Capstone 2 Project Final Report

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Problem Statement

The purpose of this project is to determine how well a pretrained transfer learning convolutional neural network (TL) can detect stylized images despite having been trained on non stylized images. In particular, this project will attempt to determine how well a TL model pretrained on the Imagenet dataset, which has a large variety of images (over 14 million at the moment) ranging from plants to animals to structures to vehicles, can detect flowers in stylized images that will be generated through an arbitrary style transfer model (AST).

The usefulness of this project comes from the fact that image detection and image generating models are becoming increasingly popular and increasingly sophisticated. With regard to image detection, a great deal of work is being done in facial recognition and automated driving. While in image generation, Generative Adversarial Networks (GAN) are used to create art. This project attempts to bring together both image recognition and image generation.

The clients for this project include anyone who is interested in developing better image recognition models, whether they are individuals or companies. While the work done here is not cutting edge, it can offer potential insight into how image recognition models "see" art. It goes beyond the usual recognition of everyday images to those that are more abstract and obscure but still retain traces of actual objects. In this sense, this project also becomes useful for artists as it may allow them some understanding of how image recognition models process their work. It's true that art is still made for human consumption, but it is increasingly being made by artificial intelligence.

As we continue to develop more human-like AI, perhaps we may wish for them to understand some of our more subjective practices such as art. Humans can in large part identify objects in various types of artwork, except perhaps in more extreme abstract art creations. Of course, art is open to interpretation, but that is well beyond the scope of this project.

Yet, in art, beauty(or in this case, aesthetics) is very much in the eye of the beholder. So, maybe it won't matter how AI interprets art because even if its interpretation is "wrong", it may very well still add to the larger conversation of engaging with art in which a wide range of voices are welcomed. And someday those voices may not necessarily only need to be human.

Project Summary

Our project involves two deep learning models. The first is a transfer learning model, which will be developed by testing three well known CNN models - VGG16, ResNet50, and DenseNet169. The second is Magenta's arbitrary style transfer model. We'll be training our TL models on over 2000 flower images that are divided among five species. Using our AST model, we'll develop 2000 images by stylizing 100 flower images using five different art styles and four different interpolation weights.

Once we determine our most accurate TL model by testing it on a subset of the original flower dataset, we'll test how well it predicts the species of stylized images. From there, we'll determine how accurate the model is with regard to certain subsets of the data, including species, art style, and interpolation weight. This latter testing of subsets of the stylized images may help us better determine whether there are certain types of images that are easier or harder for our model to predict. For instance, is it clearly easier to accurately identify flower images stylized with fractal art than that with abstract expressionism? Or are images created with 0.4 interpolation weight easier to identify than those made with 0.6 interpolation weight?

Exploratory Analysis

Flower Dataset

Our dataset has been acquired from Kaggle and was previously used in an image recognition contest. It can be found here: https://www.kaggle.com/alxmamaev/flowers-recognition

The dataset is relatively small, at 4242 images that are divided into 5 species - daisy, dandelion, rose, sunflower, and tulip. The size of each group ranges from 1055 to 734, with dandelions having the highest total and sunflowers the lowest. All of the images are in color. Below (Figure 1) is a sample image from each species:

Figure 1: From top to bottom and left to right - daisy, dandelion, rose, sunflower, tulip.

While our dataset doesn't allow for an in depth statistical analysis, because they're images and not datatables, they do allow for a descriptive analysis that may allow us to form some sense of what to expect once we run the images through both of our models.

A sampling of the images reveals that they are not all presented in the same manner. For example, some images include people; some images are close ups of a single flower, while others show a field full of a single species. Comparing species, dandelions have a large amount of variety. They can have a white feathery look, but they can also have long, thin yellow petals, which can at times resemble those of sunflowers. Roses and tulips share some colors, including pink and yellow, and in some photos of closed roses, they do somewhat resemble tulips. This variety has its pros and cons. On the upside, it does allow the model to get familiar with a particular species through several different aspects, including shape and color variation and near and far perspectives. However, this variation also results in an intersection of qualities in which the model may get confused between a dandelion and a sunflower or a rose and a tulip. As such, it's hard to predict how both of the positive and negative aspects of the original dataset will affect the overall accuracy of the stylized dataset.

We'll be dividing our dataset into train, validation, and test groups. All five species will be present in each group, and there will be a 60-20-20 split for each species among train, validation, and test groups. We'll be using the training and validation datasets to train the model and the test model to determine the test accuracy of the final model.

We'll be assuming that the recognition model will not be able to do as well on the stylized images for several reasons - stylization may cause image distortion such as blurring of object borders or border destruction due the creation of new shapes and lines; it may also cause color changes - a rose that was largely pink may end up being composed of several different colors after stylization, making it more difficult for the recognition model.

Art Styles

We'll be using five different art styles that allow for a range in aesthetics - abstract expressionism, cyberpunk, fractal, pop art, and post-impressionism. All pieces are taken from Creative Commons as to avoid any conflict arising from its use, and in many cases, the artist and name of the piece are not known. However, that did place a limitation on the selection and quality of the style images.

A brief summary of each image and general style:

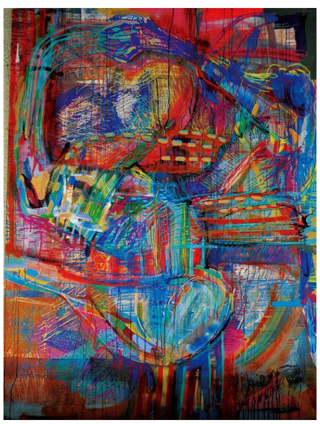
Abstract expressionism is often characterized by its perceived spontaneity and arbitrary appearance. Paint drops and splatters appear to be haphazardly strewn across a canvas, despite most works actually having involved careful planning. The piece we'll be using contains colors from across the color spectrum with lines going in all directions. It's also hard to discern what exactly the piece is portraying, made all the more difficult without a title.

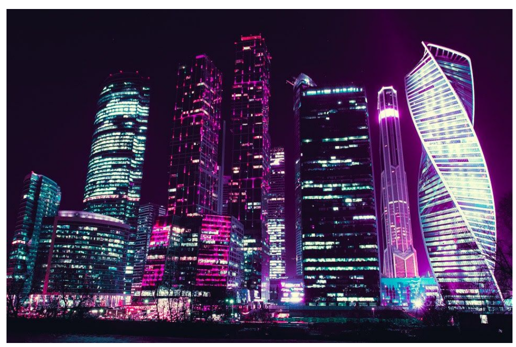
Cyberpunk imagery displays futuristic settings and characters, typically dense cityscapes and cybernetically enhanced beings. Many pieces also rely on neon colors, particularly pink, blue, and purple against dark backdrops. Such is the case with our piece, which displays tall buildings outlined in bright purple, pink, and blue and a black background.

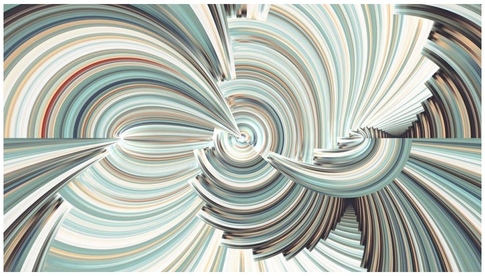
Fractal art uses repeating patterns, typically in the form of spirals and swirls or iterations of the Julia and Mandelbrot sets. Such designs can often be very elaborate and colorful, but the image we'll be using is fairly devoid of color. That's in contrast to some of our other images. That lack of color, as well as its intricate arched pattern, adds variety to our style set..

Pop art often appears in advertising and is known to use pop culture icons as its subject matter. Warhol's Campbell Soup image is one such example. Our image is a close up of DC Comics icon Batgirl (likely), stylized as if lifted from a comic book.

Post-Impressionism stands out for its reaction against Impressionism, namely by rejecting the latter's naturalistic depiction of color and light. In contrast, the former often uses unnatural, arbitrary colors, while emphasising distorted geometric forms. Our piece is Van Gogh's Women Picking Olives, which depicts a field of green, distorted trees rooted in brown dirt, against a faded sky.







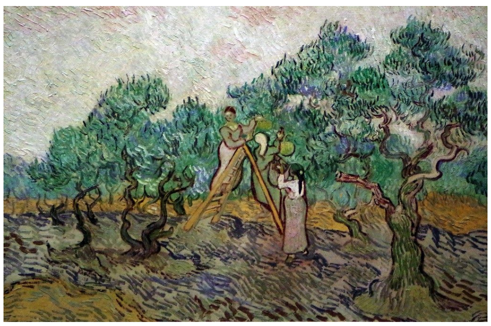


Figure 2: From top to bottom, left to right our styles for: abstract expressionism, cyberpunk, fractal art, pop art, and post-impressionism.

Magenta Neural Style Transfer Model

The neural style transfer model that we're using has been developed as a part of the Magenta project, which was begun by members of the Google Brain team and is an effort to use deep learning and reinforcement learning to generate images, drawings, and even music. We'll be using a form of style transfer referred to as arbitrary style transfer. It is a method that allows for fast style transfer for any arbitrary style.

Another advantage of this approach is that it allows us to determine how heavily we want the content image and style image to factor into the resulting stylized image. Using a scale ranging from 0.0 to 1.0, where 0.0 includes no influence from the style image and 1.0 accepts no influence from the content image, we can vary the influence of either image to varying degrees. This variation in influence is referred to as the interpolation weight.

The model works by mapping each content and style image to a 100 dimensional content and style vector, respectively. The weighted average of each vector is then used as the input for the stylized image. This is also how it's able to control the weight applied by each image for a given stylized image.

