# Exploring Computational Efficiency in Object Detection with Convolutional Neural Networks and Tensorflow

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# 1 INTRODUCTION

It seems like we are always sitting in front of screens these days. Computer screens, movie screens, phone screens, etc. are just some of the daily few we interact with. But what if we could do more than just watch? What if we maximized the business and personal interactivity potential with our screens? How many times have you been watching a tv show or movie and loved a character's outfit, car or some kind of gadget? Don't you wish you could just touch it on the screen and your web browser opens up amazon with that exact item for purchase. For the business oriented people, wouldn't you like to maximize the potential of your ads reaching your target customer? Imagine marketing that can "see" what your customer's are watching and only show them ads or products relative to their viewing likes. A person who is always watching football, baseball, and sports related movies might be more interested in a commerical advertising the current sale going on at Dick's than they would at Sephora. Targeted demographic marketing and other capabilities could be improved exponentially if our screens could see the things we are seeing and know what they are. This would need to grow from the foundation of accurate object detection in Video.

This was the original basis for this project. However when initially getting started, an ugly problem reared its head. Training object detectors is an extremely computationally expensive endeavor. Training even just a 3 layer CNN on 3,000 pictures took over 10 hours on a more than capable machine. With the need to try several different combinations of architectures, hyperparameters, and number of iterations, this wouldn’t be a reasonably feasible project. From necessity spawns innovation. And with this, comes this investigation into training optimization of Convolutional Nueral Networks.

# 2 ANATOMY OF AN IMAGE

When we render images or stream video on a screen, we see something like this:


*Illustration 1: Image of an Owl used in CNN Training*

When we look at this, we clearly see the outline, texture, features, and shapes of an owl. When a computer looks at this image, it sees an array of numbers representing pixel intensities.

```
[[  9   1  29  70 114  76   0   8   4   5   5   0 111 162   9   8  62  62]
 [  3   0  33  61 102 106  34   0   0   0   0  49 182 150   1  12  65  62]
 [  1   0  40  54 123  90  72  77  52  51  49 121 205  98   0  15  67  59]
 [  3   1  41  57  74  54  96 181 220 170  90 149 208  56   0  16  69  59]
 [  6   1  32  36  47  81  85  90 176 206 140 171 186  22   3  15  72  63]
 [  4   1  31  39  66  71  71  97 147 214 203 190 198  22   6  17  73  65]
 [  2   3  15  30  52  57  68 123 161 197 207 200 179   8   8  18  73  66]
 [  2   2  17  37  34  40  78 103 148 187 205 225 165   1   8  19  76  68]
 [  2   3  20  44  37  34  35  26  78 156 214 145 200  38   2  21  78  69]
 [  2   2  20  34  21  43  70  21  43 139 205  93 211  70   0  23  78  72]
 [  3   4  16  24  14  21 102 175 120 130 226 212 236  75   0  25  78  72]
 [  6   5  13  21  28  28  97 216 184  90 196 255 255  84   4  24  79  74]
 [  6   5  15  25  30  39  63 105 140  66 113 252 251  74   4  28  79  75]
 [  5   5  16  32  38  57  69  85  93 120 128 251 255 154  19  26  80  76]
 [  6   5  20  42  55  62  66  76  86 104 148 242 254 241  83  26  80  77]
 [  2   3  20  38  55  64  69  80  78 109 195 247 252 255 172  40  78  77]
 [ 10   8  23  34  44  64  88 104 119 173 234 247 253 254 227  66  74  74]
 [ 32   6  24  37  45  63  85 114 154 196 226 245 251 252 250 112  66  71]]
```

*Illustration 2: Matrix of Pixel Intensities*

The above illustration is a matrix representation of what a computer sees when rendering an image. This 18x18 matrix contains values ranging from 0 to 255. The higher the value, the more intense the pixel is. These 324 pixels however are representative of only a single color channel. A typical color image has 3 color channels; One for red, one for green, and one for blue.

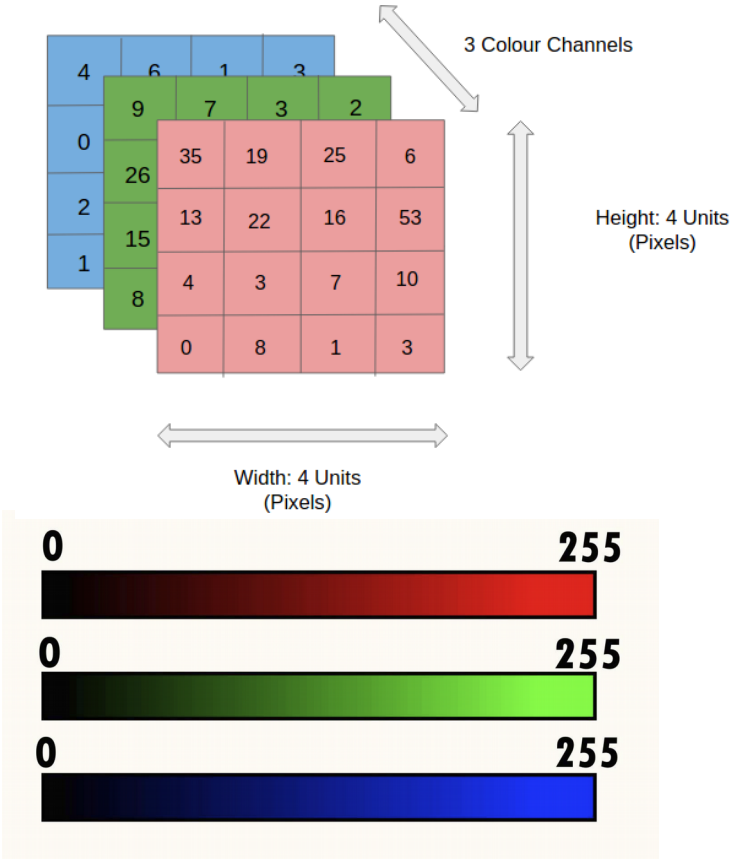



*Illustration 3: RGB Channels and Pixel Intensities*

One can start to see what the potential computational costs can add up to be. From this mere 18x18 image, there are a total of 972 pixels amongst the 3 color channels. When represented as a float 16 or float 32 matrix, meaning each number is represented as a 16 or 32 bit number respectively, this one image takes up 1.9 and 3.9 kilobytes respectively. Later on, it will be further expanded on how this issue compounds exponentially.

# 3 THE DATA

Data was chosen from the ILSVRC images database. The ILSVRC or ImageNet Large Scale Visual Recognition Competition, simply known as ImageNet, is a project that curates, labels, and distributes a large visual database for yearly competitions. Their database contains over 20 thousand categories where each category contains several hundreds to thousands of pictures. The images in this study are specifically from the 2013 database, containing the categories of:

- n01503061 – Bird
- n02099602 – Dog
- n02958343 – Car
- n04330267 – Stove

No specific thought process went into the selection of categories for this study other than the desire to have at least two organic objects and two inanimate objects. For the bird category, there are 1,445 pictures, 1,069 for the dog category, 839 car pictures, and 1,196 Stove pictures. Of the 4,549 images, the average image height is 387 pixels and the the average image width is 454 pixels. This brought about the first real decision of the project.

Convolutional layers don't require that the input image be of a fixed size. However the architecture of the CNN contains at least one fully connected layer (synonymous with the hidden layer of a neural network) and the input for this layer must be as expected. Because of this, as an image is fed forward through the CNN, in order to assure that the resultant image size is as expected for the fully connected layer, the images themselves must be reshaped to a standard size. This issue can be circumvented using a method called Spatial Pyramid Pooling. But in order to control the complexity of this study, this method was not used. The paper on Spatial Pyramid Pooling can be read here. With an average pixel height and width of 387 and 454 respectively, initially the images were to be rescaled to 500x500. This was the initial computation road block encountered.

By reshaping all images to 500x500, this consequently would create a 4549x500x500x3 array of pixel values with data type, float 32. At 32 bits per integer, this single array would be 13.6gb. Although this is doable, this is not computationally feasible. As a result, the decision was made to reshape the images to 300x300x3. This dimension would reduce the array size to 4.9gb, limit the distortion of the original image as well as prevent them from being too grainy from over enlargement that the 500x500 dimension would cause.

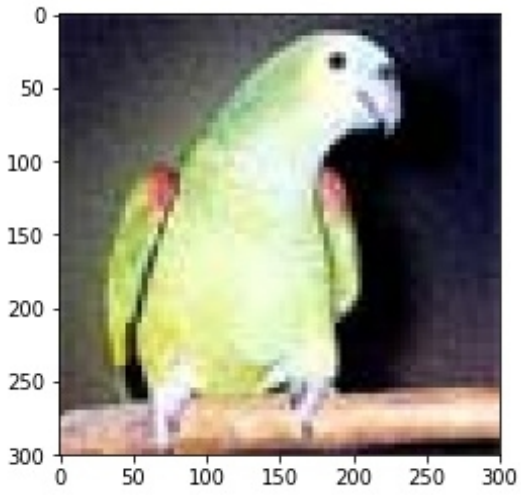



*Illustration 4: Image of original size 80x80 enlarged to 300x300 to represent the amount of graininess reshaping images can cause*

A data processing class was created in order to load all the images from disk, vectorize them into numpy arrays, and reshape them. After processing the data, it is then saved to disk via an H5 file. This class can be seen in Appendix A. This class performs an 85/15 train test split on the data before saving it to H5. The split of all categories breaks down as shown in Illustration 5.


*Illustration 5: Train Test Split of all data for the study*

# 4 Basics of a Convolutional Neural Network

A convolutional layer of a CNN, also known as a filter, is a (m x n) matrix that is overlaid an (M x N) image. This filter's size is determined by the CNN architect, and could be viewed as a hyper parameter that is tuned during training. The filter is typically smaller than the image and convolves around the matrix. The general idea of this can be seen below in illustration 4.

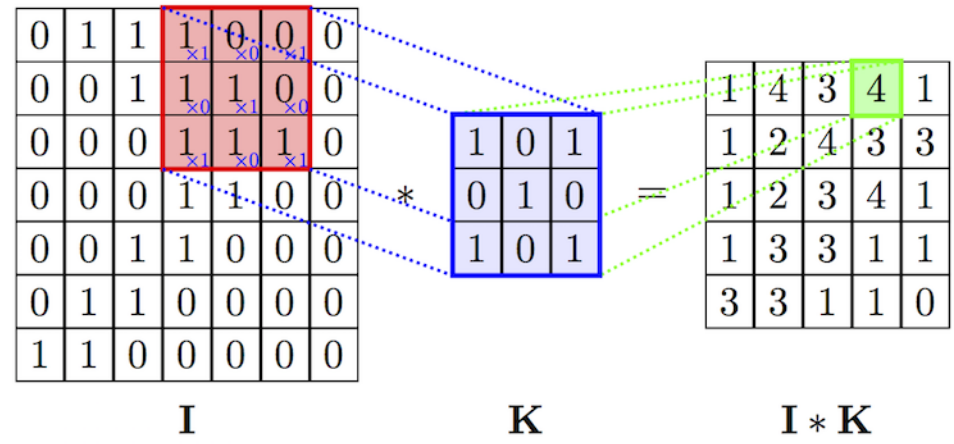



*Illustration 6: Applying a convolutional filter*

The top left corner of filter K is initially aligned with the top left corner of image I. The values of I are the pixel values for the image. The overlaid filter values are then multiplied with their corresponding pixel cell, and then all the values are summed together. The filter is then slid over by a predetermined amount of columns and the operation starts again. Once the filter has gone as far right as possible, it then resets to the left and shifts down a predetermined amount of rows. It then repeats the same process until it has convolved on the whole image. As shown, the resulting output shrinks the image by a factor of:

$$(n_H - f_H + 1) * (n_W - f_W + 1)$$

where

- $n_H$ & $n_W$ is the pixel height and width of the image respectively
- $f_H$ & $f_W$ are the height and width of the filter respectively

As seen in Illustration 4, the image is 7x7 with a 3x3 filter being applied. Therefore the resulting output is (7-3+1) x (7-3+1) = 5x5 resulting output.

So what is this filter doing? It is basically an edge detector/feature extractor. Since the filter is multiplying the pixel values and summing the result, the areas with high pixel intensity will be amplified and areas with low pixel intensity will be attenuated. The orientation of this amplification/attenuation depends on the orientation of the filter.

## 4.1 Edge Detectors

Let's look at a Vertical Edge Detector example taken from Andrew Ng's CNN deep learning Course for an illustration of whats going on.

