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Applied Data Analysis
March 8, 2023

Determining the Authenticity of Work by Camille Corot: A Predictive Model Approach

I. Background

Art forgeries are a common subject of movies, books, and fascinating real-life news stories. People are drawn into stories of complex plots to defraud a buyer or even a whole institution. Perhaps part of the intrigue is that it is so difficult to authenticate a painting with complete certainty. Since it is a difficult task that has been a necessity for hundreds of years – ever since the art market as we know it today was born – institutions and individuals alike are constantly searching for new methods to improve upon the old ones.

Camille Corot's work is frequently replicated, and even during his lifetime he accumulated a range of forgers following his work and attempting to capitalize off of his fame, particularly for his distinctive landscape paintings. Since forgers had already sprung up in the 1870s while he was still working, it is not enough to authenticate one of his paintings solely on the premise of a chemical analysis and dating. In cases where forgeries were composed during his lifetime, those paintings would have a similar chemical composition to what we would expect from a true painting, so the analysis is not in truth very helpful in reaching a conclusion. The human eye is also not the most reliable in terms of evaluating qualities of works of art. While art historians are no doubt skilled at their work and at making educated predictions of authorship, there are details in paintings which are difficult to pick up on, and of course it is impossible for a human to make a statistical comparison of the different minute details of a painting.

In my project, I trained a model to detect if a Corot painting is real or a forgery based on the visual composition of the painting. My hope was that this model would provide enough of a conclusion that then, if this were being used by a museum or auction house, the organization would be able to make an informed decision if it is worth going through a chemical analysis of the painting for further authentication. There are many factors in making the ultimate decision if a painting is real or not, and these factors include all of the visual components of a painting, the ways in which the paint has cracked, the chemical composition of the paint, the age of the canvas on which it is painted, an analysis of the dust particles trapped in the paint, a review of historic evidence to see if it is plausible that this might be a real painting. Clearly, the visual part of the painting is just the tip of the iceberg in terms of the authentication process. It is for this reason that it is imperative to develop a predictive model such as mine so that organizations can assess if it is worthwhile to continue onto these next steps. I only trained my model on Corot's paintings to make predictions for his work, but my model would be able to be used for any artist, for drawings or paintings. To apply the model to a different artist, it would be necessary to accumulate more training data to use, and in this time frame it was not feasible to collect training images for a handful of artists. The important focus was to build the model so that it was making accurate predictions for Corot, and then knowing that my model was working for his work would mean that I could apply the model to other artists in the future.

II. Method

The approach to authenticating art using statistical methods builds upon the already-established norm of basing authentication decisions on the known catalogue of an artist's work. This is the primary factor which art historians today use, so expanding this digitally is a natural progression. We are simply putting more accurate and quantitative values on predictors which have already been used for hundreds of years in qualitative ways.

This is where computer vision comes in. It is possible to run detailed statistical analyses on components of paintings to make better predictions of authorship. Existing literature on computer vision analysis of paintings tends to agree on the necessity to focus on different specific elements of images in order to correctly classify them. The main components to consider which have been used in other similar projects are a Spatial-Gray-Level Co-occurrence matrix to analyze texture, features based on edges of shapes, the Gabor function for texture analysis, color constancy, evaluating the image by splitting it into non-overlapping segments and finding statistical descriptors for each, color histograms in all four color spaces (RGB, HSV, HLS, CIELAB), global color characteristics, HOG, LBP, and wavelet statistics. (See "Literature Review" section for details.)