Running the model invokes only a small amount of code, but requires a decent amount of setup. If we're running it on Google Colab, as we did, we first need to download the pretrained model to Google Drive. Additionally, we also need to include content image and style image folders as well as an output folder. From there a short series of commands identifies the paths to each of the aforementioned files and folders as well as the interpolation weights to be considered and the content and style images sizes. When images are kept rather small, and a GPU is used to generate the images, more than 100 stylized images can be created in a matter of seconds.

It's worth noting that the output folder will include not only the stylized images but the original content and style images used as well. Thus, if you plan to run the images through an image recognition folder, it would be appropriate to delete the original images to achieve better accuracy.

Stylized Images

For our stylized images, we took 20 random images from each species and crossed them with our five styles, all for four interpolation weights - 0.2, 0.4, 0.6, 0.8 - to give us a total of 2000 stylized images. Below (Figure 3) is an example of a rose image styled with our fractal art style for four interpolation weights. Here, we have a gradual transformation from 0.2 to 0.8:

Figure 3: From left to right and top to bottom: The original rose image, the fractal art stylized images with interpolation weights 0.2, 0.4, 0.6, and 0.8.

In some cases, the 0.8 interpolation weights changes the original image to such a large extent that it's difficult even for humans to recognize whether a flower is present, much less identify the species. It may be an even more difficult task for a TL model. The following is a good example in which the original image of a field of sunflowers is completely unrecognizable in the pop art 0.8 stylized image on the right. Without having the original as a reference, we wouldn't be able to tell that there are flowers in the stylized image.

On the left, the original image of sunflowers. On the right, the same image pop art stylized image at 0.8 weight.

Transfer Learning CNN Model

The pretrained TL models that we'll be using are based on the models created by Github user hey-simone. The notebook can be found here:
https://github.com/hey-simone/flowers-classifier/blob/master/Keras_Flowers_Classifier-V1-2.ipynb

The VGG16 and DenseNet169 models were originally chosen by the author but without any real justification for their inclusion. Thus, any choices made with the original model will only be justified if the original author provided any such justification. Otherwise, we'll simply describe the process. Additionally, we'll be adding ResNet50 due to its reputation with multiclassification image problems.

Since there are five different species to identify, this will be a multiclass classification problem. In a binary classification problem, we would simply be trying to determine whether the model can detect if a flower is present. However, in our case, the model is working under the assumption that at least one flower is present in every image, and that the task is to correctly identify the correct species. In this case, there are two main factors working against high accuracy. First, a multiclass problem usually has a lower accuracy than a binary problem. Second, as we saw above, in some images, it's very difficult even for humans to determine whether a flower is present, mch less the correct species. The TL model is going to struggle with those images as well. As such, we are expecting the stylized test images accuracy to be considerably lower than the accuracy of the original test images.

Before we start, we need to set a random seed to ensure that our results are repeatable. Neural network algorithms are stochastic, meaning they rely on randomness to operate (such as initializing random weights). However, that randomness can lead to inconsistent results. By setting a random seed, we'll be using the same set of random values, allowing our model results to be repeated.

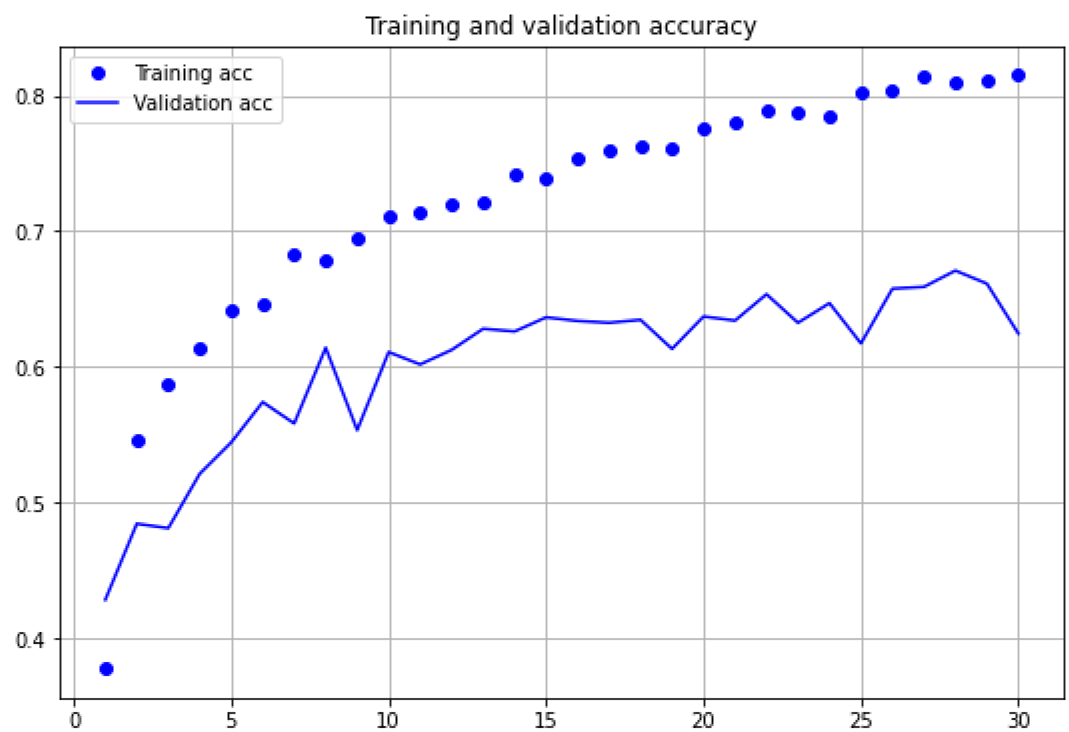
Since both Keras and Tensorflow backend have their own random seeds, we need to set both of them.

We begin by loading the image dataset, which has already been divided into training, validation, and testing groups, as detailed above. The images are then transformed into array data using ImageDataGenerator. We also normalized the images by figuring all of their pixel values by 255. Most images' pixels range between 0 and 255. The normalization process allows us to range the values between 0 and 1 instead.

We tried several different models, all pretrained on the Imagenet dataset (except for our baseline model) - VGG16, ResNet50, and DenseNet169. With all of the pretrained models, we froze most of the layers to preserve the pretrained weights. For the baseline model, we start with a series of convolutional layers and max pooling layers. The convolutional layers slide across images to create activation maps, while max pooling reduces volume and computation costs. For the convolutional layers we'll be using Rectified Linear Units, or ReLU's. Since ReLU's are linear for all positive values and zero for negative values, they are computationally cheap. And since their slope doesn't plateau, they don't suffer from vanishing gradients, which can decrease the chances of a signal propagating to the input layers, resulting in weights not adjusting and earlier layers failing to learn. Our final layer has a softmax activation with five units that correspond to the five classes or species of our dataset. We'll also be using the Adam optimizer. It can adjust the learning rate separately for each layer, including reducing the learning rate as the model gets closer to convergence. We'll also be using fit_generator because we are inputting our data through ImageDataGenerator. For most of our models, including baseline, we'll be running for 30 epochs. All of the above layers were chosen by the original author.

An initial run yields validation accuracy in the high 50's and almost perfect training accuracy, suggesting overfitting. We make some adjustments by invoking data augmentation on the training data inside ImageDataGenerator. This will allow the model to view the data from different randomized perspectives, hence increasing its generalizability. We'll also add dropout in our layers. With dropout, some layers are randomly ignored during training, giving the model a different view of the configured layer. As a result, the model will be less prone to overfitting.

The second run with our adjusted model yields validation accuracy in the mid 60's and training accuracy in the high 70's. So, it's an improvement in accuracy and overfitting. The following graphs (Figure 4) display the disparity between loss and accuracy of the training and validation data. Running the model on our test data leads to 69.1% accuracy.



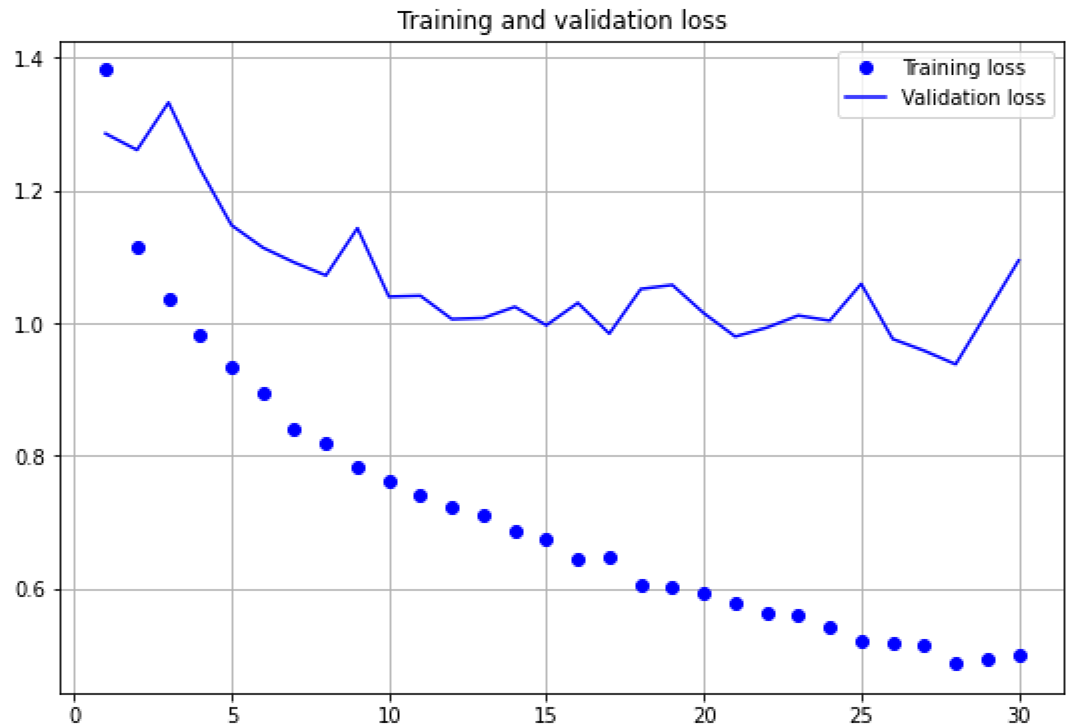


Figure 4: The training and validation accuracy and loss for our baseline model.

