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Local Binary Pattern Face Recognition Loan Recovery System: A Case Study of Nigerian Anchor Borrower Programme

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Abstract:- Face recognition is the frequently explored subdomain in the domain of image processing. This paper implements an approach for the recovery of Anchor borrowers programme in Nigeria using LBP (Local binary pattern) for feature extraction from the facial region and particular region. Experimental results using this approach was conducted on a farmer's facial images database and are found to be more promising than existing manual approach.

Keywords:- *Image processing, local binary pattern, periocular region, Anchor borrowers, database.*

I. INTRODUCTION

In the last few years, facial recognition has been known to be one of the most promising technologies in the area of image processing. Based on its power to concentrate computing energy on the portion of the picture, that holding a face [1].

After the rapid development of artificial intelligence, facial recognition has received renewed attention due to its non-intrusive nature and the fact that it is the primary method of personal identification of humans compared to other types of biometric technology. Collecting Facial recognition can be easily verified in an uncontrolled environment without the knowledge of the parties concerned

A look into the history of facial recognition reveals that it has been the subject of many research papers. [2,]-[4]. Conventional methods based on superficial learning, such as pose variations, face masks, scene lighting, image background complexity, facial expression changes, etc., as in refs [5]–[14]. I was facing a challenge. Shallow learning-based methods use only a few basic features of the image and rely on artificial experience to extract pattern features. Deep learning-based methods can extract more complex facial features [15]–[23]

Deep learning has made significant progress in solving problems that have hampered the best efforts of the artificial intelligence community for many years. It has proven to be very well suited for revealing complex structures in high-dimensional data, so it can be used in many areas of science, business, and management. Addresses the problem of learning hierarchical representations using a single algorithm or several algorithms, mainly breaking records in image recognition, natural language processing, semantic he segmentation, and many other real-world scenarios [24]–[31].

There are various deep learning approaches such as convolutional neural networks (CNN), stacked autoencoders [32], and deep belief networks (DBN) [33]. CNN is the most widely used algorithm in image and face recognition. CNN is a kind of artificial neural network that uses convolution method to extract features from input data and increase the number of features. CNN was first proposed by his LeCun and was first applied to handwriting recognition. That network is the origin of many recent architectures and has been a true inspiration for many scientists in the field. Krizhevsky, Sutskever, and Hinton achieved their best results when they published their work in the ImageNet competition [34]. Widely regarded as one of the most influential publications in the field of computer vision, we have shown that CNNs outperform handcrafted methods in detection.

Using the computing power of graphical processing units (GPUs), CNNs have achieved remarkable prominence in many areas such as image recognition, scene recognition, semantic segmentation, and edge detection. The main contribution of this paper is to obtain a powerful detection algorithm with high accuracy. In this paper, we developed a new CNN architecture by adding a batch normalization process after two different layers.

II. METHODOLOGY

A typical LBP architecture can be seen as shown in Figure 1. The structure of LBP contains Convolutional, pooling, Rectified Linear Unit (ReLU), and Fully Connected layers. LBPs are a category of neural networks that have proven very effective in areas such as image recognition and classification. A LBP is a type of feed forward neural network that consists of many layers. A LBP consists of filters or kernels or neurons with learnable weights or parameters and biases. Each filter takes some input, performs a convolution, and optionally follows it with a nonlinearity**.**

A typical LBP architecture is shown in Figure 1. LBP structures include convolutions, pooling, rectified linear units (ReLUs), and fully connected layers.

In the proposed approach, two facial images database are used in the matching analysis i.e the image database of those that benefited from the loan and those that applied to get a new loan. With the following format below:

Loan ID	Face Image	Loan Status
Xxxxxxx		Not Paid

Fig. 1: Database sample of the system

When the two databases are passed to the system the Local Binary Pattern (LBP) combined features are extracted from each face in the following format below.

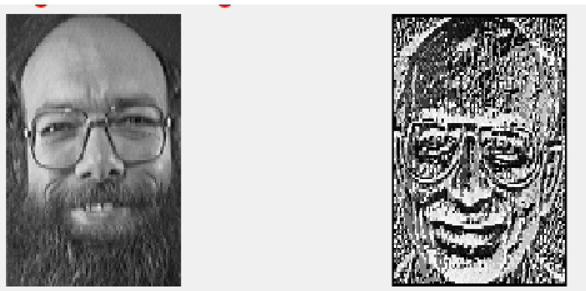

Fig. 2: Sample of extracted image and LBP image

Considering the dimension of the images might be very high Principal Component Analysis (PCA) algorithm is used for dimension reduction. LBP Features extracted from face region are compared, image histogram is generated and Euclidean distance classification is done where recognition percentage is calculated and the result is set against each individual in a report database.