I built a dataset with images of Corot's paintings which I pulled from several sources, including from LUNA, the University of Chicago Art History Department's image database. They have over 300 scanned images of his work in high resolution and data on the provenance of each image. I also pulled images from the Metropolitan Museum of Art, the National Gallery of Art in Washington DC, and the British National Gallery of Art. I also pulled images of both known forgeries – paintings that people claimed to be real but have been de-authenticated – and of recent replica paintings.[1] In the preprocessing stage for the analysis done on entire paintings, I made images all the same size (1000x1000).[2]

When I was creating folders for my data – of "Corot" and "Forgery" to be used by the model to learn classification – I had to rely on how the images were classified in LUNA/the museum websites. All of these images were confirmed to be real/authenticated by the various institutions which they are associated with. There is the potential for error within this, though, since it is generally accepted that there are forgeries sitting in museum collections that have been "confirmed" as authentic. Of course, I did not know which these might be when I was building my training set for real/forgery, so it is possible that I unknowingly added forgeries to my "real" pool when building this dataset. If I did that, then my model would have recognized this as a real painting, so I would have accidentally skewed my model. This is a bit of a chicken-and-egg issue since I am trying to detect forgeries with my model but if I have trained the model with a certain image then it will continue to classify it based on what it learned in the training stage. Realizing this issue is one of the worst problems with my model, and this is of course the real-world problem that my model is trying to fix.

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[1] There are companies such as www.1st-art-gallery.com where you can order a custom replica painted by a talented artist, but this is obviously completely fake. Images of these replicas will be necessary to train the model.
[2] This decision to make the images the same size is based on reading the papers I collected, since it was a commonly recurring part of their process to work only with images of the same size.

I decided to focus on Corot's paintings instead of drawings since I could not find sufficient examples of forged drawings, so it would have limited my model significantly without enough examples of forgeries to train on. I used OpenCV in Python for all of the feature extraction for the images. I ended up splitting my analysis ideas into two branches: I trained a model on entire images in high resolution, and I trained a model on patches of images. Training a model on entire images focuses on the features in the paintings – shapes such as people, trees, and buildings – whereas patching images focuses on brushstrokes and texture.

In my literature review, I found that researchers have commonly tried a multitude of methods including k nearest neighbor, k means clustering, support vector machine, multiple linear regressions, and convolutional neural networks to try to classify works of art. Originally, I intended to also try all of these different methods, but then in the interest of time I decided that I would only work on a convolutional neural network since all of these published papers said that the CNN models always had a much higher accuracy – on average, CNNs had roughly double the accuracy of these other models. For this reason, I decided that it made more sense to work on refining my CNN since I only had approximately 50 hours to work on this project. If I had been able to spend much more time, I would have tried to expand my method to make my own comparisons in this way.

III. Literature Review

In my research, it became apparent that this approach to authentication – using predictive models to dissect the minute visual components of a painting – is currently being employed primarily in academia. There is a Swiss Company, Art Recognition, that is commercializing this technology, although their methods and components of their model are not published anywhere, with the exception being that they say that they use a training dataset of approximately 200 images.[3] The company has used their model to claim that the only Titian painting in Switzerland, "Evening Landscape with Couple," has an 80% chance of being fake. The museum in which it resides has not stripped it of its attribution though since they say that the "authentication" was done without the museum's consent. The prediction was also only based on the visual analysis of the painting and not any of the other factors I mentioned previously which are generally considered necessary for a true authentication.

In academic papers, predictive modeling to determine authenticity or authorship of a painting are helpful background research for my purposes. This idea is not an entirely new one – for the past decade or so various researchers have attempted to build models such as this, and as Python packages in particular are advancing, it is possible to get better predictions and apply this method to a farther reach of problems. My hope was that my model will perform excellently for Corot and choosing him as my target artist was a conscious decision based on how prolific he was and how many forgeries of his are out there. His wide variety of styles – it was decades before he finally developed his silvery, hazy landscape style for which he is most well-known – in particular made this an excellent challenge in building my model because his different artistic eras look like they could have been by entirely different artists. I was hoping that my model would be able to correctly attribute paintings even within these less well-known eras.

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[3] This was a beneficial piece of information for me since it gave a good idea of the minimum number of images I needed. I ended up building a dataset of approximately 220 images.

