DROWSINESS DETECTION OF DRIVERS USING CNN

A MAJOR PROJECT REPORT

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in partial fulfilment for the award of the degree

Of

BACHELOR OF TECHNOLOGY

IN

INTRODUCTION TO COMPUTER NETWORKS

श्रद्धावान् लभते ज्ञानम्

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This is to certify that the major project report entitled “**DROWSINESS DETECTION OF DRIVERS USING CNN”** submitted by

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in partial fulfilment of the requirements for the award of the **bachelor of Master of Technology** in **COMPUTER SCIENCE ENGINERRING** is a bonafide record of the work carried out under my guidance and supervision at Amrita School of Engineering, Chennai.

Signature

Dr. Aasha Nandhini

CSE professor

This project report was evaluated by us on ……………...

INTERNAL EXAMINER EXTERNAL EXAMINER

ACKNOWLEDGEMENT:

I offer my sincere pranams at the lotus feet of Universal guru, MATA AMRITANANDAMAYI DEVI who blessed me with her grace to make this a successful project.

I express my deep sense of gratitude to Dr. P Shankar, Principal, Amrita School of Engineering, Chennai for his kind support. I would like to extend my gratitude and heartfelt thanks to Dr. Aasha Nandhini CSE Department for her constant help, suggestions and inspiring guidance. I am grateful to my guide, Department of CSE , for his invaluable support and guidance during the course of the major project work. I am also indebted to Dr. Prasanna Kumar, Chairperson of Department of AI, ASE, Chennai for his guidance.

I specially thank our director Sri I B Manikandan who supported us in every possible manner.

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1. ABSTRACT:

Every day, 1200 road accidents occur in India, with 400 of them ending in instant death and the rest inflicting major damage. Sleepiness, which may be generated by both sleep and alcohol, is the most prevalent cause of these crashes. Drivers may become sleepy as a result of long periods of driving or drinking, which is the most distracting issue for them.When you're driving beside them, the driver and numerous passengers may perish as a result of the distraction. It kills everyone inside the automobile as well as those in the surrounding area. To prevent such accidents and drowsiness here proposes a system that alerts the driver if he/she feels drowsy, we are attempting to create a reliable and accurate method for identifying distracted drivers. We demonstrate a CNN-based approach for detecting distracted driving. The Inception V3 architecture has been updated for this job, and several regularisation techniques have been included to boost performance.

2. INTRODUCTION :

Numerous accidents have occurred as a result of driver exhaustion, tedious road conditions, and adverse weather conditions. According to the National Highway Traffic Safety Administration (NHTSA) and the World Health Organization (WHO), roughly 1.35 million people die each year as a result of car accidents around the world. In general, road accidents are caused by insufficient driving skills. If the motorist is inebriated or drowsy, certain issues can emerge. The most common sorts of fatal accidents have been linked to the driver's exhaustion. When drivers fall asleep behind the wheel, they lose control of the vehicle. Advanced technology is required to build smart or intelligent vehicle systems.This study implements a mechanism that notifies the driver whether he or she is drowsy or daydreaming. In the behavioral-based approach, a camera monitors the driver's eye blinking, eye closure, face detection, head posture, and other behaviours .

