Deep Learning Food Classifier

Capstone Project

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Definition

Project Overview

Millions of images are uploaded to the internet daily and with the explosion of accessible data one problem still remains to be solved confidently by any of the major companies. The problem is image classification and despite a growing number of companies providing this service the accuracy of the services are overall still no match for the human eye.

Deep learning is a subset of machine learning techniques that are based on feature learning and in recent years have been used heavily in the machine learning industry including image classification. This is a series of techniques that extract useful representations from datasets and is often heard with neural networks which is a model which loosely represents the neurons within the human brain. A neural network consists of a series of connected nodes which each takes a weighted input and produces an output. The accuracy of the neural network is improved by updating its weights during training through a technique known as backpropagation.

Although neural networks such as multi layered perceptrons have had success in the past with image classifications, they suffer from a major problem with considering the spatial structure of the data. Hence, pixels that are close to each in the image have the same relevance as pixels far away.

Convolutional neural networks solves these problems by using a 3D representations of the image rather than a one dimensional input that MLPs take. The representation would consists of channels (in image recognition this could be the 3 colours: red, green and blue) and each channel would be a 2D matrix. The channels are passed through different types of hidden layers before the final fully connected layer which produces the final result for the classification, an example would be softmax. Hidden layers such as pooling layers takes a convolutional layer as input and can be used to reduce the size of the dataset to avoid overfitting and the computational complexity of the CNN. Examples include AlexNet[1],

[1] AlexNet winner of ILSVRC 2012, used 8 layers

ResNET[2] and VGG[3], which are used in competitions such as the Large Scale Visual Recognition Challenge (ILSVRC).

Hence the objective of the project is to build a neural network that can classify food from images into specific labels. After researching different datasets that were free to use for academic purposes on the internet, I have chosen the UECFOOD-256 dataset. The dataset was chosen because the training set had labels which will solve the problem discussed and included foods that I feel the normal person would be familiar with. Other datasets I've looked into were Food-5K and Food-11[4] but the number of labels and training data was much smaller.

The target of the project is to create a convolutional neural network that can obtain a top 5 accuracy rate of 50% which it comes to classifying food.

Problem Statement

Modern smartphones have lead to an explosion of images on the internet. In recent years the number of photos uploaded to social media sites have grown exponentially to the rate where millions are now uploaded daily onto the internet. The increase in data however brings new challenges to the users and companies.

Organising and search images have become more challenging as photos are lost in a mess of unstructured data dumps on the net, images unlike documents cannot be searched without meta data. Social media and photo sharing companies have allowed users to manually tag or label photos but this process is usually tedious and laborious, a more automated solution was needed.

Whilst the scope of image classification is vast, I will be focusing on one particular use case and that is the classification of food. A significant proportion of images being uploaded are food and in particular photos of people's lunches. However, users are still having to add tags or labels manually to describe their dish. If this problem can be solved, users on sites such as Instagram would no longer have to hashtag their dish manually and business could also utilize this service to provide all sorts of applications for customers. For example, imagine an app that could tell you what recipes you can cook from a photo of your ingredients!

Our goal is to construct a model that can take a raw image of food and classify it against one of the 256 labels we have in the dataset. Prior to constructing the model we perform a cross validation split on the dataset in training, validation and test data. Afterwards we will use the Keras ImageDataGenerator to perform augmentation on the images before passing the training data to our CNN.

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[2] ResNET winner of ILSVRC 2015, used 152 layers
[3] VGG used 19 layers
[4] https://mmspg.epfl.ch/food-image-datasets

The CNN comprises of 2D convolutional layers, dropout layers and pooling layers to extract features, preventing overfitting and reduce the spatial dimensions of the data as it flows through the network. Once at the dense layer we apply a transformation on the dataset and perform the softmax function which assign a probability to each of the labels. Top 1 and top 5 accuracy will be calculated to determine the success of the model once it has been trained.

Metrics

In our model we use the default setting for the accuracy metrics in Keras. As a result keras will use categorical accuracy as it will, by default, detect the output shape of the model and realise we are performing a classification. As a result, our training and validation targets need to be one hot encoded. Other metrics that Keras can offer are binary accuracy (determines if the input is considered correct or incorrect) and sparse categorical accuracy (in which case our targets will not be one hot encoded).

Once the models are trained against the validation set they will run against the isolated test results. For each test data, the model will return an array of numbers. Each index corresponds to the label within our dataset and the value within the index represents the likelihood of being the correct result. For example, if we had three labels and the result from a prediction was [0,0.1,0.9] then the model is 90% certain label 3 is the correct result.

Success is measured using with the classifier being able to determine the top 1 and top 5 scores. A top 1 score is the percentage of outcomes when the top class (i.e. the predicted label with the highest probability) matches the target label. A top 5 score is the same but one of the top 5 predicted labels with the highest probabilities matches the target label. The results will be displayed further on in a confusion matrix.

Analysis

Data Exploration

The model is performing supervised learning to classify images into specific labels using a convolutional neural network. In order to train the model weights, we need to obtain a set of images and labels as the input. CNNs will require a suitable number of images to create enough filters to provide accurate results, given the problem at hand which is to classify foods into categories we will need thousands of images to reach our target of 50% top 5 accuracy. Datasets needs to be clean i.e. the training image needs to match up with the label and then able to be processed into the correct input size and shape for the CNN. This would include transforming the image to a square and potentially reduce the resolution to improve training times (but not too much that it'll affect performance).

The dataset I have chosen is UECFOOD-256[5] which was used for research in The University of Electro-Communication in Tokyo and is free to use for non-commercial activities. The dataset has 256 labels for different kinds of dishes. Our pre-processing step should include image re-sizing as the current data vary from 200 to 900 pixels for both the height and width. All images have colour layers which allow us to add extra channels to our CNN.

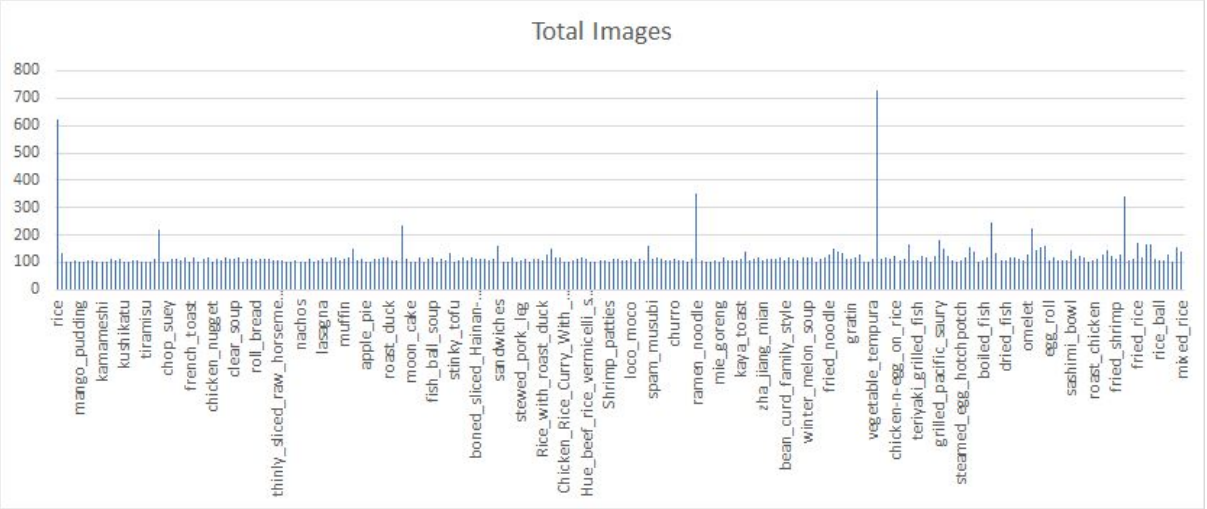
If the model becomes accurate, we could potentially add more categories and data to the training set to classify more dishes. The dataset contains exactly 31,651 images, which should hopefully be enough to train a suitable model and reach the performance target.

Exploratory Visualization

The model is performing supervised learning to classify images into specific labels using a convolutional neural network. In order to train the model weights, we need to obtain a set of images and labels as the input. CNNs will require a suitable number of images to create enough filters to provide accurate results, given the problem at hand which is to classify foods into categories we will need thousands of images to reach our target of 50% accuracy. Datasets needs to be clean i.e. the training image needs to match up with the label and then able to be processed into the correct input size and shape for the CNN. This would include transforming the image to a square and potentially reduce the resolution to improve training times (but not too much that it'll affect performance).

The UECFOOD-256[6] dataset has 256 labels and the training data is distributed almost evenly across the datasets (with approximately 130-180 images per folder) with the exception of two labels that have an abnormally larger dataset. The largest 2 labels have 728 (miso soup) and 20 (rice) which is far larger than the mean number of 122 of images per label. Our pre-processing step should include image re-sizing as the current data vary from 200 to 900 pixels for both the height and width. All images have colour layers which allow us to add extra channels to our CNN. The dataset contains exactly 31,651 images, and although some of the labels have a bigger training set than others, most are have a dataset close to the mean and median size.

[5] http://foodcam.mobi/dataset256.html
[6] http://foodcam.mobi/dataset256.html



Algorithms and Techniques

In the last decade the rise of available data and increased computing power lead to companies investing in machine learning. These techniques allowed companies to perform analysis on large amounts data that would otherwise be impossible to do manually, one of which was called deep learning.

Deep learning is a series of techniques which extracted features from datasets to solve problems such as classification, optimisation or decision making. The term deep learning refers to the layout of the model which includes an input layer, multiple hidden layers and a final activation layer. The more hidden layers that a model has, the deeper it is going to extract features. Each layer consists of a series of nodes which resembles the neurons within a brain and hence the name neural network.

Convolutional neural networks

Convolutional neural networks (CNN) were specifically designed to extract features from images. Unlike multi layered perceptrons in other neural networks, CNN takes a multi dimensional input thus allowing it to extract features with spatial awareness. The input can also be comprised of multiple channels which can be used to represent colours e.g. red, green blue.

After the input layer, the model consists of the hidden layer(s) and the activation layer. The hidden layers comprises of convolutional layers which extract features from the previous layer and pooling layers which compresses the data from the previous layer. Both uses a sliding frame for the calculations and there are options to pad the data if the frame goes beyond the bounds of the input.

The data flows through the model, calculating the weights of the nodes as it reaches to the activation layer which produces the final result. Once the result is produced, the margin of error is calculated and fed backwards in a technique known as back propagation. The

weights of the nodes are updated in the process and the margin of error reduced, several iterations are performed until the weights do not change any more.

When training our model it is important follow the cross validation process. Cross validation enables us to split the dataset into three parts: training data, validation data and testing data. During the training process training data is used as input to train the model whilst the validation dataset is used to calculate the accuracy of the model in each iteration. Testing data is kept separate from the training process and used to calculate the final accuracy of the model.

Convolutional layers will use the ReLU activation function to avoid the vanishing gradient problem because it's gradient is always 1 when positive. It has a performance boost[7] when handling negative values (negative values are represented as 0) which makes calculations much simpler. The padding for the sliding window will be 'same' which automatically pads the window if it reaches the edge of the image rather than discarding the information, thus reduce data loss.