In the paper "Feature Selection for Paintings Classification by Optimal Tree Pruning," the team employs a decision tree instead of a neural network. This team was working to create a model which would classify a painting as either by the artist Johan Dijkstra or by Jan Wiegers, both of whom were Dutch expressionist artists. As such, they had similar styles, similar subjects, and employed color in similar ways. Choosing these two artists is slightly different from my approach since I am making a prediction based only on one artist, but it is also quite similar in that I am essentially choosing between two artists as well – Corot or "Other." For this data, they collected 147 paintings by Dijkstra and 160 by Wiegers, and this collection was done by scanning high resolution diapositives.

This paper is particularly illuminating because in their methods they identify that they will be extracting seven categories of features from the images and focusing on these features also has the result of uncovering knowledge about an artist that might otherwise be difficult to put into words. These seven features are:

1. Spatial-Gray-Level Co-Occurrence Matrix (GLCM) which computes texture features
2. Features based on edges to detect object boundaries or changes in color
3. The Gabor function for texture analysis
4. Color constancy, based on extracting regional maxima and minima along color scales
5. Statistical descriptors for each of nine non-overlapping areas of the paintings
6. Color histograms in every color space
7. Statistical descriptors of global color spaces

This paper uses decision trees for features, hoping to mimic decisions that humans would use if they were faced with authenticating art or choosing between two artists for authorship. This model had an approximate 80% accuracy, but I am going to use a convolutional neural network instead and base my use of features on multiple regression results. I am choosing to use a neural network since that is more common in other literature and produces good results. Their metric of success was the percent accuracy which the model was able to identify the artist based on their collected data of these paintings and their authors.

Another paper, "Detection of Forgery in Art Paintings Using Machine Learning," explores different models for determining authenticity, pulling 2000 images total from five famous artists and four features rather than seven. This is not as developed of a project since its main goal was to figure out which models would be most beneficial to solving the problem rather than have a robust detection of a forgery. The paper's setup was essentially to lay the framework, showing which models have higher accuracy, and saying that this could be applied to various datasets to get predictions. This paper, unlike the last, sampled several different methods, as follows:

1. kNN
2. SVM
3. K-Means Clustering
4. Ensemble Algorithm
5. CNN

The four features they used were:

1. Histogram of oriented gradients (HOG)
2. Color
3. Lines
4. Local binary patterns (LBP)

In total, they found that the kNN model gave the highest accuracy – of 80%. This was the same accuracy as for the previous paper using decision trees. The CNN showed maximum validation accuracy on two classes, and k-means clustering led to poor accuracy. This was helpful for my project planning purposes, as I had wanted to use all of those methods. I am still planning to use them all and compare accuracies, and I am going to add to my list of features to use in my model. I am going to use the seven features from the previous paper as well as HOG and LBP.

The last paper I explored in depth is "A Digital Technique for Art Authentication," which explained the importance of using wavelets as features. This was the most technically challenging and mathematically-focused paper, and its goal was to authenticate drawings by Pieter Bruegel the Elder. This method relies heavily on fractal dimension analysis of works of art, since pen lines or brushstrokes are an inherent flag of identity for an artist. Their model looks for inconsistencies in first- or higher-order wavelet statistics, although the paper itself did not explain their results. I am fascinated by their approach, however, and would also like to include wavelet statistics in my work as another method which I will use.