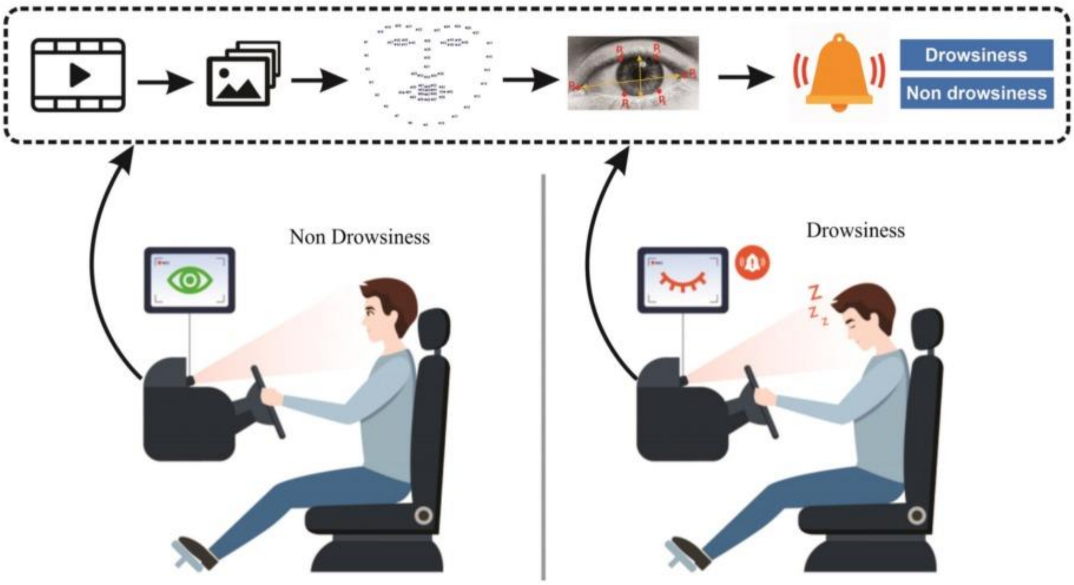


Fig1 Drowsiness Detection

The number of automobiles on the road in the United States is rapidly increasing. The most serious issue with increased traffic is the rise in the number of traffic accidents. Driver Insomnia, drinking, and carelessness are all major factors. Scenario of an accident Taking these considerations into account. The situation of driver behaviour is a key concern for advanced driving assistance systems are being designed. Driver Drowsiness detection is an automobile safety feature that detects when a driver is drowsy. When a driver becomes drowsy, it helps to avoid accidents. Driver Inattention could be caused by a lack of awareness owing to tiredness and distraction when driving. The system sends a real-time alarm to the driver. In this paper , further, we'll discuss what are all models being used previously by researchers in this field and how we approach.

3. LITERATURE REVIEW:

Drowsy driving is one of the common causes of road accidents resulting in injuries, even death, and significant economic losses to drivers, road users, families, and society. There have been many studies carried out in an attempt to detect drowsiness for alert systems. They present the prospect of developing a drowsiness detection system for car drivers using three types of methods: EEG and EOG data processing, as well as driver picture analysis, in this paper. The authors have described the study on the first two approaches in prior works. They have introduced the possibility of detecting the driver's drowsy or aware condition based on visuals in this study. Taken while driving and analyzing the driver's eye state: open, half-open, and closed Two types of artificial intelligence are used for this. A single hidden layer network and an autoencoder network were used as neural networks.[1]

A fundamental problem for road traffic accident systems is the improvement of embedded systems for detecting and avoiding tiredness in a vehicle. To avoid drowsiness while driving, an alert system that can detect a drop in driver concentration and transmit a signal to the driver is required. According to studies, the majority of traffic accidents occur when the motorist is preoccupied while driving. The author proposed, reviewed, and presented a portable Driver Alertness Detection System (DADS) to estimate the driver's level of concentration based on a color detection approach employing facial recognition in this study. A small camera will be mounted on the front visor to record facial expressions and eye movements. They mentioned they tested DADS on 26 people and were able to get a 100% detection rate in favorable lighting conditions and a low detection rate at night.[2]

A minimal network structure was proposed based on facial landmarks to identify drowsy drivers. The method presented a lightweight model and achieved more than 80% accuracy. This study focused only on eye facial landmarks without detecting the yawning of the drivers. Moreover, the method was based on a multilayer perceptron classifier with three hidden layers, which is a limitation that leads to low accuracy. To have good accuracy and detection in low light conditions we developed and designed These networks based on the INCEPTION V3 and VGG16 advanced networks, which are more memory and complexity efficient. The suggested networks are excellent feature extractors because they can automatically record and learn key sleepiness characteristics. the application of a transfer learning technique to effectively address the issues of quick training, a small training dataset, and improved accuracy; The experimental results show that the proposed methods achieve an accuracy of 94%.In the next section of our paper, we’ll see how we are implementing modules and models.

