

Deep Art: Learning Artistic Style via Residual and Capsule Networks

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Abstract

We experiment with various architectures in an effort to build an artistic style classifier capable of classifying artwork from the WikiArt dataset according to seven different art genres, such as cubism and impressionism. To study how object identification tasks relate to style recognition tasks, we experiment with transfer learning from the ResNet architecture trained on the ImageNet dataset and visualize the activations of the final layers. We additionally test the CapsNet model on our data, an architecture which shows great improvements on MNIST but has not yet been used in other domains. Finally, we build a custom model that merges the ResNet and CapsNet architectures.

Our goal in this project is to 1) build an art classifier that can automatically label the genre of new pieces of art, and 2) investigate how architectures designed for object identification transfer over to the domain of artistic style classification. We will focus on transfer learning with the ResNet-50 architecture (He et al., 2015) as well as the recently developed CapsNet architecture (Sabour et al., 2017), which has shown great improvements on digit recognition for the MNIST dataset but has not yet been tested in other domains. In addition, we will implement our own architecture that combines features from both networks. Finally, we will visualize the activations of our networks in order to see which features our model notices.

2. Background

2.1. Related work

Art classification is a complex task, often a challenge, even for experts. A variety of different methods have been employed recently for art classification including ultraviolet fluorescence, x-radiography and paint sampling (Johnson et al., 2008). Previous work on art classification includes both traditional methods, based on hand-crafted features as well as methods where the features are automatically learned from the images. While feature engineering can be useful in terms of understanding the behavior of the classifier and interpreting the results, classifiers based on handcrafted features do not in most cases perform well on art classification. Learning the features automatically from the images, usually leads to classifiers of higher accuracy, as shown in (Tan et al., 2016), where an accuracy of 54.5% over 25 styles was achieved.

In (Sablatnig et al., 1998), the structure of brush strokes was examined as a main attribute to identify personal artistic styles. A computer-aided top-down classification and recognition system was developed, proving that stroke arrangements can be a stable method to detect artist-specific styles. (Lombardi), took a more general, style-independent approach on painting classification. More specifically, the

1. Introduction

Convolutional Neural Networks (CNN) are the foundational framework for most computer vision tasks today. CNNs have been very successful in tasks such as object recognition, with many modern architectures able to outperform humans in image classification challenges on ImageNet and other datasets. However, much less research has been applied to classification tasks pertaining to artwork. We believe that optimizing neural networks to learn artistic style would have widespread benefits for both artists and collectors alike.

WikiArt (WikiArt; cs chan) is one of the first and most comprehensive online art encyclopedias, developed in 2013. The WikiArt dataset currently has 150,000 artworks spanning 54 genres and is continually adding to their database. Recently, the company Artsy has built on the WikiArt dataset and collected 800,000 art pieces to use for their Art Genome Project. Artsy is currently hand-labelling each piece of artwork with 1,000 genes in order to match art collectors with new pieces based on their preferences. Needless to say, hand-labelling images is a time-consuming and costly process.

palette description algorithm was used to compare color content in images and performed similarly to color description techniques (e.g. hue histogram, saturation histogram) requiring less storage. Results showed that algorithms preserving frequency and spatial color features do not necessarily optimize the accuracy of painting classification. Supervised (k-NN) and unsupervised techniques (Agglomerative Hierarchical Clustering, Self-Organizing Maps, Multidimensional Scaling) were demonstrated to be equivalent to data quality metrics. Previous work (Jou & Agrawal, 2012) also includes training on basic (color histogram) and advanced features (HOG descriptors) to classify paintings by 5 artists. Several classification techniques were used, with the Naive Bayes classifier giving the maximum accuracy of 65%. In a more recent approach (Mensink & Van Gemert, 2014), image features were encoded using Fisher vectors to classify digitized artworks (paintings, photographs etc.) of the Rijksmuseum dataset by artist, type, materials and year of creation. 1-vs-all linear SVM classifiers were used for all creators in artist classification, type categorization and material labeling. For estimating the year of creation, the use of an SVM classifier followed by a type regressor was proven to be more effective than a single regressor.

Regarding the use of automatic feature learning, a Convolutional Neural Network (PigeoNET) was trained in (Van Noord et al., 2015) to recognize and attribute unseen artworks to artists. The Rijksmuseum Challenge dataset was used to optimize and assess the performance of PigeoNET. Results showed that PigeoNET is very accurate in attributing artworks (more than 70%) and will probably perform even better in more extended datasets. In another prior work (Bar et al.), a CNN was applied to extract low-level visual features from the ImageNet dataset. The deep network was combined with the PiCoDes binary descriptor and different low-level descriptors to recognize artistic styles. The results showed that the most accurate method was the combination of Decaf encoding with PiCoDes, which outperformed low-level descriptors. A more recent approach (Lecoutre et al., 2017), also employed deep architectures: Deep neural networks were pre-trained on ImageNet to detect artistic styles. It was proven that retraining the layers of the network improves the performance (20 retrained layers gave the optimal performance) of the method. The model was tested on a Wikipaintings dataset and an independent source, showing that the classifier did not overfit. ResNet architecture performed better than AlexNet reaching over 90% accuracy.

2.2. Residual Networks

When building neural networks, we prefer to add depth over width in order to minimize parameters and prevent over-fitting. In theory, a neural network can learn any representation with a sufficiently deep architecture. However, deeper networks are prone to saturation and vanishing

gradient problems, causing the error rate to plateau early on. In practice, the training error rate in deeper networks is often higher than the training error rate in shallower networks.

The ResNet solves this problem by introducing an identity short-cut connection, illustrated below. It is easier for these residual blocks to learn the identity mapping, in which case the additional layers do not modify the input. Because the ResNet can use identity blocks to imitate a shallower model, adding layers to the ResNet will not degrade performance. In fact, experiments show that a 1001-layer deep ResNet outperforms shallower versions. (Kaiming He) To summarize, residual networks are deeper than vanilla neural networks but require a similar number of weights and do not have problems with saturation.

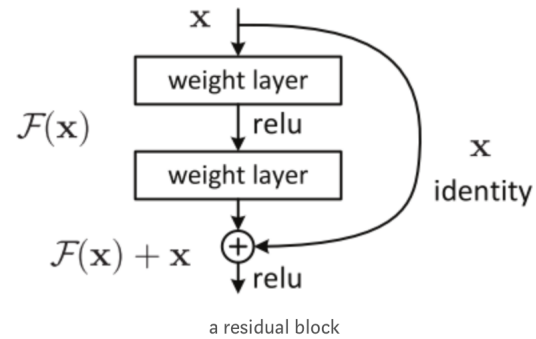


Figure 1. An illustration of the residual block (Fung)

2.3. Transfer Learning

Transfer learning describes the process of training a model on a new task by transferring and utilizing the knowledge learned by another model that was trained on a related task (Torrey & Shavlik, 2009). A more formal definition of transfer learning is given in (Pan & Yang, 2010) by Pan and Yang:

"Given a source domain D_S and learning task T_S , a target domain D_T and learning task T_T , transfer learning aims to help improve the learning of the target predictive function $f_T(\cdot)$ in D_T using the knowledge in D_S and T_S , where $D_S \neq D_T$, or $T_S \neq T_T$."

In practice, transfer learning has been applied with success in Machine Vision, Reinforcement Learning and Natural Language Processing. Regarding Machine Vision, (Sharif Razavian et al., 2014) trained a new model using features of a large model, built on ImageNet. In (Ganin

& Lempitsky, 2015) a model capable of confusing source and target domains was created, using transfer learning. Furthermore, both (Bousmalis et al., 2016) and (Sener et al., 2016) employed transfer learning techniques to train models on domain-invariant representations. In reinforcement learning, progressive neural networks that can learn from already trained models have been discussed in (Rusu et al., 2016), whereas in (Fernando et al., 2017) successful transfer learning is demonstrated in Pathnet, a neural network that uses genetic algorithms during training. In natural language processing, transfer learning has been applied to text classification (Do & Ng, 2006), (Raina et al., 2006) as well as spam filtering (Bickel). Other novel approaches involving transfer learning include (Ruder et al., 2017), where transfer learning is employed to extend Knowledge Distilling (proposed by Hinton et al in (Hinton et al., 2015)) to the domain adaptation and (Ruder & Plank, 2017), where Bayesian optimization was applied for transfer learning data selection.

2.4. Capsule Networks

A major limitation of Convolutional Neural Networks is that they are unable to capture the relative spatial relationship between features in an image and are not viewpoint invariant. To be concrete, this means that it is difficult for a CNN to identify a nose when it is looking at it from a new angle and the CNN will also not necessarily notice if the nose is in the wrong position on a face. (Colyer) In an attempt to address this inefficiency, another type of neural network was recently introduced by Sabour et al. (Sabour et al., 2017): The Capsule Network. Capsule networks use capsules to retain viewpoint invariant knowledge and spatial structure. These capsules perform complex internal computations on their inputs and then output a vector which encodes a variety of instantiation parameters related to a particular feature, such as position, orientation, scale, thickness, and texture. The length of the capsule output vector is squashed to be no more than one so that it can represent the probability that a feature is present, while the elements of the vector encode its properties. Thus when an entity is viewed in a new orientation, the length of the associated vector (probability it exists) should stay the same while the orientation (instantiation parameters) will adjust accordingly. (Pechyonkin)

For instance, when working with the MNIST dataset, each capsule holds various spatial information about each digit. Figure 2 illustrates how spatial information about the digits is stored inside the Capsule Network for MNIST.

Scale and thickness	6 6 6 6 6 6 6 6 6 6 6
Localized part	6 6 6 6 6 6 6 6 6 6 6
Stroke thickness	5 5 5 5 5 5 5 5 5 5 5
Localized skew	4 4 4 4 4 4 4 4 4 4 4
Width and translation	3 3 3 3 3 3 3 3 3 3 3
Localized part	2 2 2 2 2 2 2 2 2 2 2

Figure 2. How spatial information about the MNIST digits stored inside the Capsule Network (Sabour et al., 2017)

The network then uses a dynamic routing system called routing-by-agreement to send the vector to the appropriate parent in the next layer. For example, a capsule which observes noses will send its vector to the parent capsule looking for faces. This serves as an alternative to max-pooling, the commonly used routing system which causes neurons to ignore all but the most active feature in the previous layer. Finally, the CapsNet uses a margin loss function at the last digit class layer, where a long output vector in digit class k implies that class k is present. The total loss is the sum of the losses over all digit capsules, adding a penalty if 1) the class is present and the length of the associated vector is small, or 2) the class is absent and the length of the relevant vector is large. In the original paper, the formula is:

$$L_k = T_k \max(0, m^+ - \|v\|) + \lambda(1 - T_k) \max(0, \|v_k\| - m^-)^2$$

where $m^+ = 0.9$, $m^- = 0.1$, and $T_k = 1$ iff a digit from class k is present. (Sabour et al., 2017)

A simple Capsule Network architecture is shown in Figure 1.

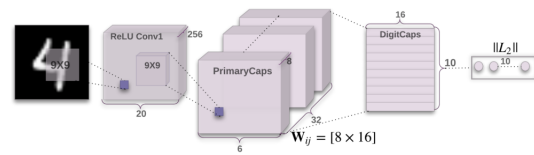


Figure 3. A simple Capsule Network Architecture (Sabour et al., 2017)

Experiments demonstrate that Capsule Networks encode more robust representations for digit classes on MNIST than traditional convolutional networks: Result show that an under-trained Capsule Network, which achieved 99.23% accuracy on the expanded MNIST test set achieved 79% accuracy on the affnist test set, outperforming a conventional convolutional model with a comparable number of parameters, as the latter scored similar accuracy (99.22%) on the expanded MNIST test set but only managed 66% on the affnist test set (Sabour et al., 2017).

2.5. Visualisation

Each convolutional layer learns template matching filters after training. These filters have the highest output when their input image is close to the template. For example, a filter might have a nose template that activates when there is a nose in the input image. Activation maximization is a method used to visualize such a template. If we use activation maximization to visualize the nose filter, for instance, we should produce an image that looks somewhat like a nose.

