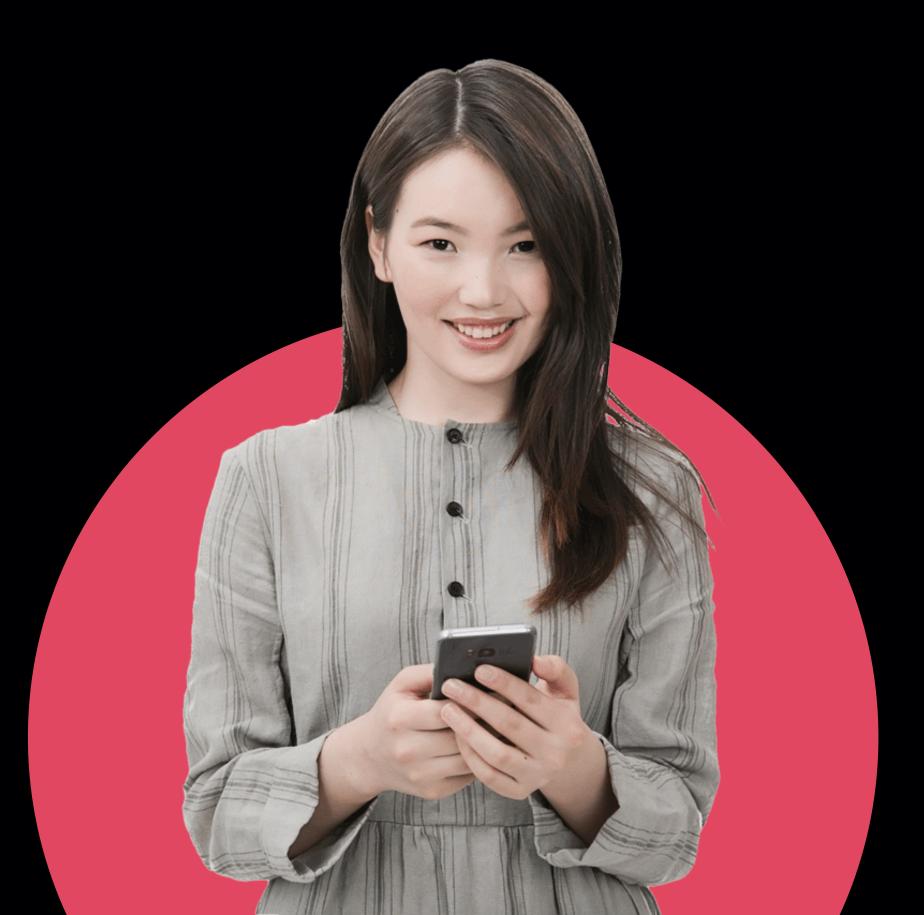


## PROBLEM STATEMENT

Road accidents have increased significantly in recent years as a result of driver distraction from various activities including talking on the phone or drinking while driving. Despite extensive research, the projected solutions are either computationally expensive or have a slow reaction time.





## ABSTRACT

In order to address this issue, we will first train a Deep Learning model that is computationally more affordable and has a faster response time. We will then deploy this model on the web using Django to obtain a realistic experience.











c0: safe driving

c1: texting - right

c2: talking on the phone - right

c3: texting - left

c4: talking on the phone - left

## DATASET USED

- Stateafarm dataset Of kaggle
- It contains 22424 Images
- 15692 are used as training and 2237 as a test images
- image size of 640\*480\*3
- Dataset was of 10 classes
- different classes are Safe driving, texting-right, talking on phone-right, texting left, talking on phone-left,Operating radio, Drinking, Reaching Behind, Hair and makeup, talking to passenger



## DATA AUGMENTATION

#### **Preprocessing**

Each image in the dataset has been downsized to 224\*224\*3 pixels, after which the photos have been subjected to transforms like vertical shift, horizontal shift, random zoom, and shear with 0.2 range.

#### Normalization

To ensure that each input (in this case, each pixel value) comes from a standard distribution, normalisation has been done. In other words, the pixel value range in one input image matches the pixel value range in another image.

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## VGG 16 ARCHITECTURE

#### 01

Andrew Zisserman and Karen Simonyan first proposed the VGG model in 2013 and created a prototype for the 2014 ImageNe

#### 03

Conv-1 Layer has 64 number of filters, Conv-2 has 128 filters, Conv-3 has 256 filters, Conv 4 and Conv 5 has 512 filters.

#### 02

They concentrated on having 3x3 convolution layers with stride 1, and they consistently employed the same padding and maxpool layer with stride 2.

