

# **PROJECT REPORT**

On

**HYBRID MODEL FOR LASSITUDE DETECTION SYSTEM IN  
DRIVERS USING DEEP LEARNING AND AUTOMATIC  
BRAKING SYSTEM WITH LI-FI COMMUNICATION  
SYSTEM**

Submitted for Partial Fulfilment of Award of

**BACHELOR OF TECHNOLOGY**

In

**Electronics & Communication Engineering**

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**Dr. APJ ABDUL KALAM TECHNICAL UNIVERSITY,  
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**Department of Electronics and Communication Engineering**

**SRMCEM**

**CERTIFICATE**

Certified that the project entitled **“Hybrid Model For Lassitude Detection System In Drivers Using Deep Learning And Automatic Braking System With Li-Fi Communication System”** submitted by **Mayank Pandey (1812231073)**, **Mimansa Tripathi (1812231074)** and **Om Mishra (1812231086)** in partial fulfilment of the requirements for the award of the degree of Bachelor of Technology (ECE) of Dr. APJ Abdul Kalam Technical University, is a record of students’ own work carried under our supervision and guidance. The project report contains results of original work and studies carried out by students and the contents do not forms the basis for the award of and other degree to the candidate orto anybody else.

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**DECLARATION**

We hereby proclaim that the project entitled **“Hybrid Model For Lassitude Detection System In Drivers Using Deep Learning And Automatic Braking System With Li-Fi Communication System”** set forth by us in the partial fulfilment of the requirements for the award of the degree of Bachelor of Technology (Electronics and Communication) of Dr. A.P.J. Abdul Kalam Technical University, is record of students own work carried under the supervision and guidance of Er. Bramh Prakash Dwivedi (Assistant Professor, ECE Department). To the best of our knowledge this project has not been submitted to Dr.A.P.J. Abdul Kalam Technical University or any other University or Institute for the award of any degree.

## **ACKNOWLEDGEMENT**

It gives me a great sense of pleasure and contentment to present this major Project Work entitled “**Hybrid Model For Lassitude Detection System In Drivers Using Deep Learning And Automatic Braking System With Li-Fi Communication System**” undertaken during B.Tech Final Year. We are so privileged to have got proper guidance and support throughout the making of this project . We are so thankful for the guidance and assistance that we got as without it the making of the project could not be imagined.

We owe a special and sincere debt of gratitude to our project guide **Er. Bramh Prakash Dwivedi (Assistant Professor, ECE Department)**, without whose cognizant efforts my endeavors would not have seen the light of the day. By giving proper guidance whenever needed and supporting us throughout the making of the project .We could not thank him enough for making time for us and solving our queries despite his busy schedule.

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We would also like to thanks **Prof.(Dr.) Indu Prabha Singh (Associate Director Engineering) and Dr.Vibha Srivasata ( Head Of Department)** for giving us such a wonderful opportunity to expand our knowledge for our own branch and giving constant encouragement, support and guidance which helped in successfully completing our project work.

Last but not the least, we would like to thank our parents for their blessings and well wishes. They patiently helped us and stood by our side as we went through our work. Thanking those from the bottom of our heart who always extended a helping hand whenever needed.

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## **PREFACE**

The project work focuses on Lassitude Detection Technique that helps to avoid accidents and gives a better approach towards curbing road accidents caused due to lassitude. The proposed technique uses deep learning for image processing and feature extraction and for the determination of higher accuracy rates.

The **First chapter** gives the information about lassitude that causes various road accidents and also presents the various surveys conducted for road accidents caused due to lassitude. It also gives insights about the different technologies used. The **Second Chapter** gives details about the literature reviewed which helped us to understand the tools and methods that have been used for the lassitude detection and LI-FI Communication for optical Communication.

The **Third Chapter** explains the proposed design methodology in detail, it briefly describes the sub-modules and various performance evaluation parameters . The **Fourth Chapter** defines the various architectures used , comparison of Classifiers and also Feature Extraction and Classification.

The **Fifth Chapter** illustrates the implementation of vehicle (hardware) prototype and various systems and components used for the making of an effective system. The **Sixth Chapter** discusses about the various results obtained , and accuracy and performance evaluation of the system at different stages.

The **Seventh Chapter** discusses about the advantages and the application of the proposed lassitude detection technique. The conclusion of the project work has been presented in the **Eighth Chapter**. The **Ninth Chapter** gives reviews on the future scope of the proposed approach in this project work.

## **ABSTRACT**

Being alert and careful along the way is one of utmost significance and this form distraction of the driver along the way is an important cause of concern. However, psychology of human kind is individual that makes persons completely prone to accident. Forceful while being troubled is utterly reckless and results in history-altering mistakes independently in addition to remainder of something.

While driving, one must be extremely cautious, and even if one drives carefully, another driver on the road may not do so, resulting in an accident. So because of this we need a effective method to resolve this issue.

In this study however, a real-time vision-based technique for detecting driver weariness is provided. In this study, the Haar Cascade classifier was used to recognize the driver's face characteristics. First, the Haar feature-based object identification method is used to find the face. To detect the region of the face we have used functions present in the OpenCV library .

The presence of an eye is then determined. The following step is to examine the open/close state of the eyes, followed by sluggishness based on the series condition of the eyes. On a frame-by-frame basis, the correlation coefficient Haar Classifier technique is used to determine the state of each feature. The use of vision-based driver tiredness detection is a natural, non-intrusive, and practical means of monitoring a driver's alertness.

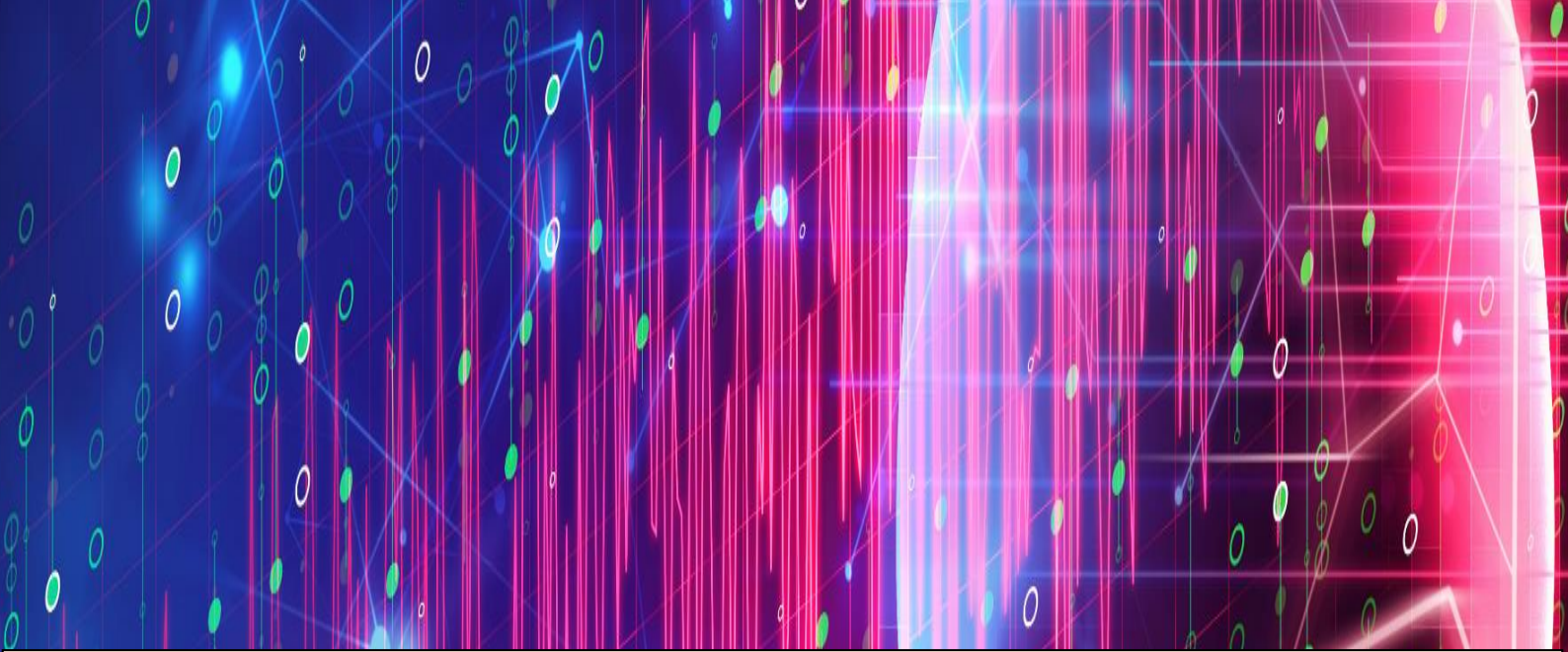
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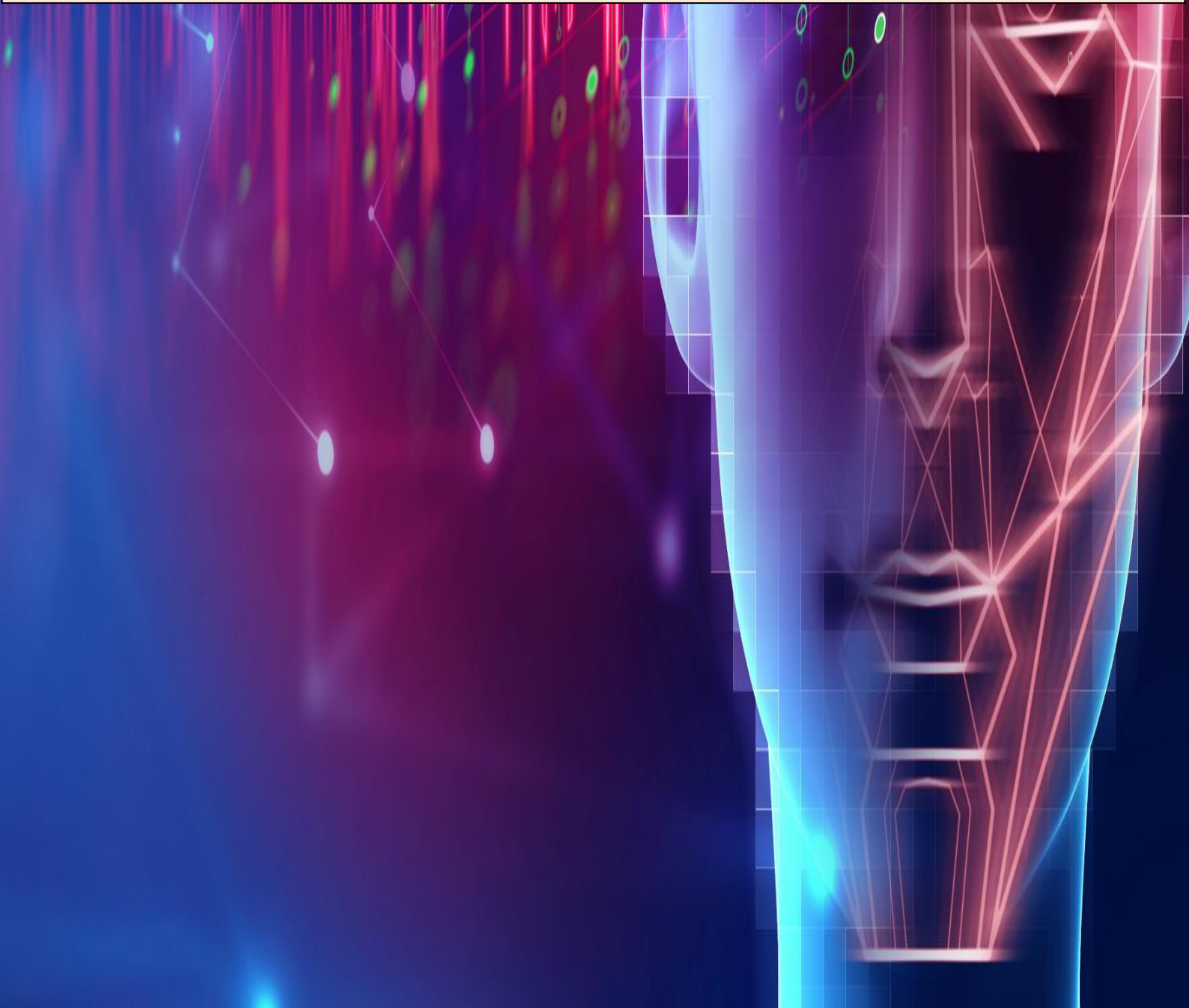
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# **CHAPTER 6**

## **RESULT AND DISCUSSIONS**



# **CHAPTER 1**

## **INTRODUCTION**

### **1.1 Overview**

Distracted driving is a dangerous and hazardous fatal flaw of most of the drivers onroad. This mostly happens when a driver has not had enough sleep which is also known as drowsy driving, but can also be because of just being ignorant, insincere for a while.

Lassitude is a major problem these days, it becomes a serious issue while someone is driving a vehicle. It can put several lives in danger either it may be pedestrians walking on road or passenger inside the vehicle or driver itself. Even after vast burgeon of technologies relating to lassitude detection system, reports have found major accidents taking place due to fatal driving. Earlier models have worked upon different technologies namely as internet of things (IOT), microprocessors and sensors. While our model uses deep learning approach for accurate lassitude detection in drivers. Here, our task is to establish such a system that will recognize the accurate state of drowsiness in drivers before occurring of this and can send an optical signal to other nearby vehicles, thus preventing major collisions and simultaneously implementing mechanical system in drowsy driver's vehicle.

Distracted Driver is a major cause for concern as being alert and attentive on roads is of utmost importance. Negligence on the road can end up in altering one's life completely by death of a close person, or someone due to your own negligence. About a lac accidents were reported according to NHTSA each year due to drowsy driving. Their action time of the driver gets dampened due to distractions.

Getting distracted and falling asleep suddenly is a common mistake and can happen to any one at anytime due to monotony of the driving or just tiredness. It can be prevented by taking precautions by the drivers themselves. But often people misjudge even the fact about their level of fatigue.

Hence developing an efficient driver distraction detecting system is of prime importance to prevent road accidents and mishaps. As part of our major project, we explored the various techniques in use to detect driver getting distracted and developed an efficient distracted driver detection system.

## 1.2 ROAD ACCIDENTS DUE TO LASSITUDE

Based on analysis performed by US government:

- An approximate of about 1 in 25 adult drivers (who are 18 years or older) are noticed and have been reported of getting in sleep or getting involved over phone calls while driving in an estimate of around one month.



**Figure 1. 1:** Driver getting distracted while driving

Yawning or blinking frequently, looking elsewhere and being lost in the thought, difficulty remembering the past few miles driven, or talking to people, texting on the phone, missing their exit, drifting from the main lane using a mobile phone, focusing on songs, or changing the song tune, eating or grabbing food while driving or colliding with the footpath lane are some signs of a driver being distracted from his/her task. On the basis of a report on a survey in about closely 150,000 people in 20 states.

- It is reported that around 4.3% of people are falling asleep while driving and around 1% of people met with accident.
- Also, it is noticed that people who have slept less than 5 hrs are at the high risk of getting engaged in road accident due to lack of concentration.

### 1.3 SURVEY OF ROAD ACCIDENTS

The National Highway Traffic Safety Administration(NHTSA) approximatesthat in 2017 drowsy driving was the main reason for 91,000 crashes whichresulted in 50,000 injuries and near about 800 expires or deaths.

According to a report published by NHTSA (National Highway Traffic Safety Administration) a survey of the road accidents from year 2011 to 2018 caused due to drowsy driving was published given in Table 1.

**Table 1:** Survey of road accidents by NHTSA

YEAR	DRIVER INVOLVED IN FATAL CRASHESWHO WERE DROWSY	PERCENTAGE OF ALL DRIVERS INVOLVEDIN FATAL CRASHES	FATALITIES INVOLVINGDROWSY DRIVING
2018	1221	2.4%	785
2017	1319	2.5%	697
2016	1332	2.5%	803
2015	1275	2.6%	824
2014	1306	2.9%	851
2013	1234	2.8%	801
2012	1221	2.4%	835
2011	1173	2.7%	810

As per survey done by Ministry of Road and Transport in India in 2019 various type of fatalities and injuries are shown in Table 2:



**Table 2 : Survey of road accidents by MRT**

S.No.	Traffic rules violation	Number of accidents	Persons Killed	Persons injured
1.	Over-speeding	53,366	10,885	48,280
2.	Drunken driving/consumption of alcohol & drug	2,337	586	2,020
3.	others	19,294	4,117	16,960

## 1.4 MACHINE LEARNING

Machine learning (ML) is the procedure of implementing mathematical models of data to assist a computer grasp in the absence of direct instruction. It's regarded a fragment of artificial intelligence (AI). Machine learning utilizes algorithms to recognize patterns within data, and those patterns are then used to create a data model that is utilized to make predictions. With abundance in the flow of data and experience, the results of machine learning are becoming more precise— in the same way , how humans get better with more exercise.

The workability of machine learning has made it a great choice in scenarios where the data is dynamic, the nature of the work in hand is always shifting, or coding a solution would be effectively impossible.

## 1.5 DEEP LEARNING

Deep learning is established on the branch of machine learning, which is a submodule of artificial intelligence. Since neural networks evaluate the human brain and so does deep learning.

In deep learning, nothing is used explicitly. Basically, it is a machine learning that uses various nonlinear processing units for performing feature extraction along with transformation.

