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Drivers Drowsiness Detection For Analysis Eye Movement Using Machine Learning

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Abstract— Distracted and drowsy driving has turned into a serious safety problem in the world, with serious injuries and deaths occurring as a result. The drivers have a tendency to indulge themselves in risky behaviours like using the mobile phone, yawning, eating, drinking or checking other things besides the road hence, putting themselves at risk of accidents. A proposed paper is a Driver Dangerous Behaviour Detection System (based on an intelligent driver and dangerous behaviour detection system). It is made on Python, open CV, MediaPipe, and YOLO to track the driver behaviour on a web camera in real-time. MediaPipe Face Mesh identifies facial landmarks to identify how closed the eyes are, the rate of blinking, yawning and head position as a sign of drowsiness. YOLO singles out some of the distracting behaviours such as eating and using a mobile phone. In case of unsafe behaviour, real-time warnings and alarm notifications are produced to alert a driver. Remote monitoring is done by sending email notices to registered users using automated email. It is possible to integrate into Django web application to securely authenticate and maintain users. The solution suggested will offer a cost-efficient, low-cost and real-time safety system that enhances driver awareness, mitigates the risk of accidents, and adds to intelligent transportation systems.

Keywords - Driver Monitoring, Drowsiness Detection, YOLO, MediaPipe, Computer Vision, Deep Learning, OpenCV, Real-Time Detection, Driver Safety, Intelligent Transportation.

I. INTRODUCTION

Road accidents have been a significant issue of concern across the world, and driver distraction and drowsiness have been cited to contribute significantly. Unsafe behaviour, which includes using mobile phones, eating, drinking, yawning, and looking off the road, will decrease the level of attention and slow reaction time and risk of accidents greatly. The conventional vehicle safety systems mainly involve mechanical car performance and car control mechanisms but fail to monitor the behaviour of the driver. The developments in computer vision and artificial intelligence have led to smart systems that can be used to track the activities of drivers in real time. OpenCV, MediaPipe, and YOLO are the technologies that can identify face features and objects with high accuracy and thus dangerous behaviour can be identified quickly. The creation of a real-time driver dangerous behaviour detection system will improve driver awareness, road safety and lessen the risk of accidents. Driver monitoring systems have changed significantly with time. The initial methods used indirect signs like steering wheel movements, vehicle speed, and lane deviation to determine fatigue among drivers. These techniques were not usually accurate and consistent. The use of camera-based surveillance systems facilitated through deep learning technology offers better accuracy in monitoring as the facial expressions, eye movements, and the head direction are examined. MediaPipe provides high-quality facial landmark detection in determination of eye closure and yawning. YOLO is a real-time object detector that is able to identify mobile phones and other distracting items. OpenCV is used to carry out image analysis and video processing. These technologies can be combined to allow the use of cheap hardware in detection at high precision and speed. Nevertheless, much of the available remedies is more concerned with fatigue detection and does not consider various types of risky behaviour. It is thus necessary to have a better driver monitoring system that is able to identify various unsafe behaviors.

The major reasons behind the development of such system can be attributed to the enhancement of road safety, and minimization of accidents due to driver negligence and fatigue. Inefficiency in terms ofinformation about the drowsiness or distraction can have serious outcomes most of the times. Early warnings and a detection system can drastically reduce the possibility of accidents and save lives. The use of artificial intelligence and deep learning methods to address real-world transportation problems improves the practical use of computer vision applications like OpenCV, MediaPipe, YOLO and web integration using Django. Email notification can be used to monitor remotely by one of the authorized users, as well as family members and fleet managers. Development of intelligent transportation systems contributes to better driving and greater safety of the roads. There are a number of issues associated with the development of a real-time driver monitoring structure. Light variations, camera movement and driver movement can affect the accuracy of identifying facial landmarks. YOLO object detection involves optimizing and training of models. It is still important to balance the high processing latency and the high accuracy. False alert should be minimized in order to avoid unnecessary disturbance. It will need an effective backend management to be integrated with Django-based web-based systems. Email notification has to be done in time. Frame skipping and image resizing are some of the performance optimization methods that can be used to optimize systems using low-end hardware. The simultaneous control of several behaviour detections needs to be properly programmed and optimized in calculation.