The model will be compiled with RMSprop as the optimizer which adjusts the rate decay with the change in the gradient as it approaches the optimum. Categorial entropy loss will be used as the loss function which is more performant for back propagation over means squared error.

Transfer Learning

If the accuracy of the results are below the target specified earlier, transfer learning will be used for feature extraction from a well known CNN. This will require the weights of an existing CNN to be loaded before applying my model as the final layers. The weights of the exiting CNN will be frozen as the my model is training.

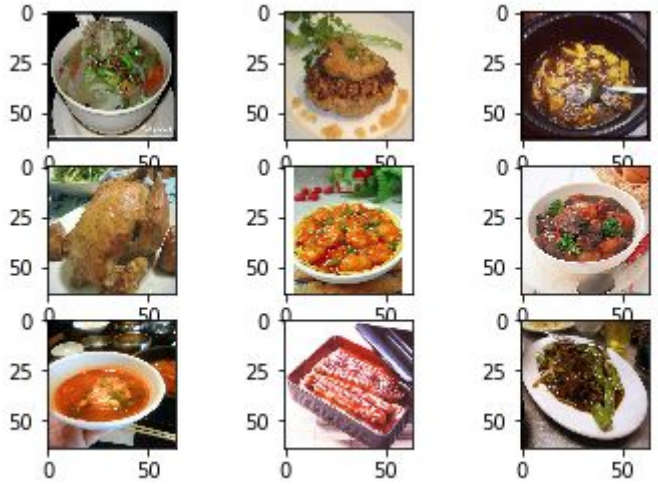
After training and running the model a few times, there's the option to fine tune individual layers of the base model. This would involve looking at each individual layers and deciding which ones to unfreeze or even remove from the model. This step will be out of scope for this project.

Data Augmentation

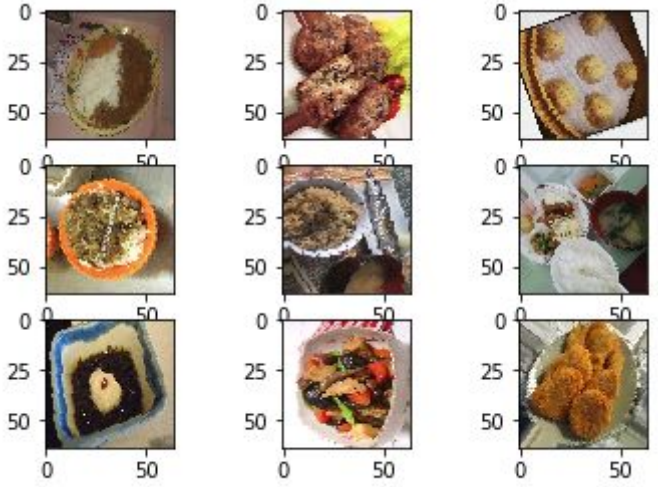
Data is the key component to the success of any deep learning classifier and data augmentation is a technique that allows us to build models with little data. The image augmentation process involves taking the existing training data and making copies of it after applying a series of transformations on it. This helps generalize the existing training set and the extra data helps prevent overfitting in the model. Here are examples of the augmentation process on our training data:

[7] AlexNet uses ReLU which reaches the 25% training error rate ten times faster than tanh neurons

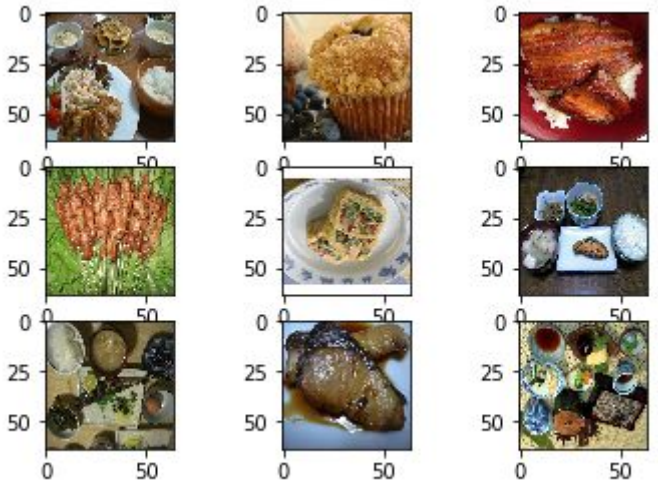
No Augmentation



Random Rotations



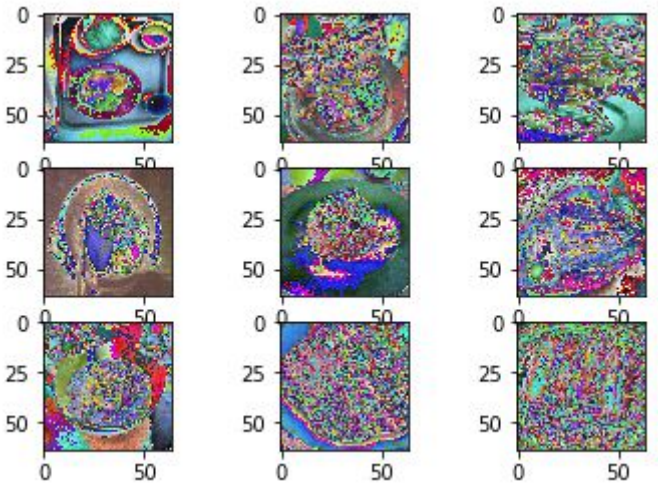
Random Flips



Random Shifts

Feature Standardization

This is applied to ensure they have the properties of a standard normal distribution of mean 0 and standard deviation of 1. This is important to ensure the data is not affine transformed invariant i.e. there's no linear function that can transform one image onto another.



ZCA Whitening

The ZCA whitening process is applied to reduce redundancies in the data and find features that strong differentiators for the classification process. Hence data that are highly correlated with each other will be merged together (in PCA this will be an eigenvector). In this project we will choose to use ZCA over PCA as it retains the spatial qualities of the original image during the whitening[8].

Benchmark

Data Preprocessing

UECFOOD-256[9] was used for research in The University of Electro-Communication in Tokyo and is free to use for non-commercial activities. The dataset has 256 labels for different kinds of dishes and each folder contains the images corresponding to the numerical value of the label. For example, folder 1 corresponds to rice.

The mapping between numbers and labels were stored in a text file on one line which had to be manually edited to be comma delimited. Once properly formatted, the labels can be read by pandas.

Cross validation was performed on the images to split into training (70%), validation (20%) and testing (10%) sets. This was performed using the sklearn libraries and running the cross validation function twice. The images were then transferred to the sub folders train, valid, test within food-images.

Model Design and Tuning Strategy

During the project I wish to experiment with the following parameters to see which makes a positive effect on the test results:

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[8] Learning Multiple Layers of Features from Tiny Images

[9] http://foodcam.mobi/dataset256.html

- Image size
- Number of hidden layers
- Image augmentation with random shifts, rotations, normalization
- ZCA Whitening
- Dropouts
- Nodes per layer

In the project I will start with implementing the benchmark design which will be a simple CNN with one convolutional layer and one pooling layer with images resized to 64 pixels. I will then increase the number of hidden layers and note the effect on the results before increasing the number of pixels.

Afterwards I'll run the same tests with image augmentation, dropouts, zca and testing different layers/nodes to find which features are having a positive effect. Once I've found a model that provides the best results given the hardware limitations I shall proceed with transfer learning and note the results as well.

The models will have have a verbose level of 1, which will provide information regarding the training loss and accuracy and the validation loss and accuracy. An indication of overfitting will be a decreasing loss per epoch but also a decrease in validation accuracy.

Implementation

The project experiments are separated into three categories: basic classifiers without augmentation, classifiers with augmentation without normalization, classifiers with augmentation and normalization on training set and finally classifiers using transfer learning. The strategy is to continually improve our test results by running models that quick to train on our hardware first to get feedback before creating more complicated models that take longer to train.

Basic classifiers without image augmentation

These models are simplest of our experiments and aim to investigate the effect of the following properties on our test results:

- Pixel size
- Number of convolutional layers

Basic model

Our simplest model will be a simple CNN consisting of one convolutional layer and one pooling layer on a pixel size of 64.

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_1 (Conv2D)            (None, 64, 64, 16)        208
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 32, 32, 16)        0
_________________________________________________________________
global_average_pooling2d_1 ( (None, 16)                0
_________________________________________________________________
dense_1 (Dense)              (None, 256)               4352
=================================================================
Total params: 4,560.0
Trainable params: 4,560.0
Non-trainable params: 0.0
_________________________________________________________________
Pixel size 64, channels 3, number of conv layers 1, number of pool layers 1
Checkpoint at basic.pixel.64.conv.1.pool.1.hdf5
```

```
Epoch 4/5
Epoch 00003: val_loss improved from 5.43231 to 5.39899, saving model to saved_w
eights/basic.pixel.64.conv.1.pool.1.hdf5
35s - loss: 5.4181 - acc: 0.0234 - val_loss: 5.3990 - val_acc: 0.0243
Epoch 5/5
Epoch 00004: val_loss improved from 5.39899 to 5.35789, saving model to saved_w
eights/basic.pixel.64.conv.1.pool.1.hdf5
35s - loss: 5.3818 - acc: 0.0243 - val_loss: 5.3579 - val_acc: 0.0236
Top 1 test accuracy: 2.3598%
Top 5 test accuracy: 7.6310%
CPU times: user 7min 18s, sys: 1min 45s, total: 9min 4s
Wall time: 3min 4s
```

The logs show a constant decline on the training loss yet an increase on the validation accuracy (up to the 4th epoch). This is an encouraging indication that the model is not overfitting.

Benchmark model

In the next model I've kept the number of pixels the same but added another convolutional and pooling layer and this form the basic benchmark I use in the other experiments.

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_2 (Conv2D)            (None, 64, 64, 16)        208
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 32, 32, 16)        0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 32, 32, 32)        2080
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 16, 16, 32)        0
_________________________________________________________________
conv2d_4 (Conv2D)            (None, 16, 16, 64)        8256
_________________________________________________________________
max_pooling2d_4 (MaxPooling2 (None, 8, 8, 64)          0
_________________________________________________________________
global_average_pooling2d_2 ( (None, 64)                0
_________________________________________________________________
dense_2 (Dense)              (None, 256)               16640
=================================================================
Total params: 27,184.0
Trainable params: 27,184.0
Non-trainable params: 0.0
_________________________________________________________________
Pixel size 64, channels 3, number of conv layers 3, number of pool layers 3
```

```
Epoch 4/5
Epoch 00003: val_loss improved from 4.97392 to 4.91378, saving model to saved_w
eights/basic.pixel.64.conv.3.pool.3.hdf5
66s - loss: 4.9186 - acc: 0.0439 - val_loss: 4.9138 - val_acc: 0.0461
Epoch 5/5
Epoch 00004: val_loss improved from 4.91378 to 4.81903, saving model to saved_w
eights/basic.pixel.64.conv.3.pool.3.hdf5
66s - loss: 4.8207 - acc: 0.0524 - val_loss: 4.8190 - val_acc: 0.0529
Top 1 test accuracy: 5.6696%
Top 5 test accuracy: 16.6411%
CPU times: user 14min 55s, sys: 3min 30s, total: 18min 26s
Wall time: 5min 42s
```

Adding the extra layers have improved the top 1 accuracy to 5.67% which is a 3.31% from the previous model of 2.41%, top 5 also more than doubled in performance to 16.64%. The extra has helped the model extra more features from the images which improves the classification process.

