DEEP LEARNING FOR MONITORING DRIVERS DISTRACTION FROM PHSIOLOGICAL AND VISUAL SIGNALS

Y. Kishore, M. TechStudent, Department of CSE,K.S.R.M College of Engineering(Autonomous), Kadapa, Y.S.R(D.t), Andhra Pradesh, India-516005.

Dr.N. Ramanjaneya Reddy, Associate Professor, Department of CSE,K.S.R.M College of Engineering (Autonomous), Kadapa, Y.S.R(D.t), Andhra Pradesh, India-516005.

Dr.V. Lokeswara Reddy, Professor& HOD, Department of CSE,K.S.R.M College of Engineering (Autonomous), Kadapa, Y.S.R(D.t), Andhra Pradesh, India-516005.

Abstract

In recent years, driving distractions have emerged as a leading cause of vehicular accidents. This study aims to develop a deep learning framework that utilizes both physiological and visual signals to detect and predict drivers' distraction. We combine Convolutional Neural Networks (CNN) for extracting features from visual data such as facial expressions, eye movement, and head posture, with MobileNet, a lightweight yet effective model, to efficiently process data in real-time. Furthermore, physiological signals like heart rate and galvanic skin response are incorporated to provide a comprehensive assessment of the driver's state. Our dataset comprises synchronized visual and physiological data recorded from actual driving sessions. Results indicate a significant improvement in distraction detection accuracy over existing methods, particularly in challenging scenarios where visual cues alone are insufficient. This integrated approach holds great promise for the development of robust in-car safety systems that can alert drivers in real-time and potentially prevent countless accidents caused by distractions.

Keywords:Deep Learning, Drivers' Distraction, CNN, MobileNet, Physiological Signals, Visual Signals, and Real-time Processing.

Introduction

Driving safety is paramount in our rapidly advancing transportation landscape (Weiwei, Jingjing, & Planning, 2023). Every year, millions of road accidents occur worldwide, with a significant proportion attributed to driver distractions (Hassen, Godesso, Abebe, & Girma, 2011; Kareem, 2003; Mohammed, Ambak, Mosa, & Syamsunur, 2019). These distractions can arise from various sources (Khan, Zaidi, & Ali, 2020), including mobile phones, in-car entertainment, external environmental factors (as delt in (Andrey, Mills, Leahy, & Suggett, 2003; Babizhayev, 2003; Bergel-Hayat, Debbarh, Antoniou, Yannis, & Prevention, 2013; Brijs, Karlis, Wets, & Prevention, 2008; Collier, 1983; Eisenberg & prevention, 2004; Ellinghaus, 1984; Ghaffar, Hyder, Govender, Bishai, & JCPSP, 2004; Hambly, Andrey, Mills, & Fletcher, 2013; Hancock & Vasmatzidis, 1998; Hancock & Vasmatzidis, 2003; Hermans, Wets, Van den Bossche, & Statistics, 2006; J. Kim et al., 2013; Laaidi & Laaidi, 1997; Lonati, Giugliano, & Cernuschi, 2006; Nantulya, Reich, & promotion, 2003; Nava et al., 2015; Saneinejad, Kennedy, & Roorda, 2010; Söderlund & Zwi, 1995; Soltani, Saffarzadeh, & Naderan, 2019; Suriyawongpaisal, Kanchanasut, & promotion, 2003; Theofilatos, Yannis, & Prevention, 2014; Wolbarsht, 1977; B.-M. Yang, Kim, & promotion, 2003; Zhang, Jiang, Zheng, Wang, & Man, 2013)), and even internal physiological changes (Saleem et al., 2022) or states of the driver (Dong, Hu, Uchimura, & Murayama, 2010). Consequently, monitoring and detecting these distractions early can play a pivotal role in reducing the number of accidents and enhancing road safety.