4. METHODOLOGY:

4.1. DATA COLLECTION AND PREPROCESSING

Computer vision tasks include detecting eyeballs and their parts, estimating gaze, and determining the frequency of eye blinking. We've been working on these tasks in the domain of driver behaviour for the past few years, which has resulted in the collection of a large amount of testing data collected under real-world situations. As a result, we present the MRL Eye Dataset, a large-scale collection of human eye images. This dataset contains low- and high-resolution infrared photos taken under various lighting situations and by various instruments. The dataset can be used to test a variety of features or trainable classifiers. The photos are separated into numerous categories to facilitate comparing algorithms easier, and they are also excellent for training and testing classifiers.

subject ID	In the dataset, the data consist of 37 different persons (33 men and 4 women)
image ID	The dataset consists of 84,898 images
gender [0 - man, 1 – woman]	The dataset contains the information about gender for each image (man, woman)
glasses [0 - no, 1 - yes]	The information if the eye image contains glasses is also provided for each image (with and without the glasses)
eye state [0 - closed, 1 - open]	This property contains the information about two eye states (open, close)
reflections [0 - none, 1 - small, 2 – big]	The data has annotated three reflection states based on the size of reflections (none, small, and big reflections)
lighting conditions [0 - bad, 1 - good]	Each image has two states (bad, good) based on the amount of light during capturing the videos
sensor ID [01 - RealSense, 02 - IDS, 03 - Aptina]	At this moment, the dataset contains the images captured by three different sensors (Intel RealSense RS 300 sensor with 640 x 480 resolution, IDS Imaging sensor with 1280 x 1024 resolution, and Aptina sensor with 752 x 480 resolution)

Table1 - PROPERTIES OF DATASET

Among all the attributes the most important attributes are lighting conditions, eye state, and reflections. After Image dataset is been collected , a code snippet is used to seggrate images into different directorys called test and train . And Image is being scaled to 0-1 range .now image is ready for traing.

