SCHOOL OF COMPUTER SCIENCE AND ENGINEERING

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Driver Drowsiness Detection System

A Project Report

Under the Guidance of,
Prof.A.Srivani

By

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DECLARATION BY THE CANDIDATE

We hereby declare that the project report entitled "Driver Drowsiness Detection System" submitted by us to Vellore Institute of Technology, Vellore in partial fulfillment of the requirement for the award of the degree of B. Tech CSE is a record of J- component of project work carried out by us under the guidance of Prof. A.Srivani. We further declare that the work reported in this project has not been submitted and will not be submitted, either in part or in full, for the award of any other degree or diploma in this institute or any other institute or university.

Place : Vellore Institute of Technology, Vellore.

Date :26th August, 2022

Signature of the faculty **Signature of the Candidate**

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1. INTRODUCTION

1.1 ABSTRACT:

The amount of fatalities resulting from auto or traffic accidents is one of the most prevalent problems afflicting today's society. Since 2005, it has been projected that 17 accidents have happened every hour in India, according to a Statista analysis. In 2019 alone a total of 151.4 thousand deaths occurred. The proposed system basically functions as a "driver drowsiness detection system," sounding an alarm if it detects the driver's eyes closed for longer than 15 seconds. A region of interest (ROI) will be created from the webcam image of the eye, which will be fed to a classifier for additional analysis using deep learning approaches in conjunction with computer vision. Depending on whether the eyes are open or closed, the classifier will notify and sound the alarm. This will entail image processing to some extent for the analysis.

The main objective is to create a system that continuously scans the retina of the eye to detect driver drowsiness. This will keep an eye on the driver and aid in preventing such car crashes. We use an alarm or buzzer to notify the driver when drowsiness is detected. The vehicle's speed can be slowed down. By controlling this traffic, the number of accidents can be kept to a minimum.

1.2 Background Of The Problem:

Drowsy driving is a major problem that is one of the major causes of accidents on roads. The risk, danger, and often tragic results of drowsy driving are alarming. Drowsy driving is the dangerous combination of driving and sleepiness or fatigue. The National Highway Safety Administration estimates that drowsy driving results in 1,550 deaths, 71,000 injuries, and more than 100,000 accidents per year. This usually happens when a driver has not slept enough.

No one knows the exact moment when sleep comes over their body. Falling asleep at the wheel is clearly dangerous but being sleepy affects your ability to drive safely even if you don’t fall asleep.

Drowsiness:

- Makes you less able to pay attention to the road.
- Slows reaction time if you must brake or steer suddenly.
- Affects your ability to make good decisions.

In this project, we try to rectify this problem by making a detection system that alarms on identifying any drowsiness in the driver.

1.3 MOTIVATION OF THE PROPOSED WORK:

Accidents caused by drivers who pass out have grown in frequency, maybe as a result of increased workload, stress, etc. Numerous people who drive at night on the highway may be fatigued, which could cause them to fall asleep behind the wheel and cause serious accidents.

According to a study, drowsy drivers who are weary cause a large number of traffic accidents. This also poses a threat to other vehicles on the road who are unaware of the possibility of an out-of-control vehicle. When a driver is sleep deprived and exhausted, it can have serious adverse effects on their ability to respond quickly, concentrate, and be aware of what is going on around them while driving. Their inability to manage their speed as a result of paying insufficient attention to the road can impede their ability to make decisions.

1.4 FOCUS OF THE PROPOSED WORK:

The drowsiness detection system is capable of detecting drowsiness quickly. The system which can differentiate normal eye blink and drowsiness can prevent the driver from entering a state of sleepiness while driving. The system works well irrespective of the driver wearing spectacles and under low light conditions also. During the monitoring, the system is able to decide if the eyes are closed or opened. When the eyes have been closed for too long a warning signal is issued.

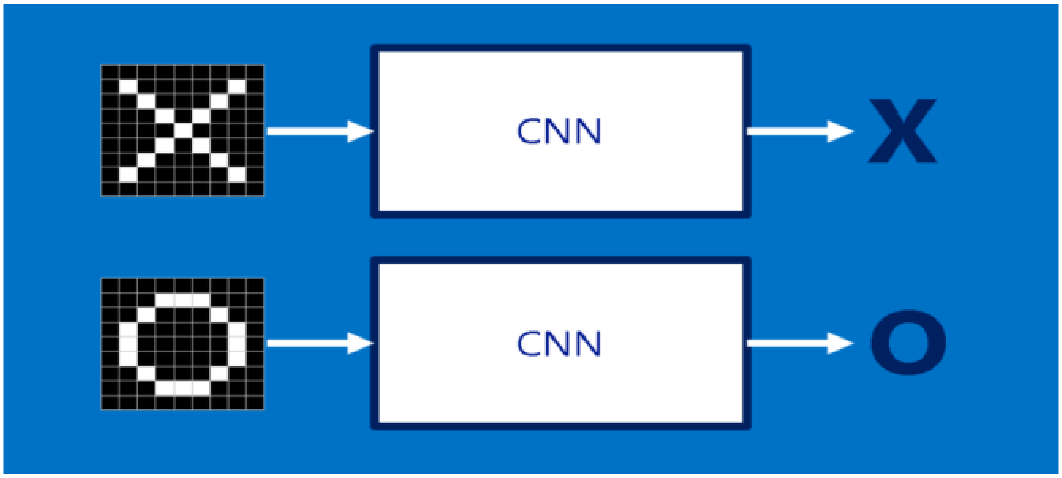
2. OVERVIEW AND PLANNING

2.1 Proposed Work:

In our proposed work, we will use the Keras model using Convolutional Neural Networks (CNN). The convolutional neural network is a special type of deep neural network that works very well for the purposes of image classification. CNN basically contains an input layer, an output layer, and a hidden layer that can contain multiple numbers of layers. The convolutional work is done on these layers using a filter that makes 2D matrix multiplications in the layer and filter.

CNN model architecture consists of the following layers:

- Convolutional layer; 32 nodes, kernel size 3
- Convolutional layer; 32 nodes, kernel size 3
- Convolutional layer; 64 nodes, kernel size 3
- Fully connected layer; 128 points



Dataset :

The dataset will be an Open CV dataset for image processing purposes. For the dataset, we are trying to figure out the source which can be either from the open source or created by us.

2.2 Hardware Requirements:

Webcam: For the live implementation in the vehicles we would need a real-time camera to detect the driver’s face.

Personal Computer: To develop a prototype for the project. Operating System: Windows or Linux.

