SINING: An Application for Recognizing the Painting Styles of famous Filipino artists using Convolutional Neural Networks

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***Abstract*— Paintings are a vital part of humanity's history, and with the huge collection of this comes with the difficulty of classifying and storing them digitally. SINING is a mobile application that can classify a painting according to an artist' style, specifically styles of Fernando Amorsolo, Benedicto Cabrera, Carlos Francisco and Juan Luna. SINING allows the user to take a picture of a painting for classification, it then segments it into nine and feeds it into nine neural network models. SINING has a general prediction rate of 0.8 but takes around 50 seconds to classify.**

***Index Terms*— Convolutional Neural Network, Painting Recognition, Painting Styles, Filipino Arts, Filipino Artists**

I. Introduction

A. Background of the study

According to Stecker [1], art is anything that is created by a human that is purposed to move human emotion, the greatness of it is proportional to how strong it can stir the most amount of culturally knowledged humans for a long period of time. With this said, many have focused on this throughout history. This lead to the expansion of art, in which numerous have dabbled on paintings.

Paintings have diverse art styles depending on the artist that makes them, but with the numerous artists that existed and exists, various styles have already been developed; with this it becomes increasingly difficult to classify them. This proves to be a problem given that exhibits are "primarily acts of classification." [2], and aside from this there has been an interest to digitize paintings, for their availability [3]; therefore meta data, such as painting styles, date and artists, should be identified about the painting.

With this, it is important to understand the artists' style to further understand the paintings. In this study, the term: Artist's style, refers to the artist's general decision or preference on creating paintings, like the composition, lighting, color scheme, subject matter and more. This study will also be focusing on paintings made by Filipino artists. Many artists have greatly contributed to Philippine history, their paintings have portrayed controversies and has roused emotion from Filipinos; an example of which would be Juan Luna's Spoliarium, illustrated in Figure 1. His painting has shown others the capabilities of Filipinos despite being considered a "barbarian colony" [4]; it had opened the eyes of many. Juan Luna spending most of his time in Europe had developed his style there, along with many of his colleagues Felix Hidalgo, and others; the place he stayed and the people he was with had influenced his style. These factors would manifest in his paintings, creating a distinct painting style, which would assist in classifying and deriving data from his paintings; this applies to other Filipino artists as well. Understanding their style opens up opportunities for painting style recognition.

Painting style recognition is a process that relies on vision science, which is brought up by vision scientists who have an interest to "uncover the mysteries of visual perception" which is filled with ambiguities [5]. These ambiguities are resolved through conventions and constraints [5], which could be processed through image processing and convolutional neural network. With emergence of the interest in this field, numerous scientists have conducted their own research. It has been observed that works on computer vision techniques on analyzing artworks have increased in quantity and quality, this further confirms that the community has focused on the topic for sometime [6].

Fig 1: Spoliarium by Juan Luna

B. Significance of the study

As mentioned in the background of study, it is important to understand the painting styles of our artists, not only due to their historical importance but also for the preservation of history; wherein we would be able to digitize their works. Juan Luna alone created numerous paintings, to be able to digitize them would be quite tedious and would require time and effort. This application will provide an interface for classifying artists' painting styles.

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C. Objectives of the study

Generally, the study intends to create an application to digitally recognize painting styles of Filipino artists using a convolutional neural network for image recognition. The specific objectives of the study includes:

1) To develop an application for painting recognition for the painting styles of Juan Luna, Fernando Amorsolo, Carlos Francisco, and Benedicto Cabrera;
2) To train a convolutional neural network using the captured image set from various museums; and
3) To evaluate the performance of the convolutional neural network in recognizing the artists' styles.

D. Scope and Limitations

Four famous Filipino artists will be considered for this study, namely: Juan Luna, Fernando Amorsolo, Carlos Francisco, and Benedicto Cabrera, seen in Figure 2. These were chosen to represent the different generations of artists. The time-line was determined from the National Museum's website and the list of National artists; starting from Juan Luna in the 19th century (1800-1900), Fernando Amorsolo in the 1900s, Carlos Francisco in the 1930s, and Benedicto Cabrera in 1960s.

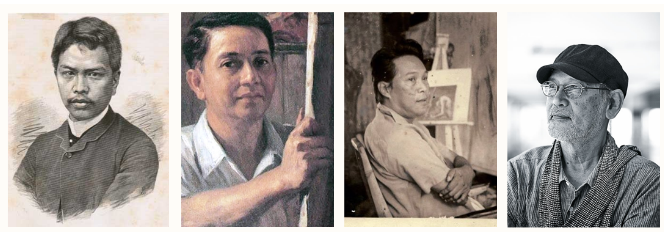

Fig 2: (from left to right) Juan Luna, Fernando Amorsolo, Carlos Francisco and Benedicto Cabrera

II. Review of related literature

With the digital age, there has been an interest to digitize art works, and with this, there is a need to know details about the artwork; this creates a problem seeing as it requires the time and effort of art scholars and historians to identify the piece of work [7]. With this, numerous studies have been conducted to find ways to effectively classify and/or generate information from paintings.

A. Significance of Art

Art and paintings are an important part of a developing community, it preserves the culture and cultivates the thought process of the youth, developing their critical thinking and creativity. With creativity comes innovation which brings about new business ideas and inventions. Art engages tourism, through the preservation of heritage through museums and the showcase of creativity through art galleries and exhibits [8], exhibits especially are seen as acts of classification, given that they have to choose specific artworks to fit with the theme or idea of the exhibit itself [2].

