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# ALERTING DISTRACTED DRIVERS USING CNN

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***Abstract-- Driver distraction could be a leading thing about n-crashes,to cut back vehicle accidents and improve transportation safety, a system which will classify distracted driving is extremely desirable and has attracted much research interest in recent years. With a goal to scale back traffic accidents and improve transportation safety, this project proposes a driver distraction detection and alerting system which identifies various varieties of distractions through a camera by observing the motive force and alerts the motive force by a buzzer. In deep learning, a Convolutional neural network could be a class of deep neural networks, most typically applied to analysing visual imagery and our goal is to create a high-accuracy model to differentiate whether a driver is driving safely or conducting a specific reasonably distraction activity. A multi-layer CNN network is made within the model and therefore the key parameters of the input layer, convolution layer, pooling layer, fully connected layer, and output layer are optimized in addition. The results of the experimental analysis show that the accuracy of the proposed method can reach 97.31%, which is above that of the present machine learning algorithms. As a result, the suggested strategy improves the accuracy of distracted driving recognition.***

***The input of our model is images of the driver taken in the car and the model is trained with the dataset created by ourselves. If the driver distracts from driving it will be classified as distracted and develops an alert that reminds the driver to focus on the driving task when he/she gets distracted. In general, most of the existing systems are not fit for real applications as they are wearable, induce discomfort and take a long time to make a decision.***

***Keywords: Convolutional neural networks, data augmentation techniques, deep learning methods, distracted driver ,alerting system .***

## 1. Introduction

Road traffic accidents are the leading reason for death by injury and therefore the tenth leading reason for all deaths globally. per annum, the lives of roughly a pair of 0.5 million folks are restrained as a result of a road traffic crash. Road traffic injuries cause extended economic losses to people and their families. Road traffic crashes price most countries three-dimensional their gross domestic product. Over a simple fraction of all road traffic deaths globally occur among folks ages fifteen to forty-four their best earning years. Moreover, the incapacity burden for these people accounts for sixty p.c of all. In keeping with the planet Bank, the road crash mortality rate is thrice higher in low-income countries compared to high-income countries, and statistics.

There are several types of distractions. The majority of research on this topic is divided into three categories: manual, visual, and cognitive. Visual distractions depict a situation in which the driver's eyes are taken off the road due to the presence of some visual representation away from the road. The tracking of eyes and facial landmarks is required for this research. The driver is "mentally" distracted if he or she is daydreaming or lost in thought. Manual distractions consider the driver's posture and, in most cases, hand tracking.[1]

Distracted driving will increase the possibility of a motorcar crash. Distracted driving is any activity that diverts attention from driving together with talking or texting on your phone, uptake and drinking, applying makeup, and not betting on the road. There square measure three main forms of distraction that square measure visual, manual, and psychological feature .visual driving distraction cause you to require your eyes off the road eg: check your GPS, or song taking part in on the radio. Manual distractions taking your hands off the wheel embody uptake, drinking, and checking your phone. psychological feature causes you to require your mind off driving.

Distracted Driving is that the act of driving whereas partaking in different activities that distract the driver's attention removed from the road. Distractions area unit shown to compromise the protection of drivers, passengers, pedestrians, (and people and different people and folks) from other vehicles. Cellular device use whereas behind the wheel is one amongst the foremost common varieties of distracted driving. in step with National Safety Council reports exploitation mobile phones whereas driving ends up in one.7 million folks die in road crashes every year. associate calculable four hundred,000 folks were harmed and a pair of,841 were killed. NHTSA estimate that 660,000 drivers use some style of device whereas driving. Texting and driving cause twenty fifth of all automobile crashes that's one out of each four automobile accidents. So, so as to cut back such accidents and improve safe driving, we tend to launched a project to spot erratic driving. we tend to introduce a system during this project that determines whether or not the motive force is driving safely or partaking in any distraction activities. It accomplishes this by utilizing the driver's pictures. A camera mounted within the automobile captures the image of the motive force, which is then pre-processed to spot the driver's action. once it detects that the motive force is distracted, it'll sound an associate alarm to alert the motive force.