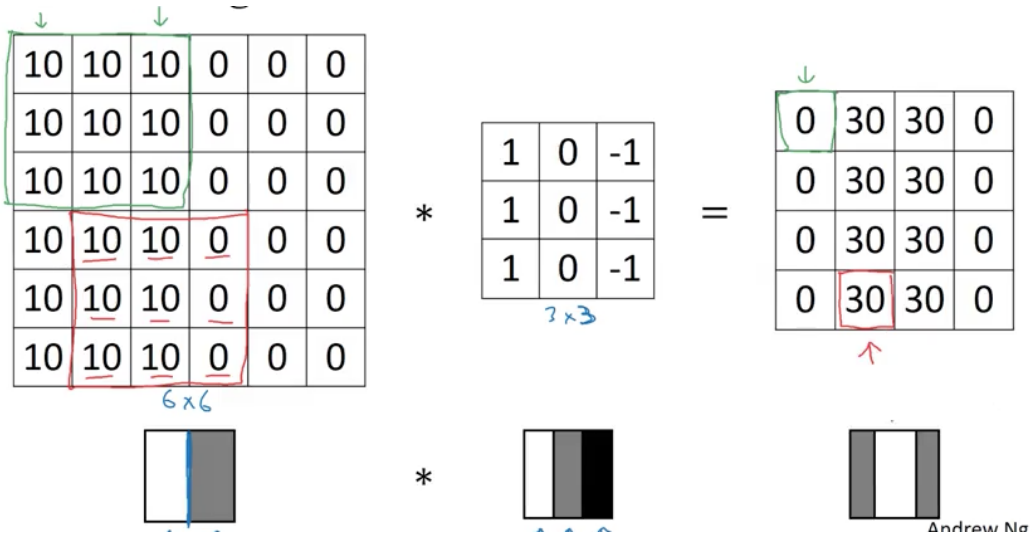



*Illustration 7: Vertical Edge Detector as Explained by Andrew Ng; Convolutional Neural Networks - Deep Learning Specialization*

The first 3 columns have pixel intensity 10 and the last 3 have pixel intensity 0. This results in the image seen below it. The left side of the image is white where the right side of the image is gray, with an obvious edge boundary between the two. As the filter convolves around the image, it reduces to pixel values to 0 everywhere except for where the edge existed between the two pixel intensities. This filter is a vertical edge detector. If this filter was rotated 90 degrees, it would then become a horizontal edge detector. When these filters are convolved around an actual RGB image, the following is produced:

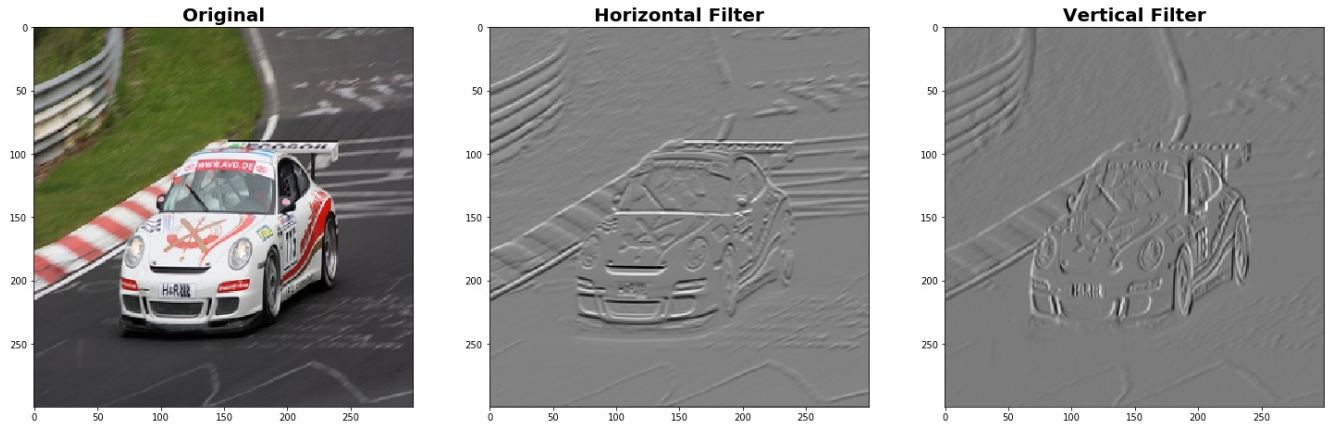



*Illustration 8: Applied Vertical and Horizontal Filters on an RGB Image*

After applying the horizontal and vertical filters on the image, it is shown how these filters highlight those edges which appear horizontal and vertical for each respective filter. All other edges, patterns,

and shapes are attenuated. The images are fed in as 300x300x3 array. Notice that the output of these images retain this 300x300 shape. This is due to padding.

## 4.2 Padding

Padding is the act of taking our (M x N) image (300x300) in this case and adding extra rows and columns of 0 values around it. This is done because when convolving the filter around the image, the middle pixel values are are involved in several instances of the convolutional process. The pixels on the sides however are convolved on less frequently due to their position at the borders. Because of this, a lot of information at the borders are lost. By adding 0 padding, we are able to convolve on these border pixels more often, thus preserving information at the borders. Padding also serves as a way to control output of the convolutional layers. If we need a specific output size, we can ensure we get it by incorporating padding. This process is highlighted in illustration 7 which 0 pads a 32x32 image.

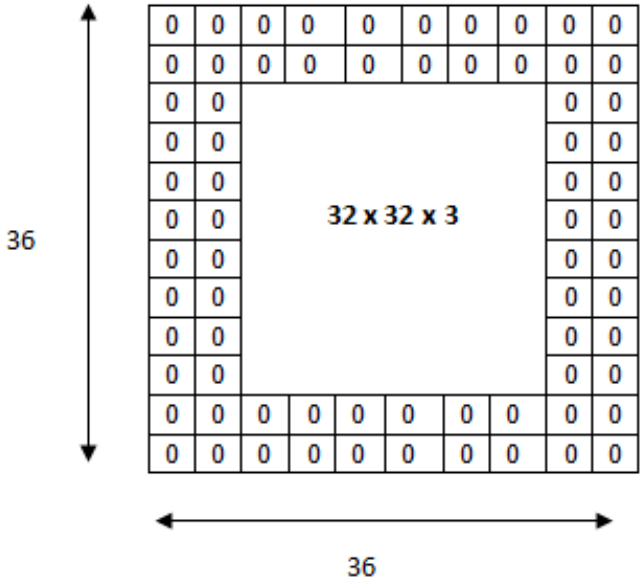



*Illustration 9: Zero Pading for CNNs*

When applying a 5x5 filter to this 32x32 image, the resulting output after adding the 4 columns and rows of zeros, remains 32x32. Padding however is not the only alteration/transformation that is typically applied to a fed image.

## 4.3 Pooling Layer

A very common practice after feeding an image into a convolutional filter is to then feed that output into what is known as a “Pooling Layer”. This layer acts as yet another filter. There are two types of pooling layers; Max pooling nad Average pooling. Max pooling will be discussed here, but the idea of average pooling can be inferred from the explanation.

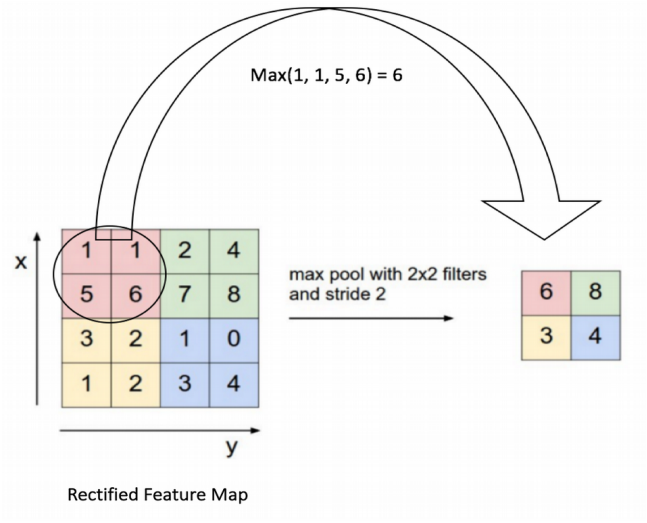



*Illustration 10: Example of a 2x2 Max Pooling Filter*

A max pool filter simply overlays a filter on the image as shown above and simply returns the largest value in the filter. The filter is then slid over by a predetermined amount of cols and the step is repeated. This pooling layer is used for 2 different reasons

1. It reduces the dimensionality of the data. The pool layer is a non trainable layer that simply takes the highest value in an array. As seen above we are reducing the size of our image (in that example) by 75%. This well have great computational effects during training. However there is an inherent issue with this. We are throwing away 3/4 of our data.
2. The model needs to be invariant to small perturbations in the data. The model shouldn't be trained so precisely that it looks for an exact pixel in an exact location. It should generalize well to any image with the object of interest in any orientation, size and shape. The pooling layer injects this variance into the model. The convolution layer tries to identify some important structure in some region of the data while the pooling layer obscures the exact location of this structure.

After applying a pooling layer to the original images with the edge detectors, it results with effectively the original image, but at compressed dimensionality.

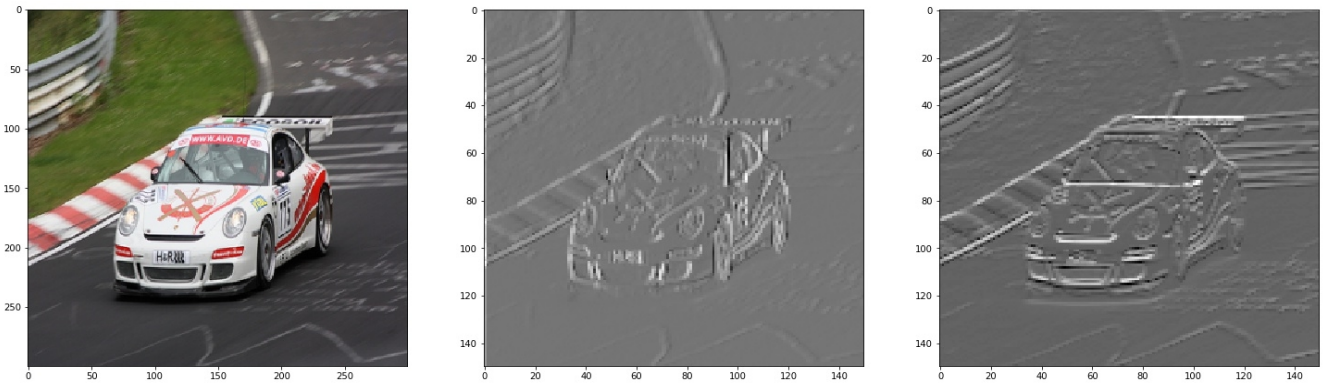


*Illustration 11: Image filtered through a Edge Detector Convolutional Filters and a Max Pool Layer*

The results from the convolutional layer is fed into the pooling layer where the empirical features and edges that were extracted are preserved, but the location of these features have changed. The output size of the images are now 150x150.

## 4.4 Striding

Until now the intuition has been that the filter is slid in each direction by only 1 column or row. This doesn't have to be the case. It can be increased how many positions the filters move by designating the "strides" of the filter. Illustration 10 shows the implementation of a 3x3 filter with a stride of 2.

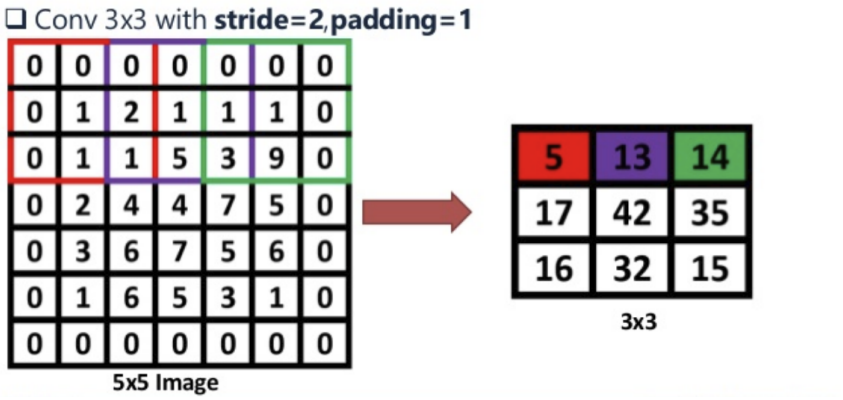



*Illustration 12: Implementing strides on a filter. It can be seen that the purple filter starts at column 3 instead of column 2, representing a stride of 2 after the red filter*

It is now not uncommon in more recent CNNs to remove the use of a pool layer all together in favor of just increasing strides on the convolutional layer. It serves the same purpose of introducing variance into the model, but now has the downside of bearing weights that need to be saved in memory and trained. This can make it computationally expensive in comparison to a pooling layer. With the incorporation of padding and stride, the resultant output shape of an image function needs to be updated to account for these transformations.. With both padding and strides, the resulting image size is now:

$$\frac{n_H + 2p - f_H}{s} \text{ x } \frac{n_W + 2p - f_W}{s}$$

where:

- p is padding. It is 2*p because if you want one layer of padding, a layer of zeros is added to the left and right side of the image for vertical axis, and a layer of zeros is added to the top and bottom side of the image for horizontal axis.
- s is the number of strides for the filter to take while convolving around the image

And this is the basic premise of a CNN. Filters convolve around an image searching for features and edges. The resulting convolution sometimes is then fed through a pooling layer which is a non trainable feature reduction layer. These convolution layers and pooling layers are stacked together to create the architecture of a CNN. The vertical and horizontal filters were specifically chosen for this basic introduction. But in the context of a real CNN, filters are randomly initialized and learned during training (excluding the pooling layer). Each filter learned will be responsible for searching for specific features in various orientations of an image. This wasn't meant to be an in depth lesson on CNNs, and as a consequence, a lot of intuition is left to the reader.