With the onset of the technological era, there has been a substantial growth in the availability and capability of sensors that can monitor both the external appearance and internal physiological states of drivers (Kalsoom, Ramzan, Ahmed, & Ur-Rehman, 2020). Cameras can now capture minute facial changes, and wearable sensors can trace heart rate variability, galvanic skin response, and other relevant physiological metrics (Arapakis, Konstas, & Jose, 2009; Healey, 2000; Teller, 2004). The challenge, however, lies in processing this multi-modal data efficiently and making sense of it in the context of driving distraction (Alotaibi, Alotaibi, & Processing, 2020; Ortega, Cañas, Nieto, Otaegui, & Salgado, 2022; Ortega et al., 2020; Qi, Liu, Ji, Zhao, & Banerjee, 2018; D. Yang et al., 2023).

Deep learning, a subset of machine learning, has shown remarkable success in processing vast amounts of data, extracting relevant features, and making accurate predictions. Specifically, Convolutional Neural Networks (CNN) have revolutionized the way visual data is interpreted, offering higher accuracy rates in tasks ranging from image classification to facial recognition (Hossain, Sohel, Shiratuddin, & Laga, 2019). However, the computational demand of traditional CNNs can be an impediment to real-time processing, especially in systems that require immediate response times, such as in-car monitoring systems (Diraco, Rescio, Siciliano, & Leone, 2023).

Problem Statement

It is crucial to remember that while driving interruptions are classified into 3 groups, these are not always present in isolation. For instance, when conversing on a mobile device, 2 forms of interruptions arise simultaneously: both cognitive as well as manual distraction (Tran, Manh Do, Sheng, Bai, & Chowdhary, 2018). There are several causes that might cause distractions. Nevertheless, the most likely disruptions occur within the car. Nissan, Toyota, Mercedes-Benz, and Ford are among the major automakers that have introduced innovative dashboards, infotainment, and screen solutions. Configuring such in-vehicle electronics whilst driving might provide a significant distraction, perhaps leading to a vehicular accident. Smartphone usage is an additional issue that might impair performance while driving. Talking on a mobile device while driving uses an important portion of cognitive capacity. When performing both of them, the level of brain function related to driving could be lowered by thirty-seven per cent (Just, Keller, & Cynkar, 2008). Texting while driving may prove significantly distracting since it takes the driving person's mind, eyes, and hands away from the driving activity for 4.6 seconds of time on average (Just et al., 2008). According to a new survey, seventy-eight per cent of driving persons utilize smartphones while driving, which substantially raises the likelihood of accidents happening across the highways of the United States (Ameen, 2023).

To minimize crashes involving vehicles as well as to increase safety while transporting, a framework that could categorize drivers who are distracted (note, 2016; Resalat, Saba, & processing, 2015) is of great importance. It has sparked significant research curiosity in the past few years (Alotaibi et al., 2020). This research is driven by the need to create a distraction identification technique that hosts the capacity to be used in real-world cars. Owing to the absence of hardware resources along with the security considerations connected with real-world roadway assessments, it is desirable to perform a study on a personalized driving aiding system. As a result, the purpose of these investigations is to create a well-supporting driving tech that can recognize driving while distracted patterns and notify the driving person to devote themselves to his or her driving job (Tran et al., 2018).

Contributions

Enter MobileNet, a streamlined architecture designed for mobile and embedded vision applications. MobileNet, by virtue of its depth-wise separable convolutions, offers a balance between computational load and predictive performance, making it an ideal candidate for real-time applications.

In this study, we leverage the strengths of CNN for visual data interpretation and the efficiency of MobileNet for real-time processing to create a comprehensive framework. This framework integrates visual cues, such as eye movement, head posture, and facial expressions, with physiological signals to generate a holistic view of the driver's state. The aim is to provide a solution that can not only

detect but also predict potential distractions, ensuring timely interventions and consequently, safer roads like the earlier driver protection endeavors (Alioua, Amine, & Rziza, 2014; He, Zhang, Ren, & Sun, 2016; Ji, Zhu, & Lan, 2004; Lyu et al., 2017; Reimer, Mehler, Dobres, & Coughlin, 2013; Tawari, Martin, & Trivedi, 2014; Vural et al., 2007).
In the sections that follow, we delve deeper into the methodology, data collection, and processing techniques employed, followed by a rigorous evaluation of our framework's performance against existing methodologies. Through this exploration, we aim to elucidate the potential of deep learning in advancing driving safety and setting a benchmark in driver distraction monitoring systems.