## 2. Related Work

In the field of machine learning and computer vision, real-time image-based driver distraction detection is a hot topic, with many models and algorithms proposed and analysed by researchers. This section examines the existing technologies for detecting distracted driving behaviors, which are classified by sensor modality and detection method.

### 2.1 Detection of distractions using a sensing modality

Sensing modalities are sensors that measure the same type of energy and process it in similar ways, whereas modality refers to the raw input used by the sensors. To detect driver distraction, three types of sensor modalities are currently used.

a.Physiological data includes electroencephalograms (EEGs) and electrocardiograms (ECGs) (ECG). Brain activity reflected in EEG signals, for example, and heart rate inferred from ECG signals, for example, are used as feature vectors to detect driver weariness, a sort of distraction. Physiological data, in general, ensures reliable and timely findings.[6] They are, nevertheless, unsuitable for real-world applications. Drivers are required to wear these physiological sensors around their body, which may cause pain and interfere with their driving movements.[7]

b.Vehicle control data, such as steering wheel movements and pedal positions, are examples. Jin et al., for example, developed a system that detects cognitive distraction using solely vehicle control data. They claimed that distracted drivers manipulate the steering wheel and apply the pedals in a different manner than regular drivers. [8]They also stated that while distracted, drivers prefer to extend the gap to the leading vehicle or drive faster than usual when there is no leading vehicle. In 2008, Ranney warned that

distraction would cause a loss of control, causing the vehicle to slip off the road. Distraction detection based on such vehicle control data is usually correct, but making a decision can take a long time.

c.Visual information includes photos or videos of the driver's facial expressions, eye movements, and body motions. Visual information ar the foremost unremarkably used modality for distinguishing driver distraction. they supply valuable data for decisive a driver's level of distraction. as an example, Tabrizi et al. used PERCLOS (Percentage of Eye Closure) to observe the driver's temporary state.[10] The frequency and length of a driver's eye glances for a secondary task ar combined to produce a complete mensuration of eyes off the road. FaceLab, a pc vision system that allows a period of time mensuration of eye gaze utilizing the top and eye-tracking algorithms, is employed to spot distracted driving in varied comes. Park and Trivedi extensively utilized facial traits to observe inattentive eye gaze in drivers. mistreatment of the worldwide motion technique and color applied mathematics analysis, relevant countenance was retrieved. [11]Pohl and colleagues developed a distracted driving detection system that supported gaze direction and head position. The distraction level was classified once decisive as the fast distraction. Kircher et al. developed 2 different detection techniques whereas mistreatment gaze direction as a mensuration for distraction classification. For distraction detection, Murphy-Chutorian et al. used the driver's head position. To observe the driver's eyes, infrared (IR) cameras were used, which were then wont to monitor the driver's vigilance. For distinguishing distractions, driver expressions like yawning were conjointly thought-about. Craye and Karray's investigation concerned observance of the driver's right-hand movement to observe distracted driving behaviors.

### 2.2 Detection method

There are several methods for detecting driver distraction, including:

a.Thresholding: Thresholding is the most basic method for detecting distractions, in which a feature value is compared to a specified threshold. for example, Tabrizi et al. used a constant threshold to identify drowsiness in the PERCLOS value.

b.Traditional machine learning: To detect driver distraction, a variety of traditional machine learning algorithms have been used. Jin et al. used a Support Vector Machine (SVM) to detect cognitive distraction using vehicle control data as feature vectors. SVM classification of distraction used eye movements as a feature. Based on vision and lane tracking data, SVM was also utilized to detect distraction.[12] Cray et al. suggested a system for detecting distracted driving actions based on a Hidden Markov Model (HMM). The driver's face and right arm must be detected for their method to work. Gu and Ji employed Bayesian networks to model the uncertainty and calculate the probability of driver weariness or distraction, taking into account the inherited uncertainty associated with the face traits. Eskandarian et al. used Neural Networks to identify driver tiredness by combining steering wheel movements and face data.

## 3. Problem Definition

Many states now have laws prohibiting texting, cell phone use, and other forms of distraction while driving. We believe that computer vision can help governments improve their efforts to prevent distracted driving-related accidents. Our algorithm detects and alerts drivers who are engaging in distracted driving behavior. This type of product could be installed in automobiles to prevent accidents caused by distracted driving.