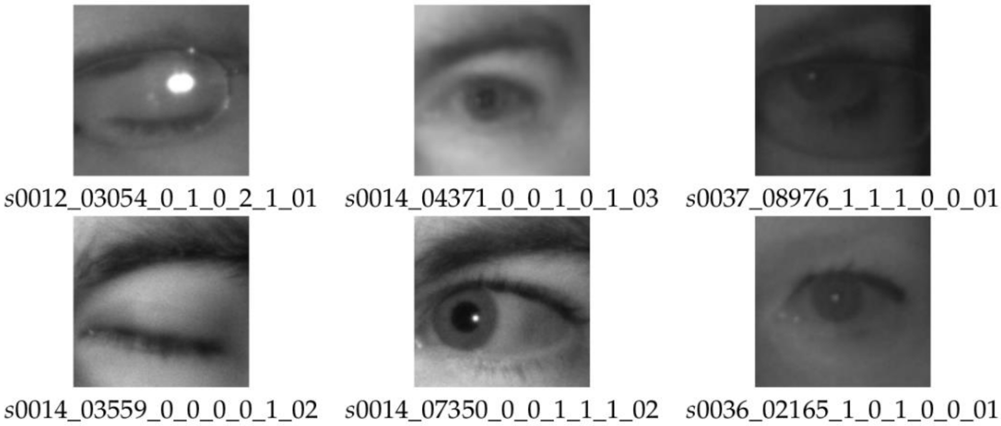


FIG2 DATASET

4.2. WORKFLOW

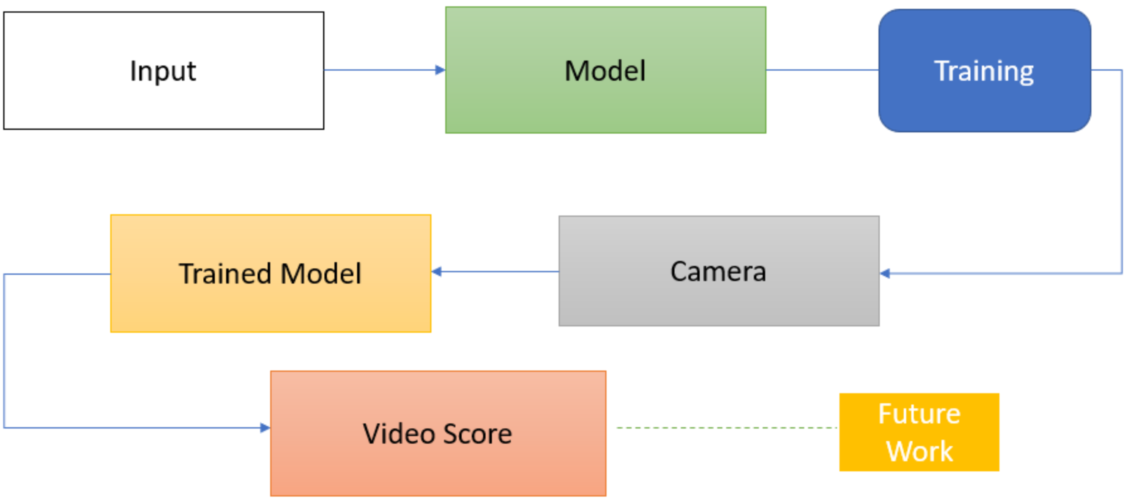
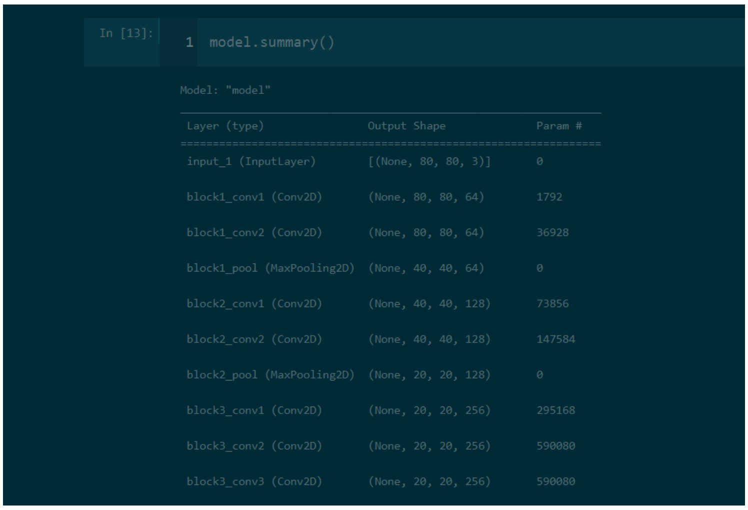


Fig 3 WORKFLOW OF OUR MODEL

4.3. TRANSFER LEARNING AND CNN MODEL



```
In [13]:  1  model.summary()

Model: "model"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_1 (InputLayer)        [(None, 80, 80, 3)]       0

 block1_conv1 (Conv2D)       (None, 80, 80, 64)        1792

 block1_conv2 (Conv2D)       (None, 80, 80, 64)        36928

 block1_pool (MaxPooling2D)  (None, 40, 40, 64)        0

 block2_conv1 (Conv2D)       (None, 40, 40, 128)       73856

 block2_conv2 (Conv2D)       (None, 40, 40, 128)       147584

 block2_pool (MaxPooling2D)  (None, 20, 20, 128)       0

 block3_conv1 (Conv2D)       (None, 20, 20, 256)       295168

 block3_conv2 (Conv2D)       (None, 20, 20, 256)       590080

 block3_conv3 (Conv2D)       (None, 20, 20, 256)       590080
```

Fig4. MODEL SUMMARY

TRANSFER LEARNING

Machine Learning models have historically been built on the idea that if the training and test data are collected from the same feature space and distribution, the model would operate effectively.We'd have to design a new model if the feature space or data distribution changed. It is costly to build a new model from the ground up each time and collect a new set of training data. Transfer Learning eliminates the requirement for the work associated with recollecting large volumes of training data. People may intelligently use information gained earlier for a different job or area to tackle new issues faster or with better solutions, which is the motivation for transfer learning utilized in Machine Learning and Deep Learning.

