Art Authentication System using Deep Neural Networks

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Abstract - The goal of this initiative is to help detect paintings made by an artist using a profound neural network of convolution. The image is filtered through thousands of neurons with millions of connections to extract patterns of content, style patterns and characteristics of an artist's paintings. These are then context-sensitively combined using optimization algorithms that find the best ways to combine everything together (that is to extract characteristics). We examine the paintings set and identify the paintings that the same artist has painted. The training set and test set consists of images of the artwork and their class labels (painters).

Key Words: Paintings, Convolutional Neural Networks, Optimization

1. INTRODUCTION

Image classification is the task of capturing an image input and outputting a class or class probability that best describes the image. For humans, this recognition task is one of the fi rst skills we learn from the moment we are born and it is one that comes as adults naturally and easily. Without even thinking twice, the environment in which we are as well as the objects that surround us were able to be identified quickly and seamlessly. When we see an image or just look at the world around us, most of the time we can immediately characterize the scene and label each object without even consciously noticing it. In this project, we tend to classify paintings on the basis of their respective painters by using a class of biologically inspired vision model called the Deep Convolutionary Neural Network (DCNN) that was inspired.

DCNN has been widely used in a wide range of fields in recent years, including computer vision, natural language processing, image processing, etc. Convolutionary Neural Networks are found in deep learning to provide the most accurate results in solving problems in the real world. Because of their ability to joint feature and classi fier learning, DCNNs achieve better classification accuracy on large scale datasets. DCNN in image processing is a potential trend in image recognition development. The main scope lies in the art field.

In [1] it introduces a Deep Neural Network-based artificial system that creates high perceptual quality artistic images. To separate and recombine content and style of arbitrary images, the system uses neural representations, providing a neural algorithm for creating artistic images.

Similar techniques are adopted in [2] which introduces a simple and easy way to regulate large convolutional neural networks. Replaces conventional deterministic pooling operations with a stochastic procedure, randomly selecting the activation according to a multinomial distribution within each pooling region given by activities within the pooling region.

All the above mentioned techniques has its own disadvantages. In most of the systems, an accuracy of not more than 60% is only achieved. So in order to improve the overall efficiency of the system we propose a model based on DCNN. A given painting is examined and we determine its artist by passing unique datasets of art as input.

2. SYSTEM MODEL

Using deep convolutional neural network to identify an authentic work of art. An artificial system is introduced based on a neural network of deep convolution that detects forgery of high perceptual quality artistic images. A user's requirements are to test an image and determine whether or not the painting is original. The developer's requirements are unique image datasets by various painters as a training set, converting data sets to predefined dimensions, creating predictive models using unsupervised machine learning, accepting user input in a compatible format and predicting whether the image is original or not.

A deep convolutional neural network is used here that process visual informations hierarchially. For image synthesis average pooling operation is used which improves gradient flow and more appealing results are produced. To visualize images gradient descent is used. The overall sequence of events can be depicted using a flowchart as in the figure.

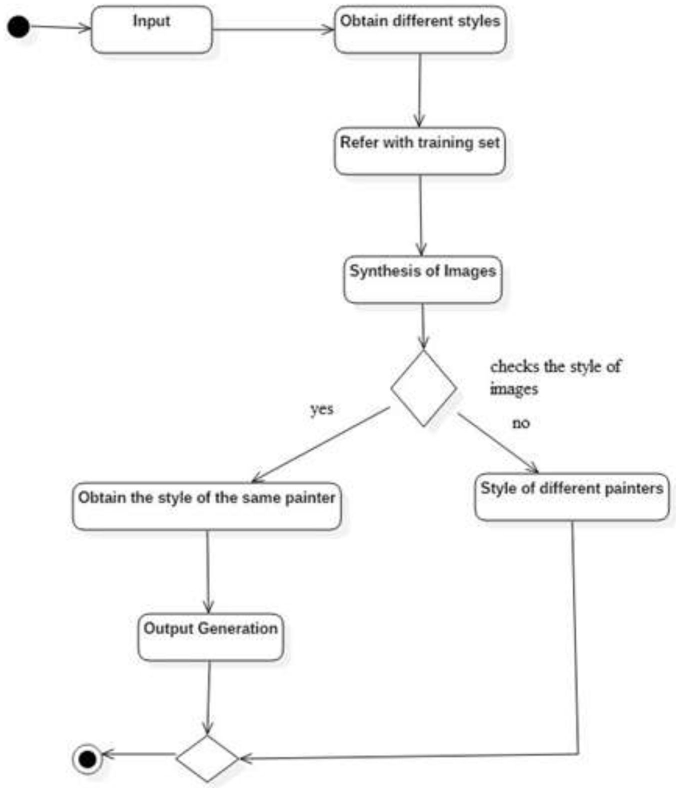

Figure 1- Flow chart

2. IMPLEMENTATION

To configure a network you must create a config file. Config file describes the network structure, training parameters and all other possible configuration.The number of layers must be specified which describes the network structure and input/output size.