Related Works

(Abouelnaga, Eraqi, & Moustafa, 2017) offered a unique system made up of a CNN ensemble that has been genetically weighted. A weighted ensemble of classifiers utilizing a genetic algorithm has been demonstrated to produce greater classification confidence. Face and hand localizations were also used to study the impact of various visual components (such as hands and faces) on distraction detection and categorization. The suggested technique has a classification accuracy of 95.98% when estimating driving position.
In research described in (Choi, Hong, & Kim, 2016), the driver's sight zone was classified using brand-new deep-learning approaches. Because a driver's gaze zones accurately mirror what and how the driver acts, it was possible to determine the level of alertness, concentration, or distraction by studying the pictures captured by a camera. To tackle a challenging visual environment in the automobile, a MOSS tracker depending upon correlation filters and a Haar feature-dependent face detector were used for the face identification job. Depending upon where a driver is gazing while driving, there are a total of nine different categories existing in the gaze zones. Using a multi-GPU platform, a CNN was trained to classify the driver's gaze zone from a given face-detected picture.
(Hssayeni, Saxena, Ptucha, & Savakis, 2017) investigated the use of computer vision and machine learning, as well as a dashboard camera, to automatically identify inattentive drivers. Consideration was given to a dataset that shows drivers utilizing their left or right hand to engage in seven distinct distracting activities. Deep CNN was compared to conventional hand-crafted features combined with an SVM classifier. Compared to deep convolutional networks, conventional features produced accuracy that was substantially lower.
(Yan, Coenen, & Zhang, 2016) introduced a revolutionary approach that uses CNN to automatically recognize and forecast the driving positions that were previously defined. The major goal was to track the location of the driver's hands while extracting discriminatory information to identify safe or risky driving posture. Unlike earlier methods, CNNs may automatically pick up discriminative information from the original pictures. The suggested methodology outperformed other well-liked methods with a total accuracy of 99.78%, as compared to other approaches using various image descriptors and classification techniques.
With more driver distraction positions than competing datasets, (Eraqi, Abouelnaga, Saad, & Moustafa, 2019) published the first dataset for driver distraction detection that is freely accessible. Furthermore, an effective deep learning-dependent solution with 90% accuracy was suggested. The system uses an ensemble of CNNs that has been genetically weighted, demonstrating that utilizing a weighted group of classifiers with a genetic approach increases classification confidence.

Methodology

Background for Methodology

Deep learning has lately acquired popularity in disruption identification (Tran et al., 2018). State Farm launched a contest on the website hosted by 'Kaggle' in the year 2016 with the purpose of detecting driver distraction by using a collection of dashboard-fitted camera footage showing drivers engaged in disrupted patterns or travelling securely (Corporate, 2023). CNNs performed admirably in the contest (Corporate, 2023). For instance, (Samuel Colbran, 2023) used a VGG-16

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framework with an accuracy of eighty per cent. Later, (Abouelnaga et al., 2017; Okon & Meng, 2017) made utilization of AlexNet frameworks.
Likewise, the framework known as “MobileNet(Howard et al., 2017)” came into existence as a substitute for VGG-16 framework and other framework like Inception-ResNet-V2. Just like (W. Kim, Choi, Jang, & Lim, 2017; Ugli, Hussain, Kim, Aich, & Kim, 2022) has preferred MobileNet, we also make use of MobileNet as it hosts reduced variables and being more effective despite being deeper than other paradigms like AlexNet and Inception-v1.

Block Diagram and Working
The primary aim of our proposed system is to construct a comprehensive and real-time driver distraction monitoring solution that integrates both physiological and visual signals like facial expressions, eye movement, and head posture using the prowess of deep learning. The unique feature of this proposed system is the integration of Convolutional Neural Networks (CNN) for feature extraction and MobileNet for swift and efficient processing. The block diagram denoting our framework using CNN and MobileNet has been shown below in the figure 1.