Three main reasons for the distracted driver are :

1. Manual Distractions: Manual distractions are those that require a driver to take his or her hand off the steering wheel.
2. Visual Distractions: Visual distractions are those that cause the driver to take his or her eyes off the road.
3. Cognitive Distractions

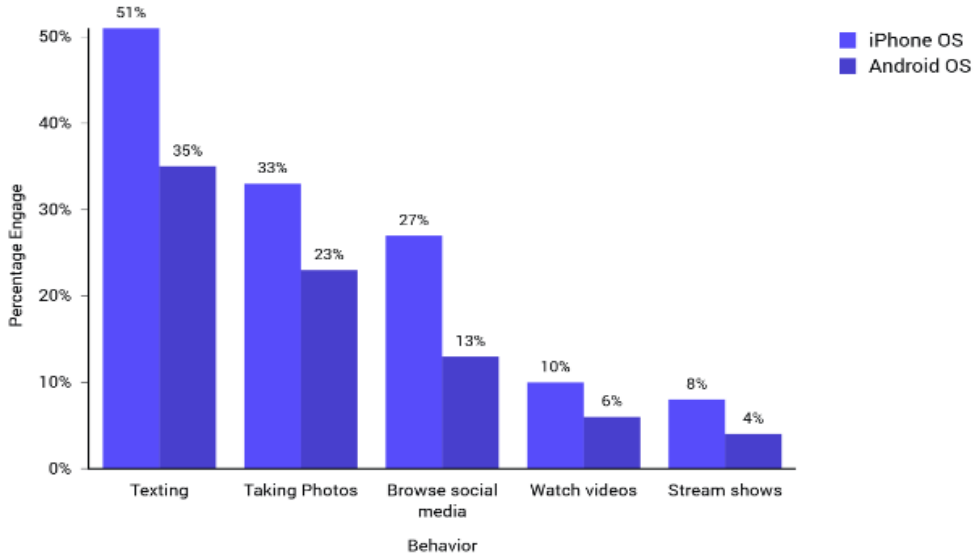



fig 1.distracted driving behavior by the operating system

The fig shows the percentage of drivers distracted by the operating system. There are many other distractions than the operating system .52.5% of respondents reported eating while driving, a 4.2 percent decrease from the previous year. Other behaviors include:

texting (23.6 percent )

Taking photographs (11.7 percent )

Makeup application (6.5 percent ).

A whopping 3.4% admitted to drinking and driving! While 36.4% of participants agree that using a mobile device impairs your ability to drive, 36% admit to using a cellphone while driving.[12]

Here, given a set of 2D dashboard camera photos, an algorithm must be constructed to identify each driver's activity and determine whether they are driving carefully, talking on their phone, or taking a selfie with their pals in the back seat, among other things.

This can then be used to automatically detect distracted drivers using dashboard cameras. The following tasks must be completed in order for the algorithm to be developed.

- Pre-process the driver photos by downloading them.
- Create and train a model to classify driver photos.
- Using different techniques, test the model and improve it further.

The system automatically detects the distracted driver and alerts the driver using a buzzer sound and a vibrator to come to his or her normal state.

**4. Metrics**

Submissions are evaluated using the multi-class logarithmic loss. Each image has been assigned to a single true class. A set of expected probabilities must be submitted for each image (one for every image).The Formula is then,

$$logloss = -\frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{M} y_{ij}\log(p_{ij}),$$

where N denotes the number of images in the test set, M denotes the number of image class labels, log denotes the natural logarithm, is 1 if observation I belongs to class j and 0 otherwise, and is the predicted probability that observation I belongs to class j.[12] Because the provided probabilities for a given image are rescaled before being scored, they are not needed to amount to one (each row is divided by the row sum).To avoid the log function's extremes, predicted probabilities are replaced withThe metric multi-class logarithmic loss chosen over accuracy because it provides the probability of the predictions rather than just saying yes or no.