B. Painting Style Recognition

Masuda, Yamamoto, Kato and Tanahashi conducted a study titled "A method of Style Discrimination of Oil Painting Based on 3D range Data" [9], in which the 3D data is measured through a three-dimensional range finder found in the Virtual System Laboratory at Gifu University. The art style is known through the extraction of the Gaussian and Mean curvature from the range image of the painting; this is done given that the touch of an artist would greatly affect these factors. Prior to this, geometric features such as dots and lines made by different brushes were measured from the data set collected for this research which consists of a set of 3 artists with 3 paintings each. 1 out of 3 paintings was used for testing and the remaining as training data; these were tested using 3 methods: Gaussian curvature, Mean curvature and the combination of both. This gave a 100 percent recognition rate with the "distinction result of height condition" equal to 73.68.

Wang, Sun, Sun and Lv has brought out a research paper titled "Neural network-based Chinese ink-painting art style learning" [10], in which image analysis and back propagation neural network is used to learn art styles. They conducted this through three steps, pre-processing, feature extraction and applying the back propagation (BP) neural network on the features. Pre-processing is done to acquire the set of primitives, which is a "small are of pixels and its correlative parameters", this is done through image segmentation and skeleton extraction. The features are then extracted through the primitives' histogram and gray level co-occurrence matrix; with these features the BP neural network is applied to classify the ink-painting style. The data set collected is composed of 35 ink paintings from different art styles, from this collection 500 image primitives are extracted. From this method, it was discovered that the node number of hidden layers is inversely proportional to the training error.

Zhen-Ya conducted a research titled "The key technologies of painting style rendering based on image" [11], where they apply artistic media simulation and simulation with processing of artistic creation into creating an artwork. This is done through four steps, pre-processing which consists of image segmentation and smoothing, skeleton extraction, stroke generation and image rendering. The stroke is generated through the algorithm of Strassman and Pham, which would then be able to render a painting. This resulted to an algorithm that is able to generate a painting given an image.

Yang and Xu conducted a research titled "Learning to recognize the art style of paintings using multi-ues" [12], where SVM is used to classify using the following features: color contrast, blank-leaving and uniformity of illumination. The algorithm developed is called CoCBI, named after the features to be extracted; with this it is compared to 2 other algorithms, Spatial Pyramid Matching (SPM) and Spare coding Spatial Pyramid Matching (ScSPM), which are considered to be a traditional classification method. A data set containing 2 art styles, with 100 images each has been collected; these are all tested 10 times in terms of algorithm, type of features and cost times, the final result would be derived from the mean of all 10. Results in terms of algorithm dictates that CoCBI averagely gets a 13 percent higher classification rate compared to SPm and 2 percent compared to ScSPM. CoCBI also gets an accuracy of 96 percent while a single feature would only achieve up to 92 percent at best and 60 percent at worst. Aside from that, CoCBI only takes 60 seconds to classify while SPM takes 360 and ScSPM 720, with these it can be said that CoCBI is better than the traditional methods.

Sheng and Jiang conducted a study entitled “Recognition of Chinese artists via windowed and entropy balanced fusion in classification of their authored ink and wash paintings (IWPs)” [13], which extracts local and global features through a histogram-based method from the pre-processed gray scale IWP images. Edge detection to identify the representative stroke, window function to the edges to detect the representative local region; and to complete the process a back-propagation neural network to classify the local and global features. A data set of 5 Chinese artists 100 IWPs was halved for the testing and training. The designed algorithm has proven to surpass both the MHMM and C4.5 decision tree method, with the increase of artists the proposed algorithm has been observed to reduce slower compared to the two benchmarks.

Zou, Cao, Li, Huang and Wang instigated a research titled “Chronological classification of ancient paintings using appearance and shape features” [14], where they extract 5 types of features namely: the sub image, SIFT(Scale-Invariant Feature Transform) shape features, kAS (k-Adjacent-Segments) shape features, combination of SIFT and kAS, and the combination of a refined SIFT features using the deep-learning network and kAS. A data set of 660 Flying-Apsaras from Mogao Grottoes were collected, where 220 images are from the infancy period, 220 images from the creative and 220 images from the mature period. The SIFT shape features is extracted using the vlFeat3 tool and kAS shape features extracted using the k-Adjacent-Segments detector4; with the extracted features the Support Vector Machine (SVM) classifier with the RBF as a kernel using libSVM tool2 was used to train and test. It has been observed that the combination of a refined SIFT and kAS had the best results while the kAS alone had the worst; the ranking is as follows refined SIFT+kAS, SIFT + kAS, SIFT and kAS.

C. *Recent studies*

Sun, Zhang, Wang, Ren and Jin instituted a study titled “Monte Carlo Convex Hull Model for classification of traditional Chinese painting Meijun” [15], where the proposed algorithm consists of the use of k-means clustering with the use of minimum bounding box algorithm. A database of 180 paintings made of 6 traditional Chinese artists were collected, in which 80 percent has been allocated for training and the rest for evaluation. Four other approaches were tested for comparison, namely: MHMM , Convolutional Neural Networks, Multi-kernel Learning method and Spare lasso Algorithm. The results have proven that the Monte Carlo Convex Hull - SVM exceeds the benchmark approaches and displays a level of robustness.

