



**BIRLA INSTITUTE OF TECHNOLOGY, MESRA**

PROJECT TITLE

# Artist Recognition

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## Objective

Artist recognition of fine art paintings is a challenging problem primarily handled by art historians with extensive training and expertise. It is very difficult to recognize the artist for billions of dollars' worth of art which are found every year for which as it requires a lot of expertise in the artistic field. Every year, paintings worth billions are found. The value of the painting highly depends upon the artist and hence identifying the artist becomes of utmost significance. Artist recognition can also help in preventing the forgery of paintings. In this project, we intend to provide an accurate and fast method for artist recognition.

# Introduction

Artist recognition is the task of recognizing the artist simply by observing their artwork without further information provided for cataloguing art, especially as art is increasingly digitized. Artist recognition is traditionally performed by art historians and curators with expertise and familiarity in this field. As the art collections have grown immensely in the past decades due to newer findings, it is challenging to efficiently label and identify the art pieces. Also, many artists from the same period will have similar styles. It is a rather complex problem due to the wide variety and vastness.

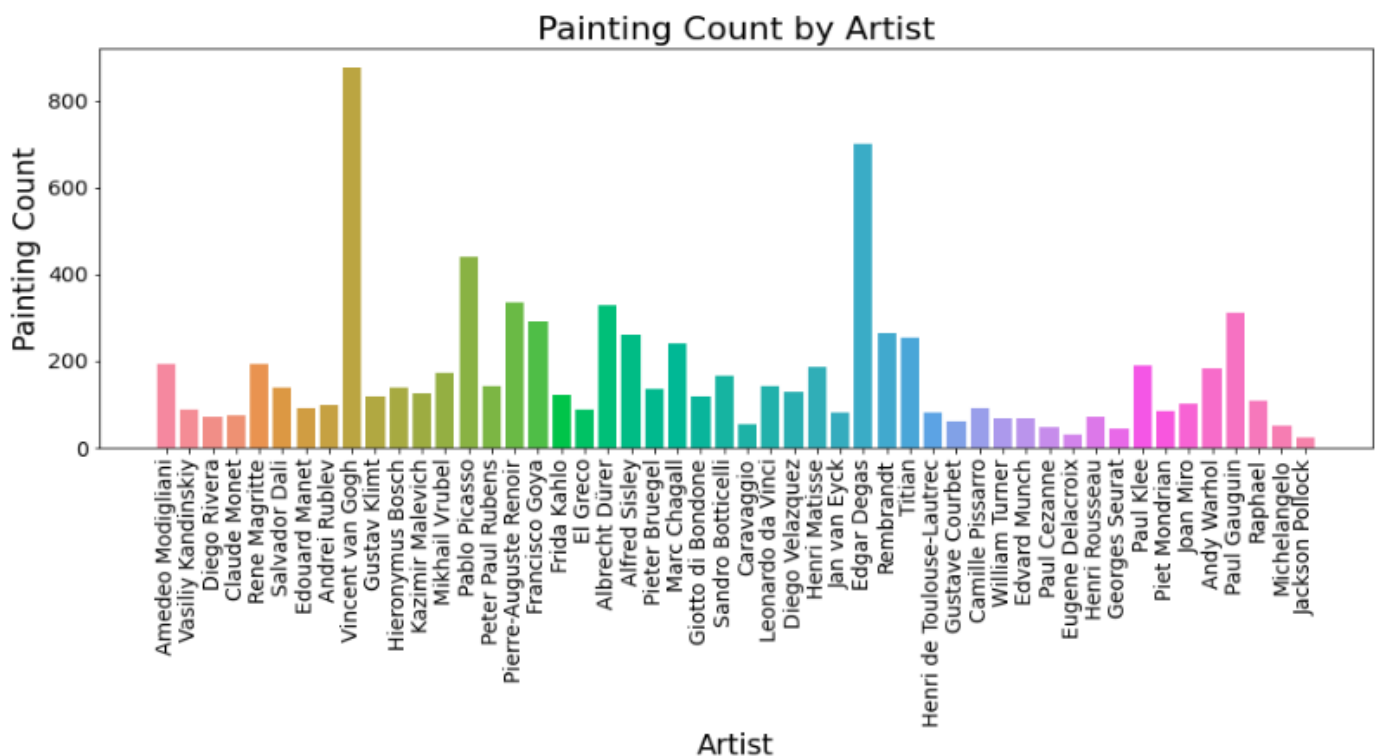
Previously, differentiating characteristics as features were defined explicitly for this task. But it was difficult to perform artist recognition due to the varying features, styles, and subjects of the artists. So, instead of explicitly defining features, we aim to train a Convolution Neural Network (CNN) to extract distinguishing features followed by fully connected layers to perform the task of artist recognition. It is based on the hypothesis that every artist has a unique style of art. So, we can design a CNN to determine the best possible feature representation of paintings and hence perform artist recognition.