The proposed system has many applications in different areas of transportation such as personal automobiles, buses, trucks, and commercial fleets. The behaviours of drivers can be monitored by the fleet management organizations to make sure that they comply with the safety standards. Safety in driving habits among the young drivers may be checked by parents. Intelligent transportation infrastructures allow centralized data analysis and monitoring through integration. The data of driver behaviour can be stored and analyzed through cloud connectivity and assessed over long periods. The next improvement can involve the mobile application to track the real-time performance, night-vision camera to perform the low-light functionality and the IoT-based expansion to enhance the functionality. It is possible to integrate such systems as the in-built security mechanisms in automobile makers. One of the main contributions of the accident prevention and the enhancement of road safety is a low-cost and efficient driver monitoring framework.

II. LITERATURE SURVEY

YOLO is a model that detects objects in images in a single convolutional neural network, whereas the R-CNN model operates in multiple stages [1]. The system subdivides the image into grids and estimates bounding boxes and class probabilities at the same time. YOLO is highly fast, and this technique is ideal in real-time applications. The authors indicated that YOLO is both accurate and is able to operate in real-time [2]. The significance of this paper to driver monitoring systems is that it allows distracted behaviour of mobile phone use, eating and drinking to be detected quickly. The given project is based on the application of YOLO in identifying risky driver behavior. The speed, accuracy, and efficiency of YOLO render it a lot more applicable to a real-time system of detecting dangerous behaviour of drivers [3].

Facial landmarks including nose, eyes and mouth can be detected by the system in real time. The primary strength of this technique is that it is fast, and it is able to recognize landmarks within a millisecond. This renders it to be applicable in real-time. The model is trained by the authors with a huge set of data in order to enhance precision [4]. Facial landmark recognition is significant in driver monitoring systems. It assists in the detection of eye closure, blinking and yawning. These characteristics can be employed to identify drowsiness on the part of a driver [5].

This paper forms the basis of contemporary facial landmark detectors including MediaPipe Face Mesh. The idea of landmark detection presented in the proposed project is employed to detect fatigue in drivers [6]. This study shows how fast and accurate detection of facial landmarks are essential in safety critical system of the computer vision system to detect eye movement and blinking patterns. In case the eyes of the driver are closed over a duration of time, the system will identify the drowsiness and an alert will appear [7]. It is an image processing system that identifies facial features by using picture algorithms. The authors experimented on the real-time conditions with the system and got good results in terms of accuracy [8]. In this study, it is demonstrated that eye closure is a significant indicator of fatigue in drivers. The system however only detects drowsiness but fails to detect distracted behaviours like using a mobile phone. As noted in this paper, driver monitoring systems play a significant role in enhancing road safety problems. The suggested project enhances this method because it identifies a variety of hazardous behaviours with the help of deep learning and object detection [9].

Image processing to monitor eye position and fatigue detection were also applied by the authors. The system gave an alert when the eyes of the driver were closed over a long period of time. The system was put into real time driving tests [10]. The findings indicated that eye tracking is useful in the detection of fatigue. Nevertheless, the system had drawbacks in the detection of other hazardous behaviours because it needed sophisticated hardware. The significance of this paper is that it shows the relevance of eye monitoring when it comes to the safety of drivers. The proposed project is based on the same concepts but it enhances performance through the use of modern deep learning models like MediaPipe and YOLO [11]. Such technologies are more accurate and and quicker in performance. It applies machine learning to interpret facial behaviour. Facial landmarks and head pose can be correctly detected on OpenFace [12]. This toolkit has been applicable in driver monitoring system as it assists in detecting driver attention and fatigue. The authors established that OpenFace is effective in real-time. This study reveals the significance of facial analysis when detecting behaviour. Open Face, however, uses more computing resources [13]. The suggested project employs MediaPipe Face Mesh that has the same functionality and is more effective. The present paper presents important information about researches concerning facial behaviour analysis through computer vision as well as the utilisation of simple features and machine learning to identify faces as they appear in the real world in the present time [14]. The key benefit of such an approach is that it is fast and efficient. This is an algorithm that has been extensively applied in computer vision. It forms the basis of current face detection systems [15]. But it suffers weaknesses when it comes to identifying a face and behaviour. The reason why this paper is significant is that it presented face detection in real time. MediaPipe, a more precise landmark detection method is used in the proposed project which has advanced techniques. This study gave the basis of contemporary systems of facial analysis [16].

