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HANDMADE EMBROIDERY PATTERN RECOGNITION: A NEW VALIDATED DATABASE

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ABSTRACT

Patterns of handmade embroidery are an important part of the culture of a number of African people, particularly in Nigeria. The need to digitally document these patterns emerges in the context of its low patronage despite its quality and richness. The development of a database will assist in resuscitating the dying art of Handmade Embroidery Patterns (HEP). The patterns of handmade embroidery are also irregular and inconsistent due to the manual method, and creativity involved in its production. Developing an automatic recognition of HEP will therefore create a system where machine embroidery can be made, or automated to mimic the creativity and peculiar intricacies of traditional handmade embroidery patterns. This study developed handmade embroidery pattern database (HEPD) that can be used for many processes in the field of pattern recognition and computer vision applications. Samples of handmade embroidery patterns were collected from three different cities in South-Western, Nigeria. Pre-processing operations such as image enhancement, image noise reduction, and morphology were performed on the collected samples using image-processing toolbox in MATLAB. This work developed a validated new dataset of handmade embroidery patterns containing two categories of embroidery patterns with a total number of 315 images in the database. It evaluated the database for recognition process using cellular automata as feature extraction technique and support vector machine as its classifier. The performance metrics employed are sensitivity, specificity and accuracy. For the two classes of images considered, 72% sensitivity, specificity of 93% and accuracy of 80% were obtained for grayscale image. For the binary image, an accuracy of 72% with sensitivity of 82% and 65% specificity were obtained. The result obtained showed that the grayscale image exhibits an efficient accuracy than binary image.

Keywords: *Database, Yoruba, Handmade Embroidery Patterns, Image Processing, Pattern Recognition, Traditional*

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1. Introduction

This work is part of a larger study with the aim to develop an automatic recognition system for handmade embroidery patterns on traditional African clothes. This is with the view to improving the growing trend of handmade embroidery as compared to machine embroidery. As a first task in the work, a digital database of images of embroidery patterns was created.

Handmade embroidery on dresses is an art that is popularly practiced in many African countries. The need to digitally document the embroidery emerges from the need to preserve images of the design. However, handmade embroidery provides an artistic and personal signature on creative works making its presentation practical documentation of cultural heritage. The understanding and awareness of the African art are fading in people's memory especially in Nigeria. This disappearance has led to the gradual vanishing of the African art forms faster than they are being documented (Forni & Steiner, 2018). There is constant advocacy for revisiting and revitalizing the traditional craft practices in Nigeria. In the 21st century, less attention is paid to craft development and specializations, and almost none to embroidery pattern aside from its use on apparels. The rapid diminishing of the artistic mode and forms calls for an urgent attention in order to prevent future loss of these valuable arts.

There are various types of African art traditions each aimed at exploring adequate volume of different branches of learning; anthropology, history, folklore, archaeology, and ethnology. These arts vary from smelting, blacksmithing, woodcarving, calabash carving, leather working, basketry, weaving, embroidery, pottery to cloth dyeing and so on. All of these crafts generate patterns of various kind. Among the Yoruba (largely in South Western Nigeria where data was collected) Apprenticeship training system is the most common and preferred method of training trade's secret in Yoruba visual and verbal arts. Oral traditions are another channel that Yoruba race has employed in keeping their beliefs, trade, culture, history etc. (Umoru-Oke, 2017:30). However, most arts and crafts are family-based and gender-based specialization, including embroidery which is acquired through a non-family-based apprenticeship system (Adebisi & Akinsooto, 2016). This implies that embroidery, which attracts non-family apprentices, is prone to disappearance. As such, there is a need to salvage the art of embroidery through techniques such as data banks for which documented images can be obtained. Moreover, the development of the recognition algorithm for the embroidery pattern require an urgent attention to preserve the pattern (Lee & Ji, 2016). To achieve this, an efficient feature extraction technique to extract the distinguishing characteristic such as thickness, shape, texture and brightness of the pattern is required. Far less attention has been paid to automatic image recognition and classification of embroidery patterns (Jimoh *et al.*, 2019).

