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Deep Learning Solutions for Real-Time Driver Distraction and Drowsiness using Alerts

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Abstract: - The rising incidence of road accidents due to driver distraction highlights the pressing need for robust monitoring systems to improve road safety. The Driver Distraction & Drowsiness Alert System is a significant advancement in this area, utilizing machine learning and deep learning techniques to address the dangers of distracted and drowsy driving. In the past researchers presented drowsy driver detection systems with existing machine learning algorithms. The proposed system focuses on developing a highly accurate detection model capable of identifying subtle signs of driver distraction and drowsiness. The proposed system offers a method for evaluating the level of driver fatigue using various convolutional neural network (CNN) models to analyze images of drivers extracted from video. Driver distraction and facial sleepiness expressions were detected using various features such as eye position, mouth position, head positioning and angle. Beyond the theoretical framework, the system extends its impact through the creation of a practical application. The user-friendly application integrates the sophisticated detection algorithms into real-time driver monitoring, delivering timely alerts to prevent potential accidents caused by fatigue. The system also attempts to send alarming notifications to driver's relatives in case of an emergency. This paper provides a comprehensive overview of the research methodology, emphasizing the seamless fusion of advanced algorithms and practical application, ultimately contributing to the ongoing efforts aimed at making our roads safer for everyone.

Keywords: Deep Learning(DL), Computer Vision, Image Processing, Convolutional Neural Network(CNN), Rectified Linear Unit(ReLU)

I. INTRODUCTION

Drowsiness is a state of feeling sleepy. Although drowsiness may seem temporary, lasting only for a few minutes, its effects can be catastrophic [27]. The primary reason for drowsiness is often fatigue, which diminishes alertness and the ability to concentrate. However, other factors contributing to drowsiness can include lack of focus, medication side effects, sleep disorders, alcohol consumption, or working irregular shifts [27]. Individuals experiencing drowsiness are unable to anticipate when they might fall asleep [29]. The main effects of drowsy driving include inability to focus, poor judgment, delayed reaction, wrong estimation of distances and speeds and of course falling asleep when driving [30]. Drowsy driving presents a significant threat to road safety worldwide, contributing to a substantial number of accidents and fatalities each year. With the advancement of technology, researchers and engineers have been striving to develop innovative solutions to detect and mitigate the risks associated with drowsy driving. According to the National Highway Traffic Safety Administration (NHTSA), drowsiness of drivers is a significant factor contributing to car accidents and fatalities on the roads. The police and hospital reports indicate that 100,000 car accidents and over 1,500 deaths occur each year due to drowsy driving [28]. NHTSA estimates that drowsy driving is responsible for approximately 1,550 fatalities, 71,000 injuries, and $12.5 billion in financial losses [28]. However, NHTSA acknowledges that quantifying the exact number of accidents or fatalities caused by drowsy driving is challenging, and the reported figures may be underestimated [28].

This paper emphasizes on driver's distractedness and drowsiness leveraging the power of deep learning algorithms. By employing state-of-the-art machine learning techniques, it aims to accurately identify signs of driver fatigue in real-time, thus preventing potential accidents and saving lives on the road. The driver's facial features, focusing on key areas such as the eyes, mouth as well as head positioning are analyzed. By monitoring the degree of eye closure and the frequency of blinking, signs of drowsiness, such as prolonged periods of eyelid drooping or slow blink rates can be detected. Additionally, changes in the shape and movement of the mouth, such as yawning or slackened jaw muscles, serve as supplementary indicators of fatigue. Through advanced image

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processing techniques and deep learning algorithms, the system accurately interprets these facial cues in real-time. This work aims to evaluate the efficacy of software tools in processing and interpreting drowsiness of drivers. This system is built upon a deep learning model trained on a dataset of approximately 41,790 images, capable of accurately identifying signs of driver drowsiness. The model is integrated into a user-friendly application developed using React, Node.js and MongoDB. The application captures continuous frames of the driver at 100 ms intervals from the camera, which are then processed by the model to predict whether the driver is drowsy, distracted or active. In the event of detecting drowsiness, the system issues a warning buzzer to the driver to take immediate action. If the driver fails to respond to the buzzer, an alert is sent to a registered family member through the Telegram app containing the driver's location. This real-time intervention mechanism aims to prevent potential accidents caused by driver fatigue.