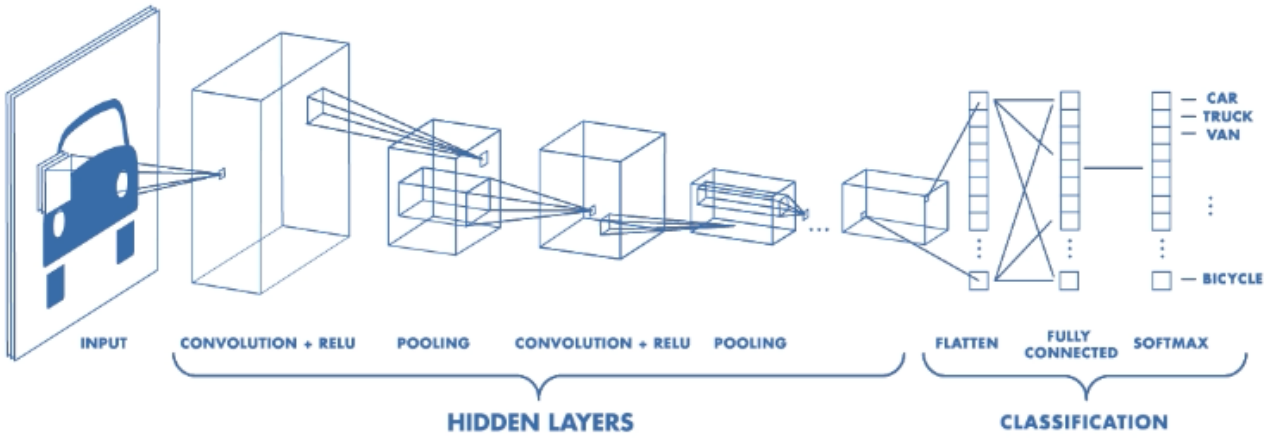



*Illustration 13: A full Convolutional Neural Network (CNN)*

# 5 MODEL ARCHITECTURE

A few different CNN structures were rapidly prototyped in order to determine initial performance. Ultimately a 4 layer model was settled upon in order to conduct the optimization study. The input layer is obviously the ?x300x300x3. The “?” is a placeholder in tensorflow signaling the model that there will be a certain amount of training samples passed to the model determined at runtime. However, all other dimensions will be set and should be expected as such. The first convolutional layer contained 10 different convolutional filters followed by a pooling layer. The second layer also contained 10 different convolutional filters. This time it neglected the use of a pooling layer. Finally, the third layer was constructed using 20 different filters. The third layer did make use of a pooling layer. After the final convolutional layer, the outputs are fed into a fully connected layer with the 4 output nodes representing one of the 4 different categories. The logits from this fully connected layer are then fed into a softmax function. A full breakdown of the CNN architecture is as follows

| Layer | Filters | Filter Shape | Strides | Padding | Variables | Trainable |
|---|---|---|---|---|---|---|
| **1st Convolutional Layer** | 10 | 7x7 | 2 | SAME | 493 | Yes |
| **1st Pooling Layer** | 1 | 4x4 | 2 | VALID | NONE | No |
| **2nd Convolutional Layer** | 10 | 2x2 | 2 | SAME | 170 | Yes |
| **3rd Convolutional Layer** | 20 | 3x3 | 2 | SAME | 190 | Yes |
| **2nd Pooling Layer** | 1 | 2x2 | 2 | VALID | NONE | No |
| **Fully Connected Layer 1** | N/A | N/A | N/A | N/A | 720 | Yes |

A quick note on the architecture. Where padding says “SAME”, this simply means that whatever the input shape is of the incoming data, it will be zero padded so that the output will still be the same shape. At least it would be the same shape if a stride of 1 was implemented. However since a stride of 2 is used, the resulting shape won’t be the same shape as the input. Where padding says “VALID”, this means no padding is implemented and the resultant shape will follow that of the equations mentioned in section 4.4 with a value for “p” of 0.

In relation to the structure of the graph, Tensorflow has built in functionality that allows one to monitor training realtime with Tensorboard. It creates the graph in the direction of which the tensors

flow. The W's are the filters for each convolutional layer that is learned during training. Following the input "x" of the graph at the bottom right, the following happens:

- Input Image (300x300x3) is convolved upon by 10 separate filters in the first layer (W1) and outputs a (75x75x10) tensor
- Second layer receives the output from the first layer and is convolved upon by another 10 separate filters (W2) and outputs a (38x38x10) tensor
- Third layer receives the output from the second layer and is convolved upon by 20 separate filters (W3) and outputs a flatten array of 720 values
- Fully Connected layer receives the flatten vectored and outputs a prediction

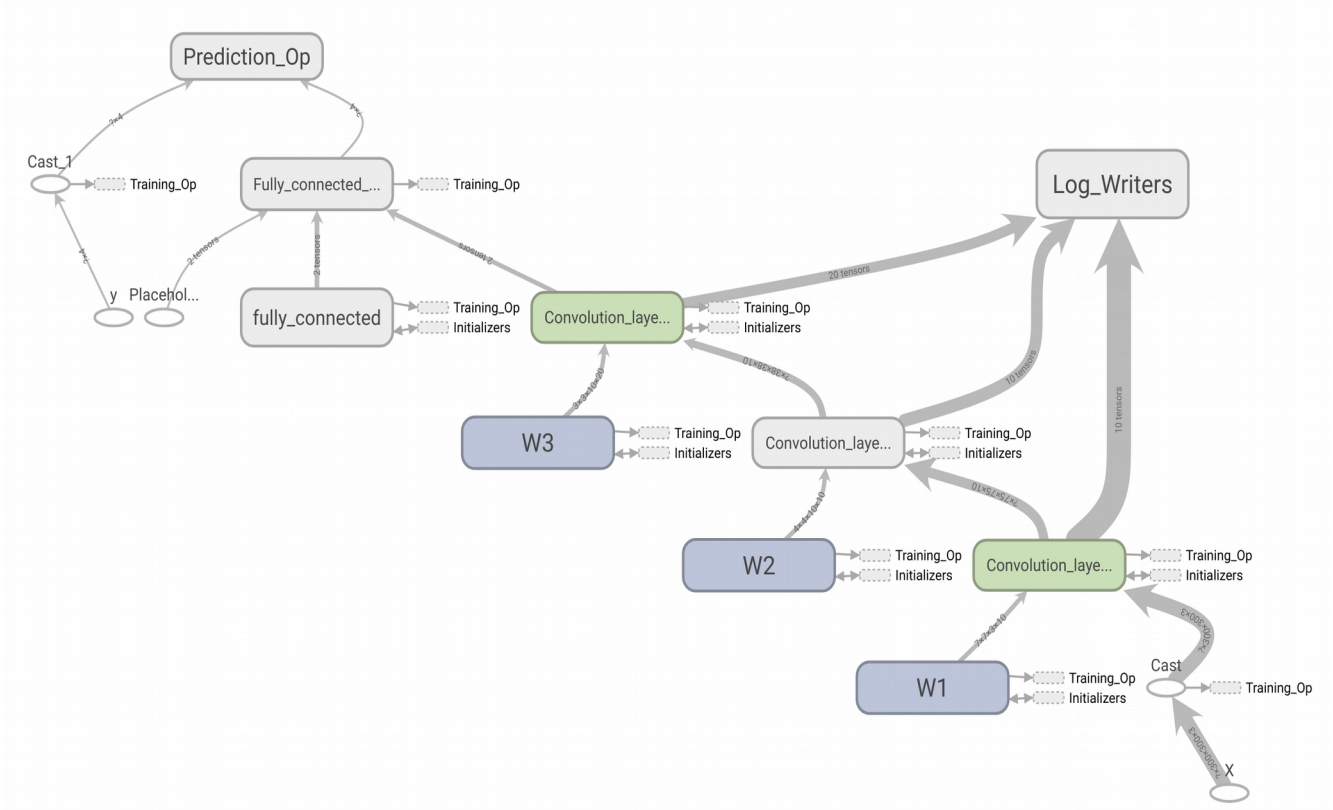



*Illustration 14: Tensorboard Graph Representation of the Trained CNN Model*

# 6 RGB BASELINE

Not only is memory space a primary concern when training CNNs, but also training speed. Training full RGB images took several hours of training. This is not uncommon in the world of object detection and computer vision algorithms. But the nasty downside to this is hyperparameter tuning can take hours to days to really dial the model in. In regards to this study's CNN, the typical hyperparameters of learning rate and regularization constant were tuned. However, the optimizer for backpropagation was adam optimizer which comes with its own hyperparameters. Finding a good initial baseline for the RGB model took 3 days due to training time, hyperparameter tuning and overall CNN architecture. Large CNNs can learn very complex data, but at a tricky cost. Initial tested models produced extremely poor results even after hours of epochs. The problem encountered was that the model was big enough to the point that it suffered from vanishing gradients.

## 6.1 VANISHING GRADIENTS

A full comprehensive mathematical discussion on vanishing (and exploding) gradients are out the scope of this paper. It is merely brought up in this instance because it was an initial problem seen while trying to establish a baseline model. A CNN works in the same was as a traditional deep neural network. Data is fed forward through the network where a prediction is made. The error is calculated between the predicitons and true values. The model is then traversed backwards performing back propagation to train the model on its "mistakes". On sufficiently large enough models, when back propagation commences, the later layers in the model learn more quickly than the earlier layers. In the simplest explanation, this is due to multiple derivatives being multiplied by the derivative of an early layer. As the derivates are taken, traversing backwards, they result in very small numbers (<< 0). Small numbers multiplied by small numbers equals an even smaller number. As a consequence, the earlier layers in the model are updated very slowly and learn even slower. This is a simple explanation of the vanishing gradient problem. To see a great step by step intuitive and mathematical explanation of this gradient problem, see this article.

To combat this problem, a 4 layer network was discovered to work the most suitably in the days of searching for the best architecture. This deep of a model allowed all layers to learn at a suitable rate while being able to generalize to the complexity of the data. In conjunction with this, RELU activation functions were chosen for each convolutional layer instead of sigmoid or tanh due to it's ability to suppress the vanishing gradient problem. Sigmoids and tanh functions restrict the output of numbers in the activation layer to a value between 0 to 1 and -1 to 1 respectively. A consequence of this is the derivative of such small numbers results in even smaller numbers. Weight updating was monitored realtime during training to ensure neither vanishing nor exploding gradients were being realized via Tensorboard

During training, the weights are updated in a tensor flow log writer. This log stores information such as cost, weights distributions and histograms as well as image rendering through each layer of the CNN. The weights from the RGB Model are displayed on the right. Each update to the log is written after every 10th Epoch. The y-axis of the graphs represent the Epoch and the x-axis is the histogram distribution.

It can be seen that layer 3 weights are going through the most dramatic changes after each Epoch. Layer 1's updates appear less dramatic the longer the model learns. This exemplifies the potential pitfall of vanishing gradients as well as the explanation that earlier layers learn much slowly than later layers. The effect of these weights will be shown in the next section.

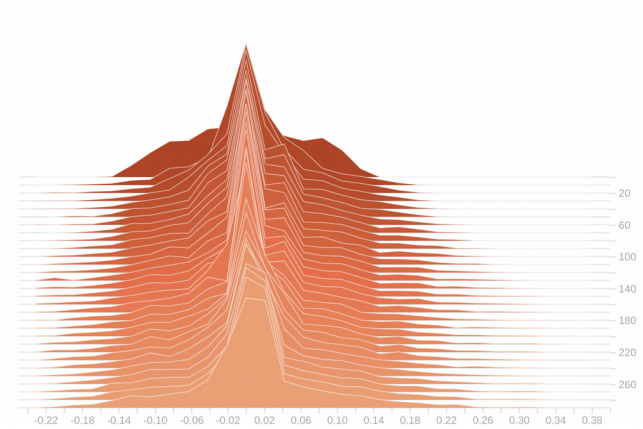



*Illustration 15: Convolutional Layer 3 Weights*

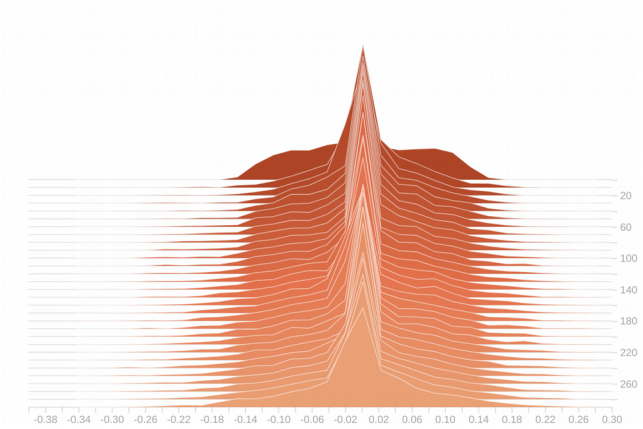



*Illustration 16: Convolutional Layer 2 Weights*

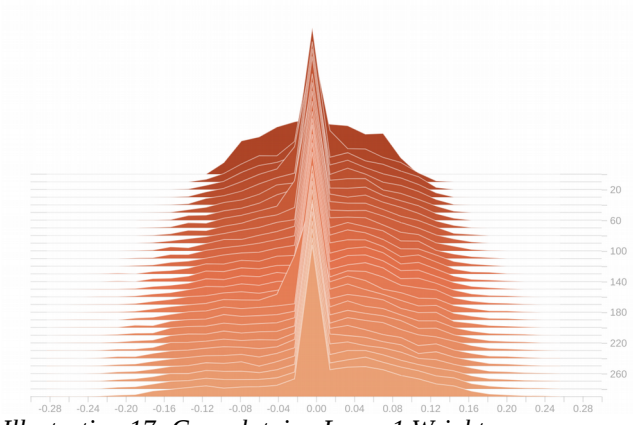



*Illustration 17: Convolutaion Layer 1 Weights*

## 6.2 BASELINE PERFORMANCE

From the model as outlined in previous sections, the initial baseline performance was respectable, but took sometime to train. A custom Tensorflow class was constructed in order to facilitate the training, logging, and prediction methods of the model. This class can be seen in Appendix B. The class implements early stopping for both increasing  cost and floor value cost. If the cost increases 20 epochs, training is terminated. Conversely if the difference between cost(t + 1) and cost(t) is less than 0.0001, training is terminated. The results for RGB baseline after 300 Epochs are shown in illustration 16