Benchmark model using 128 pixels

For the next experiment I've kept the model the same and increased the pixel size of the image to 128 with the expectation that more detail would increase the classification process.

```
Epoch 4/5
Epoch 00003: val_loss improved from 4.67917 to 4.60851, saving model to saved_w
eights/basic.pixel.128.conv.3.pool.3.hdf5
119s - loss: 4.6439 - acc: 0.0490 - val_loss: 4.6085 - val_acc: 0.0501
Epoch 5/5
Epoch 00004: val_loss improved from 4.60851 to 4.56674, saving model to saved_w
eights/basic.pixel.128.conv.3.pool.3.hdf5
117s - loss: 4.5757 - acc: 0.0531 - val_loss: 4.5667 - val_acc: 0.0501
Top 1 test accuracy: 5.8262%
Top 5 test accuracy: 18.1471%
Wall time: 10min 26s
```

The results are encouraging with top1 accuracy of 5.83% and 18.14% for top 5, both of which were slightly better than the 64 pixel model. and was steadily improving with each epoch thus showing no signs of overfitting. This model might even improve further if we increased the number of epochs.

Benchmark model using 256 pixels

For the next experiment I shall increase the number of pixels to 256.

```
Epoch 3/5
Epoch 00002: val_loss improved from 4.82432 to 4.70545, saving model to saved_w
eights/basic.pixel.256.conv.3.pool.3.hdf5
456s - loss: 4.7429 - acc: 0.0422 - val_loss: 4.7054 - val_acc: 0.0416
Epoch 4/5
Epoch 00003: val_loss improved from 4.70545 to 4.66186, saving model to saved_w
eights/basic.pixel.256.conv.3.pool.3.hdf5
458s - loss: 4.6649 - acc: 0.0470 - val_loss: 4.6619 - val_acc: 0.0487
Epoch 5/5
Epoch 00004: val_loss improved from 4.66186 to 4.58268, saving model to saved_w
eights/basic.pixel.256.conv.3.pool.3.hdf5
456s - loss: 4.5996 - acc: 0.0525 - val_loss: 4.5827 - val_acc: 0.0525
Top 1 test accuracy: 6.1127%
Top 5 test accuracy: 17.5263%
Wall time: 39min 15s
```

A slight improvement to the top 1 accuracy and no signs of overfitting either after 5 epochs which suggests the model could continue training, However, since the training took 39 mins and over 35GB of memory and thus I've decided to not pursue experiments with pixel sizes greater than 128.

Classifiers with basic image augmentation

As discussion earlier in the project, image augmentation allows us to build more powerful classifiers by reusing our existing dataset in different ways. The ImageDataGenerator I used allows us to generate a larger dataset with using random rotations, flips and shifts on the existing training set. I've set the rotation range to 90 degrees and the flips and shifts parameter to 0.2 which I will keep consistent throughout the project.

Basic augmentation of 3 convolutional layers

The experiments started with the same benchmark mode of 3 convolutional layers.

```
Checkpoint at nozca.nostd.pixel.128.conv.3.pool.3.hdf5
Epoch 1/5
700/700 [==============================>.] - ETA: 0s - loss: 5.4835 - acc: 0.0227Epoch 00000: val_loss improved from inf to 5.419
84, saving model to saved_models/nozca.nostd.pixel.128.conv.3.pool.3.hdf5
701/700 [==============================] - 248s - loss: 5.4839 - acc: 0.0227 - val_loss: 5.4198 - val_acc: 0.0230
Epoch 2/5
700/700 [==============================>.] - ETA: 0s - loss: 5.3568 - acc: 0.0247Epoch 00001: val_loss improved from 5.41984 to
5.30336, saving model to saved_models/nozca.nostd.pixel.128.conv.3.pool.3.hdf5
701/700 [==============================] - 248s - loss: 5.3566 - acc: 0.0247 - val_loss: 5.3034 - val_acc: 0.0220
Epoch 3/5
700/700 [==============================>.] - ETA: 0s - loss: 5.2441 - acc: 0.0267Epoch 00002: val_loss improved from 5.30336 to
5.30116, saving model to saved_models/nozca.nostd.pixel.128.conv.3.pool.3.hdf5
701/700 [==============================] - 248s - loss: 5.2431 - acc: 0.0266 - val_loss: 5.3012 - val_acc: 0.0284
Epoch 4/5
700/700 [==============================>.] - ETA: 0s - loss: 5.1607 - acc: 0.0313Epoch 00003: val_loss improved from 5.30116 to
5.25499, saving model to saved_models/nozca.nostd.pixel.128.conv.3.pool.3.hdf5
701/700 [==============================] - 249s - loss: 5.1616 - acc: 0.0313 - val_loss: 5.2550 - val_acc: 0.0267
Epoch 5/5
700/700 [==============================>.] - ETA: 0s - loss: 5.0813 - acc: 0.0344Epoch 00004: val_loss improved from 5.25499 to
5.05010, saving model to saved_models/nozca.nostd.pixel.128.conv.3.pool.3.hdf5
701/700 [==============================] - 248s - loss: 5.0825 - acc: 0.0344 - val_loss: 5.0501 - val_acc: 0.0333

CPU times: user 1h 6min 8s, sys: 7min 47s, total: 1h 13min 56s
Wall time: 20min 57s
```

The results are very promising with a steady increase with validation accuracy after each epoch. The top 1 accuracy of 3.89% is lower than our basic model with image augmentation, however, I believed we could push the results higher using dropouts of 0.5.

Basic augmentation of 3 convolutional layers with 0.5 dropouts

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_4 (Conv2D)            (None, 128, 128, 16)      208
_________________________________________________________________
dropout_1 (Dropout)          (None, 128, 128, 16)      0
_________________________________________________________________
max_pooling2d_4 (MaxPooling2 (None, 64, 64, 16)        0
_________________________________________________________________
conv2d_5 (Conv2D)            (None, 64, 64, 32)        2080
_________________________________________________________________
dropout_2 (Dropout)          (None, 64, 64, 32)        0
_________________________________________________________________
max_pooling2d_5 (MaxPooling2 (None, 32, 32, 32)        0
_________________________________________________________________
conv2d_6 (Conv2D)            (None, 32, 32, 64)        8256
_________________________________________________________________
dropout_3 (Dropout)          (None, 32, 32, 64)        0
_________________________________________________________________
max_pooling2d_6 (MaxPooling2 (None, 16, 16, 64)        0
_________________________________________________________________
global_average_pooling2d_2 ( (None, 64)                0
_________________________________________________________________
dense_2 (Dense)              (None, 256)               16640
=================================================================
Total params: 27,184.0
Trainable params: 27,184.0
Non-trainable params: 0.0
_________________________________________________________________
Pixel size 128, channels 3, number of conv layers 3, number of pool layers 3
Checkpoint at nozca.nostd.dropouts.pixel.128.conv.3.pool.3.hdf5
```

```
Epoch 3/5
700/700 [==============================>.] - ETA: 0s - loss: 5.1011 - acc: 0.0358
Epoch 00002: val_loss improved from 5.36983 to 5.30049, saving model to saved_m
odels/nozca.nostd.dropouts.pixel.128.conv.3.pool.3.hdf5
701/700 [==============================] - 361s - loss: 5.0997 - acc: 0.0357 -
val_loss: 5.3005 - val_acc: 0.0337
Epoch 4/5
700/700 [==============================>.] - ETA: 0s - loss: 4.9863 - acc: 0.0426
Epoch 00003: val_loss improved from 5.30049 to 5.26305, saving model to saved_m
odels/nozca.nostd.dropouts.pixel.128.conv.3.pool.3.hdf5
701/700 [==============================] - 362s - loss: 4.9841 - acc: 0.0433 -
val_loss: 5.2630 - val_acc: 0.0304
Epoch 5/5
700/700 [==============================>.] - ETA: 0s - loss: 4.8923 - acc: 0.0488
Epoch 00004: val_loss improved from 5.26305 to 5.16554, saving model to saved_m
odels/nozca.nostd.dropouts.pixel.128.conv.3.pool.3.hdf5
701/700 [==============================] - 360s - loss: 4.8893 - acc: 0.0495 -
val_loss: 5.1655 - val_acc: 0.0316

CPU times: user 1h 29min 17s, sys: 19min 59s, total: 1h 49min 16s
Wall time: 30min 18s
```

Adding the dropouts lowered the overall top 1 accuracy of the model to 3.46% and top 5 to 11.77% which wasn't surprising considering the number of layers and epochs remained the same.

Basic augmentation of 3 convolutional layers with 0.3 dropouts and 10 epochs

For the next model I was less afraid of over fitting and increased the number of epochs to 10 whilst making the dropouts less extreme with a value of 0.3.

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_7 (Conv2D)            (None, 128, 128, 16)      208
_________________________________________________________________
dropout_4 (Dropout)          (None, 128, 128, 16)      0
_________________________________________________________________
max_pooling2d_7 (MaxPooling2 (None, 64, 64, 16)        0
_________________________________________________________________
conv2d_8 (Conv2D)            (None, 64, 64, 32)        2080
_________________________________________________________________
dropout_5 (Dropout)          (None, 64, 64, 32)        0
_________________________________________________________________
max_pooling2d_8 (MaxPooling2 (None, 32, 32, 32)        0
_________________________________________________________________
conv2d_9 (Conv2D)            (None, 32, 32, 64)        8256
_________________________________________________________________
dropout_6 (Dropout)          (None, 32, 32, 64)        0
_________________________________________________________________
max_pooling2d_9 (MaxPooling2 (None, 16, 16, 64)        0
_________________________________________________________________
global_average_pooling2d_3 ( (None, 64)                0
_________________________________________________________________
dense_3 (Dense)              (None, 256)               16640
=================================================================
Total params: 27,184.0
Trainable params: 27,184.0
Non-trainable params: 0.0
_________________________________________________________________
Pixel size 128, channels 3, number of conv layers 3, number of pool layers 3
Checkpoint at nozca.nostd.dropouts.10.epochs.pixel.128.conv.3.pool.3.hdf5
```

```
Epoch 7/10
700/700 [==============================>.] - ETA: 0s - loss: 4.8153 - acc: 0.0563Epoch 00006: val_loss improved from 5.07412 to
4.98084, saving model to saved_models/nozca.nostd.dropouts.10.epochs.pixel.128.conv.3.pool.3.hdf5
701/700 [==============================] - 363s - loss: 4.8152 - acc: 0.0563 - val_loss: 4.9808 - val_acc: 0.0527
Epoch 8/10
700/700 [==============================>.] - ETA: 0s - loss: 4.7559 - acc: 0.0594Epoch 00007: val_loss did not improve
701/700 [==============================] - 362s - loss: 4.7552 - acc: 0.0593 - val_loss: 5.0504 - val_acc: 0.0380
Epoch 9/10
700/700 [==============================>.] - ETA: 0s - loss: 4.6974 - acc: 0.0639Epoch 00008: val_loss improved from 4.98084 to
4.92358, saving model to saved_models/nozca.nostd.dropouts.10.epochs.pixel.128.conv.3.pool.3.hdf5
701/700 [==============================] - 362s - loss: 4.6983 - acc: 0.0638 - val_loss: 4.9236 - val_acc: 0.0508
Epoch 10/10
700/700 [==============================>.] - ETA: 0s - loss: 4.6495 - acc: 0.0675Epoch 00009: val_loss improved from 4.92358 to
4.86330, saving model to saved_models/nozca.nostd.dropouts.10.epochs.pixel.128.conv.3.pool.3.hdf5
701/700 [==============================] - 363s - loss: 4.6495 - acc: 0.0674 - val_loss: 4.8633 - val_acc: 0.0579

CPU times: user 2h 58min 42s, sys: 40min 59s, total: 3h 39min 42s
Wall time: 1h 55s
```

Our experiments finally hit pass the 5% milestone and ended with a top 1 accuracy of 5.33% and validation accuracy of 18.73%. The logs showed very positive signs that the model was performing well with a constant rise of validation accuracy and decreasing training accuracy. The models are taking longer to train and uses roughly 10GB of RAM during the training process (which is 20GB less than the data augmentation with normalization).