CPU/GPU:A good GPU is essential for a machine learning project. Training models are hardware intensive tasks , and a decent GPU will ensure that the calculation of neural networks runs smoothly. Compared to CPUs, GPUs are much better at managing machine learning tasks.Needed GPU is 8gb for prototyping and 10-11gb for better training.

RAM: When running deep learning tasks it is important to have better RAM.A minimum of 8GB RAM can do the job for most machine learning tasks, 16GB RAM and above is recommended for most deep learning tasks.

2.3 Software Requirements:

Credible and successful prototype needs the frame of robust software supporting and complementing the functionalities provided by its hardware counterparts. In our project too, for developing an exemplary system for detecting drowsiness of the driver and consequently alerting him/her, we need to mandate certain proprietary tools of software:

Python (A Version Not Preceding 3.6): A high-level general-purpose programming language very useful for performing several ML and AI-based tasks due to its ease of use, greater readability, extensive library and modular support, etc.
TensorFlow: An open-source software library comprising a collection of tools/methods for AI & ML, with a specific focus on deep neural networks’ training.
Keras: An open-source library that is instrumental in providing a Python interface for artificial neural networks, which finds common applications in face/image recognition.

OpenCV: A library of programming tools specially curated for computer vision applications of detecting and recognizing and also analyzing face and visage features like eyes, hair, etc.
Pygame: This is essentially a set of Python modules intended for designing video

3. LITERATURE SURVEY AND REVIEW

An Introduction to Convolutional Neural Networks

Authors: Keiron O'Shea and Ryan Nash

Journal: ResearchGate, November 2015

This document provides a brief introduction to CNNs, discussing recently published papers and newly formed techniques in developing these brilliantly fantastic image recognition models. This introduction assumes you are familiar with the fundamentals of ANNs and machine learning.

Convolutional Neural Networks differ from other forms of Artificial Neural networks in that instead of focusing on the entirety of the problem domain, knowledge about the specific type of input is exploited. This in turn allows for a much simpler network architecture to be set up.

Understanding of a Convolutional Neural Network

Authors: Saad ALBAWI, Tareq Abed MOHAMMED

Journal: ICET2017, Antalya, Turkey

One of the most popular deep neural networks is the Convolutional Neural Network (CNN). It takes this name from the mathematical linear operation between matrixes called convolution. CNN has multiple layers; including a convolutional layer, non-linearity layer, pooling layer, and fully- connected layer. The convolutional and fully- connected layers have parameters but pooling and non-linearity layers don't have parameters. CNN has an excellent performance in machine learning problems.

In this paper, we discuss the important issues related to Convolutional Neural networks (CNN) and explain the effect of each parameter on the performance of the network. The most important layer in CNN is the convolution layer Which takes most of the time within the network.

Research and Implementation of CNN Based on TensorFlow

Authors:Liang Yu1, Binbin Li1,* and Bin Jiao1

Journal: IOP Conference Series,04/2022

TensorFlow is Google's open-source machine learning and deep learning framework, which is convenient and flexible to build the current mainstream deep learning model. This paper writes a program and calls the open-source TensorFlow library to establish a deep learning model: CNN.

With the visual tool TensorBoard, the paper display this deep learning model structure, test results, and trend curves verifying the validity of the model. Compared with the classical convolutional neural network, a layer of convolution and pooling operations are added, and the second convolution pooling operation is convenient for deeper levels to extract a richer feature quantity, and it finally achieves a recognition accuracy of 99.15%.

Real-Time Driver-Drowsiness Detection System Using Facial Features

Authors: Deng, Wanghua, and Ruoxue Wu.

Journal: *Ieee Access* 7 (2019): 118727-118738.

Through face tracking and facial key point identification, the authors of this research suggest a unique technique for determining a driver's level of drowsiness. The authors have proposed a new algorithm namely MC-KCF to monitor the driver's face using CNN and MTCNN, which is an improved version of the KCF algorithm. They defined the facial regions of detection on the basis of facial key points. The drowsiness condition of the driver was also evaluated based on the state of their eyes and mouth. The experimental results showed that the proposed system achieved around 92% accuracy.

A Real-time Driving Drowsiness Detection Algorithm With Individual Differences Consideration

Authors: You, F., Li, X., Gong, Y., Wang, H., & Li, H.

Journal: *Ieee Access* 7 (2019): 179396-179408.

The real-time driving drowsiness detection system suggested in this paper takes into account the individual characteristics of the driver. To detect the facial region, a deep cascaded convolutional neural network was built, which gets over the issue of poor accuracy brought on by artificial feature extraction. The frontal driver facial landmarks in a frame are located using the Dlib toolbox. Eyes Aspect Ratio, a new parameter based on eye landmarks, is introduced to measure the driver's tiredness in the current frame. The proposed system has two modules: offline training and online monitoring, which account for variations in the size of the driver's eyes. The proposed system could have explored multi-features such as head and mouth fusion methods to enhance the algorithm.

Driver Safety Development: Real-Time Driver Drowsiness Detection System Based on Convolutional Neural Network

Authors: Hashemi, Maryam, Alireza Mirrashid, and Aliasghar Beheshti Shirazi.

Journal: *SN Computer Science* 1 (2020)

In the proposed system in this paper, Convolutional Neural Networks (CNN) are employed with reference to the two objectives of real-time application, including high accuracy and fastness, to detect the falling asleep state of the driver as the indicator of sleepiness. Three potential networks are presented, one of which is a Fully Designed Neural Network (FD-NN), while the other two use Transfer Learning in VGG16 and VGG19 with additional designed layers (TL-VGG). The experimental results indicated that the FD-NN network is more reliable for real-time tasks and it provides higher accuracy.

Real-Time System for Driver Fatigue Detection Based on a Recurrent Neuronal Network

Authors: Ed-Doughmi, Younes, Najlae Idrissi, and Youssef Hbali.

Journal: Journal of imaging (2020)

The technique described in this research applies a recurrent neural network to a sequence frame of a driver's face as a way to analyze and predict driver drowsiness. The authors of this study utilized repeating neural network architecture multi-layer model-based 3D Convolutional Networks to identify driver drowsiness. They used a dataset to help build and accept the proposed model. The ConvNet 3D architecture achieved an accuracy of close to 97% on all data used. Better accuracy could have been achieved by using a more customized dataset that provides an environment close to the scenario a driver experiences in real-time.

A Deep Learning Based Approach for Real-time Driver Drowsiness Detection

Authors: Anis-Ul-Islam Rafid; Atiqul Islam Chowdhury; Amit Raha Niloy; Nusrat Sharmin.

Journal name: smart technologies in machine learning, 2021.