While we saw a modest improvement to our baseline model, it's probably wiser to use a pretrained model. For all, except the base model, we'll invoke several callbacks: ReduceLRonPlateau, which reduces the learning rate if the learning begins to stagnate; EarlyStopping, which stops the process if there isn't any improvement in the validation loss after a set number of epochs; and ModelCheckpoint, which saves the model and/or weights after the the most improved epochs.

For each model, we'll begin by only unfreezing the last layer. We'll then make adjustments in hopes of possibly improving the accuracy. We'll start with VGG16. VGG16 has 12 convolutional layers interspersed with max pooling and 4 fully connected layers for a total of 16 layers. It also has a 1000-way softmax classifier. In our initial run, without making any adjustments and using an Adam optimizer, we only achieve validation accuracy in the mid 60's. We then decide to freeze several of the layers in the convolutional base, only allowing four trainable weights. That allows us to increase our accuracy to the mid 70's, but the model is now overfitting.

We then unfreeze several of the layers from the previous run, which increases our accuracy to the high 70's , while still overfitting, and results in a test accuracy of 84%, a solid improvement over our base model. The improvement is also evident when comparing the VGG16 training and validation graphs (Figure 5) to the baseline model:

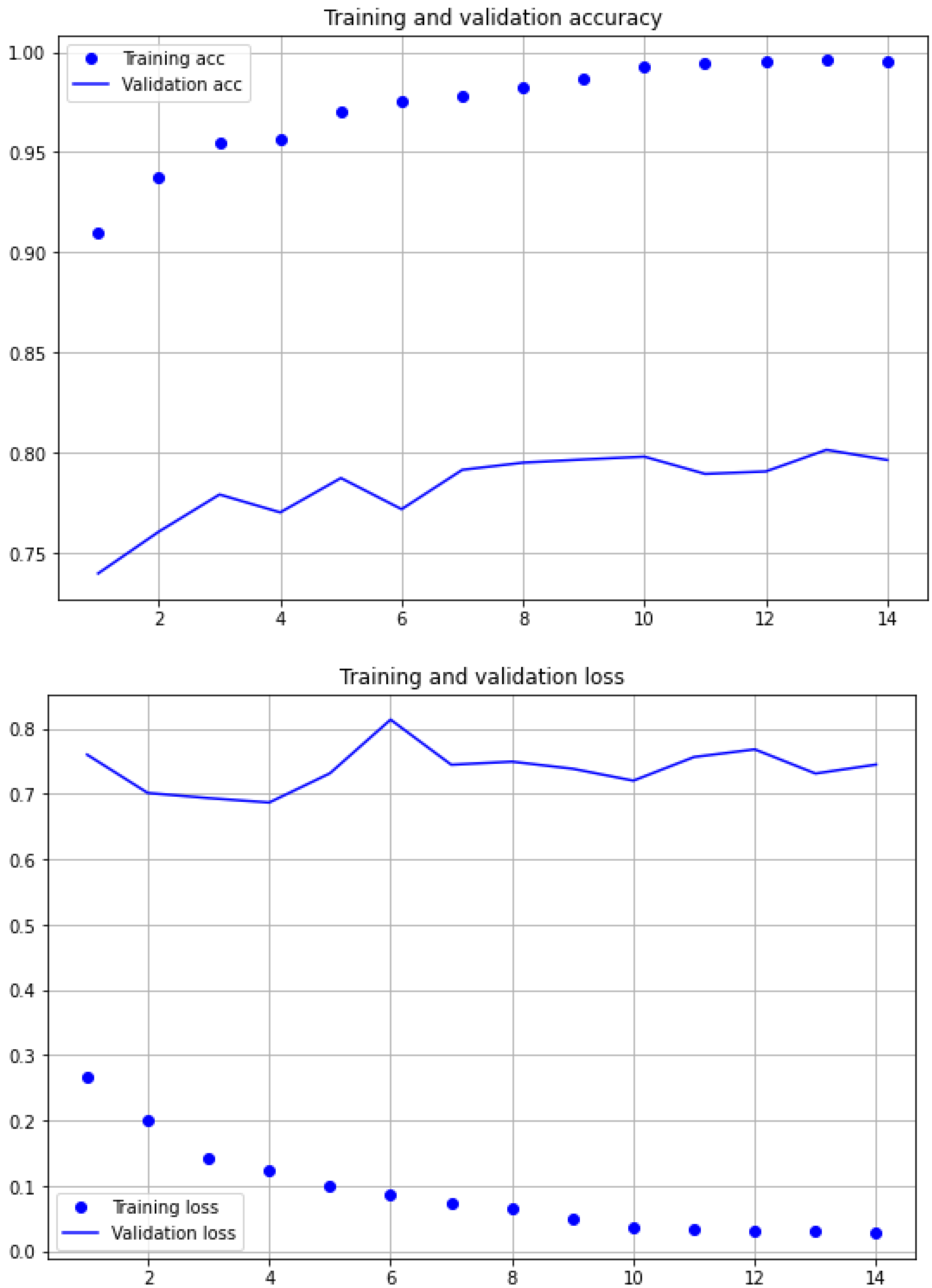
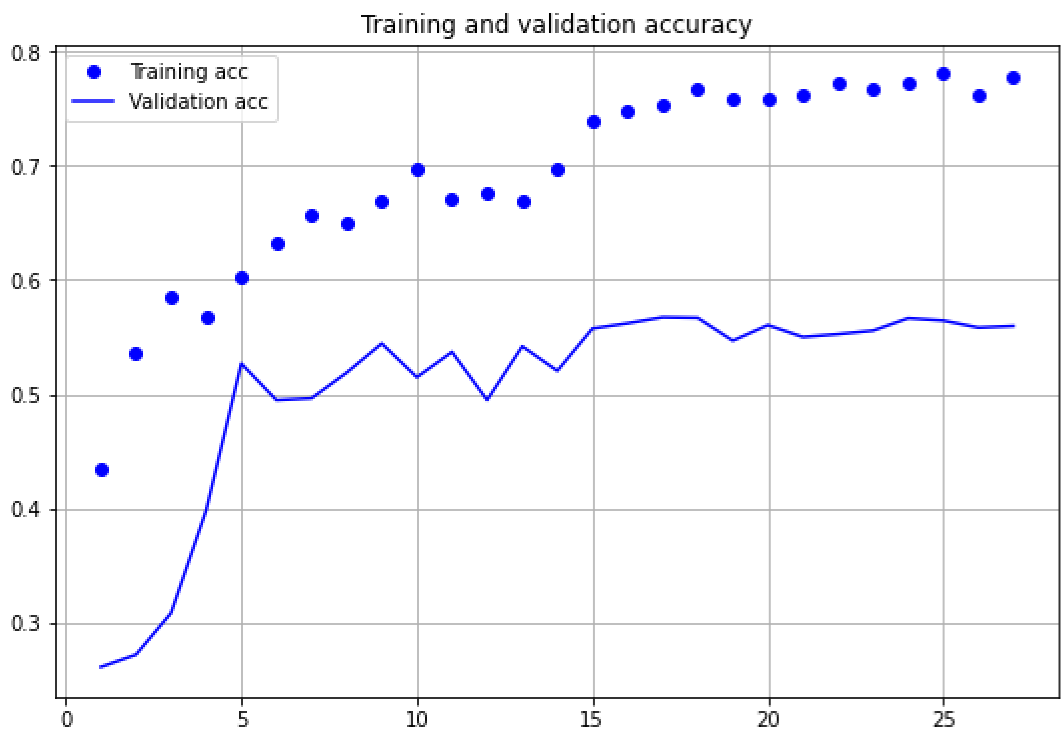


Figure 5: The training and validation accuracy and loss for our VGG16 model.

Next, we evaluate a ResNet50 model. ResNets are often regarded as improvements over VGG models. A unique feature that they have is skip connections, which allow original input to be added to the output of the convolutional block. This can help with the vanishing gradient problem that many CNN models face. We'll be using a similar process to that of the VGG model.

For our ResNet50 model, we begin by freezing all but four layers. Using an Adam optimizer, we find that the validation accuracy is in the low 50's and overfitting is quite high. We then decide to unfreeze many of the layers that we initially froze, allowing for 44 trainable weights. However, there fails to be any improvement in accuracy or overfitting. In fact, our test accuracy is only 63%, which is both disappointing and surprising given that ResNets are often touted for their strong results. It's not immediately clear why this model performed so poorly. It may be that we didn't train the correct weights. Perhaps at a later time, when we aren't working against a deadline, we may revisit this model and try other modifications.