Basic augmentation of 4 convolutional layers with 0.3 dropouts and 10 epochs

With a dropout strategy that I was comfortable with, I increased the number of convolutional layers to 4.

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_14 (Conv2D)           (None, 128, 128, 32)      416
_________________________________________________________________
dropout_11 (Dropout)         (None, 128, 128, 32)      0
_________________________________________________________________
max_pooling2d_14 (MaxPooling (None, 64, 64, 32)        0
_________________________________________________________________
conv2d_15 (Conv2D)           (None, 64, 64, 64)        8256
_________________________________________________________________
dropout_12 (Dropout)         (None, 64, 64, 64)        0
_________________________________________________________________
max_pooling2d_15 (MaxPooling (None, 32, 32, 64)        0
_________________________________________________________________
conv2d_16 (Conv2D)           (None, 32, 32, 64)        16448
_________________________________________________________________
dropout_13 (Dropout)         (None, 32, 32, 64)        0
_________________________________________________________________
max_pooling2d_16 (MaxPooling (None, 16, 16, 64)        0
_________________________________________________________________
conv2d_17 (Conv2D)           (None, 16, 16, 128)       32896
_________________________________________________________________
dropout_14 (Dropout)         (None, 16, 16, 128)       0
_________________________________________________________________
max_pooling2d_17 (MaxPooling (None, 8, 8, 128)         0
_________________________________________________________________
global_average_pooling2d_5 ( (None, 128)               0
_________________________________________________________________
dense_5 (Dense)              (None, 256)               33024
=================================================================
Total params: 91,040.0
Trainable params: 91,040.0
Non-trainable params: 0.0
_________________________________________________________________
Pixel size 128, channels 3, number of conv layers 4, number of pool layers 4
Checkpoint at nozca.nostd.morenodes.dropouts.10.epochs.pixel.128.conv.4.pool.4.hdf5


Epoch 7/10
700/700 [==============================>.] - ETA: 0s - loss: 4.5333 - acc: 0.0804Epoch 00006: val_loss did not improve
701/700 [==============================] - 454s - loss: 4.5346 - acc: 0.0802 - val_loss: 5.0331 - val_acc: 0.0389
Epoch 8/10
700/700 [==============================>.] - ETA: 0s - loss: 4.4744 - acc: 0.0848Epoch 00007: val_loss improved from 4.98213 to
4.86061, saving model to saved_models/nozca.nostd.dropouts.10.epochs.pixel.128.conv.4.pool.4.hdf5
701/700 [==============================] - 455s - loss: 4.4759 - acc: 0.0847 - val_loss: 4.8606 - val_acc: 0.0654
Epoch 9/10
700/700 [==============================>.] - ETA: 0s - loss: 4.4092 - acc: 0.0947Epoch 00008: val_loss did not improve
701/700 [==============================] - 453s - loss: 4.4112 - acc: 0.0946 - val_loss: 5.0988 - val_acc: 0.0405
Epoch 10/10
700/700 [==============================>.] - ETA: 0s - loss: 4.3583 - acc: 0.0978Epoch 00009: val_loss improved from 4.86061 to
4.78247, saving model to saved_models/nozca.nostd.dropouts.10.epochs.pixel.128.conv.4.pool.4.hdf5
701/700 [==============================] - 446s - loss: 4.3595 - acc: 0.0977 - val_loss: 4.7825 - val_acc: 0.0623

CPU times: user 3h 20min 29s, sys: 1h 5min 18s, total: 4h 25min 47s
Wall time: 1h 14min 45s
```

The extra layer made a positive change to our top 1 and top 5 accuracies bringing them to 6.10% and 20.63%. The training time doubled with the extra complexity and for the next experiments I decided to vary the number of nodes.

Basic augmentation of 4 convolutional layers with 0.3 dropouts, more nodes and 10 epochs

For the next model, the number of layers were kept the same but the number of nodes were increased in the first layers.

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_14 (Conv2D)           (None, 128, 128, 32)      416
_________________________________________________________________
dropout_11 (Dropout)         (None, 128, 128, 32)      0
_________________________________________________________________
max_pooling2d_14 (MaxPooling (None, 64, 64, 32)        0
_________________________________________________________________
conv2d_15 (Conv2D)           (None, 64, 64, 64)        8256
_________________________________________________________________
dropout_12 (Dropout)         (None, 64, 64, 64)        0
_________________________________________________________________
max_pooling2d_15 (MaxPooling (None, 32, 32, 64)        0
_________________________________________________________________
conv2d_16 (Conv2D)           (None, 32, 32, 64)        16448
_________________________________________________________________
dropout_13 (Dropout)         (None, 32, 32, 64)        0
_________________________________________________________________
max_pooling2d_16 (MaxPooling (None, 16, 16, 64)        0
_________________________________________________________________
conv2d_17 (Conv2D)           (None, 16, 16, 128)       32896
_________________________________________________________________
dropout_14 (Dropout)         (None, 16, 16, 128)       0
_________________________________________________________________
max_pooling2d_17 (MaxPooling (None, 8, 8, 128)         0
_________________________________________________________________
global_average_pooling2d_5 ( (None, 128)               0
_________________________________________________________________
dense_5 (Dense)              (None, 256)               33024
=================================================================
Total params: 91,040.0
Trainable params: 91,040.0
Non-trainable params: 0.0
_________________________________________________________________
Pixel size 128, channels 3, number of conv layers 4, number of pool layers 4
Checkpoint at nozca.nostd.morenodes.dropouts.10.epochs.pixel.128.conv.4.pool.4.hdf5
```

```
Epoch 7/10
700/700 [==============================>.] - ETA: 0s - loss: 4.4428 - acc: 0.0901Epoch 00006: val_loss improved from 4.93847 to
4.72674, saving model to saved_models/nozca.nostd.morenodes.dropouts.10.epochs.pixel.128.conv.4.pool.4.hdf5
701/700 [==============================] - 781s - loss: 4.4435 - acc: 0.0900 - val_loss: 4.7267 - val_acc: 0.0803
Epoch 8/10
700/700 [==============================>.] - ETA: 0s - loss: 4.3655 - acc: 0.0992Epoch 00007: val_loss did not improve
701/700 [==============================] - 779s - loss: 4.3635 - acc: 0.0997 - val_loss: 4.7523 - val_acc: 0.0674
Epoch 9/10
700/700 [==============================>.] - ETA: 0s - loss: 4.3033 - acc: 0.1070Epoch 00008: val_loss did not improve
701/700 [==============================] - 773s - loss: 4.3021 - acc: 0.1069 - val_loss: 4.9446 - val_acc: 0.0520
Epoch 10/10
700/700 [==============================>.] - ETA: 0s - loss: 4.2313 - acc: 0.1154Epoch 00009: val_loss did not improve
701/700 [==============================] - 775s - loss: 4.2321 - acc: 0.1152 - val_loss: 4.8067 - val_acc: 0.0595

CPU times: user 6h 18min 20s, sys: 1h 45min 32s, total: 8h 3min 52s
Wall time: 2h 10min 32s
```

Increasing the number of nodes managed to boost the top 1 accuracy to 9.19% and top 5 accuracy to 25.62%. Validation accuracy did drop after the 7th epoch whilst the training accuracy continued to climb thus giving an indication of overfitting.

Image augmentation with normalization

Feature wise normalization and standardization are turned on to set the mean of the dataset to 0 and to divide the data by its standard deviation.

Augmentation with normalization of 3 convolutional layers

I started off with the simple 3 convolutional layer model:

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_1 (Conv2D)            (None, 128, 128, 16)      208
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 64, 64, 16)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 64, 64, 32)        2080
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 32, 32, 32)        0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 32, 32, 64)        8256
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 16, 16, 64)        0
_________________________________________________________________
global_average_pooling2d_1 ( (None, 64)                0
_________________________________________________________________
dense_1 (Dense)              (None, 256)               16640
=================================================================
Total params: 27,184.0
Trainable params: 27,184.0
Non-trainable params: 0.0
_________________________________________________________________
Pixel size 128, channels 3, number of conv layers 3, number of pool layers 3
Checkpoint at nozca.pixel.128.conv.3.pool.3.hdf5
```