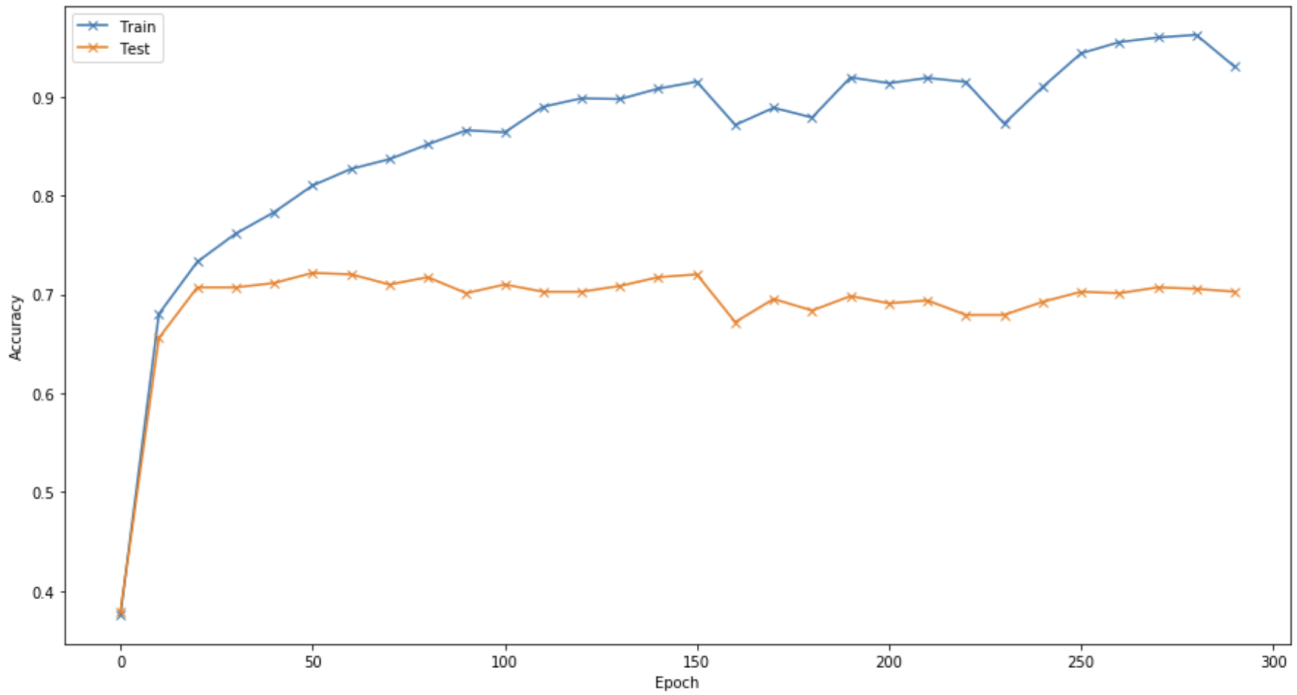



*Illustration 18: Train and Test set accuracy for RGB CNN*

The accuracy for the training set reached over 96% at Epoch while accuracy for the test set reached 72% at Epoch 50. Afterwards it continue pretty flat during the rest of training. This is a sign of overfitting on the training set. But for the current purposes, it served as a valid baseline. Training spanned 300 Epochs and took 6.3 hours. This breaks down to 75.6 seconds per Epoch.

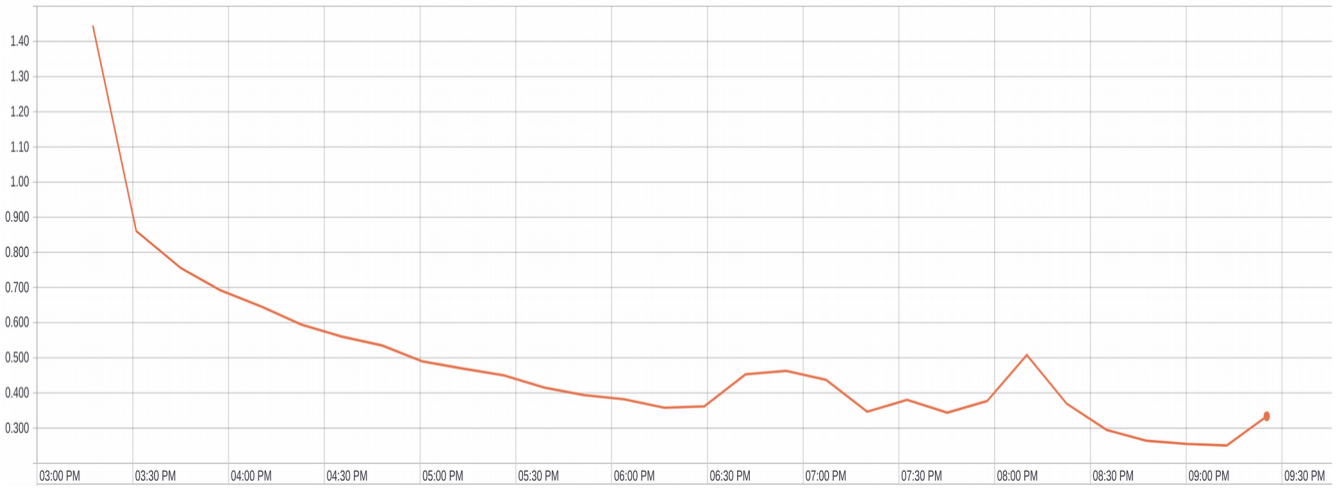
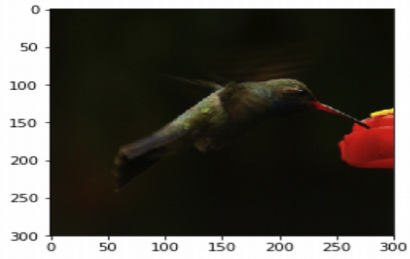
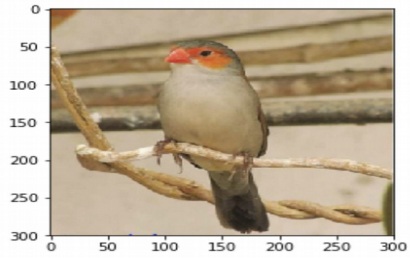



*Illustration 19: RGB Training Cost With Respect to Time*

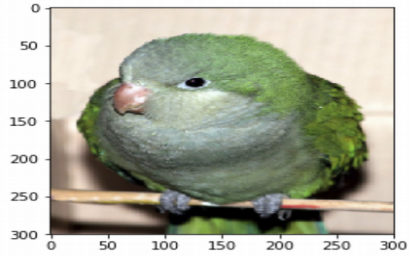
During training, the model class saves a checkpoint of the model every 10th Epoch. This checkpoint saves all weights and biases for that training Epoch. Further investigation was done on model metrics for both the best performing model on the train set and the best performing model on the test. Those results are as follows. The Train Set metrics are on the left and the Test Set metrics are on the right.



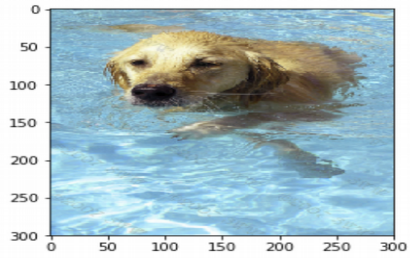
This is a Bird



This is a Bird



This is a Stove

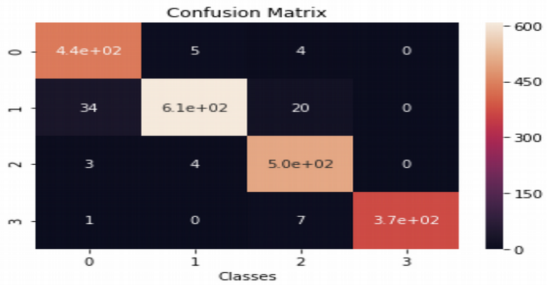


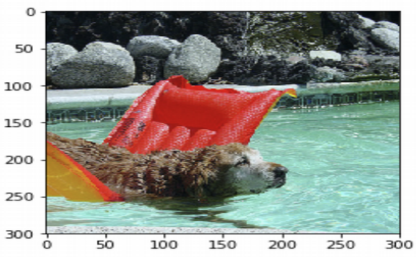
This is a Dog

Accuracy: 96.1%

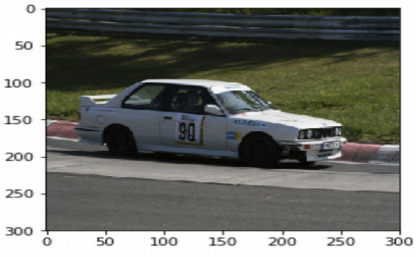
Out[110]:

| | F-Beta | Precision | Recall | Support |
|---|---|---|---|---|
| **Dog** | 0.949079 | 0.920168 | 0.979866 | 447 |
| **Bird** | 0.950666 | 0.985390 | 0.918306 | 661 |
| **Stove** | 0.963740 | 0.942164 | 0.986328 | 512 |
| **Car** | 0.989362 | 1.000000 | 0.978947 | 380 |



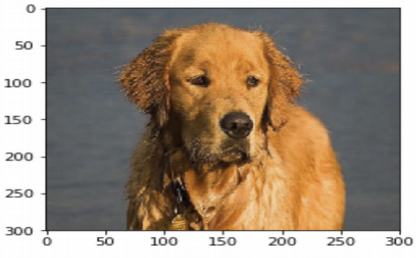



This is a Bird



This is a Car

This is a Stove

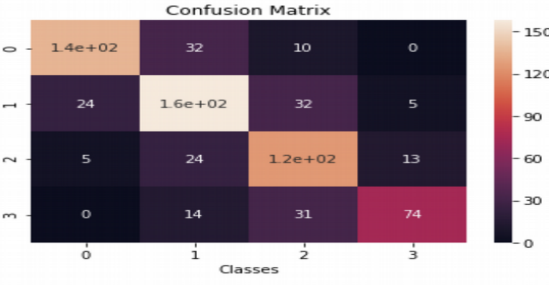


This is a Dog

Accuracy: 72.18155197657394%

Out[113]:

| | F-Beta | Precision | Recall | Support |
|---|---|---|---|---|
| **Dog** | 0.793003 | 0.824242 | 0.764045 | 178 |
| **Bird** | 0.706935 | 0.692982 | 0.721461 | 219 |
| **Stove** | 0.684932 | 0.631313 | 0.748503 | 167 |
| **Car** | 0.701422 | 0.804348 | 0.621849 | 119 |



The best model on the training set performed amazing, with high precision and Accuracy for all 4 categories. It even resulted in perfect precision when classifying cars. The test set metrics are too bad either. It is a decent car and dog classifier. However, it did take 6.3 hours to run through 300 Epochs and clearly there is an overfitting problem. Typical object detectors are trained on tens of thousands of images. Only +4000 were used here. What is wanted is the ability to still achieve high accuracy while reducing training time. The first idea that came to mind was performing training on the same images, but only in Grayscale.

# 7 GRAYSCALE MODEL

An image is converted from RGB to grayscale most commonly by taking the average of the 3 pixel color intensities and converting them to a single value. Therefore, we are reducing our size constraints for each image by 2/3. This is removing some of the "information" contained in the data, but since CNNs are mostly edge and shape detectors, the idea was hopefully the loss of information didn’t translate to a loss of performance. The intrinsic shape of the object in the image is preserved, but the color is just removed.