The technique works well in identifying human beings and objects. It is reasonably accurate and well performing. The application of deep learning methods has become popular, whereas HOG was in widespread use. Nevertheless, the more accurate and faster deep learning algorithms include YOLO. The significance of this paper is that feature-based object detection was introduced [17]. YOLO is also implemented in the proposed project as it is more efficient than HOG. This study led to the creation of new methods of object detection systems today. It is very accurate with respect to image recognition and object detection. Deep learning is applied broadly in various modes like driver monitoring [18]. This document discusses the reasons why deep learning is better than the conventional approach. Deep learning models suggested in the proposed project include YOLO and MediaPipe. Such models are able to give proper detection. This study indicates that deep learning is significant to the current computer vision systems [19]. It is more accurate than the old systems. Nonetheless, Faster R-CNN is not as fast as YOLO. The significance of this paper is that it enhanced the object detection. YOLO has been applied in the proposed project due to its speed in detection. The study was used in the development of modern object detection [20].

III. PROBLEM STATEMENT

One of the major international safety issues is road accidents due to driver distraction and drowsiness. Driving while involved in unsafe activities like phone use, eating, drinking, yawning, or looking off the road causes a lack of concentration, a rise in reaction time, and a high probability of accidents. Ignorance about the risky behaviour also increases the level of risk. Current safety measures in vehicles are mostly oriented at the mechanical performance of the vehicle but not the behavioural surveillance. Some of the existing driver monitoring systems are based on costly devices such as infrared cameras and special sensors, which is a limitation to both affordability and scalability. Most of the systems will only identify one behaviour (e.g. eye closure) and not a combination of several distractions. In many applications, real-time alert generation and remote monitoring capabilities are still not available. A machine learning-based, low-priced, and real-time driver behaviour monitoring device that can detect various harmful behaviours and provide instant feedback is thus needed. The combination of deep learning and computer vision methods facilitates the ability to detect more accurately, provide better awareness to the driver as well as reduce the road accidents.

IV. EXISTING SYSTEM

The current driver monitoring systems are mostly concerned in eye closure and facial feature analysis of driver drowsiness. Some of these methods take the form of indirect clues with steering wheel movement, deviation trends, alongside variations in vehicle speed used to determine the degree of fatigue. The limited accuracy produced by the indirect techniques of measurement is usually occasioned by the variation in the environment and behaviour. Monitoring systems which operate on cameras use machine learning and computer vision algorithms to detect the frequency of blinking eyes and yawning, which makes them more accurate than sensor-based solutions. Although there are improvements, the majority of solutions that are available only detect drowsiness and do not detect other dangerous behaviours like using mobile phones, eating, drinking, or excessive head movement. The limitation of high implementation cost is also a big constraint to the implementation especially in the system that needs infrared cameras and other specialized hardware components. Latency to process some of the implementations limits effective real time generation of alerts. Automated email alerts are not usually available as remote notification. There is limited integration with web-based monitoring systems to control users and track their activities. These limitations decrease usability in the field, cost-efficiency and general efficiency in the actual field of driving.