```
Checkpoint at nozca.pixel.128.conv.3.pool.3.hdf5
Epoch 1/5
Epoch 00000: val_loss improved from inf to 4.90287, saving model to saved_weights/nozca.pixel.128.conv.3.pool.3.hdf5
129s - loss: 5.0285 - acc: 0.0346 - val_loss: 4.9029 - val_acc: 0.0356
Epoch 2/5
Epoch 00001: val_loss improved from 4.90287 to 4.86432, saving model to saved_weights/nozca.pixel.128.conv.3.pool.3.hdf5
129s - loss: 4.8326 - acc: 0.0369 - val_loss: 4.8643 - val_acc: 0.0405
Epoch 3/5
Epoch 00002: val_loss improved from 4.86432 to 4.63306, saving model to saved_weights/nozca.pixel.128.conv.3.pool.3.hdf5
130s - loss: 4.6988 - acc: 0.0450 - val_loss: 4.6331 - val_acc: 0.0422
Epoch 4/5
Epoch 00003: val_loss improved from 4.63306 to 4.51280, saving model to saved_weights/nozca.pixel.128.conv.3.pool.3.hdf5
128s - loss: 4.5676 - acc: 0.0544 - val_loss: 4.5128 - val_acc: 0.0585
Epoch 5/5
Epoch 00004: val_loss improved from 4.51280 to 4.49072, saving model to saved_weights/nozca.pixel.128.conv.3.pool.3.hdf5
128s - loss: 4.4689 - acc: 0.0656 - val_loss: 4.4907 - val_acc: 0.0604
Standardizing data
Top 1 test accuracy: 6.6380%
Standardizing data
Top 5 test accuracy: 14.8520%
Wall time: 11min 4s
```

There were no signs of overfitting and the accuracy results were 6.64% for top 1 accuracy and 14.85% for top 5 accuracy. These are better than the same model with basic augmentation which had a top 1 hit rate of 3.89% and a top 5 hit rate of 13.48%.

Augmentation with normalization of 3 convolutional layers with 0.5 dropouts

I decided to add dropout layers (with a setting of 0.5) to see the effect on our current models with the expectation of a reduction in overfitting. The number of epochs for the next set of experiments was increased to 10 to ensure we get the best set of weights possible.

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_1 (Conv2D)            (None, 128, 128, 16)      208
_________________________________________________________________
dropout_1 (Dropout)          (None, 128, 128, 16)      0
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 64, 64, 16)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 64, 64, 32)        2080
_________________________________________________________________
dropout_2 (Dropout)          (None, 64, 64, 32)        0
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 32, 32, 32)        0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 32, 32, 64)        8256
_________________________________________________________________
dropout_3 (Dropout)          (None, 32, 32, 64)        0
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 16, 16, 64)        0
_________________________________________________________________
global_average_pooling2d_1 ( (None, 64)                0
_________________________________________________________________
dense_1 (Dense)              (None, 256)               16640
=================================================================
Total params: 27,184.0
Trainable params: 27,184.0
Non-trainable params: 0.0
_________________________________________________________________
Pixel size 128, channels 3, number of conv layers 3, number of pool layers 3
Checkpoint at nozca.multi.nodes.dropout.10.epochs.pixel.128.conv.3.pool.3.hdf5
```

```
Checkpoint at nozca.multi.nodes.dropout.10.epochs.pixel.128.conv.3.pool.3.hdf5
Epoch 1/10
Epoch 00000: val_loss improved from inf to 5.04254, saving model to saved_weights/nozca.multi.nodes.dropout.10.epochs.pixel.12
8.conv.3.pool.3.hdf5
257s - loss: 5.0317 - acc: 0.0327 - val_loss: 5.0425 - val_acc: 0.0392
Epoch 2/10
Epoch 00001: val_loss improved from 5.04254 to 4.89634, saving model to saved_weights/nozca.multi.nodes.dropout.10.epochs.pixe
l.128.conv.3.pool.3.hdf5
249s - loss: 4.7243 - acc: 0.0460 - val_loss: 4.8963 - val_acc: 0.0427
Epoch 3/10
Epoch 00002: val_loss improved from 4.89634 to 4.83447, saving model to saved_weights/nozca.multi.nodes.dropout.10.epochs.pixe
l.128.conv.3.pool.3.hdf5
247s - loss: 4.5617 - acc: 0.0595 - val_loss: 4.8345 - val_acc: 0.0471
Epoch 4/10
Epoch 00003: val_loss improved from 4.83447 to 4.77578, saving model to saved_weights/nozca.multi.nodes.dropout.10.epochs.pixe
l.128.conv.3.pool.3.hdf5
249s - loss: 4.4439 - acc: 0.0722 - val_loss: 4.7758 - val_acc: 0.0484
Epoch 5/10
Epoch 00004: val_loss improved from 4.77578 to 4.74961, saving model to saved_weights/nozca.multi.nodes.dropout.10.epochs.pixe
l.128.conv.3.pool.3.hdf5
250s - loss: 4.3512 - acc: 0.0786 - val_loss: 4.7496 - val_acc: 0.0424
Epoch 6/10
Epoch 00005: val_loss improved from 4.74961 to 4.68993, saving model to saved_weights/nozca.multi.nodes.dropout.10.epochs.pixe
l.128.conv.3.pool.3.hdf5
245s - loss: 4.2814 - acc: 0.0869 - val_loss: 4.6899 - val_acc: 0.0751
Epoch 7/10
Epoch 00006: val_loss did not improve
249s - loss: 4.2334 - acc: 0.0909 - val_loss: 4.6929 - val_acc: 0.0533
Epoch 8/10
Epoch 00007: val_loss improved from 4.68993 to 4.64696, saving model to saved_weights/nozca.multi.nodes.dropout.10.epochs.pixe
l.128.conv.3.pool.3.hdf5
248s - loss: 4.1824 - acc: 0.0977 - val_loss: 4.6470 - val_acc: 0.0683
Epoch 9/10
Epoch 00008: val_loss improved from 4.64696 to 4.62042, saving model to saved_weights/nozca.multi.nodes.dropout.10.epochs.pixe
l.128.conv.3.pool.3.hdf5
248s - loss: 4.1418 - acc: 0.1054 - val_loss: 4.6204 - val_acc: 0.0721
Epoch 10/10
Epoch 00009: val_loss did not improve
247s - loss: 4.1093 - acc: 0.1079 - val_loss: 4.6371 - val_acc: 0.0653
Standardizing data
Top 1 test accuracy: 7.7841%
Standardizing data
Top 5 test accuracy: 14.1834%
Wall time: 41min 53s
```

Adding dropout layers and increase the number of epochs has improved the top 1 and top 5 accuracies to 7.78% and 14.18%. We can see from the logs that the best weights were calculated at epoch 6 which would've been missed had we kept the epoch limit to 5.

Augmentation with normalization of 4 convolutional layers

For next experiment we add another convolutional layer and remove the dropout layers:

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_1 (Conv2D)            (None, 128, 128, 16)      208
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 64, 64, 16)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 64, 64, 32)        2080
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 32, 32, 32)        0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 32, 32, 64)        8256
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 16, 16, 64)        0
_________________________________________________________________
conv2d_4 (Conv2D)            (None, 16, 16, 128)       32896
_________________________________________________________________
max_pooling2d_4 (MaxPooling2 (None, 8, 8, 128)         0
_________________________________________________________________
global_average_pooling2d_1 ( (None, 128)               0
_________________________________________________________________
dense_1 (Dense)              (None, 256)               33024
=================================================================
Total params: 76,464.0
Trainable params: 76,464.0
Non-trainable params: 0.0
_________________________________________________________________
Pixel size 128, channels 3, number of conv layers 4, number of pool layers 4
Checkpoint at nozca.10.epochs.pixel.128.conv.4.pool.4.hdf5
Checkpoint at nozca.10.epochs.pixel.128.conv.4.pool.4.hdf5
Epoch 1/10
Epoch 00000: val_loss improved from inf to 5.04271, saving model to saved_weights/nozca.10.epochs.pixel.128.conv.4.pool.4.hdf5
135s - loss: 5.0013 - acc: 0.0352 - val_loss: 5.0427 - val_acc: 0.0313
Epoch 2/10
Epoch 00001: val_loss improved from 5.04271 to 4.88181, saving model to saved_weights/nozca.10.epochs.pixel.128.conv.4.pool.4.h
df5
136s - loss: 4.7469 - acc: 0.0401 - val_loss: 4.8818 - val_acc: 0.0411
Epoch 3/10
Epoch 00002: val_loss improved from 4.88181 to 4.45437, saving model to saved_weights/nozca.10.epochs.pixel.128.conv.4.pool.4.h
df5
134s - loss: 4.5500 - acc: 0.0566 - val_loss: 4.4544 - val_acc: 0.0612
Epoch 4/10
Epoch 00003: val_loss did not improve
134s - loss: 4.4044 - acc: 0.0739 - val_loss: 4.5181 - val_acc: 0.0650
Epoch 5/10
Epoch 00004: val_loss improved from 4.45437 to 4.36447, saving model to saved_weights/nozca.10.epochs.pixel.128.conv.4.pool.4.h
df5
134s - loss: 4.2824 - acc: 0.0865 - val_loss: 4.3645 - val_acc: 0.0871
Epoch 6/10
Epoch 00005: val_loss improved from 4.36447 to 4.30311, saving model to saved_weights/nozca.10.epochs.pixel.128.conv.4.pool.4.h
df5
134s - loss: 4.1879 - acc: 0.0960 - val_loss: 4.3031 - val_acc: 0.0906
Epoch 7/10
Epoch 00006: val_loss did not improve
132s - loss: 4.1050 - acc: 0.1045 - val_loss: 4.4628 - val_acc: 0.0854
Epoch 8/10
Epoch 00007: val_loss improved from 4.30311 to 4.20705, saving model to saved_weights/nozca.10.epochs.pixel.128.conv.4.pool.4.h
df5
134s - loss: 4.0336 - acc: 0.1160 - val_loss: 4.2071 - val_acc: 0.1004
Epoch 9/10
Epoch 00008: val_loss did not improve
134s - loss: 3.9649 - acc: 0.1208 - val_loss: 4.3137 - val_acc: 0.0808
Epoch 10/10
Epoch 00009: val_loss did not improve
133s - loss: 3.9119 - acc: 0.1290 - val_loss: 4.5181 - val_acc: 0.1045
Standardizing data
Top 1 test accuracy: 9.6466%
Standardizing data
Top 5 test accuracy: 20.3438%
Wall time: 22min 42s
```

Both top 1 accuracy improved from 7.78% to 14.18% and top 5 improved from 14.85% to 20.34% when compared to the previous model.

Augmentation with normalization of 4 convolutional layers, with 64 nodes

So far the results have shown that adding more layers have shown a positive influence on the results and for the next experiment the number of nodes will increase to 64 in the current layers we have.

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_1 (Conv2D)            (None, 128, 128, 64)      832
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 64, 64, 64)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 64, 64, 64)        16448
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 32, 32, 64)        0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 32, 32, 64)        16448
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 16, 16, 64)        0
_________________________________________________________________
conv2d_4 (Conv2D)            (None, 16, 16, 64)        16448
_________________________________________________________________
max_pooling2d_4 (MaxPooling2 (None, 8, 8, 64)          0
_________________________________________________________________
global_average_pooling2d_1 ( (None, 64)                0
_________________________________________________________________
dense_1 (Dense)              (None, 256)               16640
=================================================================
Total params: 66,816.0
Trainable params: 66,816.0
Non-trainable params: 0.0
_________________________________________________________________
Pixel size 128, channels 3, number of conv layers 4, number of pool layers 4
Checkpoint at nozca.64.nodes.10.epochs.pixel.128.conv.4.pool.4.hdf5
```

```
Checkpoint at nozca.64.nodes.10.epochs.pixel.128.conv.4.pool.4.hdf5
Epoch 1/10
Epoch 00000: val_loss improved from inf to 4.83574, saving model to saved_weights/nozca.64.nodes.10.epochs.pixel.128.conv.4.poo
l.4.hdf5
391s - loss: 5.0161 - acc: 0.0363 - val_loss: 4.8357 - val_acc: 0.0351
Epoch 2/10
Epoch 00001: val_loss did not improve
382s - loss: 4.7596 - acc: 0.0419 - val_loss: 4.8601 - val_acc: 0.0441
Epoch 3/10
Epoch 00002: val_loss improved from 4.83574 to 4.58296, saving model to saved_weights/nozca.64.nodes.10.epochs.pixel.128.conv.
4.pool.4.hdf5
375s - loss: 4.5841 - acc: 0.0529 - val_loss: 4.5830 - val_acc: 0.0514
Epoch 4/10
Epoch 00003: val_loss improved from 4.58296 to 4.46207, saving model to saved_weights/nozca.64.nodes.10.epochs.pixel.128.conv.
4.pool.4.hdf5
377s - loss: 4.4093 - acc: 0.0738 - val_loss: 4.4621 - val_acc: 0.0615
Epoch 5/10
Epoch 00004: val_loss did not improve
374s - loss: 4.2675 - acc: 0.0853 - val_loss: 4.8006 - val_acc: 0.0713
Epoch 6/10
Epoch 00005: val_loss did not improve
374s - loss: 4.1618 - acc: 0.1009 - val_loss: 4.7836 - val_acc: 0.0596
Epoch 7/10
Epoch 00006: val_loss improved from 4.46207 to 4.40521, saving model to saved_weights/nozca.64.nodes.10.epochs.pixel.128.conv.
4.pool.4.hdf5
398s - loss: 4.0701 - acc: 0.1085 - val_loss: 4.4052 - val_acc: 0.0844
Epoch 8/10
Epoch 00007: val_loss did not improve
401s - loss: 4.0008 - acc: 0.1191 - val_loss: 4.7117 - val_acc: 0.0762
Epoch 9/10
Epoch 00008: val_loss improved from 4.40521 to 4.16932, saving model to saved_weights/nozca.64.nodes.10.epochs.pixel.128.conv.
4.pool.4.hdf5
374s - loss: 3.9323 - acc: 0.1264 - val_loss: 4.1693 - val_acc: 0.1135
Epoch 10/10
Epoch 00009: val_loss did not improve
389s - loss: 3.8697 - acc: 0.1354 - val_loss: 4.2742 - val_acc: 0.0893
Standardizing data
Top 1 test accuracy: 11.4613%
Standardizing data
Top 5 test accuracy: 15.6638%
Wall time: 1h 4min 43s
```

Adding more nodes pushed the top 1 accuracy to 11.46% but the top 5 accuracy dropped to 15.66%. Validation results were improving slowly from each epoch but is starting to show signs of overfitting at the end. I decided to increase the number of nodes further to 128 for each convolutional layer. The drop in top 5 results was unexpected but this could just be an anomaly.