Tabarestani, Eslami and Torkamni-Azar, conducted a research entitle “Painting Style Classification in Persian Miniatures” [16], in which Local Binary Pattern (LBP), Patterns of Oriented Edge Magnitudes (POEM) and a combination of LBP and POEM is used for classification. The data set collected is composed of 154 Traditional Negar-Gari paintings, and 164 Modern Negar-Gari paintings of artists Farshchian, Mehregan, Tajvidi, Aghamiri, Behzad and their students. With the features extracted from the data set, it is then classified using the Support Vector Machine (SVM), with 25 percent of the data set as the training size and the remaining for testing. The results show that LBP can determine traditional Negar-Gari perfectly with an overall recognition rate of 32.93 percent, the POEM however has difficulty classifying the traditional Negar-Gari with an overall recognition rate of 29.01 percent, and the combination of both, it generated a better recognition rate of 34.36 percent.

Gultepe, Conturo and Makrenhchi conducted a research titled “Predicting and grouping digitized paintings by style using unsupervised feature learning” [17], where 3 kinds of feature extraction techniques are implemented: Unsupervised feature learning with K-means (UFLK), Principal component analysis (PCA), and no feature extraction wherein raw pixels is used as features. A data set containing 8 styles, Art Nouveau, Baroque, Expressionism, Impressionism, Realism, Romanticism, Renaissance, and Post-Impressionism, with 847 paintings each. With the features extracted from the data set, it is then applied to the SVM algorithm or spectral clustering algorithm, with 80 percent for training and 20 percent for testing. This then resulted with the best classification performance from the UFLK(3000 features) with an F-mac of 0.469, following by PCA(300 components) with 0.278 and raw pixels with 0.288; UFLK(500 features) also scored the best clustering performance with F-mac of 0.212 followed by raw pixels with 0.197 and PCA(100 components) with 0.212.

Badea, Florea, Florea and Vertan has instigated a study titled “Can we teach computers to understand art? Domain adaptation for enhancing deep networks capacity to de-abstract art” [6], where they tested the performance of Convolutional Neural Networks (CNN). For comparison, state-of-the-art algorithms were also tested, namely: AlexNet by Krizhesky et al, VGG-type networks by Simonyan and Zisserman, Residual Network (ResNet), Algorithm by Gatys et al which transposes style through “representing an image where content and style are separable”, inverse mapping of a deep CNN by which was learned by Ulyanov et al and Johnson et al, and lastly Laplacian filters with preset weights. A dataset of 63 000 images consisting of 10 classes: Abstract, Cityscape, Genre, Illustration, Landscape, Nude, Portrait, Religious, Sketch, Study and Still Life. Results indicate that efficiency is superior regarding older styles (beginning till Post-Impressionism), acceptable with modern style (Minimalism, Abstract, Color field painting), while inferior regarding more abstract styles (Surrealism, Naive art, Cubism, Pop art). This depicts that CNN has difficulty understanding artworks with higher abstractions.

In the study “Can we teach computers to understand art? Domain adaptations for enhancing deep networks capacity to de-abstract art” the algorithm proposed by Ulyanov, Lebedev, Vedaldi and Lempitsky, [18] was mentioned, this is further discussed in their paper titled “Texture Networks:

Feed-forward Synthesis of Textures and Stylized Images". The purpose of their paper was to be able to come up with an algorithm that would be lightweight and would surpass the speed of previous methods. This was done by focusing the burden of computing to the learning process; their approach consisted of training "feed-forward convolutional networks" to produce numerous samples, and to "transfer artist style" to different images.

As seen in the paper of both Badea et al and Ulyanov et al, they have used approaches that involved convolutional neural networks (CNN). Layers are used in CNN to extract features, which enables it to obtain high performance on style classification. Effectiveness of this approach has been proven in the classification of: style as shown in Bar, Levy and Wolf's paper, artist in David and Netanyahu, genre in Cetinic and Grgic and even object recognition in paintings in Crowley and Zisserman [3].

III. Materials and Methods

1) Data sets: The data set will be acquired from the painting collection available in the National Museum of Fine Arts and Bencab Museum. Four Filipino artists will be considered for this study, namely: Juan Luna, Fernando Amorsolo, Carlos Francisco and Benedicto Cabrera.

Each artist will have a data set of 20 images each, excluding the augmented data sets.The images will be represented through 9 overlapping square rationed segments which will be scaled down to a 250 x 250 pixel image.

A total of 100 paintings from artists out of the scope of study will also be considered for testing, these, however, will not undergo augmentation. Each painting was taken using the camera of the mobile phone Samsung Note 8. The specification of the camera used is shown in Table I.

Model Name	Samsung Note 8
Resolution	12 Megapixels
Sensor Size	1/2.55 type (26 mm)
Pixel Size	1.4m

Table I: Camera specifications to be used for image gathering.

2) Image Augmentation: As part of our data set, the image will be cropped into a square ratio, which we will be used for augmentation using OpenCV v3.0 with Python v3.6; it will be rotated 90 degrees (counter and clockwise), sheered , flipped horizontally and vertically.

3) Neural Network training: The data set, including the augmented images, will be used for the transfer learning process for Inception-v3, the architecture illustrated in Figure 3. A sample of the training images is seen in Figure 4, these are the overlapping cropped outputs from the painting "Banana Vendor" by Benedicto Cabrera; it was cropped into 1:1 square ratio and re-sized into 250x250 pixel image. The training process will generate a Tensorflow model that will be loaded into the mobile application.

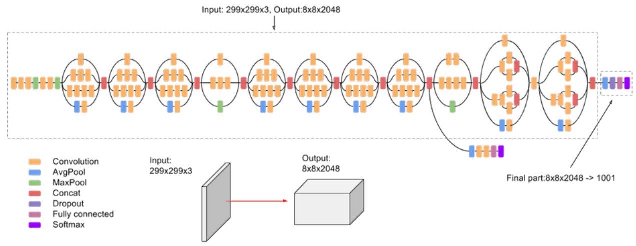

Fig 3: Inception-v3 architecture

Fig 4: Sample training images for Inception-v3

4) Mobile Application: A mobile application will be developed to utilize the smart phone's working camera that will interact with the Tensorflow model created during image training. The application will be created using the Android Mobile Development. The application has two ways to acquire the testing image.