The output of each preceding layer is taken as input by each one of the progressive layers.

Deep learning models are focused on the precise features themselves by needing few guidance from the programmer and are useful in solving the hindrance of dimensionality. Deep learning algorithms come into picture mainly when we have a large number of inputs and outputs.

Since deep learning has been evolved by the machine learning, which itself is a subset of artificial intelligence and as the idea behind the artificial intelligence is to mimic the human behavior, so same is "the idea of deep learning to build such algorithm that can mimic the brain".

Deep learning is implemented with the use of Neural Networks, and the idea behind the motivation of Neural Network is the biological neurons that are similar with the brain cells.

### **1.5.1 CONVOLUTIONAL NEURAL NETWORKS**

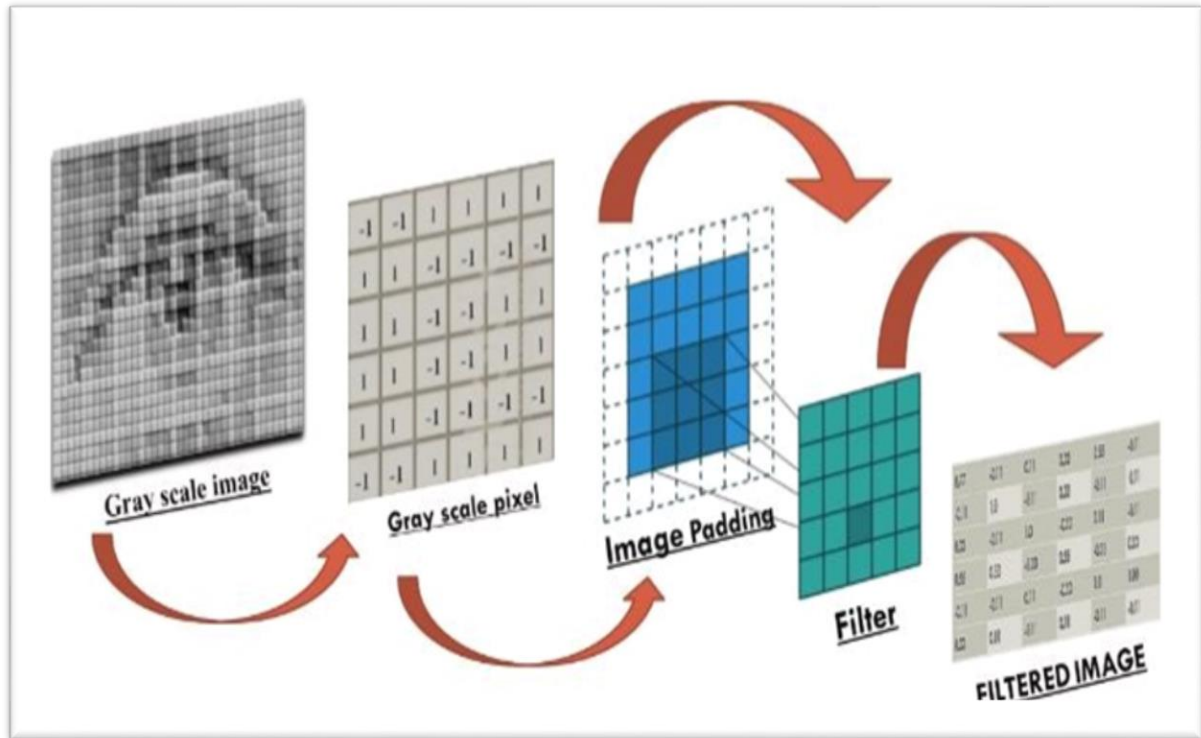
Convolutional Neural Networks are a unique kind of neural network primarily used for image classification, clustering of images and object recognition. CNNs make use of unrecognized construction of hierarchical image representations. To achieve the best accuracy, deep convolutional neural networks are suggested more than any other neural network.

#### **CONVOLUTION LAYER**

Convolution is a method of combining two sources of data in an orderly manner; it is a transformation from one function to another. The main and very important task of this layer is to make the image blurry and sharpened, it is not confined to this only it has many uses. CNNs are used to set up the communication patterns between neurons in adjacent layers.

Features like edges are available or not in the input provided image are detected by CNNs which are having Kernels/Filters.





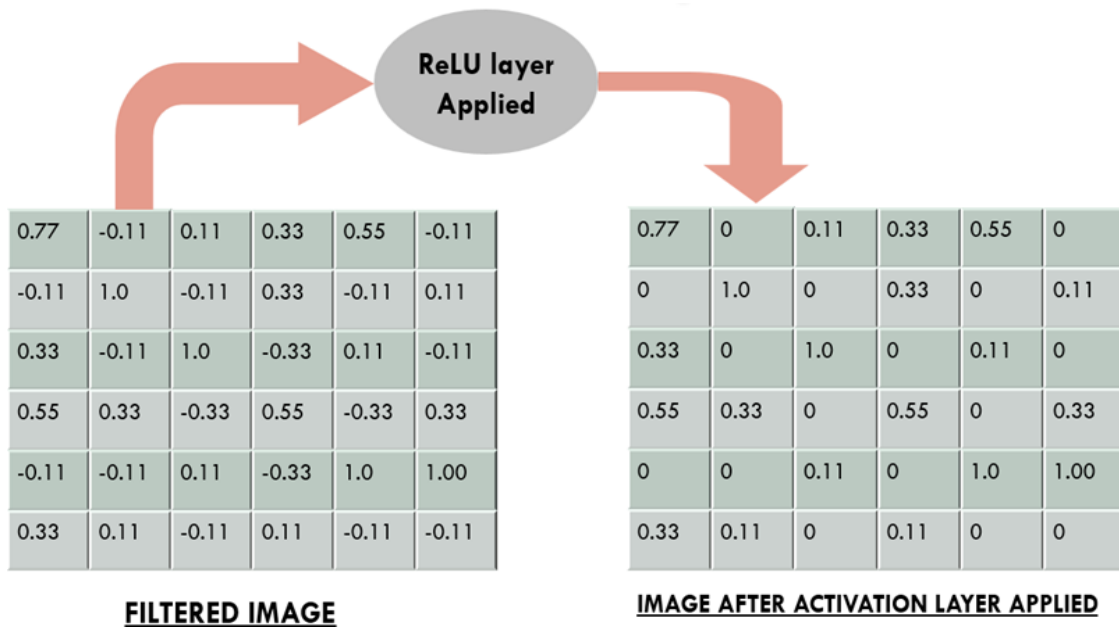
**FIG 1.2:** Pictorial representation of convolution operation

## ACTIVATION LAYER

Negative values in the filtered image on this layer are removed and replaced with zeros to avoid summing the values to zero. The activation function is one of the most important aspect of the neural network architecture. Activation Function present in hidden layer performs the task that how much efficient is our model and it will provide good results at real cases or not. This function or layer used in output layer helps in determining the model's capability of producing best prediction.

**Table 3 :** Activation Layer process

$x$	$f(x)=x$	$F(x)$
-3	$f(-3)=0$	0
-5	$f(-5)=0$	0
3	$f(3)=3$	3
5	$f(5)=5$	5



**Fig 1.3 :** ReLU layer applied

### **POOLING LAYER:**

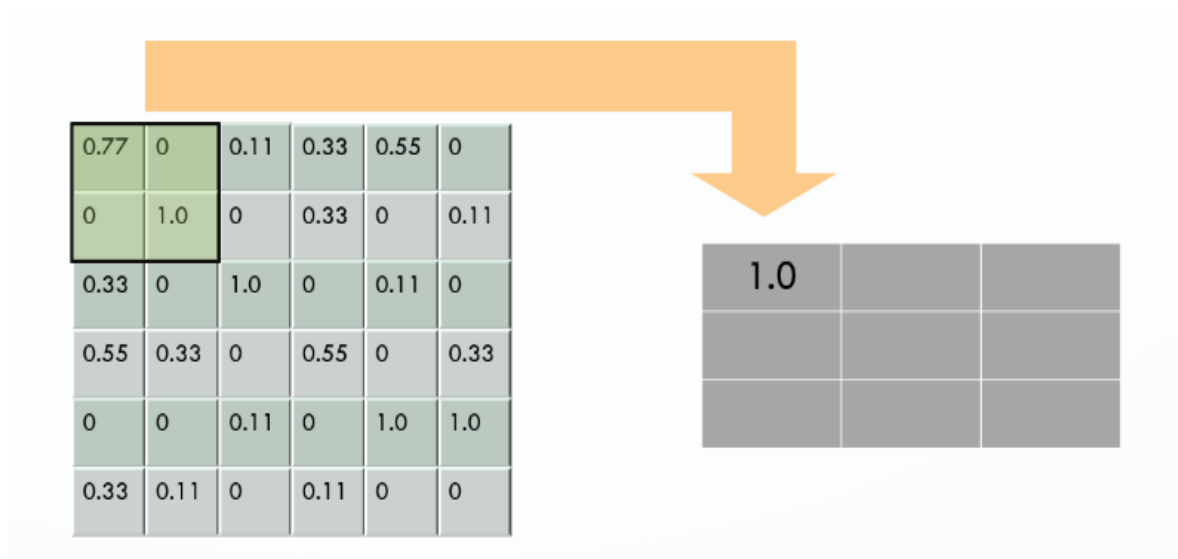
In this layer, the resultant image after applying the activation layer will be shrunk to smaller image.

Steps involved in this process:

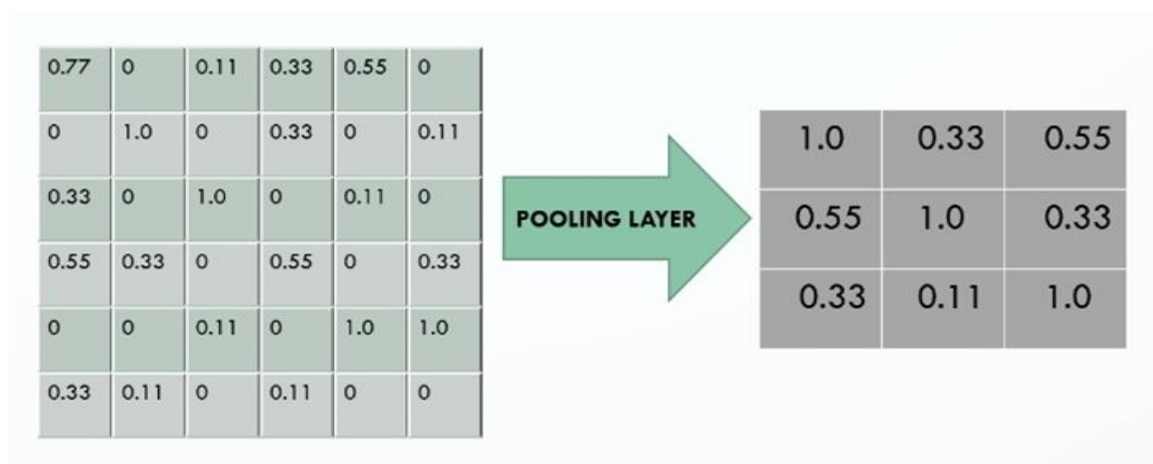
Take a window size(usually 2 or 3)

- a) Take a stride
- b) Take your window across your filtered image

- c) Take the maximum value from each window



**Fig 1.4 :** Pooling Operation on first window



**Fig 1.5 :** Pooling Operation on whole picture

## FULLY CONNECTED LAYER

Dense layer is very fundamental layer where every neuron plays an important role and each neuron collects input from all the neurons of previous layer therefore it is known as Dense layer.

It is used in classification of images based on CNN. In contrast, the dense layer performs a matrix-vector multiplication.

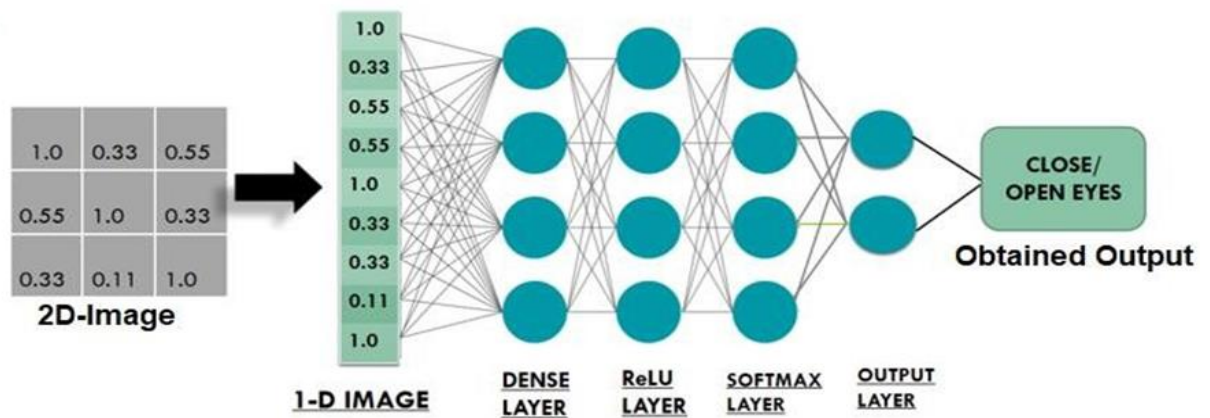


Fig 1.6 :CNN Operation

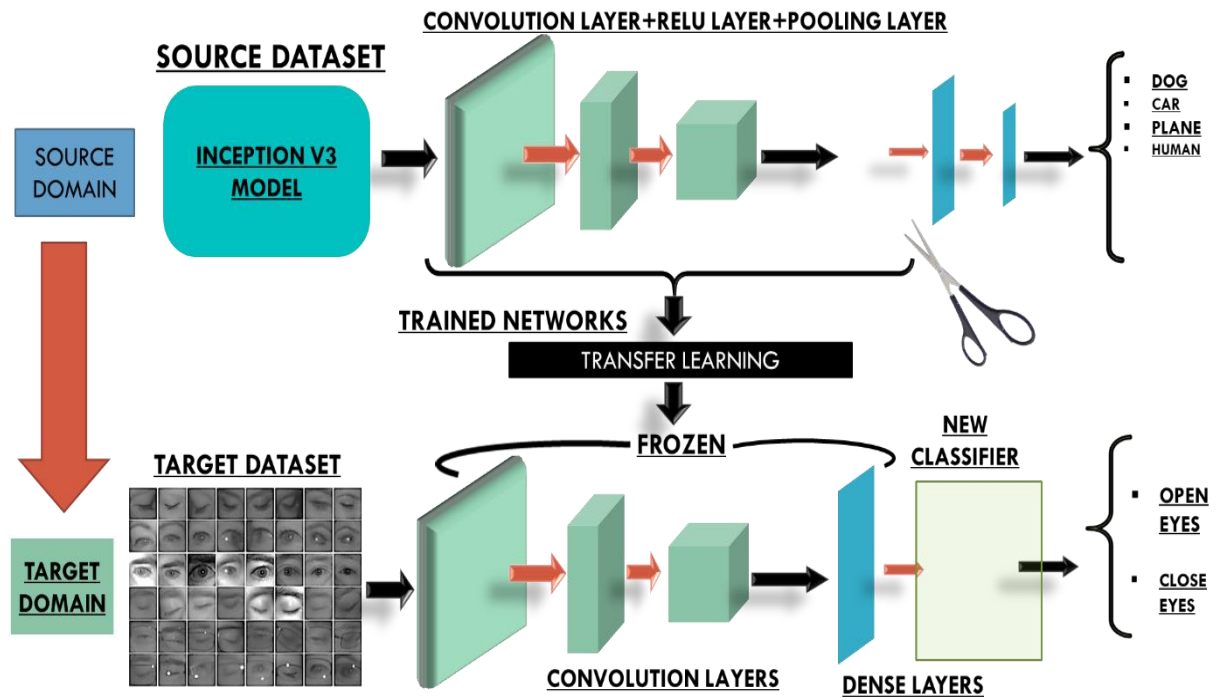
## 1.5.2 TRANSFER LEARNING

Transfer learning (TL) is a research problem in machine learning (ML) that focuses on storing knowledge gained while solving one problem and applying it to a different but related problem. For example, knowledge gained while learning to recognize cars could apply when trying to recognize trucks.

This area of research bears some relation to the long history of psychological literature on transfer of learning, although practical ties between the two fields are limited. From the practical standpoint, reusing or transferring information from previously learned tasks for the learning of new tasks has the potential to significantly improve the sample efficiency of a reinforcement learning agent.

## 1.6 NEED OF TRANSFER LEARNIG FOR THIS PROJECT

- A) To decrease the computation time.
- B) Transfer learning ensures high accuracy of the model.
- C) Since making CNN from scratch gives lower accuracy we used transfer learning for better accuracy.