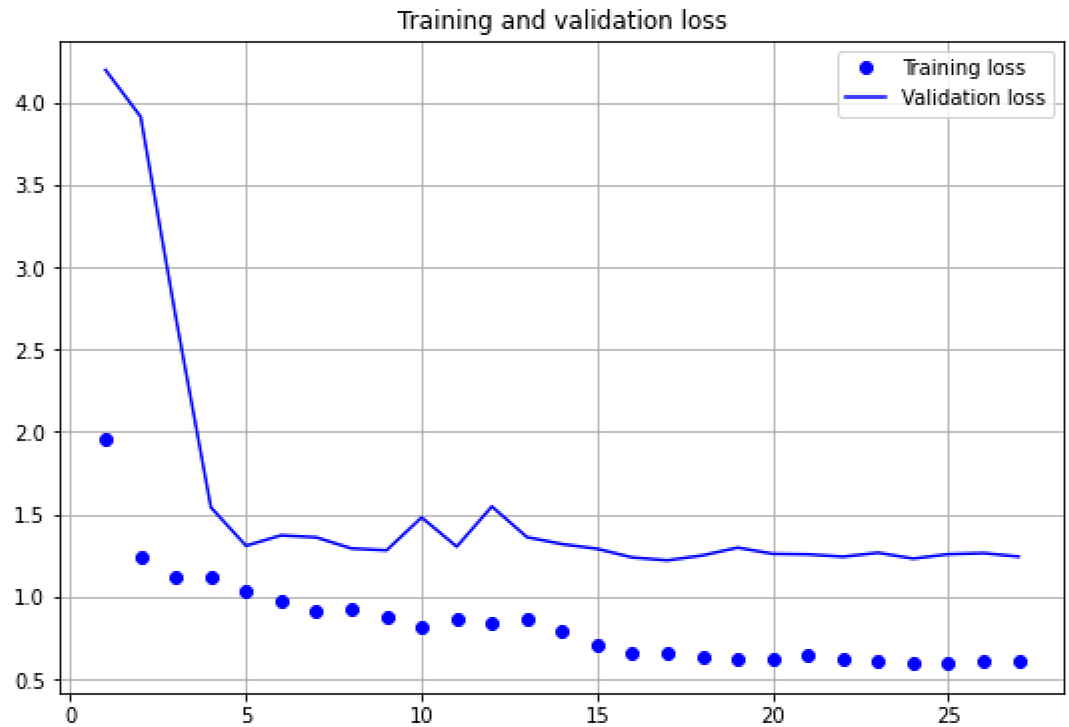


Figure 6: The training and validation accuracy and loss for our ResNet50 model.

Finally, we try a DenseNet169 model. DenseNets typically require fewer parameters than traditional CNNs. Additionally, each layer in a DenseNet has access to the original image and the gradients from the loss function. They also concatenate output and input feature maps rather than summing them.

As with our previous two models, we'll start by freezing some of the layers of the model. After freezing, we have four trainable layers. Our validation accuracy is in the low 80s and overfitting is rather high. Next, we unfreeze some of the previous frozen layers and run the model again. The accuracy and overfitting don't seem to be affected much. Running the test set on the DenseNet model yields 90% accuracy, and that makes it our best performing model.

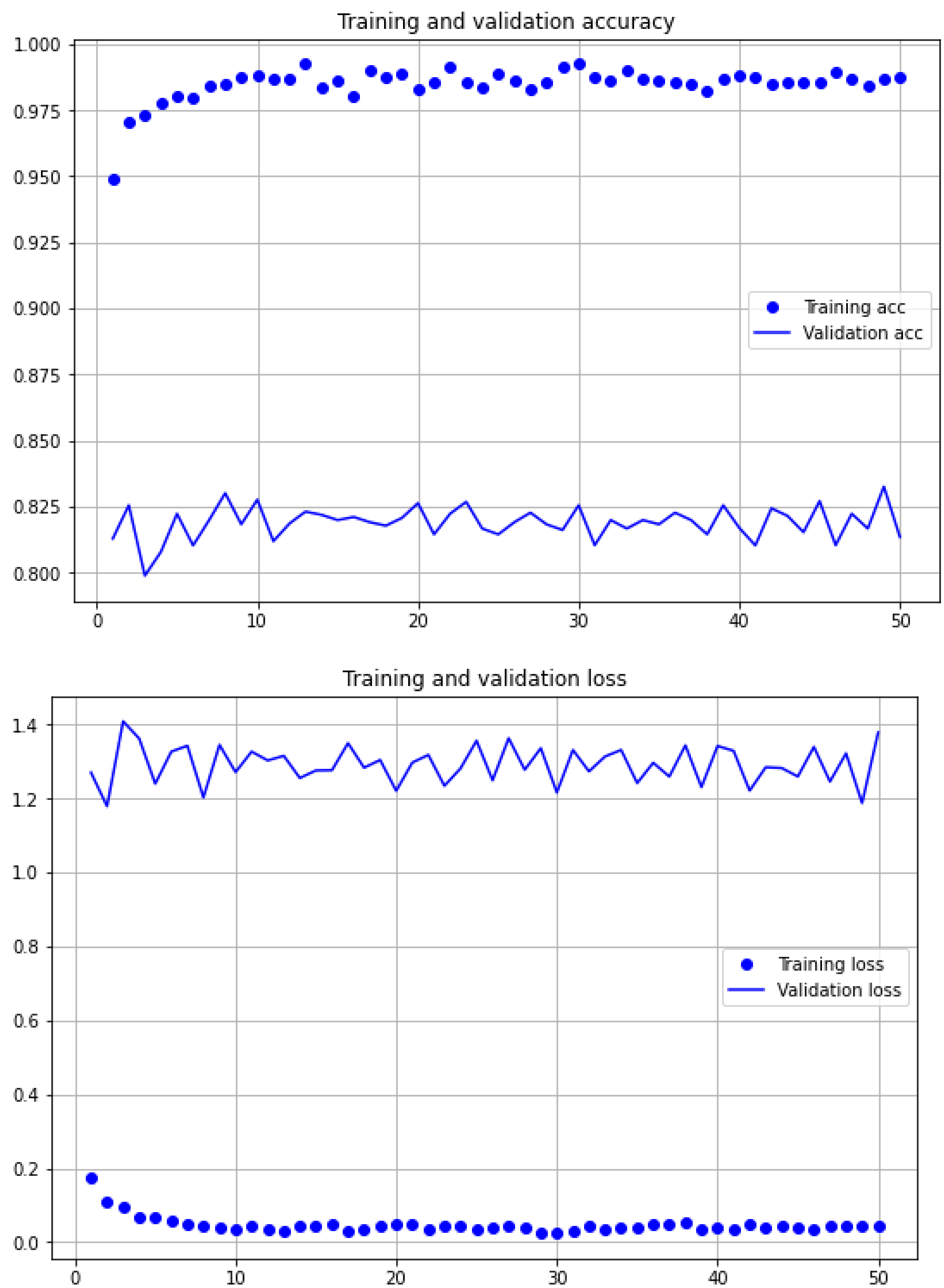


Figure 7: The training and validation accuracy and loss for our DenseNet169 model.

The following is a table (Table 1) of the test results from all four of our models:

Test Loss and Accuracy for Four CNN Models

	Test Loss	Test Accuracy
Baseline	0.87	69.1%
VGG16	0.50	84.1%
ResNet50	1.10	69%
DenseNet169	0.59	90%

Table 1: A summary of the results on our testing dataset.

Since DenseNet169 is our best performing model, we'll use it to test our stylized image set. As expected, due to the reasons mentioned earlier, the model does quite poorly with the dataset, achieving a test loss value of 0.313 and a test accuracy value of 61%.

Cyclical Learning Rate

As we saw in the previous section, with some adjustments to some of the DenseNet model layers, we were able to achieve a satisfactory 90% accuracy for our test images but had a terrible 61 % accuracy of our stylized images. In an effort to increase both of these accuracies, we're going to implement a cyclical learning rate (CLR), which is part of Tensorflow's optimizer library. The learning rate hyperparameter is a vital part of the gradient descent process and controls how much our model is changed in response to the estimated errors. A learning rate that's too small may cause the model to get stuck, while a learning rate that's too large may result in a model skipping past the optimal minimum.

We could have used one of several approaches for increasing our accuracy, but what makes CLR appealing is that rather than sticking with a single learning rate for an entire training/test run, CLR allows for a change of the learning rate during the run. This 'resetting' of the learning rate may allow the model to find other local minima if the loss rate appears to have stalled for a number of epochs. As a result, the model may find a more optimal minimum than it would have settled on otherwise. This would potentially allow the model to generalize better and, in return, increase its accuracy.

We'll implement CLR through the Adam optimizer. Rather than having a constant learning rate, we'll set a range starting at 1e^-11 and having a maximum rate of 1e^-5. As with the previous DenseNet model, we'll run this for 50 epochs.