The approach used to include a Convolutional Neural Network (CNN) model is suggested in this paper to identify the driver's tiredness in real-time. The Center Face algorithm is used for face detection and also the haar algorithm.

Advantages:

- Designed to prevent accidents when the driver is getting drowsy by beeping an alarm.
- Uses the CNN model which automatically detects the important features without any human supervision.
- It records the driver's steering behavior the moment the trip begins.

Disadvantages:

- To ensure the system works efficiently with inside the system, the test data needs to be great in size from anywhere from hundreds of thousands to millions of test data.
- Requires a lot of knowledge about the model of Deep learning to ensure proper design of the system.

IoT-Based Smart Alert System for Drowsy Driver Detection

Authors: Anil Kumar Biswal, Debabrata Singh, Binod Kumar Pattanayak, Debabrata

Journal name: wireless communications and mobile computing,2022

The face landmark algorithm is used in this paper as a proper way of eye detection. When the driver's fatigue is detected, the IoT module issues a warning message along with the impact of collision and location information, the existing techniques are based on psychological or vehicle-based approaches to detect drowsiness.

Advantages:

- For the present paper, the existence of a system is assumed, which is diagnosis or prediction based, with high sensitivity and specificity, having a high acceptance and high effectiveness.
- The human-machine interface (HMI) is designed in an acceptable way
- The warning is based on a combination of modalities with an optimal frequency and amplitude

Disadvantages:

- It includes technical complexity and connectivity power dependence.
- Higher cost to implement.
- Another limitation is it purely dependent on external factors like road marking, climatic, and lighting conditions.

Drowsy Driver Detection and Alert System using Pulse Sensor

Authors: Ezeonyi Nnaemeka. Uchenna. 2Alumona Theophilus Leonard.

Journal name: The International Journal of Engineering and Science (IJES),2020.

The drowsy driver detection and alert system designed in this project is a simple system that employs reflectance photoplethysmography for sensing the driver's pulse and also The sensor sends its output to a processor which is programmed to actuate an alerting device if the driver is sensed to be drowsy.

Advantages:

- The driver drowsiness detection is based on an algorithm, which begins recording the driver's steering behavior the moment the trip begins.
- It then recognizes changes over the course of long trips, and thus also the driver's level of fatigue.
- These sensors are also a non-intrusively measured heart pulse wave from the driver's heart.

Disadvantages:

- These sensors in this paper are not necessarily accurate in sports where you move your hands vigorously or flex the muscles and tendons near the sensor.
- It has the Limited ability to accurately measure heart rate through dark or tattooed skin.
- It is more likely to be worn incorrectly than a heart rate sensor with a chest strap.

Unsupervised Drowsy Driving Detection with RFID

Authors: Chao Yang, Student Member, IEEE, Xuyu Wang.

Journal name: IEEE TRANSACTIONS ON VEHICULAR TECHNOLOGY,2020.

In this paper, they proposed a driving drowsiness detection system by detecting the nodding movements of drivers. The nodding movements were detected by using the received phase values in RFID tag responses and also it consists of a proposed tag deployment scheme to effectively deal with the high noisy driving environment.

Advantages:

- It is an effective, low-cost driving fatigue detection system to sense driver's nodding movements using commodity RFID

- It uses radio waves to transmit signals that activate the tag
- Once activated, the tag sends a wave back to the antenna, where it is translated into data.

Disadvantages:

- Implementation can be difficult sometimes.
- Based on many papers it is stated that many studies have determined that vehicle-based measures are a poor predictor of performance error risk due to drowsiness.
- It is a time-consuming process as it works on tags and readers. a small mistake can impact the entire system.

Driver Drowsiness Detection Using Behavioral Measures And Machine Learning Techniques: A Review Of State-Of-Art Techniques

Authors: Mkhuseli Ngxande, Jules-Raymond Tapamo; Michael Burke

Journal name: Pattern Recognition Association of South Africa and Robotics and Mechatronics (PRASA-RobMech)

This research examines machine learning methods for drowsiness detection, including support vector machines, convolutional neural networks, and hidden Markov models. According to the analysis, support vector machines are the most often used method for detecting sleepiness. Although convolutional neural networks outperformed the other two methods they also demonstrated the necessity for larger datasets and accepted benchmarking metrics for sleepiness detection. Future research will concentrate on developing a good dataset that includes a wide variety of different races in order to make sleepiness comparisons that are more accurate.

Driver Drowsiness Monitoring System Using Visual Behavior and Machine Learning

Authors: Kumar, Ashish, and Rusha Patra.

Journal name: IEEE Symposium on Computer Applications & Industrial Electronics

In this study, a less expensive real-time driver sleepiness detection system with tolerable accuracy was built. This project can be used to lessen the number of accidents brought on by tiredness and the resulting loss of life and property. The accuracy is 92 percent when the authors combine the Dlib package with logistic regression, and it is 86 percent when they combine the Haar Cascade classifier with logistic regression. Since the accuracy of the model using the dlib Library and Logistic Regression is higher, it is used. When eyeglasses were worn, the Haar Cascade classifier was unable to recognize the eyes effectively, which is why it is not their preferred detector algorithm.

MachineLearning Systems For Detecting Driver Drowsiness

Authors: Esra Vural, Müjdat Çetin, Aytül Erçil, Gwen Littleworth, Marian Bartlett & Javier Movellan

In-Book: In-Vehicle Corpus and Signal Processing for Driver Behavior (pp.97-110)

In this study, a system for the automatic detection of video-induced sleepiness in the driver. Prior strategies are emphasized based on hypotheses on possible predictive behavior sleepiness. Here, an automated measurement system of facial expressions was used to mine naturally occurring behavior during actual episodes of sleepiness. The initial is this work, beyond eyeblinks, to identify meaningful relationships between facial expression and weariness. Moreover, the project identified a probable link between the head roll, the sleepiness of the driver, and the coupling of the head roll with a steering action while sleepy.

An Investigation of Early Detection of Driver Drowsiness Using Ensemble Machine Learning Based on Hybrid Sensing

Authors: Jongseong Gwak,Akinari Hirao, and Motoki Shino

Journal name: IEEE International Conference on Intelligent Transportation Systems

This paper attempted to distinguish alert and slightly drowsy states using machine learning algorithms with a focus on the early identification of driver drowsiness. These algorithms were based on hybrid assessments of driving performance, behavioral traits, and physiological markers. The hybrid measurements captured during a DS experiment were converted into a dataset with 10-s data segments. Several machine learning methods were used to classify awake and barely sleepy phases. The findings show that early, highly accurate identification of a driver's mildly sleepy state is possible when using a hybrid approach and non-contact sensors. These findings show that early and highly accurate identification of a driver's mild sleepiness is possible when employing a combination of non-contact sensors and hybrid measures. Through actual driving experiments, the authors have promised to continue to increase the accuracy and usability of the drowsiness detection system in future work.