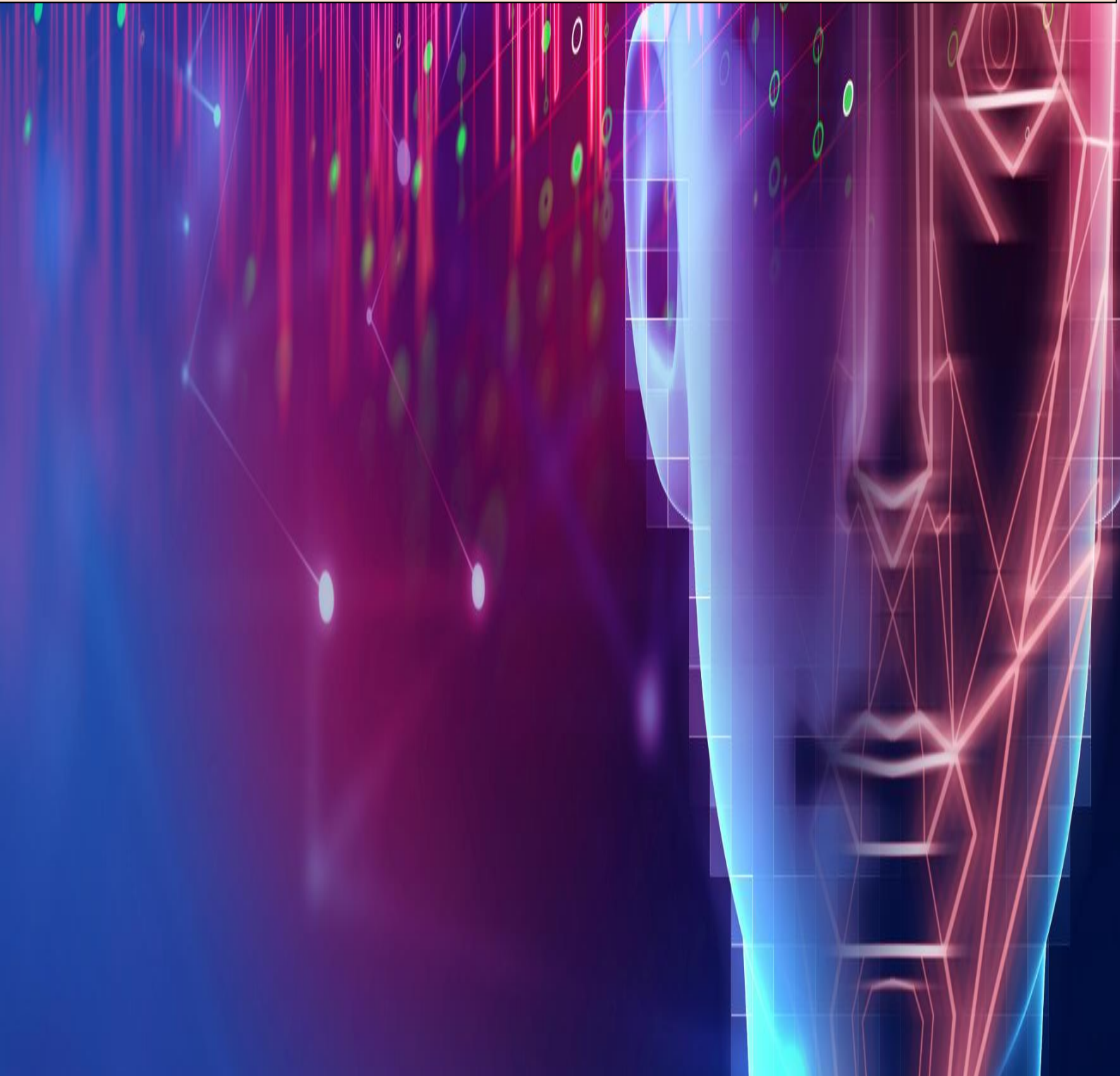
**Fig 1.7 :** Transfer Learning Process





# **CHAPTER 2**

## **LITERATURE STUDY**



## CHAPTER 2

### LITERATURE STUDY

#### **2.1 Pre-Processing of Image:**

When the image are acquired for various kind of scenarios, it gets distorted due to various types of noises. So, the noise filtering techniques will be played an important role for image classification . In previous decades there are various kinds of techniques have been performed.

**O. Appial et al. (2020)** proposed different types of filter for image pre-processing. They are working on Real-Time motion detection based on computer vision using stationary camera. They are using Median Filter (MF) which is a nonlinear filter and otsu filter for segmentation and Temporary Median are using for background updation [2].

**T.L.L et al. (2017)**proposed a visible light based gaze tracking for wearable eye trackers. They are using RANSAC algorithm which are used for outliers identification. They are using two scenarios – the first one in outdoor condition and the second one is indoor condition. They are using two-level Binarization which are implemented in both indoor and outdoor conditions [3].

#### **2.2 Model Training Techniques:**

There are various techniques have been used in previous decades. For behaviour detection, RNN is used in various model. CNN (Convolution Neural Network) is the best approach for model training which gives accurate result with minimum loss. When we are build a CNN architecture from scratch it will give less accurate result as compared to transfer learning approach..

**A. Altameen et al. (2021)** proposed the real-time drowsiness detection system using machine learning methodologies. They developed a system which are based on emotion detection method using support vector machines (It is used to choose the extreme points that help in creating the hyperplane.). In proposed method, they are using Viola-Jones method for face identification. Their results showed 83.25% accuracy in various scenarios. Thus, the training of CNN architecture from scratch takes a lot of computational time to train a model [4].

**R. Jabbar et al. (2020)** proposed a system based on neural network methodologies. In this paper, they are trackingfacial expression using CNN algorithm to identify drowsiness. They trained their model on various dataset like without glasses and with glasses in day or night. In their model, there are five convolutional layer are used (ReLu, MaxPooling, Dropout and Softmax). In this model they are using Dlib library for eye detection. Their results showed 83.33% accuracy [5].

**M. Y. Machaca et al. (2018)** proposed a system using Matlab to detect drowsiness with the help of eye blinking frequency. In this system there is a limit of 5 blinks for a period of time. They are using PERCLOS method to determine the percentage of the closing of the eyes. Their whole model is based on three scenarios sleep time, sleep environment and work schedule for drowsiness detection [6].

**S. S. Kulkarni et al. (2017)** proposed a model using Raspberry Pi using camera and GPS Module. They are determining size of pupil using Haar cascade features and compared with normal size of the pupil. In their model, after drowsiness detection message will be received on cellphone and buzzer will beep [7].

**K. Saleh et al. (2017)** developed an algorithm of LSTM and Recurrent Neural Networks(RNN) to classify drivers behaviors through sensors. They are determining acceleration along X-axis, acceleration along y-axis, acceleration along z-axis, Roll angle, Pitch angle, Yaw angle, vehicle speed, distance to ahead vehicle, number of detected vehicles [8].

**F.You et al. (2019)** proposed a real time drowsiness detection approach using deep cascaded convolutional neural network. Their algorithm works in two modules- offline training and online monitoring. In offline training they are using DCCNN & Dlib toolkit for facial landmark and in online monitoring they are using SVM classifier for detection of open and closed eye [9].

### **2.3 Accident Prevention Techniques**

Accident prevention is the most important part in that decade. There are various techniques proposed by the authors for accident prevention. In the previous two decades, several techniques have been presented for accident prevention.

**P. Krishnan (2018)** developed a system which are used for collision detection using Li-Fi and ultrasonic sensor. Their system based on vehicle-to-vehicle communication using optical communication. The Li-Fi transmitter is situated in rear side of vehicle and Li-Fi receiver is situated in front side of another vehicle. In this paper, they are using ultrasonic sensor for determining distance between two vehicle [10].

**M. S. Rezwan et al. (2018)** proposed a system which will detect obstacles using Sonar Sensor. They are using arduino which will execute emergency brakes. In this paper, they are using LED and LCD as a warning signal. When both vehicles are between 60cm to 50cm then LED will blink and LCD shows warning text and reduce the 33% velocity and if distance between 50cm to 40cm then 66% velocity will be reduce [11].

### **2.4 Summary of Findings:**

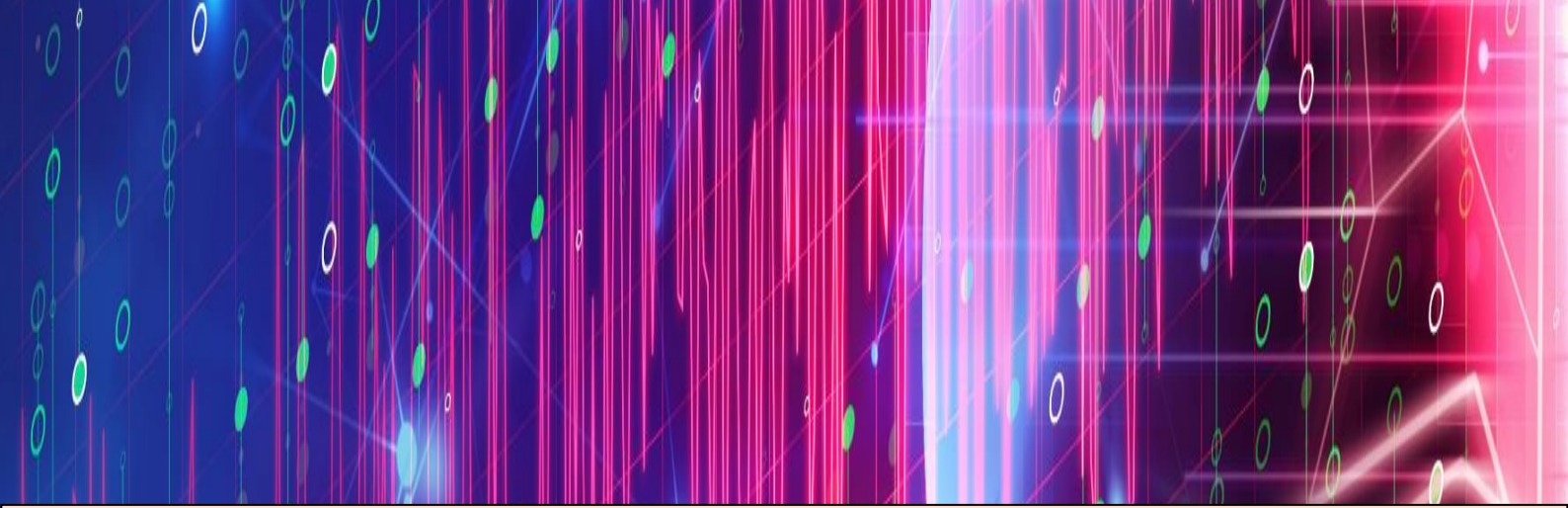


The above discussed literature survey have been summarized under Table 4 . Here are the some points based on the literature survey –

- a) The pre-processing technique is used to reduce the distortion in the in the acquired image. Median Filter (MF) is useful to suppress the noise.
- b) Model training is an important part of deep learning and also for classification. CNN gives good results as compared to RNN and takes less computational time.
- c) Various accident prevention techniques have been used in previous decades but Li-Fi technology played a very exceptional role in accident prevention.

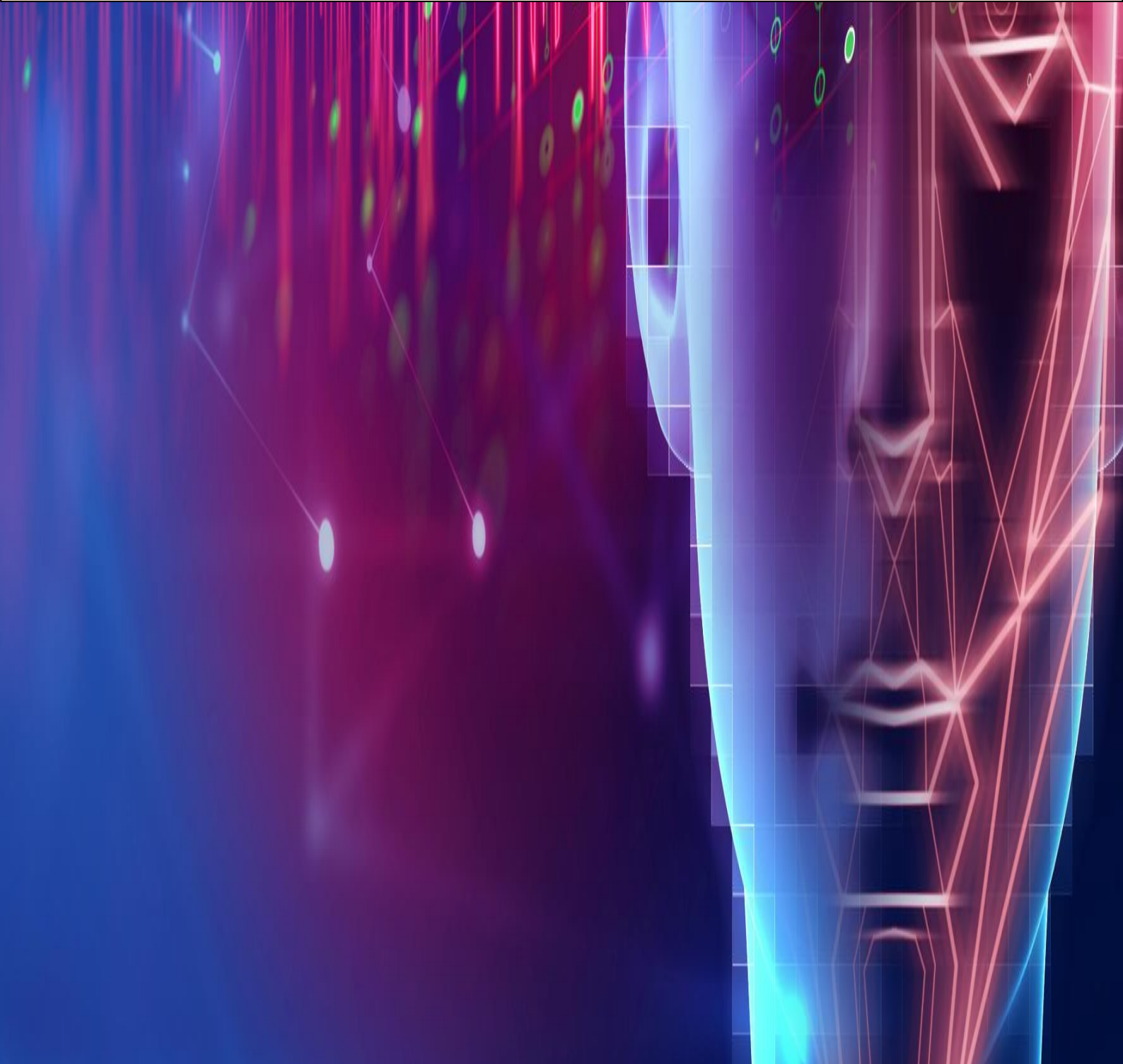
**Table 4 :** Summary of findings

Contribution	Title	Approaches
<b>O. Appial et al. (2020)</b>	Real-Time Motion Detection and Surveillance using Approximation of Image Pre-processing Algorithms	Median Filter
<b>A. Altameen et al. (2021)</b>	Early Identification and Detection of Driver Drowsiness by Hybrid Machine Learning	SVM
<b>M. Y. Machaca et al. (2018)</b>	Design of a Vehicle Driver Drowsiness Detection System through Image Processing using Matlab	PERCLOS
<b>K. Saleh et al. (2017)</b>	Driving Behavior Classification Based on Sensor Data Fusion Using LSTM Recurrent Neural Networks	LSTM and RNN
<b>F.You et al. (2019)</b>	A Real-time Driving Drowsiness Detection Algorithm With Individual Differences Consideration	DCCNN and Dlib



# **CHAPTER 3**

## **PROPOSED DESIGN METHODOLOGY**



## CHAPTER 3

### **PROPOSED DESIGN METHODOLOGY**

#### **3.1 MOTIVATION**

Lassitude becomes a serious issue while someone driving vehicle. It can put several lives in danger either it may be pedestrians walking on road or passenger inside the vehicle or driver itself. Distraction while driving comprises every activity that diverts or attracts the driver's attention from driving and makes them forget about being alert and cautious on the road. Some common distractions while driving are using smartphones, talking and texting from the phone while driving, changing the music channels or eating and drinking. Even a slight negligence on the road can result in life altering accidents where there might be loss of property, health or even life. Some findings also show that sleepiness also effect people at work. Peoples may lose their attention due to lassitude, while dealing with bulky machine at work and this may cause severe injuries analogous to accident cause while driving vehicle. Research has also shown that driver fail to detect their state of lassitude after driving from a long time and this can be one of the causes of numerous crashes happen near to destination. Such an accident is ignored by lassitude detection technologies by analysing the state of sleepiness on a number of inputs.

The purpose of this project is to develop a lassitude detection system. The focus will be placed on designing a system that will accurately monitor the open or closed state of the driver's eyes in real-time. By monitoring the eyes and will warn the driver in the case of lassitude and apply automatic brakes and communicate the warning message to vehicles in range through Li-Fi.

#### **3.2 PROJECT OBJECTIVES**

**Aim:**The aim of our project is Real time lassitude detection in drivers for giving better approach to reduce accidents with the use of deep learning and Li-Fi communication.

To accomplish this proposed project work, the entire methodology has been methodized into four modules which as described below:

##### **Module 1:**

**1.1** Preprocessing the eye data acquired from MRL eye dataset for training and testing.

**1.2** Training and performance analysis of the acquired data by using different CNN architecture (Vgg-16, inception V3, MobileNetV2).

**Module 2:**

Real time detection for capturing most relevant visual trait from the cropped Region Of Interest (ROI) using Haar- Cascade Classifier.

**Module 3:**

Implementation of hardware(vehicle) prototype with Automatic Braking System.