# Proposed Method

We intend to perform artist recognition using Deep Learning. A convolutional neural network is used to extract features from the paintings followed by fully connected layers that predict the artist of the painting. The process consists of data collection, Data Pre-processing and augmentation, model selection, hyperparameters tuning, training and finally testing on unseen data. The entire process is discussed in detail as follows: -

## 1.Data collection

For this purpose, we decided to use the “Best Artworks of all time” dataset which is publicly available at Kaggle. It consists of more than eight thousand paintings of 50 artists collected from the internet. The images vary widely in shape and size. A separate CSV file provides information like the name, period, genre, and bio of the artists.



Various artists in the dataset have fewer than 50 paintings, so to ensure sufficient sample sizes, we have used only the artists with 100 or more paintings in the dataset.

Therefore, the dataset consists of paintings from 30 artists from a wide variety of styles and periods. We split this dataset into training and test sets using an 80-20 split per artist.

## 2. Data Pre-processing and Data Augmentation

As the images are of varying shapes and sizes, we re-scale the images into a size of (224,224,3). Since the amount of training data is limited, we augment the data to increase the quantity and diversity of data. Various augmentation techniques like flipping, rotation is simultaneously applied.

An original Image of Joan Miro

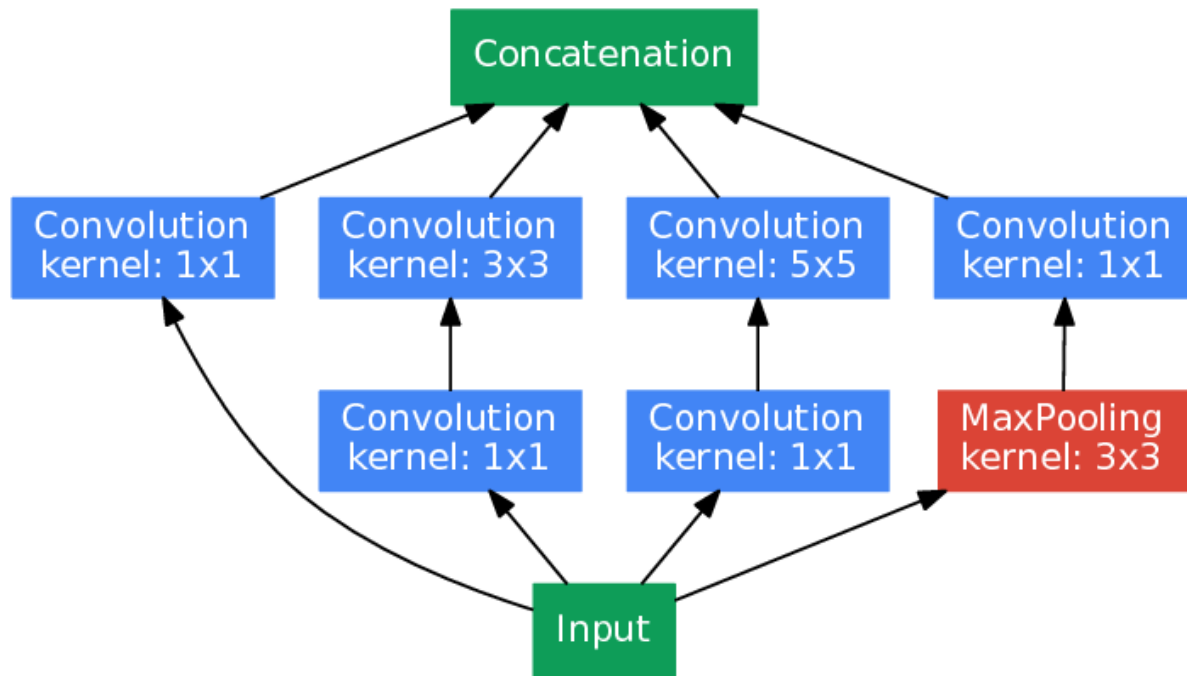


A transformed Image of Joan Miro



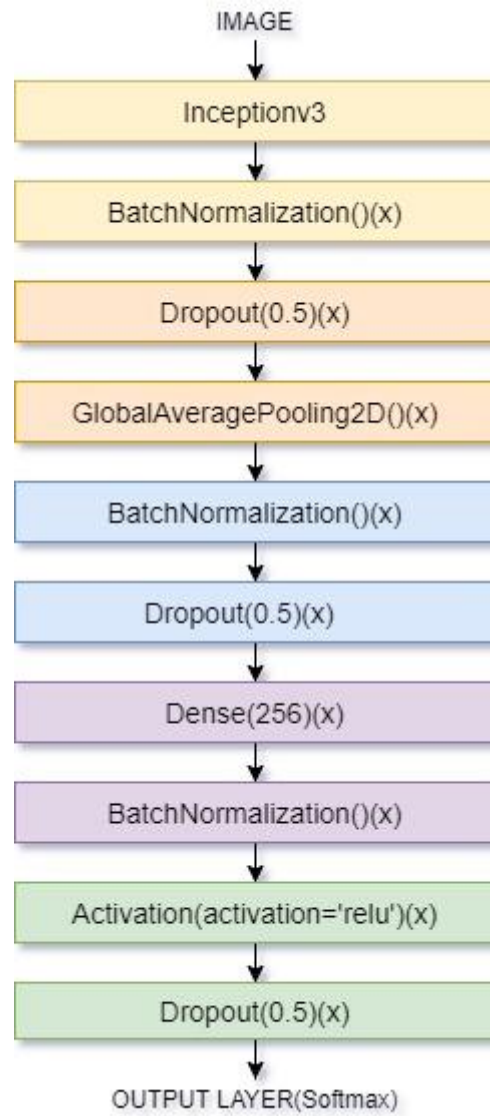
## 3. Method construction and Hyperparameter tuning

We develop and tune an InceptionV3 model for this purpose. The network takes a 224 x 224 x 3 image as input. An inceptionV3 network consists of multiple Inception blocks followed by fully connected layers.



Block diagram of an Inception block

We use transfer learning to speed up the learning process. The Inception network is initialized with pre-trained weights. The inception network layers are trainable as well. It is followed by fully connected layers with a SoftMax output layer. Dropout and Batch normalization layers are added to prevent overfitting. Adam optimizer with a learning rate equal to 0.0001 is used to optimize the weights.