IV. My Solution

Approaching this problem required me to learn a lot about computer vision. The majority of my time in the beginning of the process was spent reading about how convolutional neural networks actually work (since I didn't want to be employing models from Python packages without a solid understanding of what they were doing). Building the dataset itself also took a large amount of time since I had to download high-quality versions of the images and crop out all frames. The most difficult part of building the dataset was finding images of forgeries. One of the reasons why I was so drawn to this problem is that there are an estimated enormous number of Corot forgeries out in the world, but most of them have not yet been properly identified as forgeries. There are actually many reasons why someone might not want to come forward to have their work authenticated. One is the sheer expense: to hire a person to authenticate is incredibly expensive, as it is to hire the company I mentioned who uses CNNs to authenticate. Another is reason is that for Corot paintings especially, a lot of them – real and not – came to the market in Europe directly following World War II. It is likely that most of these were stolen by Nazis or that the families were forced to sell them, so as soon as one is brought to a company and its presence is established, it becomes a legal issue of returning the work to the descendants of the original owners from whom it was stolen. There are also concerns with the cost of insurance for a confirmed painting. Most people do not want to pay higher premiums so would rather not know the true value of their property. These factors cause problems for authentication companies, museums, and auction houses, since with more data on forgeries and real works of art it is easier to establish authenticity of other works.

Since I was working with a limited number of images, it was difficult not to overfit or underfit the model. I kept fine-tuning my model, trying different numbers of layers and adjusting batch number, epochs, steps per epoch, and validation steps. Unfortunately, due to the low number of images that I was working with, it was only possible to have 20 epochs with 20 steps per epoch in order for the model to run fully and be able to give validation accuracy results.

Keras was the core package I used since all of its built-in features made it possible to easily build the CNN. Its documentation is robust which was helpful given my initial complete lack of knowledge on the subject. All of the code I wrote was largely based on Keras documentation – most of the code I needed depended on just understanding the different components of each function and adjusting input values and parameters.

V. Results

I expected that the model trained with patches of paintings rather than features of paintings would have higher accuracy, and this turned out to be true. Intuitively this makes sense. A forgery is supposed to contain features that are similar to an artist's real work: having a neural network predict that a painting was a Corot based on the presence of trees and a few figures (just as one example) was a mistake since any forgery would have contained these features anyway. The idea in distinguishing a real painting from a forgery is on the actual technique and brushstrokes – that is where the differences will be pronounced.

For the model trained on full paintings in the RGB color space, there was a training accuracy of 0.8800, a training loss of 0.3804, a validation accuracy of 0.8600, and a validation loss of 0.4166 in the final layer.