Drowsiness Detection System Design By Using Image Processing

Authors: Mohsen Poursadeghiyan, Research Center in Emergency and Disaster Health, University of Social Welfare and Rehabilitation Sciences, Tehran, Iran

Journal Name: Iran J Public Health v.47(9); 2018 Sep PMC6174048

One of the primary factors in driving accidents, which is a major cause of the many fatalities on the road each year, is drowsiness. The degree of tiredness can be detected using a variety of techniques, although those that rely on image processing are faster and more precise than those that don't. This study's objective was to employ image-processing methods to gauge a driving simulator's level of tiredness. Levels of tiredness in drivers are directly correlated with blink frequency and length. Data entered into the network for testing and data entered into the network for training had mean squared errors of 0.0623 and 0.0700, respectively. In the meantime, the detection system's accuracy rate was 93 percent.

Driver drowsiness detection using ANN image processing

Authors: Vesselenyi Tiberiu, Rus Alexandru, Mitran Tudor, Tataru Bogdan, and Moldovan Ovidiu 2016 12th International Congress of Automotive and Transport Engineering (CONAT) (Brasov) VEHICLE DRIVER DROWSINESS MONITORING AND WARNING SYSTEM 873-880

Journal Name: T. Vesselenyi et al 2017 IOP Conf. Ser.: Mater. Sci. Eng. 252 012097

The study in the paper looks at the viability of creating a drowsiness detection system for car drivers using three different types of techniques: EEG and EOG data processing, as well as driver picture analysis. The research on the first two methods has been covered by the authors in earlier papers. The prospect of detecting a driver's alert or drowsy state using photos captured while they were driving and an analysis of the driver's eyes open, half-open, and closed positions have been investigated by the authors of this research. One hidden layer network and autoencoder networks, two different types of artificial neural networks, were used for this purpose.

A DROWSY DRIVER DETECTION SYSTEM FOR HEAVY VEHICLES

Authors: Richard Grace, Carnegie Mellon Research Institute, Pittsburgh, PA

Journal Name:0-7803-5086-3 /98/$10.00 ©1998 IEEE

Driver drowsiness/fatigue is an essential cause of combination-unit truck crashes. The foundation of a system to potentially reduce accidents caused by drowsy driving can be drowsy driver identification techniques. We discuss work done at the Carnegie Mellon Driving Research Center to create such in-car driver monitoring systems, where actual fleet operations involving commercial truck drivers were observed. The drivers drove cars that could track both driving psychophysiology and vehicle performance.

The Carnegie Mellon DRC has worked hard to create a video-based system that can identify tiredness in heavy vehicle truck drivers. The work is solidly supported by field research that was also carried out at the DRC.

Drowsiness Detection of a Driver using Advanced Machine Learning for Light Motor Vehicle Collision

Authors: KAVITHA DEVI C S,1Asst.Professor, 2345UG Student 1 Department of Electronics and Communication Engineering, 1 Dr Ambedkar Institute of Technology, Bangalore, India

Journal Name: International Journal of Creative Research Thoughts (IJCRT)IJCRT2107609

This paper proposes a Real-Time Drowsiness Detection System (RT-DDS) applicable in motor vehicles with the help of conventional Computer Vision applications. The system used a variety of computer vision applications, such as blink rate, eye closure, and yawning, to swiftly and accurately detect a driver's tiredness while operating a car and adjust the driver accordingly. The suggested effort attempted to reduce the rising number of traffic accidents while maintaining simple and reliable procedures.

This research, Paper, focuses on the real-time detection of intoxication from alcohol and driver tiredness. This recognizes several auto accidents that occur as a result of driver intoxication or sleepiness. Alcohol gas sensor application and computer vision are integrated into an embedded system to achieve this.

Based on real-time fatigue detection, a driver alertness detection system was proposed. The suggested method accurately picks up on tiredness and eye blinks. Image processing algorithms were used to determine the eyes' location.

Detection of drowsiness using a driver monitoring system

Authors: Chris Schwarz National Advanced Driving Simulator, University of Iowa, Iowa City, Iowa.

Journal Name: H. E. C. van der Wall, R. J. Doll, G. J. P. van Westen, I. Koopmans, R. G. Zuiker, J. Burggraaf, A. F. Cohen. (2021) Using machine learning techniques to characterize sleep-deprived driving behavior.

The model that used DMS alerts was higher than the one that used simplest automobile alerts; however, the aggregate of the two completed the pleasant. The fashions have been powerful at discriminating low degrees of drowsiness from mild to excessive drowsiness; however, they had been now not powerful at telling the difference between mild and severe levels. A binary version that lumped drowsiness into 2 classes had an area below the receiver working characteristic (ROC) curve of 0.897. Blinks and saccades had been shown to be predictive of microsleeps; but, it may be that detection of microsleeps and lane departures occurs too overdue. consequently, it's far encouraging that the model becomes in a position to distinguish moderate from mild drowsy driving. using automation may additionally make automobile-based indicators useless for characterizing motive force states, presenting further motivation for a DMS.

3.1 EXISTING WORK:

For the purpose of identifying drowsiness in drivers, numerous techniques have been created, and some of them are currently in use. In order to prevent accidents like these, research into detecting driver drowsiness is currently ongoing. Physiological, vehicle-based, and behavioral techniques are frequently employed to detect sleepy drivers. The system will assess whether the individual is able to drive based on physiological techniques such as heartbeat, pulse rate, steering-wheel grip pressure, and temperature difference between the interior and outside of the vehicle. are used to identify driver fatigue levels. Heart rate variability (HRV), steering-wheel grip pressure, as well as temperature differential, make it possible to evaluate the driver's level of exhaustion indirectly. Acceleration, steering movements, and accelerator patterns are examples of vehicle-based techniques. The horizontal symmetry of the eyes can be used to determine eye location changes which use a standard webcam to detect eye blinks in real-time at 110 frames per second for a 320x240 resolution. According to experimental findings in the JZU eye-blink database, the suggested system identifies eye blinks 94% accurately with a 1% false positive rate. Drivers' eyes and faces can be used to identify weariness using a small infrared night vision camera that is pointed directly at the driver's face and watches the driver's eyes. In this study, we have put up a system to deal with this global issue.

