Artist Identification From Paintings Using Convolutional Neural Network (CNN)

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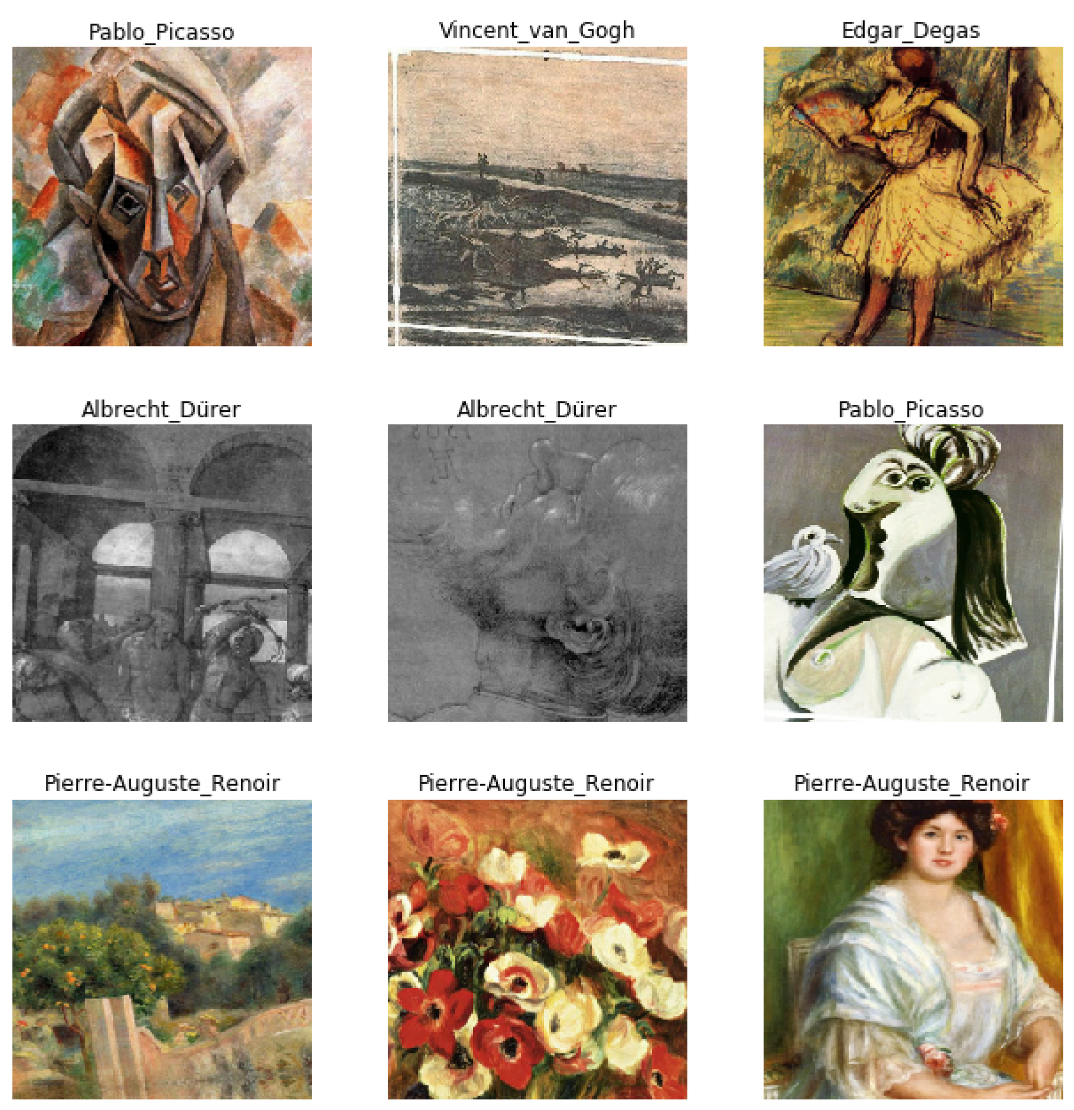
1. Introduction