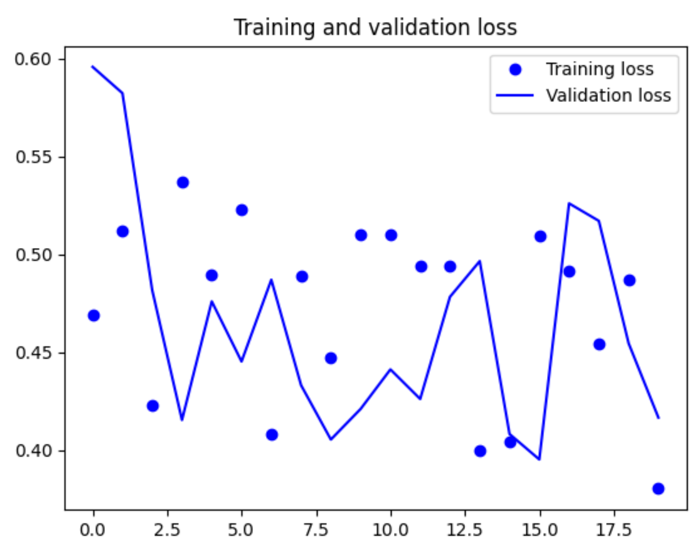

Figure 1. RGB full painting loss values

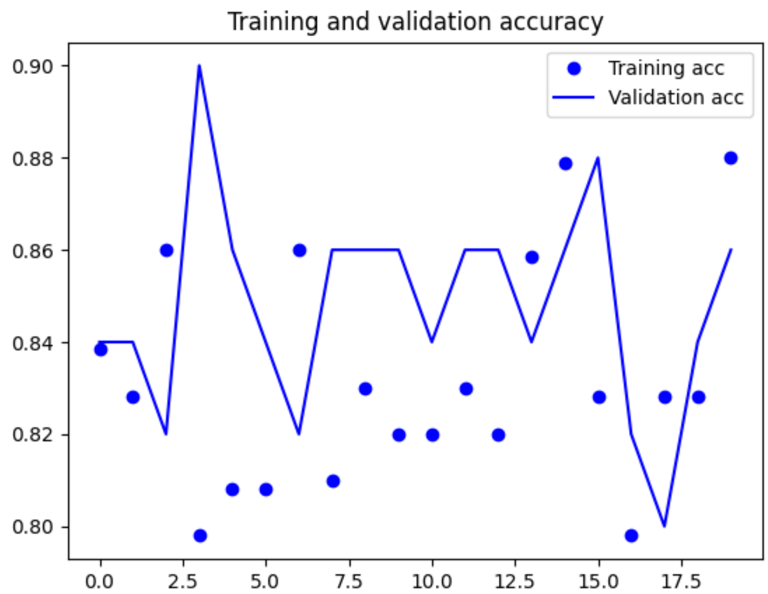

Figure 2. RGB full painting acc values

For the model trained on full paintings with grayscale images, the training accuracy was 0.7980, the training loss was 0.4741, the validation accuracy was 0.8400, and the validation loss was 0.4718.

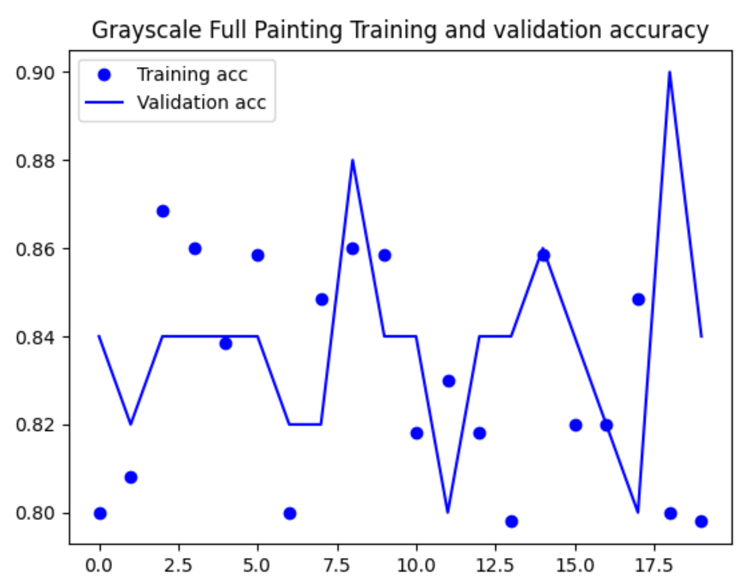

Figure 3. Grayscale full painting accuracy.

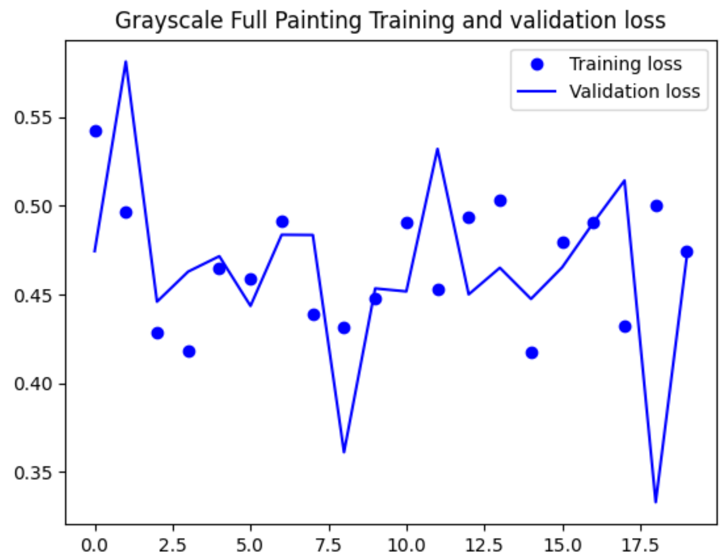

Figure 4. Grayscale full painting loss.

