ISSN No:-2456-2165

# Performance Evaluation of Selected Feature Extraction Techniques in Digital Face Image Processing

Ismaila Folasade. M.
Computer Science Department
Osun State Polytechnic, Iree, Nigeria

Afolabi O. Adeolu
Department of Cybersecurity Science,
Ladoke Akintola University of Tech Ogbomoso, Nigeria

Ismaila W. Oladimeji,
Computer Science Department,
Ladoke Akintola University of Technology,
Ogbomoso, Nigeria

Alo Oluwaseun O.
Department of Information System,
Ladoke Akintola University of Tech,
Ogbomoso, Nigeria

**Abstract:- Digital image processing is the use of computer algorithms to analyze digital images. Digital image processing, involves many processing stages of which feature extraction stage is important. Feature extraction involves reducing the number of resources required to describe a large set of data. However, choosing a feature extraction techniques is a problem because of their deficiencies. Thus, this paper presents a comparative performance analysis of selected feature extraction techniques in human face images. 90 face images were acquired with three different poses viz: normal, angry and laughing. The face images were first pre-processed and then subjected to selected feature extraction techniques (Local binary pattern, Principal component analysis, Gabor filter and Linear discriminant analysis). The extracted features were then classified using Backpropagation neural network. The results of recognition accuracy produced by Gabor filter, PCA, LDA and LBP at 0.76 threshold are 76.7%, 72.2%. 78.9% and 85.6%. Hence, it can be deduced that LBP performed the best among the four selected feature extraction techniques.**

***Keywords:-*** *Digital Image Processing, Feature Extraction, Local Binary Pattern, Principal Component Analysis, Gabor Filter, Linear Discriminant Analysis.*

## I. INTRODUCTION

Digital image processing is a field that explains the use of computer algorithms to analyze digital images. The action of retrieving an image from source, usually a hardware-based source for processing (webcam or camera). Several images have been subjected to digital classifications like trauma-related data [15]; hypertensive data [41]; cancer data [36]; [39] used Baboon, House, Lena and Peppers; [41] plant leaf diseases; [19] concrete surface images; [46] breast cancer, facial images [9] etc. Digital image processing involves four stages viz; image acquisition, pre-processing, feature extraction and classification. [12], [43].

Feature extraction is related to dimensionality reduction (also named a feature vector) [40], [3]. Feature extraction method can be either holistic or local. The holistic feature extraction techniques are principle component analysis [39], [33], linear discriminate analysis [28], [29], independent component analyse (ICA) [37] are used to extracted the features of the whole facial images or sub-images. Although considerably good recognition accuracy can be obtained using holistic-based techniques but the limitation is that they cannot control illumination and local variations are difficult to describe. Using holistic algorithms, the global structure of the image is pin-pointed and the correlation between the images is computed. Many scholars have employed local-based feature extraction techniques to overcome the drawbacks of holistic-based feature extraction techniques. The most local feature methods that are used in face recognition systems are: local binary patterns (LBP) method [4], discrete wavelet transform (DWT) method [24] and Gabor filter [27], [20].

However all these techniques have pros and cons. LBP is an appearance-based method which produce relatively good results even at variability of the images collection. LBP is relatively insensitive to illumination changes, and its computational simplicity**.** However, It is sensitive to noisy pixels wherein the value of the pixels can be easily affected by the erroneous surrounding pixels. The PCA technique18 converts each two dimensional image into a one dimensional vector. This vector is then decomposed into orthogonal (uncorrelated) principle components (known as eigenfaces). PCA improves the performance of the machine learning algorithm as it eliminates correlated variables that don't contribute in any decision making.; helps in overcoming data over fitting issues by decreasing the number of features; and produces results in high variance which improves visualization. However, PCA produces low interpretability of principal components [2]. Gabor filtering is a popular approach to extract features from the face images with different orientations by convolving the image with the Gabor wavelet basis function. However, Every image produces a large number of Gabor filtered images depending upon the number of scale and orientation

ISSN No:-2456-2165

[25]. The most prominent shortcomings of Gabor filter are the orientation selectivity and spatial locality. LDA is a dimensionality reduction and classification technique commonly used in machine learning and pattern recognition. In the context of classification it aims to find a linear combination of features that best separates different classes or categories of data. It seeks to reduce the dimensionality of the feature space while preserving as much of the class separability information as possible. Hence the aim of this work is to compare the performances of some selected feature extraction techniques on image classification system.