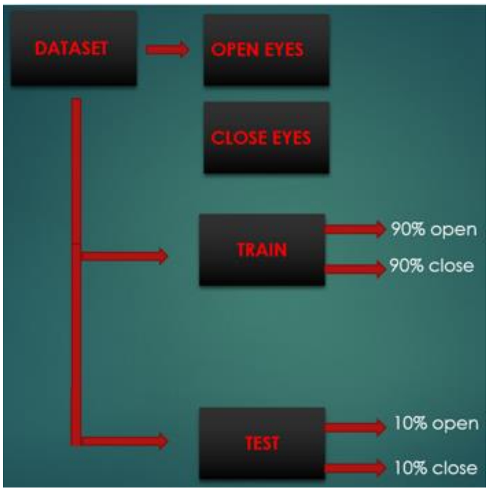


Fig 5. DATASET DESCRIPTION

CNN MODEL :

TRANSFERLEARNING - VGG 16:

The network receives a dimensioned picture as input (224, 224, 3). The first two layers share the same padding and have 64 channels with 3*3 filter sizes. Following a stride (2, 2) max pool layer, two layers with 256 filter size and filter size convolution layers are added (3, 3). Following that is a stride (2, 2) max-pooling layer, which is identical to the preceding layer. There are then two convolution layers with filter sizes of 3 and 3 and a 256 filter. There are two sets of three convolution layers after that, as well as a max pool layer. Each filter has 512 filters (3, 3) of the same size and padding. After that, the picture is sent to a convolution layer stack of two. We employ 3*3 filters instead of 11*11 in AlexNet and 7*7 in ZF-Net for these convolution and max-pooling layers. It also employs 1*1 pixel to adjust the number of input channels in some of the levels. After each convolution layer, there is 1-pixel padding (same padding) applied to prevent the image's spatial information from being lost.

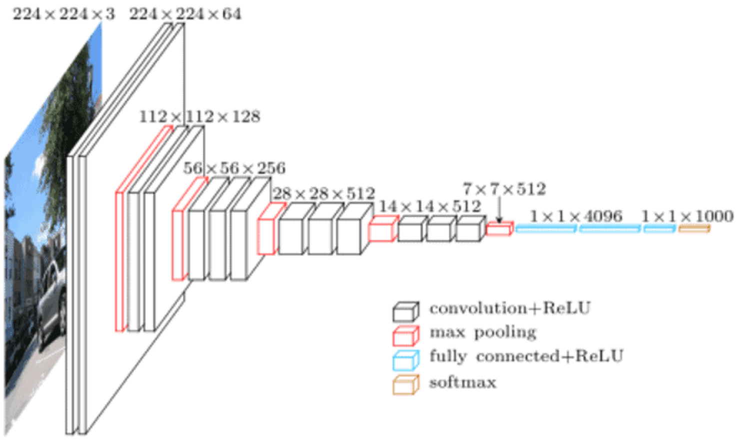


Fig 6 TRANSFER LEARNING MODEL

INCEPTIONV3 :

Inception Networks (GoogLeNet/Inception v1) **are** more computationally efficient than VGGNet, both in terms of the **number** of parameters created by the network and the cost incurred (memory and other resources). If an Inception Network is changed, special care must be taken to ensure that the computational advantages are not lost. As a result, because **of** the unpredictability of the new network's performance, adapting an Inception network for multiple use cases becomes an issue. Several strategies for improving the network have been proposed in an Inception v3 model to loosen the restrictions for faster model adaption. Factorized convolutions, regularisation, dimension reduction, and parallelized calculations are among the approaches used.

