

Design and Implementation of a Real-Time Machine Embroidery Classification System

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ABSTRACT

Embroidery is the craft of decorating fabric or other materials using a needle to apply thread or yarn. Embroidery may also contain other materials such as beads, pearls, sequins and quills. The possibility of using mobile app to identify types of embroidery is an outstanding idea that will become an important tool among the wearers of the African native dress to be able to identify the type of embroidery they are interested in sewing. This study aims to collect different sample of machine embroidery, design a model for recognizing the collected embroidery sample, implement and evaluate the performance of the model designed. Samples of different machine embroidery were collected from various embroiderers within Osogbo, Southwestern Nigeria. The collected samples were examined using distinguishing characteristics (thickness, colors, brightness and shape), augmented and later preprocessed. The model was implemented using a convolution neural network in a python environment. A mobile-based embroidery classification system was developed and the performance of the system was evaluated with accuracy of 84.91% using real-time testing with the android app interface. The developed system was able to recognize the 20U and Tinko machine embroidery, which serves as a help to the African native dress lovers or wearers. The system can be deployed to embroiderers to eliminate any element of doubt on any kind of embroider made on customer's fabric.

1. INTRODUCTION

Machine embroidery is an art of using a sewing machine to create patterns on fabrics (Griffrey, 2014). It is used commercially in product branding, corporate advertising and uniform adornment. It is employed in the fashion industry to make designs on garments and clothings (Kuo and Juang, 2016). Machine embroidery is used by hobbyists and crafters to decorate gifts, clothing and home decor. Examples include designs on quilts, pillows and wall hangings. There are about three types of machine embroidery patterns commonly used in Nigeria, which include Tinko, 20U and Coil. In this study, 20U and Tinko embroidery patterns were considered for classification process. Machine embroidery recognition as subjected to this research work is solely based on the aspect of embroidery as an art of creating designs on African attires or cloths. The recognition and classification of the embroidery patterns are essential due to the problem faced while differentiating various kinds of embroidery patterns on clothes. This problem leads to gradual fading of the embroidery pattern, hence the development of this study to save the dying art. The need to provide a real-time solution to this problem emerges in the context of the availability of mobile devices.

The field of pattern recognition is concerned with the automatic discovery of regularities in data through the use of computer algorithms and to take actions such as grouping the data into different classes (Bishop, 2016). The patterns of machine designs are additionally sporadic and conflicting because of the manual strategy and inventiveness associated with its creation (Xin and Wang, 2019). Machine embroidery involves the use of an embroidery machine to make a design on a piece of fabric or cloth, a process that is not as labour intensive as hand embroidery, and requires less time. The other division of machine embroidery is the computerized or digital embroidery in which embroidery patterns are created using advanced digital technology (Yang *et al.*, 2014). The computer and the digitizing software do most of the work in perfecting the design and embroidery especially for mass production basis; it is usually done in textile mills. With this type of machine embroidery technique, there is less effort given and no time wasted at all.

Image pattern recognition is the problem of prospecting how to recognize image patterns which is part of the problems people who loves embroidery designs face (Koontz *et al.*, 1975). However, an image pattern recognition system as subject to this study generally consists of the use of camera that acquires the machine embroidery pattern samples to be recognized, a feature extraction process to obtain distinguishing features from images for recognition, and a classification method that classifies the image based on the extracted features. Jimoh *et al.* (2019) worked on automatic detection of edges in handmade embroidery patterns. A novel cellular edge detection algorithm for handmade embroidery patterns was developed. It was observed that popular edge detection approaches (i.e., Canny, Prewitt, Robert, and Sobel) use multiple stages to detect the image edges, and also, they are applied to regular and consistent structured patterns. However, in nature, African indigenous handmade embroidery patterns are irregular with many complexities. Therefore, the study proposed a computational model to solve the problem and deployed Cellular Automata (CA) combined with Cellular Learning Automata (CLA).