In order to generate an input image that maximizes the filter output activations, the Keras *visualize_activation* function takes raw image pixels as input then tries to minimize the Activation Maximization Loss, because a small activation loss implies a large filter activation. Thus we have a simple optimization problem - we minimize the Activation Maximization Loss by taking the derivative of the loss with respect to the input, then use gradient descent to update the input until we have generated the optimal template. This final template is the image which *visualize_activation* returns. To implement the function in Keras, we simply specify the model and the arguments for *filter_indices* and *layer_idx*, directing the function to the appropriate filter in the layer of interest. For example, we could direct the function to visualize a filter in the output layer, specifically the filter that classifies an image as a cat. There are also optional parameters to modify the back-propagation technique, the gradient descent method, and other arguments, as explained in the documentation. (Kotikalapudi)

3. Dataset

3.1. Overview

In deep learning systems it has been well established that both the architecture and the amount of training data used are fundamentally important to the success of a model. It is often said that, 'a dumb algorithm with lots and lots of data beats a clever one with modest amounts of it' (Domingos, 2012). Motivated by this idea, a large dataset known as the 'WikiArt Dataset' was chosen to train the deep neural models (WikiArt; cs chan). WikiArt is one of the largest publicly known art datasets consisting of around 100,000 paintings labelled by their artist, genre, and style, which is particularly suitable for supervised learning. For the purposes of this paper, the artist and genre will be discarded, allowing supervised learning to be performed on the style of the paintings alone.

The paintings found in the WikiArt dataset come from 26 different styles, spanning from Realism to Abstract Expressionism, as well as varying widely in terms of dimension. As is often the case with real world datasets, there is class

Style Labels	
Class ID	Type
0	Art Nouveau Modern
1	Baroque
2	Cubism
3	Expressionism
4	Impressionism
5	Symbolism
6	Realism

Table 1. The different types of art styles and their corresponding class ID present in the reduced data set.

imbalance amongst the styles and as such needs to be dealt with accordingly.

3.2. Preprocessing

Due to limited computational resources, it was necessary to reduce the number of data used to train the models. This was done by (1) Reducing the number of classes to be classified from 26 to 7, and (2) Choosing randomly 2000 paintings from each class, discarding the rest. Not only this resulted in a manageable dataset within resources, but also tackled the problem of imbalanced classes. The remaining style types and their corresponding class ID in our reduced dataset can be seen in ???. To test the generality of our models, we split this reduced data set into a training and a test set with a ratio of 80:20. Lastly, in order for the models to take these paintings as input, they must have the same dimension. There are two main ways of doing this: (1) scale all paintings to the same size, or (2) take a number of crops with specified dimensions. As we are only concerned with the style of the paintings, it is intuitively more important to preserved pixel-level details rather than the larger structures of a painting. These details are not preserved by scaling paintings and as such this problem was solved by taking crops. An important consideration to make during the cropping process is the dimension of the smallest painting in the dataset. This dimension acts as an upper-bound for the cropping dimension and is crucial for determining how much larger structure is to be considered within the model. To avoid the case where the cropping dimension is too small, leading to loss of important information, the smallest 10% of paintings were removed. The reduced dataset now consists of 9000 paintings, where each painting is split into four crops of our chosen dimensions.

Given the large amount of data after cropping and the processing needed before passing the data into the models, a decision was made to store the cropped images to disk. This

decision was made due to limited amount of memory allocated, allowing for more data to be used to train the models as well as a larger crop to be taken, hopefully giving rise to an improvement in accuracy.

4. Methodology

4.1. Setup

As mentioned previously, our purpose is to compare performances of different networks distinguishing between the 7 different styles in our dataset. In order to do so we did the following:

Transfer Learning on the ResNet.

First, we experimented with transfer learning on the ResNet-50 network. Specifically, we used the pre-trained weights on the ImageNet dataset, and then fine-tuned them using our paintings dataset. It is important to note that during the procedure, it was necessary to replace the last 1000-class softmax layer of the network with a 7 class softmax layer, which corresponded to our seven classes of styles. We additionally experimented with various fine-tuning methods, described below:

- In Experiment 1, we fine-tuned all layers of the ResNet using our dataset.
- In Experiment 2, we froze the all the layers up to and including “activation_13”, about $\frac{1}{3}$ of the network which had a total of 49 activation layers (c.f. appendix A). When fine-tuning the weights on our dataset, the frozen layers do not learn. The rationale behind such a setup is that we expect the initial layers on a CNN to merely detect edges and simple shapes, so those initial layers do not need to be fine-tuned for a new dataset. Training those layers from scratch would only result in longer training times, so it is a good idea to experiment with leaving those layers untrained.
- In Experiment 3, we only fine-tune the final classification layer of the network. This indicates whether the features learned on the ImageNet dataset are also capable of discriminating between our paintings, in which case freezing all but the final layer should give good results.

CapsuleNet training from scratch

When we experimented with the CapsuleNet, we trained the model from scratch with a random initialisation. We did not use transfer learning because the CapsNet is fairly new and had only been trained on MNIST, which is very different from our dataset and has a resolution that is far too small for our purposes (28 by 28). In terms of computational complexity, the CapsNet took too long to train for us to

experiment extensively with many alternatives and different methods of training. This is because the CapsNet has more elements to train, as it relies on activation vectors which encode both the probability of the presence of a feature (indicated by vector length) and the orientation of the feature (pose parameters). Specifically, according to Geoffrey Hinton, the transformation matrices have n^2 parameters rather than just n .

A custom Network trained from scratch

We noticed that the first block of the CapsuleNet was composed of a regular CNN, and hence thought it would be interesting to replace this by the ResNet network. The rationale behind this is that it might be more effective to use the representations of the ResNet (over the massive ImageNet dataset), rather than learning representations from scratch through a standard convolutional layer (and our much smaller training set). As such, we created a custom network, which we named CustomNet, in the following way:

- We first used the convolutions of the ResNet (stripping away the ResNet output) and loaded the ImageNet weights.
- We then froze this part of the network so that these weights would be unaffected by training.
- We finally routed the output of this configuration through the capsule layers of the CapsNet, which produced the final seven class outputs.

In this way, we effectively replaced the convolutional layers in the CapsNet by a whole ResNet network. We also made an alternative model in which we added dropout layers to avoid over-fitting.

4.2. Evaluation metrics

In order to evaluate our models, gain an understanding of their behaviour and allow us to compare model performance, we relied on two different evaluation metrics:

Loss and Accuracy on the training and test sets

The primary performance measure we used for our networks is the classification accuracy. This is calculated as $\frac{n_{tp}}{n_{total}}$, the ratio between the number of correct classifications to the total number of examples, and is sensible in our case as the datasets we are using are very balanced. Along with the accuracy, we also keep track of the cost, which is the categorical cross-entropy for the ResNet and the margin loss for both the CapsNet and CustomNet. These metrics were evaluated on both the training and test sets.

Moreover, in order to gain insight into (1) how various hyper-parameters affected the performance of our networks, and (2) the effectiveness of training, we kept track of these metrics after each epoch of training.

Layer Visualisation

Second, we used layer visualizations to gain insight into the behaviour of our networks. More specifically, we applied the visualisation techniques described in section 2.5 to visualise the activations for each output class. This allowed us to visualize the input that would maximise the activation for each of our chosen styles. The reason we chose this visualisation technique over others is that it works well on all of our chosen architectures, and hence is well-suited for comparison purposes.

4.3. Implementation details

4.3.1. CODE STRUCTURE, LIBRARIES AND HARDWARE

Our code base is composed by (1) a set of APIs implementing the helper functions we need in order to train, run and evaluate our models and (2) a set of scripts actually performing these functions. Each of the APIs is packaged in a python package in a folder named after its functionality. All in all, our project directory has the following structure:

```
DeepArt
|
| — Preprocessing : Contains the functions
|   necessary for the preprocessing
|   of the Data (extracting , cropping ,
|   splitting ect.) .
|
| — Capsnet : Contains the code for the
|   capsuleNet model, which was
|   adapted from Xifeng Guo's
|   implementation . [*]
|
| — CustomNet : Contains the code the for
|   CustomNet model, which was constructed
|   through a combination of the Resnet
|   and the Capsnet .
|
| — TransferLearning : Contains the
|   functions necessary for the transfer
|   learning on the Resnet .
|
| — Visualisation : Contains the functions
|   necessary for visualising the
|   layers and the training history of the
|   models .
|
| — Utilities : Contains general utilities
|   helper functions .
|
| — Scripts : Contains all the scripts that
|   use the APIs above in order to
```

```
train , run , test and evaluate our
models .
— SavedData : Folder containing all the
  saved data from the experiments
  and trained models .
— Wikiart : The Dataset .
```

Listing 1. : (Guo)]DeepArt project code structure. [*]: (Guo)

In making our implementation, the main libraries we relied on are the following :

- **Keras.io** (Chollet et al., 2015), a deep learning API implemented on Tensorflow (Abadi et al., 2015) that has the advantage of higher level of abstraction compared to the later.
- **Keras-vis** (Kotikalapudi & contributors, 2017), a Layer-visualisation library.
- **XifengGuo/CapsNet-Keras** (Guo), a keras implementation of the capsuleNet network, which we adapted to our setup.

Finally, in order to run our scripts, we used UCL's *Blaze* server, a shared machine with four GeForce GTX titan X GPUs, which we were able to utilize thanks to Tensorflow (Abadi et al., 2015).

4.3.2. MAIN SCRIPTS

ResNet Script

In this script we are doing the transfer learning on the ResNet-50 network, according to the four experiments described in section 4.1. The paintings are loaded, split into training and test sets and cropped in order to conform to the ResNet input dimensions (and for all the input data to have the same size). Specifically, we used a pixel size of (224,224) pixels per crop, and performed 4 crops per painting. Then we ran the experiments described in section 4.1. Each experiment includes the following stages:

- Load the ResNet with the pre-trained ImageNet weights. To accomplish this, we use the ResNet-50 implementation in Keras.
- Change the last layer of the model to have 7 output classes.
- Freeze the number of layers appropriate for each experiment so that the weights of the frozen layers will not be fine-tuned.
- Fine-tune the model using our dataset.
- Save the re-trained model and training histories for later assessment.

To fine-tune the ResNet, we trained over 40 epochs, applying Adam optimization with a batch-size of 128 and categorical cross-entropy loss. We additionally use early-stopping on the validation set with a patience of 2, which we chose as to save up computational resources, and as transfer-learning experiments usually require fewer epochs to fine-tune their weights. As we noted in the previous section, we track the loss and accuracy of the model throughout the procedure.

CapsNet Script

This script trains the CapsuleNet from scratch. Again, the paintings are loaded, cropped, then split into training and validation sets. Because of memory constraints on the *Blaze* machine, we applied a cropping dimension of (100,100) and used 4 crops per painting. We then trained the model over 10 epochs. The optimiser used was still Adam with a batch size of 16 (due to the limited memory resources). We used the margin loss function, described in section 2.4. At the end of training, the model is saved along with the training history and performance metrics at each epoch.

CustomNet Script

In the CustomNetwork, we used the output of the ResNet as the input to the capsule layers. In order to do so and respect consistency in layer-by-layer dimensionality, we needed to modify the kernel size of the capsule layer from 9 (value used in the CapsNet) to 3. We also added a dropout layer with dropout probability 0.5.

In the CustomNet training script, we load and crop the data in the same way, then train the CustomNet using input dimension (224,224), 10 epochs, batch size 32, the Adam optimiser, and the margin loss function. We also train the model with and without the dropout layers. Finally, we save the trained networks and the training history.

Visualisation Scripts

To visualise the network layers, we load the saved models, run the visualisation functionalities using the keras-vis API (Kotikalapudi & contributors, 2017), then save the visualisations in Portable Network Graphics (.png) format. We save one visualisation per output class, which as we saw in section 2.5 represents the input to the network that maximises the activation of that class.