The analysis of repeat size and weave type identification of fabrics were considered in the work of Zheng (2014). The work employed Harris detector to extract region of interest and clustered the interest points by image patch appearance. Makov Random Field model was adopted for the classification process. The color and region separation of an embroidery type were focus of the work. The classification of stitches in machine embroidery as well as the problem of inconsistency in machine computer embroidery were analyzed (Rupka *et al.*, 2014). The work of Sarrafzadeh *et al.*, (2016) developed Human Epithelial cells type 2 (HEp-2) patterns database and evaluated it for automatic classification process. Various classification methods have been employed ranging from Support Vector Machine (SVM), K-nearest Neighbour (Moeskops *et al.*, 2015), Deep neural network and random forest (Wang, 2015) for the automatic recognition of images.

In the work of Ferraro *et al.,* (2015) various datasets were reviewed for vision and language; and identified similarities and differences among the datasets considered with the view to overcoming the challenges of complex languages and abstract concept used by most of the existing datasets. The work did not include building a database but made recommendations as regards quality metrics for evaluating and the requirements for developing datasets. Mimicry and negotiation behavior were investigated in Bilakhia *et al.*, (2015). The database developed in Ponomarenko *et al.,* (2015) was with the aim to enhancing information processing that requires stimulus set with distinguishing feature sets.

The Arabic Handwritten character database in (Alkhateeb, 2105) was validated for recognition process. The work collected seven thousand text images from hundred writers which is a bit different from other databases. The work of Sarrafzadeh *et al.,* (2016) developed a system for the recognition of Human Epithelial cells pattern. The author used an open dataset obtained from MRBrainS13 database and evaluated using various machine learning techniques. This study, therefore, developed handmade embroidery database for the automatic recognition of handmade embroidery patterns.

Other aspects of this paper are arranged as follows. Section 2 describes on the databases and Section 3 presents the material and methods of the work. The testing and validation of the database and the result were discussed in Sections 4 and 5, respectively. Section 6 concludes the paper.

1.1 Patterns in African Cloth Embroidery

The process of making handmade embroidery requires a considerable amount of time and patience to include the details and accomplish the design. It also requires clear eyesight and skillful experience in manipulating the fabric and thread. In handmade embroidery, there are countless possibilities of expression and experimentation with stitches and motifs by the embroiderer. Beyond this, embroidery is a classic art form that requires great creativity and skills by the artists who use different geometric shapes and patterns to create a decorative effect on fabric. Embroidery on fabrics is generated through two (2) types of techniques: (i) Manual and (ii) Automated (Àdiji & Ògúndùyílé, 2016). In the manual techniques, all the processes are achieved by the use of hand, while the automated technique involves the use of a machine to make a design on fabric or cloth. There are lots of materials, decorative threads and stitches that can be found in handmade embroidery, the range is enormous, and this craft requires a measure of patience and time (Arsalan, 2011).

The machine embroidery process is not as labor intensive as handmade embroidery because it requires less time and less creativity. The other categories of machine embroidery are the computerized or digital embroidery in which embroidery patterns are created using advanced digital technology. The computer and the design software do most of the work in perfecting the design and embroidery especially, for mass production. With this type of machine embroidery technique, there is less effort given and no time wasted at all. In hand embroidery, all the processes are done manually from the stitches to the further embellishment of the design. However, the resulting design is more beautiful with delicate personal touches. These personal touches are recognized as the signature of individual embroiderer which sometimes differentiates his work from another person. Handmade embroidery consists of complex, intricate styles and designs of embroidery that stand out, especially when one chooses the right fabric as well as thread colors (Arsalan, 2011). As a traditional way of fabric embellishment, handmade embroidery promotes creativity and allows imagination to run wild. People prefer hand embroidery patterns because it allows creativity flow and can make people wearing it to be unique. The identifying nature of the embroidery comes out when it is done by hand, it gives freedom to do anything, with endless possibilities. It improves creativity because the real beauty and uniqueness are in the embroidery designs, which are handmade (Arsalan, 2011).

The significant difference between hand and machine embroidery is in the stitching process, handmade embroidery allows for a variety of stitches in varying thicknesses of thread in such a way as to make every work unique, machine-made embroidery is regular and completely uniform; every piece is virtually identical (Awuyah, 2012). In comparison, most machine-made embroidery is monotonous and repetitive in nature. This may however be due to laziness on the part of the maker since it is usually faster to create with deft touches, rather than trying new forms and patterns. Each piece of handmade embroidery is unique, even when using the same pattern; artists have the discretion to vary color and stitches which may sometimes be influenced by their mood. Hence, two completely identical pieces cannot be found; every piece is unique (Couture, 2017).