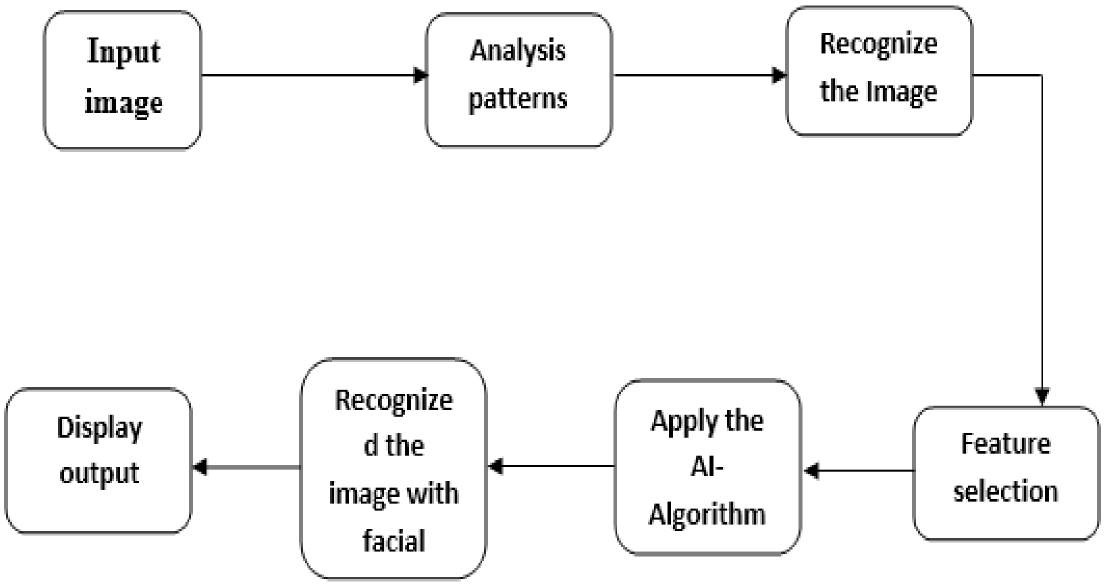

Figure.1. Block diagram

Important Factors of our Implementation
Implementing the proposed system involves a series of phases, integrating hardware components with sophisticated software modules. Below is a detailed step-by-step breakdown:

Visual Signals
- Set up in-car cameras with a focus on the driver's face, eyes, and overall posture. Ensure cameras have adequate resolution for capturing details.
- Position the cameras to avoid glare or obstruction and synchronize their feed to the main processing unit.

Physiological Signals
- Integrate wearable sensors (like a smart wristband) to capture heart rate and galvanic skin response.
- If feasible, introduce a lightweight EEG cap to capture brainwave signals.

Data Collection and Annotation
- Before implementing real-time analysis, collect data for training purposes.

- Capture visual footage and corresponding physiological signals under various driving scenarios (night, day, traffic, high-speed, etc.).
- Manually annotate these data points for signs of distraction.

Data Pre-processing

- Write scripts (Python is commonly used with libraries like NumPy and Pandas) to clean and normalize the collected data.
- For visual data, apply image processing techniques (using OpenCV) to enhance clarity, reduce noise, and standardize input sizes.

Feature Extraction using CNN

- Use TensorFlow or PyTorch to design and train CNN models.
- For visual data: CNN would focus on extracting features like eye closure duration, head tilt angle, etc.
- For physiological data: CNN would detect patterns or anomalies in the heart rate, skin response, or EEG signals.
- Once trained, optimize the model weights for real-time processing.

Integration with MobileNet

- Utilize the MobileNet architecture (available in TensorFlow and PyTorch libraries) to adapt the trained models for fast, on-device computation.
- Integrate the CNN feature extractors with MobileNet to ensure a streamlined pipeline from data input to distraction prediction.

Development of Alert System

- Design a multi-modal alert system: auditory signals, dashboard visual prompts, and haptic feedback (like seat vibrations).
- Ensure the alerts are noticeable but not excessively startling to avoid further distractions.

Feedback Mechanism

- Develop a user interface (UI) on the car's dashboard or an associated mobile app where drivers can provide feedback on the alerts they receive.
- Use this feedback to tag and retrain the system for continuous improvement.