3.2 LIMITATIONS OF EXISTING WORK :

The limitations of the existing system are, that the level of drowsiness is measured as:-

1. Subjective measurements are unable to detect rapid variations more frequently than every 5 minutes.
2. Another drawback of subjective assessments is that they cause the driver to become more awake, which lowers their level of tiredness.
3. The public's acceptance of driver drowsiness technology in general, and behavioral monitoring in particular, is a major hurdle because of worries about data storage and privacy protection.
4. The greatest way to quickly wake up sleepy and exhausted drivers is to set an alarm, however, there was no alarm to wake the driver up.
5. This system's inability to recognize whether a driver is drowsy even while their car is in the right lane presents another obstacle.
6. Data loss during recording is a possibility since sensors can separate during vehicle-based recordings owing to weather changes, and lighting variations can potentially interfere with behavioral recordings.
7. The likelihood that a motorist would be drowsy has been linked to sleep disorders since they frequently impair sleep quality.

3.3 RESEARCH GAPS:

- Concerns about data storage and privacy protection are a significant barrier to the public's acceptance of driver drowsiness technology in general and behavioral monitoring in particular.
- Another problem is that this technology can't tell if a motorist is drowsy even if their automobile is in the appropriate lane.
- Sleep problems have been associated with an increased risk of drowsy driving because they frequently affect the quality of sleep.

3.4 OBJECTIVES OF PROPOSED WORK:

1. The alarms are used to immediately correct the driver's recognized aberrant behavior.
2. The components make it simple to create interfaces with other drivers.
3. By informing the driver via the alarm system, his life may be saved.
4. The vehicle's speed can be managed with the help of this mechanism.
5. Accident rates can be decreased in order to preserve traffic management.
6. The system in the real world can use these very practically.

4. PROPOSED METHODOLOGY

4.1 METHOD USED:

The model we will make use of is done by Keras using Convolutional Neural Networks (CNN). A special type of deep neural network that performs exceptionally well for image categorization is the convolutional neural network. In essence, CNN consists of an input layer, an output layer, and a hidden layer with the potential for several hidden layers. These layers are subjected to convolutional processing using a filter that multiplies the layers' 2D matrices.

The number of hidden layers to be used in our model shall be evaluated by calculating the accuracy obtained using our model against the number of hidden layers used in it. We will increment the number of hidden layers used in our model until we get our desired accuracy.

The process of determining the drowsiness state starts with us recording the driver. Then, we detect the face in each frame and create a region of interest. From the region of interest obtained, we detect the eyes of the subject in question. Now, our classifiers will be used to categorize if the subject’s eyes are open or closed. The state of drowsiness is evaluated by the value “Score”, which we will use to determine how long a person closes their eyes.

4.2 ALGORITHMS OF THE PROPOSED WORK:

Step 1 – Take an image as input from a camera.

Step 2 – Detect the face in the image that has been in the frame and create a Region of Interest (ROI).

Step 3 – Detect the eyes from the Region of Interest and feed them to the classifier.

Step 4 – Classifiers will be used to categorize whether eyes are open or closed.

Step 5 – Calculate the score up to which a driver's eyes are closed to check whether the person is drowsy.