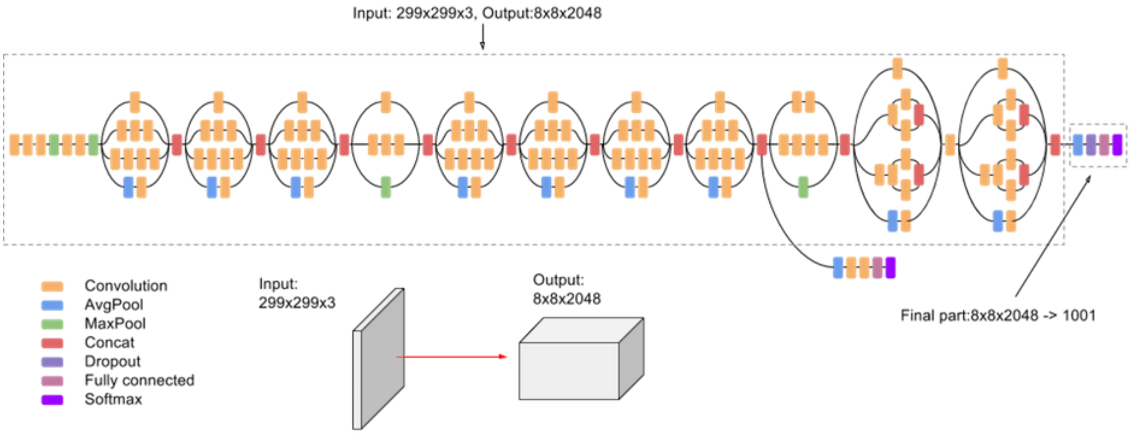


Fig7 INCEPTION V3 ARCHITECTURE

5. DISCUSSION AND RESULT :

Using the dataset , we tried two different CNN models in order evaluate based on ensemble . In Fig 9, We have achieved a prominent score on both the models VGG16 and InceptionV3.

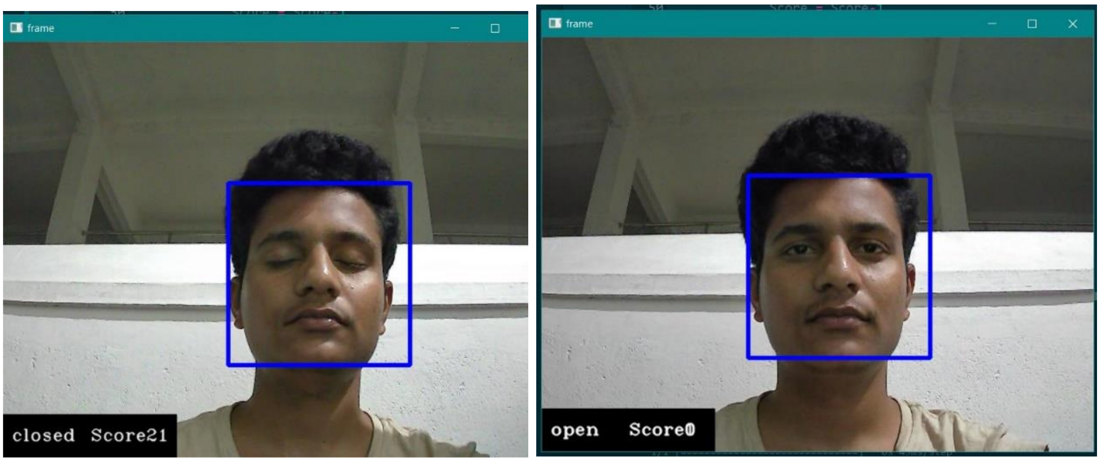
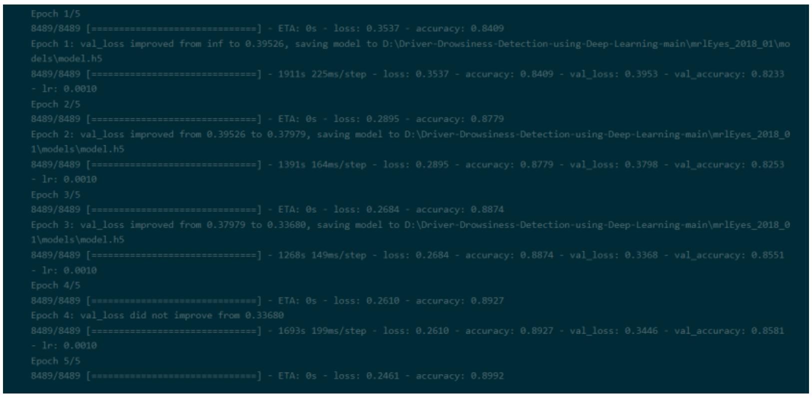
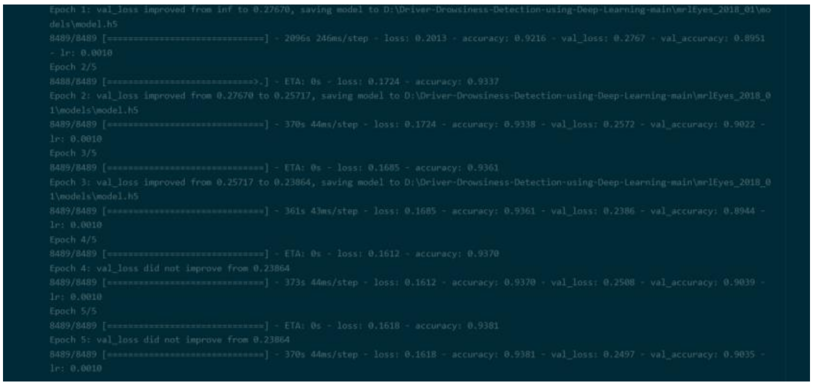