**Module 4:**

Developing transmitter receiver circuit on the front-end and back-end of vehicle prototype respectively for data transmission through Li-Fi Communication System.

### **3.3 PROPOSED DESIGN METHODOLOGY**

The block diagram of the proposed methodology for this project work is shown in Figure 3.1. Acquiring frames, preprocessing, ROI detection and classification of state of eye through CNN architecture and a decision can be made for applying automatic braking system and Li-Fi communication system.

### **3.3 Description of Sub-Modules**

**Module 1:**

In 1.1, Preprocessing of data. This sub-module has been divided into two parts as follows:

Firstly, the dataset is divided into three different folders (Validation data, Training data, Test data) as shown in Fig 3.3.1.

Preprocessing of data through image data generator (Target size, shear range, zoom, rescale etc).

In 1.2, the training of the acquired dataset using Inception-V3 architecture. This sub-module is divided into three parts as follows:

- Firstly, the CNN model A with layers (Dense layer, Flatten layer, Relu activation layer, Softmax layer) imported from keras.
- Inception-V3 CNN model B is added to the model A and output layer of model B is removed and new classification layer is made for classification of state of eye.

- Now, model is trained and validated and analysis of performance is done.

### **Module 2:**

In Module 2, the detection of eyes is done through web-cam and preprocessing of image through Open-CV and ROI are detected by haar cascade classifier. This detection is done as follows:

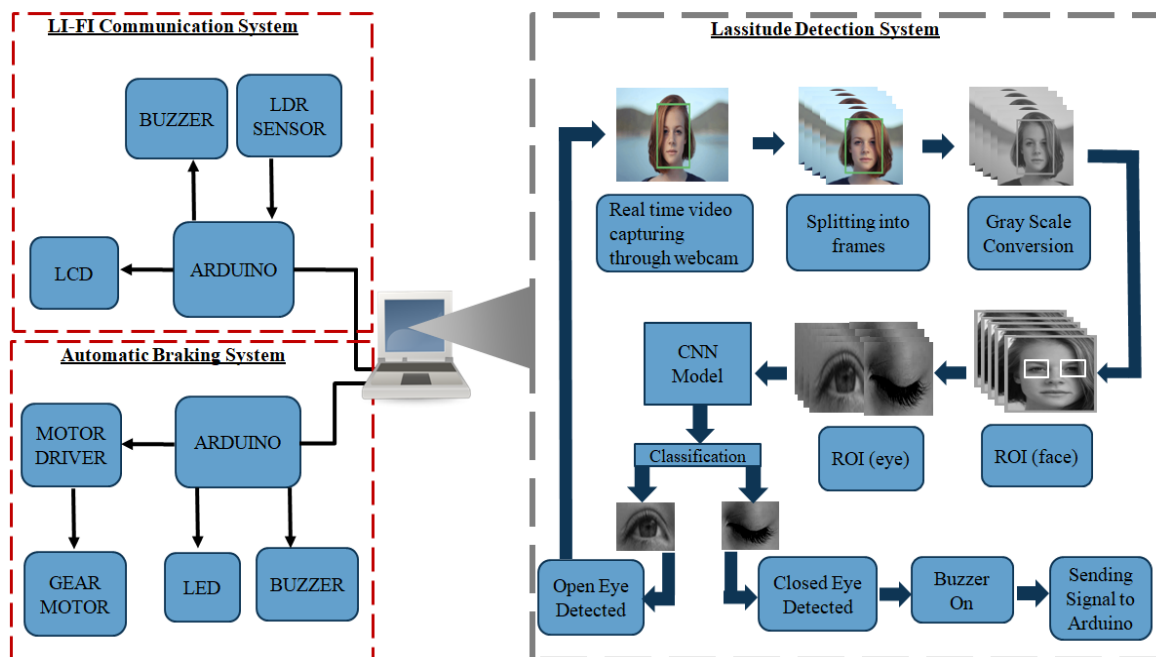
- a) Real time video captured through Web-Cam and splitting it into frames followed by preprocessing(rescaling, grey-scale conversion).
- b) Firstly, ROI(face) is detected after that ROI(eyes) are acquired from the image.
- c) The images are classified into open or close by trained CNN model.

### **Module 3:**

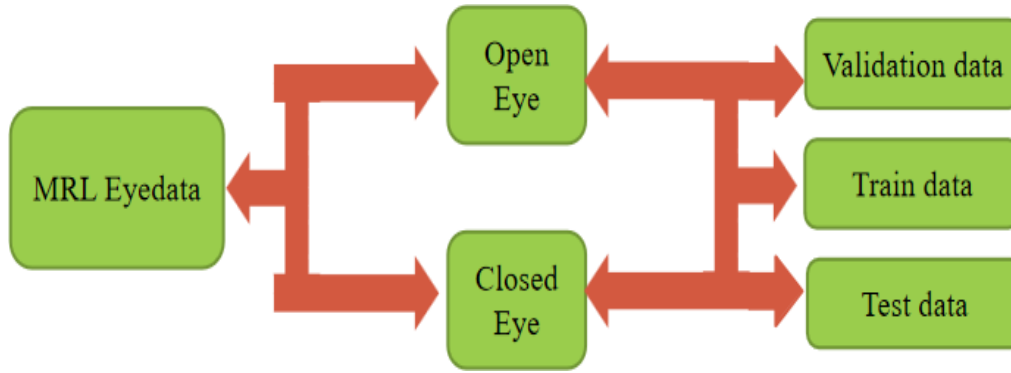
In Module 3, implementation of hardware(vehicle) prototype with Automatic Braking System is done. After the detection, signal is send to arduino and it disconnects the motor driver from power and stops the vehicle. And turn on the LED.

### **Module 4:**

Developing transmitter and receiver circuit on vehicle prototypes for data transmission through Li-Fi communication system. After the signal received from the vehicle through LED a warning message will appear on screen of vehicle.



**Fig 3.1:** Block diagram



**Fig 3.2:** Splitting of data into three data set

**Table 5 :** Dataset for training and testing

<b>Train Data</b>	<b>92000</b>
<b>Test Data</b>	9200
<b>Validation Data</b>	47000

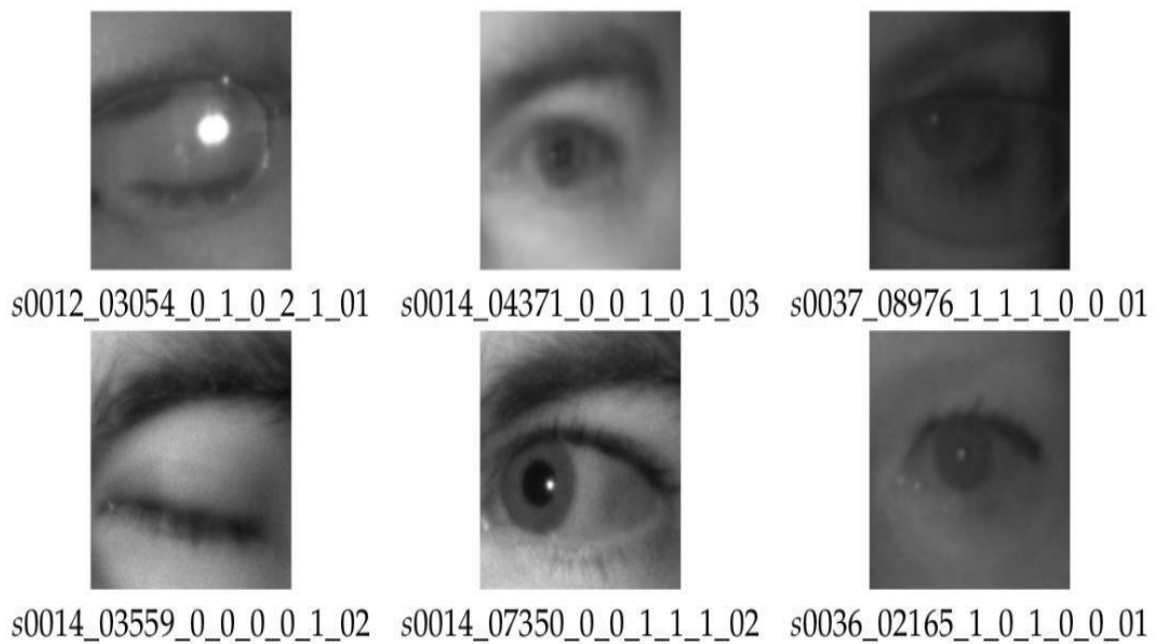
### 3.4 Data Collection (Database for the Experimental Setup)

The MRL Eye Dataset is a massive collection of human eye images. This dataset contains low-resolution 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 different groups to facilitate comparisons of methods easier, and they are also suitable for training and testing classifiers.

The recognition of various facial expression, facial features like eyes, blinking frequency of eyes or gaze estimation are some of the important thing in computer vision. MRL Eye Dataset, it is one of the best data set of human eyes. So to make our model robust and resize we have used different type of images which are different from each other like gender, if a person is wearing glasses or not, what is the eye state of that person, is there any reflection or not, if there is how big or small it is after that lighting condition like each image has two state bad and good depending upon the amount of light during capturing and at last image captured by different sensor.

The following properties were annotated in the dataset in the following order:

- subject ID; In the dataset, we conducted surveys from 37 multiple parties (33 men and 4 women)
- gender [0 - man, 1 - woman]; Here image is used like male and female.
- glasses [0 - no, 1 - yes]; Information on whether the eye picture contains eyeglasses is also supplied for each image (with and without the glasses)
- eye state [0 - closed, 1 - open]; This property keeps track of two different eye states (open, close)
- reflections [0 - none, 1 - small, 2 - big]; Based on the size of the reflections, we identified three different sorts of reflection states (none, small, and big reflections)
- lighting conditions [0 - bad, 1 - good]; Each image has two states based on the amount of light available during video shooting (poor, good).
- sensor ID [01 - RealSense, 02 - IDS, 03 - Aptina]; Photos from three different sensors have now been added to the collection ( IDS Imaging sensor with 1280 x 1024 resolution, Aptina sensor, Intel RealSense )



**Fig 3.3:** Image annotations

### 3.5 Performance Evaluation

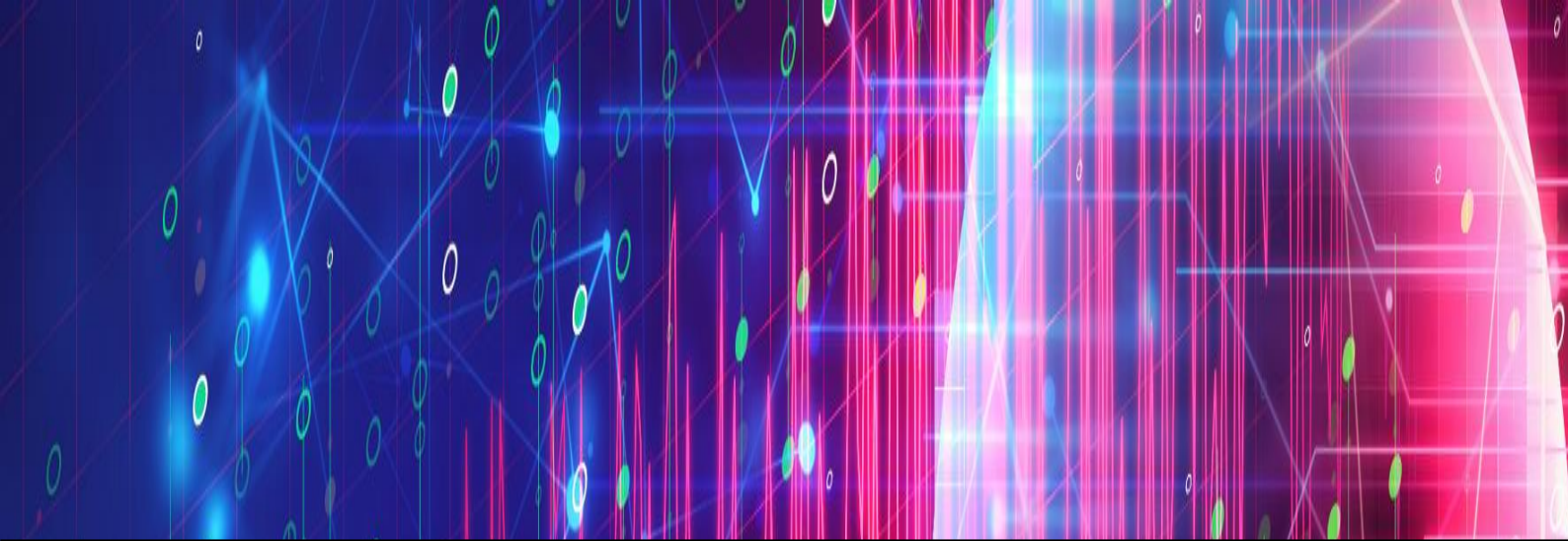
There are various parameters on which evaluation of lassitude detection model which are (accuracy, True Positive Rate, False Positive Rate, Precision).

- ❖ Accuracy denotes the model performance of correctly predicting the state of eye.
- ❖ Loss indicates the flaw in the predictions of state of eye.
- ❖ True Positive rate is a measure of actual correctly predicted state of eye.
- ❖ False Positive rate is a measure of actual wrongly predicted state of eye.
- ❖ Precision is the ration of true positive to the total positive and negative.

**Table 6 :** Performance Evaluation Parameters

<u>ACCURACY</u>	$\frac{TP + TN}{TP + TN + FP + FN}$	Where, TP= True Positive TN= True Negative FP= False Positive FN= False negative
<u>LOSS</u>	$\sum_{k=1}^n (u - \hat{u})$	U = Actual Value Ū=Predicted Value k = Batch Size
<u>TRUE POSITIVE RATE</u>	$\frac{TP}{(TP + FN)}$	Where, TP= True Positive FN= False negative
<u>FALSE POSITIVE RATE</u>	$\frac{FP}{FP + FN}$	Where, FP= False Positive FN= False negative
<u>PRECISION</u>	$\frac{TP}{TP + FP}$	Where, TP= True Positive FP= False Positive





# **CHAPTER 4**

## **VARIOUS ARCHITECTURES , FEATURE EXTRACTION AND CLASSIFICATION**



## CHAPTER 4

### VARIOUS ARCHITECTURES AND FEATURE EXTRACTION- CLASSIFICATION

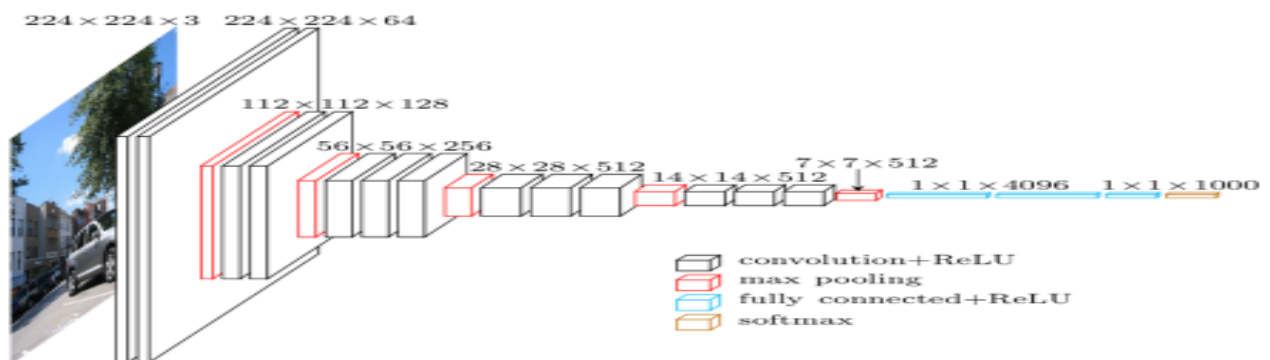
#### 4.1 CNN ARCHITECTURES

CNN is a type of deep learning algorithm which are used for data processing. CNNs are identical to other neural network but they have extra series of layer. There are various layers are used in CNN like convolution layer, pooling layer, fully connected layer. It can also be used for image recognition and classification like to classify an image as being a man or woman. In deep learning CNN is a very powerful tool for various application.

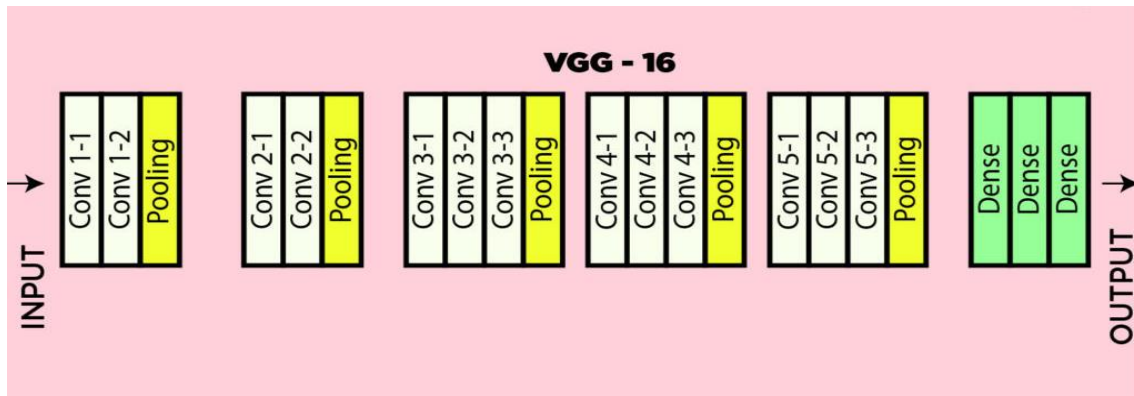
##### 4.1.1 VGG-16:

VGG-16 is a very powerful architecture for recognition and classification. Every year there is a competition arranged by ImageNet for recognition and classification. In first task there will be detection of object from 200 classes and in second task is to classify images from 1000 labelled categories. VGG-16 performed very well and won the first and second place in 2014.