- The application will utilize the phone's camera, which will capture an image of the painting through a square ratio camera view, as illustrated in Figure 5, painting should be taken within the square view.
- Users may choose an image stored in their device, image chosen will be cropped into a square ratio-ed image.

Fig 5: Phone's camera with a square view

The input image chosen/captured will undergo classification via interaction with the Tensorflow model. The results will return the percentages of classification by displaying the percentage of each artist detected in the image, shown in Figure 6, and link the wikipedia page on the artist with the highest percentage.

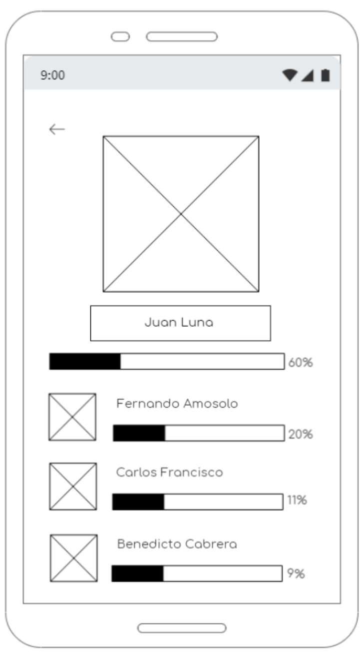

Fig 6: Sample results of the classification.

IV. RESULTS AND DISCUSSION

SINING has been developed following four main procedures.

1) Data sets: In order to prepare the data set for neural network training, the images from the museums (Bencab museum and National Museum of Fine Art) had to prepared. Photos of the paintings of Amorsolo, Luna, Cabrera and Francisco was taken, but not in the order of the artists themselves. The photos were taken in the order they were shown in the museum — which were not necessarily by the artists. Before the photos could be augmented and prepared, it first had to undergo through sorting by artists.

Once sorted, a function had to be made to detect the frames of the painting and crop out the wall behind it, if it was seen in the photo. After this script was done, the developer realized that some paintings had very large paddings between the painting and the frames, so the large paddings also had to be cropped. The reason for this is because the padding was not the choice of the painter but rather the choice of the museum, and it had no contribution to the art style of the artist. Each painting was then cropped into a square ratio.

2) Image Augmentation: Once sorted and cropped, it then undergo through augmentation, which would help with the accuracy of the trained model. Six augmentations were use on the data set, namely: rotate 180 degrees, clockwise and counterclockwise, horizontal and vertical flip and skew; a sample of each is shown in Figure 7.

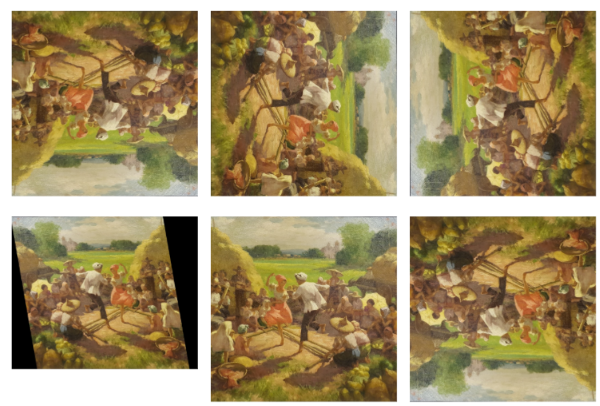

Fig 7: Sample augmentations; rotate 180 degrees, rotate clockwise, rotate counterclockwise, skew, horizontal flip, and vertical flip (left to right, top to bottom)

After each image has been augmented, they are now cropped into 9 overlapping segments. These were all done in python functions, where it would save each segment in the folder hierarchy shown in Figure 8; given this, a shell script had to be made to move each segment of each artist into their own folder segment as seen in Figure 9.

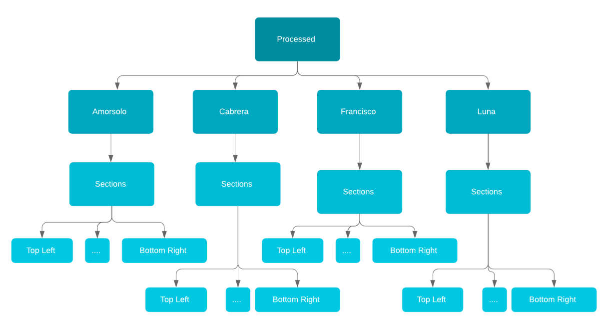

Fig 6: Python module folder hierarchy

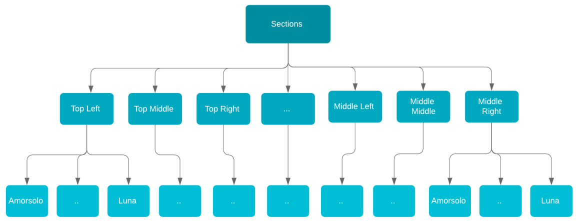

Fig 7: Shell script folder hierarchy

3) Neural Network training: The paintings have been prepped and augmented, but this results to only 140 paintings per artist as training data, which is too limited to be able to represent the artist thoroughly. With this, the data set had to undergo 5-fold cross validation, to ensure the training set would cover the art style properly in the model.