1.2 Yorùbá and Hausa Embroidery Patterns

Embroidery is one of the crafts in Nigeria that undergo series of changes in styles, motifs, and designs (Oladipo, 2011). Some commonly used materials include beads, metal strips, sequins, quills, and pearls. Various types of embroidery design had been popular until recently when floral motifs are combined with linear types and geometrical shapes (Oladipo, 2011), these are modern styles of the day on dresses, caps and even at the edge or helm of dresses. The designs and styles could turn a simple dress into an exotic and elegant one worn by kings, chiefs, nobles, the rich, especially during special occasions.

The pattern can be classified into modern or traditional among the *Yorùbá* and there is a unique traditional design on the embroidered *agbádá* which are in slanting position around the neck of the wearer, while the modern styles take several shapes, lines, and patterns that are unique (Oladipo, 2011). The traditional and modern designs are adaptable for fabric, depending on preference. For example, embroidery on woven fabric *aṣọ òkè* which are mostly worn among the Yorùbás during ceremonies, show that the patterns are worked around the neck of *dànsíkí* or *agbádá*, round the trousers mouth or the cap and this gives uniqueness to the outfit (Anderson, 1979). The sample of the traditional design on the embroidered *agbádá* is shown in

Figure 1. The *agbádá* is the daily wear of the *Yorùbá* men and is mostly common throughout Western Nigeria. It is cut in a simple square with a full and loose sleeve with the neck and front embroidered with rich and intricate patterns **(**Jefferson**,** 1973).

Embroidery patterns are mostly used among the *Yorùbá* and Hausa, their dresses and caps are heavily embroidered and many of their designs are in geometric and non-geometric shapes. The style has the tendency to trill and appeal to the generality of people whose love for it is amazing. Embroidery is created by the artisan on the different type of fabric such as guinea brocade, damask and may offer types of new materials which brings out the significance of thread with which it is worked. It is an art of making a pattern on textiles, leather, using threads of wool, linen, silk and needle (Ojo, 2000**)**. Machine-made embroidery is just like a print, all the copies look exactly the same, the color, the stitches, the final product are all exactly the same. The extreme detailing in the design (little and minute details) can be taken care of while doing embroidery by hand which cannot be done by machine (Arsalan, 2011). In addition to this, handmade embroidery process supports all types of fabric to be decorated with stitches. This is something that makes it different from other types of embroidery. The three categories of embroidery are shown in Figure 2 (a), (b) and (c).

Machine embroidery inclines to follow the regular pattern and every stitch is exactly the same and completely uniform. Each stitch of machine embroidery is like four times of the computerized embroidery. In computerized embroidery, the stitches are tiny and follow the regular pattern. The designs of computerized embroidery reside within the computer, so the user's creativeness cannot be applied and enhanced or changed to one's choices. The computerized embroidery gives a robotic feel in terms of appearance. The stitches of hand embroidery are thicker than the machine and computerized embroidery and every stitch is not exactly the same. However, hand embroidery is considered for this research work because of its peculiar features.

Figure 1. Jákàn on Embroidered Agbádá

(a) Machine Embroidery (b) Computerized Embroidery (c) Handmade Embroidery

Figure 2. Embroidery Patterns

2. Background

This section presents the background to the construction of the Handmade Embroidery Patterns (HEP) database. In this section, the process of the construction of HEP database is described, from the image selection to storage identification. This process is divided into the following stages:

- Image selection, Type and Location
- Digital Image Capture
- Digital Image Processing
- Image Labelling
- Storage Identification

2.1 Image Selection, Type and Location

The first stage of the creation of the database is the collection of handmade embroidery patterns. The reason for its choice lies in the nature of the pattern and its current state of use. This is with the view to sustaining the originality of the craft. The first part of this section was carried out by surveying and interviewing the embroiderer, designers, the local craftsmen practicing machine and handmade embroidery; and different designers who use computerized or digital embroidery in different cities of *Ọ̀sun* and *Ọ̀yọ́*. Based on the information obtained during the interviewing, it was deduced that the craft of handmade embroidery has more complexities involved in its production, but it gives a unique pattern. The reason for its uniqueness is that machine embroidery is restricted in terms of stitches, size and material. It was also discovered during interrogation process with the domain expert that the generality of the handmade embroidery pattern practiced in Nigeria are relatively similar and bear the same name.