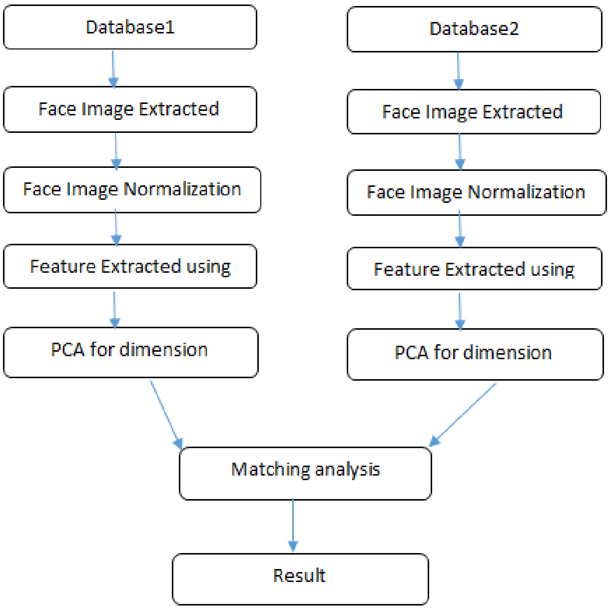

Fig. 3: Block diagram of the system

A. Data collection and preprocessing

For recognition of face images, farmer's database was used [1]. Containing 100 face images. The images of faces have some noise and irregularities. So that the preprocessing operations like filtering, normalization, RBG conversion are performed on face images .

B. Local Binary Pattern (LBP)

Local binary pattern (LBP) provides an efficient way for texture description. LBP is faster as compared to any other feature extraction algorithm. It is a non-parametric approach and very demanding in the domain of machine vision and image processing [2][4].

*Consider a 3*3 pixel with (pc, qc) intensity value be Ic and local texture as*
$L = l(t0, t1, t2, t3, t4, t5, t6, t7)$ where t_n (n=0,1,2,3,4,5,6,7) corresponds to the grey values of the eight encompassing pixels. These encompassing pixels are threshold with the middle value
tc as $l(r(t_0 - t_c), \text{- - - - -}\ r(t_7 - t_c))$ and therefore the r(x) is outlined as

$$r(x) = \begin{cases} 0, & x < 0 \\ 1, & x \geq 0 \end{cases} \qquad (1)$$

As the given pixel of LBP pattern is outlined as an ordered set of binary comparisons and using following equation resulting value can be obtained [5][6].

$$LBP(pc, qc) = \sum_{n=0}^{7} r(tn - tc)2^n \qquad (2)$$

C. Principle Component Analysis (PCA)

PCA is used for feature extraction and reduce the dimensionality of the images. Which transfigure a number of associated pixel value into a number of disassociated pixel value called as eigenfaces. It also calculates an optimized and compact description of the dataset. Sometimes the extracted features are large in size which leads to a memory problem, computation problem and many more. The performance of face recognition system is influenced by dropping some of the extracted features. So, here PCA is used to reduce the dimensionality. The extracted features are decumbent to noise. Using PCA, this problem can be minimized. The PCA algorithm has the following step:

- Assemble a training set of images (M number of face images)
- Resampled all the images to common pixel resolution R*C
- Individual image is converted to a single vector or single row which contain R*C elements. i.e.
- [R1 R2 R3 - - - - - - RC]
- The training set is then accumulating into a single matrix S which consists of M column. i.e.

$$\begin{array}{c} \begin{vmatrix} R_1 & R_1 & \ldots\ldots\ldots\ldots\ldots & R_z \\ R_2 & R_2 & \ldots\ldots\ldots\ldots\ldots & R_2 \\ \ldots & \ldots & \ldots\ldots\ldots\ldots\ldots & \\ \ldots & \ldots & \ldots\ldots\ldots\ldots\ldots & \\ R_x & R_c & \ldots\ldots\ldots\ldots\ldots & R_c \end{vmatrix} \\ \text{C1} \quad \text{C2} \quad \cdots\cdots \quad \text{CM} \end{array}$$

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D. Classification

Classification can be done on the basis of extracted feature. For classification, there are a number of techniques but in this approach, Euclidean distance is used. Each training set C compared with the test images C_{test} using Euclidean distance, εi on the image histogram.