V. METHODOLOGY

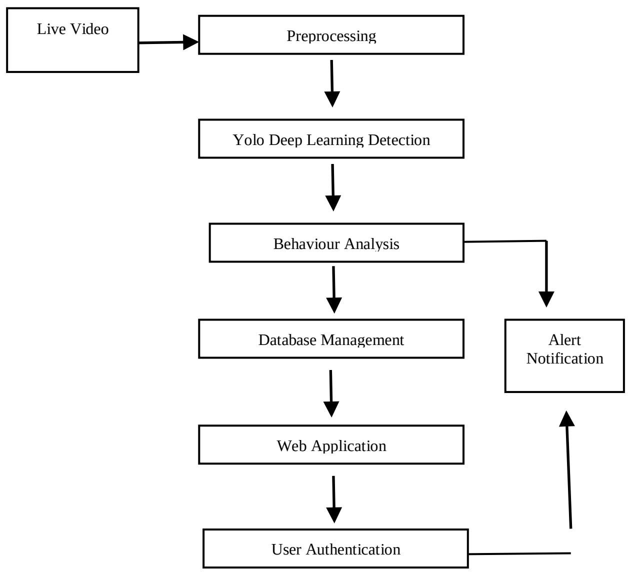

Fig 1. System Architecture

A. *Video Input Module*

The methodology starts with constant receiving of live video streams with the help of VideoCapture API of OpenCV. Frames are drawn out at adjustable timings so as to balance processing load and retain real time responsiveness. There is a buffering mechanism which maintains the stability of the streams at all times. Frame rate control adjusts the video capture and inference rate such that video processing time lag is avoided. Resolution scaling is used basing on hardware capacity so that there are no performance bottlenecks. The process of handling errors identifies the loss of connection with the camera and automatically recreates the stream. On-line learning of video input is associated with structured learning, which allows detecting behaviour correctly and on time.

B. *Preprocessing Module*

The wet frames are resized to the input resolution size of the YOLO model, e.g. 416x416 or 640x640 pixels. Pixel normalization brings the intensity value in the range of 0-1 to enhance the convergence of the neural network. Noise filtering is useful in cases of bad lighting. Computational throughput may be enhanced with the aid of batch processing techniques. Strong resistance towards changes in illumination and pose is enhanced by data augmentation techniques applied in the training. Streamlined preprocessing guarantees that the features are extracted efficiently and that there should be a balance between the speed and accuracy of detection.

C. *Deep Learning Detection Module*

YOLO algorithm splits the given image into grid cells and predicts object bounding boxes and the probability of the object class in one forward pass. The weights of a pre-trained model are loaded on during the system start-up and are optimized to detect distraction-related objects. Confidence scores are calculated during inference and Non-Maximum Suppression eliminates redundant detections. An adjustable probability threshold is used to make sure that only a high probability detection raises an alarm. CUDA supported by the use of the GPU can boost processing speed and provide real-time performance. Performance Detection is validated by using evaluation metrics like precision, recall, and mean Average Precision (mAP). This kind of methodology is reliable and effective in detecting distracted driving behaviours.

D. *Alert Generation Module*

An event-driven alert mechanism is triggered when the confidence of detection is more than predefined thresholds. Frames that are detected are annotated and stored together with metadata. It generates a special incident identifier to use as a tracking item. The alerts are sent asynchronously to the web dashboard without affecting the current inferences. Detection time, type of behaviour and confidence level are the logging mechanisms. Integration to email or SMS notifications can be optional and further extends the channels of communication. This is because alert generation based on events will enable a quick response and reduce latency between detection and warning.

E. *Database Management Module*

A relational database schema is created on the basis of SQLite that stores user credentials and detection logs. SQL injection vulnerabilities are avoided by parameterized queries. The security of authentication is increased by password hashing algorithms. The events of detection are stored in an indexed form based on the time when they were recorded to facilitate retrieval and analysis. Data integrity and recovery are guaranteed by the backup mechanisms. The structured database management ensures confidentiality, integrity and availability of the stored records, and has lightweight deployment requirement..

F. *Web Application and Authentication Module*

The Django structure deploys a structured application development architecture which is based on MVC. The secure log in is accomplished by the techniques of hashed password verification and session control. User session handling is done by secure cookie. The dashboard will dynamically retrieve the detection logs in the database and display them. The detection engine and backend services can communicate with each other using REST API endpoints. Role based access control provides administrative rights and limit access to sensitive information. The robustness and security is improved by input validation and error handling. This kind of architecture guarantees scalable, secure, and easy interaction with the driver monitoring system.

VI. PROPOSED SYSTEM

The proposed system presents the idea of an intelligent Driver Dangerous Behaviour Detection System that uses the techniques of deep learning and computer vision. The Python, OpenCV, MediaPipe, YOLO, and Django are used to implement the system and achieve the ability to monitor the behaviour of drivers in real time. The input of the video happens through a webcam, and individual frames are analyzed using the OpenCV. MediaPipe Face Mesh identifies facial features such as mouth, head position and eyes. The calculation of the Eye Aspect Ratio (EAR) allows the identification of the long closed eye condition and unnatural blinking that are signs of drowsiness. Yawning behaviour is detected by Mouth Opening Ratio (MOR) measurement. Head pose estimation finds out the presence of gaze deviation, which is indicative of distraction. Besides the facial analysis, an object-detecting model of the type of YOLO can detect distracted behaviours like mobile phone usage, eating, and drinking. The model is high processing speed with high accuracy in detection which makes it fit well in real time deployment. An interface provides instant visual notifications about dangerous behaviour and an audio alarm to alert the driver up on its detection. This kind of integrated monitoring will improve the awareness of drivers and minimize the risk of accidents as well as adding to smart transportation safety systems.