The second part of this section is the collection of handmade embroidery pattern and two categories of the pattern were collected in *Ìbàdàn, Ilé-Ifẹ̀* and *Òsogbo*, South-West, Nigeria. The pre-processed images were used to create the HEP database and the ground truths were obtained by collection of information from various domain experts. Information on HME were obtained from 15 different domain experts in three different cities in Nigeria. The domain experts were interrogated and among the information collected include the following:

- Brief history of embroidery in Nigeria.
- Materials used.
- Steps involved in producing the pattern.
- Categories of patterns produced.
- Types of pattern and pattern name for each type.
- Reason for the naming convention.

2.2 Digital Image Capture

The images are captured by the use of a Fujifilm, 16 Megapixel 8× optical zoom digital camera from handmade embroiderer shop in various cities of *Ọ̀sun* and *Ọ̀yọ́*. After data capture, data was rescaled and normalized to reduce redundancy in the next preprocessing stage. The digital camera used to capture the patterns have the following camera details:

- Fujifilm 16 Megapixel resolution 8× optical zoom
- Camera Model: FinePix JZ250/JZ260
- F - stop: f/2.9
- Expose time - 1/400 seconds
- ISO-Speed - ISO-100
- Exposure bias - 0 step
- Focal Length - 4mm
- Max aperture - 3.07
- Metering mode - Pattern
- Flash mode - No

2.3 Digital Image Processing

The database was created by capturing the embroidery images of handmade embroidery pattern with digital camera. The images were captured with Red, Green and Blue (RGB) color components. In the pre-processing operations cropping, image size reduction, enhancement and compression were carried out on the acquired images and the area of the cloth which has pattern was smoothened with pressing iron to have a smooth pattern. The images were saved in Tagged Image File Format (TIFF) with image size of 900×1920 pixels and compressed using JPEG tool. The pre-processing operations were carried out using tools in MATLAB. Samples of the data in the dataset are shown in Figure 3. Each image in the database has patterns located around the neck down to the chest of the designed attire. Most of these designs are men's clothing. The naming nomenclature made up of the acronym generated from *Yorùbá* and *Hausa* name.

(a) Hemming Style (b) Twist Style

Figure 3**.** Examples of Handmade Embroidery

2.4 Image Labelling and Storage Identification

The validation data contain images of the embroidery pattern obtained from embroiderers in three different cities. The information used for the naming of embroidery patterns are collected from various embroiderer in different cities. Two classes of handmade embroidery images are present in the database.

The first one is the hemming style (called Títa or Chinbaki) and the second one is the twist style (called Zubi or Dídà). The HEP database contains three hundred and fifteen (315) images with variations in size and style. Some of the images in the database occurred in two or more variations resulting in a total of 1240 distinct images. The hemming type is ninety-eight (98) in number and twist type comprises of two hundred and seventeen (217). The images arranged in alphabetical order are written in *Yorùbá* and *Hausa* language. This is because the art of embroidery in the location covered in South Western Nigeria are practiced largely by these two ethnic groups.

The validation data are shown in Table 1 and the acronym 1 is the image name coding generated using *Yorùbá* image name while acronym 2 is the image name coding generated using *Hausa* image name. The coding of the image names was generated for *Yorùbá* and for *Hausa* language. Using the *Yorùbá* name, the coding of the image name was derived using the first and last letter of the first word, first and second to the last letter of the second word for names with two words. Also, the first and last letter of the first word, the first letter of the second word and the first letter of the last word were used for the names with more than two words. Likewise, for the *Hausa* name, the first letter of each word for image name with more than three words was used. Also, for the name with three words, the first letter of first two words and the first and second to the last letter of the third word are used.

Table 1. Validation data

SN	Yorùbá		Hausa	
	Image Name	Acronym 1	Image Name	Acronym 2
1.	Dídà Alábẹkan	DA.AA1.001	Zubi Me Aska Daya	ZM.AD1.001
2.	Dídà Alábẹkan	DA.AD2.002	Zubi Me Aska Daya	ZM.AD2.002
3.	Dídà Alábẹmẹ́fà	DA.AF1.003	Zubi Me Aska Shida	ZM.AS1.003
4.	Dídà Alábẹmẹ́fà	DA.AF2.004	Zubi Me Aska Shida	ZM.AS2.004
5.	Dídà Alábẹméjì	DA.AJ1.005	Zubi Me Aska Biyu	ZM.AB1.005

3. Materials and Methods

In this section, the techniques used for the classification model are presented.