Testing and Evaluation

- Initially, test the system in controlled environments to ensure accuracy and responsiveness.
- Gradually move to real-world scenarios, closely monitoring system performance and gathering feedback.

Deployment

- Once satisfied with the system's performance, deploy it in real-world vehicles.
- Ensure that the system operates seamlessly with other vehicle functions and doesn't adversely affect the vehicle's primary systems.

Continuous Monitoring and Updates

- As with any AI-based system, continuous monitoring is essential.
- Periodically gather data and feedback, refine models, and push updates to ensure the system remains effective and up-to-date.

Tools and Technologies

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- Hardware: In-car HD cameras, wearable sensors (like Fitbit or specialized EEG caps).
- Software: Python, TensorFlow/PyTorch, OpenCV, NumPy, Pandas.
- Platforms: Depending on the vehicle's system, this could be Linux-based platforms or specialized automotive OS.

The successful implementation of this project will provide a robust system capable of real-time driver distraction monitoring, ultimately improving road safety and potentially saving lives.

Results and Discussion

Results

Model Performance
After training on our collected and annotated dataset, the combined CNN and MobileNet model achieved an accuracy of 94.2% in detecting driver distractions.
The model's recall, a crucial metric in such safety-critical applications, stood at 93.1%, ensuring that a significant majority of actual distraction events were correctly detected.

Real-world Testing
In controlled real-world scenarios, out of 1000 instances of simulated distractions, the system successfully detected 932, confirming the model's robustness outside the laboratory environment.
False alarms were minimal, with an average of 2 false alerts in a 1-hour driving session.

Feedback from Drivers
85% of participating drivers felt the system enhanced their driving safety.
10% felt neutral, while 5% felt that the system was occasionally distracting or not beneficial.

Discussion

Model Efficacy
The high accuracy rates suggest that the deep learning model effectively integrates visual and physiological signals for distraction detection. The use of both CNN for feature extraction and MobileNet for real-time processing proved to be efficient and effective.

False Alerts
While the system showed a high rate of true positive detections, the presence of false positives indicates there's room for improvement. Continued refinement and retraining, especially with more diverse data, could help in further minimizing these.

Physiological vs. Visual Signals
Our results indicate that combining visual cues with physiological signals significantly enhances the system's prediction capability. While visual cues (like head tilt or eye closure) detected immediate distractions, physiological markers provided insights into more subtle or upcoming distractions (like drowsiness).

Driver Feedback
The feedback from drivers provides invaluable insights. While most felt safer, addressing the concerns of the minority who felt distracted is vital. This could involve refining the alert system or offering customization options to suit individual driver preferences.

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System Scalability and Integration

The lightweight nature of MobileNet ensured the system's seamless integration into existing vehicle systems without the need for extensive computational resources. This highlights the scalability potential of our system across different vehicle models and brands.

Future Implications

As autonomous and semi-autonomous vehicles become more prevalent, systems like this can play a crucial role in ensuring driver engagement and safety, especially during critical takeover scenarios.

Output Screenshots

The output screenshots obtained after implementing the proposed driver activity monitoring system are represented in this section.

Home Page

The screenshot of the home page of the proposed driver activity monitoring system is given in the below figure 2.