In first layer, 64 channels are used then after a max pool layer is used with stride  $2 \times 2$ , then 2 convolution layer with 128 channel is used, then one maxpool layer is used with stride  $2 \times 2$ , then 3 convolution layer with 256 channel is used, then after maxpool layer with  $2 \times 2$  stride is used, then 3 convolution layer with 512 channel is used, then maxpool layer with stride  $2 \times 2$  is used, then 3 convolution layer with 512 channel is used then at last maxpool layer is used with stride  $2 \times 2$



**Fig 4.1:** VGG-16 Architecture



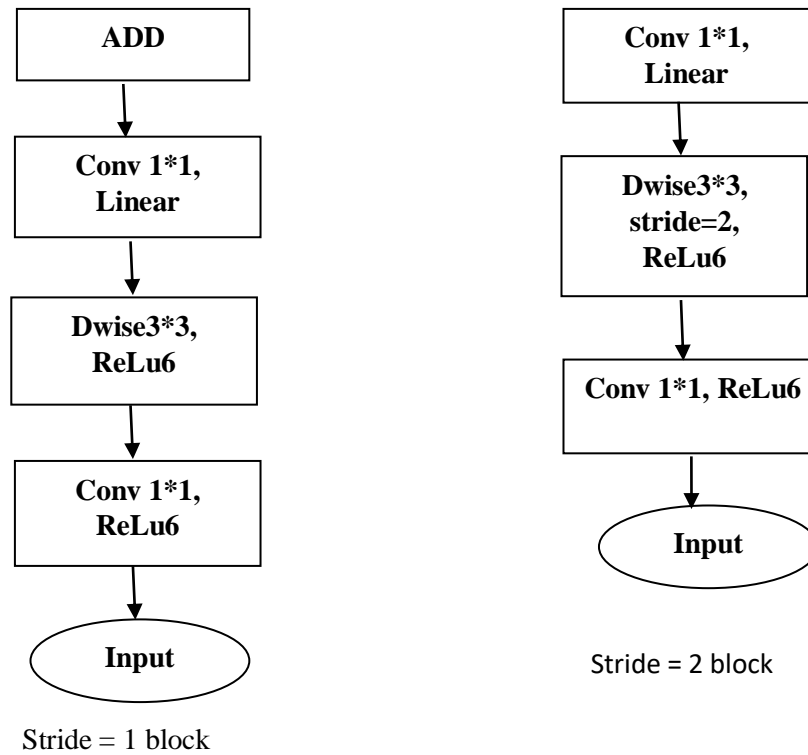
**Fig 4.2:** VGG-16 Architecture map

#### 4.1.2 MOBILE NET V2

MobileNetV2 is an inverted residual structure in which non-linearity in narrow layers are removed. MobileNetV2 is used for feature extraction, object detection and segmentation. In MobileNetV1, there are 2 layers- depthwise convolution and  $1 \times 1$  convolution called point wise convolution. But in MobileNetV2, two types of blocks are used- one is residual block and another for down sizing. There are three layers are used in these blocks- first layer is  $1 \times 1$  convolution with ReLU6, the second layer is depthwise convolution without non-linearity.

**Table7:** MobileNet V2 Architecture

Input	Operator	t	c	n	s
$224^2 \times 3$	Conv2d	-	32	1	2
$112^2 \times 32$	bottleneck	1	16	1	1
$112^2 \times 16$	bottleneck	6	24	2	2
$56^2 \times 24$	bottleneck	6	32	3	2
$28^2 \times 32$	bottleneck	6	64	4	2
$14^2 \times 64$	bottleneck	6	96	3	1
$14^2 \times 96$	bottleneck	6	160	3	2
$7^2 \times 160$	bottleneck	6	320	1	1
$7^2 \times 320$	Conv2d $1 \times 1$	-	1280	1	1
$7^2 \times 1280$	Avgpool $7 \times 7$	-	-	1	-
$1 \times 1 \times 1280 \times 1280$	Conv2d $1 \times 1$	-	k	-	-



**Fig 4.3:** MobileNetV2 Convolution Block

### 4.1.3 INCEPTIONV3

In deep learning, Inception V3 is a convolutional Neural Network which is used for image classification. Inception V1 was the previous version of Inception V3. It has various advantages over Inception V1 like higher efficiency, less computation time. In Inception V3, there are 42 layers used. Inception V3 architecture was first introduced as GoogLeNet. In InceptionV3, the convolution layers are factorize into smaller layer which reduces the number of parameters.

In our lassitude detection model we are using Inception V3 architecture using transfer learning. In transfer learning, we freeze the convolution layers of inception V3 architecture and add new classifier for classification at the output which will classify open or closed eye.

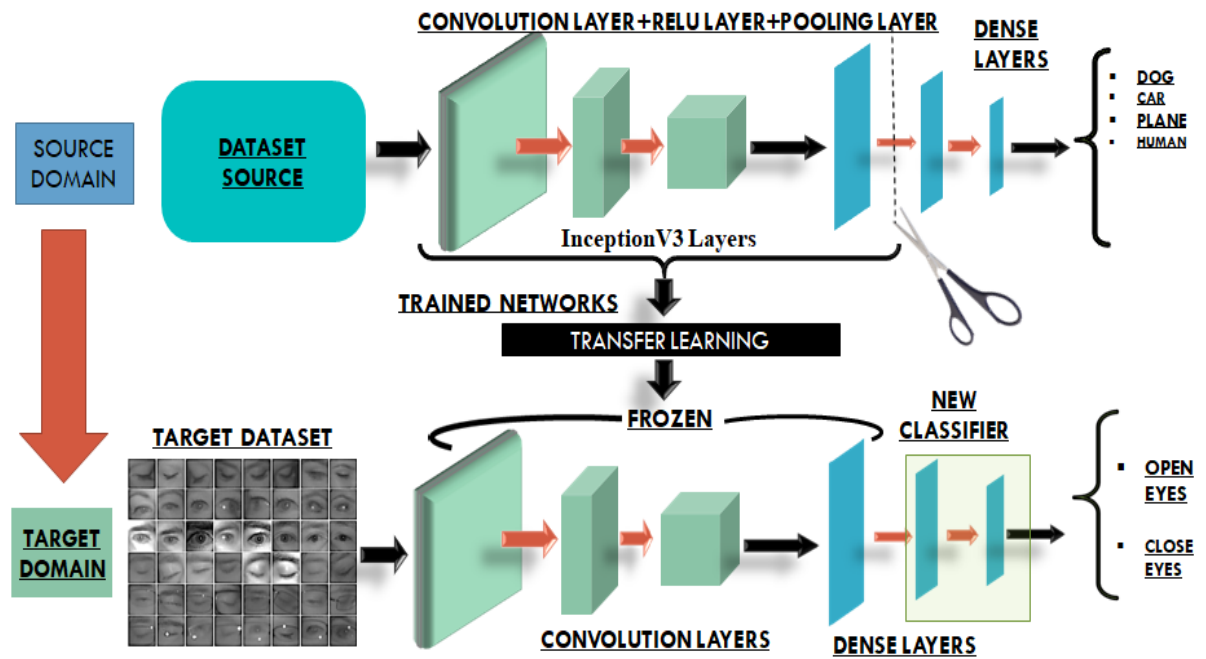


Fig4.4: Inception V3 with transfer learning

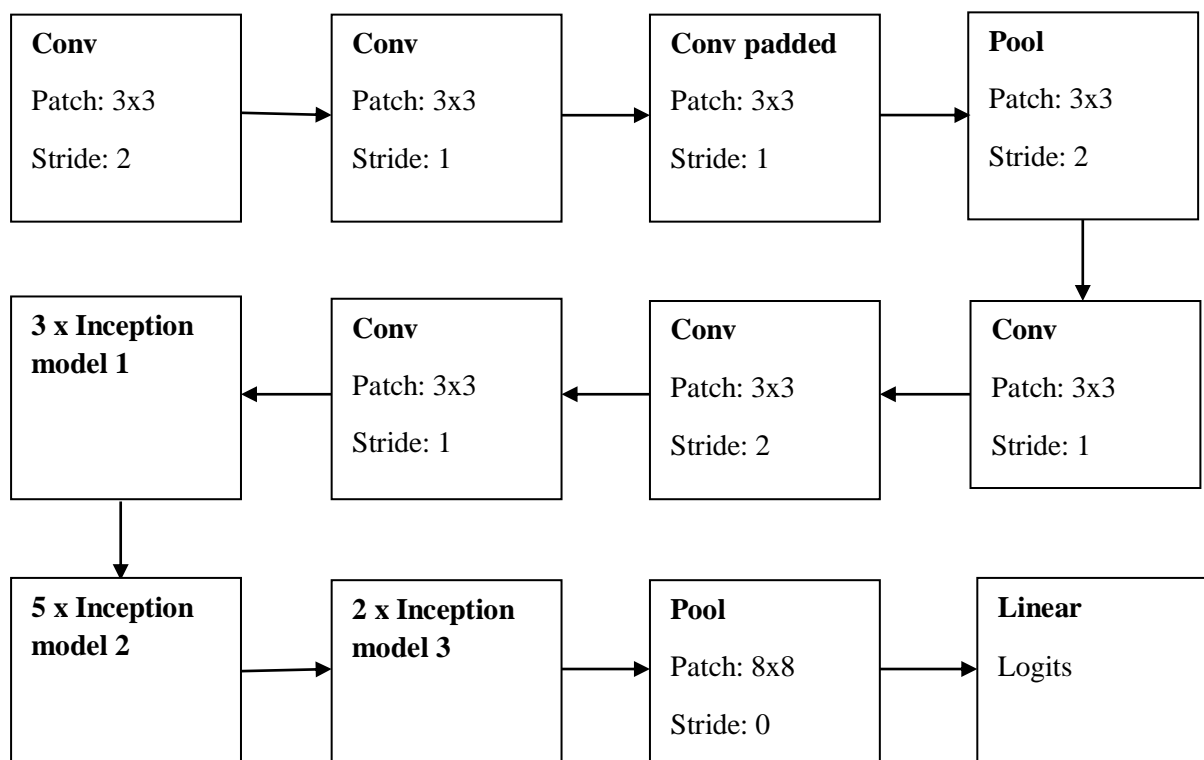


Fig 4.5 : Basic Architecture of Inception V3

## 4.2 FEATURE EXTRACTION

Feature extraction techniques have various advantages like it reduce overfitting risk, high accuracy, high data visualization. With the help of feature extraction we can reduce number of features by creating new features. We can also use feature selection technique which help to discard less important features. We are using Haar features extraction technique in this project.

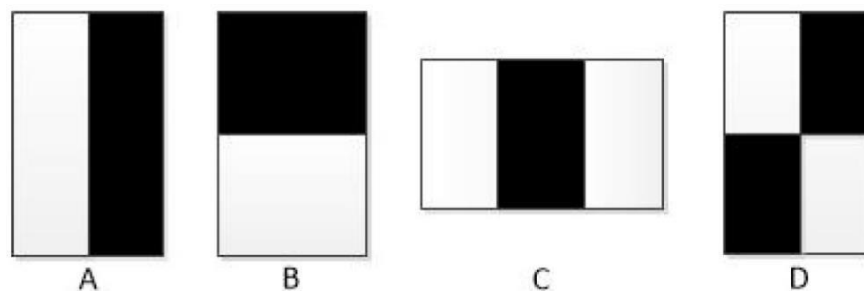
### 4.2.1 HAAR FEATURE EXTRACTION:

There are basically three types of haar like feature

Edge Feature : it is used to detect the edges within the picture.

LineFeature: It is used to detect the vertical lines.

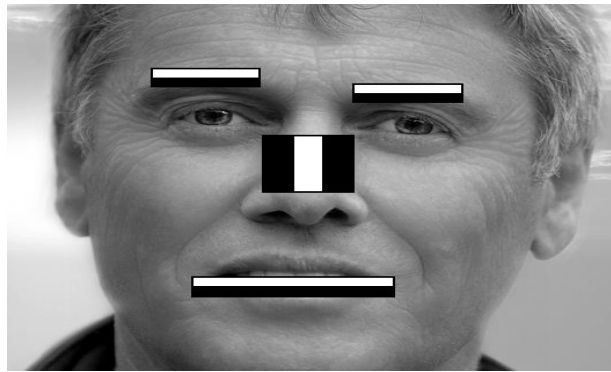
FourRectangleFeature: It is used to detect the diagonal lines in an image.



**Fig 4.6:**Haar Feature

So here the white bar represent pixel in an image which is closer to the light source and the black ones are which are farther from the light source. So by the help of these we will detect the relevant feature of human face.





**Fig 4.7:**Haar Feature Processing

So here we can see that how haar like feature is applied to both eye region and bridge of the nose.

So here we assign pixel intensity to every single pixel like 0 for white and 1 for black, this is the ideal case, but in real case scenario we will get a grayscale image where every pixel is different from each other.

So here we assign value between 0 to 1 to every pixel like if a pixel is close to 0 like 0.1 and if it is closer to black we will assign value like 0.8 or 0.9.

After that we will calculate the sum of white pixel intensity and similarly black pixel intensity, and find the value of delta which is the difference of dark pixel intensity and white pixel intensity. So if the value is closer to 1, then more likely we have found a haar feature.

## 4.2.2 INTEGRAL IMAGE:

0.1	0.1	0.2	0.1	0.7	0.1
0.2	0.3	0.2	0.7	0.8	0.2
0.1	0.4	0.3	0.3	0.1	0.3
0.1	0.5	0.1	0.1	0.2	0.8
0.1	0.4	0.8	0.5	0.6	0.5

**Figure 4.8:** Original Image

As the haar feature have to be applied to the image many times so computation time increases. So, integral image approach is taken for reducing computation time.

Here the values in yellow box are added and put in other matrix in the redbox.(pixels to the left and up are added)

Integral Image 1

Fig 4.9:

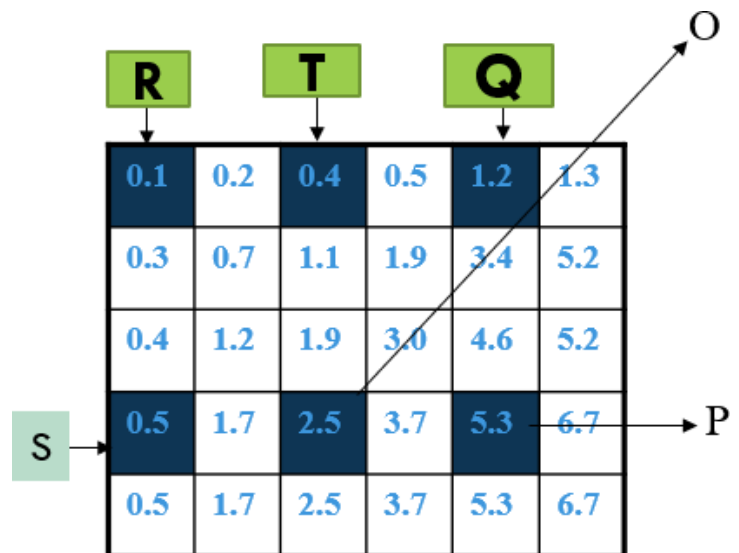


Image 2

### 4.2.3 TRAINING:

- There are 180,000 window size but only few sets of features are useful for detecting face.
- Adaboost training is a machine learning algorithm for selecting the appropriate feature for face detection.
- Provide lots official image data to algorithm for training.