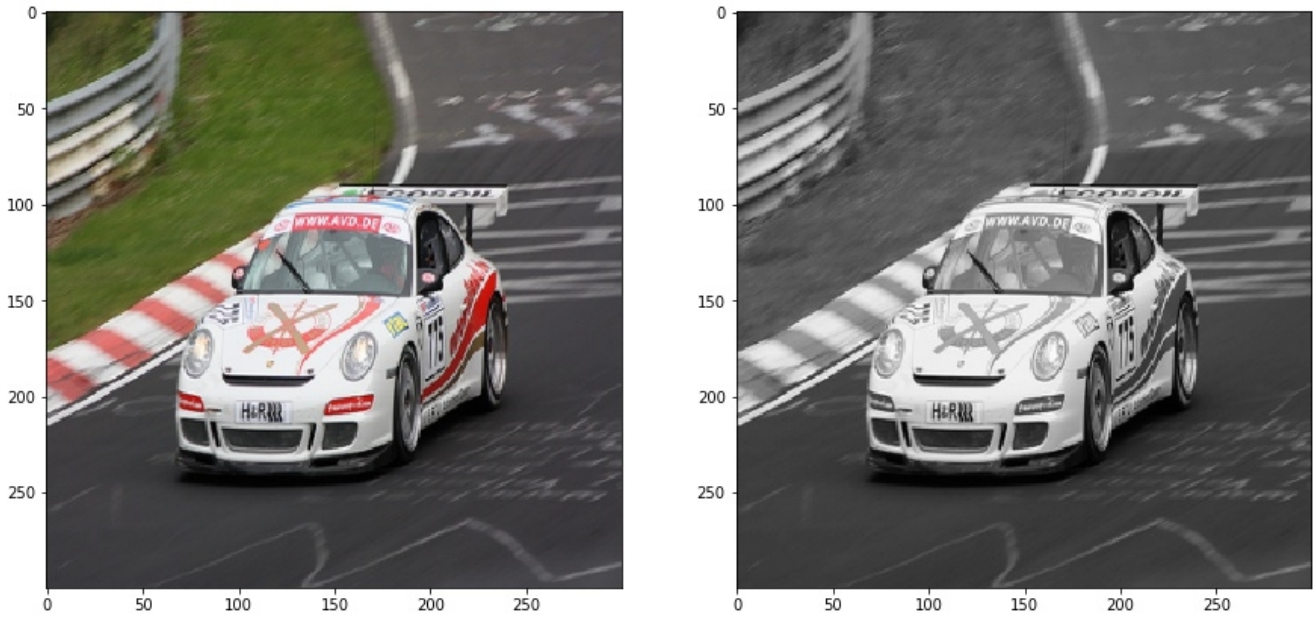



*Illustration 20: RGB Image Converted to Grayscale*

The two images above are the same, but not in size. As an array, the color image has dimension 300x300x3 whereas the grayscale image on the right is 300x300x1. The resulting array sizes are 1MB and 360KB respectively.

# 7.1 GRAYSCALE PERFORMANCE

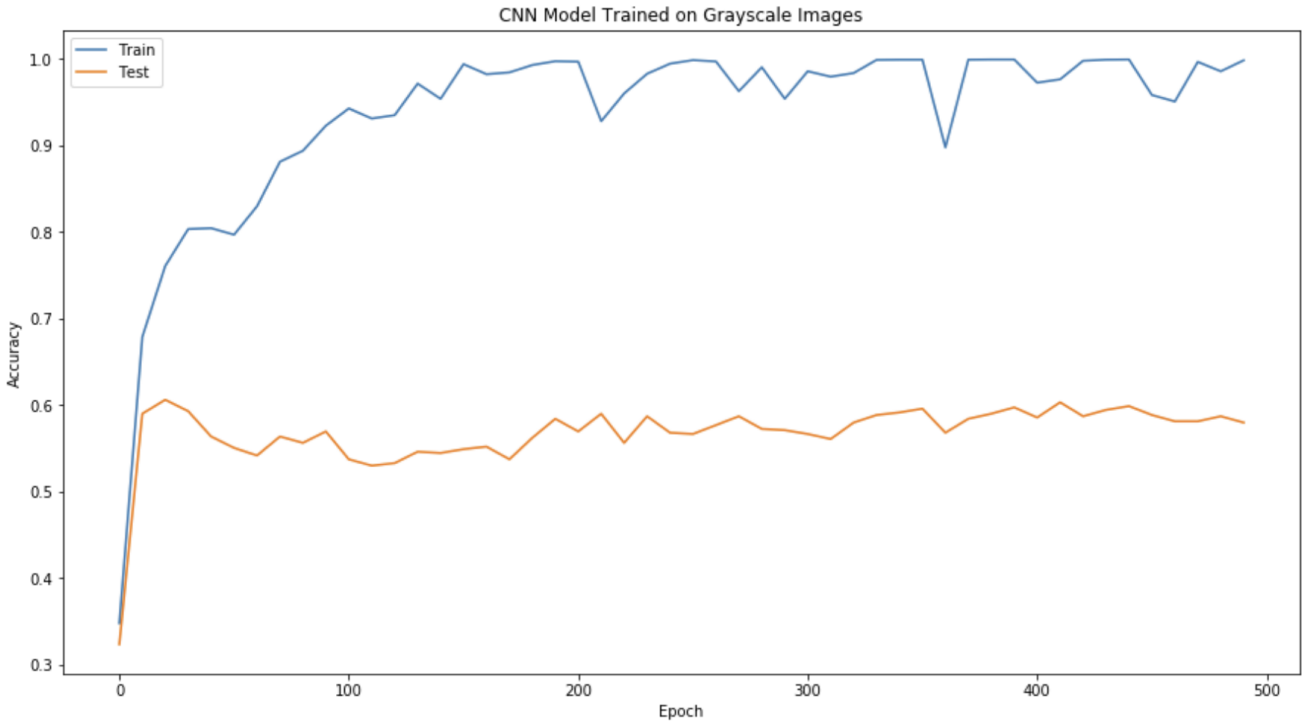



*Illustration 21: Training and Test Set Accuracy for Grayscale Model*

By converting to Grayscale and using the same CNN architecture, it was only able to achieve 61% accuracy on the test set. Meanwhile, it did achieve 99.9% accuracy on the training set. Again, it is grossly overfitting the training data as seen with the RGB images. On the plus side however, with full RGB data, training took 6.3 hours to go 300 Epochs, where it took only 5.1 hours to go 500 Epochs with the grayscale data. This breaks down to about 36.7 seconds per Epoch, a reduction of 51.4% training time. This will save us some time training various different CNN architectures while tuning hyperparameters to try and attenuate our current overfitting problem. In the mean time, let's look at the metrics of the best performing models a little closer

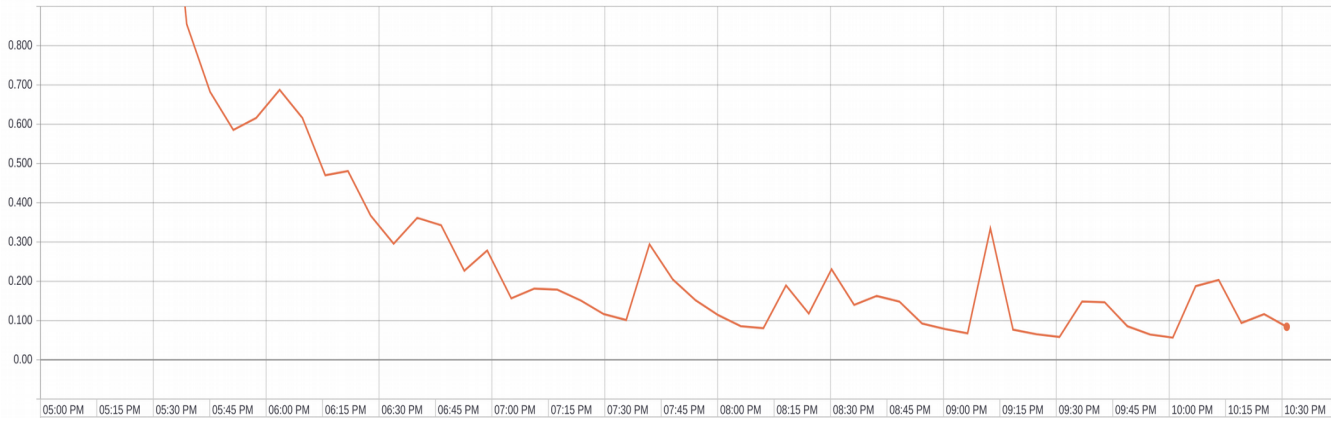
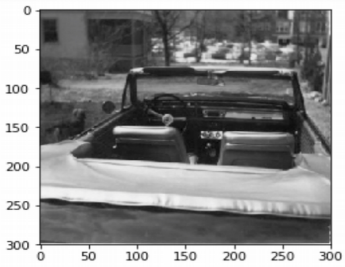
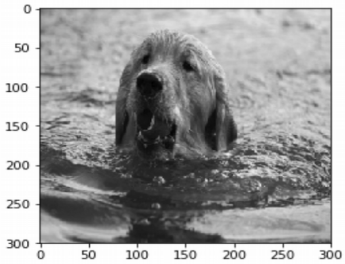


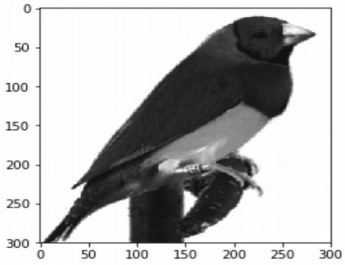

*Illustration 22: Grayscale Training Cost with Respect to Time*



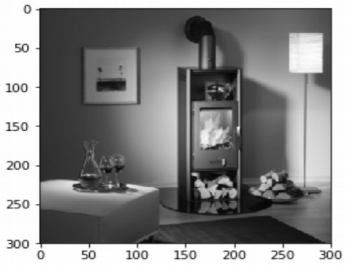
This is a Car



This is a Dog



This is a Bird

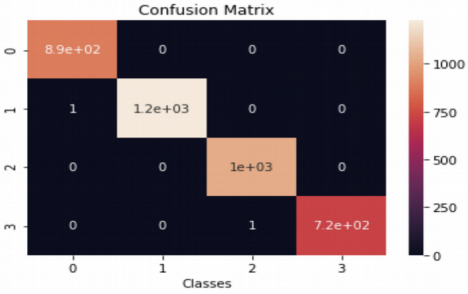


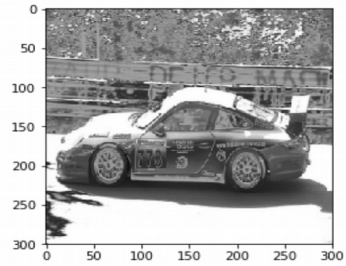
This is a Stove

Accuracy: 99.9482669425763%

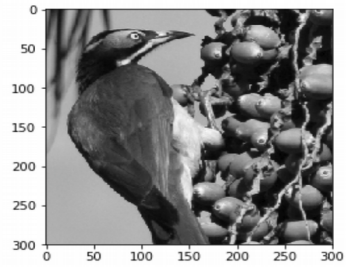
Out[129]:

| | F-Beta | Precision | Recall | Support |
|---|---|---|---|---|
| **Dog** | 0.999439 | 0.998879 | 1.000000 | 891 |
| **Bird** | 0.999592 | 1.000000 | 0.999184 | 1226 |
| **Stove** | 0.999514 | 0.999029 | 1.000000 | 1029 |
| **Car** | 0.999305 | 1.000000 | 0.998611 | 720 |

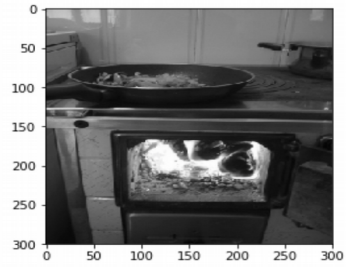


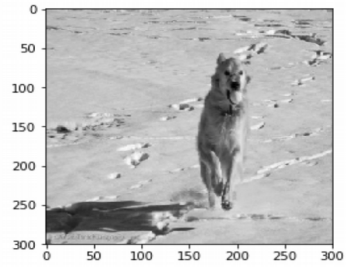
This is a Stove



This is a Bird



This is a Stove

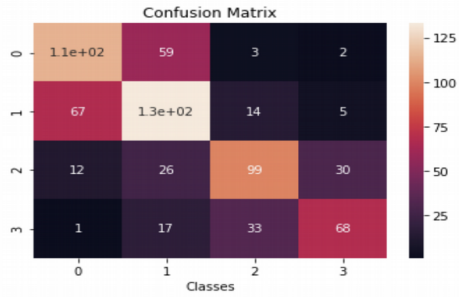


This is a Dog

Accuracy: 60.61493411420204%

Out[133]:

| | F-Beta | Precision | Recall | Support |
|---|---|---|---|---|
| **Dog** | 0.612903 | 0.587629 | 0.640449 | 178 |
| **Bird** | 0.585903 | 0.565957 | 0.607306 | 219 |
| **Stove** | 0.626582 | 0.664430 | 0.592814 | 167 |
| **Car** | 0.607143 | 0.647619 | 0.571429 | 119 |



After further model metrics investigation it appeared that with a 2/3 in data reduction size came a 10% accuracy penalty when training the same model with the same data. Again, the training set metrics are on the left and the test set metrics are on the right. This isn't surprising since we did reduce data density in the images for the model to learn from. The hope was that even with the reduction in "infromation" the edges of each object in the images would still be defined enough for the model to detect accurately. Since the goal is for the model to learn the edges of dogs, birds, stoves, and cars essentially, maybe we can enhance the grayscale images to make it easier for the model to detect them.