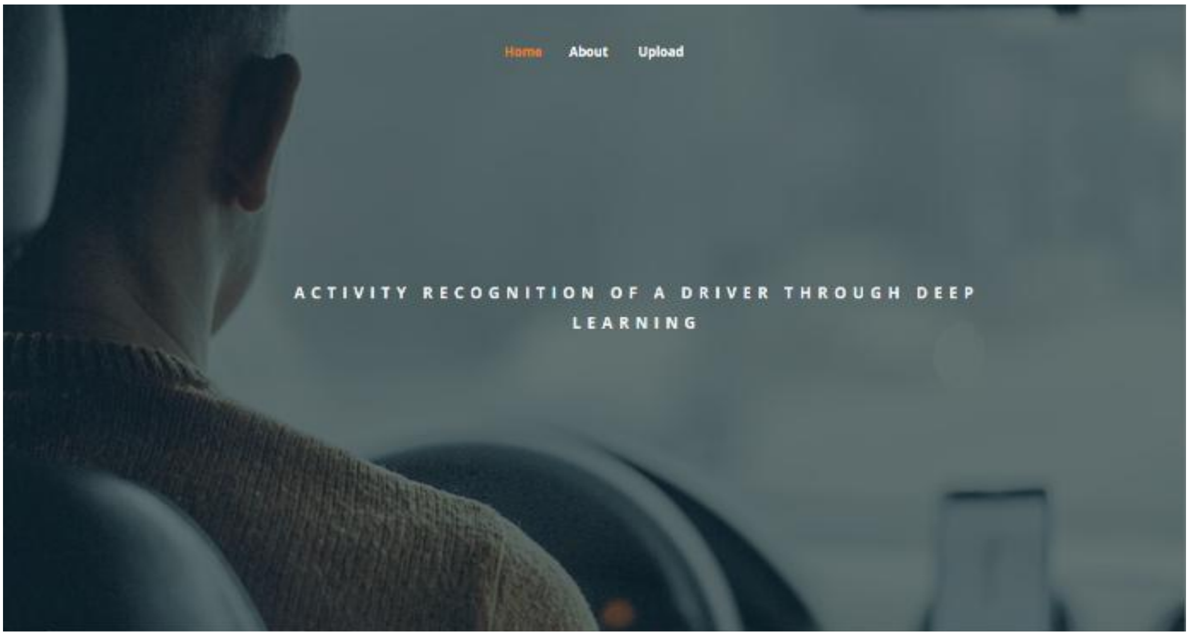

Figure.2. Screenshot of the home page

About Page

The screenshot of the about page of the proposed driver activity monitoring system is indicated in the below figure 3. The description of the project is provided in this about page.

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Figure.3. Screenshot of the about page

Upload Page

The screenshot of the upload page of the proposed driver activity monitoring system is denoted in the below figure 4. Here there is an input field to upload a driver activity image.