For the cross validation, 20 percent of the data set would be chosen for testing and the rest for training. Each segment would have five classifying groups, with different training and testing data sets; example of training photos illustrated in Figure 10. Do note that there are 20 paintings, with 7 augmentation each painting, segmented into 9 parts placed in 5 groups (for cross validation), this makes it 25,200 images each artist — making it a total of 100,800 images. All in all it would be around 6GB.

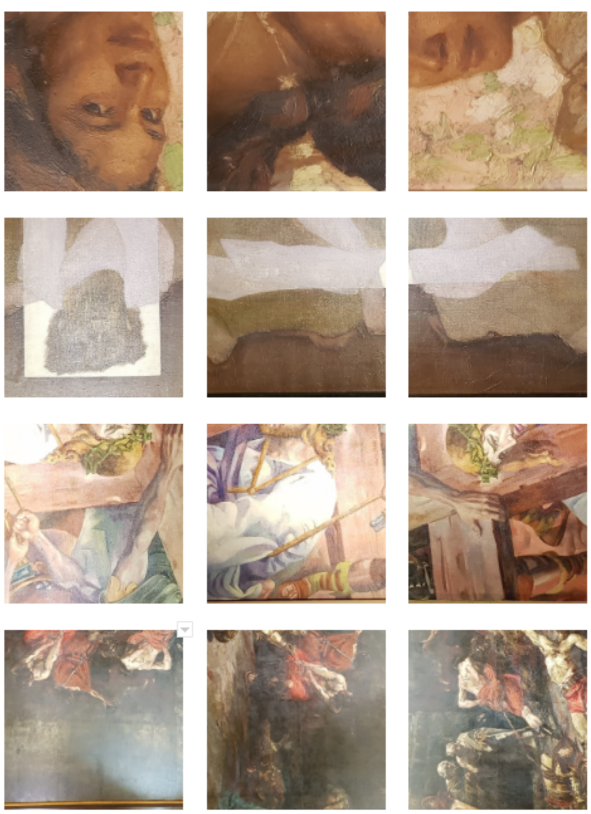

Fig 10: Sample training photos: Amorsolo, Cabrera, Francisco and Luna (top to bottom)

Once the dataset has been separated into classifying groups, a shell script was made to go through each segment and train each class set, which totalled to 45 neural networks. Each time the train module was called, it had to have access to the root and would take around 30-40 minutes each. This took me at least 3 days to completely train all — this counting during night hours and between classes. With the trained models, it was then tested with the remaining 20 percent, these were tested with a python module and the artist with the highest classification rate were saved in a text file. The overall classification rate per group in each segment is illustrated in Table I; with this, the highest rate would be chosen narrowing it down to 9 neural networks, these will be used for mobile application.

Section	1	2	3	4	5
TL	0.76	0.86	0.79	0.84	0.83
TM	0.77	0.80	0.77	0.80	0.84
TR	0.73	0.80	0.79	0.85	0.80
ML	0.77	0.87	0.76	0.83	0.82
MM	0.86	0.86	0.75	0.83	0.78
MR	0.75	0.87	0.86	0.81	0.75
BL	0.79	0.91	0.75	0.80	0.78
BM	0.81	0.91	0.79	0.81	0.80
BR	0.74	0.90	0.77	0.83	0.83

Table II: Cross Validation classification rates of each group

4) Mobile Application: Early on the development of the mobile app, Expo CLI was used; it is a command-line interface to assist the developer with developing applications in React Native. It was a set of tools that was wrapped around the application, that would help with building it and accessing the device's capabilities.

Expo, however, did not function as expected; it was seen to take long to load and lagged quite a bit with updating the codebase — sometimes it would not load at all. Some react-native packages also had a problem with expo and would give out an error or would not work as intended — example of which is react-native-camera; do note that as of 2019 there is no official react-native camera, so their incompatibility proved to be a functionalities. Most importantly, native modules cannot be added in Expo, which is a problem given that later on the classifier (which is written in native code) had to be added.

By the time these issues had arised, the interface for the home screen and output screen had already been developed, as illustrated in Figure 11. So these interfaces had gone through some changes once it had been decided redevelop the application in another CLI instead.

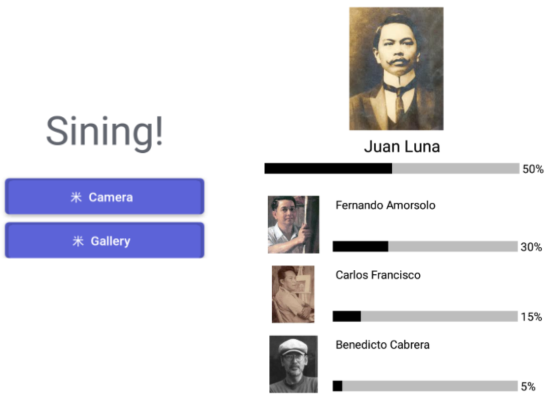

Fig 11: Initial home screen (left) and output screen (right)

From Expo, the whole codebase for the application had to be completely restarted in React Native CLI.

With React Native, it was more reactive on building and updating the code on the application. The react-native-camera module worked instantly and was able to use another package to access the camera roll of the device. Home screen and output screen was modified and a Splash screen was added, these are illustrated in Figure 12. The output screen presents the top Artist and the name of the artist redirects the user to their wiki webpage.