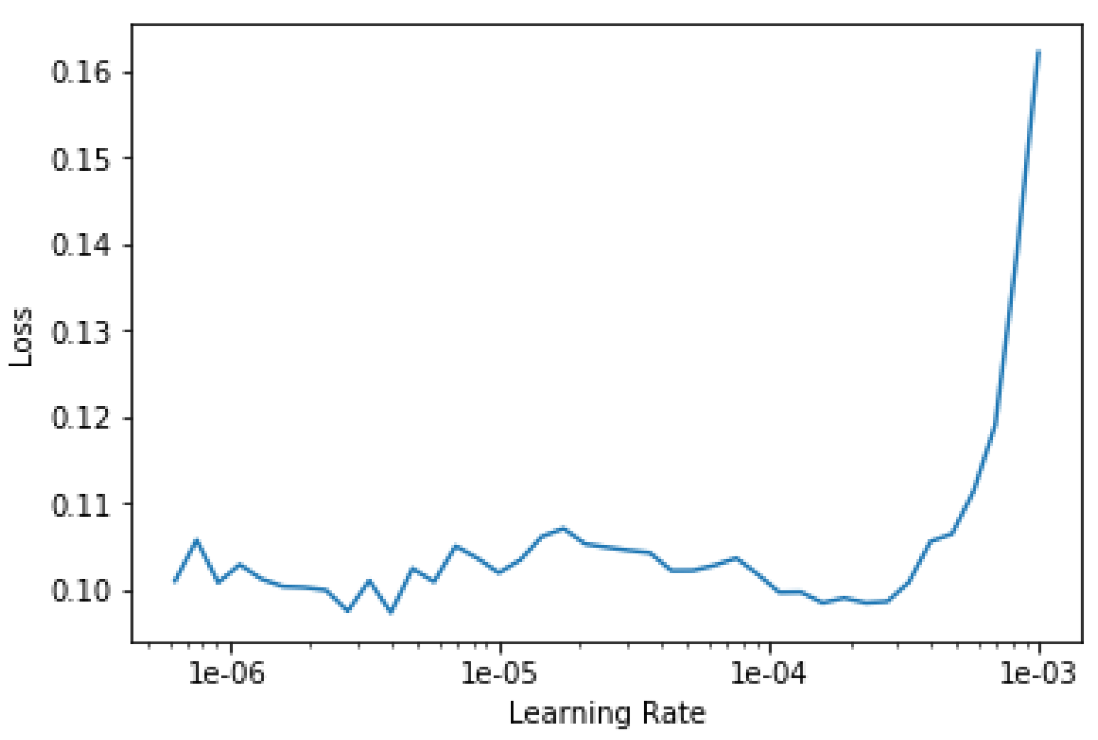
For our CMPS 287 project, we decided to tackle the issue of artist identification from paintings. Our aim is to accurately identify the artist of a painting using transfer learning by training different Convolutional Neural Networks (CNNs) with varying Residual Networks (ResNet). We have acquired our dataset from the Kaggle competition "best-artworks-of-all-time". Previously, most attempts at identifying artists from paintings used Linear SVMs, Multi-class SVMs, or Naive Bayes classifiers. Due to the high-dimensional nature of the paintings, numerous features had to be extracted in order to get meaningful results; however, this poses a problem since it is field specific. Such features included Line Features, TextonHistograms, Color Histograms, Geometric Probability Map, brush strokes, and Geometry Specific Histograms. Such attempts would explicitly learn distinctive features, which would perform on artists with varying painting styles, but our aim with the CNN was to make it learn features on its own instead.

2. Dataset

We acquired the dataset from Kaggle's "best artworks of all time" competition. Initially, the dataset consisted of 2,319 artist with paintings varying from 1-1500 per painter. Due to such an extreme imbalanced dataset, we opted on subsampling (Under-sampling) down to 1,500 paintings, each painter having 300 paintings. As a pre-processing step, we zero-centered the images and normalized them. We then re-sized the images to (224x224) center crop and our dataset was ready for training. Additionally, FastAI offers a doFlip function which trains the same images on various rotations as a means of reducing over-fitting. However, we didn't flip the images due to the sensitivity of the data.