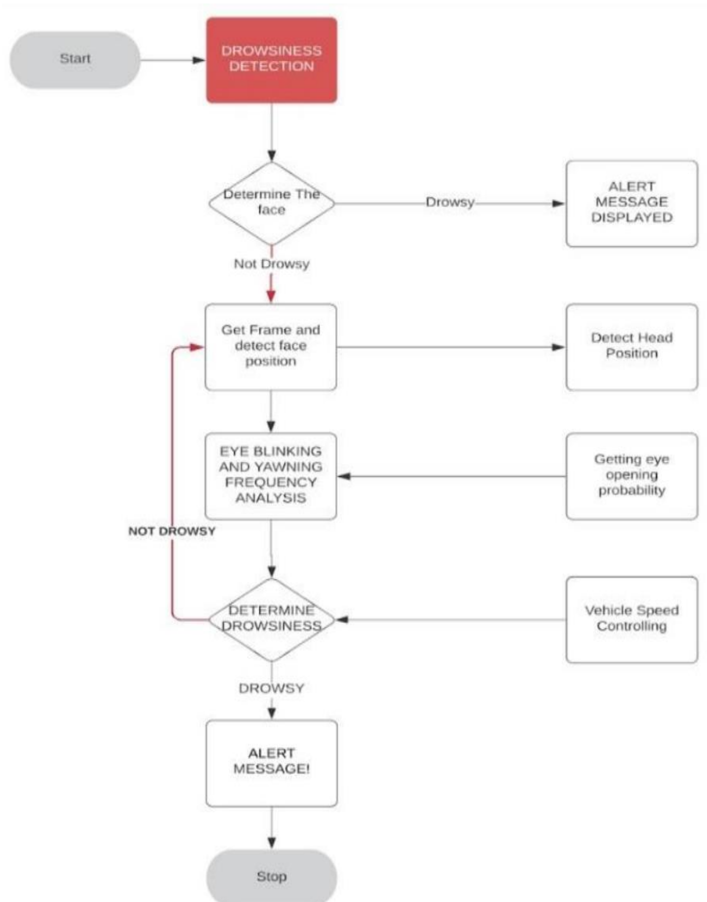


Fig 1. Flowchart of Proposed Work

4.3 ARCHITECTURE DIAGRAM:

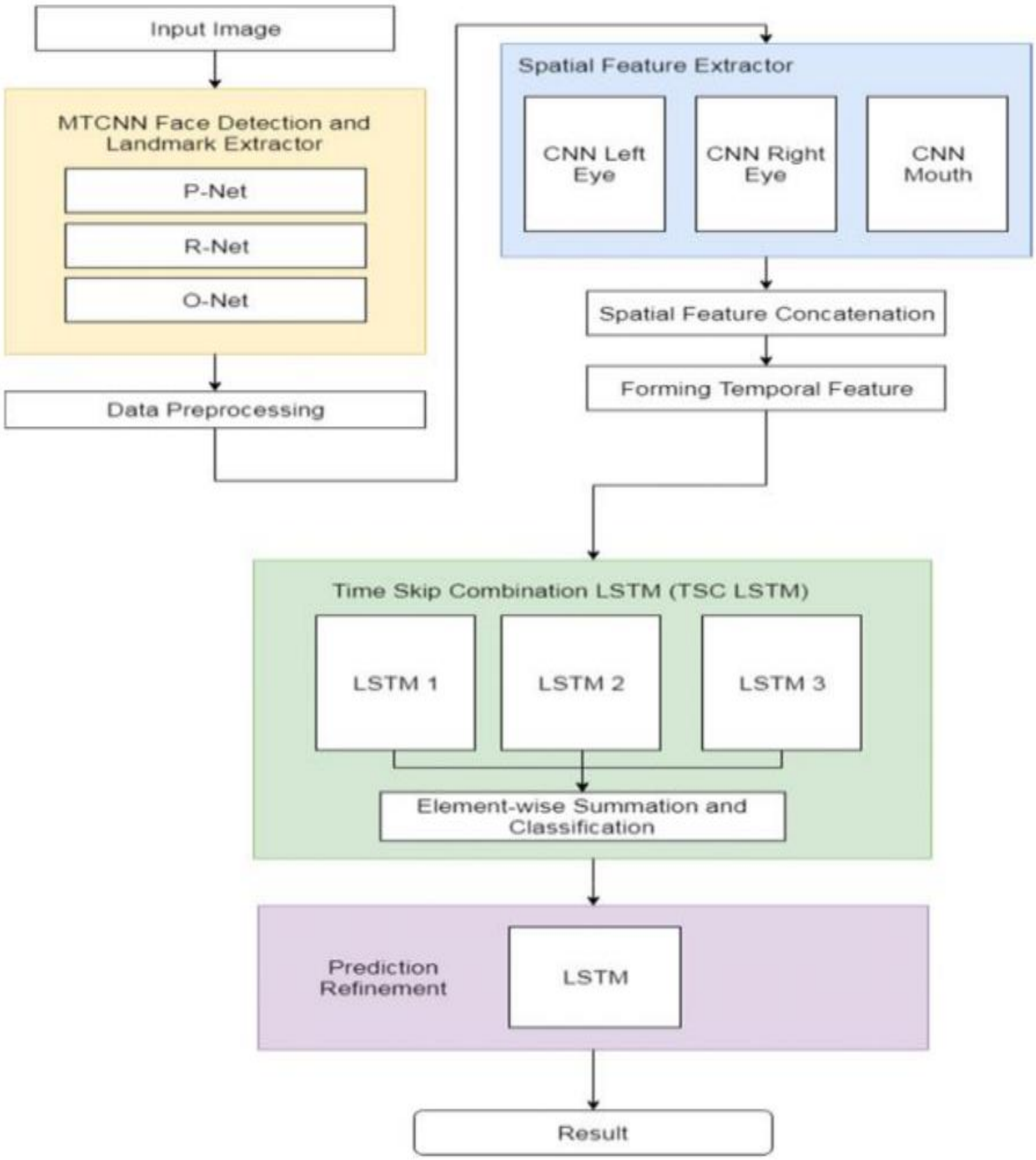


Fig2. Architecture Diagram

4.4 APPLICATIONS:

- Our model, which is a Drowsiness Detection system, is a safety technology that can prevent accidents caused by sleep-deprived drivers or who fell asleep while driving.
- The trained model predicts the driver's condition and informs him by the buzzer/alert system that we have implemented in our system thus preventing them from falling asleep and pushing them to focus on driving.
- A low-cost model which gives better accuracy can help people to use it for a long period of time.
- People sitting inside the car can analyze the image that is captured in each frame and help the driver not to sleep while driving.
- Several car manufacturers, including Audi, Bugatti currently offer drowsiness detection systems that monitor a vehicle's movements and driver movements, such as steering wheel angle, lane deviation, time-driven and road conditions, and face of the driver. So our model will be more efficient which can be used in these vehicles or small-scaled vehicles.
- Our model will provide better training since neural networks that have been used in our model give better results and it has been trained in a very short time. By this, our application can provide the stakeholders with the ability to use our Product more easily.
- Provide performance feedback to the fatigue management system, and/or provide compliance information to enforcement officials.

5. SYSTEM IMPLEMENTATION

5.1 SAMPLE CODE:

Model.py

```
import os
from keras.preprocessing import image
import matplotlib.pyplot as plt
import numpy as np
from keras.utils.np_utils import to_categorical
import random,shutil
from keras.models import Sequential
from keras.layers import Dropout,Conv2D,Flatten,Dense, MaxPooling2D,
BatchNormalization
from keras.models import load_model
def generator(dir, gen=image.ImageDataGenerator(rescale=1./255),
shuffle=True,batch_size=1,target_size=(24,24),class_mode='categorical' ):
 return
gen.flow_from_directory(dir,batch_size=batch_size,shuffle=shuffle,color_mode='grayscale',c
lass_mode=class_mode,target_size=target_size)
BS= 32
TS=(24,24)
train_batch= generator('data/train',shuffle=True, batch_size=BS,target_size=TS)
valid_batch= generator('data/valid',shuffle=True, batch_size=BS,target_size=TS)
SPE= len(train_batch.classes)//BS
VS = len(valid_batch.classes)//BS
print(SPE,VS)
# img,labels= next(train_batch)
# print(img.shape)
model = Sequential([
 Conv2D(32, kernel_size=(3, 3), activation='relu', input_shape=(24,24,1)),
 MaxPooling2D(pool_size=(1,1)),
 Conv2D(32,(3,3),activation='relu'),
 MaxPooling2D(pool_size=(1,1)),
#32 convolution filters used each of size 3x3
#again
 Conv2D(64, (3, 3), activation='relu'),
 MaxPooling2D(pool_size=(1,1)),
#64 convolution filters used each of size 3x3
#choose the best features via pooling

#randomly turn neurons on and off to improve convergence
 Dropout(0.25),
#flatten since too many dimensions, we only want a classification output
```

```
 Flatten(),
#fully connected to get all relevant data

Dense(128, activation='relu'),
#one more dropout for convergence' sake :)
 Dropout(0.5),
#output a softmax to squash the matrix into output probabilities
 Dense(2, activation='softmax')
])
model.compile(optimizer='adam',loss='categorical_crossentropy',metrics=['accuracy'])
model.fit_generator(train_batch,
validation_data=valid_batch,epochs=15,steps_per_epoch=SPE ,validation_steps=VS)
model.save('models/cnnCat2.h5', overwrite=True)
```