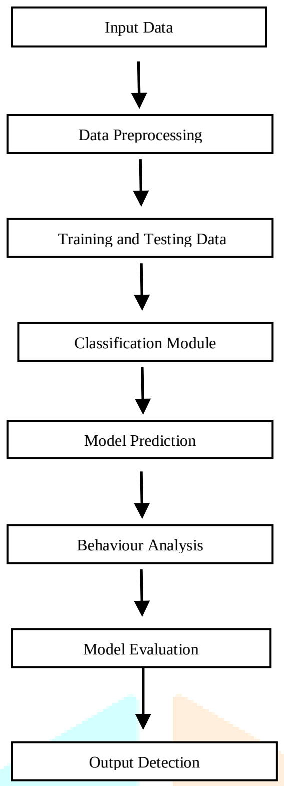

Fig 2. Proposed System

The system has an email notification capability. In case of the first occurrence of dangerous behaviour, an automated email notification is sent to the registered user. Family members or supervisory authorities are open to remote tracking of the safety of the drivers. It can be integrated with a Django-based web-application to allow the registration of users, their login, and monitoring facilities. The suggested framework is low cost, computer efficient and it can identify several threatening behaviours in real time. The integrated monitoring and alert mechanisms lead to improvement of driver safety, the risk of accidents, and the contribution to intelligent transportation systems.

Module Description

A. User Authentication and Management

The User Authentication and Management Module deals with the registration of users, their logout and log-in. This is implemented with the Django framework that offers secure authentication functions and the ability to manage the session. In the process of registration, the user information (user name, email address and passwords) is gathered and stored in the database in an encrypted and hash format. Only authenticated access can be made when interpreting the driver monitoring system. Only authorized users have access to information in session management. Detection sessions and alert notification can be associated with a particular user account to personalize. Structured access control and database management guarantee security authentication, privacy protection and independent multi-user access.

B. Video Capture Module

Video Capture Module allows obtaining a live video of the driver on a webcam interface. The process of implementation is carried out on the basis of the functions of OpenCV which allows access to a camera and extracting frames. Video frame is digitized and converted into digital images which are processed further. The frames are sent to detection modules where they are analysed in regards to behaviour. Live streaming is taken care of with low latency. Frame resolution adjustment enhances the efficiency of calculation and lessens the load of processing. Frame resizing and frame skipping are performance optimization methods that make it responsive. Video acquisition is the main source of input that needs to be continuously and constantly to achieve good monitoring of the driver.

C. Face Detection and Facial Landmark Module

Module will recognize the face of the driver and extract important facial features. Face Mesh MediaPipe is a deep learning powered landmark detection system that uses 468 points of facial landmarks, personalities such as eyes, mouth, nose, head orientation. Isolated landmarks allow to analyze the eye movement, blinking habits, and mouth opening. Blinking frequency and long closure are detected with the help of eye position tracking. The analysis of mouth landmarks helps to determine yawning behaviour. The reason is that head position landmarks indicate the direction of gaze and provide the detection of head position deviation. Facial landmark extraction is essential due to its high detection rate and real-time operation in controlling fatigue and attention.

D. Drowsiness Detection Module

The Drowsiness Detection Module takes a facial landmark data to detect fatigue. Eye Aspect Ratio (EAR) calculates the eye landmark coordinates in order to see whether eyes are open or closed. A long shutting period after set time limits denotes possible drowsiness. The Mouth Opening Ratio (MOR) is computed by measuring the mouth landmark points in order to identify yawning behaviour that is a typical fatigue symptom. Head pose estimation measures the tilt or the rotation of the head in a direction different to the forward direction. The constant measurement of EAR, MOR, and head orientation values allow classifying the driver state according to some predetermined threshold parameters. Unsafe conditions are caused by detection which sends signals to the alert generation mechanism.