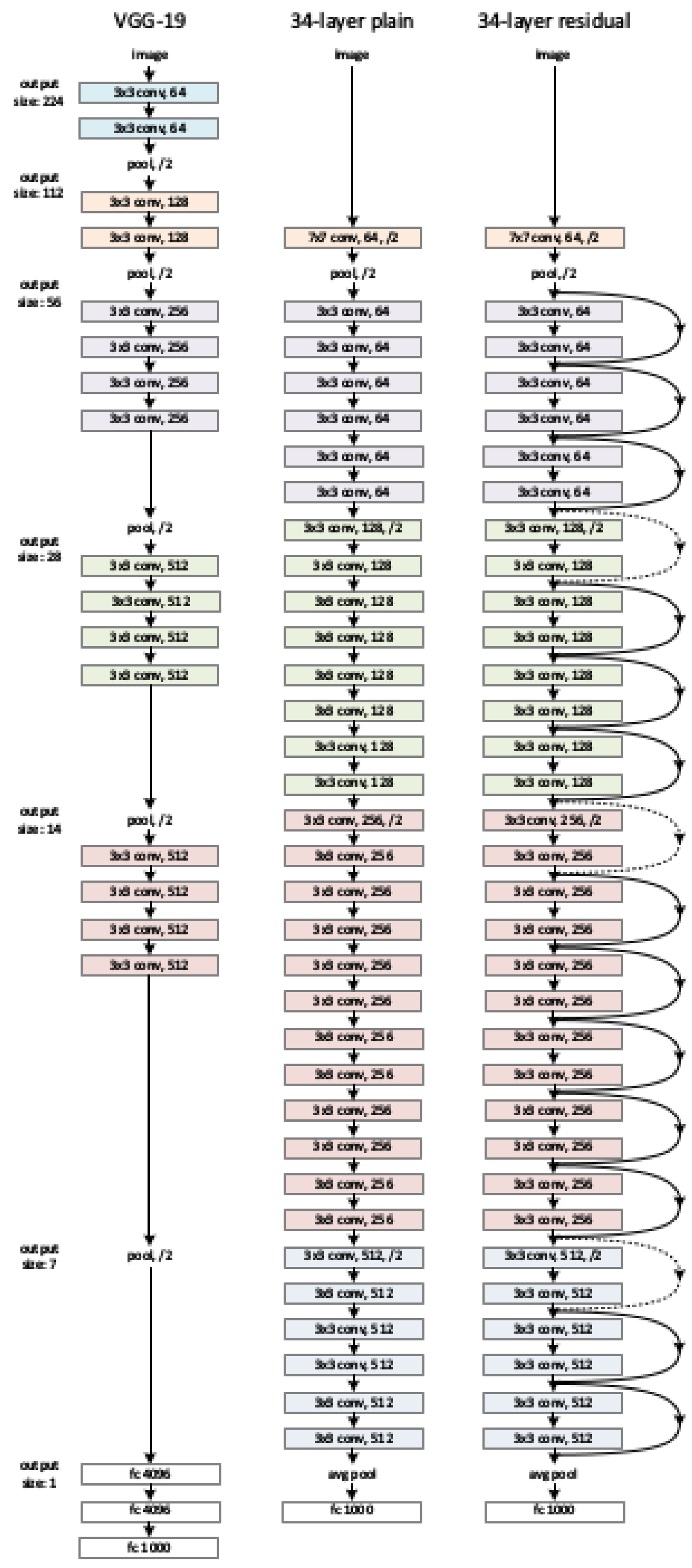


3. Final Epoch Learning Rate



4. Model Selection

We opted on training a Convolutional Neural Network (CNN) with varying Residual Networks (ResNet). Every network we use takes as input a (3x224x224) RGB image and outputs the scores for each of the 5 artists present in our dataset. We opted on training three different ResNet architectures. The goal of this paper is to evaluate the performance of each network on classifying artists from paintings. We first tried to use Pytorch; however, we then read how optimized fast.ai is so we decided to use it. Using fast.ai was a bit challenging due to the documentation being a bit unclear, but it is a very powerful library. (We believe that it really helped us get a higher accuracy). Additionally, because our best model was the ResNet-152, we will show its layers below:



5. Results

After downloading the different ResNet models with weights pre-trained on the imagenet dataset. By default, only the fully connected layers at the top are unfrozen. To train the layers we used the fit one cycle method (from fast.ai), which basically changes the learning rate (slice learning rate based on graph) over time to achieve better results. After we trained the fully-connected layers, we unfreezed the other layers and trained the whole network. FastAI provides a technique to enhance transfer learning called differential learning rates, which allows us to set different learning rates for different parts in the network. The above steps were done iteratively to each of the ResNet pre-trained models and the results were as follows for the ResNet-152 model:

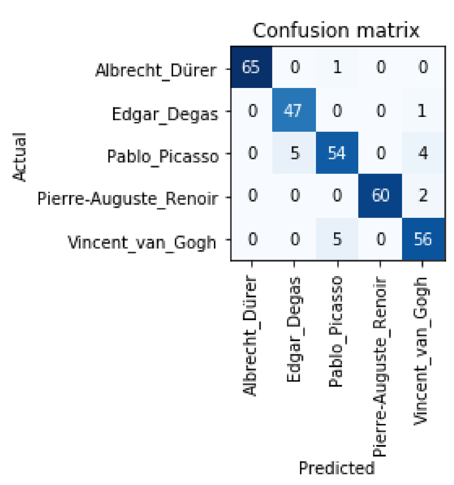


Table 3: **ResNet-152 Network Results**

epoch	tran-loss	valid-loss	error-rate	accuracy
0	1.038	0.452	0.147	0.853
1	0.657	0.454	0.153	0.847
2	0.478	0.425	0.137	0.863
3	0.325	0.196	0.070	0.930
4	0.250	0.202	0.083	0.917
5	0.170	0.178	0.063	0.937
6	0.142	0.160	0.060	0.940
7	0.135	0.159	0.060	0.940
8	0.125	0.162	0.060	0.940