## 5 Analysis

### 5.1 Data Exploration

Each driver photograph in the given dataset was captured in a car while the driver was doing anything in the car (texting, eating, talking on the phone, makeup, reaching behind, etc). This data was sourced from Kaggle (State Farm Distracted Driver Detection competition). The following are the files descriptions that are listed below :

- imgs.zip-zipped folder of all (train/test)images
- sample_submission.csv-a sample submission file in the correct format
- driver_imgs_list.csv-a list of training images ,their subject(driver)id ,and
- classid
- driver_imgs_list.csv.zip
- sample_submission

The10 classes to predict are:

c0:safedriving
c1:texting-right
c2:talkingonthephone-right
c3:texting-left
c4:talkingonthephone-left
c5:operatingtheradio
c6:drinking
c7:reachingbehind
c8:hairandmakeup
c9:talkingtopassenger


fig 2. dataset

5.2 Dataset and Image Pre-processing

There are 102150 photos altogether. There are 17939 training photos, 4485 validation images, and 79726 training images all told. All of the training and validation photos fall under one in every of the ten categories listed above. Each image incorporates a resolution of 640x480 pixels and is coloured.[13] Each image must be pre-processed before being sent to the classifier, as demonstrated in Figure 2 by the float chart of image pre-processing. Each image is first became a high-dimensional 640 480 3 matrices supported the RGB values of every pixel, then scaled to a 64 64 3 matrix using CV2 to extend the classifier's computing performance, then flattened into a vector. A numerical label within the range of 0-9 is assigned to every flattened vector supported the category to which it belongs. We shuffle the complete training data set and divide it into the training set and therefore the validation set by 80% / 20%, then pile each training sample along the column axis. [14]As a result, the ultimate training set matrix Xtrain has the dimension (17939, 12288), the ultimate training label vector Xtrain has the dimension (17939,); the ultimate validation set matrix Xval has the dimension (4485, 12288), and therefore the final training label vector Yuval has the dimension (4485, 12288). (4485,).

5.3 Exploratory Visualization

The training dataset's count of photos for each class is calculated, and the graph is presented as shown below. It is clear from the graph that the distribution is uniform. In addition, the training dataset shows that there is little class imbalance.

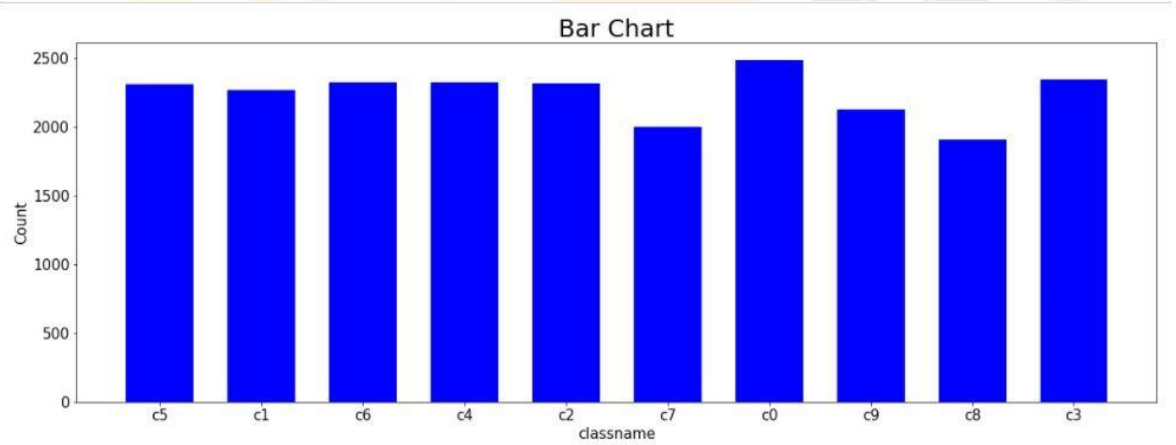



fig 3.Image Count for each class - Training dataset

5.4 Benchmark

As a benchmark, we choose the model with a Public Leaderboard score of 0.08690 (multi-class logarithmic loss). [15]The initial CNN architecture was constructed and trained using a typical CNN design. In between the four convolutional layers, there are four maximum pooling layers. Each of the convolutional layers has its filters upgraded from 64 to 512. Before utilizing the completely linked layer, dropout and a flattening layer were also employed.