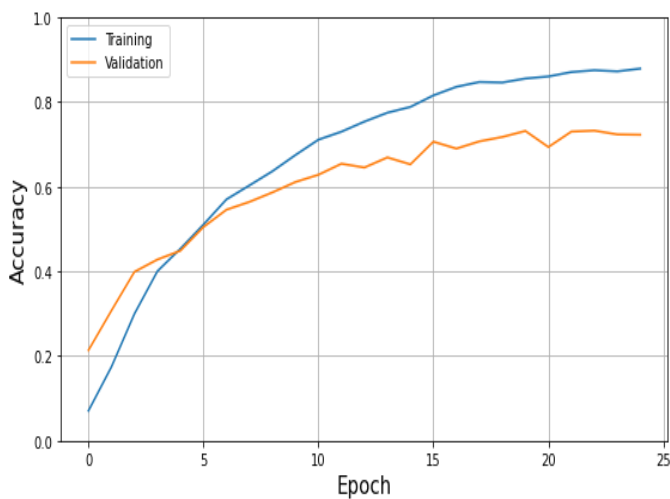


Proposed Model for Artist Recognition

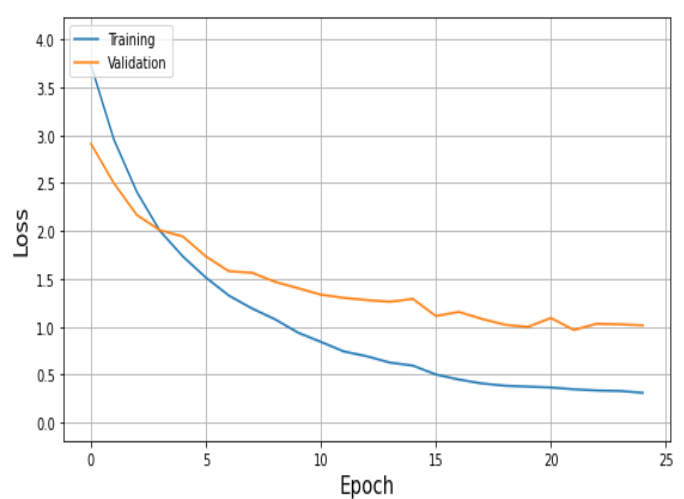
## Result

The trained model exhibits an accuracy of 85% on the training set and 70% on the test set. A baseline CNN model (a couple of convolution layers followed max pooling and a fully connected layer) has a 43% training accuracy and 42% test accuracy (as mentioned in the research paper “Artist Identification with Convolutional Neural Networks by Nitin Viswanathan”). Hence the proposed method performs much better than a baseline CNN method.