Furthermore, the system includes a feedback mechanism for drivers to report false positives, allowing for continuous improvement of the model's accuracy. This paper also provides a comprehensive overview of the proposed system, detailing the methodology, results, and implications.

II. Literature Survey

This section highlights the methodologies and strategies used in the past to identify diver's drowsiness. Some of the methods include Driving Patterns, Image based measures and Physiological Based Methods as well. Driving Pattern-Based Methods analyze driving patterns, considering factors like vehicle features, road conditions, and driving techniques. For instance, monitoring steering wheel movement or lane deviation helps assess a driver's style. Lane deviation is another indicator of sleepiness, but these methods depend on specific vehicle and road contexts [5] [24].

Image-Based Measures: These measures involve capturing and analyzing the driver's facial expressions and movements through cameras or visual sensors. Specifically, the signs of drowsiness that can be detected through this approach include the driver's eye movements, such as blinking patterns or drooping eyelids, mouth movements like yawning or lack of expression, and head movements, like nodding off or sudden jerks.

Physiological Based Methods: These approaches utilize physiological data from sensors like electrocardiograms (ECG), electroencephalograms (EEG), and electrooculography (EOG). EEG signals provide insights into brain activity. Key signals include delta, theta, and nascence. When a driver is drowsy, theta and delta signals increase, while nascence signals remain relatively stable. Although this system achieves high precision (over 90%), it requires intrusive detectors, which can be uncomfortable. Non-intrusive bio signal methods are less accurate but more user-friendly [22] [23].

Hybrid methods: utilize a combination of different types of measures to extract features that indicate driver drowsiness employs a combination of, biological, image based and vehicle based measures to extract drowsiness features. By analyzing data from various measures this results in a system which has a better performance and is reliable [25] [26].

Ahmed et al. [11] proposed a deep learning approach using a convolutional neural network (CNN) model to detect driver drowsiness. They utilized a public dataset from Kaggle consisting of 2,900 images classified into four categories based on eye and mouth states. The dataset included features such as gender, age group, head position, and illumination conditions. The authors developed a CNN model with Conv2D, MaxPooling2D, Flatten, Dropout, and Dense layers to identify the state of the eyes and mouth for drowsiness detection. They also employed a pre-trained VGG16 model for transfer learning and compared its performance with the proposed CNN model. The evaluation metrics used were accuracy, precision, recall, and F1-score. The proposed CNN model achieved an accuracy level above 90%, outperforming the VGG16 model, which achieved an accuracy of 74%. The study emphasized the importance of considering various evaluation metrics beyond just accuracy to comprehensively assess the model's performance. K Nizar, Hairol Jabbar et. al [12] proposed a driver drowsiness detection system which utilized an internal web camera as the input tool and a speaker for the output alarm. It employed Eye Aspect Ratio (EAR) and Mouth Aspect Ratio (MAR) algorithms, along with OpenCV and dlib's 68 facial landmarks, to determine drowsiness in real-time based on eye blinking and yawning. The system performed face analysis, followed by parallel eye closure and mouth opening detections after capturing the driver's face through the live stream. Specifically, eye closure was tracked using the EAR algorithm with a threshold value of 0.25, while yawning was detected using the MAR algorithm with a threshold value of 35. A. Nahvi and M. Tashakori et al. [3] made use of A thermal camera was used to extract the face temperatures of the forehead and cheeks. Two sessions were used to study thirty participants. The supratrochlear artery-covered forehead regions of the patients were chosen. Every frame of the thermal image contained a tracking and identification of the target regions. At each of the three drowsiness levels—wakefulness, moderate drowsiness, and excessive drowsiness—the skin temperature signal was retrieved for every subject. A methodology developed by Choi, Hyun-Soo, et al. [4] employs a brief two-second EEG segment to detect and alert users to instantaneous sleepiness states like a lapse. A classifier using XGBoost and feature extraction using MPSD are included in the suggested framework. The MPSD effectively extracts useful spectrum information from the EEG data. XGBoost uses spectral information to identify tiredness with success. Chai, Meng, et al. [5] developed a system that identified effective parameters for detecting drowsy driving by extracting 11 steering wheel metrics. Through variance analysis, the parameters Ellipse, Amp_D2_Theta, NMRHOLD, and SW_Range_2 were selected as the most effective for assessing driver drowsiness. To confirm the impact of variance analysis and the robustness of the selected parameters, MOL, SVM, and BP models were constructed using all eleven parameters and a subset of three parameters from the four mentioned. P. Tumuluru et al [13] presented a novel approach called SDDD (Stacked Ensemble Model for Driver Drowsiness Detection) aimed at effectively detecting driver drowsiness using lightweight deep learning models like MobileNet-V2, SqueezeNet, and ShuffleNet. The stacked ensemble model achieves the highest accuracy at 86.1%, with a precision of 84.1% and a recall of 81.0%.