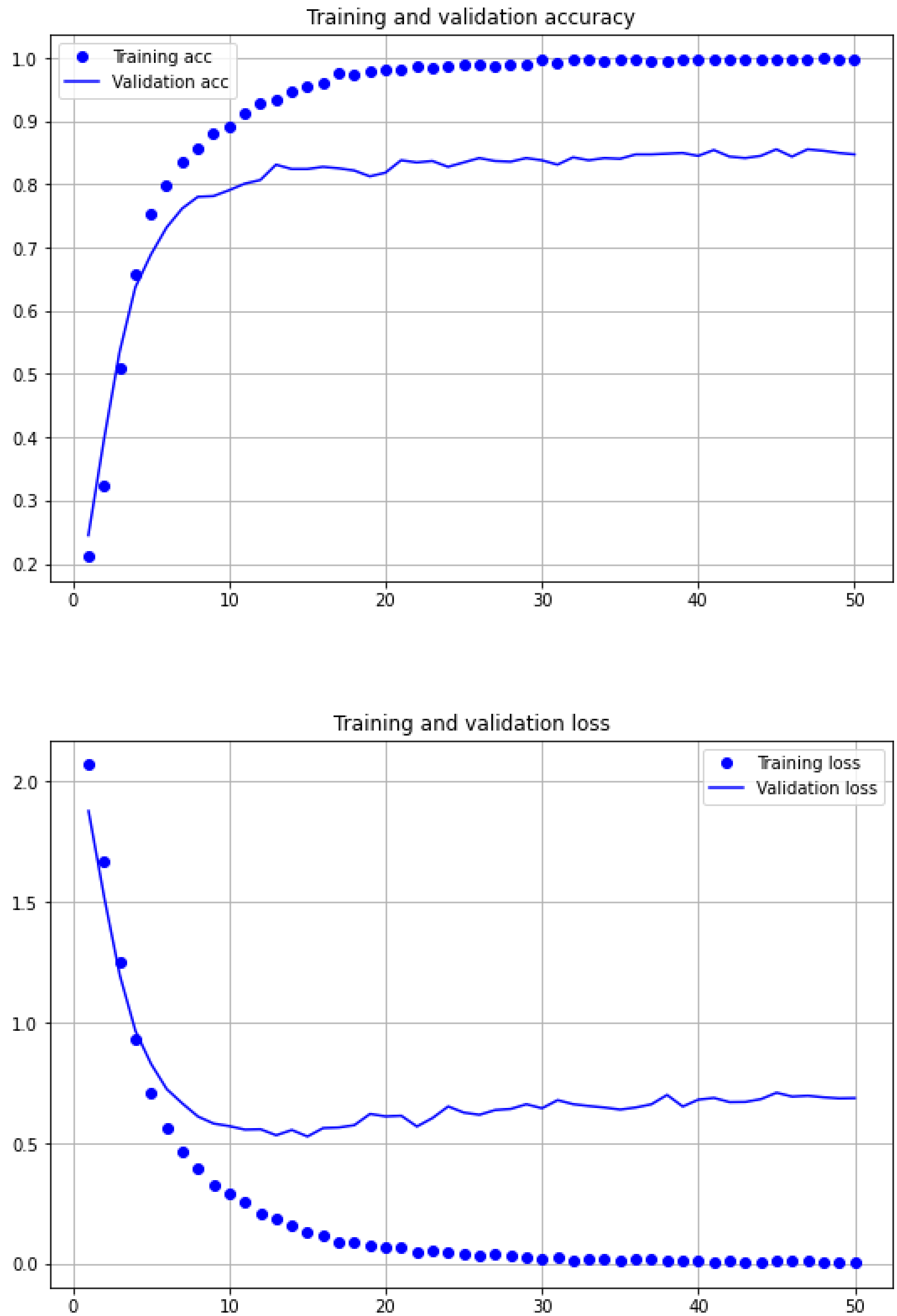


Figure 8: The training and validation accuracy and loss for our CLR DenseNet169 model.

We see only a slight increase in accuracy for the test images - 91.1%. The training loss, however, has been reduced significantly to 0.334. The stylized images show a much better increase in accuracy - 69.6% with a nice reduction in the training loss to 1.51. It appears that our original model was having issues with an optimal learning rate, particularly with the stylized images. While we had used ReduceLRonPlateau for our original model, and reduced by a factor of 0.01 if there wasn't a loss reduction within 5 epochs, CLR appears to have done a better job at finding a lower minimum, at least for the stylized images. It may have been that we set our patience too low for LRonPlateau, causing our model to converge too quickly.

Test Time Augmentation

As a final method to increase our accuracy, we'll be applying test time augmentation (TTA) to our CLR model. We had already augmented our data by using ImageDataGenerator, but we had made more significant augmentations to the training data than any of the other datasets. As we saw with our baseline model, augmenting the training data helped increase our accuracy. With TTA, we are able to apply similar augmentations during our test runs. Hopefully, it will allow for similar gains in accuracy.

For TTA, we'll be applying a modified version of the code written by Jason Brownlee. More information on the specifics of the code can be found here:
https://machinelearningmastery.com/how-to-use-test-time-augmentation-to-improve-model-performance-for-image-classification/

TTA allows for creating multiple augmented copies of every image in the test set, creating, in a sense, more data for the model to analyze and, potentially, reducing generalization error. The model will make a prediction on each image and return the ensemble. For this particular implementation, we'll be making five additional copies of each image. After some trial and error, we find a large increase in accuracy with the following augments:
horizontal flip = True, width_shift_range=0.1, height_shift_range=0.1, shear_range=0.15, zoom_range=0.1. We run the model 10 times on each both the test and stylized data and average the accuracies to get a final accuracy for each dataset.

We see a significant increase in accuracy with a simple flip augmentation. For our test set, the accuracy increases to 95.6%, while the stylized set accuracy jumps to 75.9%. The standard deviation for both datasets are small, at 0.015 and 0.037, respectively. Just by creating augmented data and allowing the model to see the images from different perspectives, we were able to achieve an accuracy gain. In the table below (Table 2), we're able to see a nice evolution in the accuracies of our datasets as we further tuned our model.

Accuracies for all DenseNet Models for Test and Stylized Image Sets

Model Version	Test Images Accuracy	Stylized Images Accuracy
Original DenseNet169	90%	61%
DenseNet169 + CLR	91.1%	69.6%
DenseNet169 + CLR + TTA	95.6%	75.9%

Table 2: A summary of all DenseNet model accuracies for both the test and stylized datasets.

Neither the test set nor the stylized set saw much of a gain in accuracy from CLR. However, the accuracy gains for both datasets are remarkable through TTA, particularly for the stylized set which increased by 15% percentage points . We now have a model that can predict flower species with near 96% accuracy. But, more importantly for the purposes of this project, our model can predict the species of the stylized images with 76% accuracy. While this still seems too low to be considered a significant achievement, consider that it started at around 61% accuracy. Plus, as we mentioned earlier, many of those stylized images are difficult to decifier, even for humans. In a good portion of those images not only is it difficult to tell the species, it's hard to even make out whether flowers are present at all. In fact, most humans might not be able to achieve 76% accuracy on the stylized dataset. As such, our achievement is significant because part of the aim of every image recognition model is that it should be able to perform better than humans, and we may have come close to achieving that here.

Accuracy per Species, Style, and Weight

For the final part of the project, we'll be looking at the accuracies among species, styles, and interpolation weights to get a better sense of where the model succeeded and where it faltered. Doing so might allow us to determine possible trends or patterns and give us further insight into how our model works.

We had originally hoped to use the CLR model with TTA. However, we ran into several issues with that process. So, for the sake of time, we'll simply be using the CLR model without TTA for our accuracy calculations. While it may not give us quite the same accuracies, it should still give us a good idea of where our model excelled and struggled. At a later time, we may revisit this issue and attempt to use the TTA model in this process.

Creating the dataframes involves using ImageDataGenerator to normalize the images as well as adding the same augmentations that we used for TTA for both our test and stylized images. However, this process will be calculating the accuracy in batches of 32 (we ran into RAM issues trying to calculate the accuracy on one image at a time) and it won't be creating 5 additional copies per image as TTA had. Once the labels and predictions are correctly matched up the filenames, we have our two dataframes and are ready to proceed with our accuracy calculations.

For our test image dataframe, we created a column listing the actual species value for each image and paired that with the prediction column to create a new column listing whether the prediction was correct, 1 for correct and 0 for incorrect, for a given image. We then created a function that calculated the mean correct for each species, which is the same as its accuracy in this context. The results are displayed below in Table 3 and Figure 9.

Accuracy per Species - Test Images

Species	Accuracy
daisy	0.948
dandelion	0.957
rose	0.88
sunflower	0.95
tulip	0.832

Table 3: Accuracy per species for test images

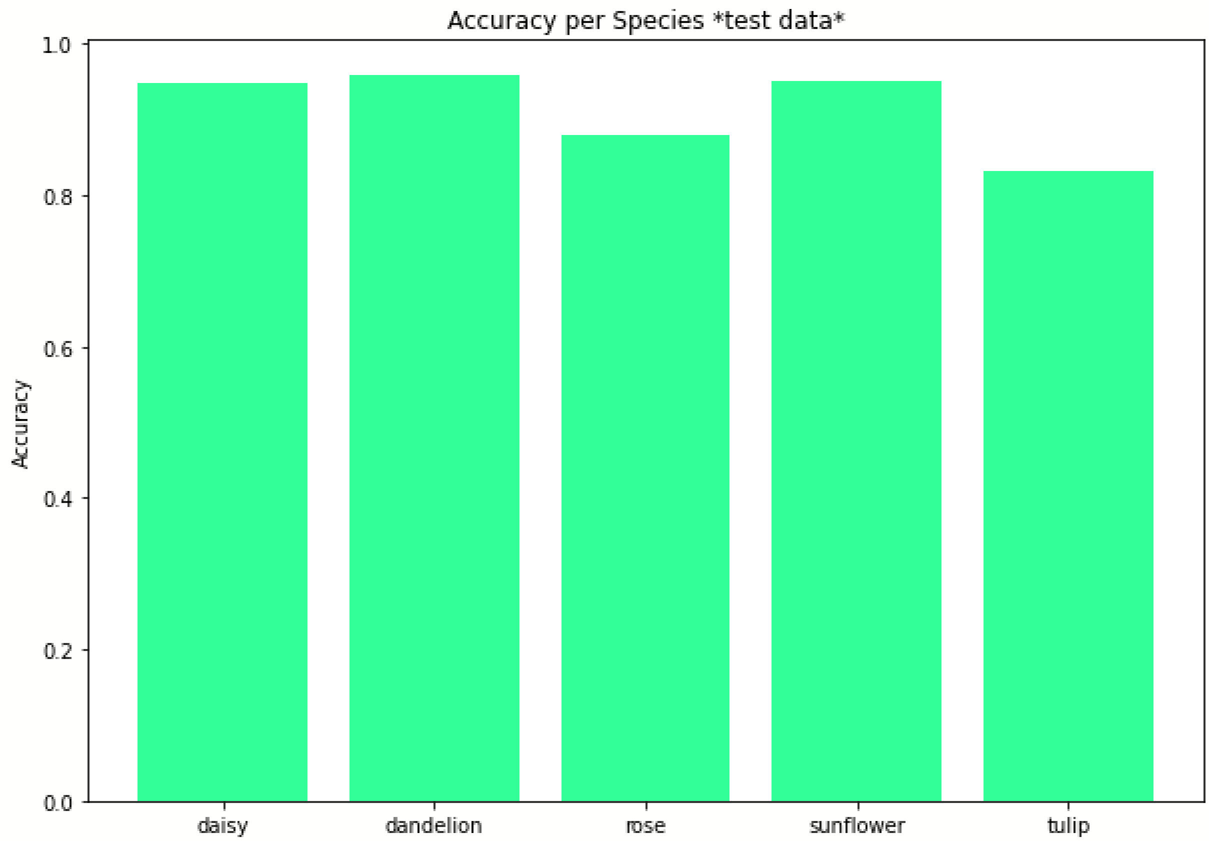


Figure 9: Accuracy per species for test images

With our test images, our model did fairly well with most of the species, but struggled the most with tulips, with roses having the next lowest accuracy. Dandelions, despite having two different appearances, had the highest accuracy. Looking at the dataset, we find that tulips come in a much larger color range than any of the other species, which may have made it difficult to classify them better. By using groupby, we also find that the model most often misidentified tulips as roses, making up almost half (15 of 33) of the incorrect predictions. Similarly, when we look at rose misidentifications, more than half (12 of 19) are incorrectly labeled as tulips. These errors make sense as there are more similarities, both structural and color, between roses and tulips than among any of the other species.