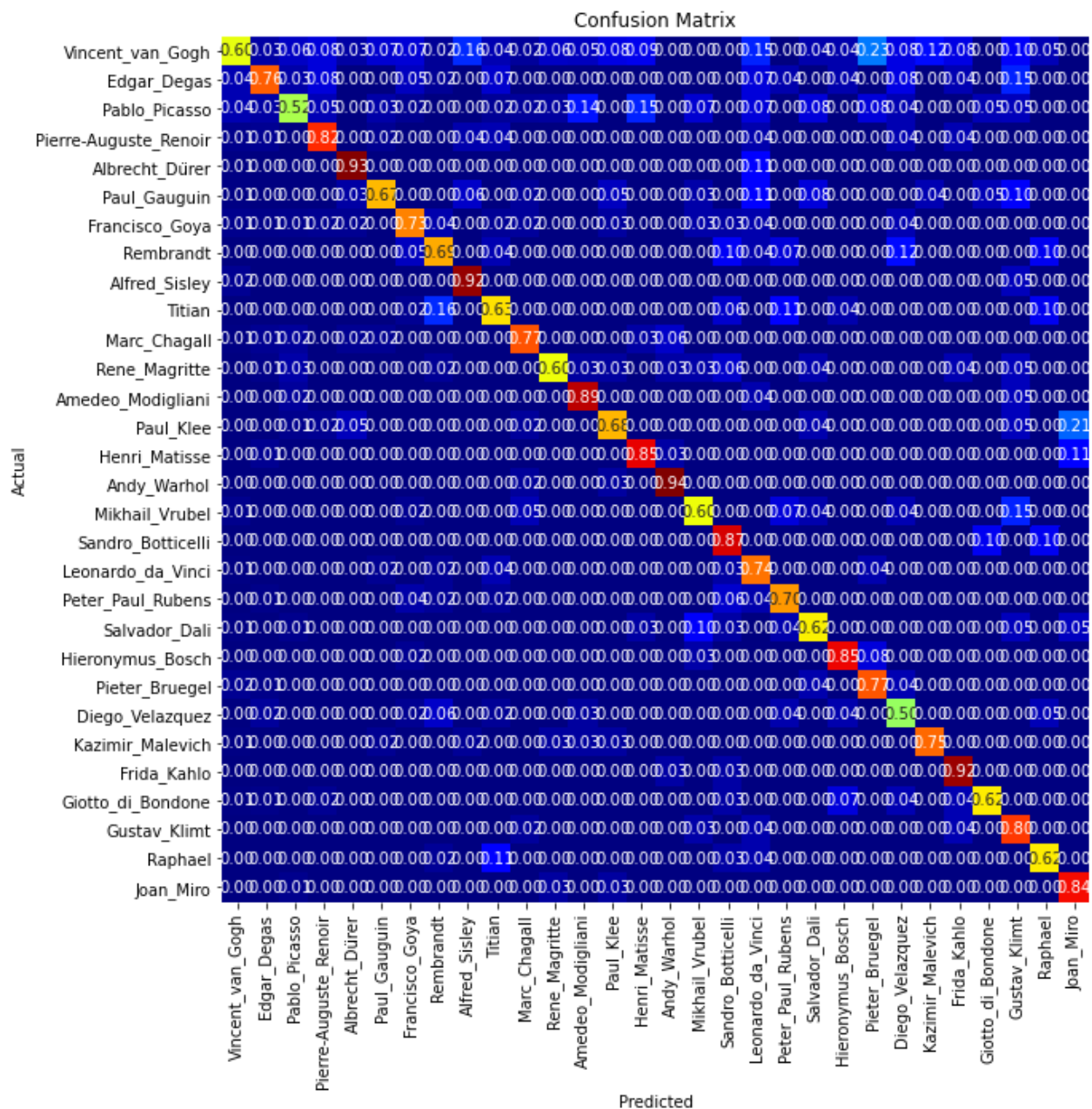
Model Accuracy



Model Loss







The above confusion matrix shows the ratio of paintings that were correctly recognised by the model for each artist.

We then use this model for artist recognition for unseen paintings.

Actual = Edgar Degas  
Predicted= Edgar Degas  
Probability = 96.58 %



Actual = Salvador Dali  
Predicted= Salvador Dali  
Probability = 79.61 %



Actual = Rembrandt  
Predicted= Rembrandt  
Probability = 98.52 %



Actual = Paul Gauguin  
Predicted= Paul Gauguin  
Probability = 99.07 %



Actual = Diego Velazquez  
Predicted= Rembrandt  
Probability = 52.40 %



Actual = Vincent van Gogh  
Predicted= Vincent van Gogh  
Probability = 51.28 %



Actual = Rembrandt  
Predicted= Rembrandt  
Probability = 99.52 %



Actual = Rembrandt  
Predicted= Rembrandt  
Probability = 97.07 %



Actual = Andy Warhol  
Predicted= Andy Warhol  
Probability = 99.94 %



Actual = Sandro Botticelli  
Predicted= Sandro Botticelli  
Probability = 93.75 %



When the model was tested for 10 paintings, it predicted 9 correctly with an average confidence of over 80%. The painting for which the artist was predicted wrong had a very low confidence of 52%.

## **Conclusion**

We tested our model with over a variety of artist paintings and came on to the conclusion that our model produces satisfactory results on the various test sets we introduced in the project. We introduced the problem of artist recognition and applied a variety of CNN architectures which maximized classification accuracy. Our dataset consists of at least 100 paintings per artist for 30 artists over a wide variety of styles and time periods. The best network, based on Inception NetV2 pre-trained on ImageNet with transfer learning, outperforms baseline CNN approaches by a significant margin. It produced an accuracy of 85% on the training set and 70% on the test set.

## **Future Scope**

For future work, we would like to dive deeper into the model representations and try to quantify how much of the predictions come from the style of an image versus the content. We would also like to expand our dataset and see how the network handles classifying more artists with fewer paintings for artists. We used 30 artists with more than, but our original dataset has 50 artists. We would switch to using all available images for the artists we use in our dataset instead of using an equal number per artist. This would result in an unbalanced dataset, but if we expand to using more artists, we should still be able to take advantage of the larger sample sizes for certain artists and classify them with high accuracy.