III. Methodology

The problem aimed to address in this paper is the detection of driver's distractedness and drowsiness, a significant contributing factor to road accidents worldwide. Drowsy driving can lead to slower reaction times, decreased vigilance, and impaired thinking, increasing the risk of accidents. Despite its severity, the subtle signs of driver fatigue often go unnoticed, leading to potentially dangerous situations on the road. The main goal is to develop a System that can accurately identify signs of distractedness and driver fatigue in real-time, thus preventing potential accidents. The system should be capable of issuing timely warnings to the driver and, if necessary, alerting a registered family member or responsible person

A. Data Collection

The first stage of the methodology involved the collection and preprocessing of data. The data used in this paper is the Driver Drowsiness Dataset (DDD), which is a collection of extracted and cropped faces of drivers from the videos of the Real-Life Drowsiness Dataset. The process of data collection involved the extraction of frames from videos as images using VLC software. These images were then processed using the Viola-Jones algorithm, a machine learning approach for object detection, to extract the region of interest from the captured images. The region of interest in this context refers to the facial features of the drivers, which are crucial in detecting signs of drowsiness. The DDD is composed of RGB images, with two classes representing the states of the driver: Drowsy and Non-Drowsy. Each image in the dataset has a size of 227 x 227 pixels. The dataset is quite extensive, containing more than 41,790 images in total. The file size of the dataset is approximately 2.32 GB. Once the data was collected, it underwent a preprocessing stage to prepare it for the deep learning model. This involved normalizing the pixel values and converting the images to grayscale to reduce computational complexity. Additionally, the dataset was split into training and testing sets, ensuring that the model could be evaluated on unseen data. Through this rigorous data collection and preprocessing stage, it is ensured that the deep learning model has a robust and representative dataset to learn from, thereby increasing the accuracy and reliability of the drowsiness detection system. The subsequent sections of this paper will delve into the model development and application development stages of the methodology.

B. Model Training

This research paper investigates the utilization of deep learning methodologies for the detection of drowsiness in drivers based on RGB images. The dataset employed comprises images of dimensions 227x227 pixels with three color channels (RGB). Through rigorous experimentation and analysis, the paper examines the efficacy of employing convolutional neural networks (CNNs) to accurately discern the presence of drowsiness in drivers in real-time scenarios. To ensure robust model training and evaluation, the dataset is split into training (80%) and testing (20%) sets, with a fixed random seed (42) to ensure reproducibility.

Convolutional Neural Network (CNN), a type of deep learning model particularly effective for image classification tasks. The architecture of our CNN is designed to extract meaningful features from the input images and use these features to classify the state of the driver as either drowsy or alert.