We use a similar process for doing a bit of feature engineering for our stylized dataframe as well, except in addition to a species column and column telling us whether a prediction was correct, we're also adding columns detailing the style and weight of each image. Starting with species (in Table 4 and Figure 10), we get results that differ quite a bit from the species results from our test images.

Accuracy per Species - Stylized Images

Species	Accuracy
daisy	0.55
dandelion	0.434
rose	0.79
sunflower	0.843
tulip	0.772

Table 4: accuracy per species for stylized images

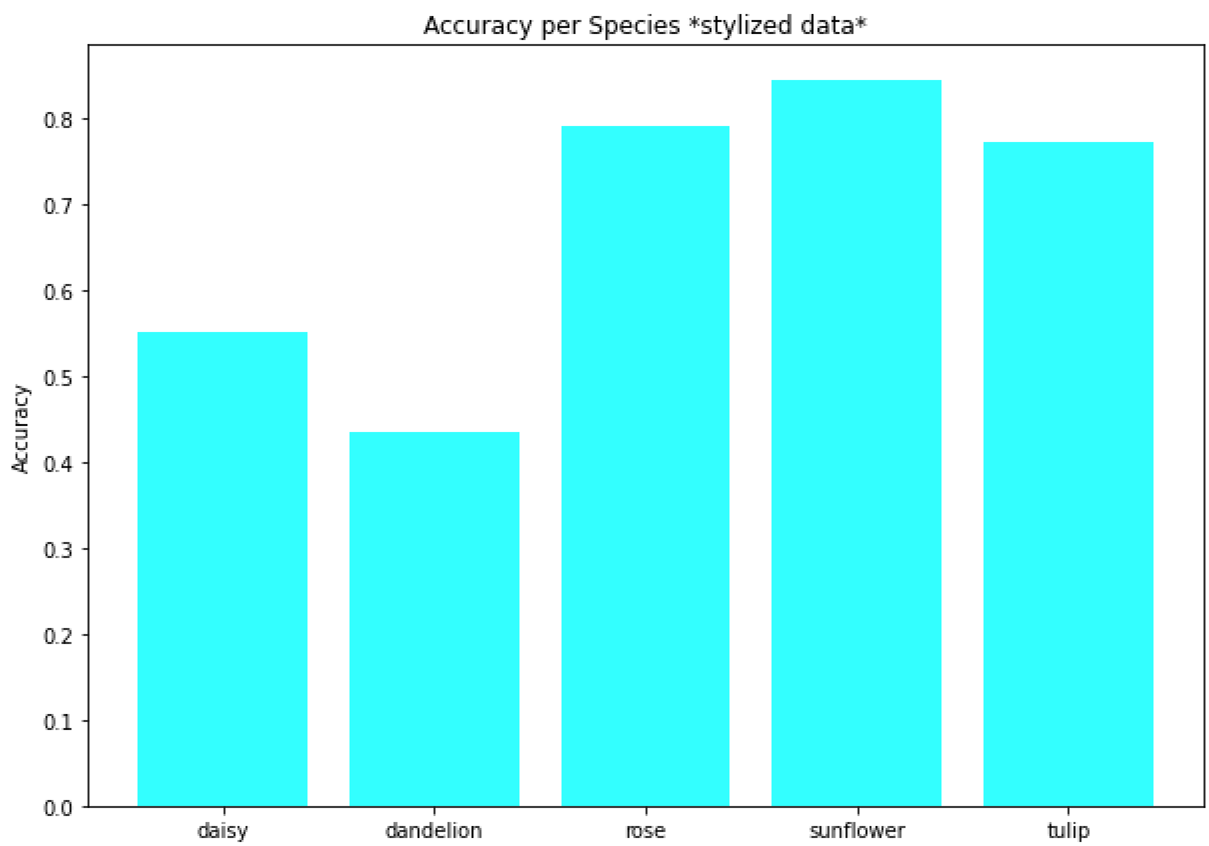


Figure 10: accuracy per species for stylized data

As expected, the accuracy per species has decreased. While the model performed well when predicting sunflowers, roses, and tulips, it did especially poor with dandelions, which, initially, is very surprising given that they had the highest accuracy with our test images. Viewing the dandelion images, we can speculate that part of the reason for the abysmal performance may have to do with how much more easily dandelions tend to 'disappear' or blend into the background at higher interpolation weights compared to other species. Plus, given that tulips were the most difficult to predict in the test images, it's a bit surprising that they are one of the stronger performers for the stylized images. It's not immediately clear why. The same issues regarding wide variation in colors and shape similarities to roses still exists. However, it's clear that the distinguishing features of daisies and dandelions were altered enough for the model to drastically lose accuracy.

Further, it's odd that such a large number (90%) of the incorrect guesses for dandelions were roses, sunflowers, and tulips. Dandelions can occasionally resemble sunflowers once they develop yellow petals, but roses and tulips don't structurally resemble dandelions. One possible explanation may be that the influence of the styles often added reds, yellows, oranges, and yellows to an image. That, combined with the blending of the dandelion into the background have fooled the model into thinking species were present that actually weren't. Additionally, we see that in our stylized images, the model still continues to confuse roses and tulips, with 71 of 91 tulips misidentified as roses and 68 of 85 roses mislabeled as tulips.

Moving onto our style analysis, we'll use the same function that we used for analyzing species. We find a large accuracy disparity among the styles, as seen in Table 5 and Figure 11:

Accuracy per Style

Style	Accuracy
abstract expressionism	0.703
cyberpunk	0.678
fractal	0.65
pop art	0.543
post impressionism	0.813

Table 5: accuracy among styles

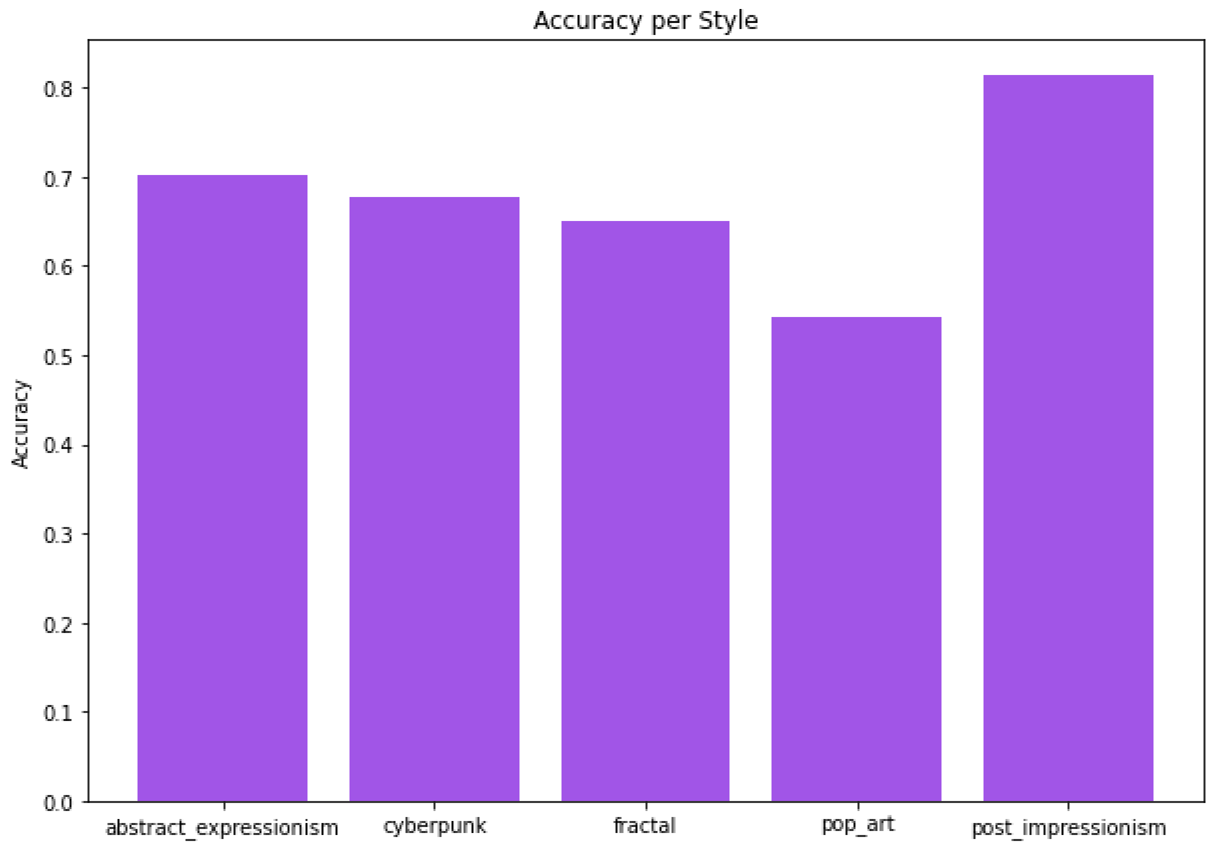


Figure 11: accuracy per style

In some sense, it's not a big surprise that post-impressionist pieces were more accurately predicted than the other styles and that pop art was the least accurate. Post impressionist images appear to create less structural distortion, while also making fewer changes to the original image colors. Pop art, on the other hand, particularly at stronger weights, creates bolder, brighter images in which nuances (such as petal separation) often disappear and colors are dramatically saturated.