Fig8 OUTPUT GENERATED SCORE BY OUR MODEL



(a)



```
Epoch 1: val_loss improved from inf to 0.27670, saving model to D:\Driver-Drowsiness-Detection-using-Deep-Learning-main\mrlEyes_2018_01\models\model.h5
8489/8489 [==============================] - 2096s 246ms/step - loss: 0.2013 - accuracy: 0.9216 - val_loss: 0.2767 - val_accuracy: 0.8951 - lr: 0.0010
Epoch 2/5
8488/8489 [============================>.] - ETA: 0s - loss: 0.1724 - accuracy: 0.9337
Epoch 2: val_loss improved from 0.27670 to 0.25717, saving model to D:\Driver-Drowsiness-Detection-using-Deep-Learning-main\mrlEyes_2018_01\models\model.h5
8489/8489 [==============================] - 370s 44ms/step - loss: 0.1724 - accuracy: 0.9338 - val_loss: 0.2572 - val_accuracy: 0.9022 - lr: 0.0010
Epoch 3/5
8489/8489 [==============================] - ETA: 0s - loss: 0.1685 - accuracy: 0.9361
Epoch 3: val_loss improved from 0.25717 to 0.23864, saving model to D:\Driver-Drowsiness-Detection-using-Deep-Learning-main\mrlEyes_2018_01\models\model.h5
8489/8489 [==============================] - 361s 43ms/step - loss: 0.1685 - accuracy: 0.9361 - val_loss: 0.2386 - val_accuracy: 0.8944 - lr: 0.0010
Epoch 4/5
8489/8489 [==============================] - ETA: 0s - loss: 0.1612 - accuracy: 0.9370
Epoch 4: val_loss did not improve from 0.23864
8489/8489 [==============================] - 373s 44ms/step - loss: 0.1612 - accuracy: 0.9370 - val_loss: 0.2508 - val_accuracy: 0.9039 - lr: 0.0010
Epoch 5/5
8489/8489 [==============================] - ETA: 0s - loss: 0.1618 - accuracy: 0.9381
Epoch 5: val_loss did not improve from 0.23864
8489/8489 [==============================] - 370s 44ms/step - loss: 0.1618 - accuracy: 0.9381 - val_loss: 0.2497 - val_accuracy: 0.9035 - lr: 0.0010
```

(b)

Fig9.(a) Accuracy Test of VGG16 (b) Accuracy Test of InceptionV3

6. CONCLUSION :

Drowsiness can be detected promptly using the drowsiness detection system. The technology can distinguish between regular eye blink and drowsiness, preventing the driver from falling asleep while driving. Regardless matter whether the driver wears glasses or not, the technology performs admirably in low-light situations. The technology can detect whether the eyes are closed or open during the monitoring. When the eyes are closed for an extended period of time, a warning signal is given. The system's ultimate purpose is to determine whether or not the driver is drowsy. Drowsiness is identified based on the driver's eye movements, and an alarm is created based on eye blinks to notify the driver and limit the vehicle's speed, as well as the notification of a parking light. Many accidents will be avoided as a result of this, and the driver and vehicle will be safer. Only the most expensive and elegant cars have a system that ensures driver safety and vehicle security. Driver security and safety can be accomplished in a regular car using eye detection.