A CNN model consists of three main layers: the input layer, hidden layers, and an output layer. The input layer receives images, with the number of neurons corresponding to the number of pixels in the image. The hidden layers process the output from the input layer, with the number of hidden layers determined by the model and the amount of data. Each hidden layer may have a different number of neurons, typically more than the number of pixels in the image. The output layer receives the output from the hidden layers and applies a logistic function to determine the likelihood scores for each class. Feature maps generated by applying filters to each layer of the CNN capture the features detected by the network. Visualizing these feature maps can provide insights into the features learned by the CNN. In this study, a custom CNN model was employed to detect driver drowsiness by identifying the state of the eyes, head, mouth as well as spatial angle at which head is present. The model's performance heavily depends on the size of the dataset, and the DDD dataset was split into a 70-30 ratio in which 29,250 images were present in the training dataset and was deemed sufficient for training the proposed model. The CNN model architecture used in this study consisted of Conv2D, MaxPooling2D, Flatten, and Dense layers, which are briefly described in the text.

i. Conv2D Layer - The Keras Conv2D layer is utilized for performing two-dimensional convolutions, where it convolves a kernel with the input data to generate output tensors. This kernel acts as a convolution matrix or mask, capable of various operations like blurring, sharpening, edge detection, etc., when convolved with an image. During convolution, the kernel slides over the input data, conducting element-wise multiplication, and aggregating the results to produce a single output. In the context of colored images with RGB channels, the convolution is carried out independently for each channel, and the outcomes are combined to form the final output.

ii. Layer MaxPooling2D - Embodying the features that lie under the filter's coverage zone involves running a two-dimensional filter over each channel of the feature map as part of the pooling step. A pooling operation called max pooling selects the peak element from the feature map area that the filter has surrounded. Consequently, the max-pooling layer's creation would yield a feature map that includes the most noticeable elements from the previous feature map.

iii. Layer Flattening - A matrix generated from convolutional and pooling layers can be flattened into a single features vector while preserving batch size. This layer is necessary since ANNs receive a one-dimensional array as input.

iv. Dense Layer -

In this layer, every neuron sends inputs to every other neuron. The dense layer uses the convolutional layers' output to classify the image. After a single set of procedures, this process produces a structure with a small number of components and parameters that yield accurate results.

Various models trained and tested various models on the DDD dataset and selected the one with best accuracy for our web application.

1. ResNet (Residual Network): ResNet is a deep convolutional neural network architecture characterized by residual connections, which allow the network to learn residual mappings, enabling training of very deep networks with improved accuracy. It has been widely adopted in various computer vision tasks due to its effectiveness in learning hierarchical features

2. VGG (Visual Geometry Group): Known for its simplicity, the VGG convolutional neural network architecture consists of several convolutional layers, max-pooling layers, and fully connected layers in order of precedence. Even with its simple architecture, VGG is a foundation for many contemporary architectures and has demonstrated good performance on image classification tasks.