# 8 HISTOGRAM EQUALIZATION

Histogram Equalization is a process of enhancing the contrast of grayscale images. The proper definition, as defined by the University of Utah Scientific Computing and Image Processing Institute, is

> “Histogram equalization is a method to process images in order to adjust the contrast of an image by modifying the intensity distribution of the histogram. The objective of this technique is to give a linear trend to the cumulative probability function associated to the image. The processing of histogram equalization relies on the use of the cumulative probability function (cdf). The idea of this processing is to give to the resulting image a linear cumulative distribution function. Indeed, a linear cdf is associated to the uniform histogram that we want the resulting image to have.”

This can be better explained with the help of visual aids. From a grayscale image, a histogram of all its pixel intensities can be rendered and their associated CDF.

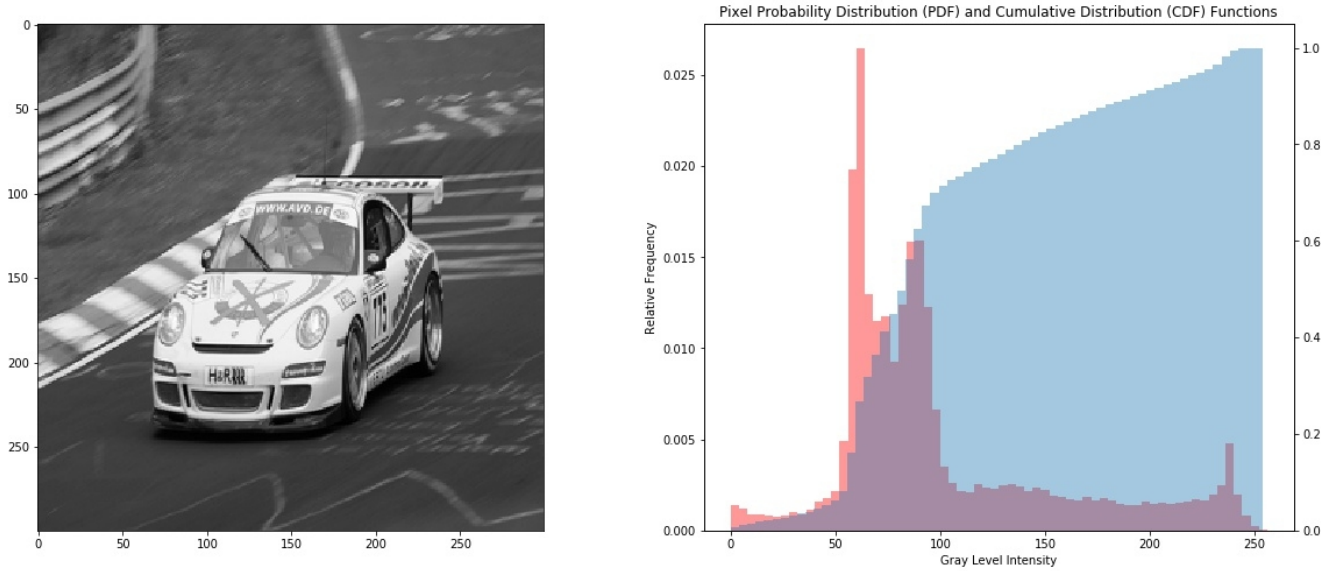



*Illustration 23: Grayscale Image with Pixel Intensity Histogram and CDF*

The CDF or cumulative distribution function is the probability that the a variable takes a value less than or equal to a specified x in the domain. The blue bars in the right image are the CDF for the grayscale car. The process of histogram equalization interpolates the histogram values so that the resulting CDF is a linear line. The mathematics behind this are starightforward, but out of scope for this paper.

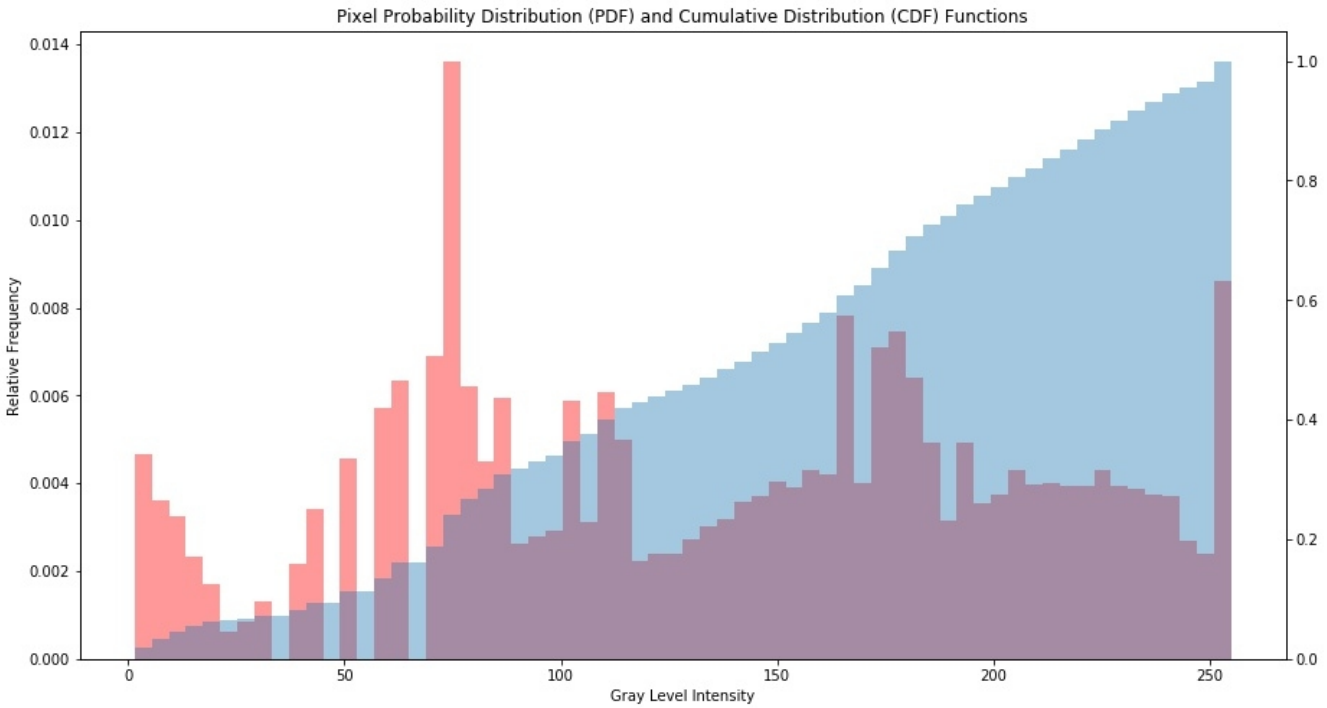



*Illustration 24: Equalized Histogram on Grayscale Image*

Notice that after the equalization process, the CDF is nearly linear. This process maintains the original image but improves contrast and in some cases sharpens the image as well.

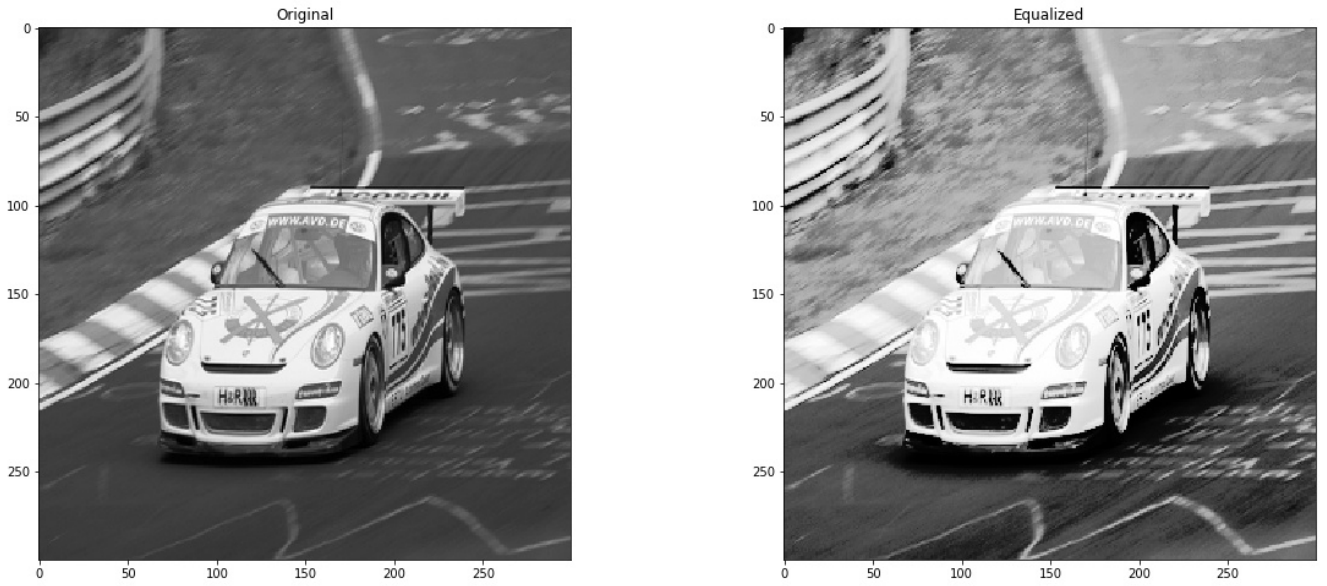



*Illustration 25: Before and After of Equalized Image*

## 8.1 EQUALIZATION PERFORMANCE

All grayscale images were equalized for both the training set and the test set and then ran through the grayscale model trained in the previous section. There were two models (Epochs) to test it

on, the best performing model for the training set (Epoch 380) and the best performing model for the test set (Epoch 20) as seen in Illustration 18. The Equalized data performed as follows:

Accuracy: 78.45318158303157%

Out[32]:

| | F-Beta | Precision | Recall | Support |
|---|---|---|---|---|
| **Dog** | 0.729229 | 0.780051 | 0.684624 | 891 |
| **Bird** | 0.786156 | 0.794338 | 0.778140 | 1226 |
| **Stove** | 0.828351 | 0.822010 | 0.834791 | 1029 |
| **Car** | 0.783055 | 0.727924 | 0.847222 | 720 |

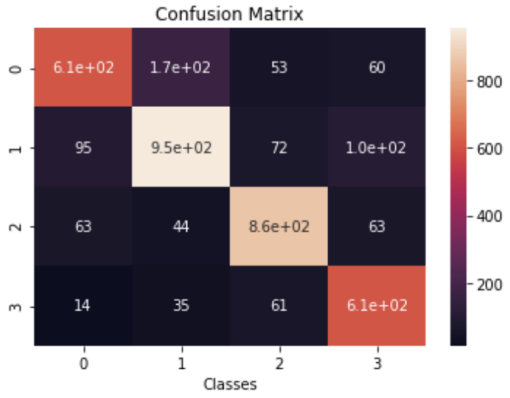



*Illustration 26: Equalized Training Data - Epoch 380*

Accuracy: 61.69167097775479%

Out[34]:

| | F-Beta | Precision | Recall | Support |
|---|---|---|---|---|
| **Dog** | 0.491468 | 0.627178 | 0.404040 | 891 |
| **Bird** | 0.631658 | 0.588318 | 0.681892 | 1226 |
| **Stove** | 0.694758 | 0.737186 | 0.656948 | 1029 |
| **Car** | 0.612903 | 0.537736 | 0.712500 | 720 |

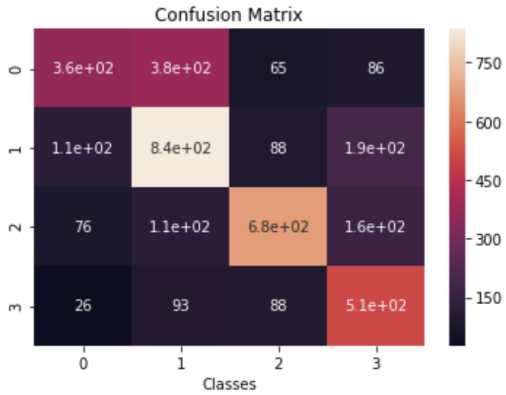



*Illustration 27: Equalized Training Data - Epoch 20*

Accuracy: 54.904831625183014%

Out[92]:

| | F-Beta | Precision | Recall | Support |
|---|---|---|---|---|
| **Dog** | 0.431655 | 0.600000 | 0.337079 | 178 |
| **Bird** | 0.595388 | 0.550388 | 0.648402 | 219 |
| **Stove** | 0.606061 | 0.613497 | 0.598802 | 167 |
| **Car** | 0.519573 | 0.450617 | 0.613445 | 119 |