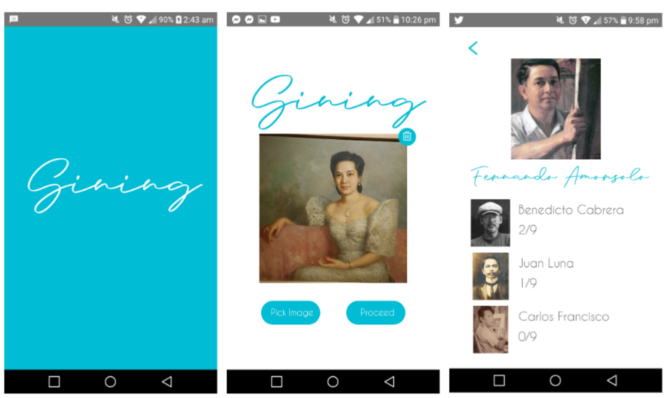

Fig 11: Splash, Home and Output screen (left to right)

With the interfaces done, the model now had to be integrated with the application. Do note that the testing code used for cross validation was written in python, however mobile applications cannot run the python code, without any additional python tools — native code had to be written instead. Compared to the usual react-native code, native code needed to be rebuilt every time the code was modified, which made the development time longer.

Now two main native code functionalities were needed — image divider and classifier. The image divider divides the chosen image, through camera roll or camera, into nine and inputs each portion into the corresponding model (bottom left into the bottom left model). The divider had no problem but developing the classifier module took quite some time. this is because one module is worth 80 mb, which made the build time 3-5 minutes long — around 3x more than the usual build time. Once the classified module works on one model, it should also work on nine — this is where the build time spikes, from 3-5 minutes to 20-25 minutes; this is due to the size of the whole application itself which is 773 mb. Aside from this, testing out one image would take five seconds, thus nine would take around one minute.

5) Testing: The models were then tested with their corresponding artists and also artists out of the scope of the study, to further understand how the model works and what it identifies. Five paintings (out of the training set) per artist were tested, in which the results are illustrated in Figure 12. It had been seen that despite Francisco's impressive classification rate in Cross Validation — ranging from 0.83 to 1.0 — it was actually Cabrera who was able to get the highest classification rate. Upon further observation, the chosen testing set happened to represent Cabrera's style more fittingly — which were "rhythmic brush strokes, flowing lines and spirited body movements" [19]. Aside from this, his choice of subject was prominent as well in the testing data, which largely depicted women in swirling bundled fabrics [20] and traditional filipiniana dresses.

Artist	Total Classification rate
Amorsolo	0.6
Cabrera	1
Francisco	0.8
Luna	0.8

Table III: Overall Prediction rate of each painting. Images of paintings tested are shown in the Appendix

In addition to this, another five paintings from different artists were tested out, results as seen in Table IV. Aside from Cabrera's brushstrokes and subject choice, his painting style was also more abstract than the rest of the artist in the scope. This dates all the way back to his years in UP College of Fine arts where he took inspiration from his professor Jose Joya, who was a leading abstract artist at that time [21], thus the reason why Co's painting was labelled under Cabrera, painting seen in Figure 13. Zosimo's Rural Scene, illustrated in Figure 14, was classified as Luna and much like most of Luna's painting, it was full of vigorous brushstrokes, nervous jagged lines and an interplay of light and shadow [22]; aside from this it is also a landscape painting — one of which Luna had an abundance of. Amorsolo, much like Hidalgo, went to Madrid to study Fine Arts, in which both have received similar classical training [23] — hence why Hidalgo's El Asesinato del Gobernador, seen in Figure 15, was classified under Amorsolo. Hieronymus Bosch by Froilan Calayag (seen in Figure 16) , classified under Francisco, was well rendered with smooth gradients and packed with elements throughout the painting, much like most of Francisco's paintings. Lastly, Salvador Cabrera's Artist's Mother, illustrated in Figure 17 was labeled Amorsolo, due to the subject of the painting which was a portrait of a single person in front of a dark background, in which was a prominent subject in his training data set.

Paintings	Predicted artist	Prediction rate
Almost Mad by Charlie Co	Cabrera	0.55
Rural Scene (Bahay Kubo) by Zosimo Flores	Luna	0.66
El Asesinato Del Gobernador Bustamante by Felix Hidalgo	Amorsolo	0.77
After Hieronymus Bosch by Froilan Calayag	Francisco	0.7
Artist's Mother by Salvador Cabrera	Amorsolo	0.55

Table IV: Prediction rates of Filipino paintings from artists out of the scope of study.