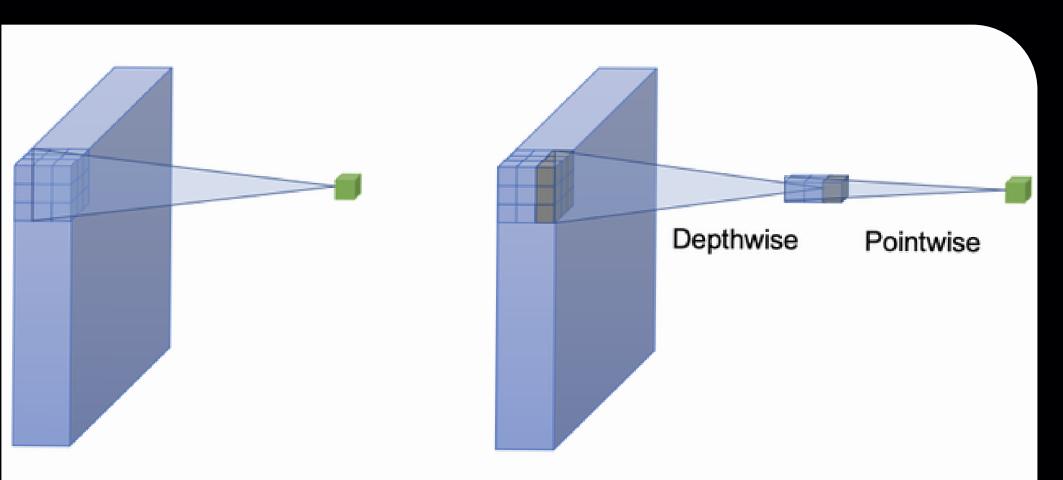
#### 04

VGG16 has a total of 138 million parameters.

	Softmax
fc8	FC 1000
fc7	FC 4096
fc6	FC 4096
	Pool
conv5-3	$3 \times 3$ conv, $512$
conv5-2	$3 \times 3$ conv, $512$
conv5-1	$3 \times 3$ conv, $512$
	Pool
conv4-3	$3 \times 3$ conv, $512$
conv4-2	$3 \times 3$ conv, $512$
conv4-1	$3 \times 3$ conv, $512$
	Pool
conv3-2	$3 \times 3$ conv, 256
conv3-1	$3 \times 3$ conv, 256
	Pool
conv2-2	$3 \times 3$ conv, 128
conv2-1	$3 \times 3$ conv, 128
	Pool
conv1-2	3 × 3 conv, 64
conv1-1	3 × 3 conv, 64
	Input

VGG16

## SEPARABLE CONV



e 3: Standard convolution and depthwise sepa

A SEPARABLE CONVOLUTION IS A PROCESS IN WHICH A SINGLE CONVOLUTION CAN BE DIVIDED INTO TWO OR MORE CONVOLUTIONS TO PRODUCE THE SAME OUTPUT. A SINGLE PROCESS IS DIVIDED INTO TWO OR MORE SUBPROCESSES TO ACHIEVE THE SAME EFFECT.

MAINLY THERE ARE TWO TYPES OF SEPARABLE CONVOLUTIONS

- SPATIALLY SEPARABLE CONVOLUTIONS.
- DEPTH-WISE SEPARABLE CONVOLUTIONS.

01

#### **Optimizer**

With beta 1 = 0.9 and beta 2 = 0.999, we employed the Adam as an optimizer.

03

#### **Learning Rate**

We tested different learning rates in order to prevent overfitting, and when the learning rate was equal to 0.0001, the model performed well.

05

#### **Activation Function**

When applying the dense layer, we used leakyRelu as the activation function between the hidden layers and softmax.

02

#### **Loss function**

Here, we utilise a categorical cross entropy loss function to assess how well the model is performing.

04

#### **Epochs**

The best version of the model was at 55 epochs after we trained the model for 55 no epochs over 55 epochs because we discovered the model was overfitting.

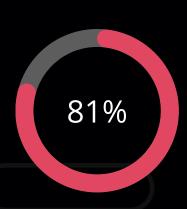
06

#### **Evaluation metrics**

Accuracy is one of the measures we used to gauge how well our model performed.

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# DEPLOYING THE MODEL



#### Streamlit APi

To obtain a true sense of the model, we deployed it using the Streamlit api.