## II. RELATED WORKS

Reference [44] designed a face recognition system using gabor filter based elastic bunch graph matching technique and the result is 94.29% accuracy for seventy input images. However, there is degradation in recognition rate due to increased in number of images.. The other drawback is that it produces poor recognition accuracy if the lighting conditions arenot constant during the enrolment and verification process [21]. Reference [9] developed an effective and real time face recognition system. The system was tested on YALE Face database B and ORL Face Database. The acquired facial database were extracted with PCA. The correct recognition rate achieved using the Mahalanobis distance is 92.3% in comparison to the 73.1% for the normal PCA with euclidean distance. [17] investigated the effectiveness of combining Independent Component Analysis (ICA) with Gabor algorithm (called I-Gabor) as feature extractor from eye and nose of known faces. The resultant features matrices were trained with support vector machine for classification and performances were evaluated with false acceptance rate, false rejection rate and accuracy.

Reference [25] performed feature extraction on face images by regulating the scale and orientation parameters of Gabor Filters. In order to select significant features only, different properties of the features like entropy, correlation coefficient and variance are analysed. Removal of irrelevant features, effectively by Gabor filter reduced dimensionality of the feature space without sacrificing accuracy which is 94.5%. [35] developed an approach to solve this limitation using salient distance features, which are obtained by extracting patch-based 3D Gabor features, selecting the salient patches, and performing patch matching operations. The simulation results produced high accuracy, significant performance improvements due to the consideration of facial element.

Reference [1] proposed a novel approach in classifying gesture into single or double handed subcategories. The approach employed morphological operation, filtered binary images to extract the geometric features. The obtained values were used to classify the single or double handed gestures. Histogram of Oriented Gradients techniques are used to extract local orientations and intensity distribution for detecting the shapes of the object. Classification was done by applying K- Nearest Neighboring algorithm on the geometric features extracted.. The result showed that the developed system produced 88.46% accuracy. [14] proposed local binary pattern variant based on gray level and structural information (CLBP_GLSI). Firstly, the authors proposed an structural texture operator called gray level and structural information (GLSI), which adopts the average gray level of image to make image converted into binary images, and binary images are encoded as border or interior pixels image by Border/Interior Pixel Classification (BIC). Secondly, by combining with CLBP_M, CLBP_S and GLSI into joint or hybrid distributions, the CLBP_GLSI are obtained. Experimental results obtained from two databases show that the best recognition accuracy for CLBP_S/M/GLSI is 95.95%, while the best results for CLBP_S/M/C is 95.47%.

Reference [23] presented a novel two-layer back propagation based neural network algorithm that is cost effective, to classify the normal, malignant and benign tumor dataset.. The acquired dataset were preprocessed to remove irrelevant features. Then, backpropagation neural network algorithm was employed to train the two-layered network. The results of correct classification rate gave by two layer neural networks and single layered backpropagation neural network are 97.12% and 96.63% respectively. [32], in their research, applied Backpropagation Neural Network to classify books using its cover. The data was in form of scanned images with three sizes and image resolution. The features extraction was done using maximally stable externally egions to identify the region of book heading, and optical character recognition to detect the heading. Then, the features extracted were transformed into a numerical matrix and then passed as input to the BPNN. The accuracies obtained using one hidden layer and 2 hidden layers were 63.31% and 79.89% respectively.

## III. MATERIALS

The section entailed the techniques to be evaluated and compared in the work. It also revealed the dataset to be used for implementing the techniques.

### *A. Dataset*

In the literature, many data have been used like trauma-related data, hypertensive data, cancer data, Baboon, House, Lena, Peppers, plant leaf diseases, concrete surface images, breast cancer, facial images etc. however, human faces were used for experimenting the techniques.

### *B. LBP method*

LBP technique was founded by [30]. This method makes it possible to explain the shape and texture of a digital image. This is executed by splitting the image into several small regions from which the features are extracted (figure 1).

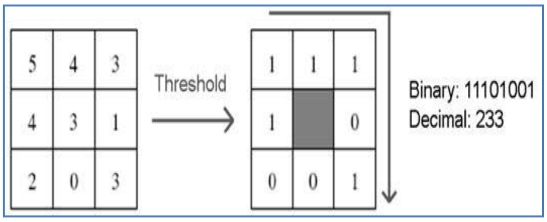


Fig. 1: The Original LBP Operator [16][30]

This operator works with the eight neighbors of a pixel, using the value of this center pixel as a threshold. If a neighbor pixel has a higher gray value than the center pixel (or the same gray value) than a one is assigned to that pixel, else it gets a zero. The LBP code for the center pixel is then produced by joining the eight ones or zeros to a binary code. However, LBP has advantage of relatively insensitive to illumination changes wherein the value of the pixels can be easily affected by the erroneous surrounding pixels and also it's computational simplicity [16].