$$\varepsilon_i^2 = (\| C_{test} - C_i \|)^2$$

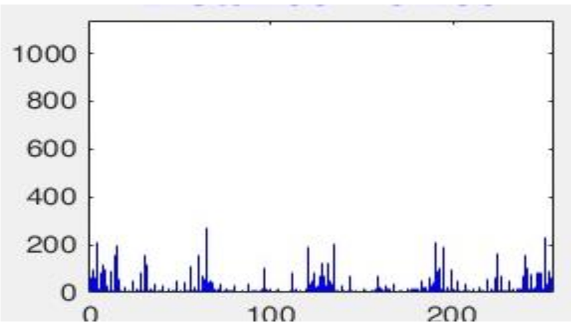

Fig. 4: Image Histogram generated from the LBP image used for classification

Algorithm

{ This algorithm call the function all images , decompose and reduce the dimensionality of the binary image it employs the use of principal component analysis PCA that can be used I the next algorithm for histogram equalization of the images}

```
Begin
numeric_Image ← uint8(all_Images);
numeric_Image2 ← uint8(all_Images2);
random_Index←round(400*rand(1));
random_Image←output_value(:,random_Index);
random_Image2←output_value2(:,random_Index);
rest_of_the_images←output_value(:,[1:random_Index-1
random_Index+1:end]);
rest_of_the_images2←output_value2(:,[1:random_Index-1
random_Index+1:end]);
L←single(mean_Removed)'*single(mean_Removed);
[V,D] ←eig(L);
% returns diagonal matrix D of eigenvalues and
matrix V whose columns are the corresponding right
eigenvectors,
V←single(mean_Removed)*V;
for i←1:size(rest_of_the_images,2);
   all_image_Signatire(i,:)
←single(mean_Removed(:,i))'*V;
end
subplot(221);
imshow(reshape(random_Image2,112,92));
title('Looking for this image',
'FontWeight','bold','Fontsize',14,'color','red');
 subplot(222);
p←random_Image-mean_value;
S←single(p)'*V;
z← [];
for i←1:size(rest_of_the_images,2)
   subplot(222);
   z← [z,norm(all_image_Signatire(i,:)- S,2)];
   if
(rem(i,10)=0),imshow(reshape(rest_of_the_images(:,i),112
,92))
end;
   E1←imhist(random_Image );
   E2←mhist(rest_of_the_images(:,i));
   E_distance ←sqrt(sum((E1-E2).^2));
   subplot(223);
imshow(reshape(rest_of_the_images2(:,i),112,92));
E1←imhist(random_Image );
E2←imhist(rest_of_the_images(:,i));
E_distance ← sqrt(sum((E1-E2). ↑2));
title(sprintf('Recognition Percentage = %0.2f',100-
E_distance/20), FontWeight','bold','Fontsize',
14,'color','blue');
subplot(223);
title(sprintf('Recognition Percentage = %0.2f',100-
E_distance/20), 'FontWeight','bold','Fontsize',
14,'color','blue');
end
```

III. RESULT AND DISCUSSION

The LBP is tested on the farmer beneficiary's database and that of new applicant farmers database that want to benefit from the loan are used. The database contains some images repetitively in few cases. In first phase, face images are normalized and reprocessed to eliminate the noise and illumination error. The experimental result obtained from LBP is shown in table I. The recognition accuracy of various faces are recorded and face identification for databases were carried out on 100 images which were meant for training and 500 images which were subjected to testing and performance evaluation was completed as show in Table I

S/ No	***Farmer_id***	***Image***	***Loan Status***	***Recognition %***	***Status***
1	*xxxx-01*	*5A*	*Paid*	*91.26*	*Eligible*
2	*xxxx-02*	*6A*	*Not paid*	*80.04*	*Not-eligible*
3	*xxxx-03*	*7A*	*Not paid*	*91.26*	*Not-eligible*
4	*xxxx-05*	*8A*	*Paid*	*87.23*	*Eligible*
5	*xxxx-06*	*9A*	*Paid*	*93.83*	*Eligible*
6	*xxxx-07*	*10A*	*Paid*	*93.60*	*Eligible*
7	*xxxx-08*	*11A*	*Not paid*	*85.21*	*Not-eligible*
8	*xxxx-09*	*12A*	*Paid*	*92.87*	*Eligible*

Table 1: Performance Evaluation OF Percentage of Recognition

The recognition processes of our proposed algorithm are shown in Figures 5A, 6A, 7A, 8A, 9A, 10A, 11A and 12A. Also each figure of Figures 5B, 6B, 7B, 8B, 9B, 10B, 11B and 12B shows different percentages of recognition.

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Fig. 5A: Image Sample before and after LBP

The percentage of recognition of Figure 5A is shown in Figure 5B with 91.26%.