Augmentation with normalization of 4 convolutional layers, with 128 nodes

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_1 (Conv2D)            (None, 128, 128, 128)     1664
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 64, 64, 128)       0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 64, 64, 128)       65664
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 32, 32, 128)       0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 32, 32, 128)       65664
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 16, 16, 128)       0
_________________________________________________________________
conv2d_4 (Conv2D)            (None, 16, 16, 128)       65664
_________________________________________________________________
max_pooling2d_4 (MaxPooling2 (None, 8, 8, 128)         0
_________________________________________________________________
global_average_pooling2d_1 ( (None, 128)               0
_________________________________________________________________
dense_1 (Dense)              (None, 256)               33024
=================================================================
Total params: 231,680.0
Trainable params: 231,680.0
Non-trainable params: 0.0
_________________________________________________________________
Pixel size 128, channels 3, number of conv layers 4, number of pool layers 4
Checkpoint at nozca.128.nodes.10.epochs.pixel.128.conv.4.pool.4.hdf5
```

```
Checkpoint at nozca.128.nodes.10.epochs.pixel.128.conv.4.pool.4.hdf5
Epoch 1/10
Epoch 00000: val_loss improved from inf to 4.94386, saving model to saved_weights/nozca.128.nodes.10.epochs.pixel.128.conv.4.po
ol.4.hdf5
905s - loss: 4.9826 - acc: 0.0339 - val_loss: 4.9439 - val_acc: 0.0381
Epoch 2/10
Epoch 00001: val_loss improved from 4.94386 to 4.58281, saving model to saved_weights/nozca.128.nodes.10.epochs.pixel.128.conv.
4.pool.4.hdf5
905s - loss: 4.6266 - acc: 0.0506 - val_loss: 4.5828 - val_acc: 0.0577
Epoch 3/10
Epoch 00002: val_loss improved from 4.58281 to 4.37873, saving model to saved_weights/nozca.128.nodes.10.epochs.pixel.128.conv.
4.pool.4.hdf5
880s - loss: 4.4006 - acc: 0.0695 - val_loss: 4.3787 - val_acc: 0.0751
Epoch 4/10
Epoch 00003: val_loss did not improve
871s - loss: 4.2212 - acc: 0.0905 - val_loss: 5.5519 - val_acc: 0.0561
Epoch 5/10
Epoch 00004: val_loss improved from 4.37873 to 4.22916, saving model to saved_weights/nozca.128.nodes.10.epochs.pixel.128.conv.
4.pool.4.hdf5
870s - loss: 4.0808 - acc: 0.1065 - val_loss: 4.2292 - val_acc: 0.0941
Epoch 6/10
Epoch 00005: val_loss did not improve
878s - loss: 3.9669 - acc: 0.1220 - val_loss: 4.3382 - val_acc: 0.0811
Epoch 7/10
Epoch 00006: val_loss did not improve
863s - loss: 3.8689 - acc: 0.1332 - val_loss: 5.2276 - val_acc: 0.0748
Epoch 8/10
Epoch 00007: val_loss did not improve
865s - loss: 3.7912 - acc: 0.1469 - val_loss: 4.7949 - val_acc: 0.0805
Epoch 9/10
Epoch 00008: val_loss improved from 4.22916 to 4.17294, saving model to saved_weights/nozca.128.nodes.10.epochs.pixel.128.conv.
4.pool.4.hdf5
863s - loss: 3.7142 - acc: 0.1597 - val_loss: 4.1729 - val_acc: 0.1031
Epoch 10/10
Epoch 00009: val_loss improved from 4.17294 to 4.15282, saving model to saved_weights/nozca.128.nodes.10.epochs.pixel.128.conv.
4.pool.4.hdf5
861s - loss: 3.6207 - acc: 0.1744 - val_loss: 4.1528 - val_acc: 0.1249
Standardizing data
Top 1 test accuracy: 12.7507%
Standardizing data
Top 5 test accuracy: 18.0038%
Wall time: 2h 27min 39s
```

The training time for 4 layers of 128 nodes more than doubled for this model from 1hrs to 2.5hrs which highlights the additional complexity we have added when increasing the number of nodes. Both the top 1 and top 5 accuracy improved slightly from the previous model to 12.75% and 18% and the validation accuracy was improving slowly towards the last epoch didn't seem to show signs of overfitting yet. However, I decided to add dropouts with a setting of 0.3 to see the effect it has on the results.

Augmentation with normalization of 4 convolutional layers, with 128 nodes, 0.3 dropouts

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_2 (Conv2D)            (None, 128, 128, 128)     1664
_________________________________________________________________
dropout_1 (Dropout)          (None, 128, 128, 128)     0
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 64, 64, 128)       0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 64, 64, 128)       65664
_________________________________________________________________
dropout_2 (Dropout)          (None, 64, 64, 128)       0
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 32, 32, 128)       0
_________________________________________________________________
conv2d_4 (Conv2D)            (None, 32, 32, 128)       65664
_________________________________________________________________
dropout_3 (Dropout)          (None, 32, 32, 128)       0
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 16, 16, 128)       0
_________________________________________________________________
conv2d_5 (Conv2D)            (None, 16, 16, 128)       65664
_________________________________________________________________
dropout_4 (Dropout)          (None, 16, 16, 128)       0
_________________________________________________________________
max_pooling2d_4 (MaxPooling2 (None, 8, 8, 128)         0
_________________________________________________________________
global_average_pooling2d_1 ( (None, 128)               0
_________________________________________________________________
dense_1 (Dense)              (None, 256)               33024
=================================================================
Total params: 231,680.0
Trainable params: 231,680.0
Non-trainable params: 0.0
_________________________________________________________________
Pixel size 128, channels 3, number of conv layers 4, number of pool layers 4
Checkpoint at nozca.128.nodes.10.droput.epochs.pixel.128.conv.4.pool.4.hdf5

Checkpoint at nozca.128.nodes.10.droput.epochs.pixel.128.conv.4.pool.4.hdf5
Epoch 1/10
Epoch 00000: val_loss improved from inf to 4.89473, saving model to saved_weights/nozca.128.nodes.10.droput.epochs.pixel.128.co
nv.4.pool.4.hdf5
1708s - loss: 4.9492 - acc: 0.0365 - val_loss: 4.8947 - val_acc: 0.0484
Epoch 2/10
Epoch 00001: val_loss improved from 4.89473 to 4.63473, saving model to saved_weights/nozca.128.nodes.10.droput.epochs.pixel.12
8.conv.4.pool.4.hdf5
1606s - loss: 4.5620 - acc: 0.0603 - val_loss: 4.6347 - val_acc: 0.0585
Epoch 3/10
Epoch 00002: val_loss did not improve
1606s - loss: 4.3290 - acc: 0.0784 - val_loss: 4.8085 - val_acc: 0.0452
Epoch 4/10
Epoch 00003: val_loss improved from 4.63473 to 4.48736, saving model to saved_weights/nozca.128.nodes.10.droput.epochs.pixel.12
8.conv.4.pool.4.hdf5
1575s - loss: 4.1634 - acc: 0.0978 - val_loss: 4.4874 - val_acc: 0.0759
Epoch 5/10
Epoch 00004: val_loss improved from 4.48736 to 4.37604, saving model to saved_weights/nozca.128.nodes.10.droput.epochs.pixel.12
8.conv.4.pool.4.hdf5
1582s - loss: 4.0207 - acc: 0.1194 - val_loss: 4.3760 - val_acc: 0.0756
Epoch 6/10
Epoch 00005: val_loss did not improve
1576s - loss: 3.9132 - acc: 0.1318 - val_loss: 4.4039 - val_acc: 0.0688
Epoch 7/10
Epoch 00006: val_loss improved from 4.37604 to 4.11383, saving model to saved_weights/nozca.128.nodes.10.droput.epochs.pixel.12
8.conv.4.pool.4.hdf5
1550s - loss: 3.8086 - acc: 0.1477 - val_loss: 4.1138 - val_acc: 0.1219
Epoch 8/10
Epoch 00007: val_loss did not improve
1558s - loss: 3.7288 - acc: 0.1623 - val_loss: 4.1206 - val_acc: 0.0974
Epoch 9/10
Epoch 00008: val_loss improved from 4.11383 to 4.08646, saving model to saved_weights/nozca.128.nodes.10.droput.epochs.pixel.12
8.conv.4.pool.4.hdf5
1558s - loss: 3.6571 - acc: 0.1725 - val_loss: 4.0865 - val_acc: 0.1184
Epoch 10/10
Epoch 00009: val_loss improved from 4.08646 to 4.08007, saving model to saved_weights/nozca.128.nodes.10.droput.epochs.pixel.12
8.conv.4.pool.4.hdf5
1570s - loss: 3.5633 - acc: 0.1877 - val_loss: 4.0801 - val_acc: 0.1230
Standardizing data
Top 1 test accuracy: 10.9838%
Standardizing data
Top 5 test accuracy: 25.9790%
Wall time: 4h 26min 28s
```

Training time nearly doubled and the top 1 result decreased slightly from 12.75% to 10.98% whilst the top 5 results rose from 18% to 25.98%. The results didn't appear to be overfitting

much. Overall having dropouts is improving the test results especially for top 5 accuracy (our aim is to reach 50%).

Augmentation with normalization of 5 convolutional layers, with 128 nodes, 0.3 dropouts

For the final model of of this category, a 5th convolutional layer was added with dropout layers added to prevent overfitting. The number of epochs was increased to 20 to ensure we get the best possible weights, unlike the other models this one was only ran once since it took an extremely long time to run.

Due to the length of the model and log statements, I've only grabbed a screenshot of the last few lines.