### *C. Gabor filter*

Hungarian-born electrical engineer Dennis Gabor developed a Gabor wavelet in 1946. It was created from one particular atom by dilation and rotation in a two-dimensional case and provides a complete image representation. Recently, Gabor functions are frequently used for classification, segmentation, or edge detection) and, more practically, pattern recognition. An image processing task can be seen in the form of a wavelet transform. The scale of a wavelet provides a magnification that allows one to see the image through the lens. Gabor functions are particularly useful in texture-based image analysis due to their ability to capture both spatial and frequency information. By applying Gabor filters at different scales and orientations, the wavelet transform can effectively extract features from an image, enabling tasks such as classification, segmentation, edge detection, and pattern recognition. This approach allows for a comprehensive representation of the image, revealing intricate details and enhancing its visual interpretation [44].

### *D. PCA*

PCA is a statistical approach used for reducing the number of variables in image classification. In PCA, every image in the training set is represented as a linear combination of weighted eigenvectors. These eigenvectors are obtained from covariance matrix of a training image set. The weights are found out after selecting a set of most relevant eigenvectors [2]. PCA eigenvector method considers each pixel in an image as a separate dimension, that is, N by N image has $N^2$ pixels or $N^2$ dimensions. To calculate eigenvector, there is a need to calculate the covariance matric C as shown in Equation 1.

$$C = A.A^T \quad \text{where } A = N^2 \text{ by } M \tag{1}$$

where N is the dimension of the image, M is the number of column vector. If eigenvector will be calculated from a covariance matrix before dimension reduction, the system would slow down terribly or run the system out of memory, due to huge computations. In order to overcome this problem, the solution is to calculate eigenvectors from the covariance matrix with reduced dimensionality. The eigenvectors will be sorted according to their corresponding eigenvalues from high to low. Then, the eigenvectors corresponding to zero eigen values are discarded while those associated with non-zero eigen values are kept. PCA improves the performance of the machine learning algorithm as it eliminates correlated variables that don't contribute in any decision making.

### *E. Linear Discriminant Analysis*

LDA is one of the supervised approach to Dimension reduction. The LDA technique is developed to transform the features into a lower dimensional space, which maximizes the ratio of the between-class variance to the within-class variance, thereby guaranteeing maximum class separability [31]. There are two types of LDA technique to deal with classes: class-dependent and class-independent. In the class-dependent LDA, one separate lower dimensional space is calculated for each class to project its data on it whereas, in the class independent LDA, each class will be considered as a separate class against the other classes [6], [47]. In this type, there is just one lower dimensional space for all classes to project their data on it. Although the LDA technique is considered the most well-used data reduction techniques, it suffers from a number of problems. In the first problem, LDA fails to find the lower dimensional space if the dimensions are much higher than the number of samples in the data matrix. Thus, the within-class matrix becomes singular, which is known as the small sample problem. This type of feature selection techniques are applicable biometrics [22], [8]; Bioinformatics [45] and chemistry [7].

### *F. Performance Metrics*

In [16], it was stated that the performance metrics to evaluated biometric systems include recognition accuracy, false match rate, false non-match rate, Specificity, Sensitivity and receiver operating characteristic (ROC). Confusion matrix was employed to estimate the values of each of the metrics.

$$Accuracy\ is\ expressed\ as\ \frac{True\ Negative + True\ positive}{Total\ Number\ of\ Images}$$

$$False\ Match\ Rate\ is\ estimated\ as\ \frac{False\ positive}{True\ negative + False\ positive}$$

$$False\ Nonmatch\ Rate\ is\ \frac{False\ Negative}{True\ Positive + False\ Negative}$$

$$Specificity\ \text{is termed}\ \frac{\text{True Negative}}{\text{True Negative} + \text{False Positive}}$$

$$\textbf{Recall is represented by}\ \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}}$$

## IV. METHODOLOGY

The work flow of the image classification system is shown in figure 2 and explained in the subsections.