5. Results and Discussion

5.1. ResNet Transfer Learning Results

The results from our transfer learning experiments with the ResNet are shown in Table 2. As we can see from the table,

retraining all parameters of the ResNet yielded an accuracy of $\approx 0.43\%$ on the test set, freezing the first few layers gave $\approx 48\%$, and retraining only the last layer resulted in $\approx 52\%$ accuracy.

ResNet Experiments		
Frozen layers	Train Accuracy	Test Accuracy
None	0.6520	0.4340
Up to activation_13	0.7410	0.4805
All except last	0.6200	0.5260

Table 2. Testing and training accuracy using transfer learning with ResNet on the WikiArt dataset.

Table 2 clearly indicates that the ResNet model trained on the ImageNet dataset is better at discriminating between our classes. In fact, the highest score is obtained while only fine-tuning the output layer of the network, leaving the pre-trained weights unchanged. Possible justifications for this behaviour are that our paintings dataset is not large or varied enough, or that we are still under-fitting the data when we train from scratch and that the model would benefit from longer training time. It is also worth noting that the model had a higher training accuracy when we re-trained the layers after activation 13 (leaving approximately $\frac{2}{3}$ of the network to re-train) than when we re-trained only the last layer, even though the testing accuracy was lower. This discrepancy indicates that we may have over-fit the model.

In order to further understand our results, we can examine the graphs of the evolution of the test set accuracy over each epoch of training. These are shown in Fig. 4.

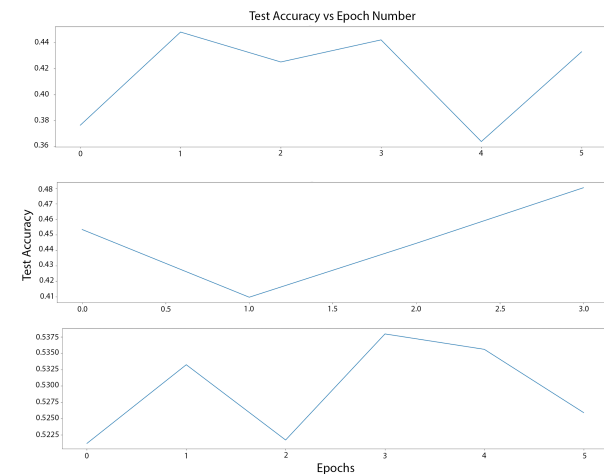


Figure 4. From top to bottom, these are the test accuracies of: Experiment 1, Experiment 2, Experiment 3

From looking at Figure 4, it is not clear that our networks

had finished learning when we stopped training: Particularly in experiment 2, training was cut-off while displaying a clear upward trend in test set accuracy. This seems to indicate that a higher value for the patience of our networks should have been used, although we were restricted by the computational resources, as we could not monopolize the Blaze machine which is shared by all students. Nevertheless, experiments 1 and 3 display a test-set accuracy that seems to fluctuate randomly, so it is entirely possible that the results obtained are also a consequence of insufficient training data.

Finally, it is interesting to observe the visualization of the last layer activations for each of our style categories (c.f. section 3). The most illustrative example is the one of Experiment 2, which is shown in Fig. 5 below. It is clear that our network learned to recognize some of the styles better than others. For instance, in class 2 we can see sharp, geometrical edges cutting off each other at various angles creating a mesh of inter-tangled geometrical shapes. This is quite reminiscent of the style of Cubism which it represents!

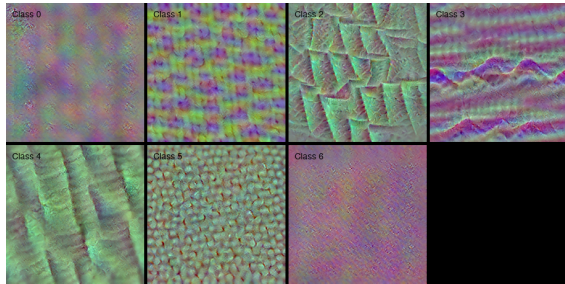


Figure 5. Visualisations of the activations in the last layer of the ResNet model from Experiment 2.

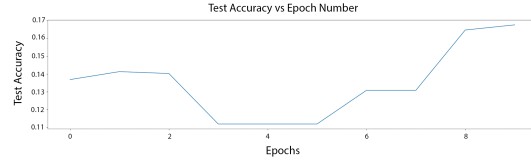
5.2. CapsNet Results

The results from the CapsNet training experiment are shown in Table 3. As we can see, the CapsNet obtained an accuracy of $\approx 16\%$, which is an indication that it has not learned much from training. This is not surprising, since the ResNet trained from scratch also had quite poor accuracy and indicates that we may have needed more training time and data.

CapsNet Experiments	
Train Accuracy	Test Accuracy
0.1520	0.1680

Table 3. Performance of the CapsNet on the Wikiart dataset

As before, in order to draw further insights on why these results were obtained, we look at the test accuracy evolution during training and the visualisations of the last layer of the CapsNet. These are displayed in Fig. 6 below.



(a) Evolution of the test set accuracy of the Capsnet over each training epoch.



(b) Visualisation of the Capsnet dense layer.

Figure 6. Capsnet Evaluation Figures

From Fig.6 two issues become apparent that possibly prevented our network to learn:

1. We stopped training while the test set accuracy was on an upward trend. This seems to indicate that we are still in the under-determined case and that given more epochs to train, the CapsNet would have obtained a higher accuracy.
2. The visualisations are very blurry and pixelated. This indicates that the cropping size of (100,10) is not sufficient to correctly capture stylistic information in the paintings (eg, topological relationships).

In both cases it seems that in order to resolve these issues we would require further computational resources. The CapsNet is very slow to train and has an extremely large number of parameters, requiring both extensive training time and additional memory.

6. CustomNet Results

The results from training our CustomNet are shown in Table 4 below. As we can see, we achieve a test set accuracy of $\approx 52\%$ in both variants of the model. The model is clearly over-fitting to the training data, as the training accuracy is $\approx 98\%$ and $\approx 91\%$, respectively, which is nearly double the testing accuracy. The test accuracy on CustomNet is not higher than the test accuracy for the ResNet model in which we trained all except the last layer. This suggests that concatenating the capsule layers to the ResNet output does not improve performance. In Fig. 7, we plot the test set accuracy evolution over the epochs of training. It is apparent that, contrary to the ResNet and CapsNet, training seems

to saturate after 2 epochs in both variants. Indeed, in both cases, the test set accuracy kept falling pretty regularly after the second epoch.

CustomNet Experiments		
	Train Accuracy	Test Accuracy
Without Dropout	0.9810	0.5150
With Dropout	0.9100	0.5175

Table 4. Performance of the CustomNet on the Wikiart dataset

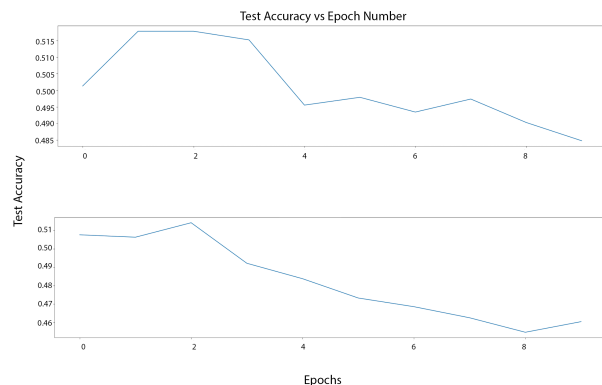


Figure 7. Evolution of the test set accuracy of the CustomNet over each training epoch. Top: Dropout case. Bottom: No-dropout case.

7. Conclusions

In conclusion, we found that it is possible to train deep neural models able to classify artworks by their style. By experimenting with three different network architectures, we showed that applying transfer learning on the ResNet architecture yielded the best results. More specifically, we examined the effect of freezing different number of layers and discovered it is best to retrain only the final layer, whilst keeping the rest frozen. This illustrates the similarities between low-level features as well as the differences in high-level features between object-recognition and art style classification. Visualisations of final layer activation of the networks were generated, showing that these types of models are successfully able to detect specific details belonging to different art styles.

The second network architecture we experimented with was the recently developed capsule network. Unfortunately, the capsule network produced poor results when classifying artistic style. Possibly due to the small amount of training data, the model was unable to capture the trends that each style imposes and therefore failed to learn effective parameters. This is evident by inspection of the corresponding

visualisations which appear to be random noise.

The last network architecture that we trained was a custom network in which we appended capsule output layers to the transfer-learned ResNet architecture. This achieved much better results than the capsule network, but did not perform better than the original ResNet model with transfer learning. This indicates that the capsule network was unable to learn low-level features of the art work, despite being able to perform extremely well on the MNIST dataset. However, we acknowledge that this may be due to insubstantial training time and data.

In the future, we would like to test the capsule network and custom network on a larger dataset and allow for longer training time. We are curious to see how the model would compare to the ResNet architecture without the computational resource constraints. If the same results hold for this experiment as well, then we would conclude that art style classification problems differ significantly from a typical object recognition problem and that there is room for improvement in this area.

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8. Appendix A

Layer (type)	Output Shape	Param #	Connected to
input_1 (InputLayer)	(None, 224, 224, 3)	0	
conv1 (Conv2D)	(None, 112, 112, 64)	9472	input_1[0][0]
bn_conv1 (BatchNormalization)	(None, 112, 112, 64)	256	conv1[0][0]
activation_1 (Activation)	(None, 112, 112, 64)	0	bn_conv1[0][0]
max_pooling2d_1 (MaxPooling2D)	(None, 55, 55, 64)	0	activation_1[0][0]
res2a_branch2a (Conv2D)	(None, 55, 55, 64)	4160	max_pooling2d_1[0][0]
bn2a_branch2a (BatchNormalization)	(None, 55, 55, 64)	256	res2a_branch2a[0][0]
activation_2 (Activation)	(None, 55, 55, 64)	0	bn2a_branch2a[0][0]
res2a_branch2b (Conv2D)	(None, 55, 55, 64)	36928	activation_2[0][0]
bn2a_branch2b (BatchNormalization)	(None, 55, 55, 64)	256	res2a_branch2b[0][0]
activation_3 (Activation)	(None, 55, 55, 64)	0	bn2a_branch2b[0][0]
res2a_branch2c (Conv2D)	(None, 55, 55, 256)	16640	activation_3[0][0]
res2a_branch1 (Conv2D)	(None, 55, 55, 256)	16640	max_pooling2d_1[0][0]
bn2a_branch2c (BatchNormalization)	(None, 55, 55, 256)	1024	res2a_branch2c[0][0]
bn2a_branch1 (BatchNormalization)	(None, 55, 55, 256)	1024	res2a_branch1[0][0]
add_1 (Add)	(None, 55, 55, 256)	0	bn2a_branch2c[0][0] bn2a_branch1[0][0]
activation_4 (Activation)	(None, 55, 55, 256)	0	add_1[0][0]
res2b_branch2a (Conv2D)	(None, 55, 55, 64)	16448	activation_4[0][0]
bn2b_branch2a (BatchNormalization)	(None, 55, 55, 64)	256	res2b_branch2a[0][0]