0.1	0.1	0.2	0.1	0.7	0.1
0.2	0.3	0.2	0.7	0.8	0.2
0.1	0.4	0.3	0.3	0.1	0.3
0.1	0.5	0.1	0.1	0.2	0.8
0.1	0.4	0.8	0.5	0.6	0.5

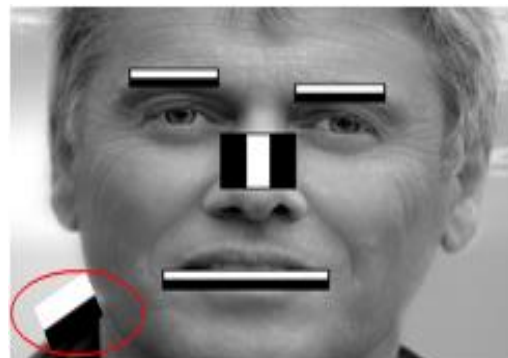
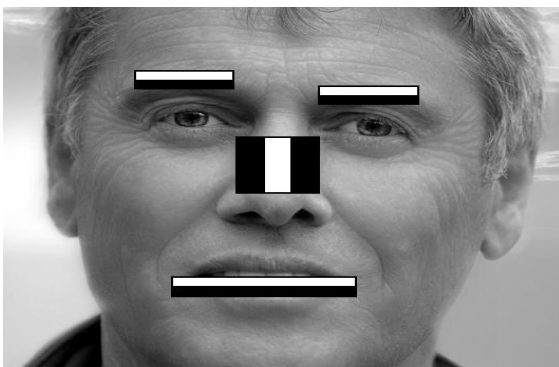
Fig4.10 Integral

ADABOOST

approximately features in 24X24



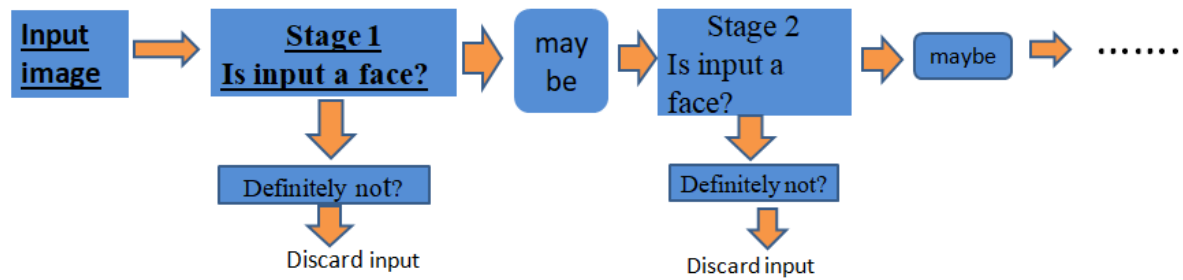
- Provide non facial image for differentiation.



**Fig 4.11:** Relevant Features  
**Fig 4.12:** Irrelevant

#### **4.2.4 CASCADE CLASSIFIER:**

- It is composed of stages each containing a strong classifier. All the features are grouped into several stages where every stage has certain number of features.
- Each stage is used to determine whether a given window is face or not.
- Trying all the features is time consuming but with cascading, the process gets faster.



**Fig 4.13**Cascade Classifier

## 4.3 CLASSIFICATION

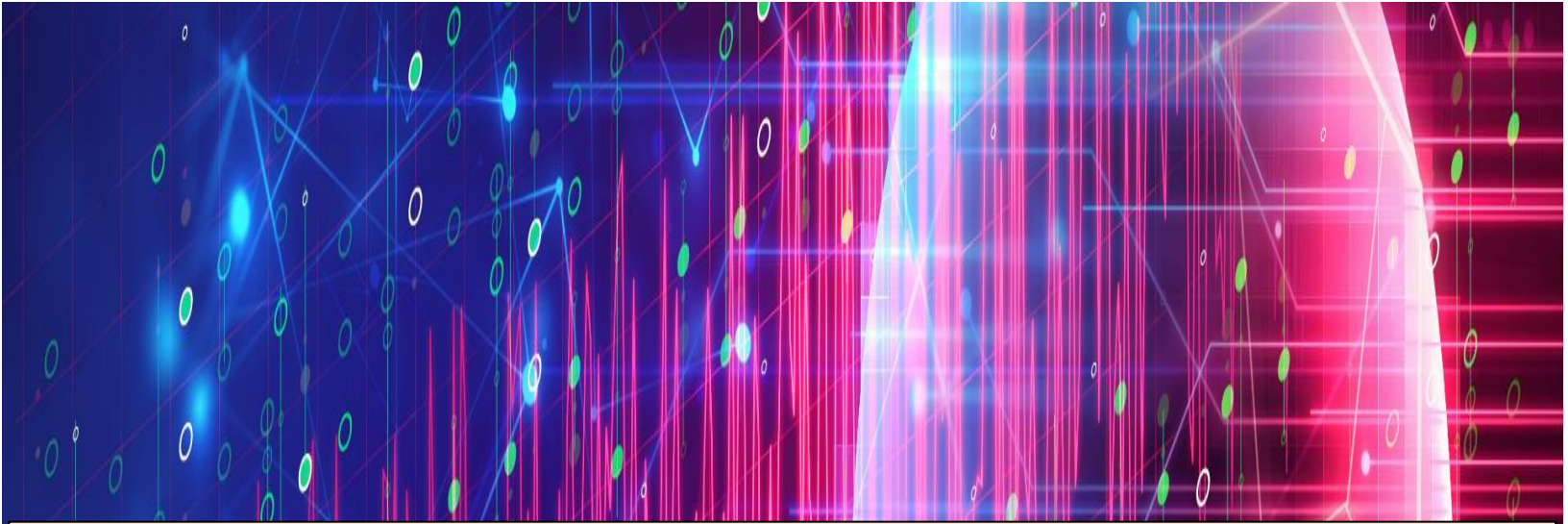
Classification is the final stage of the model by which we can predict result of the input image.

### 4.3.1 STATE OF EYES

We are using CNN classifier for eye status prediction. To insert video frame into the model, we perform some operations.

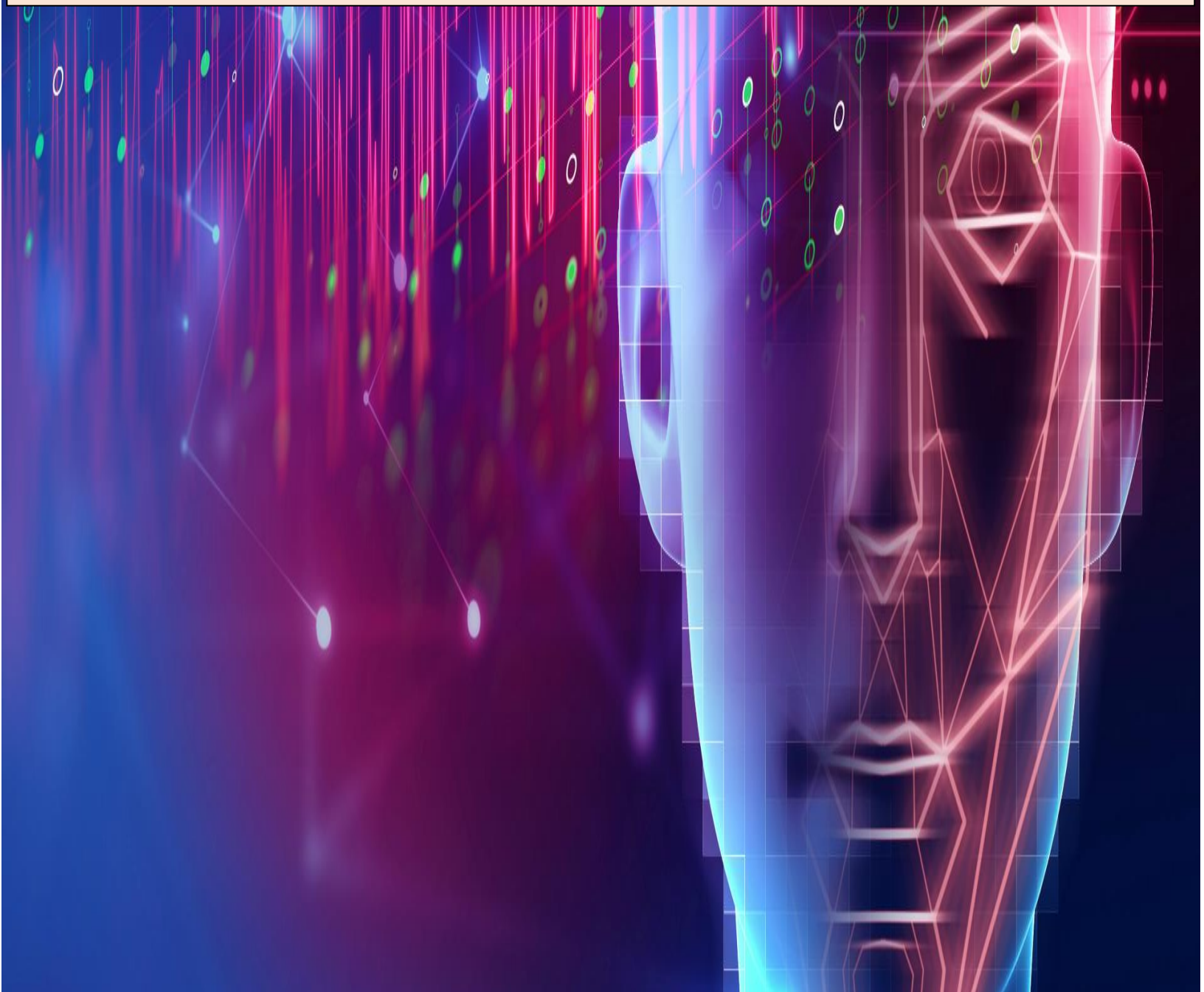
First we convert colored image into gray scale then we resize the image then we expand the dimension of the image to insert in classifier.

After model loading, we can predict eyes state whether closed or in open state.



## **CHAPTER 5**

# **HARDWARE IMPLEMENTATION**



## **CHAPTER 5**

### **HARDWARE IMPLEMENTATION**

#### **5.1 AUTOMATIC BRAKING SYSTEM**

Automatic braking system is an automated system which are useful to control vehicle velocity. In our project for automatic braking system we are using gear motor, arduino, motor driver, jumper wires and wooden plate. After the detection of drowsiness the wheels of the vehicle will be stopped and buzzer will be activated

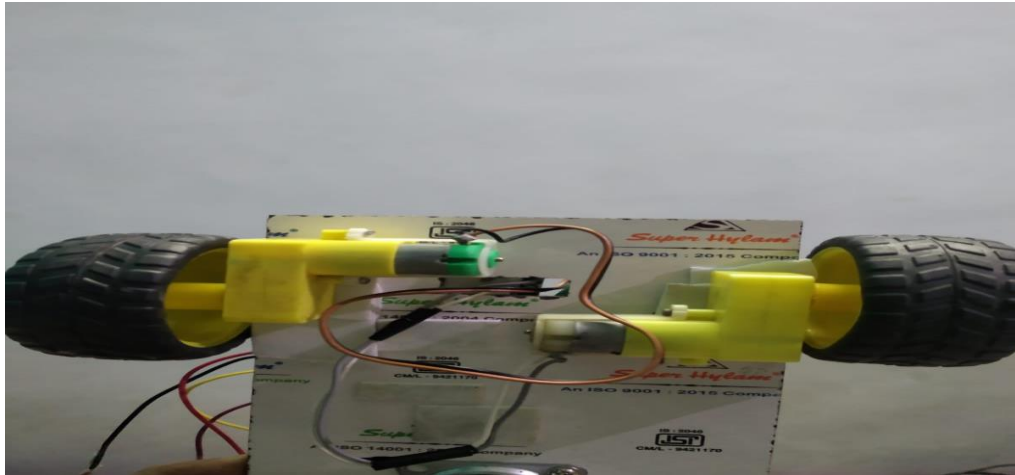
##### **5.1.1VEHICLE BASE**



**Fig 5.1:**Vehicle Base

### **5.1.2 PLACEMENT OF WHEELS**

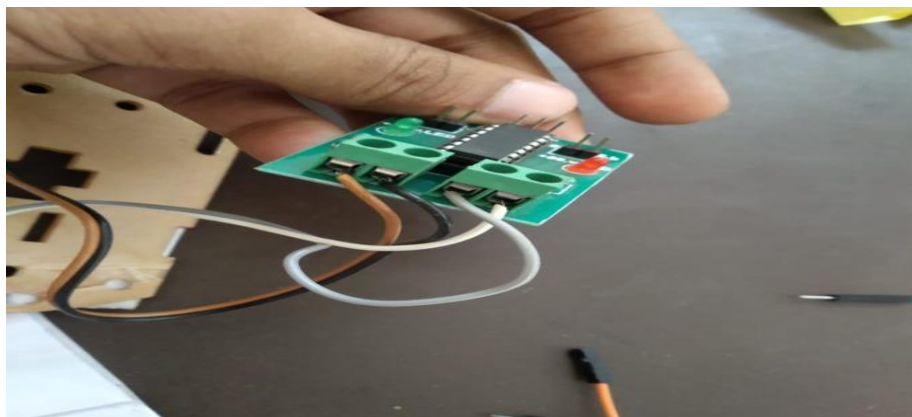
WE are using 100 rpm dc gear motor which can operate upto 12v battery. We placed wheels on the rear side of the vehicle and in front we are adjust a free wheel.



**Fig5.2:**Wheels Placement

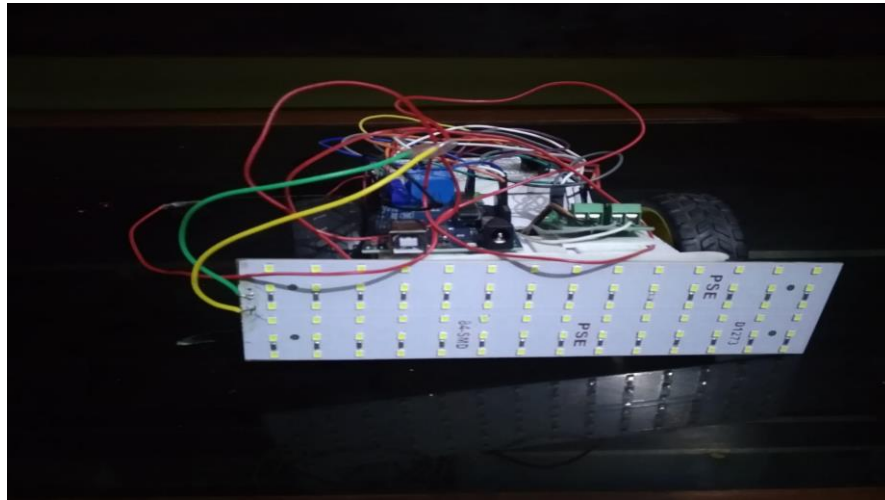
### **5.1.3 ARDUINO AND MOTOR DRIVER**

Take a vehicle and connect to motor driver and arduino using jumper wires and feed automatic braking program into the arduino.

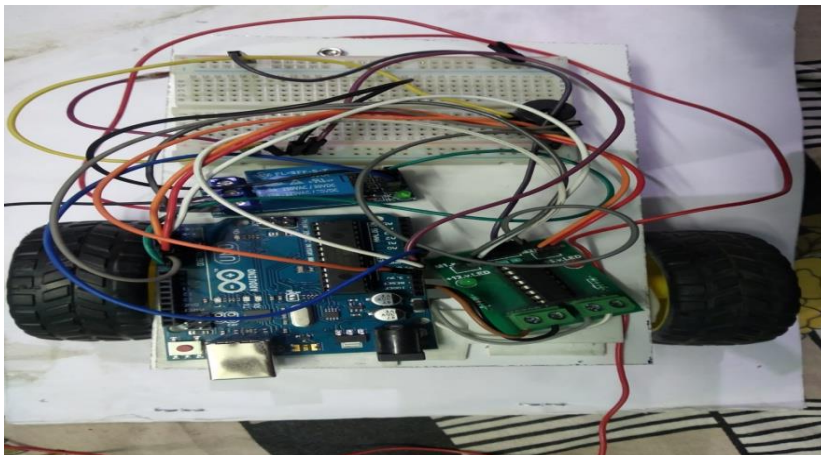


**Fig 5.3:**Motor Driver





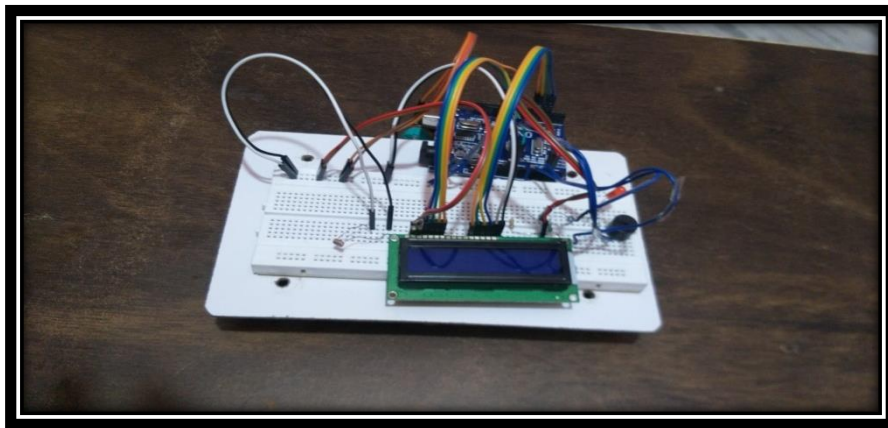
**Fig5.4:**Arduino



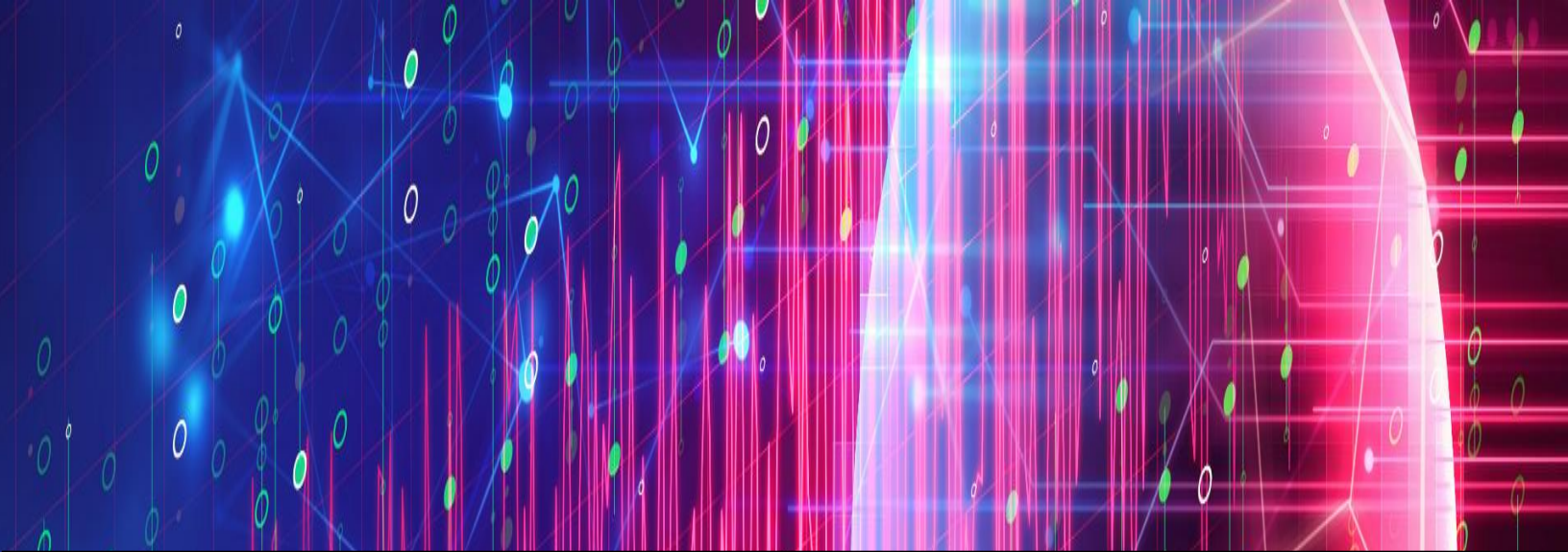
**Fig5.5:** Final Vehicle Prototype

## **5.2 LI-FI COMMUNICATION**

We are using light fidelity technique in our model by which we can send message to the previous vehicle to change their lane. For vehicle prototype we are taking same dimension 21cm length and 15cm width. We are using arduino, resistors, photoresistor, led, lcd and buzzer for optical communication.