Using groupby to count the number and value of predictions per style, we see our assumption about pop art confirmed as an overwhelming number of pop art images (91%) are identified as roses, sunflowers, or tulips despite each species only making up a fifth of each art style. Its tendency to add yellows, reds, and oranges to images lead to a high number of misidentifications. Only 7 of 400 were identified as dandelions. Compare that to post impressionist predictions, where roses, sunflowers, and tulips are still the top three style predictions but only make up 69% of the total predictions. The graph below (Figure 12) allows for a visualization of the accuracy distribution.

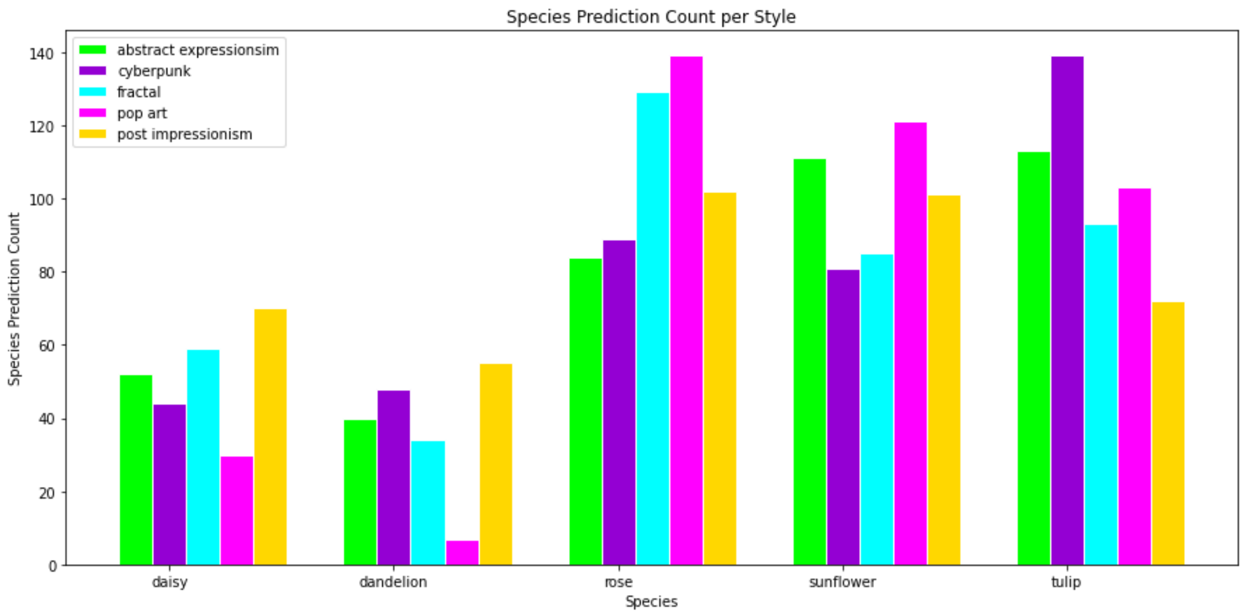


Figure 12: distribution of species predictions among styles

Finally, we'll analyze the accuracy per weight. Recall that the higher the weight value, the more influence the stylized image receives from the style image. In this case, there isn't any surprise that the accuracy decreases as the weight value increases. As we mentioned earlier, in some of the higher weighted images, it's hard to tell whether a flower is actually present, much less its species. We see a steady decrease below (Table 6 and Figure 13):

Accuracy per Weight

Interpolation Weight	Accuracy
0.2	0.78
0.4	0.722
0.6	0.648
0.8	0.558

Table 6: accuracy per weight

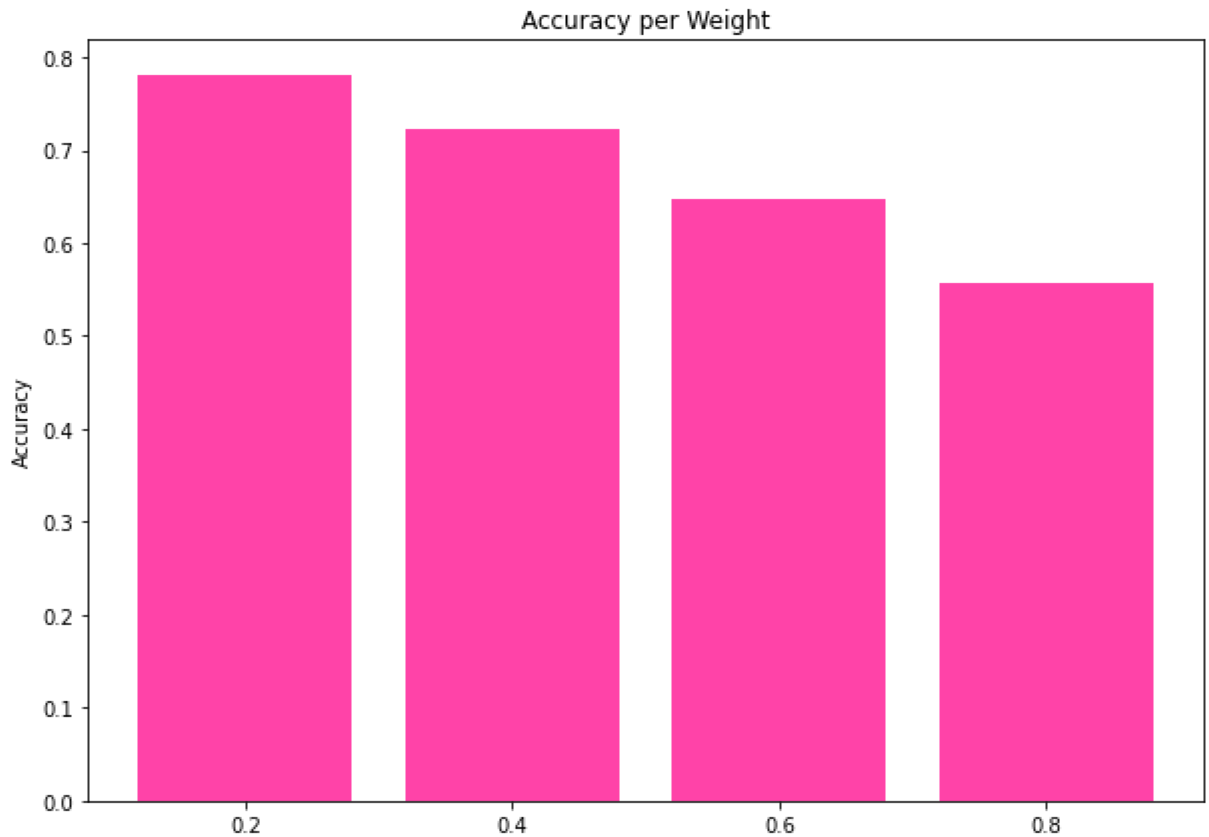


Figure 13: accuracy per weight

As we did with our styles, we'll also check the species prediction distribution among each weight. When we compare the predictions for 0.2 versus 0.8 interpolation weight, we see that, as with our style count, most of our species predictions are composed of roses, sunflowers, and tulips. For 0.2, those three make up 70% of the predictions (perfect predictions would have them making up 60%), while for 0.8 they make up 85%. Certainly the boldness of the pop art aesthetic, especially at its strongest weight, is contributing to this mislabeling. We can see the distribution below (Figure 14):

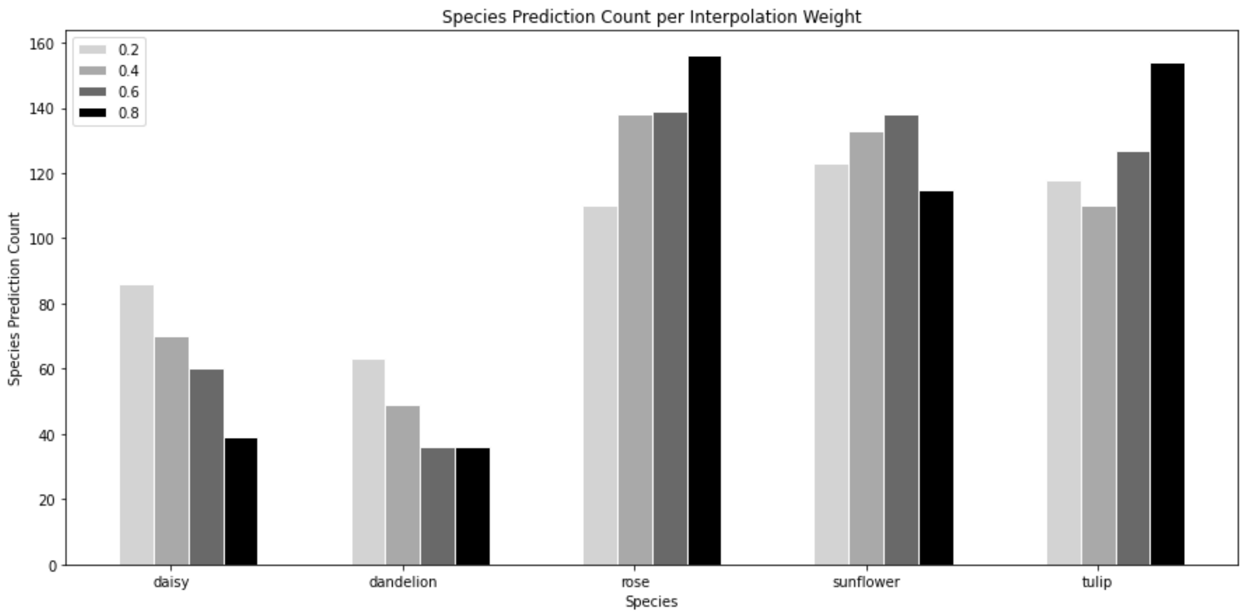


Figure 14: species prediction distribution among weights

Overall, what this analysis is suggesting is that our styles and weights are distorting our pictures in such a way that colors that weren't originally present are confusing the model and nuances especially for more delicate, distinguishing features are being washed out. Certain styles and weights, pop art and 0.8 respectively, are much more responsible for the drop in accuracy than the other features.