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660	-----				
661	activation_5 (Activation)	(None, 55, 55, 64)	0	bn2b_branch2a[0][0]	
662	-----				
663	res2b_branch2b (Conv2D)	(None, 55, 55, 64)	36928	activation_5[0][0]	
664	-----				
665	bn2b_branch2b (BatchNormalizati	(None, 55, 55, 64)	256	res2b_branch2b[0][0]	
666	-----				
667	activation_6 (Activation)	(None, 55, 55, 64)	0	bn2b_branch2b[0][0]	
668	-----				
669	res2b_branch2c (Conv2D)	(None, 55, 55, 256)	16640	activation_6[0][0]	
670	-----				
671	bn2b_branch2c (BatchNormalizati	(None, 55, 55, 256)	1024	res2b_branch2c[0][0]	
672	-----				
673	add_2 (Add)	(None, 55, 55, 256)	0	bn2b_branch2c[0][0] activation_4[0][0]	
674	-----				
675	activation_7 (Activation)	(None, 55, 55, 256)	0	add_2[0][0]	
676	-----				
677	res2c_branch2a (Conv2D)	(None, 55, 55, 64)	16448	activation_7[0][0]	
678	-----				
679	bn2c_branch2a (BatchNormalizati	(None, 55, 55, 64)	256	res2c_branch2a[0][0]	
680	-----				
681	activation_8 (Activation)	(None, 55, 55, 64)	0	bn2c_branch2a[0][0]	
682	-----				
683	res2c_branch2b (Conv2D)	(None, 55, 55, 64)	36928	activation_8[0][0]	
684	-----				
685	bn2c_branch2b (BatchNormalizati	(None, 55, 55, 64)	256	res2c_branch2b[0][0]	
686	-----				
687	activation_9 (Activation)	(None, 55, 55, 64)	0	bn2c_branch2b[0][0]	
688	-----				
689	res2c_branch2c (Conv2D)	(None, 55, 55, 256)	16640	activation_9[0][0]	
690	-----				
691	bn2c_branch2c (BatchNormalizati	(None, 55, 55, 256)	1024	res2c_branch2c[0][0]	
692	-----				
693	add_3 (Add)	(None, 55, 55, 256)	0	bn2c_branch2c[0][0] activation_7[0][0]	
694	-----				
695	activation_10 (Activation)	(None, 55, 55, 256)	0	add_3[0][0]	
696	-----				
697	res3a_branch2a (Conv2D)	(None, 28, 28, 128)	32896	activation_10[0][0]	
698	-----				
699	bn3a_branch2a (BatchNormalizati	(None, 28, 28, 128)	512	res3a_branch2a[0][0]	
700	-----				
701	activation_11 (Activation)	(None, 28, 28, 128)	0	bn3a_branch2a[0][0]	
702	-----				
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715	-----				
716					
717	res3a_branch2b (Conv2D)	(None, 28, 28, 128)	147584	activation_11 [0][0]	
718	-----				
719	bn3a_branch2b (BatchNormalizati	(None, 28, 28, 128)	512	res3a_branch2b [0][0]	
720	-----				
721	activation_12 (Activation)	(None, 28, 28, 128)	0	bn3a_branch2b [0][0]	
722	-----				
723					
724	res3a_branch2c (Conv2D)	(None, 28, 28, 512)	66048	activation_12 [0][0]	
725	-----				
726					
727	res3a_branch1 (Conv2D)	(None, 28, 28, 512)	131584	activation_10 [0][0]	
728	-----				
729	bn3a_branch2c (BatchNormalizati	(None, 28, 28, 512)	2048	res3a_branch2c [0][0]	
730	-----				
731					
732	bn3a_branch1 (BatchNormalizatio	(None, 28, 28, 512)	2048	res3a_branch1 [0][0]	
733	-----				
734	add_4 (Add)	(None, 28, 28, 512)	0	bn3a_branch2c [0][0]	
735				bn3a_branch1 [0][0]	
736	-----				
737	activation_13 (Activation)	(None, 28, 28, 512)	0	add_4 [0][0]	
738	-----				
739					
740	res3b_branch2a (Conv2D)	(None, 28, 28, 128)	65664	activation_13 [0][0]	
741	-----				
742					
743	bn3b_branch2a (BatchNormalizati	(None, 28, 28, 128)	512	res3b_branch2a [0][0]	
744	-----				
745	activation_14 (Activation)	(None, 28, 28, 128)	0	bn3b_branch2a [0][0]	
746	-----				
747					
748	res3b_branch2b (Conv2D)	(None, 28, 28, 128)	147584	activation_14 [0][0]	
749	-----				
750					
751	bn3b_branch2b (BatchNormalizati	(None, 28, 28, 128)	512	res3b_branch2b [0][0]	
752	-----				
753	activation_15 (Activation)	(None, 28, 28, 128)	0	bn3b_branch2b [0][0]	
754	-----				
755					
756	res3b_branch2c (Conv2D)	(None, 28, 28, 512)	66048	activation_15 [0][0]	
757	-----				
758					
759	bn3b_branch2c (BatchNormalizati	(None, 28, 28, 512)	2048	res3b_branch2c [0][0]	
760	-----				
761	add_5 (Add)	(None, 28, 28, 512)	0	bn3b_branch2c [0][0]	
762				activation_13 [0][0]	
763	-----				
764	activation_16 (Activation)	(None, 28, 28, 512)	0	add_5 [0][0]	
765	-----				
766					
767	res3c_branch2a (Conv2D)	(None, 28, 28, 128)	65664	activation_16 [0][0]	
768	-----				
769					
	bn3c_branch2a (BatchNormalizati	(None, 28, 28, 128)	512	res3c_branch2a [0][0]	

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770	-----				
771					
772	activation_17 (Activation)	(None, 28, 28, 128)	0	bn3c_branch2a[0][0]	
773	-----				
774	res3c_branch2b (Conv2D)	(None, 28, 28, 128)	147584	activation_17[0][0]	
775	-----				
776	bn3c_branch2b (BatchNormalizati	(None, 28, 28, 128)	512	res3c_branch2b[0][0]	
777	-----				
778					
779	activation_18 (Activation)	(None, 28, 28, 128)	0	bn3c_branch2b[0][0]	
780	-----				
781	res3c_branch2c (Conv2D)	(None, 28, 28, 512)	66048	activation_18[0][0]	
782	-----				
783					
784	bn3c_branch2c (BatchNormalizati	(None, 28, 28, 512)	2048	res3c_branch2c[0][0]	
785	-----				
786					
787	add_6 (Add)	(None, 28, 28, 512)	0	bn3c_branch2c[0][0] activation_16[0][0]	
788	-----				
789					
790	activation_19 (Activation)	(None, 28, 28, 512)	0	add_6[0][0]	
791	-----				
792	res3d_branch2a (Conv2D)	(None, 28, 28, 128)	65664	activation_19[0][0]	
793	-----				
794					
795	bn3d_branch2a (BatchNormalizati	(None, 28, 28, 128)	512	res3d_branch2a[0][0]	
796	-----				
797					
798	activation_20 (Activation)	(None, 28, 28, 128)	0	bn3d_branch2a[0][0]	
799	-----				
800	res3d_branch2b (Conv2D)	(None, 28, 28, 128)	147584	activation_20[0][0]	
801	-----				
802					
803	bn3d_branch2b (BatchNormalizati	(None, 28, 28, 128)	512	res3d_branch2b[0][0]	
804	-----				
805					
806	activation_21 (Activation)	(None, 28, 28, 128)	0	bn3d_branch2b[0][0]	
807	-----				
808	res3d_branch2c (Conv2D)	(None, 28, 28, 512)	66048	activation_21[0][0]	
809	-----				
810					
811	bn3d_branch2c (BatchNormalizati	(None, 28, 28, 512)	2048	res3d_branch2c[0][0]	
812	-----				
813					
814	add_7 (Add)	(None, 28, 28, 512)	0	bn3d_branch2c[0][0] activation_19[0][0]	
815	-----				
816					
817	activation_22 (Activation)	(None, 28, 28, 512)	0	add_7[0][0]	
818	-----				
819					
820	res4a_branch2a (Conv2D)	(None, 14, 14, 256)	131328	activation_22[0][0]	
821	-----				
822					
823	bn4a_branch2a (BatchNormalizati	(None, 14, 14, 256)	1024	res4a_branch2a[0][0]	
824	-----				
	activation_23 (Activation)	(None, 14, 14, 256)	0	bn4a_branch2a[0][0]	

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825	-----				
826					
827	res4a_branch2b (Conv2D)	(None, 14, 14, 256)	590080	activation_23 [0][0]	
828	-----				
829	bn4a_branch2b (BatchNormalizati	(None, 14, 14, 256)	1024	res4a_branch2b [0][0]	
830	-----				
831	activation_24 (Activation)	(None, 14, 14, 256)	0	bn4a_branch2b [0][0]	
832	-----				
833					
834	res4a_branch2c (Conv2D)	(None, 14, 14, 1024)	263168	activation_24 [0][0]	
835	-----				
836					
837	res4a_branch1 (Conv2D)	(None, 14, 14, 1024)	525312	activation_22 [0][0]	
838	-----				
839	bn4a_branch2c (BatchNormalizati	(None, 14, 14, 1024)	4096	res4a_branch2c [0][0]	
840	-----				
841					
842	bn4a_branch1 (BatchNormalizatio	(None, 14, 14, 1024)	4096	res4a_branch1 [0][0]	
843	-----				
844	add_8 (Add)	(None, 14, 14, 1024)	0	bn4a_branch2c [0][0]	
845				bn4a_branch1 [0][0]	
846	-----				
847	activation_25 (Activation)	(None, 14, 14, 1024)	0	add_8 [0][0]	
848	-----				
849					
850	res4b_branch2a (Conv2D)	(None, 14, 14, 256)	262400	activation_25 [0][0]	
851	-----				
852					
853	bn4b_branch2a (BatchNormalizati	(None, 14, 14, 256)	1024	res4b_branch2a [0][0]	
854	-----				
855	activation_26 (Activation)	(None, 14, 14, 256)	0	bn4b_branch2a [0][0]	
856	-----				
857					
858	res4b_branch2b (Conv2D)	(None, 14, 14, 256)	590080	activation_26 [0][0]	
859	-----				
860					
861	bn4b_branch2b (BatchNormalizati	(None, 14, 14, 256)	1024	res4b_branch2b [0][0]	
862	-----				
863					
864	activation_27 (Activation)	(None, 14, 14, 256)	0	bn4b_branch2b [0][0]	
865	-----				
866					
867	res4b_branch2c (Conv2D)	(None, 14, 14, 1024)	263168	activation_27 [0][0]	
868	-----				
869					
870	bn4b_branch2c (BatchNormalizati	(None, 14, 14, 1024)	4096	res4b_branch2c [0][0]	
871	-----				
872					
873	add_9 (Add)	(None, 14, 14, 1024)	0	bn4b_branch2c [0][0]	
874				activation_25 [0][0]	
875	-----				
876					
877	activation_28 (Activation)	(None, 14, 14, 1024)	0	add_9 [0][0]	
878	-----				
879					
	res4c_branch2a (Conv2D)	(None, 14, 14, 256)	262400	activation_28 [0][0]	

	bn4c_branch2a (BatchNormalizati	(None, 14, 14, 256)	1024	res4c_branch2a [0][0]	

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880	-----				
881					
882	activation_29 (Activation)	(None, 14, 14, 256)	0		bn4c_branch2a[0][0]
883	-----				
884	res4c_branch2b (Conv2D)	(None, 14, 14, 256)	590080		activation_29[0][0]
885	-----				
886	bn4c_branch2b (BatchNormalizati	(None, 14, 14, 256)	1024		res4c_branch2b[0][0]
887	-----				
888					
889	activation_30 (Activation)	(None, 14, 14, 256)	0		bn4c_branch2b[0][0]
890	-----				
891	res4c_branch2c (Conv2D)	(None, 14, 14, 1024)	263168		activation_30[0][0]
892	-----				
893					
894	bn4c_branch2c (BatchNormalizati	(None, 14, 14, 1024)	4096		res4c_branch2c[0][0]
895	-----				
896					
897	add_10 (Add)	(None, 14, 14, 1024)	0		bn4c_branch2c[0][0] activation_28[0][0]
898	-----				
899					
900	activation_31 (Activation)	(None, 14, 14, 1024)	0		add_10[0][0]
901	-----				
902	res4d_branch2a (Conv2D)	(None, 14, 14, 256)	262400		activation_31[0][0]
903	-----				
904					
905	bn4d_branch2a (BatchNormalizati	(None, 14, 14, 256)	1024		res4d_branch2a[0][0]
906	-----				
907					
908	activation_32 (Activation)	(None, 14, 14, 256)	0		bn4d_branch2a[0][0]
909	-----				
910	res4d_branch2b (Conv2D)	(None, 14, 14, 256)	590080		activation_32[0][0]
911	-----				
912					
913	bn4d_branch2b (BatchNormalizati	(None, 14, 14, 256)	1024		res4d_branch2b[0][0]
914	-----				
915					
916	activation_33 (Activation)	(None, 14, 14, 256)	0		bn4d_branch2b[0][0]
917	-----				
918	res4d_branch2c (Conv2D)	(None, 14, 14, 1024)	263168		activation_33[0][0]
919	-----				
920					
921	bn4d_branch2c (BatchNormalizati	(None, 14, 14, 1024)	4096		res4d_branch2c[0][0]
922	-----				
923					
924	add_11 (Add)	(None, 14, 14, 1024)	0		bn4d_branch2c[0][0] activation_31[0][0]
925	-----				
926					
927	activation_34 (Activation)	(None, 14, 14, 1024)	0		add_11[0][0]
928	-----				
929					
930	res4e_branch2a (Conv2D)	(None, 14, 14, 256)	262400		activation_34[0][0]
931	-----				
932					
933	bn4e_branch2a (BatchNormalizati	(None, 14, 14, 256)	1024		res4e_branch2a[0][0]
934	-----				
	activation_35 (Activation)	(None, 14, 14, 256)	0		bn4e_branch2a[0][0]