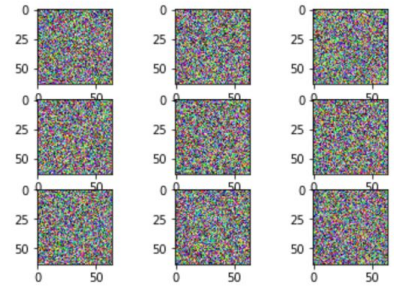
```
Epoch 17/20
Epoch 00016: val_loss did not improve
1504s - loss: 3.2331 - acc: 0.2362 - val_loss: 3.9294 - val_acc: 0.1429
Epoch 18/20
Epoch 00017: val_loss did not improve
1495s - loss: 3.1699 - acc: 0.2477 - val_loss: 3.8514 - val_acc: 0.1592
Epoch 19/20
Epoch 00018: val_loss did not improve
1496s - loss: 3.1441 - acc: 0.2573 - val_loss: 3.9795 - val_acc: 0.1214
Epoch 20/20
Epoch 00019: val_loss did not improve
1522s - loss: 3.1031 - acc: 0.2607 - val_loss: 3.8464 - val_acc: 0.1521
Standardizing data
Top 1 test accuracy: 18.1948%
Standardizing data
Top 5 test accuracy: 38.6342%
Wall time: 8h 25min
```

The model took 8h25 mins to run 20 epochs but didn't show significant signs of overfitting. The top 1 accuracy was 18.19% and the top 5 accuracy was an incredible 38.63% which is just 11.37% away from the project target. Adding more layers have certainly improved our results and the dropouts have helped prevent overfitting in our models. I stopped experiments in this category due to the length of time it takes to train models and I felt we had enough data to draw our conclusion for this category.

Image Augmentation with ZCA

ZCA can be a powerful tool in feature extraction but I quickly learnt from the experiments that it is computationally expensive to run. Running ZCA on 64 pixel images uses more than 30GB RAM on the machine with the augmentation to process.

```
: %%time
datagen = datagen_zca(train_tensors)
display_first_batch(train_tensors, train_targets, datagen)
```



```
CPU times: user 36min 25s, sys: 1min 35s, total: 38min
Wall time: 9min 45s
```

A simple model of 3 layers takes 1h 16mins to train and although I would to take the experiments further, the ZCA process is too complicated for images with 3 channels on the hardware I have.

Transfer Learning

There are several award winning neural networks that have competed in the annual ILSVRC competitions using the ImageNet database. The models are trained over hundreds of thousands of images on the world's best hardware over several days. Although an individual can't do this on their personal equipment, Keras has the pre-trained models available to use. Transfer learning involves loading the pre-training weights and model and removing the final layer of the network. A custom layer is added to perform the bespoke classification and the weights in the base layers are frozen to avoid re-training.

In this experiment I will use VGG16 [10] since I am worried about the training times and it has few layers than some of the other CNNs, it also allows smaller images which reduces the training time.

In the first experiment decided to set the pixel size to 48x48 to reduce the training complexity. Next the custom layers were a global pooling layer and a dense layer with 1024 nodes. I deliberately select a larger node size compared to our normal experiments since I believe the base model would've extracted many features at this point.

The first model took 47 mins to train and had top 1 accuracy of 12.07% and a top 5 accuracy of 30.49%. This isn't beat the top model we currently have but considering the model ran without augmentation on smaller pixel images it was a good result.

For the last transfer learning experiment I increased the pixel size to 128x128, the model took 13hrs and 30 mins to train. However, the result was 21.73% for top 1 accuracy and 49% for the top 5 accuracy. This was a 3.53% improvement for top 1 and 10.37% improvement over the our best model running with augmentation and normalization. The top

[10] http://www.robots.ox.ac.uk/~vgg/research/very_deep/

5 accuracy was 1% short of our target set out in our proposal but I decided to stop since the training process was becoming too intensive and expensive.

Challenges and complications

From the start of the project I started to encounter a few unexpected problems. The first was the labelling of the dataset, each training set was contained within numbered folder and the actual label had to be looked up within a text file. The labels within the text file was all stored on one line and delimited with spaces, which made it difficult to extract because the labels themselves had spaces. Hence it was a manual process to create the labels.txt file for pandas to read.

Another problem was the lack of memory on my laptop to run the models I create. Although I started small and gradually increased the complexity, most of the interesting ones required a large amount of RAM and computation power. The solution was to open an AWS account, set up a GPU EC2 virtual machine and then install my dependencies. Once the project was on the EBS volume, I had to configure Jupyter Notebook to be opened remotely with a password. I've documented the instructions on the ReadME.

After setting up my EC2 instance, I started running tests on the first few labels, before I let the model run across the whole dataset. At which point, the results seemed a bit random and didn't correlate to the improvements I made. Debugging in Jupyter is painful, unlike a regular IDE, you can't inspect variables or set break points. After many print statements, I finally found the issue was the way sklearn read the labels from the folders. Each folder had a number and I expected it to read it in numerical order, however, the number 10 would appear straight after 1 as it sorted it as a string type. The solution was to pad the folders with 0s.

My first batch of results was now proving to be promising, until I started to normalize my results. At which point the accuracy rate was very poor and the model didn't seem to train properly. I almost abandoned normalization until I realised I needed to standardize the validation set as well.

As the models became more complicated, the run time got exponentially worse and eventually each model was taking hours and hours to run. My AWS bill had grown to 70USD by this point and I eventually had to borrow a machine to run some of the training overnight. Although it was totally worth it when you wake up and see your top 1 and top 5 results jump from the previous model.

I had to give up on ZCA because it was incredibly expensive to run, perhaps if the images were just black and white it might have worked.

Finally the last point I'd like to make, was that I wished I knew how much of a performance impact the verbose levels make on the application. I noticed after turning the verbosity down (which removes the progress bar), the some models trained 30% faster.

Results

Model	File Name	Top 1 Accuracy	Top 5 Accuracy
Basic model	basic.pixel.64.conv.1.pool.1.hdf5	2.36%	7.63%
Benchmark model	basic.pixel.64.conv.3.pool.3.hdf5	5.67%	16.64%
Benchmark model using 128 pixels	basic.pixel.128.conv.3.pool.3.hdf5	5.83%	18.15%
Benchmark model using 256 pixels	basic.pixel.256.conv.3.pool.3.hdf5	6.11%	17.53%
Basic augmentation of 3 convolutional layers	nozca.nostd.pixel.128.conv.3.pool.3.hdf5	3.89%	13.48%
Basic augmentation of 3 convolutional layers with 0.5 dropouts	nozca.nostd.dropouts.pixel.128.conv.3.pool.3.hdf5	3.46%	11.77%
Basic augmentation of 3 convolutional layers with 0.3 dropouts and 10 epochs	nozca.nostd.dropouts.10.epochs.pixel.128.conv.3.pool.3.hdf5	5.33%	18.73%
Basic augmentation of 4 convolutional layers with 0.3 dropouts and 10 epochs	nozca.nostd.dropouts.10.epochs.pixel.128.conv.4.pool.4.hdf5	6.10%	20.63%
Basic augmentation of 4 convolutional layers with 0.3 dropouts, more nodes and 10 epochs	nozca.nostd.morenodes.dropouts.10.epochs.pixel.128.conv.4.pool.4.hdf5	9.19%	25.62%
Augmentation with norm of 3 convolutional layers	nozca.pixel.128.conv.3.pool.3.hdf5	6.64%	14.85%
Augmentation with norm of 3 convolutional layers with 0.5 dropouts	nozca.multi.nodes.dropout.10.epochs.pixel.128.conv.3.pool.3.hdf5	7.78%	14.18%
Augmentation with norm of 4 convolutional layers	nozca.10.epochs.pixel.128.conv.4.pool.4.hdf5	9.65%	20.34%
Augmentation with norm of 4 convolutional layers, with 64 nodes	nozca.64.nodes.10.epochs.pixel.128.conv.4.pool.4.hdf5	11.46%	15.66%
Augmentation with norm of 4 convolutional layers, with 128 nodes	nozca.128.nodes.10.epochs.pixel.128.conv.4.pool.4.hdf5	12.75%	18.00%
Augmentation with norm of 4 convolutional layers, with 128 nodes, 0.3 dropouts	nozca.128.nodes.10.dropout.epochs.pixel.128.conv.4.pool.4.hdf5	10.98%	25.98%
Augmentation with norm of 5 convolutional layers, with 128 nodes, 0.3 dropouts	nozca.128.nodes.10.dropout.20.epochs.pixel.128.conv.5.pool.5.hdf5	18.19%	38.63%
Transfer learning with VGG16 on 48 pixels	vgg16.pixel.48.conv.1.pool.1.hdf5	12.07%	30.49%
Transfer learning with VGG16 on 128 pixels	vgg16.pixel.128.conv.1.pool.1.hdf5	21.73%	49.00%

Model Evaluation and Validation

The best performing model in terms of both top 1 and top 5 accuracy scores was the model that performed transfer learning with VGG16 on 128 pixel images. The model achieved a

21.77% top 1 accuracy rate which was more than 3.5% better than the model I built myself (Augmentation with norm of 5 convolutional layers, with 128 nodes, 0.3 dropouts). The transfer model also achieved an 10.37% increase in top 5 accuracy when compared to our best custom model as well. The final result of 49% on the top 5 accuracy was only 1% short of the initial target that I set out in the project proposal. The final model did not have any augmentation on its training set unlike our custom models which suggests these results could be even higher if there was an opportunity to perform the augmentation process. Unfortunately due to hardware constraints this wasn't possible during the project.

Sensitivity tests were needed to test the robustness of the model and in our tests we augmented the current test tensors with random rotations, shifts and flips. The prediction results were as follows:

Random Rotations Range	Random Height Shifts Range	Random Width Shifts Range	Random Horizontal Flips	Random Vertical Flips	Top 1 Accuracy	Top 5 Accuracy
45	0.1	0.1	FALSE	FALSE	21.7285%	49.0040%
45	0.1	0.1	TRUE	TRUE	21.7285%	49.0040%
180	0.3	0.4	TRUE	TRUE	21.7285%	49.0040%

The top 1 and top 5 accuracy remained the same despite have the test images rotated, flipped and shifted around which strongly suggests the feature filters of the VGG16 are very resilient to these changes.

Justification

When I started the project I aimed to get a top 5 accuracy rate of 50% and our final model achieved 49% which was 1% off the target. In my proposal I provided the scenario where users can take an image of his food which will then automatically classified with tags. With the current top1 accuracy of 21%, one in five of his results will be incorrect, however, with a 49% top 5 accuracy means that we could potentially offer 5 suggestions to the user and it will be useful just under half the time. Hence the application can still offer some value although it may not be as accurate as a human being.