For the model that I trained on full paintings using RGBA, there was a training accuracy of 0.8485, a training loss of 0.4859, a validation accuracy of 0.8400, and a validation loss of 0.4734.

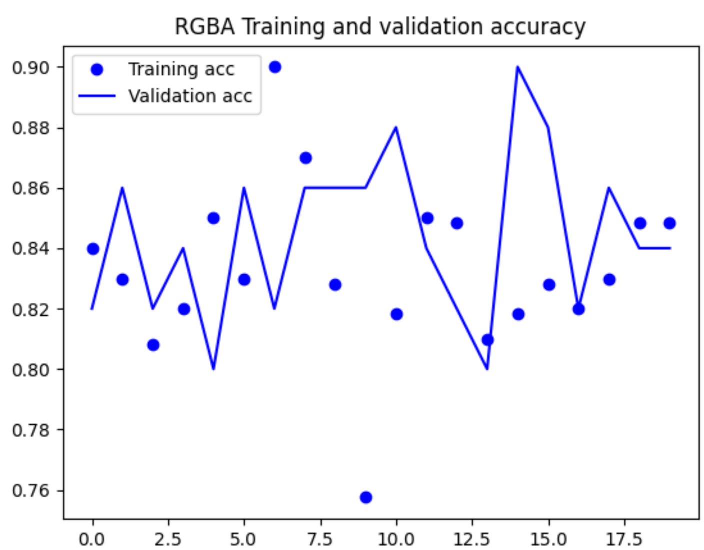

Figure 5. RGBA full painting accuracy

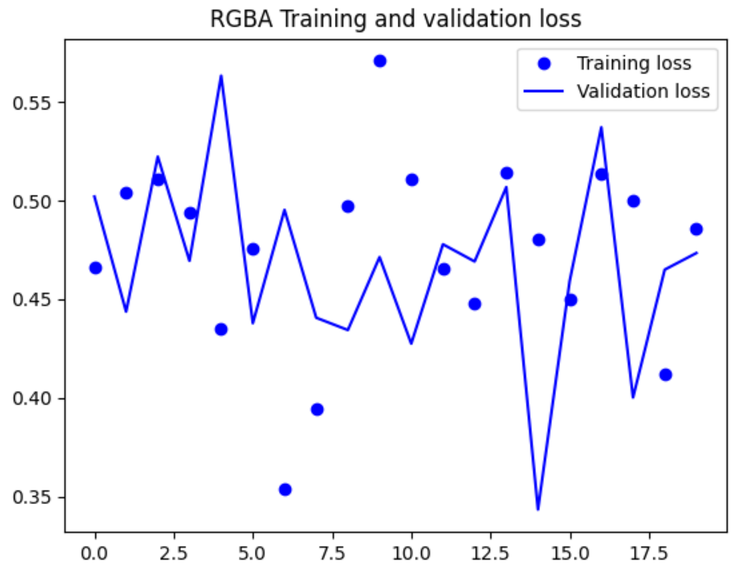

Figure 6. RGBA full painting loss.

For the model that I trained on the patches – hoping to focus on the brushstrokes – it was very difficult to optimize the model in order to get a perfect fit. I ended up with one model that overfit the data and one model that underfit the data. Neither was ideal. Since the image segmentation allowed for so many more images in the dataset, I was able to use 100 epochs, 100 steps per epoch, and 50 validation steps. For the underfitting model, there was a training accuracy of 0.5520, a training loss of 0.6878, a validation accuracy of 0.8200, and a validation loss of 0.6264. For the overfitting model, there was a training accuracy of 0.9885, a training loss of 0.0776, a validation accuracy of 0.8320, and a validation loss of 5.357.