3. Proposed Custom model: Fig.1 shows the 7 layers of proposed custom model with 7 layers, the first 4 layers are for feature extraction- initial convolution layer, max pooling layer, second convolution layer, second max pooling layer and the remaining three are for classification purposes.

```
_________________________________________________________________
 Layer (type)                Output Shape
=================================================================
 conv2d_1 (Conv2D)           (None, 126, 126, 32)

 max_pooling2d_1 (MaxPoolin  (None, 63, 63, 32)
 g2D)

 conv2d_2 (Conv2D)           (None, 61, 61, 64)

 max_pooling2d_2 (MaxPoolin  (None, 30, 30, 64)
 g2D)

 flatten_1 (Flatten)         (None, 57600)

 dense_2 (Dense)             (None, 64)

 dense_3 (Dense)             (None, 1)

=================================================================
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Fig. 1 Seven layers of proposed custom model

Our CNN's convolutional layer, which has 32 3x3 filters, is its first layer. In order to produce feature maps, this layer applies the filters to the input images, which are 128x128 pixels with three color channels (RGB). This layer uses the Rectified Linear Unit (ReLU) activation function to add non-linearity to the model, enabling it to learn more intricate patterns. A 2x2 windowed max pooling layer comes after the first convolutional layer. By calculating the greatest value in each window, this layer shrinks the feature maps' spatial dimensions (width and height). This process lowers the computational complexity of the layers that follow and helps to make the model invariant to tiny translations. Our CNN's second convolutional layer employs the ReLU activation function and has 64 3x3 filters. This layer can learn more complex features from the reduced feature maps produced by the previous max pooling layer. After the second convolutional layer, we have another max pooling layer that further reduces the spatial dimensions of the feature maps. This is followed by a flatten layer, which transforms the multi-dimensional feature maps into a one-dimensional vector. This flattened vector serves as the input to the fully connected layers of the network. The first fully connected layer has 64 neurons and uses the ReLU activation function. This layer can learn complex non-linear combinations of the features extracted by the convolutional layers. The final layer of the network is another fully connected layer with one neuron, corresponding to the binary classification problem at hand (the output is either 0 or 1). This layer uses the sigmoid activation function, which squashes the output values between 0 and 1 to represent probabilities.

C. System Architecture

The Drowsy Driver Detection System is a comprehensive application that leverages deep learning for real-time detection of driver drowsiness. The system architecture includes a frontend developed using React JS for user interaction, a backend developed using Node.js and Flask for data handling and image processing, and MongoDB for data storage. The deep learning model, trained on a dataset of approximately 39,000 images, processes the image frames received from the frontend to predict driver drowsiness. The system issues timely warnings, alerts a registered contact if necessary, and allows for continuous improvement through a feedback mechanism. Fig. 2 shows the various blocks of the proposed system.