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990				
991				
992	bn5a_branch2b (BatchNormalizati	(None, 7, 7, 512)	2048	res5a_branch2b [0][0]
993				
994	activation_42 (Activation)	(None, 7, 7, 512)	0	bn5a_branch2b [0][0]
995				
996	res5a_branch2c (Conv2D)	(None, 7, 7, 2048)	1050624	activation_42 [0][0]
997				
998				
999	res5a_branch1 (Conv2D)	(None, 7, 7, 2048)	2099200	activation_40 [0][0]
1000				
1001				
1002	bn5a_branch2c (BatchNormalizati	(None, 7, 7, 2048)	8192	res5a_branch2c [0][0]
1003				
1004	bn5a_branch1 (BatchNormalizatio	(None, 7, 7, 2048)	8192	res5a_branch1 [0][0]
1005				
1006				
1007	add_14 (Add)	(None, 7, 7, 2048)	0	bn5a_branch2c [0][0] bn5a_branch1 [0][0]
1008				
1009				
1010	activation_43 (Activation)	(None, 7, 7, 2048)	0	add_14 [0][0]
1011				
1012	res5b_branch2a (Conv2D)	(None, 7, 7, 512)	1049088	activation_43 [0][0]
1013				
1014				
1015	bn5b_branch2a (BatchNormalizati	(None, 7, 7, 512)	2048	res5b_branch2a [0][0]
1016				
1017	activation_44 (Activation)	(None, 7, 7, 512)	0	bn5b_branch2a [0][0]
1018				
1019				
1020	res5b_branch2b (Conv2D)	(None, 7, 7, 512)	2359808	activation_44 [0][0]
1021				
1022				
1023	bn5b_branch2b (BatchNormalizati	(None, 7, 7, 512)	2048	res5b_branch2b [0][0]
1024				
1025	activation_45 (Activation)	(None, 7, 7, 512)	0	bn5b_branch2b [0][0]
1026				
1027	res5b_branch2c (Conv2D)	(None, 7, 7, 2048)	1050624	activation_45 [0][0]
1028				
1029				
1030	bn5b_branch2c (BatchNormalizati	(None, 7, 7, 2048)	8192	res5b_branch2c [0][0]
1031				
1032				
1033	add_15 (Add)	(None, 7, 7, 2048)	0	bn5b_branch2c [0][0] activation_43 [0][0]
1034				
1035				
1036	activation_46 (Activation)	(None, 7, 7, 2048)	0	add_15 [0][0]
1037				
1038	res5c_branch2a (Conv2D)	(None, 7, 7, 512)	1049088	activation_46 [0][0]
1039				
1040				
1041	bn5c_branch2a (BatchNormalizati	(None, 7, 7, 512)	2048	res5c_branch2a [0][0]
1042				
1043				
1044	activation_47 (Activation)	(None, 7, 7, 512)	0	bn5c_branch2a [0][0]

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res5c_branch2b (Conv2D)	(None, 7, 7, 512)	2359808	activation_47 [0][0]
bn5c_branch2b (BatchNormalizati	(None, 7, 7, 512)	2048	res5c_branch2b [0][0]
activation_48 (Activation)	(None, 7, 7, 512)	0	bn5c_branch2b [0][0]
res5c_branch2c (Conv2D)	(None, 7, 7, 2048)	1050624	activation_48 [0][0]
bn5c_branch2c (BatchNormalizati	(None, 7, 7, 2048)	8192	res5c_branch2c [0][0]
add_16 (Add)	(None, 7, 7, 2048)	0	bn5c_branch2c [0][0] activation_46 [0][0]
activation_49 (Activation)	(None, 7, 7, 2048)	0	add_16 [0][0]
avg_pool (AveragePooling2D)	(None, 1, 1, 2048)	0	activation_49 [0][0]
flatten_1 (Flatten)	(None, 2048)	0	avg_pool [0][0]
output_predictions (Dense)	(None, 7)	14343	flatten_1 [0][0]
Total params: 23,602,055 Trainable params: 23,548,935 Non-trainable params: 53,120			
Layer (type)	Output Shape	Param #	Connected to
input_1 (InputLayer)	(None, 224, 224, 3)	0	
conv1 (Conv2D)	(None, 112, 112, 64)	9472	input_1 [0][0]
bn_conv1 (BatchNormalization)	(None, 112, 112, 64)	256	conv1 [0][0]
activation_1 (Activation)	(None, 112, 112, 64)	0	bn_conv1 [0][0]
max_pooling2d_1 (MaxPooling2D)	(None, 55, 55, 64)	0	activation_1 [0][0]
res2a_branch2a (Conv2D)	(None, 55, 55, 64)	4160	max_pooling2d_1 [0][0]
bn2a_branch2a (BatchNormalizati	(None, 55, 55, 64)	256	res2a_branch2a [0][0]
activation_2 (Activation)	(None, 55, 55, 64)	0	bn2a_branch2a [0][0]

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res2a_branch2b (Conv2D)	(None, 55, 55, 64)	36928	activation_2 [0][0]
bn2a_branch2b (BatchNormalizati	(None, 55, 55, 64)	256	res2a_branch2b [0][0]
activation_3 (Activation)	(None, 55, 55, 64)	0	bn2a_branch2b [0][0]
res2a_branch2c (Conv2D)	(None, 55, 55, 256)	16640	activation_3 [0][0]
res2a_branch1 (Conv2D)	(None, 55, 55, 256)	16640	max_pooling2d_1 [0][0]
bn2a_branch2c (BatchNormalizati	(None, 55, 55, 256)	1024	res2a_branch2c [0][0]
bn2a_branch1 (BatchNormalizatio	(None, 55, 55, 256)	1024	res2a_branch1 [0][0]
add_1 (Add)	(None, 55, 55, 256)	0	bn2a_branch2c [0][0] bn2a_branch1 [0][0]
activation_4 (Activation)	(None, 55, 55, 256)	0	add_1 [0][0]
res2b_branch2a (Conv2D)	(None, 55, 55, 64)	16448	activation_4 [0][0]
bn2b_branch2a (BatchNormalizati	(None, 55, 55, 64)	256	res2b_branch2a [0][0]
activation_5 (Activation)	(None, 55, 55, 64)	0	bn2b_branch2a [0][0]
res2b_branch2b (Conv2D)	(None, 55, 55, 64)	36928	activation_5 [0][0]
bn2b_branch2b (BatchNormalizati	(None, 55, 55, 64)	256	res2b_branch2b [0][0]
activation_6 (Activation)	(None, 55, 55, 64)	0	bn2b_branch2b [0][0]
res2b_branch2c (Conv2D)	(None, 55, 55, 256)	16640	activation_6 [0][0]
bn2b_branch2c (BatchNormalizati	(None, 55, 55, 256)	1024	res2b_branch2c [0][0]
add_2 (Add)	(None, 55, 55, 256)	0	bn2b_branch2c [0][0] activation_4 [0][0]
activation_7 (Activation)	(None, 55, 55, 256)	0	add_2 [0][0]
res2c_branch2a (Conv2D)	(None, 55, 55, 64)	16448	activation_7 [0][0]
bn2c_branch2a (BatchNormalizati	(None, 55, 55, 64)	256	res2c_branch2a [0][0]

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1155	-----				
1156	activation_8 (Activation)	(None, 55, 55, 64)	0	bn2c_branch2a[0][0]	
1157	-----				
1159	res2c_branch2b (Conv2D)	(None, 55, 55, 64)	36928	activation_8[0][0]	
1160	-----				
1161	bn2c_branch2b (BatchNormalizati	(None, 55, 55, 64)	256	res2c_branch2b[0][0]	
1162	-----				
1164	activation_9 (Activation)	(None, 55, 55, 64)	0	bn2c_branch2b[0][0]	
1165	-----				
1166	res2c_branch2c (Conv2D)	(None, 55, 55, 256)	16640	activation_9[0][0]	
1167	-----				
1169	bn2c_branch2c (BatchNormalizati	(None, 55, 55, 256)	1024	res2c_branch2c[0][0]	
1170	-----				
1171	add_3 (Add)	(None, 55, 55, 256)	0	bn2c_branch2c[0][0] activation_7[0][0]	
1172	-----				
1174	activation_10 (Activation)	(None, 55, 55, 256)	0	add_3[0][0]	
1175	-----				
1177	res3a_branch2a (Conv2D)	(None, 28, 28, 128)	32896	activation_10[0][0]	
1178	-----				
1179	bn3a_branch2a (BatchNormalizati	(None, 28, 28, 128)	512	res3a_branch2a[0][0]	
1180	-----				
1182	activation_11 (Activation)	(None, 28, 28, 128)	0	bn3a_branch2a[0][0]	
1183	-----				
1184	res3a_branch2b (Conv2D)	(None, 28, 28, 128)	147584	activation_11[0][0]	
1185	-----				
1187	bn3a_branch2b (BatchNormalizati	(None, 28, 28, 128)	512	res3a_branch2b[0][0]	
1188	-----				
1189	activation_12 (Activation)	(None, 28, 28, 128)	0	bn3a_branch2b[0][0]	
1190	-----				
1192	res3a_branch2c (Conv2D)	(None, 28, 28, 512)	66048	activation_12[0][0]	
1193	-----				
1194	res3a_branch1 (Conv2D)	(None, 28, 28, 512)	131584	activation_10[0][0]	
1195	-----				
1197	bn3a_branch2c (BatchNormalizati	(None, 28, 28, 512)	2048	res3a_branch2c[0][0]	
1198	-----				
1199	bn3a_branch1 (BatchNormalizatio	(None, 28, 28, 512)	2048	res3a_branch1[0][0]	
1200	-----				
1202	add_4 (Add)	(None, 28, 28, 512)	0	bn3a_branch2c[0][0] bn3a_branch1[0][0]	
1203	-----				
1204	activation_13 (Activation)	(None, 28, 28, 512)	0	add_4[0][0]	
1205	-----				
1206	res3b_branch2a (Conv2D)	(None, 28, 28, 128)	65664	activation_13[0][0]	
1207	-----				
1208					
1209					