net = CreateNet('../../Configs/mnist.conf');
Then, call Train function with the dataset containing the train/test samples:

net= Train(MNIST,net, 15000);
Here , MNIST is the dataset , this will train for 15000 images from the test set in a cyclic manner. In order to train longer , you can specify Inf as the last parameter, network will train until learning rate (ni) reach below the given threshold.

The training set is unbalanced and some classes are only present in the training set and some only in the test set. Additionally input images are of various dimensions. There are 79433 instances and 1584 unique painters in the training set and the test set is composed of 23817 instances.There are a total of 1584 painters in the training

The model assumes fixed-size inputs, so the first preprocessing step was to resize the smallest size of each image to 28 pixels (retaining the aspect ratio) and then crop it in the center of the larger size with 28x28 images. During this process some information gets lost and an alternative approach has not been considered where multiple crops are Irjet template taken from the same image. Random transformations (rotations, zooming, shifts, shears and ips) were applied to data during the training phase.

Then each of these images is passed on to the DCNN's convolution and pooling layers. The output is then passed on to their respective painter to a feature classifier to classifier each painting based on the unique features of each kernel painting obtained through the use of unsupervised machine learning.

3. COMPARISON

The comparison of the model formulated with the other methods is described below.

Figure 2- Confusion Matrix

We have given five paintings to the created model. The confusion matrix clearly shows the target class and the output class. The correct output is indicated by a green colour and the incorrect rate is shown as red colour for each painting and the corresponding painters.

The success rate can be depicted by means of a bar graph and is depicted in the figure below:-

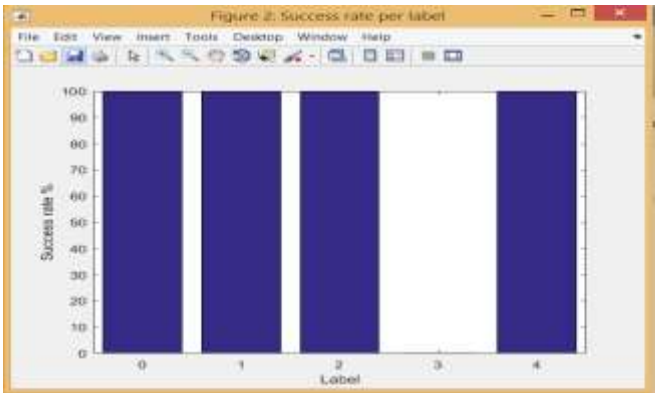

Figure 3 – Bar chart of the success rate

The accuracy of the system is 80% which suggests that it is better than the traditional systems used. The traditional techniques used had an overall accuracy of 60%. So this method is far better than the existing techniques used.

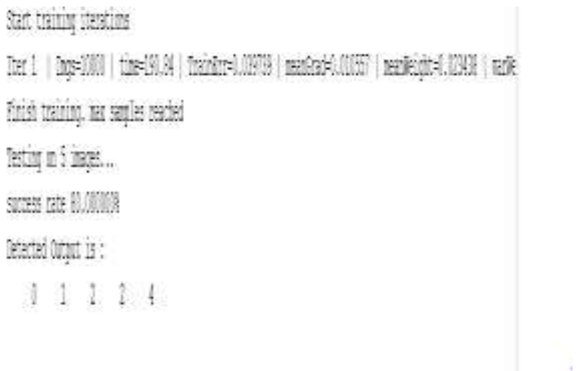

Figure 4 – Accuracy and success rate of the model

3. CONCLUSIONS

We introduced an artificial system based on a Deep Convolutional Neural Network that is based on their unique painters to identify artistic images of high perceptual quality.

The system uses neural representations that provide a neural algorithm to train and test artistic images based on their painter. Our work provides a path to an algorithmic understanding of recognition and extraction of features using DCNN and unsupervised machine learning.

The limitations of the system include:-

1. Computation becomes difficult as the number of paintings increase.
2. Time taken during execution of code increases as the number of paintings increases.
3. All the paintings of a painter may not be detected accurately

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