Loke *et al.* (2016) developed an automatic recognition of patterns and motifs on clothes. This research proposed a fast and accurate method of recognizing clothes textile design and pattern. A modified 6-channel co-occurrence matrix was used with a random forest classifier. The accuracy was tested by recognizing the clothing of fashion models and obtained results of 93%. Thogaricheti and Anuradha (2016) developed an assistive clothing pattern recognition for impaired people. This study was based on human-computer interaction (HCI) and use of computer technology, focusing particularly on the interfaces between people (users) and computers (Klinger and Dyer, 1976). The ability of visually impaired people to choosing clothes with complex patterns and colors is a great challenge. A matured camera-based model system that noticed clothing patterns in four categories (plaid, striped, pattern less, vertical and irregular) with identification of 11 clothing colors were used to recognize the patterns. The study adopted an offline transformation method and Canny edge detection for the recognition of the pattern.

Setti and Wanto (2019) worked on the analysis of the error backpropagation algorithm, this study proposed an innovative training criterion of depth neural network for maximum interval classification error. Also, the cross-entropy and M3 CE were analyzed and combined to obtain better results. The experimental results showed that M3 CE can enhance cross-entropy and good results in both databases. Schindler *et al.* (2017) worked on apparel and fashion classification using convolutional neural networks. This study presented an empirical review of applying deep Convolutional Neural Networks (CNN) to provide fashion and apparel image classification to improve meta-data enrichment of e-commerce applications. Five different CNN architectures were analyzed using clean and pre-trained models. In another work, classification of embroidered textile defects in manufacturing were considered (Kuo and Juang, 2015). A 3-D pattern was created by variable stitches and the material characteristics of embroidery thread. The embroidered textile was classified after quality control.

Loke (2018) developed a texture recognition using a novel input layer of deep convolutional neural network. A layer was presented to the CNN model as input to acquire pixel feature such as differences Jimoh *et al.*: Design and Implementation of a Real-Time Machine Embroidery Classification System

between surrounding pixels and center pixels. The work only examines the pixel properties for the texture recognition. Jimoh *et al.* (2020) developed a novel database for handmade embroidery pattern recognition and classified the two types of the handmade embroidery pattern. The study employed cellular automata as feature extraction techniques and support vector machine (SVM) for classification process. For the two classes considered, the grayscale image showed a better result.

Anuradha and Ashwini (2016) developed a clothing color and pattern recognition for impaired people. The study addressed choosing clothes with complex patterns and colors, which is a challenging task for visually impaired people. A camera-based application was developed, that automatically recognizes clothing patterns and basic colors where the result is given to the user through voice and text message. In a related work of Hussain *et al.* (2020), a woven fabric was classified using data augmentation and deep learning. The model developed used residual network (ResNet) with extraction of fabric woven features and automatic classification of the pattern.

It could be seen from the reviewed literature that little work has been done on mobile-based embroidery pattern classification. However, this study considered the availability of mobile devices and develop a real time classification system for embroidery pattern.

2. METHODOLOGY

Figure 1 shows the system design for the system developed, the stages involved are data collection, data augmentation, data preprocessing, model training, model validation, model testing, and prediction of machine embroidery using the generated model. The model was generated using Python scripts. The flowchart of the developed model for the mobile Application was shown in Figure 2. The captured embroidery images were loaded into the system and later preprocessed to prepare the images for training, validation and testing.

Data Acquisition

The machine embroidery images (Tinko and 20U) were collected from a fashion designer in Osogbo, Osun State, Nigeria. The images were captured from various positions, angles and with different backgrounds and lighting conditions. The dataset consists of 124 images of 2 types of machine embroidery as shown in Figures 3 and 4. Because of the image size, the captured images were augmented to produce more images as CNN uses lots of data.

Data Augmentation

Data augmentation help to generate new samples of dataset to augment the existing dataset by transforming the existing samples. Since CNN requires lots of data, augmentation is done on the captured images to produce more data. The augmentation techniques used are translations, rotations, cropping, flipping and scaling. The data augmentation produces additional 600 images from the captured images giving a total of 724 images.

Image Preprocessing

The preprocessing stage prepares the image for pooling and convolution. The preprocessing techniques employed are grayscale conversion and image resize. The grayscale conversion converts the RGB image to grayscale and the grayscale image was later resized to 200×200 Pixels. The preprocessed image was later fed into the CNN for training and validation.