The CNN is made up of two layers that are totally interconnected. The softmax activation function was used to set the number of nodes in the last completely connected layer to ten. All other layers were activated with the Relu function. In each of the layers, Xavier initialization was utilized. When forecasted using the test dataset and submitted to Kaggle, this yielded a Public Leaderboard score(multi-class logarithmic loss) of 2.67118.

5.5Alerting system

After collecting the data set,we have trained the images using cnn and other suitable algorithms . Using the buzzer and vibrator modules we are able to alert the driver from distraction and avoid accidents. the hardware components required for this alert system are :

1. Arduino nano
2. Buzzer
3. Vibrartor module

Arduino nano: it is the most compact of Arduino's breadboard-friendly boards. The Arduino Nano features a Mini-B USB connector and pin headers that make it easy to connect it to a breadboard.

fig 4. Arduino nano

Buzzer : There are numerous ways for a user and a product to communicate. Audio communication with a buzzer IC is one of the best methods. Understanding some technologies with configurations is thus very useful during the design process.

fig 5.Buzzer module

## 6 METHODOLOGY

6.1 Data Preprocessing

Before the model is formed and the training process begins, the data is preprocessed. The steps carried out during preprocessing are

- Initially the images are divided into training and validation sets.
- The images are resized to square images i.e.224x224 pixels.
- All three channels we reused during training process as these are color images.
- The images are normalized by dividing every pixel in every image by 255.
- To ensure the mean is zero avalue of 0.5 is subtracted.

## 7 Implementation

Initially, a conventional CNN architecture was constructed and trained. Between the four convolutional layers, there are four max-pooling layers. Each of the convolutional layers' filters was increased from 64 to 512.[15] Dropout was also utilized before the completely connected layer, along with a flattening layer. The CNN comprises two completely connected layers in total. The softmax activation function was used to set the number of nodes in the last completely connected layer to ten. All other layers were activated with the Relu function. In each of the layers, Xavier initialization was utilized.[16]

i.CNN Architecture:

A convolutional neural network (CNN, or ConvNet) may be a kind of deep, feed-forward artificial neural network that has been effectively wont to analyze visual representational process in machine learning. Convolutional networks were intended by biological processes, like the arrangement of the animal cortical region, that impressed the property pattern between neurons. Individual animal tissue neurons answer inputs solely within the receptive field, that may be a little portion of the sight view. [18]completely different neurons' receptive fields partly overlap, permitting them to hide the total sight view. as compared to alternative image classification ways, CNNs need little pre-processing. this suggests that the network learns the filters that were antecedently hand-engineered in ancient techniques. This feature of style independence from previous data and human effort may be a important profit. they are employed in image and video recognition, recommender systems, and tongue process, among alternative things. associate input and output layer, furthermore as many hidden layers, conjure a CNN. Convolutional, pooling, or totally connected layers area unit the hidden layers.

ii.Convolutional layer(CNV): A CNN's main building block is the convolutional layer. The parameters of the layer are made up of a series of learnable filters (or kernels) with a narrow receptive field but that span the entire depth of the input volume. Each filter is convolved across the width and height of the input volume during the forward pass, computing the dot product between the filter's entries and the input and providing a 2-dimensional activation map for that filter. [19]As a consequence, the network learns filters that activate when it detects a particular sort of feature at a particular spatial location in the input.

iii. Pooling layer(PL): Pooling, a type of non-linear down-sampling, is another key idea in CNNs. Pooling can be implemented using a variety of non-linear functions, the most popular of which is 7 max pooling. It divides the input image into a collection of non-overlapping rectangles and reports the maximum for each of these sub-regions. [20]The assumption is that a feature's precise placement is less relevant than its approximate location in relation to other features.