**Fig 5.6:**Front Vehicle with LED



# **CHAPTER 6**

## **RESULTS AND DISCUSSIONS**





## **CHAPTER 6**

### **RESULT AND DISCUSSIONS**

#### **6.1 ACCURACY AND LOSS**

Here, we've carried out a experiment on three architectures of CNN for transfer learning. The experiment is done on acquired dataset of MRL eye dataset. In this experiment the dataset is divided into training, validation, test dataset.

For the experiment, we made a collection of 148000 images. In this the dataset is divided into three parts training-92000 images, validation-47000, test-9200.

##### **6.1.1 ANALYSIS OF CNN ARCHITECTURES ACCURACY AND LOSS**

#### **INCEPTION-V3**

The proposed model of INCEPTION-V3 CNN architecture achieved a 95.12 percent accuracy on the training dataset, 94.39 percent accuracy on validation dataset and 95.48 percent accuracy on test dataset.

After the 14 epochs of cycle model is early stopped due to no increase in accuracy and decrease in loss.

The model's accuracy is examined and the results are depicted as follows-

**Table 8:** Analysis of Inception V3 Architecture

EPOCH	TRAINING ACCURACY	TRAINING LOSS	VALIDATION ACCURACY	VALIDATION LOSS	TEST ACCURACY	TEST LOSS
1.	0.9188	0.2037	0.9437	0.1542	0.9201	0.1749
2.	0.9330	0.1714	0.9389	0.1673	0.9287	0.1623
3.	0.9355	0.1652	0.9426	0.1517	0.9307	0.1581
4.	0.9379	0.1598	0.9427	0.1626	0.9367	0.1557
5.	0.9392	0.1599	0.9422	0.1551	0.9383	0.1507
6.	0.9412	0.1520	0.9399	0.1707	0.9399	0.1489
7.	0.9452	0.1432	0.9481	0.1499	0.9401	0.1465
8.	0.9462	0.1395	0.9439	0.1573	0.9429	0.1404
9.	0.9472	0.1358	0.9456	0.1530	0.9448	0.1391
10.	0.9452	0.1400	0.9443	0.1560	0.9439	0.1387
11.	0.9478	0.1364	0.9449	0.1597	0.9486	0.1354
12.	0.9469	0.1360	0.9435	0.1561	0.9497	0.1304
13.	0.9485	0.1375	0.9455	0.1515	0.9504	0.1297
14.	0.9512	0.1297	0.9439	0.1609	0.9548	0.1263

## VGG-16

The proposed model of VGG-16 CNN architecture achieved a 89.68 percent accuracy on the training dataset, 91.64 percent accuracy on validation dataset and 90.92 percent accuracy on test dataset. After the 10 epochs of cycle model is early stopped due to no increase in accuracy and decrease in loss. The model's accuracy is examined and the results are depicted as follows-

**Table 9:** Analysis of VGG-16 Architecture

EPOCH	TRAINING ACCURACY	TRAINING LOSS	VALIDATION ACCURACY	VALIDATION LOSS	TEST ACCURACY	TEST LOSS
1.	0.8556	0.2827	0.8624	0.2897	0.8423	0.2734
2.	0.8587	0.2714	0.8686	0.2832	0.8686	0.2602
3.	0.8635	0.2652	0.8734	0.2783	0.8713	0.2578
4.	0.8698	0.2613	0.8767	0.2737	0.8824	0.2503
5.	0.8710	0.2599	0.8934	0.2704	0.8889	0.2465
6.	0.8745	0.2556	0.9056	0.2689	0.8901	0.2456
7.	0.8831	0.2478	0.9109	0.2687	0.8965	0.2387
8.	0.8867	0.2431	0.9098	0.2654	0.9003	0.2318
9.	0.8912	0.2387	0.9123	0.2513	0.9043	0.2287
10.	0.8968	0.2267	0.9164	0.2587	0.9092	0.2197

## MOBILENET-V2

The proposed model of MOBILENET-V2 CNN architecture achieved a 91.98 percent accuracy on the training dataset, 90.63 percent accuracy on validation dataset and 91.76 percent accuracy on test dataset. After the 15 epochs of cycle model is stopped. The model's accuracy is examined and the results are depicted as follows-

**Table 10** : Analysis of Inception V3 Architecture

EPOCH	TRAINING ACCURACY	TRAINING LOSS	VALIDATION ACCURACY	VALIDATION LOSS	TEST ACCURACY	TEST LOSS
1.	0.8883	0.2437	0.8634	0.2497	0.8702	0.2398
2.	0.8810	0.2414	0.8685	0.2459	0.8776	0.2372
3.	0.8893	0.2352	0.8709	0.2408	0.8782	0.2308
4.	0.8919	0.2308	0.8731	0.2383	0.8832	0.2294
5.	0.8928	0.2299	0.8786	0.2357	0.8892	0.2285
6.	0.8967	0.2220	0.8802	0.2301	0.8912	0.2207
7.	0.8959	0.2232	0.8811	0.2265	0.8952	0.2169
8.	0.8996	0.2195	0.8839	0.2205	0.8992	0.2109
9.	0.9023	0.2158	0.8896	0.2186	0.9012	0.2086
10.	0.9045	0.2100	0.8943	0.2107	0.9052	0.2018
11.	0.9096	0.2064	0.8949	0.2081	0.9078	0.1965
12.	0.9089	0.1960	0.8935	0.2003	0.9069	0.1903
13.	0.9124	0.1975	0.8955	0.1989	0.9085	0.1894
14.	0.9158	0.1897	0.9039	0.1925	0.9112	0.1856
15.	0.9189	0.1823	0.9063	0.1976	0.9176	0.1814

## 6.1.2 COMPARISON OF ARCHITECTURES

The result of our experiment shows that INCEPTION-V3 architecture gave the best results out of VGG-16 and MOBILENET-V2 architectures. The INCEPTION-V3 run for 14 epochs and stopped due to no increase in accuracy and decrease in loss. The VGG-16 trained for 10 epoch and after that early stopped due to no increase in accuracy and decrease in loss.

The MOBILENET-V2 has been trained for 15 epoch and stopped. The accuracy of INCEPTION-V3 architecture was 95.12 on training dataset and 95.48 on test dataset.

And accuracy of VGG-16 architecture was 89.68 on training dataset and 90.92 on test dataset. And accuracy of MOBILENET-V2 was 91.89 on training dataset and 91.76 on test dataset.

The accuracy of INCEPTION-V3 was highest among all three architectures. The table below shows the comparison of accuracy and loss of all the three architectures:

**Table 11:** Comparison of Architectures

ARCHITECTURE	TRAINING ACCURACY	TRAINING LOSS	VALIDATION ACCURACY	VALIDATION LOSS	TEST ACCURACY	TEST LOSS
INCEPTION-V3	95.12	12.97	94.39	16.09	95.48	12.63
VGG-16	89.68	22.67	91.64	25.87	90.92	21.97
MOBILENET-V2	91.89	18.23	90.63	19.76	91.76	18.14

## 6.2 MODEL CHECKPOINTS

### 6.2.1 EARLY STOP

---

```
earlystop = EarlyStopping(monitor = 'val_loss', patience = 7, verbose = 3,
restore_best_weights = True)
```

---

It allows to specify model performance and monitor it. ‘Monitor’ allows to measure performance of training and check the accuracy and loss and when the model accuracy is at the highest point and model loss at lowest point, it saves it as the best weight.

**monitor:** it checks the validation and training accuracy and loss.

**patience:** No of epochs to wait before early stop if no progress on the validation set and training set.

**verbose:** It is a way to represent the training output of the neural network on users screen while its training.

**Restore\_best\_weights:** it saves the best weights or the best accuracy and loss value after the training.

### 6.2.2 LEARNING RATE

---

```
learning_rate = ReduceLROnPlateau(monitor='val_loss', patience = 3, verbose=3)
```

---

Learning rate is a tuning parameter which determines the step size at each iteration to get a minimum loss function throughout the training. The learning rate is usually between 0 and 1 and it get accordingly change while montioring the loss function. If loss function does not reduce so the learning rate is changed.

If after reducing learning rate loss function doesn't improve it will monitor for three epochs and stop the training.

### 6.2.3 CALLBACKS

---

```
callbacks = [checkpoint,earlystop,learning_rate]
```

---

Callbacks is an object which performs actions at several stages of training the model. At the start of an epoch or at end, after or before a batch etc.

It is a object which calls all the parameters inside the square bracket.

### 6.2.4 EPOCH

---

```
Epoch = 1 forward pass + 1 backward pass of of all batches of sample.
```

---

It means that while training the model there are batches in it of training data. So 1 epoch means training all the batches 1 time and initializing and updating the weights of neurons.

For our project we have taken 15 epochs for training the CNN architecture.

### 6.2.5 ITERATION

It is the number of batches needed to complete one epoch. Iteration specifies how many times a batch of data has been passed through the CNN classifier.

$$n = \frac{\text{Totalnooftrainingdatasets}}{N}$$

Where,

N = no of batches

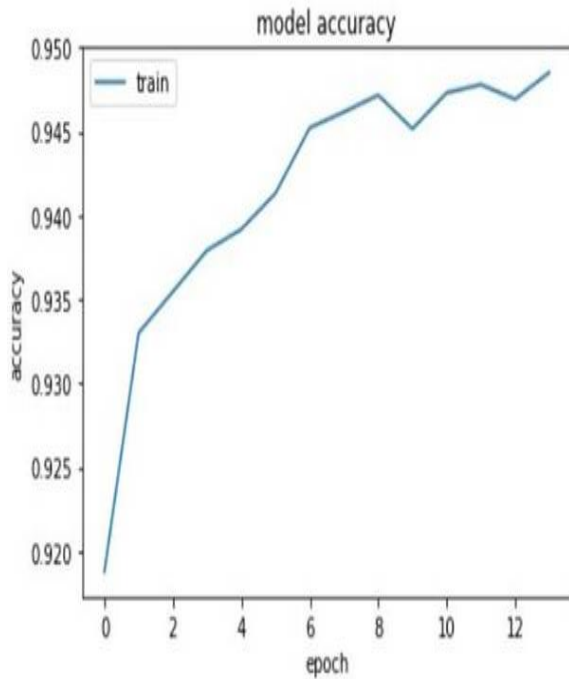
n = iterations

**Table 12 : Model Checkpoints**

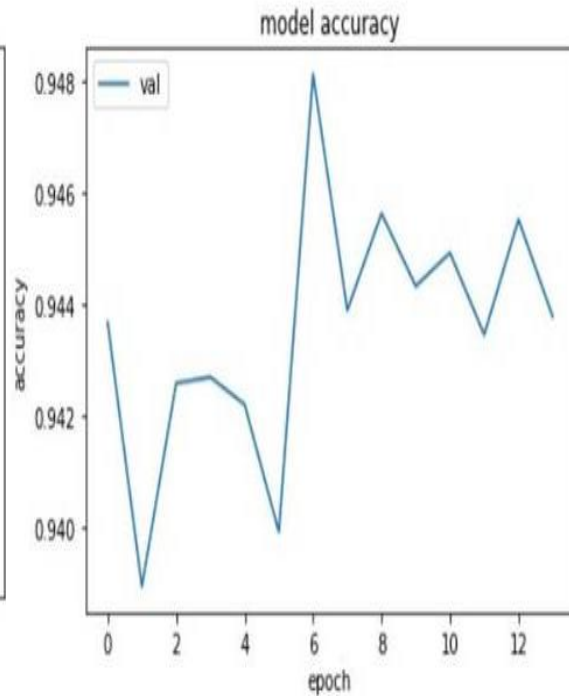
<b>CHECKPOINT</b>	monitor='val_loss', save_best_only=True verbose=3
<b>EARLYSTOP</b>	monitor = 'val_loss', patience=7, verbose = 3, restore_best_weights=True
<b>LEARNING_RATE</b>	monitor = 'val_loss', patience=3,verbose=3
<b>CALLBACKS</b>	checkpoint, early stop, learning rate
<b>EPOCH</b>	15 (randomly chosen)

## 6.3 MODEL EVALUATION

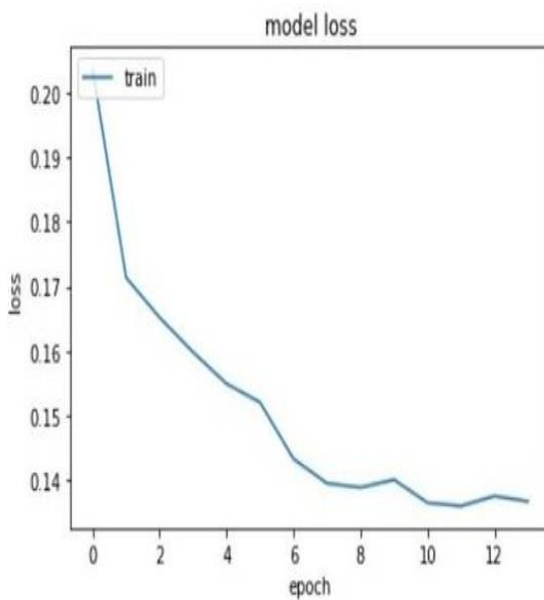
### INCEPTION-V3 GRAPHICAL ANALYSIS



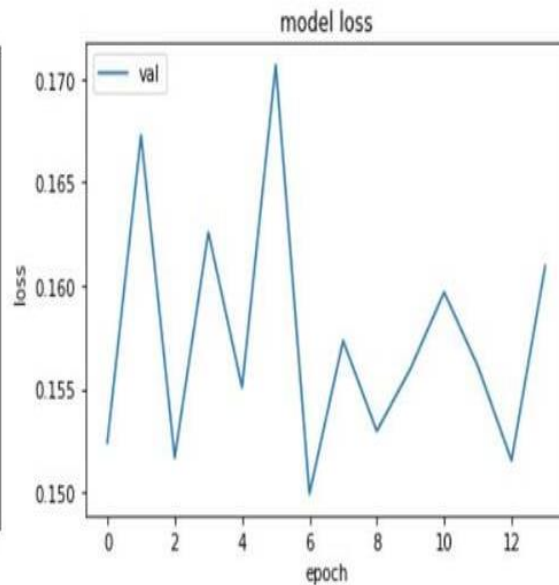
**Fig 6.1** Training Accuracy



**Fig 6.2** Validation Accuracy



**Fig 6.3** Training Loss



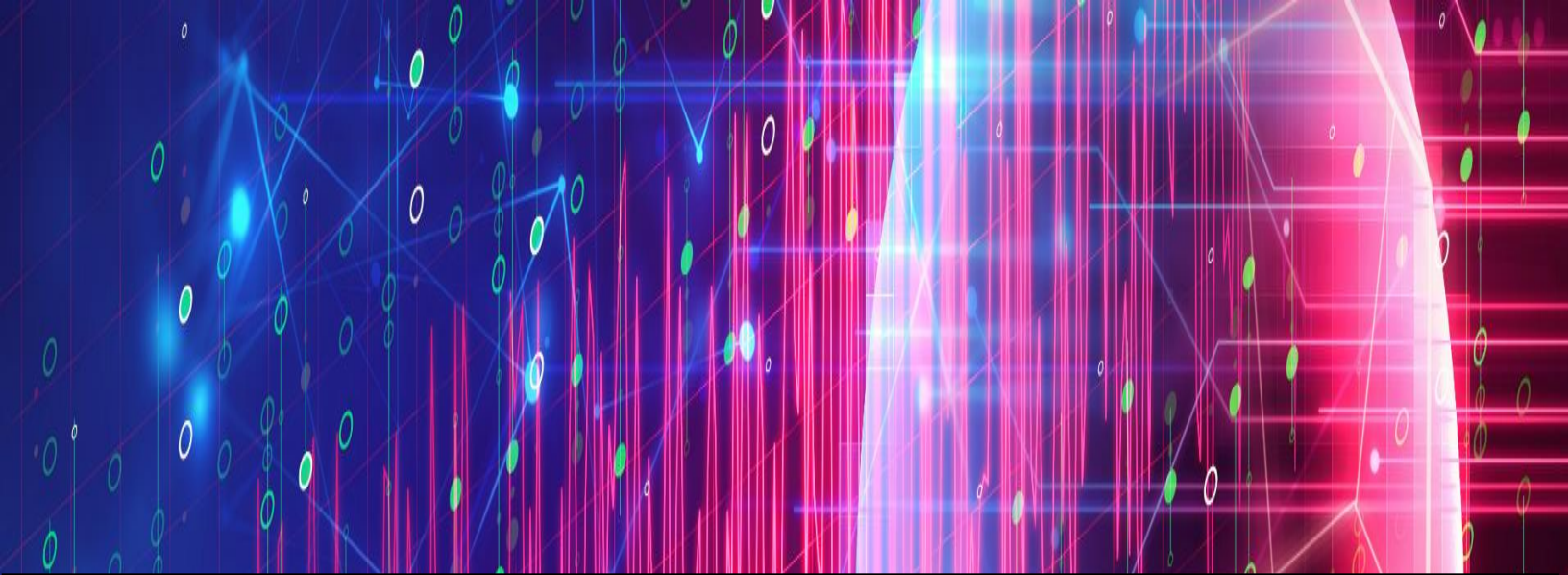
**Fig 6.4** Validation Loss



## **6.4 KEY INFERENCES AND FINDINGS**

The proposed Hybrid Model for Lassitude Detection System in Drivers using Deep Learning and Automatic Braking System with Li-Fi Communication System aims at detecting the lassitude in drivers and make decisions on basis of level of lassitude in drivers. From the results major inferences can be drawn:

- Implementing a detection system has resulted in reduced rate of accidents as well as it keeps the driver awake while driving and also if driver may get sleepy, the vehicle can be stopped automatically and keeping the safety of other drivers in mind, a warning message is also sent to other vehicles.
- Use of CNN with transfer learning and Haar cascade classifier has resulted in low computing power and fast detection with higher accuracy.
- The accuracy of the proposed model is 95.12 while training and 95.48 while testing. INCEPTION-V3 CNN architecture showed the best result in classification of state of eye.



# **CHAPTER 7**

## **APPLICATIONS AND ADVANTAGES**



## **CHAPTER 7**

### **APPLICATIONS AND ADVANTAGES**

#### **7.1 ADVANTAGES**

The proposed Hybrid model for Lassitude detection has several advantages :

- Providing real time lassitude feedback to the driver.
- Effective in preventing accidents caused by the driver getting drowsy.
- Efficacious in impeding vandalization done to nearby vehicles.
- Robustness and cost effective.
- Rendering high level security to the drivers by bringing the vehicle to halt.

#### **7.2APPLICATIONS**

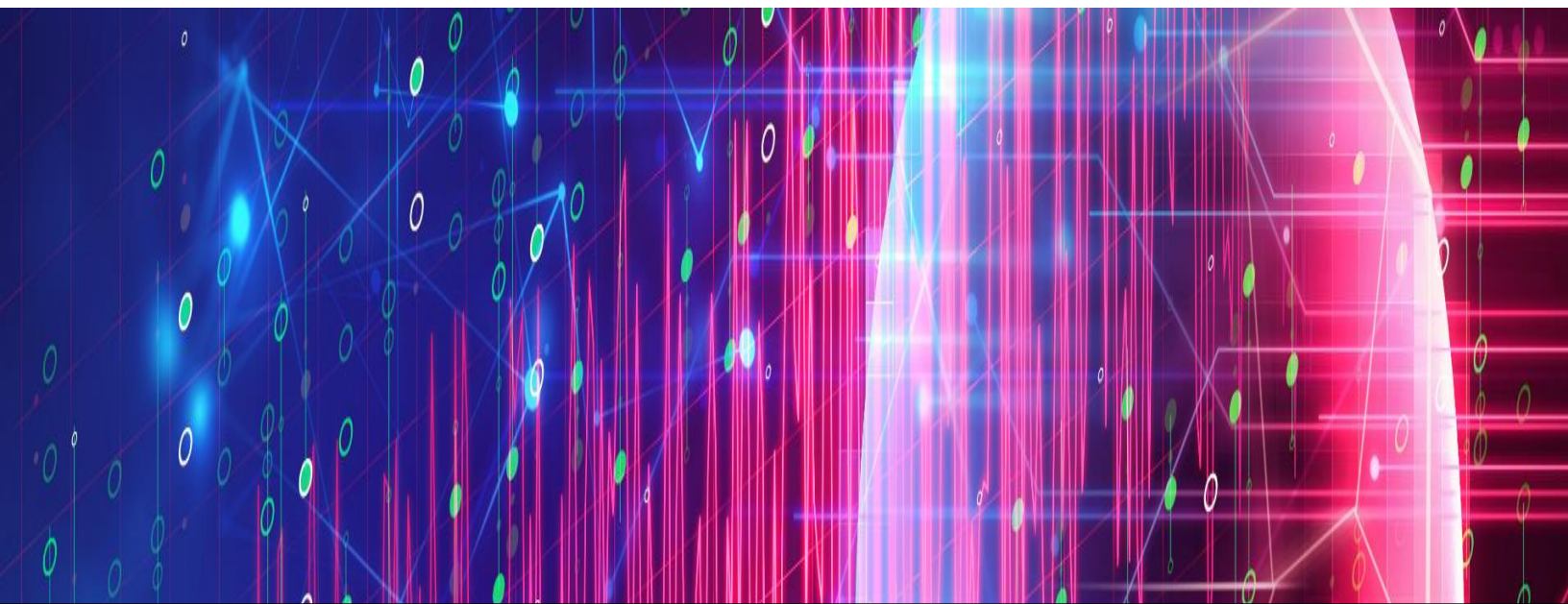
The proposed lassitude detection method overcomes numerous challenges that were faced in previous LDS models and being most efficient for heavy truck drivers and ambulance drivers. With the help of li-fi technology it not helps in lassitude detection but also works as a collision detection system. This system finds its application in :

- Efficient for drivers in heavy fog days . In bone chilling winters, when even walking out becomes a big problem and dense fog makes our visibility go negligible, even in those times one cannot sit back homeand has to step outside and drive their way through, it can be for various urgencies or official work. In that case it becomes very risky to drive as heavy fog blocks our vision and to drive in these situations one needs a system that can detect vehicles ahead and warn them.

Our proposed model not only calculates lassitude but can also work as collision detection system, it can be helpful in days when visibility gets blocked due to fog or smog.

- It finds vast applications in during night time driving. Heavy truck drivers need to export various goods to different states and that becomes quite hectic with less sleep and can often result in sleep disorders making them fall asleep while driving, here our model can work efficiently that even if they fall asleep the vehicle will automatically come to halt and vehicles at back will be alerted . Thus preventing maximum chances of heavy accidents .
- Our proposed system is highly efficacious in curbing drunk and drive cases. We all know every year many people loose their lives in accidents due to drunk and drive, it not only dooms the life of the one driving but also puts the life of others driving nearby in extreme danger.





## CHAPTER 8

## CONCLUSION



## **CHAPTER 8**

### **CONCLUSION**

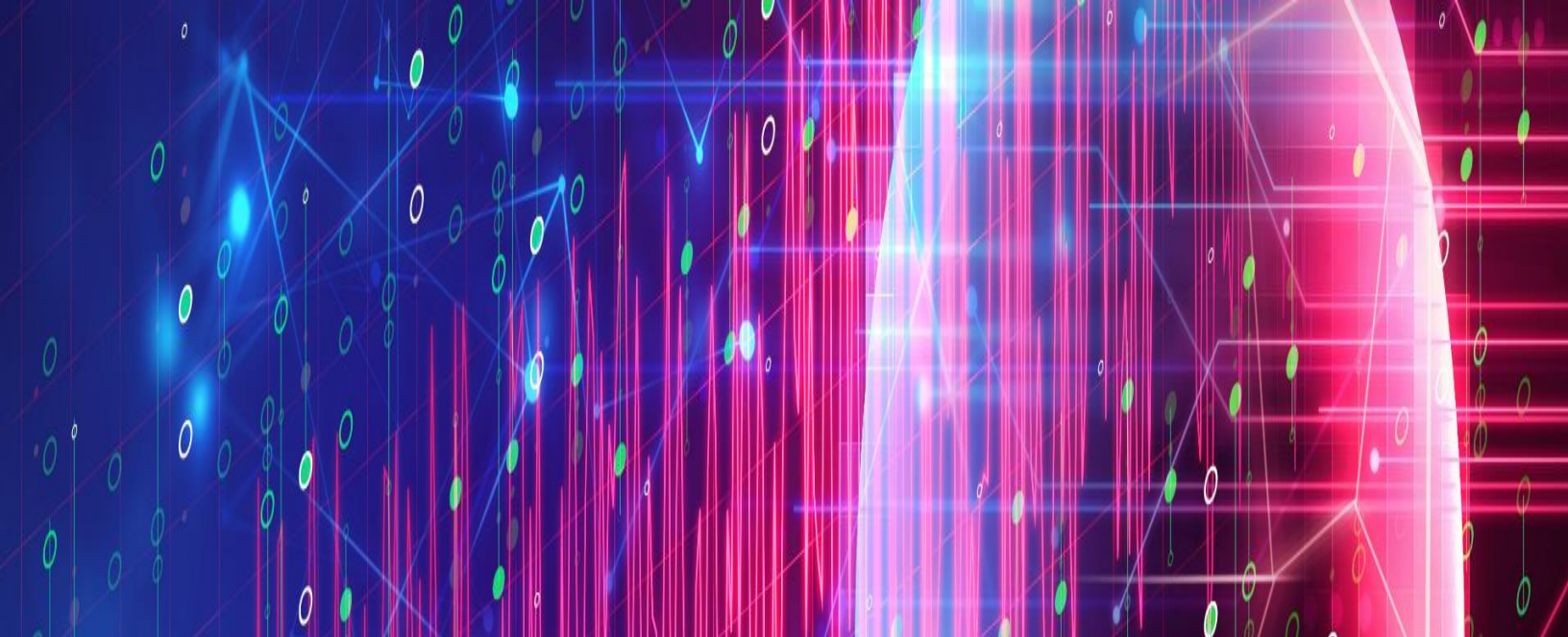
At present, most of the image recognition methods are dependent on artificial feature extraction techniques heavily. These techniques prove to be quite complex as well as take up a lot of time to train and test. Hence, various researches are underway to improve the algorithms, to make the existing algorithms more efficient, and to find better alternatives for the same.

Deep neural networks in machine learning have become a prime solution for extracting important features from images or videos. The Convolutional Neural Network (CNN) approach makes use of the fact that based on a local understanding of the image, the entire model is built up. It uses fewer parameters as the same parameters get reused multiple times in comparison to a fully connected network.

So here we have presented a novel approach to determine the tiredness or lassitude in driver by the help of their eye condition. This determines whether the driver's eye is fatigued, and if it is, an alarm is started. To identify the eye and face region we have used the Viola Jones detection method. And for the training stage we have used stacked deep convolution neural network with transfer learning. And also if the vehicle is running above a threshold speed automatic braking system will also be applied to slow the speed of the vehicle and for safety of other drivers a warning message is sent to them while they are in range through optical communication.

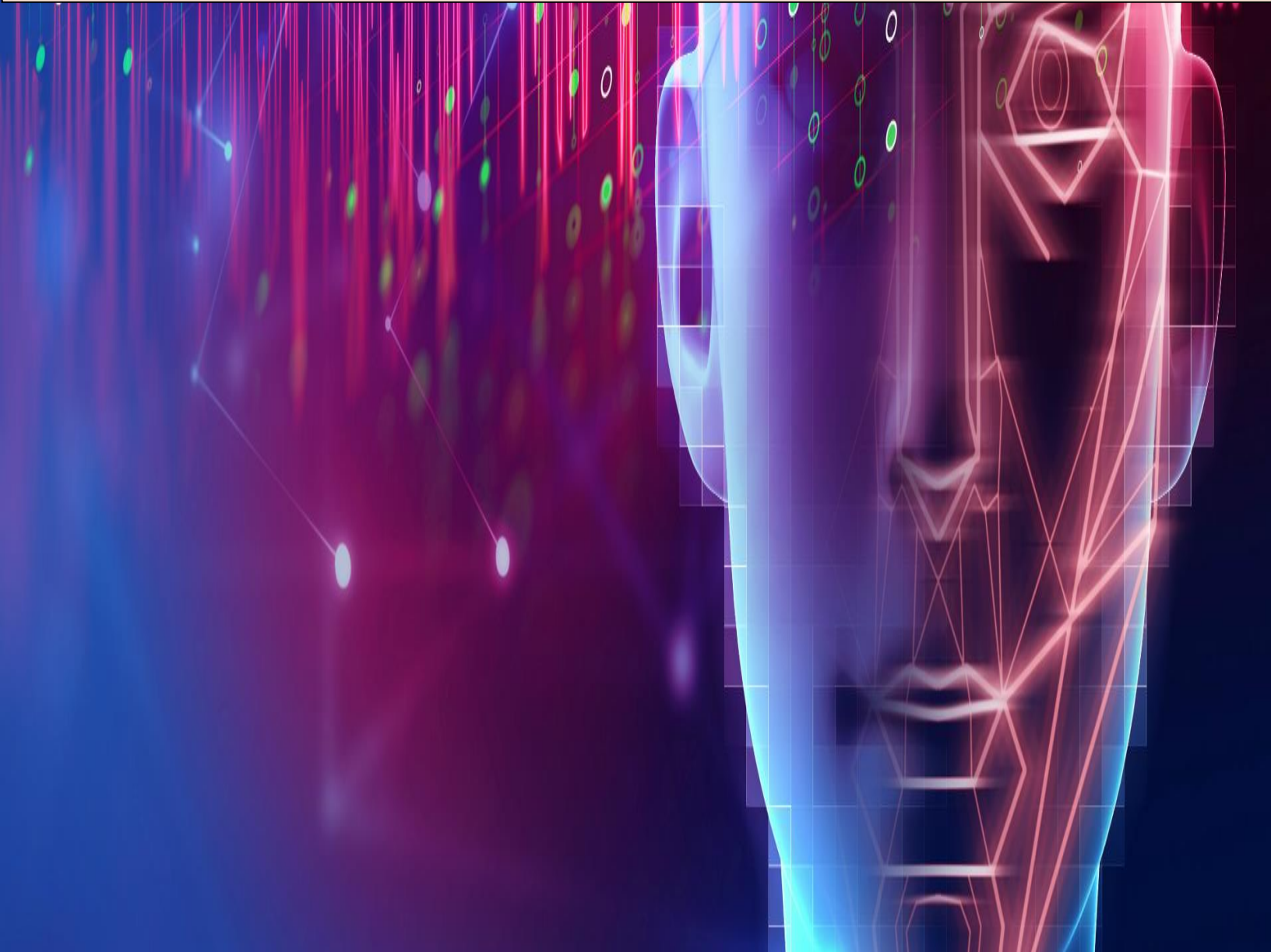
SoftMax layer determines in a CNN classifier that the driver is sleepy or non-sleepy with 95.48 percent accuracy at the current time.





# CHAPTER 9

## FUTURE SCOPE



## **CHAPTER 9**

### **FUTURE SCOPE**

One major improvement that could be done in the future is that of enhancing the lassitude dataset and adding low light image filter (in near infra-red light) to enable the model to detect lassitude in low lighting conditions. This would be beneficial as lassitude related accidents have a high chance of occurrence during night-time driving.

To capture the movement of subject in video, there is a need to involve the distance between the landmarks of face by obtaining the coordinate value of landmarks position. These movements will give a bigger sign of lassitude. And also the distance between the camera and seat should be adjusted for proper detection.

We should not only concentrate on eye feature to pick the Lassitude state, besides this, we should also use facial features (like mouth expression, yawning), body parts such as hands or legs posture to determine the state of Lassitude. Moreover, work needs to be done in incorporating yawning information of driver so that decision can be made more accurately and quickly.



## **APPENDIX - A**

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## **APPENDIX – C**

### **LIST OF ABBREVIATIONS USED**

CNN	:	Convolutional Neural Network
SVM	:	Support Vector Machine
ML	:	Median Filter
RNN	:	Recurrent Neural Network
IOT	:	Internet of Things
ROI	:	Region of Interest
TL	:	Transfer Learning
AI	:	Artificial Intelligence
TNR	:	True Negative Rate
TPR	:	True Positive Rate
FPR	:	False Positive Rate
FNR	:	False Negative Rate
ACC	:	Accuracy
CV	:	Computer Vision

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