3.1 Cellular Automata

Features such as shape, texture, color and thickness of the embroidery patterns were extracted into binary and grayscale images using cellular automata edge detection technique. Cellular Automata (CA) was employed as the feature extraction technique because of its parallelism in computing. The grayscale and binary images were obtained using *rgb2gray* function and Otsu's method in MATLAB respectively. The fundamental of CA is the cell and this cell is like a memory element that stores states of each pixel in an image. In this study, each cell can have the binary state "1" or "0" for binary image and "0…255" states for grayscale image with a total of 256 intensity levels. The cells are arranged in a spatial network called "lattice" and represent a static state. In order to make the system dynamic, a rule was introduced. The function of this rule is to define the state of the cell for the next time step. The state of the cell depends on the state of the neighborhood of the cell. For a 2-dimensional lattice used, there are basically two types of neighborhood which are (1) Moore neighborhood (with 8 neighbors) and (2) Von Newmann neighborhood (with 4 neighbors). A 2-dimensional CA is therefore defined as a 4-tuple given in Eq. 1.

$$\mathrm{CA} = <Z^2, \varphi, N, F> \tag{1}$$

where:

a) Z^2 is a 2D CA identical to input image $I_{i,j;}$
b) φ is <0…..255> for the set of finite state in grayscale image and <0,1> is the set of finite state for binary image;
c) N is the set of available neighbourhood type and;
d) F is the local rule applied.

In this study, 2D CA were considered and specific neighbourhood used is Moore neighbourhood. The type of rule employed is "Totalistic Rule" where the state of the core cell $C_{i,j}$ is dependent on the sum of the state of the neighbourhood cells and its present state. Each dead cell has state "0" and each alive state has state "1" as its value. Figure 4 depicts the Moore neighbourhood with central cell $C_{i,j}$ and its neighbourhood cells ($C_{i-1,j-1}$, $C_{i,j-1}$, $C_{i+1,j-1}$, $C_{i-1,j}$, $C_{i+1,j}$, $C_{i-1,j+1}$, $C_{i,j+1}$, $C_{i+1,j+1}$). The state of these neighbours is used to calculate the next state of the central cell according to the rule. The transition function used is given in Equation 2 processed in MATLAB R2013. The cellular edge detection algorithm used consist of 7 steps as follows:

1. Input Image
2. Setup CA map based on input image.
3. Transform into grayscale/binary pixels.
4. Count the number of neighbours.
5. Apply edge detection rule

6. Calculate the edge image based on CA rules
7. Obtain edge detected image.

$C_{i-1, j-1}$	$C_{i, j-1}$	$C_{i+1, j-1}$
$C_{i-1, j}$	$C_{i, j}$	$C_{i+1, j}$
$C_{i-1, j+1}$	$C_{i, j+1}$	$C_{i+1, j+1}$