E. *Object Detection Module*

The Object Detection Module detects distracted driving behaviour as mobile phone use, eating and drinking. It is implemented with the help of the YOLO (You Only Look Once) deep learning algorithm. YOLO is an object detector that requires a single forward pass to run video frames and does not need to process them multiple times. Bounding boxes are created around objects found and with the confidence score attached to them. Detection model is trained to identify pertinent distraction related objects, such as mobile phones, foodstuffs, and bottles. It can be deployed in real time due to high inference speed and high detection accuracy. Object detection goes hand in hand with facial analysis, to detect those behaviours unrecognized by the landmark tracking.

F. *Behaviour Analysis and Decision Module*

Behaviour Analysis and Decision Module combines the results of the drowsiness detection and the object detection modules. A combination of behavioural indicators is used to assess the condition of the driver as safe or dangerous. The behaviour states are classified into predefined rules and threshold parameters. An international state management system ensures that there is no duplication of alerts on same behaviours in a limited time span, and it minimises unwarranted notification. Decision logic is centralized which guarantees effective coordination between the modules of detection and the alert generation processes. Formatted behavioural assessment increases consistency, accuracy and stability of the total driver monitoring system.

VII. RESULT AND DISCUSSION

The proposed Driver Dangerous Behaviour Detection System with Python, OpenCV, MediaPipe, YOLO, and Django. Testing was done on a typical webcam in a variety of real-time driving conditions. The characteristic facial landmarks were recognized with the help of mediaPipe Face Mesh and the patterns of eye closure, blinking, yawning behaviour, and head movement were successfully identified. Eye Aspect Ratio method had accurate identification of drowsiness conditions. The YOLO model was shown to be highly accurate and low latency detecting distracted behaviours in mobile phone use, eating, and drinking.

The dangerous behaviour was detected and real-time alerts were produced as on-screen warning messages with alarming sounds when such behaviour was detected. The reaction time to alert was low so that drivers were notified instantly. The email notification system was used to send alert messages to registered users without much lag time. The web application built on Django made the logging in and easy access to monitoring features possible. It was able to perform efficiently on a regular computing platform without the need to use costly hardware devices.

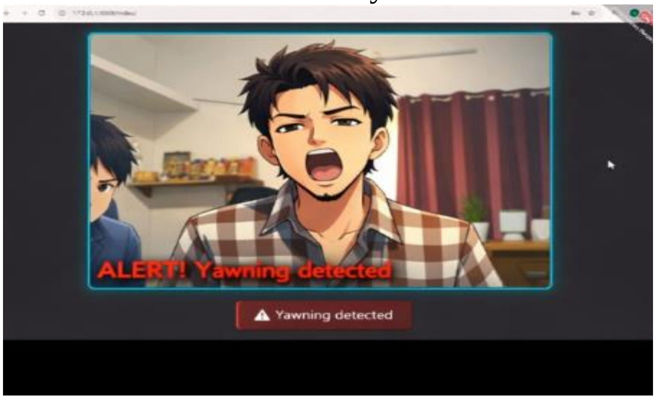

Fig 3. Output Image

Frame resizing and frame skipping were optimization techniques that were used to make processing faster and ensure real-time performance was maintained. Normal lighting conditions were observed on its stable operation. The outcomes of the experiments demonstrate that it is valid to detect hazardous driving behaviour and to generate reliable alerts to improve the safety of drivers.

Fig 4. Output Image

The Video Capture Module made use of OpenCV to obtain the real-time video input of a web camera. Frames were acquired continuously and converted to images which assisted in continuous monitoring. The techniques of resolution adjustment and performance optimization minimized the computational cost. The correct performance of detection was facilitated by proper camera placement and resolution settings. Good input frames permitted sound behavioural evaluation.