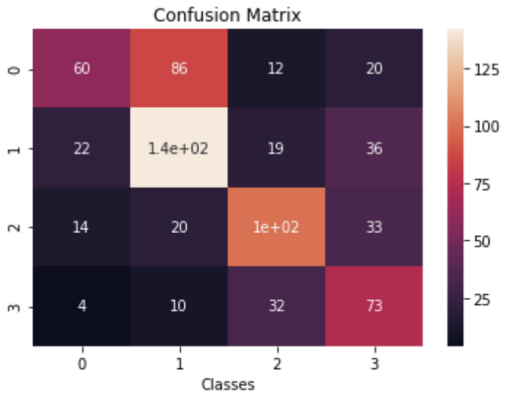



*Illustration 29: Equalized Test Data - Epoch 380*

Accuracy: 56.95461200585652%

Out[94]:

| | F-Beta | Precision | Recall | Support |
|---|---|---|---|---|
| **Dog** | 0.503226 | 0.590909 | 0.438202 | 178 |
| **Bird** | 0.615385 | 0.593220 | 0.639269 | 219 |
| **Stove** | 0.609756 | 0.621118 | 0.598802 | 167 |
| **Car** | 0.520147 | 0.461039 | 0.596639 | 119 |

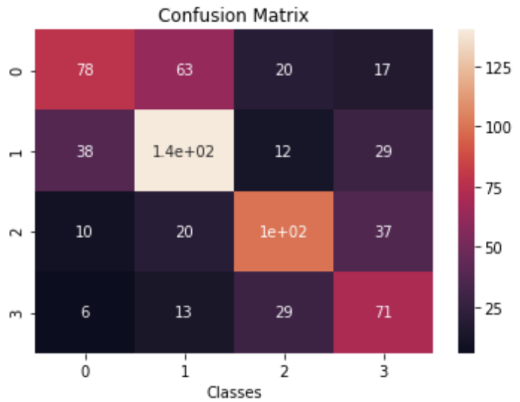



*Illustration 28: Equalized Test Data - Epoch 20*

From the metrics above, it can be seen that performance decreased for all instances. The training data dropped from 99.9% accuracy to 78.4% on its best training Epoch. Conversely, the test data dropped from 60.6% to 56.95% on its best Epoch. The latter had a less significant drop in performance, but a

drop nonetheless. The intent was to increase the models ability to detect the object's edges by improving image contrast in order to improve performance. Obviously these efforts didn't come to fruition. The next step was to retrain a model using both equalized and original images.

# 9 TRAINED EQUALIZED MODEL

Unfortunately, equalizing the images didn't provide the desired results. Still, some important qualities were extrapolated from the exercise.

1. It is much faster to train grayscale models than RGB so this would facilitate rapid prototyping and hyperparameter tuning if necessary
2. Sharpening all the images may reduce the overfitting effect currently seen during the training process.
3. We have doubled our data for the model to train and be tested on by altering the original images. This should also hopefully alleviate the overfitting issue.

The same model architecture again was used to train the model on the now 7,732 images. Half are the original grayscale and the other half are the equalized grayscales.

## 9.1 EQUALIZED MODEL PERFORMANCE

To train the 7,732 images it took approximately 75.5 Seconds/Epoch. This is exactly the time it took to train the 3,866 RGB images and is quite expected since we've added more data for the model to learn from. Unfortunately the results weren't as desired.

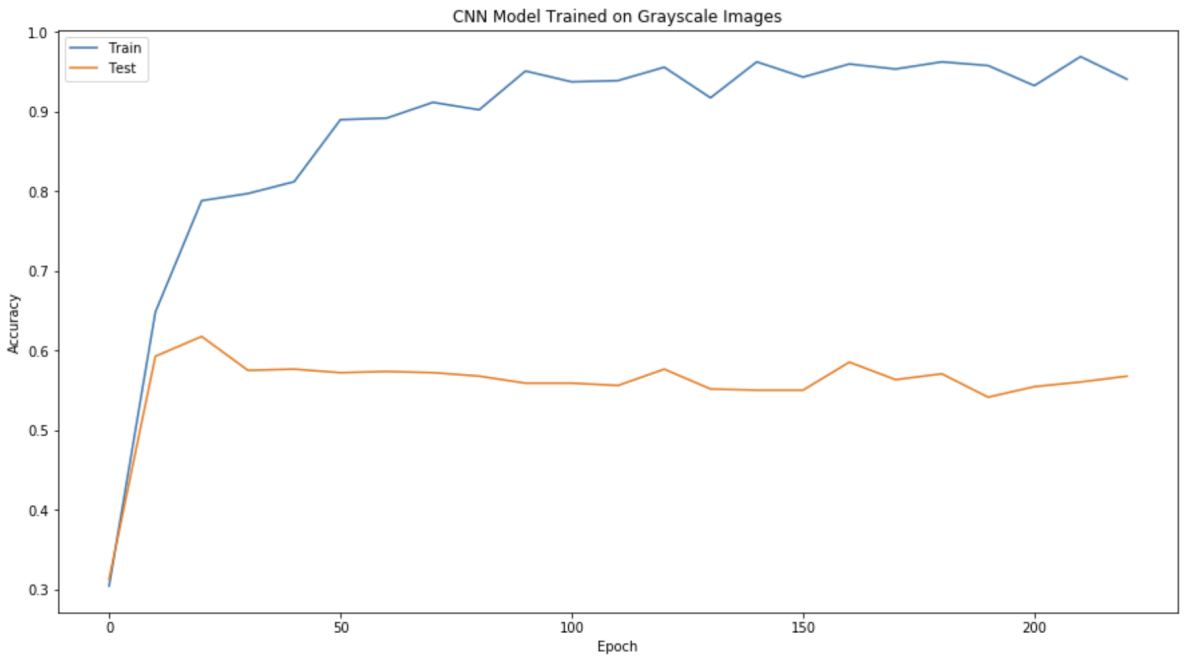



*Illustration 30: Train and Test Set Accuracy on Original and Equalized Data*

The training set reached its apex at 96% around Epoch 210. The test set however only managed to reach approximately 62% again at Epoch 20. Adding the altered images didn't alleviate the overfitting issue and only managed to improve the test set accuracy of the original model by 2%.

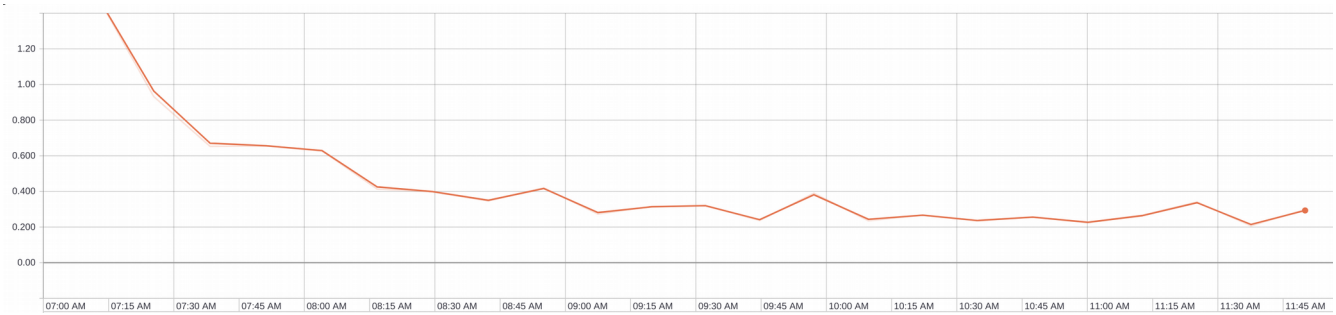



*Illustration 31: Cost with Respect to Time of Equalized and Original Images*

During training, the model reached its floor value after Epoch 229 and took 4.8 hours to train. It is possible had the early stopping constraint been removed that the model might have faired better. But given the initial geometry of the Accuracy graph, it followed the same pattern as all other models. The test set reached its peak in the earlier Epochs and then flattened out for the duration of training. The empirical metrics remain pretty close to the same as the other grayscale models as well. The training set was predicted on in conjunction with the original grayscale images and then the equalized grayscale images.

Out[138]:

Accuracy: 82.93333333333334%

| | F-Beta | Precision | Recall | Support |
|---|---|---|---|---|
| **Dog** | 0.798360 | 0.753548 | 0.848837 | 688 |
| **Bird** | 0.833253 | 0.779676 | 0.894737 | 969 |
| **Stove** | 0.855153 | 0.937405 | 0.786172 | 781 |
| **Car** | 0.829412 | 0.923581 | 0.752669 | 562 |

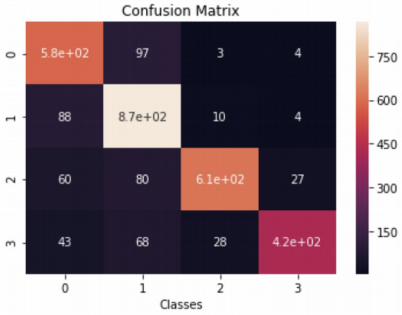



*Illustration 33: Train Set Metrics*

Out[143]:

Accuracy: 61.78623718887262%

| | F-Beta | Precision | Recall | Support |
|---|---|---|---|---|
| **Dog** | 0.634271 | 0.582160 | 0.696629 | 178 |
| **Bird** | 0.566416 | 0.627778 | 0.515982 | 219 |
| **Stove** | 0.660661 | 0.662651 | 0.658683 | 167 |
| **Car** | 0.617284 | 0.604839 | 0.630252 | 119 |

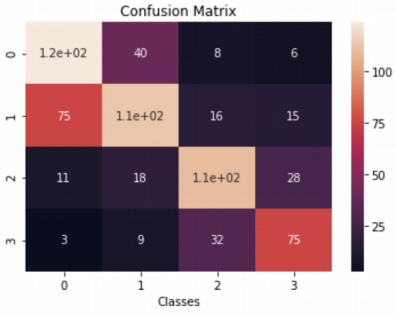



*Illustration 34: Test Set Gray Metrics*

Out[167]:

Accuracy: 59.5900439238653%

| | F-Beta | Precision | Recall | Support |
|---|---|---|---|---|
| **Dog** | 0.489028 | 0.553191 | 0.438202 | 178 |
| **Bird** | 0.625551 | 0.604255 | 0.648402 | 219 |
| **Stove** | 0.658610 | 0.664634 | 0.652695 | 167 |
| **Car** | 0.595420 | 0.545455 | 0.655462 | 119 |

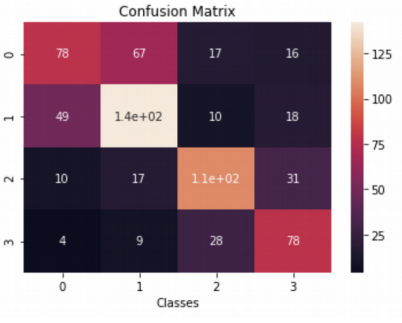



*Illustration 32: Test Set Equalized Metrics*

# 10 RESULTS

The summary statistics of all models are shown in the table below. Converting to grayscale did significantly speed up training while saving space – both hard disk and RAM. The increase of speed came at about 10% accuracy decrease on the test set. This isn't terrible considering 2/3 of the information in each image is condensed into a single array of pixel intensities

| Model | Training Examples | Test Examples | Epochs | Training Time (hours) | Seconds per Epoch | Train Accuracy (%) | Test Accuracy (%) |
|---|---|---|---|---|---|---|---|
| RGB | 3866 | 683 | 300 | 6.3 | 75.6 | 96 | 72 |
| Grayscale | 3866 | 683 | 500 | 5.1 | 36.7 | 99.9% | 60 |
| Equalized | 7732 | 1366 | 229 | 4.8 | 75.5 | 97% | 62 |

## 10.1 EXTRA CONSIDERATIONS

- Due to the time expense of running each model, not all possibilities were explored. In order to train a truly robust object detection algorithm, several thousands of training pictures are used. Even though the final model was trained using double the amount of training examples, intrinsically they were still the same images. This could be the reason for only a 2% increase in accuracy on the test set. Another model could be trained using more training images in order to explore this potential fault.
- Another point of control could be the random weight initialization. Initialization of weights has been a big topic of study in regards to CNNs and Deep Neural Networks. The starting weights can play a big role in overall performance of the model due to an early subject, vanishing and exploding gradients. Xavier initialization was utilized for all models, but the random seed generator was not kept constant. Xavier initialization is out of scope for this paper, but the original research paper can be read here. Essentially, although the same initializer was used, the same initial values themselves were not used model to model. This undoubtedly impacted the resultant of each training session.
- Touched on earlier, a point of focus is also the initial alteration of the original images themselves before being fed into the model. Each image was reshaped to a 300x300 image regardless of original size. This does have a negative impact of stretching, contorting, distorting and attenuating the resolution of the impending image. Spatial Pyramid Pooling would have alleviated this problem, but as stated earlier, this method was not implemented in order to keep the complexity to a minimum of the study.
- Finally, model architecture plays a big role as well. There are several famous model blueprints that have returned exceptional performance. These structures however require a vast amount of computing power. Some of these model structures and their respective papers are:

- AlexNet - ImageNet Classification with Deep Convolutional Neural Networks
- VGG Net - VERY DEEP CONVOLUTIONAL NETWORKS FOR LARGE-SCALE IMAGE RECOGNITION
- GoogleNet - Going Deeper with Convolutions
- Microsoft ResNets - Deep Residual Learning for Image Recognition
- And several others

# APPENDIX A – Data Processing Class

```
class load_training_data():
    def __init__(self,directory = '/home/scott/Pictures/Training Pictures/'):

        print('Navigating to Directory and Compiling Images')

        #Initialize some empty variables
        self.i = 0
        self.training_data_paths = []
        self.training_labels = []
        self.X_train = None
        self.X_test = None
        self.y_train = None
        self.y_test = None


        try:
            #Change to the directory with the images
            os.chdir(directory)
            #Make a list of all the subdirectories of different picture types
            self.sub_directories = os.listdir()
        except Exception as e:
            print(e)
            print('Please Enter a Valid Directory')



        for pos, d in enumerate(self.sub_directories):
            #Make a list of all the image names in the current sub directory
            images = os.listdir(d)
            #Create a list of full path names for every image in the current sub directory
            self.training_data_paths.extend([os.path.join(directory, d+'/'+img) for img in images])
            #Encode the target label for the current picture type
            #Dogs = (1,0,0,0) | Birds = (0,1,0,0) | Stove = (0,0,1,0) | Cars = (0,0,0,1)
            encoding = np.zeros(len(self.sub_directories))
            encoding[pos] = 1
            #Extend the list of one hot encoded training labels
            self.training_labels.extend([encoding]*len(os.listdir(d)))



        try:
            #Assert that the total number one hot encoded target labels equals the total of training examples
            assert len(self.training_data_paths) == len(self.training_labels)
        except AssertionError:
            raise(AssertionError( 'Number of Trainining Examples m = {} Does Not Match Number of Training Labels (m) = {}'.format(len(self.traini
        print('Finished Compiling Images')



    def process_images(self):
        training_images = []

        print('\nProcessing Images into n-Dimensional Arrays')
        print('-----------------------------------------------')
        #Create a list of the 3-dimensional numpy array of pixel values for each image
        training_images.extend(cv2.cvtColor(cv2.imread(path),cv2.COLOR_BGR2RGB) for path in self.training_data_paths)
        #Delete unncessary variables for RAM allocation control
        del self.training_data_paths

        #Show the average height and width in pixels of all images in the training data
        height = np.mean([d.shape[0] for d in training_images])
        width = np.mean([d.shape[1] for d in training_images])
        print('\naverage image height is',height)
        print('average image width is', width)
        #Delete unncessary variables for RAM allocation control
        del height
        del width

        print('\nreshaping images to 300x300x3')
        print('-----------------------------------------------')
        #Reshape all images to 300x300x3
        training_images_reshaped = [cv2.resize(img, (300,300), interpolation = cv2.INTER_AREA) for img in training_images]
        #Delete unncessary variables for RAM allocation control
        del training_images

        print('\nCreating {} x 300 x 300 x 3 array'.format(len(self.training_labels)))
        print('-----------------------------------------------')
        #Create a m X 300 X 300 X 3 array of all training data --> m being the total number of all pics
        tensor_data = np.vstack([img for img in training_images_reshaped]).reshape(len(self.training_labels),300,300,3)
        #Create a m X 1 X 4 array of all training labels
        self.training_labels = np.vstack([label for label in self.training_labels]).reshape(len(self.training_labels),1,len(self.sub_directories)
        #Delete unncessary variables for RAM allocation control
        del training_images_reshaped

        print('\nExecuting Train Test Split')
        print('-----------------------------------------------')
        #Create Train Test Splits
        self.X_train, self.X_test, self.y_train, self.y_test = train_test_split(tensor_data, self.training_labels, test_size = 0.15, random_state
        print('\nDone Creating Training and Testing Data at 85/15 Split!')
        #Delete unncessary variables for RAM allocation control
        del self.training_labels

        return self

    def next_batch(self, batch_size):
        #Method for batch feeding into model if RAM capacity is sufficient to load data all at once
        x = self.X_train[self.i:self.i+ batch_size]
        y = self.y_train[self.i:self.i+ batch_size]
        self.i = (self.i + batch_size) % len(self.X_train)
        return x,y

    def write_h5(self):
        print('\nWriting data to HDF5')
        print('-----------------------------------------------')
        # Method to write transformed data to hdf5
        hf = h5py.File('data.h5', 'w')

        hf.create_dataset('X_train', data=np.divide(self.X_train,255))
        hf.create_dataset('X_grayscale_train', data = np.expand_dims(np.array([cv2.cvtColor(x, cv2.COLOR_RGB2GRAY) for x in self.X_train]), axis
        hf.create_dataset('X_test', data=np.divide(self.X_test,255))
        hf.create_dataset('X_grayscale_test', data = np.expand_dims(np.array([cv2.cvtColor(x, cv2.COLOR_RGB2GRAY) for x in self.X_test]), axis =1
        hf.create_dataset('y_train', data=self.y_train)
        hf.create_dataset('y_test', data=self.y_test)
        hf.close()
        print('\nFinished Writing h5 in {}'.format(os.getcwd()))
```

# APPENDIX B – RGB Tensorflow Class

```
class cnnModel:
    def __init__(self, savefile=None, weight_initializer = tf.contrib.layers.xavier_initializer(seed =0), learning_rate=0.01, beta = 0.01):

        #Create save file path variable
        self.savefile = savefile
        #Reset any current graphs
        tf.reset_default_graph()
        #Set Random Seed
        np.random.seed(0)

        #Print Useful Model Information
        print('Creating CNN Graph')
        print('Tensorboard Log files stored in ./tf_logs/RGB/')
        print('To Activate Tensorboard Session: $tensorboard --logdir "./tf_logs/RGB/" --port 6006')
        print('Optimizer Learning Rate: {}'.format(learning_rate))
        print('L2 Regularization Constant: {}'.format(beta))

        if savefile is not None:
            print('Model Save Directory: {}\n'.format(os.path.join(os.getcwd(),savefile)))
        else:
            print('WARNING: No save directory - Model and Weights will be lost after training\n')


        #Placeholders
        self.inputs = tf.cast(tf.placeholder(dtype = tf.float64, shape = [None, 300,300,3], name = 'X'), tf.float32)
        self.labels = tf.cast(tf.placeholder(dtype = tf.float64, shape = [None,4], name = 'y'), tf.float32)
        self.hold_prob = tf.placeholder(tf.float32)

        #Convolutional Layer #1
        with tf.name_scope('Convolution_layer_1'):
            self.W1 = tf.get_variable(dtype = tf.float32, name = 'W1', shape = [7,7,3,10], initializer=weight_initializer)
            self.b1 = tf.Variable(tf.constant(0.1, shape = [10]))
            self.C1 = tf.nn.conv2d(input = self.inputs, filter=self.W1, strides = [1,2,2,1], padding='SAME', name = 'C1')
            self.A1 = tf.nn.relu(features = self.C1, name = 'A1') + self.b1
            self.P1 = tf.nn.max_pool(self.A1, ksize = [1,2,2,1], padding = 'VALID', strides = [1,2,2,1], name = 'Pool_1')

        #Convolutional Layer #2
        with tf.name_scope('Convolution_layer_2'):
            self.W2 = tf.get_variable(dtype = tf.float32, name = 'W2', shape = [4,4,self.P1.shape[3],10], initializer=weight_initializer)
            self.b2 = tf.Variable(tf.constant(0.1, shape = [10]))
            self.C2 = tf.nn.conv2d(input = self.P1, filter = self.W2, strides = [1,2,2,1], padding = 'SAME', name = 'C2')
            self.A2 = tf.nn.relu(features = self.C2 , name = 'A2') + self.b2

        #Convolutional Layer #3
        with tf.name_scope('Convolution_layer_3'):
            self.W3 = tf.get_variable(dtype = tf.float32, name = 'W3', shape = [3,3,self.A2.shape[3],20], initializer=weight_initializer)
            self.b3 = tf.Variable(tf.constant(0.1, shape = [20]))
            self.C3 = tf.nn.conv2d(input = self.A2, filter = self.W3, strides = [1,3,3,1], padding = 'SAME', name = 'C3')
            self.A3 = tf.nn.relu(features = self.C3, name = 'A3') + self.b3
            self.P3 = tf.nn.max_pool(value = self.A3, ksize = [1,2,2,1], padding = 'VALID', strides = [1,2,2,1], name = 'Pool_3')

        #Fully Connected Layer
        with tf.name_scope('Fully_connected_layer'):
            self.flatten = tf.contrib.layers.flatten(self.P3)
            self.Z1 = tf.contrib.layers.fully_connected(self.flatten, num_outputs = 4, activation_fn = None)
            self.hold_out_fc = tf.nn.dropout(self.Z1, keep_prob = self.hold_prob)

        #Prediction Operation
        with tf.name_scope('Prediction_Op'):
            self.predictions = tf.argmax(tf.nn.softmax(logits = self.hold_out_fc), 1)
            self.correct_prediction = tf.equal(self.predictions, tf.argmax(self.labels, 1))
            self.accuracy = tf.reduce_mean(tf.cast(self.correct_prediction, "float"))

        #Training Operation
        with tf.name_scope('Training_Op'):
            self.regularizers = tf.nn.l2_loss(self.W1) + tf.nn.l2_loss(self.W2) + tf.nn.l2_loss(self.W3)
            self.loss = tf.reduce_mean(tf.nn.softmax_cross_entropy_with_logits_v2(logits = self.Z1, labels = self.labels))
            self.cost = tf.reduce_mean(self.loss + (beta * self.regularizers))
            self.optimizer = tf.train.AdamOptimizer(learning_rate=learning_rate).minimize(self.cost)

        #Gloabal Variables Initializer
        with tf.name_scope('Initializers'):
            self.init = tf.global_variables_initializer()
            self.saver = tf.train.Saver(max_to_keep=500, filename='Step_number')

    def fit(self,x,y, num_epochs = 100, batch_size = 50):
        print('********* TRAINING MODEL *********')
        #Get total number of batches from input size
        num_of_batches = int(x.shape[0] / batch_size)
        #Initialize some needed variables
        prev_cost = 0
        cost_tracker = 0
        #Initialize an extra summary writer
        cost_summary_2 = tf.summary.scalar('Cost_2', self.cost)
        accuracy_summary_2 = tf.summary.scalar('Accuracy_2', self.accuracy)

        #Run the graph
        with tf.Session() as sess:
            #Initialize all Global Variables
            sess.run(self.init)

            #Initialize log writer for Tensorboard
            writer = tf.summary.FileWriter('tf_logs/RGB/', sess.graph)
            for i in range(num_epochs):
                #Initialize useful variables
                cost = 0
                batch_start = 0

                for j in range(num_of_batches):
                    #Train the model and track cost
                    _,c = sess.run([self.optimizer,self.cost], feed_dict={
                                                            self.inputs:x[batch_start:batch_start + batch_size],
                                                            self.labels:y[batch_start:batch_start + batch_size],
                                                            self.hold_prob:0.5
                                                            })

                    batch_start+=batch_size
                    cost+=c

                #Check for flat cost values over each iteration
                if np.absolute(cost - prev_cost) <= 0.001:
                    print('Cost has reached floor value @ {} - Terminate learning on Epoch {}'.format(cost,i))
                    break

                #Check for increasing cost values over each iteration
                if cost > prev_cost:
                    cost_tracker += 1
                    prev_cost = cost
                    if cost_tracker == 20:
                        self.saver.save(sess, self.savefile,global_step=i)

                        #write log files for tensorboard
                        summary = sess.run(self.merged_summaries, feed_dict = {self.inputs:x, self.labels:y, self.hold_prob:1})
                        writer.add_summary(summary, i)
                        print("Cost has increased 20 Epochs in a row - Terminate learning on Epoch {} with cost value {}".format(i,cost))
                        break
                else:
                    prev_cost = cost
                    cost_tracker = 0

                #Every 10 epochs print cost and write tensorboard logs
                if i%10 == 0:
                    #print the cost
                    print('Cost For Epoch {}: {}'.format(i,cost))

                    #save a checkpoint of the model
                    self.saver.save(sess, self.savefile,global_step=i)

                    #write log files for tensorboard
                    summary = sess.run(self.merged_summaries, feed_dict = {self.inputs:x[:1933], self.labels:y[:1933], self.hold_prob:1})
                    cost_2, accuracy_2 = sess.run([cost_summary_2,accuracy_summary_2], feed_dict = {self.inputs:x[1933:], self.labels:y[1933:], self.hold_prob:1})
                    writer.add_summary(summary, i)
                    writer.add_summary(cost_2,i)
                    writer.add_summary(accuracy_2,i)

    def predict(self, x):
        with tf.Session() as sess:
            #Restore last saved model checkpoint
            self.saver.restore(sess, self.savefile)
            #Run feed forward part of the graph for predictions
            preds, w1, w2, w3 = sess.run([self.predictions,self.W1, self.W2, self.W3], feed_dict = {self.inputs:x, self.hold_prob:1})
            results = {'predictions':preds, 'w1':w1, 'w2':w2, 'w3':w3}
            return results
```