Drowsiness Detection.py

```
import cv2
import os
from keras.models import load_model
import numpy as np
from pygame import mixer
import time
mixer.init()
sound = mixer.Sound('alarm.wav')
face = cv2.CascadeClassifier('haar cascade files\haarcascade_frontalface_alt.xml')
leye = cv2.CascadeClassifier('haar cascade files\haarcascade_lefteye_2splits.xml')
reye = cv2.CascadeClassifier('haar cascade files\haarcascade_righteye_2splits.xml')
lbl=['Close','Open']
model = load_model('models/cnncat2.h5')
path = os.getcwd()
cap = cv2.VideoCapture(0)
font = cv2.FONT_HERSHEY_COMPLEX_SMALL
count=0
score=0
thicc=2
rpred=[99]
lpred=[99]
while(True):
 ret, frame = cap.read()
 height,width = frame.shape[:2]
 gray = cv2.cvtColor(frame, cv2.COLOR_BGR2GRAY)

 faces = face.detectMultiScale(gray,minNeighbors=5,scaleFactor=1.1,minSize=(25,25))
 left_eye = leye.detectMultiScale(gray)
 right_eye = reye.detectMultiScale(gray)
 cv2.rectangle(frame, (0,height-50) , (200,height) , (0,0,0) , thickness=cv2.FILLED )
 for (x,y,w,h) in faces:
 cv2.rectangle(frame, (x,y) , (x+w,y+h) , (100,100,100) , 1 )
```

```
for (x,y,w,h) in right_eye:
 r_eye=frame[y:y+h,x:x+w]
 count=count+1
 r_eye = cv2.cvtColor(r_eye,cv2.COLOR_BGR2GRAY)
 r_eye = cv2.resize(r_eye,(24,24))
 r_eye= r_eye/255
 r_eye= r_eye.reshape(24,24,-1)
 r_eye = np.expand_dims(r_eye,axis=0)
 rpred = model.predict_classes(r_eye)
 if(rpred[0]==1):
 lbl='Open'
 if(rpred[0]==0):
 lbl='Closed'
 break
 for (x,y,w,h) in left_eye:
 l_eye=frame[y:y+h,x:x+w]
 count=count+1
 l_eye = cv2.cvtColor(l_eye,cv2.COLOR_BGR2GRAY)
 l_eye = cv2.resize(l_eye,(24,24))
 l_eye= l_eye/255
 l_eye=l_eye.reshape(24,24,-1)
 l_eye = np.expand_dims(l_eye,axis=0)
 lpred = model.predict_classes(l_eye)
 if(lpred[0]==1):
lbl='Open'
 if(lpred[0]==0):
 lbl='Closed'
 break
 if(rpred[0]==0 and lpred[0]==0):
 score=score+1
 cv2.putText(frame,"Closed",(10,height-20), font, 1,(255,255,255),1,cv2.LINE_AA)
 # if(rpred[0]==1 or lpred[0]==1):
 else:
 score=score-1
 cv2.putText(frame,"Open",(10,height-20), font, 1,(255,255,255),1,cv2.LINE_AA)


 if(score<0):
 score=0
 cv2.putText(frame,'Score:'+str(score),(100,height-20), font,
1,(255,255,255),1,cv2.LINE_AA)
 if(score>15):
 #person is feeling sleepy so we beep the alarm
 cv2.imwrite(os.path.join(path,'image.jpg'),frame)
 try:
 sound.play()

 except: # isplaying = False
 pass
```

```
 if(thicc<16):
 thicc= thicc+2
 else:
 thicc=thicc-2
 if(thicc<2):
 thicc=2
 cv2.rectangle(frame,(0,0),(width,height),(0,0,255),thicc)
 cv2.imshow('frame',frame)
 if cv2.waitKey(1) & 0xFF == ord('q'):
 break
cap.release()
cv2.destroyAllWindows()
```

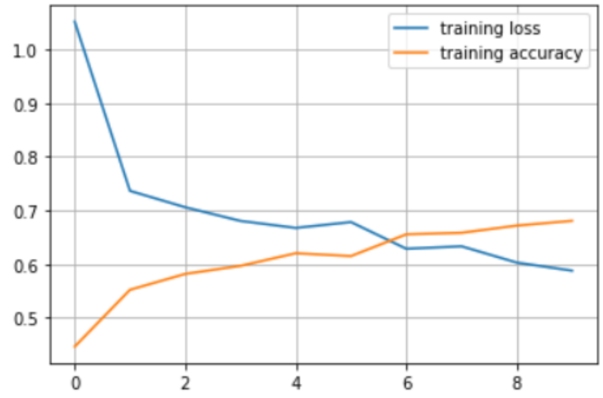
5.2 RESULTS AND DISCUSSION:

Accuracy (for 12 epochs):

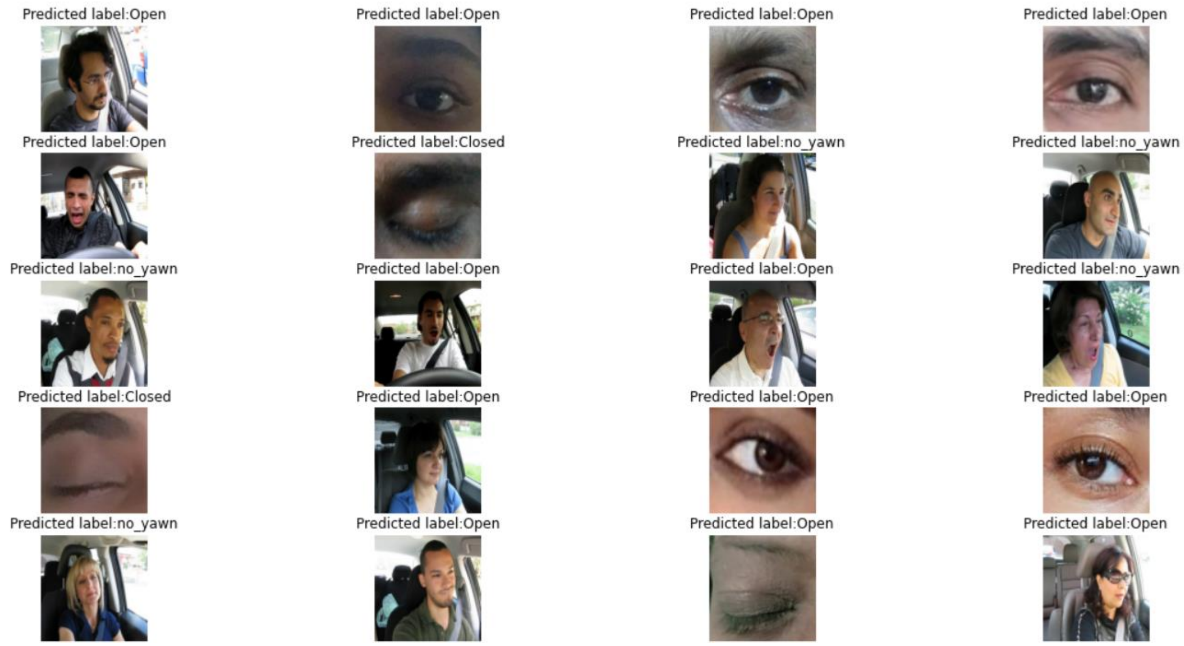
```
[ ] model.fit(train_batch, validation_data=valid_batch,epochs=12,steps_per_epoch=SPE ,validation_steps=VS)

Epoch 1/12
77/77 [==============================] - 25s 168ms/step - loss: 0.6602 - accuracy: 0.6936 - val_loss: 0.4059
Epoch 2/12
77/77 [==============================] - 12s 163ms/step - loss: 0.4111 - accuracy: 0.7906 - val_loss: 0.3610
Epoch 3/12
77/77 [==============================] - 12s 162ms/step - loss: 0.3456 - accuracy: 0.8312 - val_loss: 0.3509
Epoch 4/12
77/77 [==============================] - 12s 153ms/step - loss: 0.3340 - accuracy: 0.8324 - val_loss: 0.3540
Epoch 5/12
77/77 [==============================] - 13s 165ms/step - loss: 0.2674 - accuracy: 0.8731 - val_loss: 0.2968
Epoch 6/12
77/77 [==============================] - 13s 166ms/step - loss: 0.2438 - accuracy: 0.8846 - val_loss: 0.2467
Epoch 7/12
77/77 [==============================] - 13s 164ms/step - loss: 0.2174 - accuracy: 0.9043 - val_loss: 0.2628
Epoch 8/12
77/77 [==============================] - 13s 163ms/step - loss: 0.1875 - accuracy: 0.9207 - val_loss: 0.2245
Epoch 9/12
77/77 [==============================] - 13s 164ms/step - loss: 0.1617 - accuracy: 0.9355 - val_loss: 0.2271
Epoch 10/12
77/77 [==============================] - 12s 156ms/step - loss: 0.1340 - accuracy: 0.9454 - val_loss: 0.1949
Epoch 11/12
77/77 [==============================] - 12s 156ms/step - loss: 0.1283 - accuracy: 0.9491 - val_loss: 0.1912
Epoch 12/12
77/77 [==============================] - 13s 164ms/step - loss: 0.0967 - accuracy: 0.9622 - val_loss: 0.2033
<keras.callbacks.History at 0x7f8e345731d0>
```