Figure 4. Moore Neighbourhood

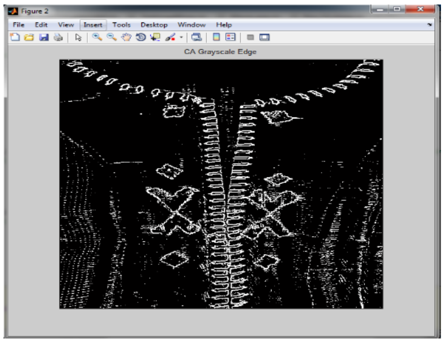


Figure 5. Edge detection of Títa embroidery

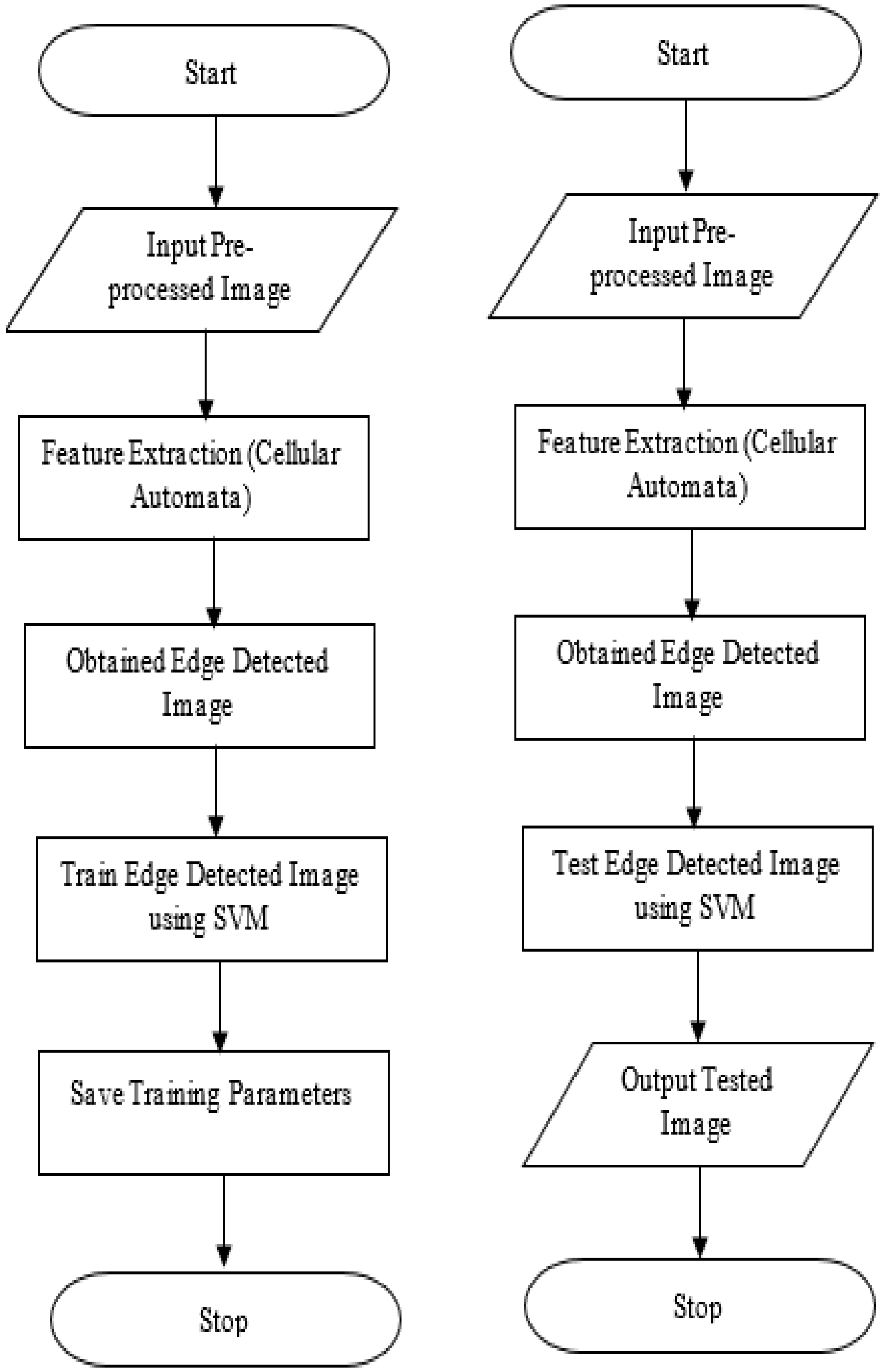
Figure 5 shows sample of edge detected image of handmade embroidery pattern. The feature such as shape, texture and thickness of the embroidery pattern were extracted and the feature vectors were obtained and used for the classification process.

3.2 Classification Model

In this section, the experiments were conducted on the classification of the two-embroidery type in the database using Support Vector Machine (SVM) written in C programming language as its classifier. The classification model for the embroidery pattern was simulated in MATLAB R2013a environment. The sample of the embroidery data was rescaled from 900×1920 to 256×256 pixels and distinguishing characteristics such as thickness, shape, texture and color of the pattern stitches obtained as feature set from the extraction stage were used for the classification process. These feature sets were assigned to an ordered set of related groups in which data are categorized based on its similarities.

$$C_{i,j}(t+1) = \delta\big(C_{i,j}(t), C_{i,j+1}(t), C_{i+1,j+1}(t), C_{i+1,j}(t), C_{i+1,i-1}(t), C_{i,j-1}(t), C_{i-1,j-1}(t), C_{i-1,j}(t), C_{i-1,j+1\,(t)}\big) \quad (2)$$

The edge image extracted from the feature extraction stage was trained using SVM written in C programming language. For the embroidery classification model, image sample of Dídà and Títa embroidery type were used. In total, 100 samples from the database were collected for the process. Sample data of the two handmade embroidery type of different sizes consisted of Dídà 68% and Títa (32%) respectively. For the recognition process, 60 of the patterns were used to train the model and 40 of the patterns were used to test the classification model. Figure 6 is the implementation stage of the classification model showing the training and testing of the handmade embroidery pattern. For the training stage, the extracted images were fed into the support vector machine and the training parameters were saved. For the testing stage, the input image from the testing sets was pre-processed and compared with the saved training parameters then output the result.