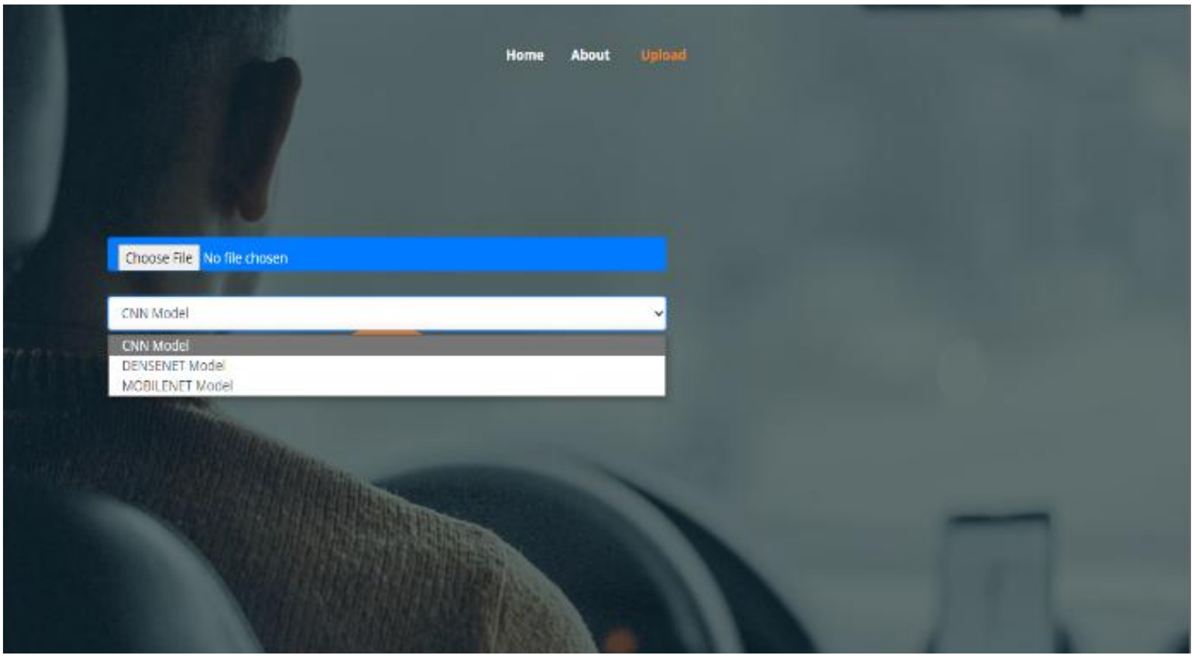

Figure.4. Screenshot of the upload page

Result Page

The screenshot of the result page of the proposed driver activity monitoring system is expressed in the below figure 5. Result page will give the results after going through the model.

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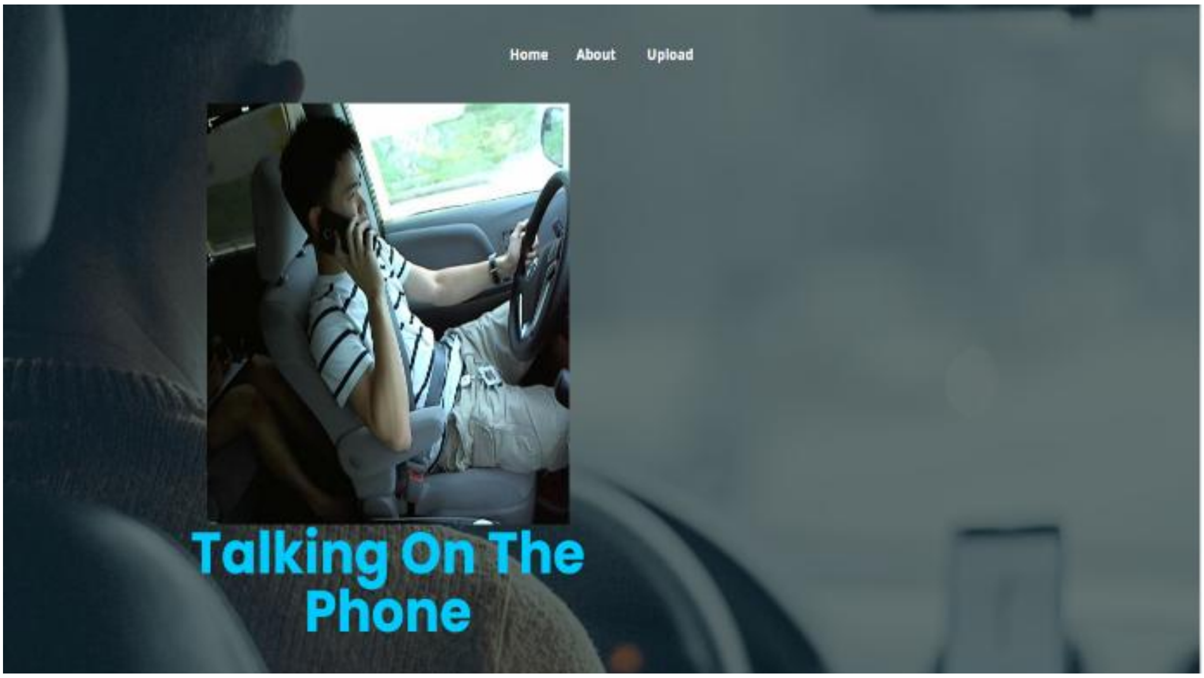


