (0, 255, 0), 1)
cv2.drawContours(frame, [rightEyeHull], -1, (0, 255, 0), 1) if ear
< EYE_AR_THRESH:
COUNTER += 1
if COUNTER >= EYE_AR_CONSEC_FRAMES:
if not ALARM_ON:
```

```
ALARM_ON = True if
args["alarm"] != "":
t = Thread(target=sound_alarm,
args=(args["alarm"],))  t.deamon
= True
t.start()
cv2.putText(frame, "DROWSINESS ALERT!", (10, 30),
cv2.FONT_HERSHEY_SIMPLEX, 0.7, (0, 0, 255), 2)
else:
COUNTER = 0
ALARM_ON = False
cv2.putText(frame, "EAR: {:.2f}".format(ear), (300, 30),
cv2.FONT_HERSHEY_SIMPLEX, 0.7, (0, 0, 255), 2)
cv2.imshow("Frame", frame) key
= cv2.waitKey(1) & 0xFF If key
== ord("q"):
break cv2.destroyAllWindows()
vs.stop()
```

APPENDIX B

SCREENSHOTS

Fig B.1 ALERT DRIVER

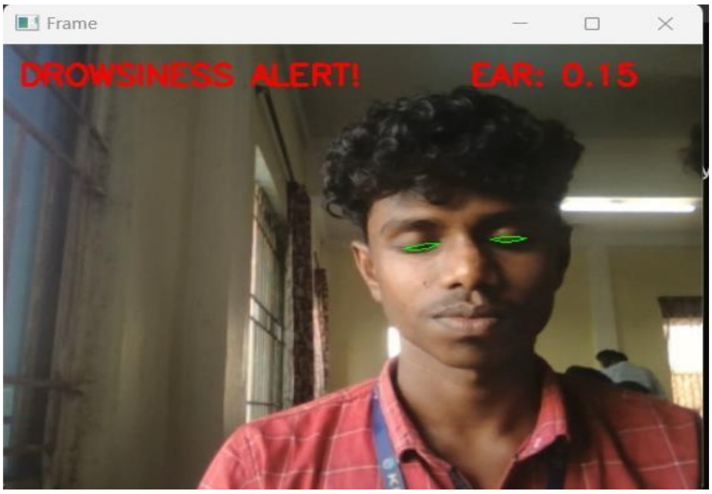

Fig B.2 ALERT MECHANISM

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