(a) Training Stage

(b) Testing Stage

Figure 6. Classification Model

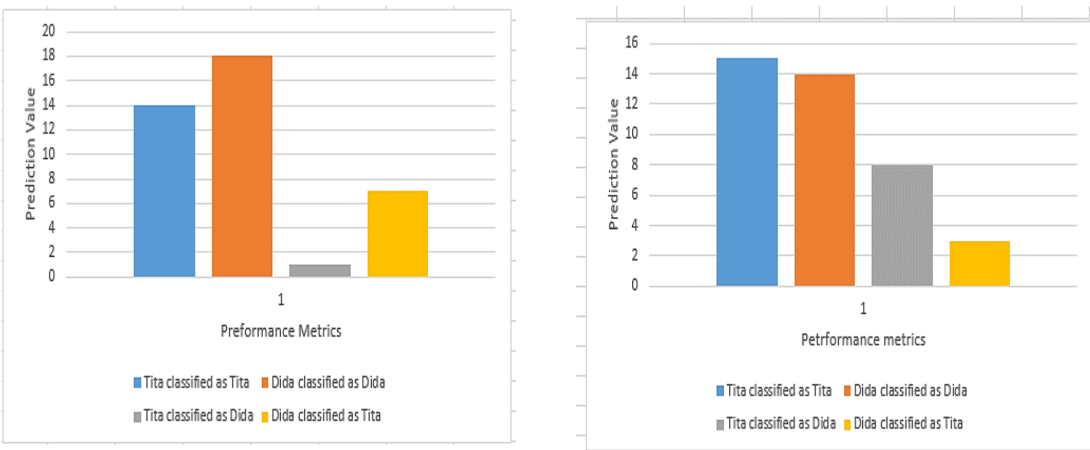
4. Model Testing and Validation

For efficiency, random samples of embroidery pattern were presented to the model as input and the performance metrics were recorded. A confusion matrix is used to describe the performance of the classification model on a set of test data for which the true value was discovered. The confusion matrix for grayscale and binary classifier are shown respectively in Tables 2 and 3. The classifier made a total of 40 predictions and out of the 40, the classifier predicted "Yes" 14 times for Títa embroidery type and "No" 1 time. However, for the second class the classifier predicted "Yes" 18 times for Dídà embroidery type and "No" 7 times for grayscale images. The classification result for grayscale and binary image are represented with a bar chart shown in Figures 7 (a) and (b) respectively. The performance metrics used to evaluate the model are sensitivity, specificity and accuracy defined in Eq. 3, 4 and 5 respectively. It was observed that for the grayscale image processed, a total of 32 data were correctly classified among 40 embroidery samples and 8 were misclassified data. Similarly, for the binary image processed, 29 data were correctly classified out of 40 embroidery samples and 11 data were misclassified. This indicates that the classification rate for grayscale image gives the best recognition performance than binary image.

$$Sensitivity = \frac{T_P}{T_P + F_N} \tag{3}$$

$$Specificity = \frac{T_N}{T_N + F_P} \tag{4}$$

$$Accuracy = \frac{T_P + T_N}{T_N + T_P + F_N + F_p} \tag{5}$$



(a) Accuracy Ratio for Grayscale Image

(b) Accuracy Ratio for Binary Image

Figure 7. Classification Result for the Embroidery Images

Table 2. Confusion Matrix for Grayscale Image

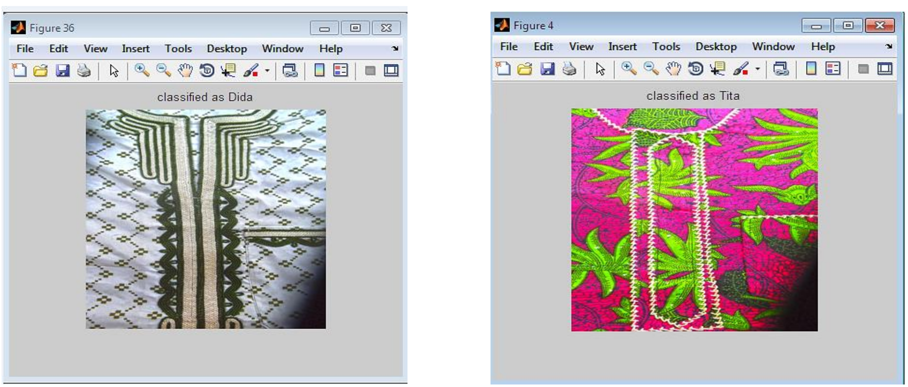
N = 40		Actual Class		
Predicted Class	Títa	Dídà	Títa	
	Dídà	18 T_P	1F_P	19
		7F_N	14T_N	21
		25	15	