The pooling layer helps to control overfitting by gradually shrinking the spatial size of the representation, reducing the number of parameters and quantity of computation in the network. A pooling layer is frequently inserted between successive convolutional layers in a CNN architecture. Another type of translation invariance is provided by the pooling procedure[21].

iv. Fully connected layer(FC): After numerous convolutional and max-pooling layers, fully connected layers are used to do high-level reasoning in the neural network. As with normal neural networks, neurons in a completely linked layer have connections to all activations in the previous layer. As a result, their activations can be calculated using matrix multiplication and a bias offset.

v. Classification Layer(CL): The classification layer, which is generally the final layer, describes how training penalizes the difference between predicted and true labels. There are a variety of loss functions that can be employed depending on the task. For forecasting a single class of K mutually incompatible classes, the Softmax loss is utilized. For forecasting K independent probability values, sigmoid cross-entropy loss is utilized.[22]

The following are the steps involved in training a CNN:

1. The entire dataset is pre-processed, including the train, validation, and test datasets (see "Data Preprocessing" section).

2. To classify photos, a simple CNN is developed. The CNN is made up of four convolutional layers and four maximum pooling layers.

3. Each convolutional layer's filters were enlarged from 64 to 512, and drop out was introduced.

4. At the end of the CNN, a flattening layer and two completely linked layers were added.

5. The number of nodes in the final fully connected layer was set to 10, which corresponds to the number of categories in the dataset, and the softmax activation function was used. This layer is used to categorize the data.

6. All other layers, as well as Xavier initialization, employed the "Relu" activation function.

7. The model is built using the optimizer 'prop' and the loss function 'categorical cross-entropy.'

8. With a batch size of 40, the model is trained for 30 epochs. When the loss for the validation dataset improved during the training process, the model parameters were preserved.

9. Finally, predictions for the test dataset were created and provided in the appropriate format.

10.Transfer Learning: Instead of training a CNN from the ground up, a pre-trained model is employed as initialization or fixed feature extractor in this method.Two types of transfer learning strategies are described below. [23]

i.ConvNet as fixed feature extractor: A pre-trained network is initialized in this method, and the last fully-connected layer is removed. This is handled as a fixed feature extractor after it has been removed. After these fixed features have been extracted, the previous year is trained using these fixed features.

ii. Fine-tuning the ConvNet: In this strategy, the weights of the pre-trained network ar fine-tuned additionally to exchange and grooming simply the classifier. You will fine-tune all of the ConvNet's layers, otherwise you will keep components of the first levels mounted (because of overfitting problems) and solely fine-tune a higher-level element of the network. [24]This is often intended by the observation that the primary layers of a ConvNet contain additional generic options (e.g., edge detectors or color blob detectors) that ought to be helpful for a large vary of tasks, however the later layers of the ConvNet become progressively specific to the small print of the categories contained within the original dataset[25].

- Python and its libraries keras and TensorFlow were used as the backend programming language.
- GPU for CNN training is a recommended software requirements then all of the photos were loaded and pre-processed, there was a lot of memory use during the training phase.
- Solution: To account for large RAM, this procedure was repeated numerous times by changing the capacity of the compute instances.
- Problems encountered: Obtaining bottleneck characteristics took time throughout the transfer learning process.
- Solution: To reduce the learning time, use a powerful GPU from the cloud.
- Problem encountered: During fine tuning, the training process took a long period (6 hours). It's possible that this is due to the use of an extremely sluggish learning rate.
- Solution: On the cost of prediction accuracy, a higher learning rate can be used.

**8. Refinement**

To obtain the initial result, a basic CNN architecture was constructed and tested. As a result, the team suffered a reasonable defeat. The first basic CNN architecture (unoptimized model) received a public score of 2.67118.[26][27] Following that, transfer learning was used to VGG 16 in order to improve the loss even more, as well as investigating two types of designs for completely linked layers. Model Architecture 1 performed well and was enhanced further by employing the strategies listed below.

• To accommodate for overfitting, a drop-out layer was introduced.

• Xavie initialization was used instead of random weight initialization.

• During pre-processing, 0.5 was subtracted to assure a zero mean.