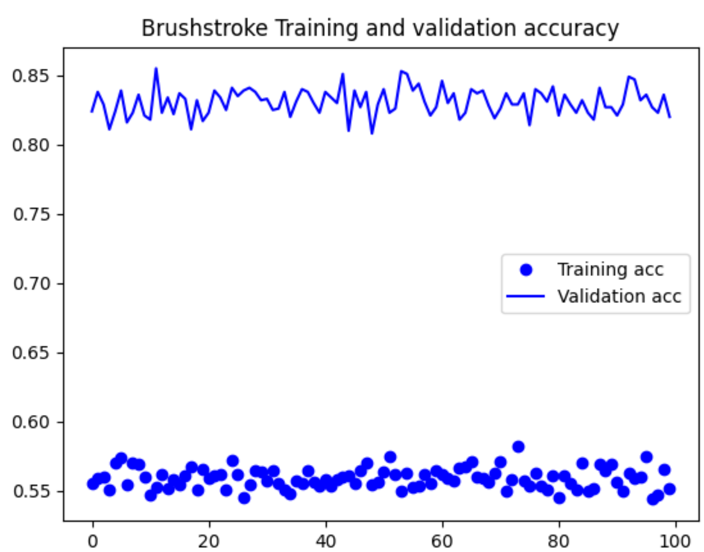

Figure 7. Underfitting brushstroke accuracy.

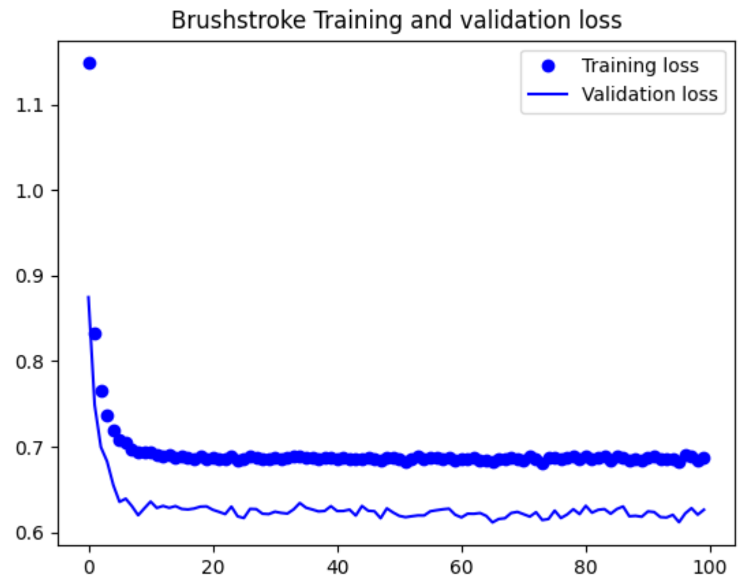

Figure 8. Underfitting brushstroke loss.

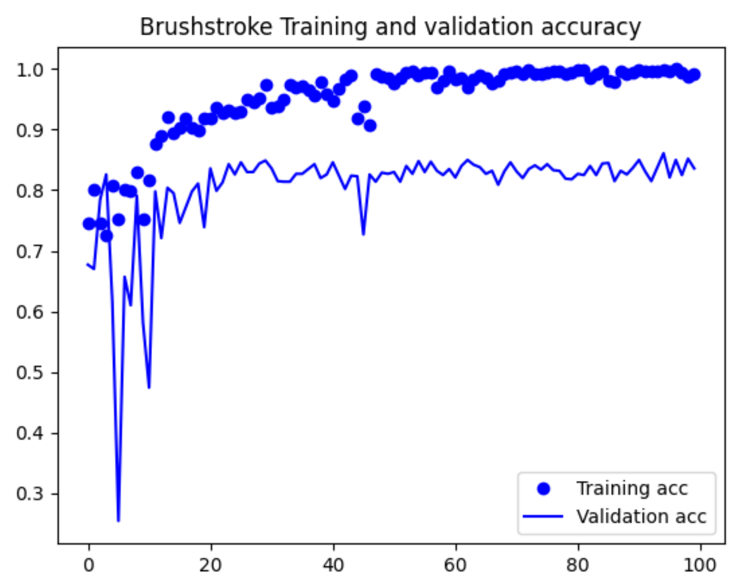

Figure 9. Overfitting brushstroke accuracy.