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1210						
1211						
1212	bn3b_branch2a	(BatchNormalizati	(None, 28, 28, 128)	512		res3b_branch2a[0][0]
1213						
1214	activation_14	(Activation)	(None, 28, 28, 128)	0		bn3b_branch2a[0][0]
1215						
1216	res3b_branch2b	(Conv2D)	(None, 28, 28, 128)	147584		activation_14[0][0]
1217						
1218						
1219	bn3b_branch2b	(BatchNormalizati	(None, 28, 28, 128)	512		res3b_branch2b[0][0]
1220						
1221	activation_15	(Activation)	(None, 28, 28, 128)	0		bn3b_branch2b[0][0]
1222						
1223						
1224	res3b_branch2c	(Conv2D)	(None, 28, 28, 512)	66048		activation_15[0][0]
1225						
1226						
1227	bn3b_branch2c	(BatchNormalizati	(None, 28, 28, 512)	2048		res3b_branch2c[0][0]
1228						
1229	add_5	(Add)	(None, 28, 28, 512)	0		bn3b_branch2c[0][0]
1230						activation_13[0][0]
1231						
1232	activation_16	(Activation)	(None, 28, 28, 512)	0		add_5[0][0]
1233						
1234						
1235	res3c_branch2a	(Conv2D)	(None, 28, 28, 128)	65664		activation_16[0][0]
1236						
1237	bn3c_branch2a	(BatchNormalizati	(None, 28, 28, 128)	512		res3c_branch2a[0][0]
1238						
1239						
1240	activation_17	(Activation)	(None, 28, 28, 128)	0		bn3c_branch2a[0][0]
1241						
1242	res3c_branch2b	(Conv2D)	(None, 28, 28, 128)	147584		activation_17[0][0]
1243						
1244						
1245	bn3c_branch2b	(BatchNormalizati	(None, 28, 28, 128)	512		res3c_branch2b[0][0]
1246						
1247	activation_18	(Activation)	(None, 28, 28, 128)	0		bn3c_branch2b[0][0]
1248						
1249						
1250	res3c_branch2c	(Conv2D)	(None, 28, 28, 512)	66048		activation_18[0][0]
1251						
1252	bn3c_branch2c	(BatchNormalizati	(None, 28, 28, 512)	2048		res3c_branch2c[0][0]
1253						
1254						
1255	add_6	(Add)	(None, 28, 28, 512)	0		bn3c_branch2c[0][0]
1256						activation_16[0][0]
1257						
1258	activation_19	(Activation)	(None, 28, 28, 512)	0		add_6[0][0]
1259						
1260						
1261	res3d_branch2a	(Conv2D)	(None, 28, 28, 128)	65664		activation_19[0][0]
1262						
1263	bn3d_branch2a	(BatchNormalizati	(None, 28, 28, 128)	512		res3d_branch2a[0][0]
1264						

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1265					
1266					
1267	activation_20 (Activation)	(None, 28, 28, 128)	0		bn3d_branch2a [0][0]
1268					
1269	res3d_branch2b (Conv2D)	(None, 28, 28, 128)	147584		activation_20 [0][0]
1270					
1271	bn3d_branch2b (BatchNormalizati	(None, 28, 28, 128)	512		res3d_branch2b [0][0]
1272					
1273					
1274	activation_21 (Activation)	(None, 28, 28, 128)	0		bn3d_branch2b [0][0]
1275					
1276					
1277	res3d_branch2c (Conv2D)	(None, 28, 28, 512)	66048		activation_21 [0][0]
1278					
1279	bn3d_branch2c (BatchNormalizati	(None, 28, 28, 512)	2048		res3d_branch2c [0][0]
1280					
1281					
1282	add_7 (Add)	(None, 28, 28, 512)	0		bn3d_branch2c [0][0] activation_19 [0][0]
1283					
1284					
1285	activation_22 (Activation)	(None, 28, 28, 512)	0		add_7 [0][0]
1286					
1287					
1288	res4a_branch2a (Conv2D)	(None, 14, 14, 256)	131328		activation_22 [0][0]
1289					
1290	bn4a_branch2a (BatchNormalizati	(None, 14, 14, 256)	1024		res4a_branch2a [0][0]
1291					
1292					
1293	activation_23 (Activation)	(None, 14, 14, 256)	0		bn4a_branch2a [0][0]
1294					
1295	res4a_branch2b (Conv2D)	(None, 14, 14, 256)	590080		activation_23 [0][0]
1296					
1297					
1298	bn4a_branch2b (BatchNormalizati	(None, 14, 14, 256)	1024		res4a_branch2b [0][0]
1299					
1300					
1301	activation_24 (Activation)	(None, 14, 14, 256)	0		bn4a_branch2b [0][0]
1302					
1303	res4a_branch2c (Conv2D)	(None, 14, 14, 1024)	263168		activation_24 [0][0]
1304					
1305	res4a_branch1 (Conv2D)	(None, 14, 14, 1024)	525312		activation_22 [0][0]
1306					
1307					
1308	bn4a_branch2c (BatchNormalizati	(None, 14, 14, 1024)	4096		res4a_branch2c [0][0]
1309					
1310	bn4a_branch1 (BatchNormalizatio	(None, 14, 14, 1024)	4096		res4a_branch1 [0][0]
1311					
1312					
1313	add_8 (Add)	(None, 14, 14, 1024)	0		bn4a_branch2c [0][0] bn4a_branch1 [0][0]
1314					
1315					
1316	activation_25 (Activation)	(None, 14, 14, 1024)	0		add_8 [0][0]
1317					
1318					
1319	res4b_branch2a (Conv2D)	(None, 14, 14, 256)	262400		activation_25 [0][0]

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1320	-----				
1321					
1322	bn4b_branch2a (BatchNormalizati	(None, 14, 14, 256)	1024		res4b_branch2a[0][0]
1323	-----				
1324	activation_26 (Activation)	(None, 14, 14, 256)	0		bn4b_branch2a[0][0]
1325	-----				
1326	res4b_branch2b (Conv2D)	(None, 14, 14, 256)	590080		activation_26[0][0]
1327	-----				
1328					
1329	bn4b_branch2b (BatchNormalizati	(None, 14, 14, 256)	1024		res4b_branch2b[0][0]
1330	-----				
1331					
1332	activation_27 (Activation)	(None, 14, 14, 256)	0		bn4b_branch2b[0][0]
1333	-----				
1334	res4b_branch2c (Conv2D)	(None, 14, 14, 1024)	263168		activation_27[0][0]
1335	-----				
1336					
1337	bn4b_branch2c (BatchNormalizati	(None, 14, 14, 1024)	4096		res4b_branch2c[0][0]
1338	-----				
1339	add_9 (Add)	(None, 14, 14, 1024)	0		bn4b_branch2c[0][0]
1340					activation_25[0][0]
1341	-----				
1342					
1343	activation_28 (Activation)	(None, 14, 14, 1024)	0		add_9[0][0]
1344	-----				
1345	res4c_branch2a (Conv2D)	(None, 14, 14, 256)	262400		activation_28[0][0]
1346	-----				
1347					
1348	bn4c_branch2a (BatchNormalizati	(None, 14, 14, 256)	1024		res4c_branch2a[0][0]
1349	-----				
1350					
1351	activation_29 (Activation)	(None, 14, 14, 256)	0		bn4c_branch2a[0][0]
1352	-----				
1353	res4c_branch2b (Conv2D)	(None, 14, 14, 256)	590080		activation_29[0][0]
1354	-----				
1355					
1356	bn4c_branch2b (BatchNormalizati	(None, 14, 14, 256)	1024		res4c_branch2b[0][0]
1357	-----				
1358					
1359	activation_30 (Activation)	(None, 14, 14, 256)	0		bn4c_branch2b[0][0]
1360	-----				
1361	res4c_branch2c (Conv2D)	(None, 14, 14, 1024)	263168		activation_30[0][0]
1362	-----				
1363					
1364	bn4c_branch2c (BatchNormalizati	(None, 14, 14, 1024)	4096		res4c_branch2c[0][0]
1365	-----				
1366					
1367	add_10 (Add)	(None, 14, 14, 1024)	0		bn4c_branch2c[0][0]
1368					activation_28[0][0]
1369	-----				
1370					
1371	activation_31 (Activation)	(None, 14, 14, 1024)	0		add_10[0][0]
1372	-----				
1373					
1374	res4d_branch2a (Conv2D)	(None, 14, 14, 256)	262400		activation_31[0][0]

	bn4d_branch2a (BatchNormalizati	(None, 14, 14, 256)	1024		res4d_branch2a[0][0]

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1375	-----				
1376					
1377	activation_32 (Activation)	(None, 14, 14, 256)	0		bn4d_branch2a [0][0]
1378	-----				
1379	res4d_branch2b (Conv2D)	(None, 14, 14, 256)	590080		activation_32 [0][0]
1380	-----				
1381	bn4d_branch2b (BatchNormalizati	(None, 14, 14, 256)	1024		res4d_branch2b [0][0]
1382					
1383	-----				
1384	activation_33 (Activation)	(None, 14, 14, 256)	0		bn4d_branch2b [0][0]
1385	-----				
1386	res4d_branch2c (Conv2D)	(None, 14, 14, 1024)	263168		activation_33 [0][0]
1387					
1388	-----				
1389	bn4d_branch2c (BatchNormalizati	(None, 14, 14, 1024)	4096		res4d_branch2c [0][0]
1390	-----				
1391	add_11 (Add)	(None, 14, 14, 1024)	0		bn4d_branch2c [0][0]
1392					activation_31 [0][0]
1393	-----				
1394					
1395	activation_34 (Activation)	(None, 14, 14, 1024)	0		add_11 [0][0]
1396	-----				
1397	res4e_branch2a (Conv2D)	(None, 14, 14, 256)	262400		activation_34 [0][0]
1398					
1399	-----				
1400	bn4e_branch2a (BatchNormalizati	(None, 14, 14, 256)	1024		res4e_branch2a [0][0]
1401	-----				
1402	activation_35 (Activation)	(None, 14, 14, 256)	0		bn4e_branch2a [0][0]
1403	-----				
1404					
1405	res4e_branch2b (Conv2D)	(None, 14, 14, 256)	590080		activation_35 [0][0]
1406	-----				
1407	bn4e_branch2b (BatchNormalizati	(None, 14, 14, 256)	1024		res4e_branch2b [0][0]
1408					
1409	-----				
1410	activation_36 (Activation)	(None, 14, 14, 256)	0		bn4e_branch2b [0][0]
1411	-----				
1412	res4e_branch2c (Conv2D)	(None, 14, 14, 1024)	263168		activation_36 [0][0]
1413					
1414	-----				
1415	bn4e_branch2c (BatchNormalizati	(None, 14, 14, 1024)	4096		res4e_branch2c [0][0]
1416	-----				
1417	add_12 (Add)	(None, 14, 14, 1024)	0		bn4e_branch2c [0][0]
1418					activation_34 [0][0]
1419	-----				
1420					
1421	activation_37 (Activation)	(None, 14, 14, 1024)	0		add_12 [0][0]
1422	-----				
1423	res4f_branch2a (Conv2D)	(None, 14, 14, 256)	262400		activation_37 [0][0]
1424	-----				
1425					
1426	bn4f_branch2a (BatchNormalizati	(None, 14, 14, 256)	1024		res4f_branch2a [0][0]
1427	-----				
1428					
1429	activation_38 (Activation)	(None, 14, 14, 256)	0		bn4f_branch2a [0][0]