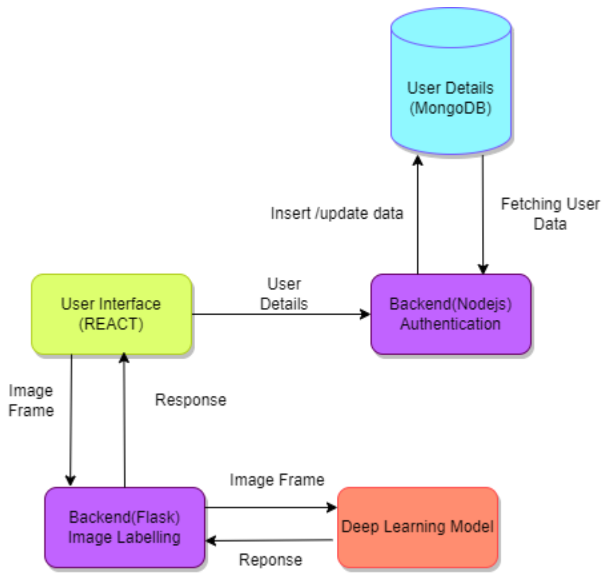

Fig. 2 Block Diagram of proposed system

React is a well-liked JavaScript user interface library that was used to create the system's user interface. Authentication and image tagging comprise the application's two backend components. The Node.js JavaScript runtime, which is based on Chrome's V8 JavaScript engine, is used to construct the authentication portion of the backend. bcrypt package is used for hashing the password. It receives the user details from the user interface frontend, verifies these details, and interacts with MongoDB to fetch or update data. The image labeling part of the backend is developed using Flask, a micro web framework written in Python. It receives the image frames from the frontend and processes these frames using a deep learning model. The processed frames are then used to predict whether the driver is drowsy or active. MongoDB, a source-available cross platform document oriented database program, is used to store user details. It interacts with the Node.js backend during the authentication process, storing and fetching user data as required. The deep learning model is the core of the image labeling process. It is trained on a dataset of approximately 39,000 images, learning to accurately identify signs of driver fatigue based on the driver’s facial features. The model is integrated into the Flask backend, processing the image frames received from the frontend in real-time. Fig. 3. depicts the workflow of the proposed system.

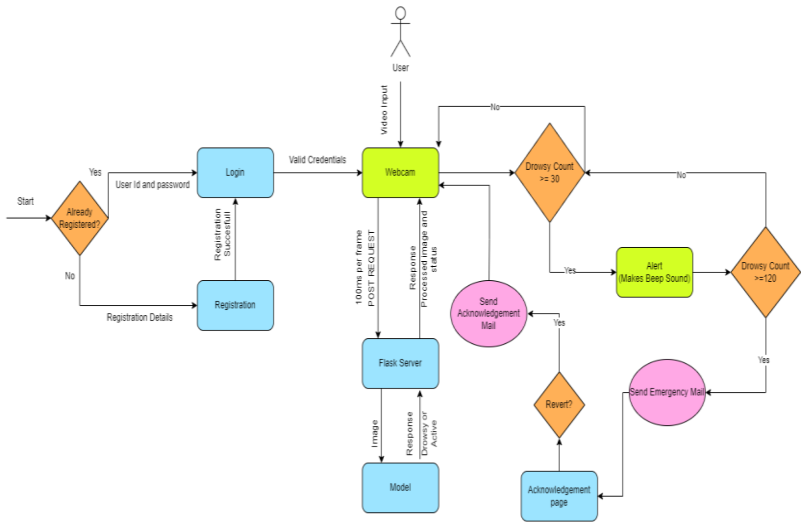

Fig. 3 Workflow of the proposed system

D. System Testing

The system is designed to detect and respond to driver drowsiness and distractions to enhance road safety. Key features include:

i. Audible Alarm: Activates when drowsiness is detected, using adjustable volume to alert the driver without excessive startling.

ii. Eyes Monitoring: Continuously tracks eye movements, focusing on parameters like eye position, openness, and blinking frequency to detect signs of fatigue.

iii. Yawning Detection: Monitors the mouth region to identify yawning, a reliable indicator of drowsiness.

iv. No Faces in Frame: Detects when the driver's face is not visible in the camera frame, indicating potential distraction or head tilt.

v. Sideways Glancing: Identifies when the driver frequently looks away from the road, signaling possible distractions.

vi. Droopy Face Detector: Detects forward tilting of the head, commonly associated with drowsiness.

These features work together to create a comprehensive understanding of the driver's alertness. When drowsiness exceeds a set threshold, the system triggers a notification and a five-second audible alert, encouraging the driver to take corrective action. This multi-faceted approach enhances driver awareness, reducing the risk of accidents.

IV. Results And Discussions

A driver's emergency contact is notified via email to join a Telegram group where they'll receive updates if the driver is detected as drowsy or distracted. If the driver becomes unresponsive, an automated message with their GPS coordinates is sent to the group. The coordinates are embedded in a Google Maps link, allowing the emergency contact to quickly locate the driver and take necessary actions, such as providing assistance or contacting authorities, enhancing the driver's safety and well-being. Fig. 4 shows the location coordinates sent along with the message to the emergency contact.