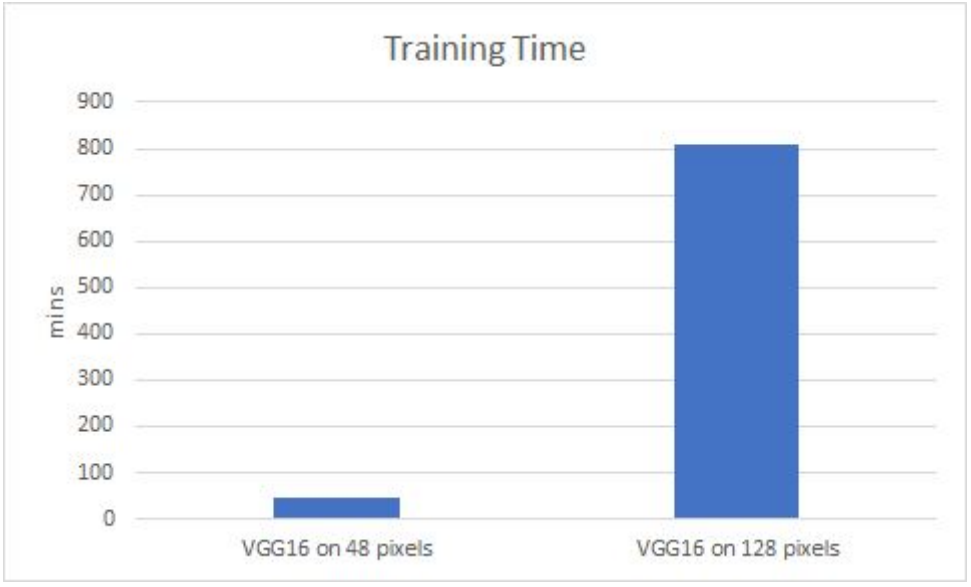
The results and experiments have proven that with better hardware we can make more adjustments and can achieve a higher accuracy rates than the ones we have now. These refinements include changing the number of layers, changing the number of nodes and using different applications for transfer learning which in all our experiments have proven to be have significant impact to the process of classification. Therefore as project we have shown there is value in investigating further and we have provided a base platform for other curious machine learning engineers to do so, hence I will say the project was a success.

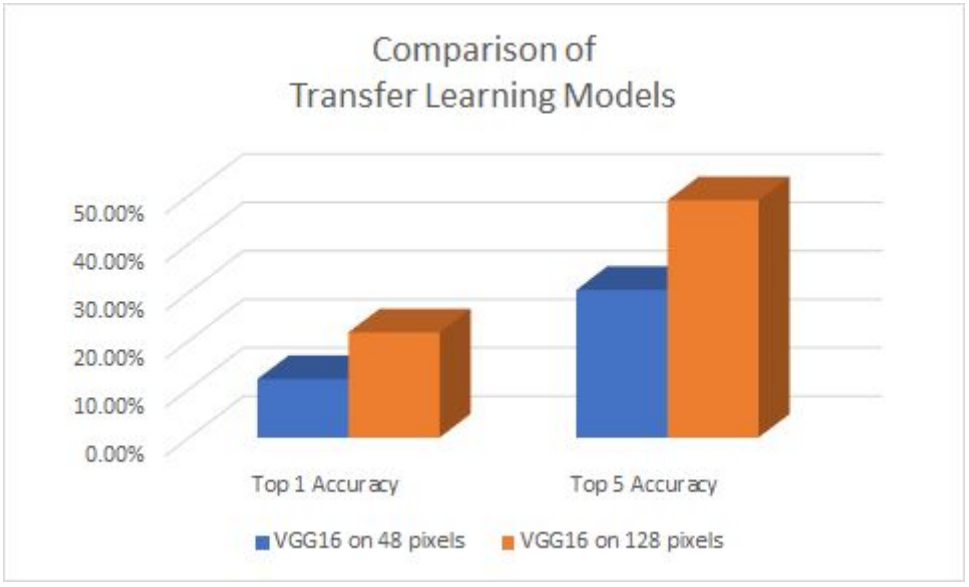
Conclusion

Free-From Visualization

The objective of the project was to investigate how to build a custom convolutional neural network to classify food images into different categories with the aim of reach a top 5 accuracy (or top 5 error rate) or 50%.

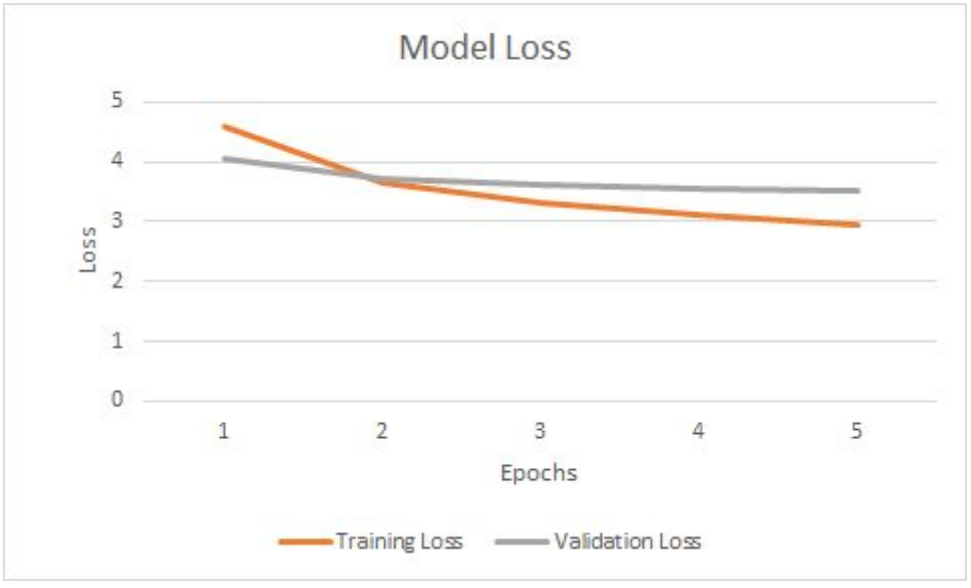
From the experiments conducted I can first conclude that increasing the pixel size of the inputs has a significant effect on your training time but also a positive effect on the test accuracies. Increasing the pixels increases the amount of data that the models take hence allows the models more opportunities to extract better features from the images. This was very apparent in the final stage of the project when using transfer learning where both results nearly doubled when the pixel size was increased from 48 to 128 pixels. However, the training time went up exponentially to from 47 mins to 13 hours which definitely limits the experiments you can run.

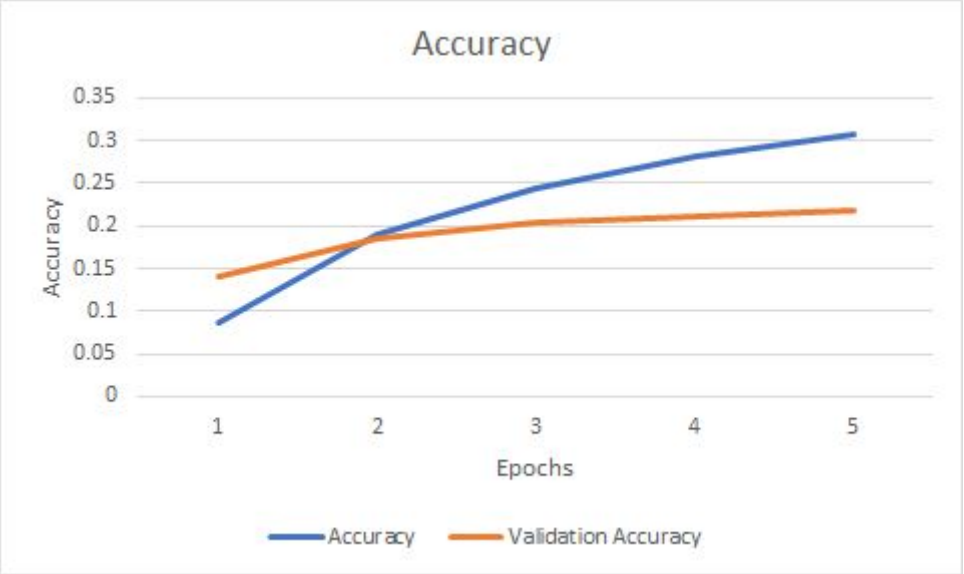




From the graphs we can visualise how increasing the performance of the application by increasing the image pixel size exponentially increases the training time.

After performing transfer learning I analysed the loss and accuracy of the training and validation sets.





From the graphs it's clear that the validation accuracy is dropping faster than the training accuracy which is a sign of overfitting. During the transfer learning process I froze the weights of the base model and added my own output layers. Hence, the majority of the weights within the model do not retrain. In order to improve the results we have to fine tune the model by selectively unfreezing certain layers and allowing the model to train towards our particular classification problem.

The experiments in the project have highlighted how increasing the number of layers and nodes will increase the accuracy of your results with an increase in training times. Overfitting can also be an issue as the training error rate continues to decrease but the validation accuracy also decreases. One method to mitigate this, dropout layers were added to ensure the weights are training correctly but to benefit from this, the number of epochs must increase as the model takes more iterations to train.

The project investigated how augmentation can influence the results and how different settings can greatly change the results. The basic augmentation methods only performed simple random flips, shifts on the training set but this effectively gives the model free data to train with and reduce the chance of overfitting.

When I decided to take augmentation further by applying feature wide normalization and standardization the results showed a clear improvement from the basic augmentation methods with the simplest model increasing from 3.89% to 6.64% in top 1 accuracy. The process, however, did become more increasingly expensive and memory intensive to train.

The results gave me confidence in my augmentation methods and I decided to experiment with the other parameters of the models: number of layers, number nodes, number of epochs and adding dropouts. The experiments became increasingly longer to train but I noticed adding more layers and increasing the number of nodes will improve the accuracy of the model. However, dropouts were needed to ensure the model does not overfit and ensure the weights are more balanced throughout the network. Of course using more dropout layers

requires more epochs as the model takes longer to find its optimal weights. However, I managed to reach a sound accuracy of 18.19% for top 1 accuracy and 38.63% for top 5 accuracy before I embarked on the next step.

Reflection

Building a neural network from scratch is difficult because it requires a large amount of data and even with augmentation, it's really difficult to train deep models and raise the accuracy rates. Hence transfer learning and I used award winning models that were pre-trained on ImageNet to improve my classification results. At first the results were disappointing but when the number of pixels were increased to 128 the model successfully achieved a 49% top 5 accuracy rate which is 1% short from the proposed target. The model could be fine tuned to improve the accuracy but since it took 13hrs to train, I decided the 49% accuracy rate was sufficient.

Improvement

Going further, the project could also investigate feature extraction with existing models from ImageNet competitions to improve results, although that too requires time to train as the base model needs to make a prediction for each of the training, validation and test sets to extract the features. We could also experiment with more layers and nodes with different dropout rates to improve results. I was also hoping to use ZCA whitening in my augmentation process, but unfortunately the process was extremely expensive to run. Even the p2 EC2 instance that I ran from AWS (with 64 GB of RAM) struggled to process images of 64 pixels. This is due to the size of the covariance matrix which grows exponentially with image size.

Final Words

I really enjoyed this project and I think the best way to learn about neural networks is to try and build one yourself. There definitely were challenges in the project that were difficult to overcome and this included debugging incorrect results, running models that didn't use all the memory on the instance and refactoring code as the notebook got bigger (you really miss an IDE like PyCharm at this point).

There's also no opportunity to write unit tests and hence it is important to check results as you progress within the project (I realised sklearn was reading my dataset folders in an unexpected order at one point). It is also important to start with smaller models to get faster feedback and results as rerunning models are very time consuming and expensive if you are hosting on a cloud provider (I've had to re-run my models several times).

Overall I am pleased with the results and understanding I have obtained from the course and will be eager to explore other techniques or frameworks (such as PyTorch).