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1430					
1431					
1432	res4f_branch2b (Conv2D)	(None, 14, 14, 256)	590080	activation_38 [0][0]	
1433					
1434	bn4f_branch2b (BatchNormalizati	(None, 14, 14, 256)	1024	res4f_branch2b [0][0]	
1435					
1436	activation_39 (Activation)	(None, 14, 14, 256)	0	bn4f_branch2b [0][0]	
1437					
1438					
1439	res4f_branch2c (Conv2D)	(None, 14, 14, 1024)	263168	activation_39 [0][0]	
1440					
1441	bn4f_branch2c (BatchNormalizati	(None, 14, 14, 1024)	4096	res4f_branch2c [0][0]	
1442					
1443					
1444	add_13 (Add)	(None, 14, 14, 1024)	0	bn4f_branch2c [0][0]	
1445				activation_37 [0][0]	
1446					
1447	activation_40 (Activation)	(None, 14, 14, 1024)	0	add_13 [0][0]	
1448					
1449					
1450	res5a_branch2a (Conv2D)	(None, 7, 7, 512)	524800	activation_40 [0][0]	
1451					
1452	bn5a_branch2a (BatchNormalizati	(None, 7, 7, 512)	2048	res5a_branch2a [0][0]	
1453					
1454					
1455	activation_41 (Activation)	(None, 7, 7, 512)	0	bn5a_branch2a [0][0]	
1456					
1457	res5a_branch2b (Conv2D)	(None, 7, 7, 512)	2359808	activation_41 [0][0]	
1458					
1459					
1460	bn5a_branch2b (BatchNormalizati	(None, 7, 7, 512)	2048	res5a_branch2b [0][0]	
1461					
1462	activation_42 (Activation)	(None, 7, 7, 512)	0	bn5a_branch2b [0][0]	
1463					
1464					
1465	res5a_branch2c (Conv2D)	(None, 7, 7, 2048)	1050624	activation_42 [0][0]	
1466					
1467	res5a_branch1 (Conv2D)	(None, 7, 7, 2048)	2099200	activation_40 [0][0]	
1468					
1469					
1470	bn5a_branch2c (BatchNormalizati	(None, 7, 7, 2048)	8192	res5a_branch2c [0][0]	
1471					
1472	bn5a_branch1 (BatchNormalizatio	(None, 7, 7, 2048)	8192	res5a_branch1 [0][0]	
1473					
1474					
1475	add_14 (Add)	(None, 7, 7, 2048)	0	bn5a_branch2c [0][0]	
1476				bn5a_branch1 [0][0]	
1477					
1478	activation_43 (Activation)	(None, 7, 7, 2048)	0	add_14 [0][0]	
1479					
1480					
1481	res5b_branch2a (Conv2D)	(None, 7, 7, 512)	1049088	activation_43 [0][0]	
1482					
1483	bn5b_branch2a (BatchNormalizati	(None, 7, 7, 512)	2048	res5b_branch2a [0][0]	
1484					

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activation_44 (Activation)	(None, 7, 7, 512)	0	bn5b_branch2a [0][0]
res5b_branch2b (Conv2D)	(None, 7, 7, 512)	2359808	activation_44 [0][0]
bn5b_branch2b (BatchNormalizati	(None, 7, 7, 512)	2048	res5b_branch2b [0][0]
activation_45 (Activation)	(None, 7, 7, 512)	0	bn5b_branch2b [0][0]
res5b_branch2c (Conv2D)	(None, 7, 7, 2048)	1050624	activation_45 [0][0]
bn5b_branch2c (BatchNormalizati	(None, 7, 7, 2048)	8192	res5b_branch2c [0][0]
add_15 (Add)	(None, 7, 7, 2048)	0	bn5b_branch2c [0][0] activation_43 [0][0]
activation_46 (Activation)	(None, 7, 7, 2048)	0	add_15 [0][0]
res5c_branch2a (Conv2D)	(None, 7, 7, 512)	1049088	activation_46 [0][0]
bn5c_branch2a (BatchNormalizati	(None, 7, 7, 512)	2048	res5c_branch2a [0][0]
activation_47 (Activation)	(None, 7, 7, 512)	0	bn5c_branch2a [0][0]
res5c_branch2b (Conv2D)	(None, 7, 7, 512)	2359808	activation_47 [0][0]
bn5c_branch2b (BatchNormalizati	(None, 7, 7, 512)	2048	res5c_branch2b [0][0]
activation_48 (Activation)	(None, 7, 7, 512)	0	bn5c_branch2b [0][0]
res5c_branch2c (Conv2D)	(None, 7, 7, 2048)	1050624	activation_48 [0][0]
bn5c_branch2c (BatchNormalizati	(None, 7, 7, 2048)	8192	res5c_branch2c [0][0]
add_16 (Add)	(None, 7, 7, 2048)	0	bn5c_branch2c [0][0] activation_46 [0][0]
activation_49 (Activation)	(None, 7, 7, 2048)	0	add_16 [0][0]
avg_pool (AveragePooling2D)	(None, 1, 1, 2048)	0	activation_49 [0][0]
flatten_1 (Flatten)	(None, 2048)	0	avg_pool [0][0]
output_predictions (Dense)	(None, 7)	14343	flatten_1 [0][0]

Total params: 23,602,055
Trainable params: 23,548,935
Non-trainable params: 53,120

Listing 2. Resnet50 Model Summary

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	(None, 100, 100, 3)	0
conv1 (Conv2D)	(None, 92, 92, 256)	62464
conv2d_1 (Conv2D)	(None, 42, 42, 256)	5308672
reshape_1 (Reshape)	(None, 56448, 8)	0
lambda_1 (Lambda)	(None, 56448, 8)	0
digitcaps (CapsuleLayer)	(None, 8, 16)	58254336
out_caps (Length)	(None, 8)	0
Total params: 63,625,472 Trainable params: 63,173,888 Non-trainable params: 451,584		

Listing 3. Capsnet Model Summary

Layer (type)	Output Shape	Param #	Connected to
input_1 (InputLayer)	(None, 224, 224, 3)	0	
conv1 (Conv2D)	(None, 112, 112, 64)	9472	input_1 [0][0]
bn_conv1 (BatchNormalization)	(None, 112, 112, 64)	256	conv1 [0][0]
activation_1 (Activation)	(None, 112, 112, 64)	0	bn_conv1 [0][0]
max_pooling2d_1 (MaxPooling2D)	(None, 55, 55, 64)	0	activation_1 [0][0]
res2a_branch2a (Conv2D)	(None, 55, 55, 64)	4160	max_pooling2d_1 [0][0]
bn2a_branch2a (BatchNormalization)	(None, 55, 55, 64)	256	res2a_branch2a [0][0]
activation_2 (Activation)	(None, 55, 55, 64)	0	bn2a_branch2a [0][0]
res2a_branch2b (Conv2D)	(None, 55, 55, 64)	36928	activation_2 [0][0]
bn2a_branch2b (BatchNormalization)	(None, 55, 55, 64)	256	res2a_branch2b [0][0]
activation_3 (Activation)	(None, 55, 55, 64)	0	bn2a_branch2b [0][0]
res2a_branch2c (Conv2D)	(None, 55, 55, 256)	16640	activation_3 [0][0]
res2a_branch1 (Conv2D)	(None, 55, 55, 256)	16640	max_pooling2d_1 [0][0]
bn2a_branch2c (BatchNormalization)	(None, 55, 55, 256)	1024	res2a_branch2c [0][0]
bn2a_branch1 (BatchNormalization)	(None, 55, 55, 256)	1024	res2a_branch1 [0][0]

add_1 (Add)	(None, 55, 55, 256)	0	bn2a_branch2c [0][0] bn2a_branch1 [0][0]
activation_4 (Activation)	(None, 55, 55, 256)	0	add_1 [0][0]
res2b_branch2a (Conv2D)	(None, 55, 55, 64)	16448	activation_4 [0][0]
bn2b_branch2a (BatchNormalizati	(None, 55, 55, 64)	256	res2b_branch2a [0][0]
activation_5 (Activation)	(None, 55, 55, 64)	0	bn2b_branch2a [0][0]
res2b_branch2b (Conv2D)	(None, 55, 55, 64)	36928	activation_5 [0][0]
bn2b_branch2b (BatchNormalizati	(None, 55, 55, 64)	256	res2b_branch2b [0][0]
activation_6 (Activation)	(None, 55, 55, 64)	0	bn2b_branch2b [0][0]
res2b_branch2c (Conv2D)	(None, 55, 55, 256)	16640	activation_6 [0][0]
bn2b_branch2c (BatchNormalizati	(None, 55, 55, 256)	1024	res2b_branch2c [0][0]
add_2 (Add)	(None, 55, 55, 256)	0	bn2b_branch2c [0][0] activation_4 [0][0]
activation_7 (Activation)	(None, 55, 55, 256)	0	add_2 [0][0]
res2c_branch2a (Conv2D)	(None, 55, 55, 64)	16448	activation_7 [0][0]
bn2c_branch2a (BatchNormalizati	(None, 55, 55, 64)	256	res2c_branch2a [0][0]
activation_8 (Activation)	(None, 55, 55, 64)	0	bn2c_branch2a [0][0]
res2c_branch2b (Conv2D)	(None, 55, 55, 64)	36928	activation_8 [0][0]
bn2c_branch2b (BatchNormalizati	(None, 55, 55, 64)	256	res2c_branch2b [0][0]
activation_9 (Activation)	(None, 55, 55, 64)	0	bn2c_branch2b [0][0]
res2c_branch2c (Conv2D)	(None, 55, 55, 256)	16640	activation_9 [0][0]
bn2c_branch2c (BatchNormalizati	(None, 55, 55, 256)	1024	res2c_branch2c [0][0]
add_3 (Add)	(None, 55, 55, 256)	0	bn2c_branch2c [0][0] activation_7 [0][0]
activation_10 (Activation)	(None, 55, 55, 256)	0	add_3 [0][0]
res3a_branch2a (Conv2D)	(None, 28, 28, 128)	32896	activation_10 [0][0]
bn3a_branch2a (BatchNormalizati	(None, 28, 28, 128)	512	res3a_branch2a [0][0]
activation_11 (Activation)	(None, 28, 28, 128)	0	bn3a_branch2a [0][0]
res3a_branch2b (Conv2D)	(None, 28, 28, 128)	147584	activation_11 [0][0]
bn3a_branch2b (BatchNormalizati	(None, 28, 28, 128)	512	res3a_branch2b [0][0]
activation_12 (Activation)	(None, 28, 28, 128)	0	bn3a_branch2b [0][0]
res3a_branch2c (Conv2D)	(None, 28, 28, 512)	66048	activation_12 [0][0]
res3a_branch1 (Conv2D)	(None, 28, 28, 512)	131584	activation_10 [0][0]
bn3a_branch2c (BatchNormalizati	(None, 28, 28, 512)	2048	res3a_branch2c [0][0]

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bn3a_branch1 (BatchNormalizatio	(None, 28, 28, 512)	2048	res3a_branch1[0][0]
add_4 (Add)	(None, 28, 28, 512)	0	bn3a_branch2c[0][0] bn3a_branch1[0][0]
activation_13 (Activation)	(None, 28, 28, 512)	0	add_4[0][0]
res3b_branch2a (Conv2D)	(None, 28, 28, 128)	65664	activation_13[0][0]
bn3b_branch2a (BatchNormalizati	(None, 28, 28, 128)	512	res3b_branch2a[0][0]
activation_14 (Activation)	(None, 28, 28, 128)	0	bn3b_branch2a[0][0]
res3b_branch2b (Conv2D)	(None, 28, 28, 128)	147584	activation_14[0][0]
bn3b_branch2b (BatchNormalizati	(None, 28, 28, 128)	512	res3b_branch2b[0][0]
activation_15 (Activation)	(None, 28, 28, 128)	0	bn3b_branch2b[0][0]
res3b_branch2c (Conv2D)	(None, 28, 28, 512)	66048	activation_15[0][0]
bn3b_branch2c (BatchNormalizati	(None, 28, 28, 512)	2048	res3b_branch2c[0][0]
add_5 (Add)	(None, 28, 28, 512)	0	bn3b_branch2c[0][0] activation_13[0][0]
activation_16 (Activation)	(None, 28, 28, 512)	0	add_5[0][0]
res3c_branch2a (Conv2D)	(None, 28, 28, 128)	65664	activation_16[0][0]
bn3c_branch2a (BatchNormalizati	(None, 28, 28, 128)	512	res3c_branch2a[0][0]
activation_17 (Activation)	(None, 28, 28, 128)	0	bn3c_branch2a[0][0]
res3c_branch2b (Conv2D)	(None, 28, 28, 128)	147584	activation_17[0][0]
bn3c_branch2b (BatchNormalizati	(None, 28, 28, 128)	512	res3c_branch2b[0][0]
activation_18 (Activation)	(None, 28, 28, 128)	0	bn3c_branch2b[0][0]
res3c_branch2c (Conv2D)	(None, 28, 28, 512)	66048	activation_18[0][0]
bn3c_branch2c (BatchNormalizati	(None, 28, 28, 512)	2048	res3c_branch2c[0][0]
add_6 (Add)	(None, 28, 28, 512)	0	bn3c_branch2c[0][0] activation_16[0][0]
activation_19 (Activation)	(None, 28, 28, 512)	0	add_6[0][0]
res3d_branch2a (Conv2D)	(None, 28, 28, 128)	65664	activation_19[0][0]
bn3d_branch2a (BatchNormalizati	(None, 28, 28, 128)	512	res3d_branch2a[0][0]
activation_20 (Activation)	(None, 28, 28, 128)	0	bn3d_branch2a[0][0]
res3d_branch2b (Conv2D)	(None, 28, 28, 128)	147584	activation_20[0][0]
bn3d_branch2b (BatchNormalizati	(None, 28, 28, 128)	512	res3d_branch2b[0][0]
activation_21 (Activation)	(None, 28, 28, 128)	0	bn3d_branch2b[0][0]
res3d_branch2c (Conv2D)	(None, 28, 28, 512)	66048	activation_21[0][0]
bn3d_branch2c (BatchNormalizati	(None, 28, 28, 512)	2048	res3d_branch2c[0][0]