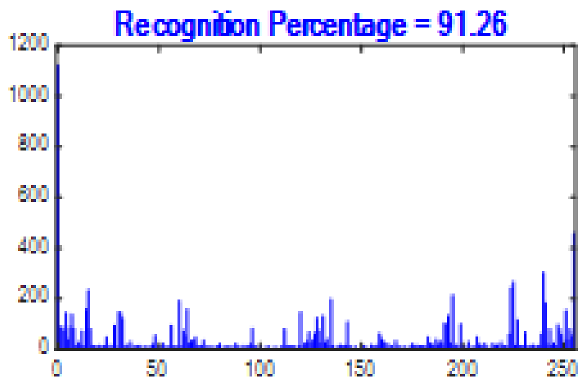

Fig. 5B: The Percentage of recognition.

Fig. 6A: Image Sample before and after LBP

The percentage of recognition of Figure 6A is shown in Figure 6B with 80.04%.

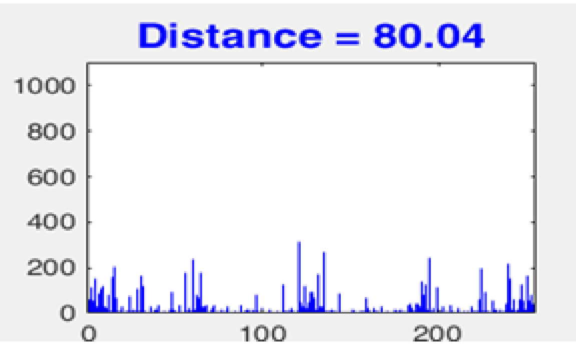

Fig. 6B: The Percentage of recognition

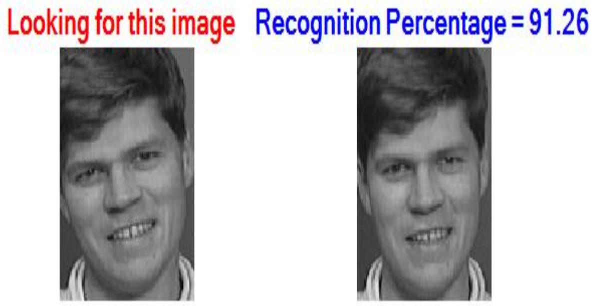

Fig. 7A: Image Sample before and after LBP

The percentage of recognition of Figure 7A is shown in Figure 7B with 91.26%.

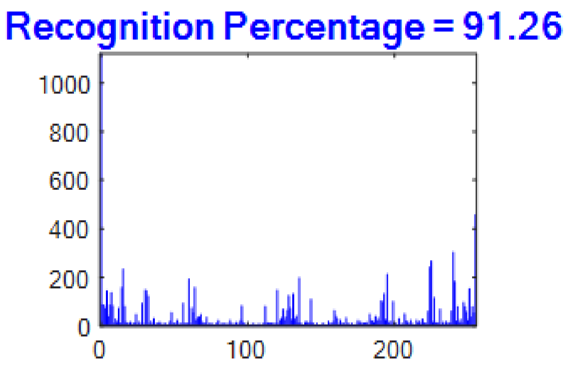

Fig. 7B: The Percentage of recognition

Fig. 8A: Image Sample before and after LBP

The percentage of recognition of Figure 8A is shown in Figure 8B with 87.23%.

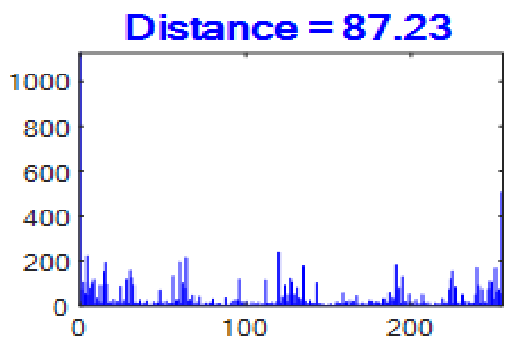

Fig. 8B: The Percentage of recognition

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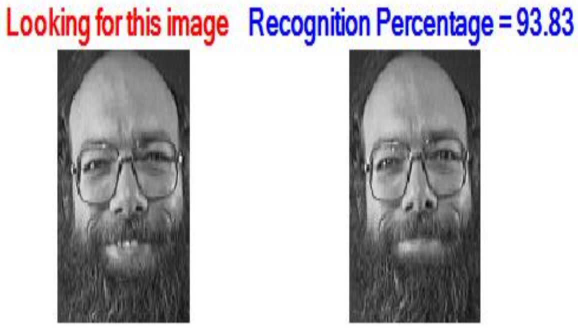

Fig. 9A: Image Sample before and after LBP

The percentage of recognition of Figure 9A is shown in Figure 9B with 93.83%.