Training, Model Generation and Testing

The training was done using Python. A total of 508 images was used to train the developed model, 72 was used for validation and 144 was used to test the model on the mobile phone. The trained model was saved,

converted into TFlite and then loaded into the mobile app code. Training helps to identify the pattern of the data. The training consists of 4 convolution layers and 4 pooling layers. The maximum pooling method was used. The training was done with a batch size of 16, input size of 200×200 , 50 epochs, validation steps of 4 and steps per epoch of 8. The rmsprop optimizer was used and the ReLU and sigmoid activation function were used. A validation accuracy of 84.91% was achieved. The performance is also evaluated in terms of specificity and sensitivity as shown in equations (1) and (2) respectively.

$$Sensitivity = \frac{TP}{TP + FN} \times 100 \quad (1)$$

$$Specificity = \frac{TN}{FP + TN} \times 100 \quad (2)$$

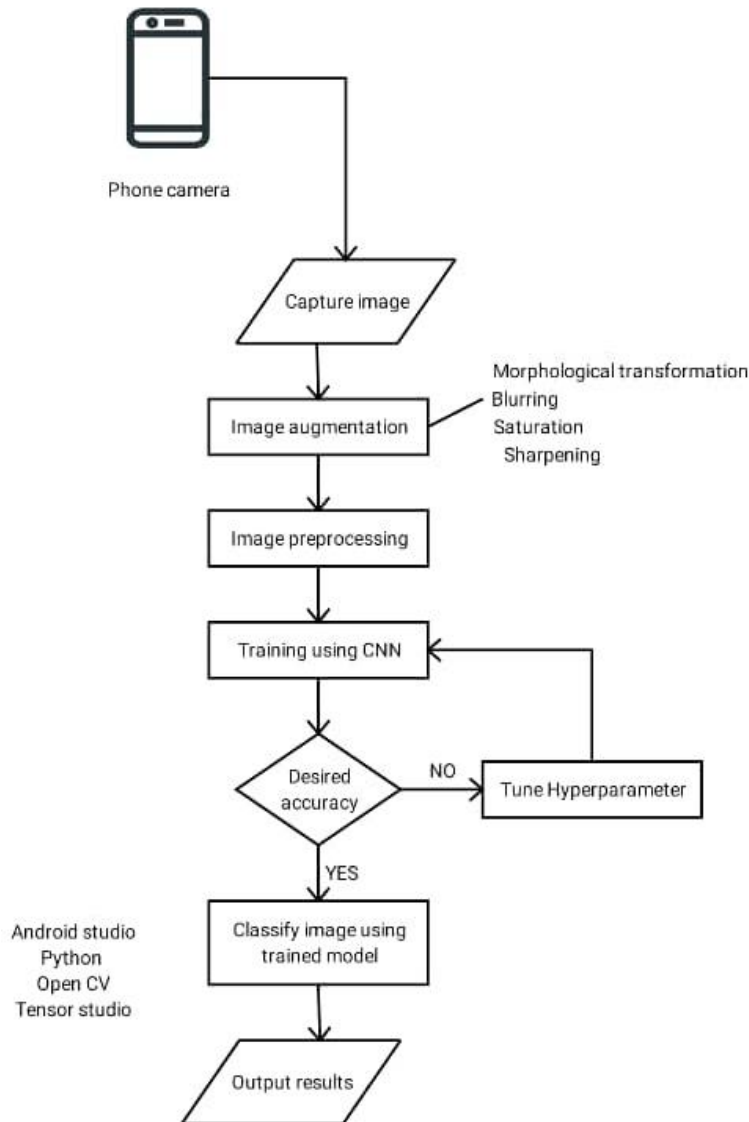


Figure 1: System Design

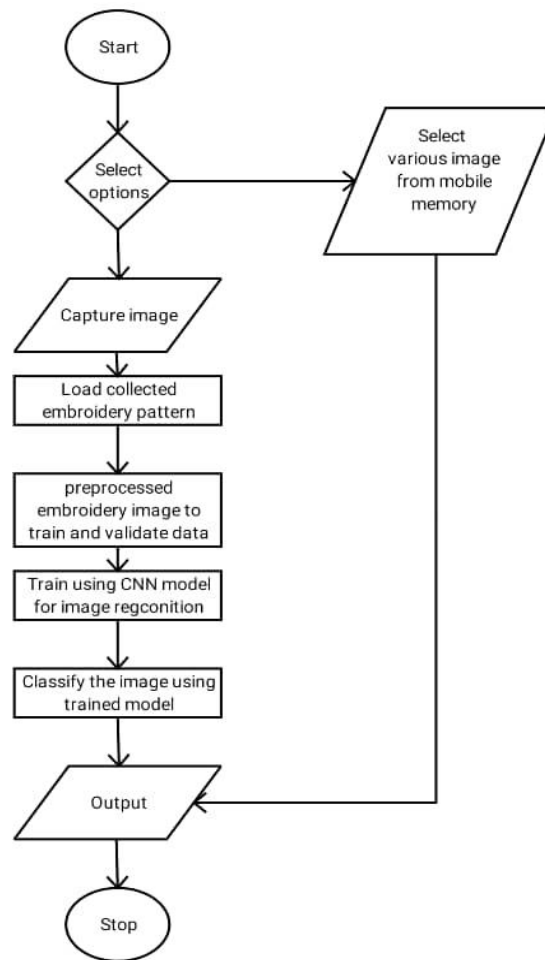


Figure 2: Flowchart of the System



Figure 3: Samples of Collected 20U Embroidery Images



Figure 4: Samples of Collected Tinko Embroidery Pattern

3. RESULTS AND DISCUSSION

The graph of the training showing the validation model accuracy at 50 epochs is shown in Figure 5. The graph shows the training accuracy and validation accuracy at each epoch up to the chosen 50 epochs. It was observed that the validation accuracy