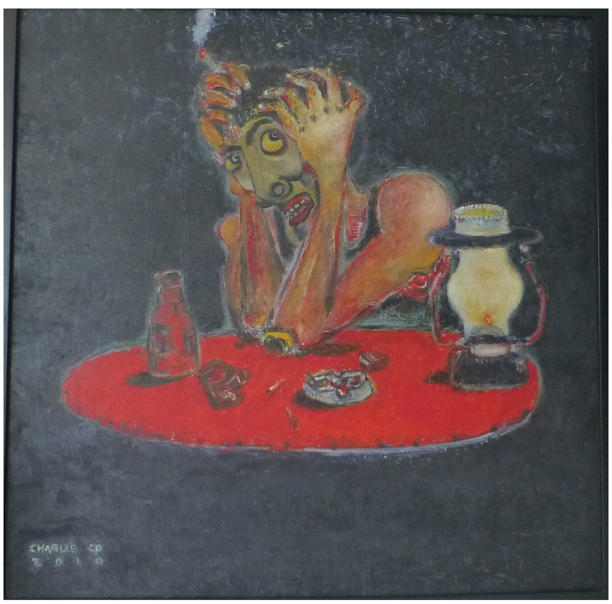

Fig 13:Almost Mad by Charlie Co

Fig 14: Rural Scene (Bahay Kubo) by Zosimo Flores

Fig 15:El Asesinato Del Gobernador Bustamante by Felix Hidalgo

Fig 16:After Hieronymus Bosch by Froilan Calayag

Fig 17:Artist's Mother by Salvador Cabrera

6) Summary: Twenty images per artist were collected from the National Museum of Fine Arts and the Bencab Museum. It was then skewed, rotated (180 degrees, counter and counterclockwise) and flipped (horizontal and vertical); the augmented images were then split into nine sections. With that, a 5-fold cross validation took place — which involved separating the training set into five classifying groups per segment, as well as training and testing each. After the testing phase, the nine models with the highest classifying rate per group was integrated into the React-native mobile application; the models had an overall recognition rate of 0.879. The app was then tested with 20 paintings — one of each artist — and 5 paintings from artists out of the scope of study; this resulted to an overall 0.8 recognition rate.

V. RECOMMENDATIONS

The prediction rate of the overall classification is generally high, but it takes at least a minute each to classify a painting. A possible solution to this is to settle with only one trained neural network for the one whole image, since it takes five seconds to classify each segment.
For future work, instead of segmenting the image, they could feed one whole image to the nine models to see if it would still give out the same or better results. Another variation to that is the segmented nine parts classified into one model instead. Lastly, focusing on the expansion of artists variations would help make the model and application more comprehensive; by doing this it could help understand what are the usual styles and subjects of the filipino artists.

VI. APPENDIX

Fig 18:Portrait of Frank Murphy (1890-1949) as Governor General by Fernando Amorsolo