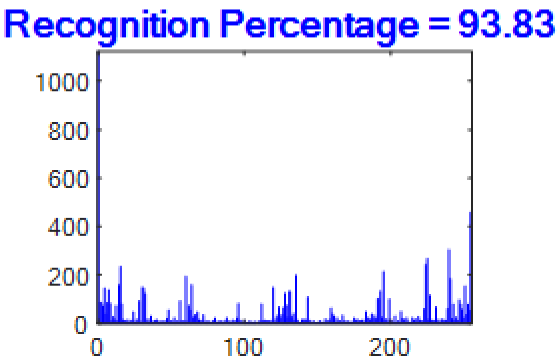

Fig. 9B: The Percentage of recognition

Fig. 10A: Image Sample before and after LBP.

The percentage of recognition of Figure 10A is shown in Figure 10B with 93.60%.

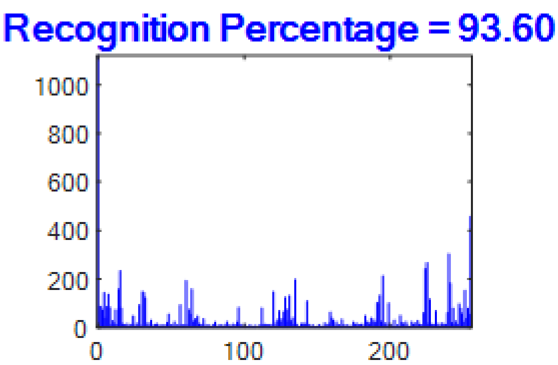

Fig. 10B: The Percentage of recognition

Fig. 11A: Image Sample before and after LBP

The percentage of recognition of Figure 11A is shown in Figure 11B with 85.21%.

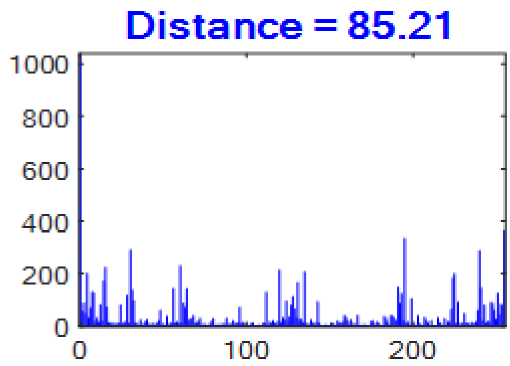

Fig. 11B: The Percentage of recognition

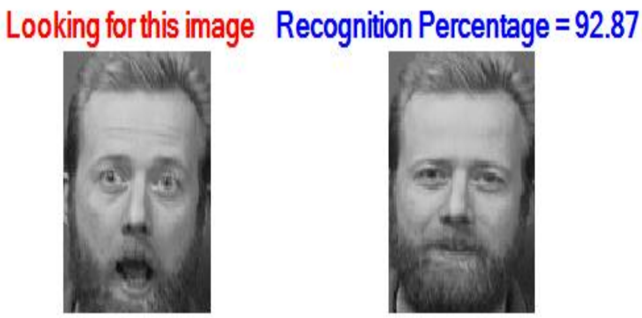

Fig. 12A: Image Sample before and after LBP

The percentage of recognition of Figure 12A is shown in Figure 12B with 92.87%.

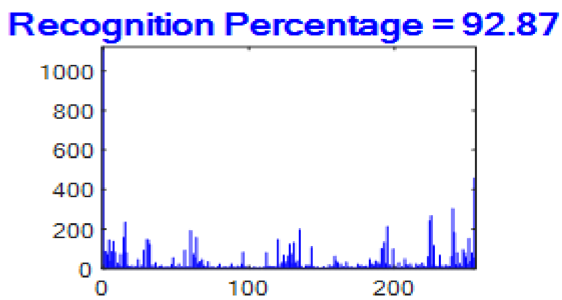

Fig. 12B: The Percentage of recognition

IV. CONCLUSION

We have developed a face recognition using Local Binary Pattern (LBP) for recovery of Anchor borrowers programme in Nigeria. The face recognition system is developed for recovery of Anchor borrowers programme in Nigeria. Based on the experimental results, it can be concluded that the application of the LBP method to recognize faces can overcome the reliability problem of face detection in lighting variables without requiring calibration and being able to detect the face correctly in an environment with uneven lighting. Our LBP based face recognition successfully recognizing the face with a promising result. For the future work, the chance is still opened to increase the capability of LBP-based ball detection system, especially to work on a faster camera with higher FPS to reduce errors. We do hope that this research will be able to improve the rate at which loan recovery will easily and reliable.

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