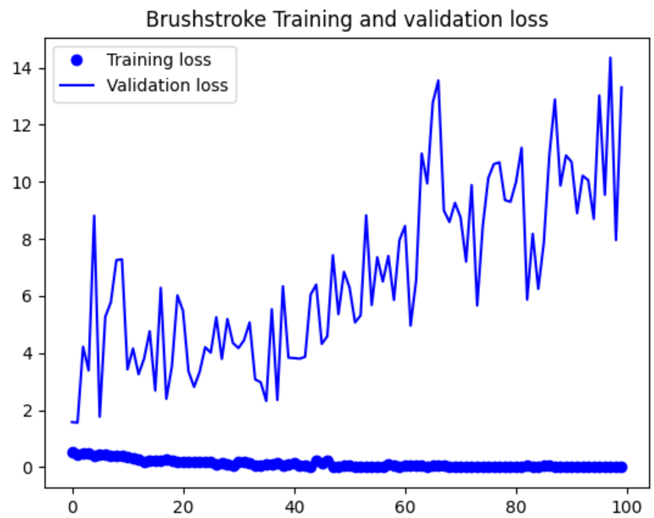

Figure 10. Overfitting brushstroke loss.

I also used Sklearn to produce a classification report for the brushstroke model and for the full-painting model using RGB coloring.

	precision	recall	f1-score	support
corot	0.87	1.00	0.93	1783
forgery	0.00	0.00	0.00	276
accuracy			0.87	2059
macro avg	0.43	0.50	0.46	2059
weighted avg	0.75	0.87	0.80	2059

Figure 11. Classification report for brushstrokes.

	precision	recall	f1-score	support
corot	0.67	1.00	0.80	14
forgery	0.00	0.00	0.00	7
accuracy			0.67	21
macro avg	0.33	0.50	0.40	21
weighted avg	0.44	0.67	0.53	21

Figure 12. Classification report for full painting model

These classification reports show that the model trained on brushstrokes as the features has higher accuracy in its predictions on the test data compared with the test data predictions for the model trained on full paintings. However, the classification report shows that the models predicted that the test forgeries were actually real – there were many false positives and no false negatives (shown by precision and recall columns, respectively). This overall shows that this project was a failure, since it always thought that paintings were real in the test data, despite having fairly good training and validation accuracy.

VI. Efforts

The majority of my time was spent fine-tuning my model. I tried to optimize it as best as possible to increase accuracy, so I kept changing parameters and running that to see test output. This took an enormous amount of time for each time I ran the model, and for each model I changed parameters about 30 separate times. I also had to spend a long time researching the Keras documentation before I changed parameters so that I was making conscious decisions rather than arbitrary changes.

VII. Implications

My results were not as accurate as I had hoped for, but they were approximately the same accuracy values as the published papers I read. I had been hoping to improve on other papers, but although I was initially disappointed, I realized that actually my work shows great promise. None of the other papers I read were attempting this same question of trying to train a neural network to distinguish between forgeries of an artist and real paintings by an artist. Those papers, as mentioned in the literature review section, were training models to distinguish between different artists' work, not between works that are supposed to look like they could be by the same artist. Considering this, my results show great potential for my model.

The next step is to refine the training data, which I would like to continue with in order to hopefully continue to improve the model. This model has high potential, seeing as the training and validation accuracy was the same as published papers have achieved for problems with an easier binary classification. After this course, I am going to continue to try to refine my model and my data and hopefully perform better on the test data. Overall, this was an incredible project and I am so excited to continue to work on it – this feels like the tip of the iceberg.

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