7. FUTURE SCOPE :

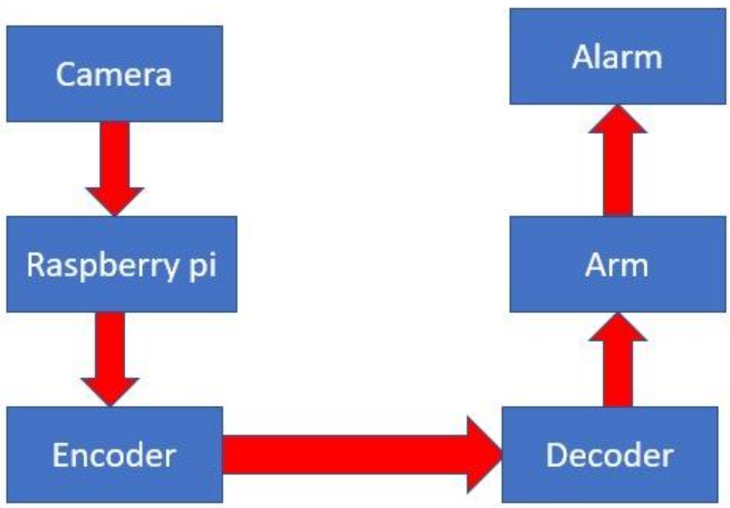


Fig Future Work Flow

Future research may concentrate on the use of external factors for tiredness measurement, such as vehicle states, sleeping hours, weather conditions, mechanical data, and so on. Drowsy driving is a big threat to highway safety.The major safety issue is exacerbated by 24-hour operations, high annual mileage, exposure to difficult environmental conditions, and rigorous work schedules.One important step in a series of preventive measures to address this problem is to monitor the driver's state of drowsiness and vigilance and provide feedback on their condition so that they can take appropriate action. There is currently no way to change the camera's zoom or direction while it is in use. Once eyes have been located, future work may automatically zoom in on them. The work will also be based on sending alerts using Internet Protocols with a help of a User Design Interference with raspberry pi.

8. REFERENCE :

[1] T. Vesselenyi, S. Moca, A. Rus, T. Mitran, and B. Tătaru, “Driver drowsiness detection using ANN image processing,” *IOP Conf. Ser.: Mater. Sci. Eng.*, vol. 252, p. 012097, Oct. 2017, doi: 10.1088/1757-899X/252/1/012097.

[2] A. M. R. Pg Hj Zahari, L. Tiong Hoo, and H. Adenin, “Microcontroller based driver alertness detection systems to detect drowsiness,” in *Ninth International Conference on Graphic and Image Processing (ICGIP 2017)*, Qingdao, China, Apr. 2018, p. 174. doi: 10.1117/12.2303552.

[3] “Active Accident Avoidance Case Study: Integrating Drowsiness Monitoring System with Lateral Control and Speed Regulation in Passenger Vehicles” Proceedings of the 2008 IEEE International Conference on Vehicular Electronics and Safety Columbus, OH, USA. September 22- 24, 2008. Pınar Boyra, John H. L. Hansen

[4] “Development of drowsiness detection system” VehicleResearch Laboratory, Nissan Center NISSAN MOTOR Co., Ltd. Hiroshi Ueno Masayuki Kaneda Masataka Tsukino

[5] “Face and eye tracking algorithm based on digital image processing “Department of Electrical Engineering, Universidad de Chile AV. Tupper 2007. Claudio A. Perez, Alvaro Palma, Carlos A. Holzmann and Christian Pera