add_7 (Add)	(None, 28, 28, 512)	0	bn3d_branch2c [0][0] activation_19 [0][0]
activation_22 (Activation)	(None, 28, 28, 512)	0	add_7 [0][0]
res4a_branch2a (Conv2D)	(None, 14, 14, 256)	131328	activation_22 [0][0]
bn4a_branch2a (BatchNormalizati	(None, 14, 14, 256)	1024	res4a_branch2a [0][0]
activation_23 (Activation)	(None, 14, 14, 256)	0	bn4a_branch2a [0][0]
res4a_branch2b (Conv2D)	(None, 14, 14, 256)	590080	activation_23 [0][0]
bn4a_branch2b (BatchNormalizati	(None, 14, 14, 256)	1024	res4a_branch2b [0][0]
activation_24 (Activation)	(None, 14, 14, 256)	0	bn4a_branch2b [0][0]
res4a_branch2c (Conv2D)	(None, 14, 14, 1024)	263168	activation_24 [0][0]
res4a_branch1 (Conv2D)	(None, 14, 14, 1024)	525312	activation_22 [0][0]
bn4a_branch2c (BatchNormalizati	(None, 14, 14, 1024)	4096	res4a_branch2c [0][0]
bn4a_branch1 (BatchNormalizatio	(None, 14, 14, 1024)	4096	res4a_branch1 [0][0]
add_8 (Add)	(None, 14, 14, 1024)	0	bn4a_branch2c [0][0] bn4a_branch1 [0][0]
activation_25 (Activation)	(None, 14, 14, 1024)	0	add_8 [0][0]
res4b_branch2a (Conv2D)	(None, 14, 14, 256)	262400	activation_25 [0][0]
bn4b_branch2a (BatchNormalizati	(None, 14, 14, 256)	1024	res4b_branch2a [0][0]
activation_26 (Activation)	(None, 14, 14, 256)	0	bn4b_branch2a [0][0]
res4b_branch2b (Conv2D)	(None, 14, 14, 256)	590080	activation_26 [0][0]
bn4b_branch2b (BatchNormalizati	(None, 14, 14, 256)	1024	res4b_branch2b [0][0]
activation_27 (Activation)	(None, 14, 14, 256)	0	bn4b_branch2b [0][0]
res4b_branch2c (Conv2D)	(None, 14, 14, 1024)	263168	activation_27 [0][0]
bn4b_branch2c (BatchNormalizati	(None, 14, 14, 1024)	4096	res4b_branch2c [0][0]
add_9 (Add)	(None, 14, 14, 1024)	0	bn4b_branch2c [0][0] activation_25 [0][0]
activation_28 (Activation)	(None, 14, 14, 1024)	0	add_9 [0][0]
res4c_branch2a (Conv2D)	(None, 14, 14, 256)	262400	activation_28 [0][0]
bn4c_branch2a (BatchNormalizati	(None, 14, 14, 256)	1024	res4c_branch2a [0][0]
activation_29 (Activation)	(None, 14, 14, 256)	0	bn4c_branch2a [0][0]
res4c_branch2b (Conv2D)	(None, 14, 14, 256)	590080	activation_29 [0][0]
bn4c_branch2b (BatchNormalizati	(None, 14, 14, 256)	1024	res4c_branch2b [0][0]
activation_30 (Activation)	(None, 14, 14, 256)	0	bn4c_branch2b [0][0]
res4c_branch2c (Conv2D)	(None, 14, 14, 1024)	263168	activation_30 [0][0]

bn4c_branch2c (BatchNormalizati	(None, 14, 14, 1024)	4096	res4c_branch2c[0][0]
add_10 (Add)	(None, 14, 14, 1024)	0	bn4c_branch2c[0][0] activation_28[0][0]
activation_31 (Activation)	(None, 14, 14, 1024)	0	add_10[0][0]
res4d_branch2a (Conv2D)	(None, 14, 14, 256)	262400	activation_31[0][0]
bn4d_branch2a (BatchNormalizati	(None, 14, 14, 256)	1024	res4d_branch2a[0][0]
activation_32 (Activation)	(None, 14, 14, 256)	0	bn4d_branch2a[0][0]
res4d_branch2b (Conv2D)	(None, 14, 14, 256)	590080	activation_32[0][0]
bn4d_branch2b (BatchNormalizati	(None, 14, 14, 256)	1024	res4d_branch2b[0][0]
activation_33 (Activation)	(None, 14, 14, 256)	0	bn4d_branch2b[0][0]
res4d_branch2c (Conv2D)	(None, 14, 14, 1024)	263168	activation_33[0][0]
bn4d_branch2c (BatchNormalizati	(None, 14, 14, 1024)	4096	res4d_branch2c[0][0]
add_11 (Add)	(None, 14, 14, 1024)	0	bn4d_branch2c[0][0] activation_31[0][0]
activation_34 (Activation)	(None, 14, 14, 1024)	0	add_11[0][0]
res4e_branch2a (Conv2D)	(None, 14, 14, 256)	262400	activation_34[0][0]
bn4e_branch2a (BatchNormalizati	(None, 14, 14, 256)	1024	res4e_branch2a[0][0]
activation_35 (Activation)	(None, 14, 14, 256)	0	bn4e_branch2a[0][0]
res4e_branch2b (Conv2D)	(None, 14, 14, 256)	590080	activation_35[0][0]
bn4e_branch2b (BatchNormalizati	(None, 14, 14, 256)	1024	res4e_branch2b[0][0]
activation_36 (Activation)	(None, 14, 14, 256)	0	bn4e_branch2b[0][0]
res4e_branch2c (Conv2D)	(None, 14, 14, 1024)	263168	activation_36[0][0]
bn4e_branch2c (BatchNormalizati	(None, 14, 14, 1024)	4096	res4e_branch2c[0][0]
add_12 (Add)	(None, 14, 14, 1024)	0	bn4e_branch2c[0][0] activation_34[0][0]
activation_37 (Activation)	(None, 14, 14, 1024)	0	add_12[0][0]
res4f_branch2a (Conv2D)	(None, 14, 14, 256)	262400	activation_37[0][0]
bn4f_branch2a (BatchNormalizati	(None, 14, 14, 256)	1024	res4f_branch2a[0][0]
activation_38 (Activation)	(None, 14, 14, 256)	0	bn4f_branch2a[0][0]
res4f_branch2b (Conv2D)	(None, 14, 14, 256)	590080	activation_38[0][0]
bn4f_branch2b (BatchNormalizati	(None, 14, 14, 256)	1024	res4f_branch2b[0][0]
activation_39 (Activation)	(None, 14, 14, 256)	0	bn4f_branch2b[0][0]
res4f_branch2c (Conv2D)	(None, 14, 14, 1024)	263168	activation_39[0][0]
bn4f_branch2c (BatchNormalizati	(None, 14, 14, 1024)	4096	res4f_branch2c[0][0]

add_13 (Add)	(None, 14, 14, 1024)	0	bn4f_branch2c [0][0] activation_37 [0][0]
activation_40 (Activation)	(None, 14, 14, 1024)	0	add_13 [0][0]
res5a_branch2a (Conv2D)	(None, 7, 7, 512)	524800	activation_40 [0][0]
bn5a_branch2a (BatchNormalizati	(None, 7, 7, 512)	2048	res5a_branch2a [0][0]
activation_41 (Activation)	(None, 7, 7, 512)	0	bn5a_branch2a [0][0]
res5a_branch2b (Conv2D)	(None, 7, 7, 512)	2359808	activation_41 [0][0]
bn5a_branch2b (BatchNormalizati	(None, 7, 7, 512)	2048	res5a_branch2b [0][0]
activation_42 (Activation)	(None, 7, 7, 512)	0	bn5a_branch2b [0][0]
res5a_branch2c (Conv2D)	(None, 7, 7, 2048)	1050624	activation_42 [0][0]
res5a_branch1 (Conv2D)	(None, 7, 7, 2048)	2099200	activation_40 [0][0]
bn5a_branch2c (BatchNormalizati	(None, 7, 7, 2048)	8192	res5a_branch2c [0][0]
bn5a_branch1 (BatchNormalizatio	(None, 7, 7, 2048)	8192	res5a_branch1 [0][0]
add_14 (Add)	(None, 7, 7, 2048)	0	bn5a_branch2c [0][0] bn5a_branch1 [0][0]
activation_43 (Activation)	(None, 7, 7, 2048)	0	add_14 [0][0]
res5b_branch2a (Conv2D)	(None, 7, 7, 512)	1049088	activation_43 [0][0]
bn5b_branch2a (BatchNormalizati	(None, 7, 7, 512)	2048	res5b_branch2a [0][0]
activation_44 (Activation)	(None, 7, 7, 512)	0	bn5b_branch2a [0][0]
res5b_branch2b (Conv2D)	(None, 7, 7, 512)	2359808	activation_44 [0][0]
bn5b_branch2b (BatchNormalizati	(None, 7, 7, 512)	2048	res5b_branch2b [0][0]
activation_45 (Activation)	(None, 7, 7, 512)	0	bn5b_branch2b [0][0]
res5b_branch2c (Conv2D)	(None, 7, 7, 2048)	1050624	activation_45 [0][0]
bn5b_branch2c (BatchNormalizati	(None, 7, 7, 2048)	8192	res5b_branch2c [0][0]
add_15 (Add)	(None, 7, 7, 2048)	0	bn5b_branch2c [0][0] activation_43 [0][0]
activation_46 (Activation)	(None, 7, 7, 2048)	0	add_15 [0][0]
res5c_branch2a (Conv2D)	(None, 7, 7, 512)	1049088	activation_46 [0][0]
bn5c_branch2a (BatchNormalizati	(None, 7, 7, 512)	2048	res5c_branch2a [0][0]
activation_47 (Activation)	(None, 7, 7, 512)	0	bn5c_branch2a [0][0]
res5c_branch2b (Conv2D)	(None, 7, 7, 512)	2359808	activation_47 [0][0]
bn5c_branch2b (BatchNormalizati	(None, 7, 7, 512)	2048	res5c_branch2b [0][0]
activation_48 (Activation)	(None, 7, 7, 512)	0	bn5c_branch2b [0][0]
res5c_branch2c (Conv2D)	(None, 7, 7, 2048)	1050624	activation_48 [0][0]

bn5c_branch2c (BatchNormalizati	(None, 7, 7, 2048)	8192	res5c_branch2c[0][0]
add_16 (Add)	(None, 7, 7, 2048)	0	bn5c_branch2c[0][0] activation_46[0][0]
activation_49 (Activation)	(None, 7, 7, 2048)	0	add_16[0][0]
conv2d_1 (Conv2D)	(None, 2, 2, 256)	8388864	activation_49[0][0]
reshape_1 (Reshape)	(None, 128, 8)	0	conv2d_1[0][0]
lambda_1 (Lambda)	(None, 128, 8)	0	reshape_1[0][0]
dropout_1 (Dropout)	(None, 128, 8)	0	lambda_1[0][0]
digitcaps (CapsuleLayer)	(None, 8, 16)	132096	dropout_1[0][0]
out_caps (Length)	(None, 8)	0	digitcaps[0][0]

Total params: 32,108,672
Trainable params: 8,519,936
Non-trainable params: 23,588,736

Listing 4. CustomNet Model Summary