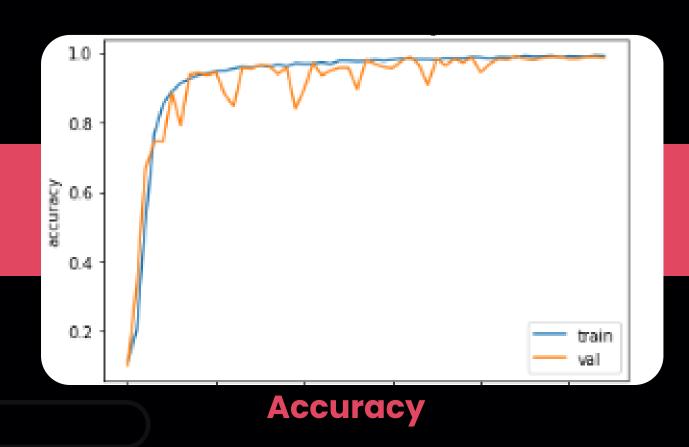
**LEARN MORE** 



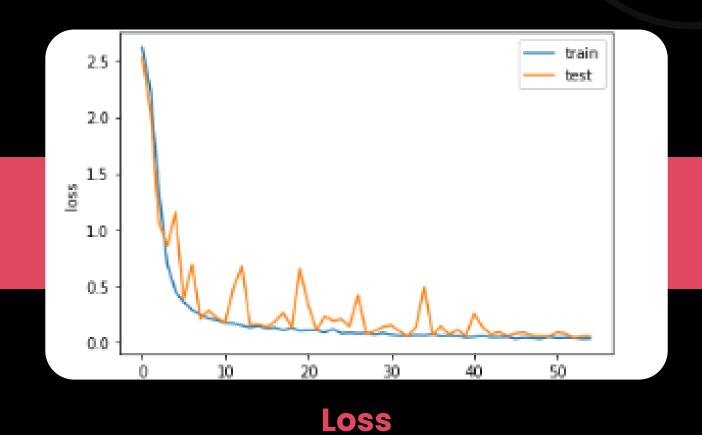
Programmers are very important.



## RESULTS



After 55 epochs, we obtained the training accuracy to be equal to 99.15 and the test accuracy to be equal to 98.66.

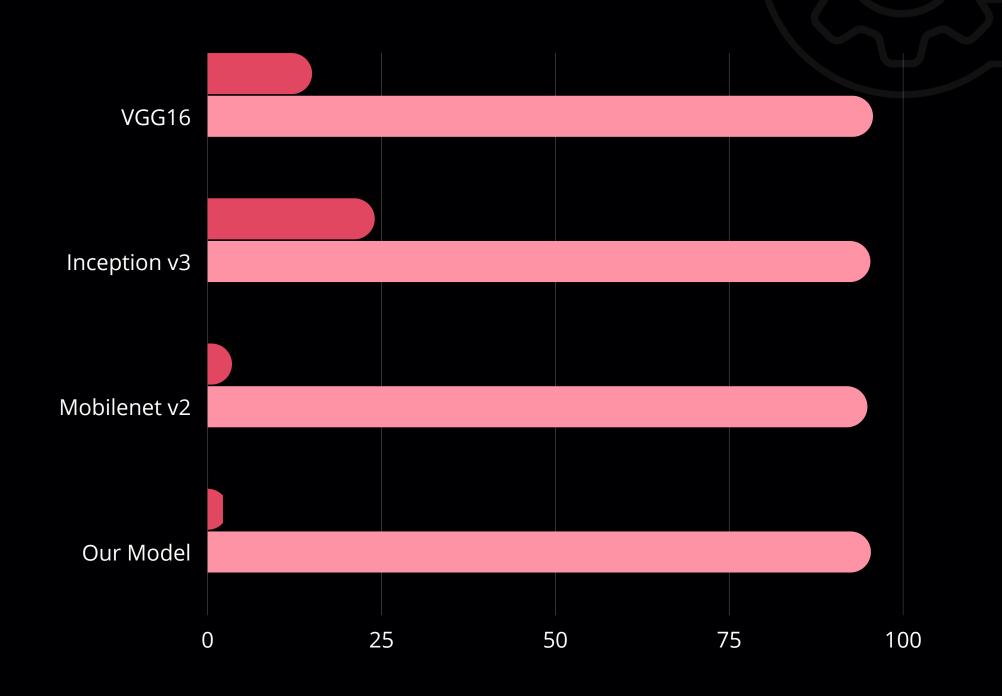


After 55 epochs, we obtained the training loss to be equal to 0.0282 and the test loss to be equal to 0.0356.



#### **Description**

Here, following the experiment, the test accuracy was 98.66 and the training accuracy was 99.15, which is slightly better than other algorithms and requires fewer parameters.

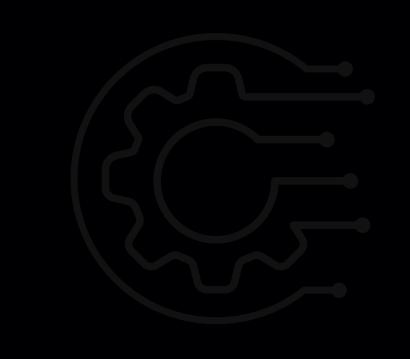




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