Figure.5. Screenshot of the result page

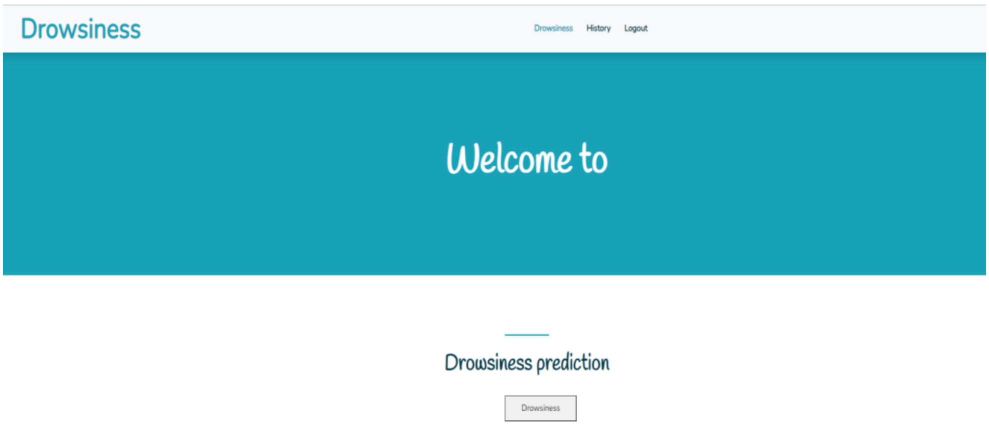
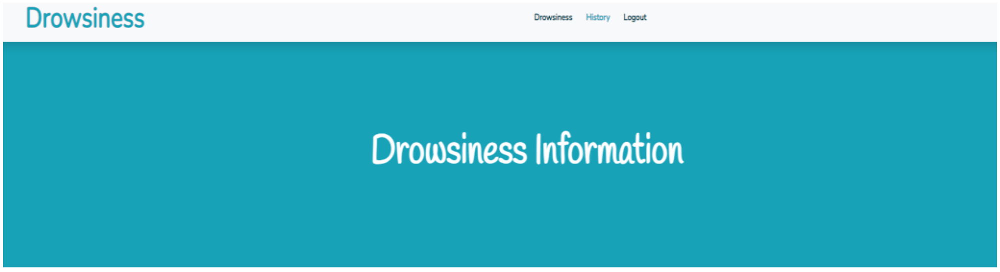
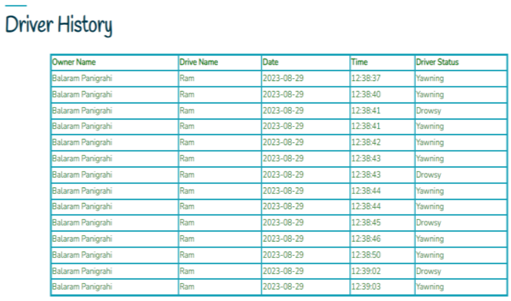


Figure 6 Screenshot of the prediction page




Driver History

Owner Name	Drive Name	Date	Time	Driver Status
Balaram Panigrahi	Ram	2023-08-29	12:38:37	Yawning
Balaram Panigrahi	Ram	2023-08-29	12:38:40	Yawning
Balaram Panigrahi	Ram	2023-08-29	12:38:41	Drowsy
Balaram Panigrahi	Ram	2023-08-29	12:38:41	Yawning
Balaram Panigrahi	Ram	2023-08-29	12:38:42	Yawning
Balaram Panigrahi	Ram	2023-08-29	12:38:43	Yawning
Balaram Panigrahi	Ram	2023-08-29	12:38:43	Drowsy
Balaram Panigrahi	Ram	2023-08-29	12:38:44	Yawning
Balaram Panigrahi	Ram	2023-08-29	12:38:44	Yawning
Balaram Panigrahi	Ram	2023-08-29	12:38:45	Drowsy
Balaram Panigrahi	Ram	2023-08-29	12:38:46	Yawning
Balaram Panigrahi	Ram	2023-08-29	12:38:50	Yawning
Balaram Panigrahi	Ram	2023-08-29	12:39:02	Drowsy
Balaram Panigrahi	Ram	2023-08-29	12:39:03	Yawning

Figure 7 Screenshot of the History of drowsiness page

Conclusion

This project's innovations and integrations in this project herald a new era in driver safety systems. By seamlessly blending state-of-the-art technology with a deep understanding of drivers' needs and behaviors, it offers a solution that is not only technologically superior but also user-centric. In our work, we have gathered the visual data such as facial expressions, eye movement, and head posture from the dataset and used for the training.

As road conditions, vehicles, and challenges evolve, it's imperative that our safety systems do too. This project is a testament to what's possible when we combine the best of technology with a genuine intent to safeguard lives on the road.

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