reached highest point at 88.68% with epoch 43, while it reached its lowest point at epoch 4 with a value of 49.06%. Also, the number of True Positives (TP), True Negative (TN), False Positive (FP), and False Negative (FN) are 67, 64, 8, and 5 respectively, given an accuracy of 90.97%. TP is 20u classified as 20u, TN is Tinko classified as Tinko, FP is Tinko classified as 20u, and FN is 20u classified as Tinko. With 67 of 20u images correctly classified as 20u images and 64 Tinko images correctly classified as Tinko image. However, only eight Tinko images were incorrectly classified as 20u and five 20u images were also incorrectly classified as Tinko images. The model shows a sensitivity and specificity of 93.06% and 88.89% respectively. The output of the model on the mobile phone is shown in Figure 6.

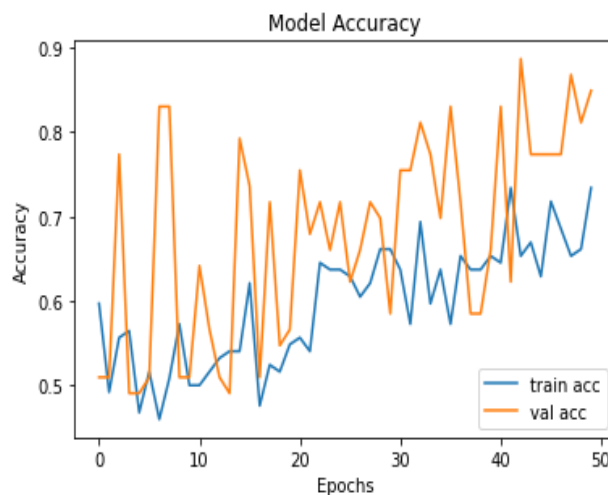


Figure 5: Plots of Accuracy vs. Epoch

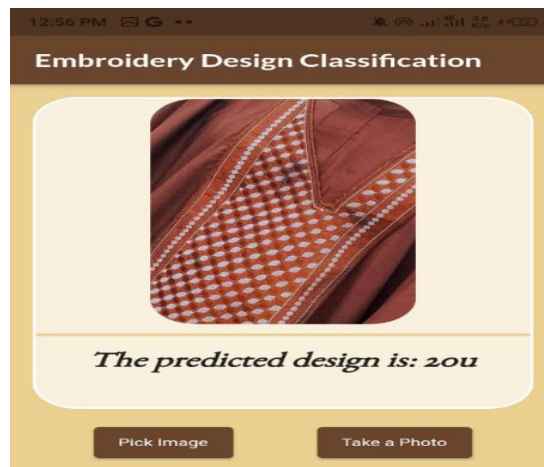


Figure 6: 20U Machine Embroidery Output

4. CONCLUSIONS

An android application for the recognition of machine embroidery was developed using TensorFlow model in Python. The images collected were preprocessed, and augmented to improve the accuracy of the performance of the model, the model prediction carried out using the test image has a validation accuracy of 84.91% confidence and a testing accuracy of 90.97%. The obtained result successfully classified different types of machine-made embroidery pattern.

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