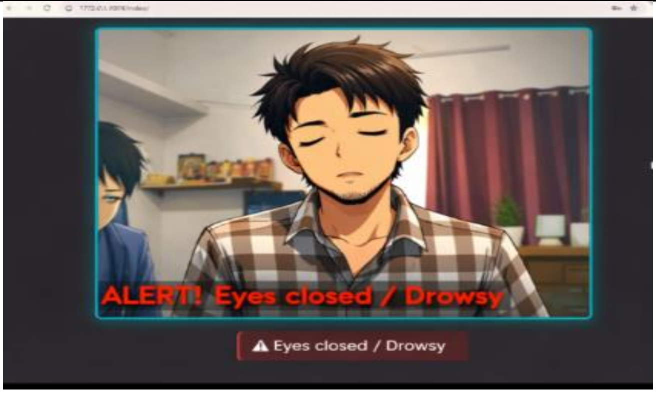

Fig 5. Output Image

The Face Detection and Facial Landmark Module utilized MediaPipe Face Mesh to recognize facial features and extract 468 landmark points, which comprised of eye regions, mouth contours and head orientation coordinates. Blink rate and protracted eye closure identification were facilitated by eye movement tracking. Yawning behaviour could be identified with the help of mouth landmark analysis. The landmarks used to establish the gaze direction were head orientation. Real-time processing was able to give the correct landmark coordinates to analyse fatigue. Features that had been extracted were passed to the drowsiness detection module to be classified.

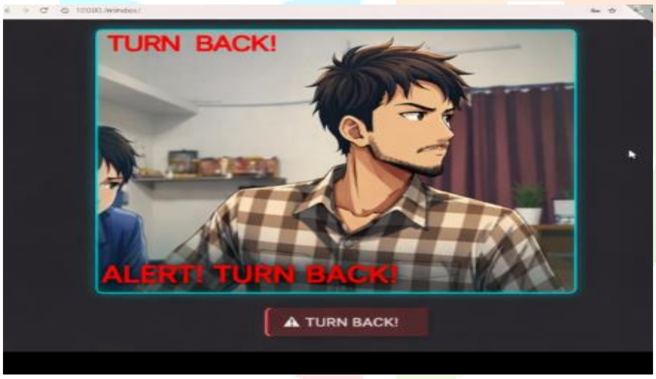

Fig 6. Output Image

The Object Detection Module used the YOLO deep learning algorithm to detect distracted drivers behaviour. Video frames were considered to identify objects like mobile phones, food items, and beverages. Bounding boxes were used to create them around objects that were identified, with classification labels and confidence scores. Fast and accurate detection that was optimally inferred was achieved and was appropriate to be deployed in real time.

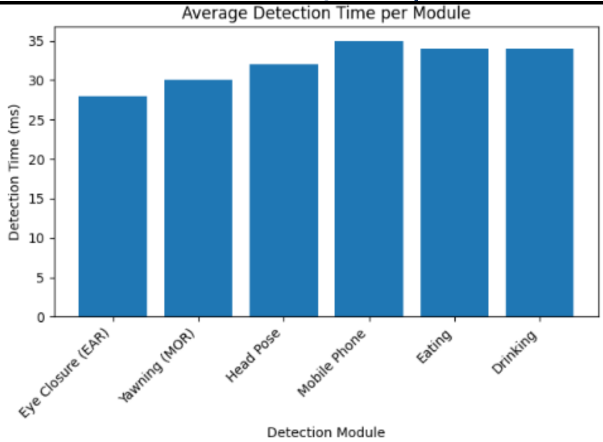

Fig 7. Average Detection Time

The behaviour analysis module was incorporated with detection outputs. Both systems operated together, which increased system functionality. MediaPipe Face Mesh and YOLO were joined, and the performance enhanced considerably. Eye Aspect ratio and Mouth Opening Ratio techniques were good in detecting the fatigue indicators like protracted closure of eyes and yawning. Object recognition was successfully applied in the distraction-related objects detection, with the use of YOLO.

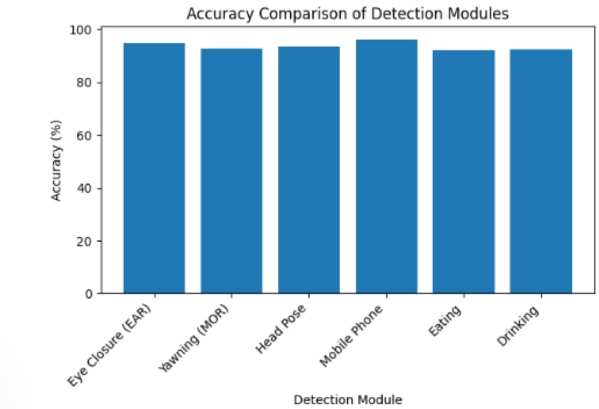

Fig 8. Accuracy Comparison

Facial and object detection modules operated together, which increased the robustness and reliability. The real-time warning system was effective in gaining attention of the drivers as there were visual warnings and audio signals. Remote supervision and increased system applicability were possible using email notification functionality. Django web interface provided an authentication security and easily interacted with users.