ISSN No:-2456-2165

*A. Data Acquisition*

Faces of thirty subjects (sample shown in figure 3) were acquired with a good sony camera of high resolution. The face poses of the 30 subjects comprises of three poses viz: normal pose, angry pose and laughing pose which made a total of 90 faces stored in the database.

Fig. 3: Sample of face subjects

➢ *Pre-processing Stage*

This section entails the steps to be adopted in preparing the subject images for face recognition system to increase the accuracy of systems. In this work, it involves image resizing (figure 4a), pose orientation (figure 4b), and colour transformation (figure 4c).

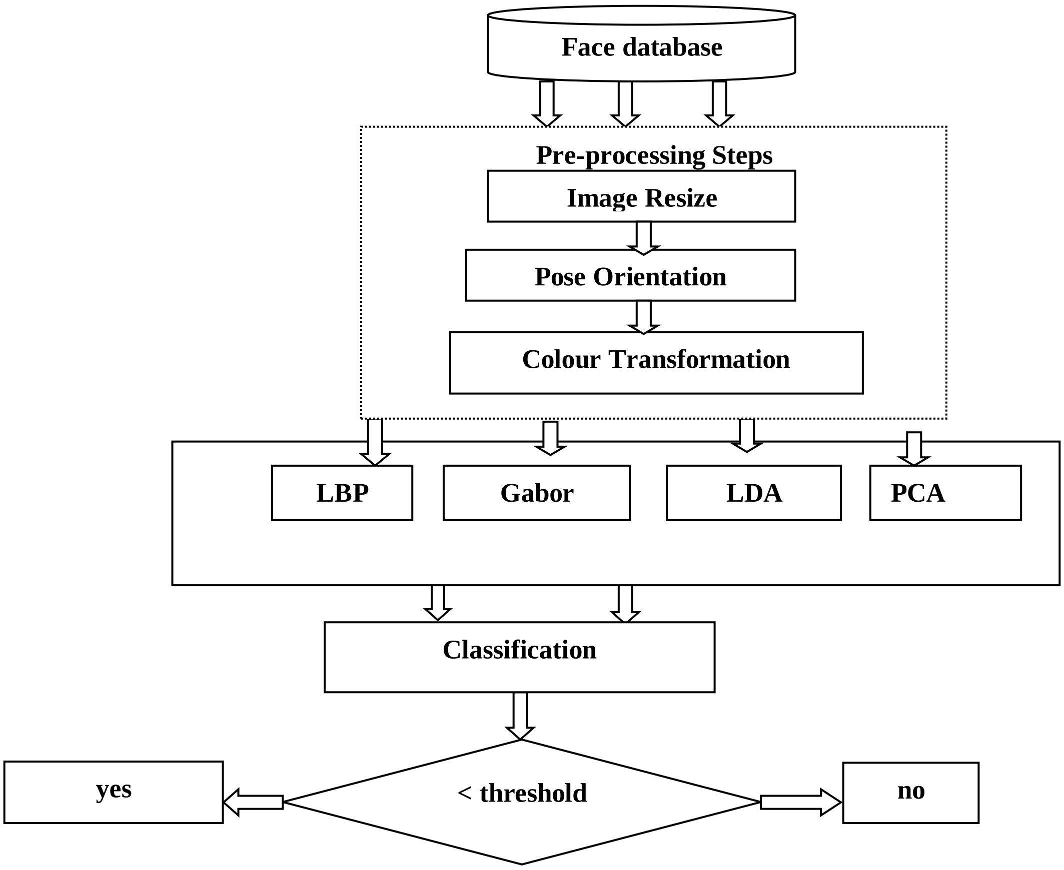


Fig. 2: Flow diagram of the Image Classification System

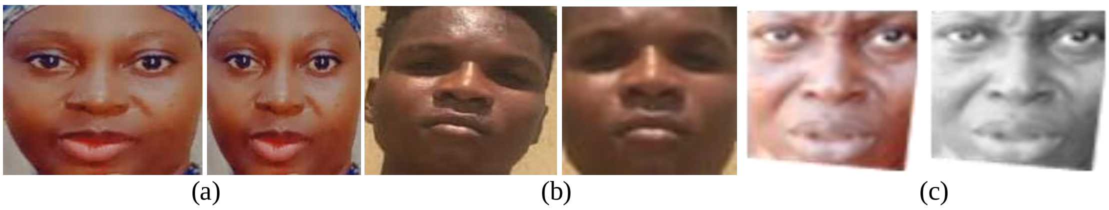


Fig. 4: Sample of pre processing outputs (a) Image resize (b) pose orientation (c) Colour transformation

## B. *Feature Extraction*

This stage involves the techniques used for dimension reduction of preprocessed images.