The accuracy we obtained after training the dataset for 12 epochs is 96%

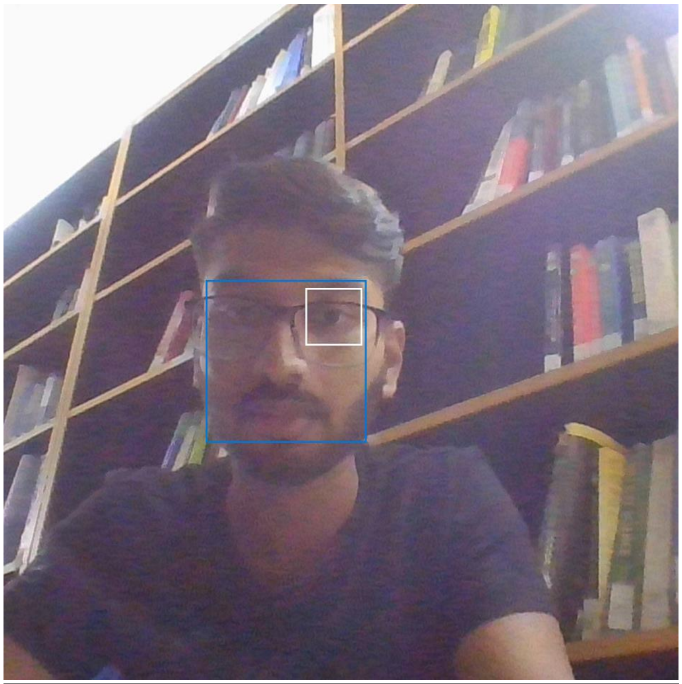
Training Loss vs Accuracy graph:



Sample Prediction :



Sample Prediction Using Input from Video Capture:



Score obtained at the above image frame from the video = 45

The threshold value set for the “Score” variable is 15 and since in the above image frame it reached 15, our system produced an alarm.

There is a parametric variable “Score” defined in our model. We will use the variable “Score” to evaluate how long the subject in question is keeping their eyes closed. The variable “Score” varies according to the duration the eyes are closed/open. If the eyes in the frame evaluated are closed, the variable “Score” increases. Else, the variable “Score” decreases.

The alarm beep goes off as soon as the variable “Score” reaches a threshold value. This threshold value is set by us, which we have obtained from analyzing/ researching other similar systems. In terms of the time duration, the subject in question is required to close their eyes for the alarm to go off is approximately 15 seconds i.e, the variable “Score” goes beyond the threshold value if the subject has kept their eyes closed for 15 seconds straight.

The evaluation criteria to validate our model is to check its accuracy. Using our dataset, we test the accuracy of our model. We check our model’s ability to correctly identify drowsy drivers.

6. CONCLUSION

6.1 CONCLUSION:

We were able to successfully implement a model that will play a sound to wake the driver up if he or she becomes drowsy and closes their eyes while driving, to sum up. We were able to develop it by combining CNN with a number of frameworks, including Keras, Tensorflow, and others, and real-time image capture for face detection. We believe that this technology will be able to prevent accidents brought on by drowsy driving. Significantly, this system may even serve to save the lives of the drivers of the vehicles. Our project's primary goal is to provide highly cost-effective solutions to real-world issues such that the buzzer will sound when a driver appears to be getting tired and closes his eyes for more than a second. Therefore, there is a drop in the accident ratio.

Some of the limitations we found in our system includes:

- In some scenarios, image frames evaluated for determining the drowsiness of a person may be deemed to be not perfect i.e, it is unavoidable that in some scenarios the necessary lighting required for us to get a proper image frame to evaluate drowsiness is not available.
- In reference to the image frames mentioned above, the possibility of predicting the state of the person correctly reduces.

6.2 FUTURE WORK:

Future research may primarily concentrate on how to measure weariness using external aspects like vehicle states, sleeping patterns, weather, mechanical data, etc. Highway safety is primarily threatened by driver drowsiness, which is a serious issue for drivers of commercial motor vehicles. This major safety hazard is a result of a number of factors, including 24-hour operations, high annual mileage, exposure to harsh environmental conditions, and rigorous work schedules. One of the most important elements in a string of preventive actions required to address this issue is to monitor the driver's level of alertness and drowsiness and give feedback on their state so they may take appropriate action. Currently, the camera's zoom or direction cannot be changed while it is in use. Future work may involve automatically focusing on the eyes once they have been located.

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