Behaviour / Module	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Avg. Detection Time (ms)
Eye Closure (EAR) Detection	94.6 %	93.8 %	95.2 %	94.5 %	28 ms
Yawning (MOR) Detection	92.8 %	91.9 %	93.5 %	92.7 %	30 ms
Head Pose Distraction Detection	93.5 %	92.7 %	94.1 %	93.4 %	32 ms
Mobile Phone Usage (YOLO)	96.2 %	95.6 %	96.8 %	96.2 %	35 ms
Eating Detection (YOLO)	91.9 %	90.8 %	92.6 %	91.7 %	34 ms
Drinking Detection (YOLO)	92.4 %	91.5 %	93.2 %	92.3 %	34 ms
Overall System Performance	**93.9 %**	**92.7 %**	**94.2 %**	**93.4 %**	**32 ms**

Table 1. Performance Metrics

The environmental factors affecting performance were the lighting and camera resolution. Lower levels of illumination influenced the accuracy of the detection. It was also important to have a good camera placement to achieve good results. Future improvements, such as incorporation of infrared cameras and more training data can additionally enhance the strength in adverse conditions. The proposed framework has a cheaper and efficient alternative compared to the traditional systems, which need particular hardware. Experimental validation is achieved through demonstrating its suitability to operate in a real world driving environment. Detection of distraction and drowsiness is effective, which helps prevent accidents and positively affect safety on the road.

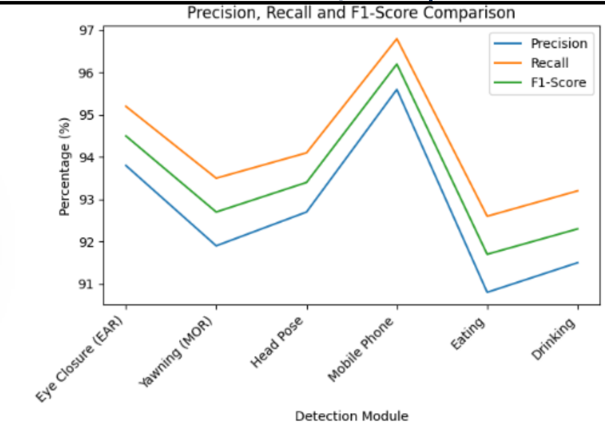

Fig 9. Comparison of Performance Metric

VIII. CONCLUSION

The Driver Dangerous Behaviour Detection System is a solution that enables the provision of road safety improvement using the technologies of deep learning and computer vision. The driver drowsiness and distracted behaviours like mobile phone use, yawning, eating, drinking and head deviation are detected in real time. MediaPipe Face Mesh and YOLO have been integrated to provide high-speed and accurate detection of objects. Onboard visual and auditory warnings are more effective in making drivers aware whereas automated email messages can help in monitoring remotely. Web integration is done using Django where there is a secure access and easy interaction. Competent implementation on low-priced hardware does not require using special sensors or costly devices. The results of implementation show the enhanced level of driver awareness and minimisation of the risk of accidents due to the proactive monitoring of behaviour. The intelligent transportation systems are contributed to through provision of a scalable, practical, and real-time driver monitoring solution that is aimed at enhancing safety and preventing accidents.

IX. FUTURE SCOPE

The Driver Dangerous Behaviour Detection System can further be enhanced by incorporating the use of advanced technologies, which will enhance functionality, scalability, and robustness. Data on driver behaviour can be stored during long periods of analysis, reporting and centralized monitoring through cloud integration. Creation of a special mobile app will be able to give real-time warnings and live tracking via smartphones, which will make it more accessible and more connected with the user. The use of infrared or night-vision camera systems will help the company improve performance when there is low light or nighttime. The detection accuracy and false positives can also be improved by training deep learning models using larger and more diverse data. By incorporating GPS technology, real-time tracking of vehicle location in the events of dangerous behaviour can be supported to facilitate fleet control and emergency management. The connectivity of IoT can enhance the communication between the equipment, the cloud servers, and the monitoring platforms to allow remote monitoring with ease. The use in commercial vehicles, the public transport infrastructure and fleet management processes can play a crucial role in enhancing the level of driver safety and help reduce the number of accidents on a large scale.

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