- *Technique One: LBP algorithm is shown in Algorithm 1.*

**Algorithm 1: The LBP algorithm** [30]

- Step 1: Set $g_c$ which corresponds to the gray value of the center pixel.
- Step 2: Set $g_p$ as the gray values of the "n" neighbour pixels.
- Step 3: Set

$$M = \begin{Bmatrix} 1, & if g_c \geq 0 \\ 0, & if g_c < 0 \end{Bmatrix} \quad (2)$$

- Step 4: Compute LBP features as described thus;

$$LBP_{p,r}(x_c, y_c) = \sum_{p=0}^{n-1} M(g_p - g_c) * 2^p \quad (3)$$

Where $x_c$ and $y_c$ represent the horizontal and vertical component of the image; $Mg_p$ and $Mg_c$ are neighborhood patterns, P represent the bit binary number resulting in $2^p$distinct values for the LBP code.

- Step 5: Output selected LBP features

- ***Technique Two:*** *PCA algorithm is shown in algorithm 2.*

**Algorithm 2: PCA [18]**

Following are steps involve;

- Step 1: Column or row vector of size $N_2$ represents the set of M images ($B_1$, $B_2$, $B_3$…$B_M$) with size N*N
- Step 2: The training set image average (μ) is described as

$$\mu = \frac{1}{m} \sum_{n=1}^{M} B_n \quad (4)$$

- Step 3: the average image by vector (W) is different for each trainee image

$$Wi = Bi - \mu \quad (5)$$

- Step 4: Total Scatter Matrix or Covariance Matrix is calculated from Φ as shown below:

$$C = \sum_{n=1}^{M} w_n w_n t = AAT \quad (6)$$

where A= [$W_1W_2W_3…W_n$]

- Step 5: Measure the eigenvectors UL and eigenvalues λL of the covariance matrix C.
- Step6: For image classification, this feature space can be utilized. Measure the vectors of weights

$$\Omega T = [w1, w2, …, wM'], \quad (7)$$

whereby,

$$H_k = U_kT (B - \mu), k = 1, 2, …, M' \quad (8)$$

- ***Technique 3: Gabor Filters*** *algorithm is shown in algorithm 3*

Algorithm 3: Gabor filter [43]

**Gabor Filters: Algorithm 3:** Algorithm to Extract Feature Vector
**Data:** *GABOR_MAG{No_of_Scale, No_of_Orient}*
**Result:** *FEATURE_VECTOR*
*Block_Size :=32 x 32, Total_Filter := 40;*
**While** ***i*** ≤ *No_of_Scale* **do**
  **While** ***i*** ≤ *No_of_Orient* **do**
    *Current_Tmg* **:=** *GABOR_M AG*{i, j} **if**
      *GABOR_M AG*{I, j}*(x,y)* **=**
        *max* ***(x,y)∊Block*** *Current_Img(x, y* **then**
          If *Current_Tmg (x, y )>* $\frac{1}{row.col}\sum_{x=1}^{row}\sum_{y=1}^{col} Current\_Tmg\ (x, y)$ **then**
  **While** *Filter_No ≤ Total_Filter* **do**
**VALUE** (*Filter_No*) **:=** *GABOR_M AG{I, j}(x, y)*
        **end**
      **end**
    **end**
    *FEATURE_VECTOR=Value;*
  ***e****nd*
**end**

- *Technique 4: LDA algorithm is shown in algorithm 4*

Algorithm 4. : LDA. [13]

- Read the training images (X = {$x_1$;$x_2$.....$x_N$}), where $x_i$(*ro x co*) represents the i[th] training image, *ro* and *co* represent the rows (height) and columns (width) of $x_i$, respectively, *N* represents the total number of training images.