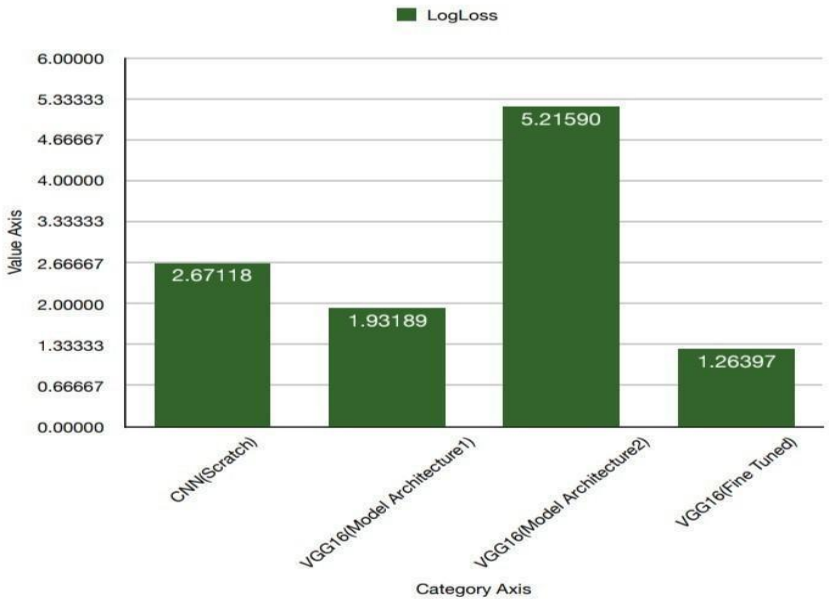
• Training was done using 400 epochs and a batch size of 16.

• To enhance the loss metric even more, VGG 16 and Model Architecture 1 were chosen, and fine tweaking was performed. The SGD optimizer was employed with an extremely slow learning rate of 1e-4. With SGD, a momentum of 0.9 was applied.[30][31]

## 9 Result

9.1 Model Evaluation and Validation

A validation set was utilized to evaluate the model during model design and development. The following table compares the Public Scores for all of the model architectures explored for this data set.




The VGG16 fine-tuned model was selected as the final architecture. This architecture and hyper-parameters were chosen since they outperformed all other model combinations.

The following are the final model parameters and training procedure details:

1. VGG16 is created, and the first 15 layers are frozen.
2. The last Conv layer, Conv block 5, has been fine-tuned.
3. Our own layer is introduced and fine-tuned (Global Average Pooling + Fully Connected layer).
4. Fine tuning is done with a very slow learning rate and an SGD optimizer.
5. Training is carried out across ten epochs with a batch size of sixteen. Finally, the model is validated using the test data set. As a consequence, the Public Score was 1.26397. This can result in a rank of 617 out of 1440 on the Public Leaderboard, putting you in the top 42.84 percent. The loss on the validation dataset was found to be 0.00751. When compared to the public score on the test dataset, this indicates that there is overfitting. Inorder to resolve overfitting we need to consider adding/increasing the drop out and L2 regularization.

9.2 Model enhancement in comparison to the benchmark model

As a benchmark model, the model with the Public Leaderboard score (multi-class logarithmic loss) of 0.08690 is employed.

1. Using the bottleneck characteristics of a pre-trained network" for VGG16 with model architecture1 was trained and tested, resulting in a rank of 1120 out of 1440 on the Public Leaderboard, or in the top 77.77 percent.

2. "Fine-tuning the top layers of a pre-trained network" was applied to VGG16, which had model architecture1 as its top layer. This resulted in additional improvement of the loss metric, which when evaluated yielded a rank of 617 out of 1440 in the Public Leaderboard, putting it in the top 42.84 percent. When forecasted using the test dataset and submitted to kaggle, this yielded in a Public Leaderboard score (multi-class logarithmic loss) of 2.67118.

## 10.Conclusion

The first two photographs were mislabeled as "c3: texting - left" when they should have been "c9: talking to passenger" when they should have been "c9: talking on the phone – right."

The third image was an example of an image that had been appropriately classified. It is classed correctly as "c1: texting - right."

Misclassifications can be caused by a variety of circumstances:

• A less clear image.

• An image with too many objects (clutter).

Due to the classification of the images that have mentionted above,the alert system were silent and the distracted driver was not alerted . since the third image was classified properly , the system was to able to alert the driver .

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