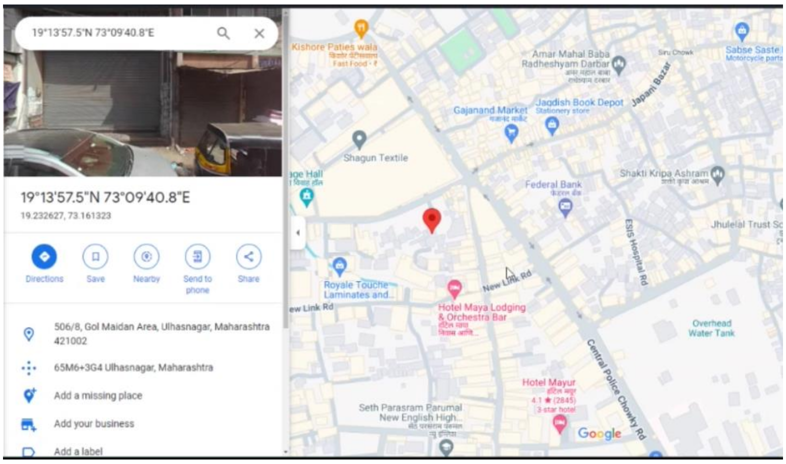

Fig. 4 Location coordinates sent along with the message to the emergency contact

If the driver regains alertness and it is determined through detection mechanisms that they are no longer experiencing drowsiness, a safety message is promptly dispatched to the designated emergency contact to reassure them of the driver's well-being. This functionality is highly beneficial as it provides peace of mind to the emergency contact, ensuring that they are promptly informed of the driver's safety status and alleviating any potential concerns or worries about the driver's condition. Additionally, it facilitates timely communication and reassurance, enabling the emergency contact to respond accordingly and take appropriate actions if necessary, while also fostering a sense of trust and confidence in the safety measures implemented within the system. Table 2 indicates the accuracy achieved through various algorithms. Fig. 5 depicts the histogram of the color scale pictures.

Table 2. Accuracy of the Algorithms used

ALGORITHMS	ACCURACY
CUSTOM MODEL	0.99159
RESNET	0.95685
VGG	0.95845

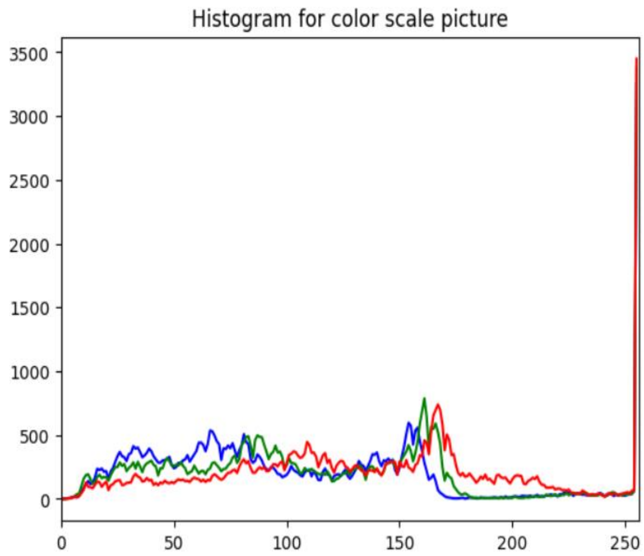

Fig. 4 Histogram of the color scale pictures

Table 3 shows the comparison of the existing approaches with the proposed system.

Table 2. Comparison of features present in the literature

Paper	Features Considered	Condition detected	Alert mechanism	Model considered	Accuracy
M. Ahmed (2023) [1]	Eyes, yawning	Drowsiness	No	CNN , VGG	74 %
K. Nizar (2023) [12]	Eyes, yawning	Drowsiness	Yes , Visual	MMOD CNN	95 %
P. Tumuluru (2023) [13]	Facial (unspecified)	Drowsiness	No	Stacked Ensemble CNN	86 %
A. Bhetuwal (2023) [14]	Eyes, Face	Drowsiness	No	Resnet-50	96 %
Tashakori M, (2021) [3]	Forehead, cheek	Drowsiness	No	SVM, KNN	82 %
S. Samir (2023) [15]	Eyes, Mouth	Drowsiness	Yes , Visual	GBRT	Unspecified
Proposed system	Eyes, Head, Mouth, Spatial angle	Drowsiness + Distraction	Yes, Visual + Sound + Telegram message	Custom CNN	99 %

V. CONCLUSION

In conclusion, the Proposed System in this paper represents a substantial progress in leveraging technology to enhance road safety. By employing deep learning algorithms trained on a substantial dataset, the system is capable of accurately identifying signs of driver drowsiness and distraction in real-time. The integration of this model into a user-friendly application allows for continuous monitoring of drivers, issuing timely warnings and alerts to prevent potential accidents brought on by exhaustion. The system's feedback mechanism also provides a pathway for continuous improvement, enhancing the model's accuracy over time. The successful development of this system showcases deep learning's potential to solve real-world problems by turning raw data into actionable insights, enhancing road safety. While currently focused on drowsy driving, the technologies used could be applied to broader driver behavior analysis, leading to more comprehensive monitoring systems. The ongoing work is committed to leveraging technology to save lives and create a safer driving environment for all.

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