Fig 19:Portrait of Jose . Laurel, Jr (1912-1998) as Speaker by Fernando Amorsolo

Fig 20:Portrait of Julieta Abad Rufino by Fernando Amorsolo

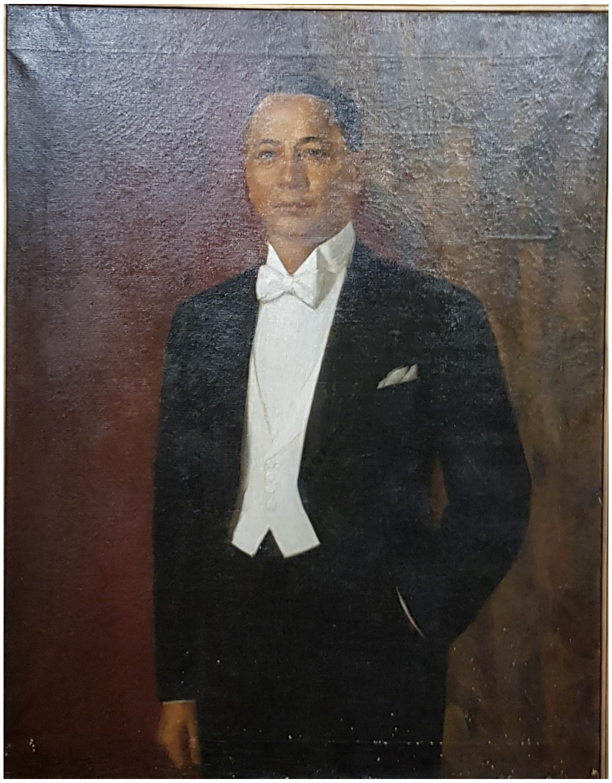

Fig 21:Portrait of Manuel Roxas (1892-1948) as President by Fernando Amorsolo

Fig 22:The Palay maiden by Fernando Amorsolo

Fig 23:TresMarias by Benedicto Cabrera

Fig 24: When The Walls Came Down by Benedicto Cabrera

Fig 25: Woman in Distress by Benedicto Cabrera

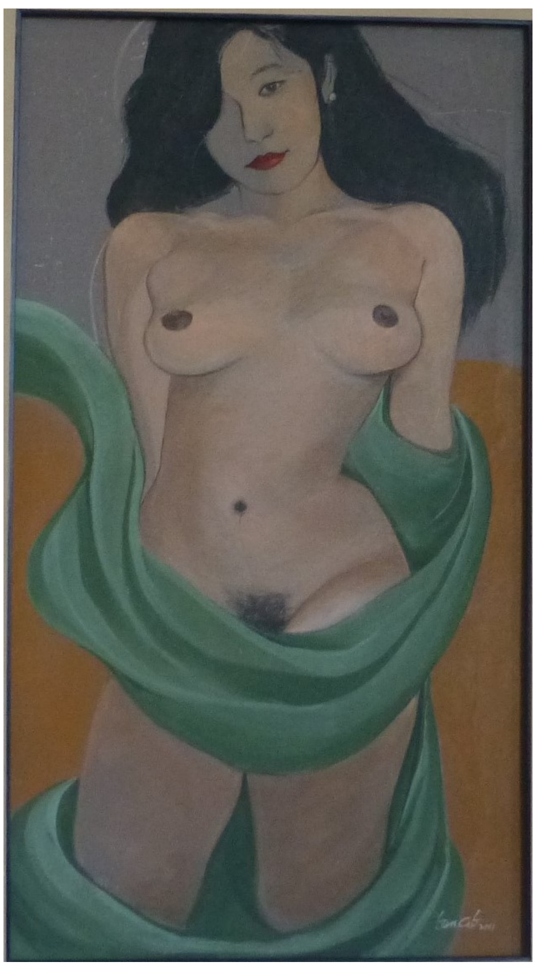

Fig 26: Woman in Green by Benedicto Cabrera

Fig 27: Woman with Fan by Benedicto Cabrera

Fig 28: Jesus Falls for the first time by Carlos Francisco

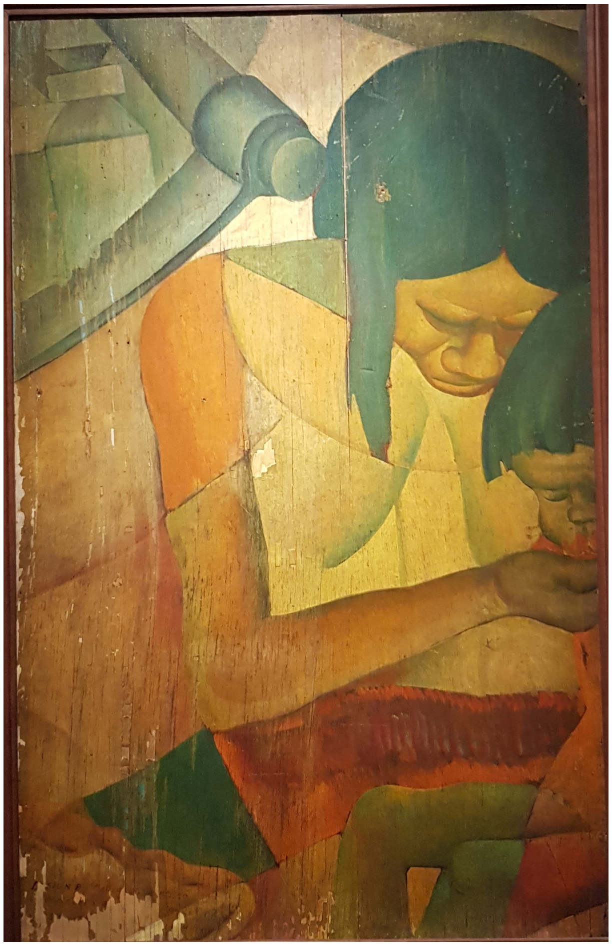

Fig 29: Fragment from the mural 500 years of Philippine History by Carlos Francisco

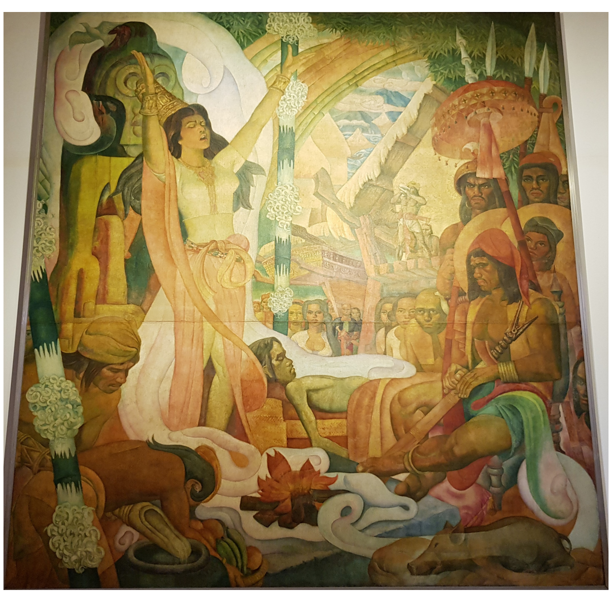

Fig 30: Pag-unlad ng panggagamot sa Pilipinas by Carlos Francisco

Fig 31: Simon of Cyrene Helps Jesus Carry the Cross by Carlos Francisco

Fig 32: The first mass in Limasawa by Carlos Francisco

Fig 33: Family Portraits of Domestic Scenes in Paris by Juan Luna

Fig 34: Japan Scenes by Juan Luna

Fig 35: Japan Scenes by Juan Luna

Fig 36: My Brother in Our Cell in Fort Santiago by Juan Luna

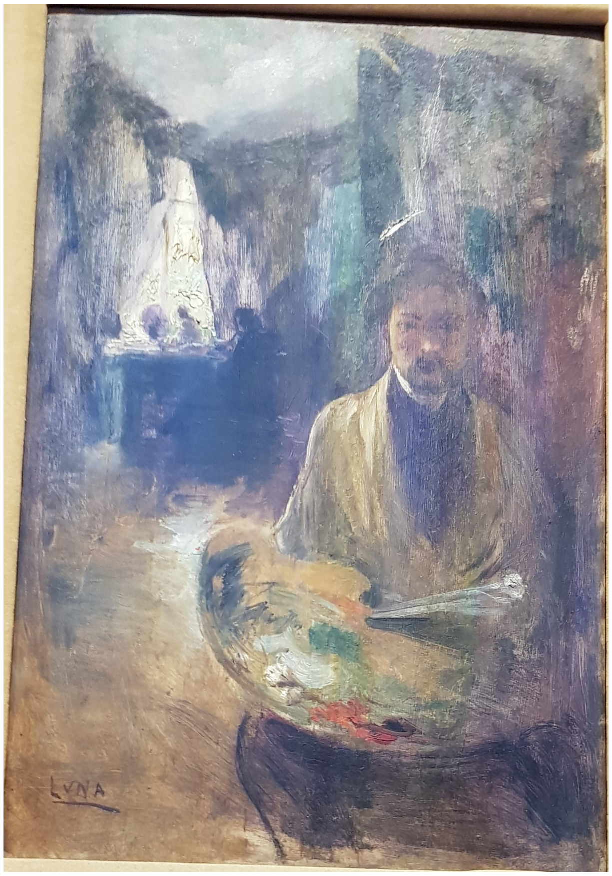

Fig 37: Self Portrait by Juan Luna

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