Takeaways

There are several thoughts that we can take away from this project, related to both AI and art. Before we discuss the issues more generally, we should focus on the specifics of this project. It's not a surprise, as this project demonstrated, that as an image veers further from its original image, and further from the types of images on which a model has been trained, that a model's accuracy will decrease. What was more of a surprise was that certain art styles were able to produce stylized images, by introducing new colors or blurring nuances, that tricked the AI into thinking flowers were present in an image that actually weren't. That speaks to a larger issue of how style transfer models can be used to make new art pieces by using specific combinations of images, styles, and weights. Hopefully, this project gives some new insight to artists as to how they could produce art that can make AI think certain images are present when they aren't. On the other hand, not all artists are interested in accuracy or fooling AI, and perhaps this project could just spark new thoughts about producing interesting works of art.

Moving to broader connections, while this work is not as cutting edge as what's currently being done in image recognition, it still gives us some sense of the challenges present in recognizing real world objects under less than ideal conditions. For example, we can draw analogies to an autonomous driving system trying to identify traffic lights, stop signs, cars, pedestrians, etc in rain, fog, or snow. Think of the weather conditions as filters or distortions of an ideal image of a traffic light or pedestrian. We then get a better idea of how difficult image recognition can be for AI when conditions deviate from the ideal. We saw a huge dropoff in accuracy once we moved from our actual images of flowers to stylized images. Yet, as we demonstrated, we were able to use several techniques like image augmentations, CLR, and TTA to vastly improve our accuracy. However, the 76% accuracy we were able to achieve would be far too inaccurate for the standards of an autonomous vehicle. And while the tools in those disciplines are much more sophisticated,the challenges are similar - it takes a lot of work to get AI to see the world as well as we do, and even more work to see it better than we do.

Finally, let's elaborate a bit more on an issue we touched on briefly at the beginning of this paper - AI and art interpretation. While there's plenty of literature on AI creating art or using AI to understand what humans find aesthetically pleasing, not much appears to be written about AI as an art interpreter or critic, partly because such a thing is even hard to imagine. Unlike the analytical, logical world of artificial intelligence, art interpretation seems so subjective and murky - something much more suited for humans than a machine.

But if one of our goals is to eventually develop artificial general intelligence, or more human-like AI, we would probably like that intelligence to have a variety of skills, including having the ability to engage in more subjective human activities. At a basic level, if AI can't recognize objects in images, can it even interpret art? Maybe it doesn't matter how good the model is at recognizing objects. Art is very open to interpretation and AI's insight, whether it's 'correct' or not, its response may open new avenues of thoughts and discussion. It hints at a deeper understanding of what counts as interpretation by AI. Is AI really interpreting in a manner similar to humans, or is it just following an algorithm - does it matter?

This project likely doesn't get us any closer to answering those questions. But perhaps it and other similar projects can be thought of as rudimentary attempts of implementing a very primitive AI art interpreter. The model's very limited in its scope and abilities, but maybe it can still persuade us to take a second look at an artistic rendering of a dandelion that AI's labeled a rose and think, "Hmm, you know, maybe that dandelion does kind of look like a rose."

And, the final takeaway is that we were able to create several beautiful images along the way:

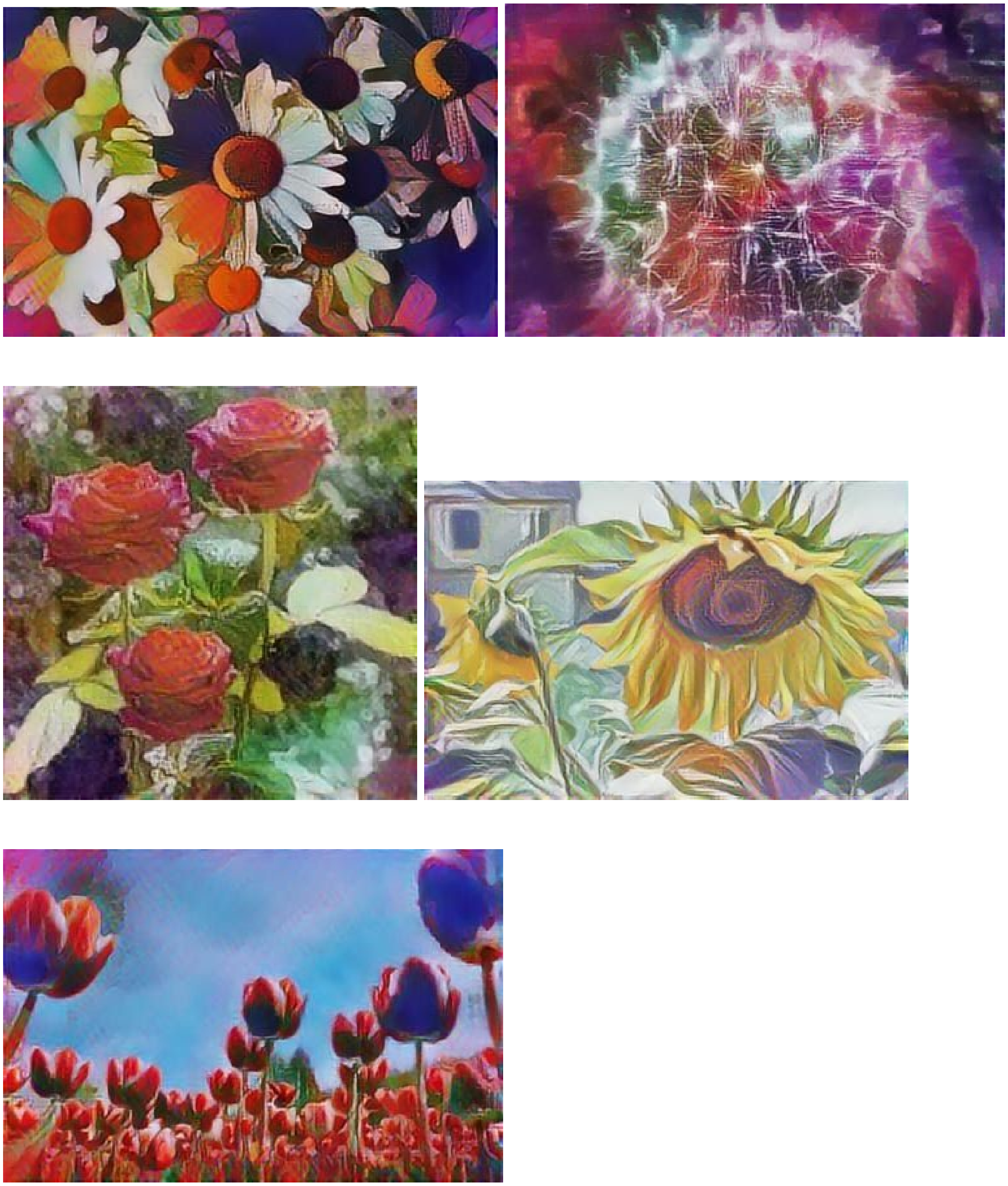


Figure 15: No analysis, just some aesthetical images. From top to bottom, left yo right - pop art daisies 0.8 weight, cyberpunk dandelion 0.4 weight, post impressionist roses 0.6 weight, fractal sunflower 0.6 weight, abstract expressionist tulips 0.2 weight

Future Work

There are several approaches we can take when building upon this project or even taking it in another direction. We can introduce other pretrained models to see if they might have a better initial performance than DenseNet169. We can also attempt to build our own robust model from scratch and train it on a wide set of data.

To increase the amount of data available for training and testing, we can expand the number of flower species and/or the art styles. It would also be interesting to test on stylized images that aren't flowers. For those more interested in creating art, it would be intriguing to use a mix of the initial images as well as stylized images and then use a GAN model to generate new works of art that could perhaps range from fairly recognizable representations of flowers to images that are much more abstract.

References

Transfer Learning Model Analysis:

https://github.com/kjd999/Springboard-files/blob/master/Capstone%20Project%202/Transfer_Learning_Initial_Models.ipynb

https://github.com/kjd999/Springboard-files/blob/master/Capstone%20Project%202/Transfer_Learning_Tuning_Models.ipynb

https://github.com/kjd999/Springboard-files/blob/master/Capstone%20Project%202/Transfer_Learning_Final_Model.ipynb

Magenta Arbitrary Style Transfer:

https://github.com/kjd999/Springboard-files/blob/master/Capstone%20Project%202/Magenta_Arbitrary_Style_Transfer.ipynb

Flower Dataset: https://www.kaggle.com/alxmamaev/flowers-recognition

Hey-simone's flower classification model analysis:
https://github.com/hey-simone/flowers-classifier/blob/master/Keras_Flowers_Classifier-V1-2.ipynb

Test Time Augmentation (Jason Brownlee):
https://machinelearningmastery.com/how-to-use-test-time-augmentation-to-improve-model-performance-for-image-classification/