Table 3. Confusion Matrix for Binary Image

N = 40		Actual Class		
Predicted Class	Títa	Dídà	Títa	
	Dídà	14T_P	8F_P	22
		3F_N	15T_N	18
		17	23	

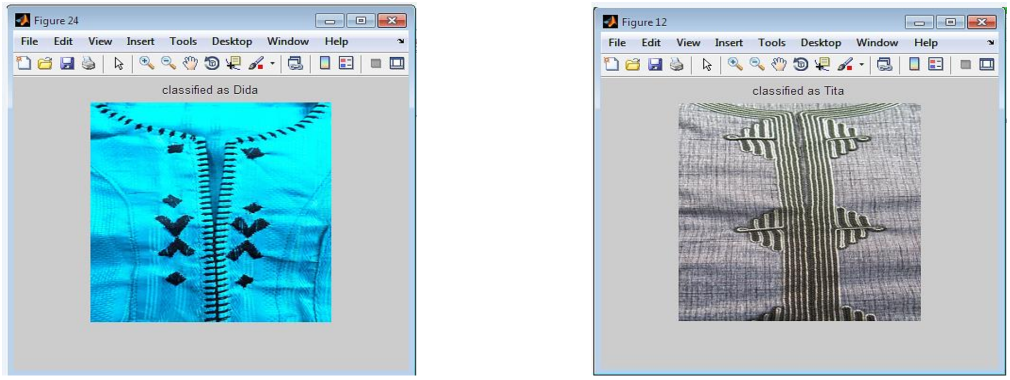
5. Results and Discussions

The model was simulated in MATLAB R2013a environment and samples of embroidery pattern were presented to the model as input. The simulation was processed on an Intel core i5 2.50 GHz machine. Two classes of result were generated as shown in Figures 8 and 9. Figure 8 (a) and (b) show the correctly classified embroidery type and Figure 9 (a) and (b) show the incorrectly classified embroidery type respectively. In Figure 8 (a), the embroidery type Dídà was correctly classified as Dídà and likewise in Figure 8 (b), the pattern was correctly classified as type Títa. Figure 9 (a) indicates a situation where the embroidery type Dídà were wrongly classified as Títa and in Figure 9 (b), the embroidery type Títa were wrongly classified as Dídà. Using the performance metric described above, the following results were recorded for the two classes of images. The sensitivity recorded was 72%, specificity of 93% and accuracy of 80% were obtained for grayscale image. For the binary image, the sensitivity, specificity, and accuracy obtained are 82%, 65% and 72% respectively. It was shown from the result that the accuracy of the grayscale image performance is more efficient than the binary image.



(a) Dídà classified as Dídà type (b) Títa classified as Títa type

Figure 8. Correctly Classified Embroidery Type



(a) Títa classified as Dídà type (b) Dídà classified as Títa type

Figure 9. Incorrectly Classified Embroidery Type

6. Conclusion and Future Work

In this study, the handmade embroidery database was established. The database comprises of three hundred and fifteen (315) images with variation in style and size. This variation will increase the usability of the database for further research benefits. Handmade Embroidery Patterns (HEP) database is a new material that uses external stimuli for research purposes. It provides a set of handmade embroidery patterns with specific characteristics such as texture, colour, brightness, thickness of the thread used for the patterns, and the shape of the patterns. This work provided experimental studies considering two classes of handmade embroidery patterns and the result obtained for the two images considered showed a high recognition rate for training and test datasets. Also, the name for the patterns collected is provided. Apart from being a repository of cultural heritage, the HEP database developed in this study will enhance developmental research in pattern recognition and machine vision applications. Future work includes exploring the effectiveness of combining machine-made and handmade embroidery pattern for classification process. The HEP database is not yet fully annotated; however, the data and current annotations are publicly available for non-commercial use at https://ifecisrg.org.ng/resource.php. This web address which contains the validation data and the images can be easily accessed using Microsoft Edge browser.

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