- Convert all images in vector representation Z = {$z_1$; $z_2$..... $z_N$}, where the dimension of *Z* is *M x_1;M = ro x_co.*
- Calculate the mean of each class $\mu_i$, total mean of all data μ, between-class matrix SB(M _M), and within-class matrix SW(M_M) of X
- Find the *k* eigenvectors of SB with nonzero eigenvalues, and denote them as U =[$u_1$;$u_2$......$u_k$](i.e. $U^T S_bU > 0$). (9)
- Calculate the eigenvalues and eigenvectors of $U^T S_WU$, and then sort the eigenvalues and discard the eigenvectors which have high values. The selected eigenvectors are denoted by *V*; thus, *V* represents the null space of $S_W$.
- The final LDA matrix (Ψ) consists of the range $S_B$ and the null space of $S_W$ as follows, Ψ =UV.
- The original data are projected on the LDA space as follows,

$$Y = X\, \Psi = XUV \quad (10)$$

## C. *Image Matching*

The image classification was done by Back-propagation neural network. The algorithm of BNN is given below. The back propagation algorithm is implemented using following steps.

- Initialize weights to small random values $W_{ih}$ ,$W_{hj}$.
- Feed input vector $X_1$,$X_2$....through Network and computing weighting sum coming into node and then apply the sigmoid function

$$S_h = (W_{ih})^T X \quad (11)$$

Where $W_{ih}$ is weights between input nodes and hidden nodes,

$S_h$ is weighting sum coming into hidden node

$$Y_h = \frac{1}{1+e^{-S_h}} \quad (12)$$

ISSN No:-2456-2165

Where $Y_h$ is probability of each hidden node for each pixel

$$S_j = (W_{hj})^T Y_h \tag{13}$$

Where $W_{hj}$ is weights between hidden nodes and output nodes,

Sj is weighting sum coming into output node

$$Y_j = \frac{1}{1+e^{-S_j}} \tag{14}$$

- Calculate error term for each output unit

$$\delta_j = Y_j(1-Y_j)(d_j - Y_j) \tag{15}$$

- Mean square error(MSE) of output node

$$e = \frac{\sum_{i=1}^{j}(d_j - Y_j)^2}{2} \tag{16}$$

- Calculate error term of each of hidden node

$$\delta_h = (W_{hj} - \delta_h)Y_h(1-Y_h) \tag{17}$$

- Adjust weights to minimize mean square error

$$W_{ih} = W_{ih} + \alpha X \delta_h + \beta(W_{ih} - W_{ih1}) \tag{18}$$

$$W_{hj} = W_{hj} + \alpha Y_h \delta_j + \beta(W_{hj} - W_{hj1}) \tag{19}$$

Repeated all the steps except 1 till MSE is within reasonable limits.

**7.** After training neural network using Training pixels, find $Y_h$ and $Y_j$ for each pixel using weights $W_{hj}$, $W_{ih}$ which is obtain from training of neural network.

8. Pixel goes in $Y_j$ class if $Y_j$ have maximum probability for this pixel. According to this all pixels of image are classified.

## V. DISCUSSION OF RESULTS

The simulation tool used was MATLAB R2012a version on Windows 7. The dataset contains 90 Face images consisting of 30 normal face, 30 angry face and 30 laughing face. Sixty of the face images were stored and are labeled known faces while remaining 30 were not stored which are labeled as unknown faces. These face images were trained and tested using 50-50 cross-validation method. The image classification system was executed with thresholds of 0.22, 0.35, 0.5 and 0.76. The results of the execution are shown in Table 1, Table 2, Table 3 and Table 4 with the performance metrics measured in percentages.

Table 1: Results of LBP-BPNN system

| Thresholds | RECALL | SPEC | FMR | FNMR | ACC |
|---|---|---|---|---|---|
| 0.22 | 71.7 | 60.0 | 40.0 | 28.3 | 67.8 |
| 0.35 | 76.7 | 70.0 | 30.0 | 23.3 | 74.4 |
| 0.5 | 85.0 | 73.3 | 26.7 | 15.0 | 81.1 |
| 0.76 | 88.3 | 80.0 | 20.0 | 11.7 | 85.6 |

Table 2: Results of PCA-BPNN system

| Thresholds | RECALL | SPEC | FMR | FNMR | ACC |
|---|---|---|---|---|---|
| 0.22 | 65.0 | 50.0 | 50.0 | 35.0 | 60.0 |
| 0.35 | 66.7 | 56.7 | 43.3 | 33.3 | 63.3 |
| 0.5 | 71.7 | 60.0 | 40.0 | 28.3 | 67.8 |
| 0.76 | 75.0 | 66.7 | 33.3 | 25.0 | 72.2 |

Table 3: Results of Gabor-BPNN system

| Threshold | RECALL | SPEC | FMR | FNMR | ACC |
|---|---|---|---|---|---|
| 0.22 | 66.7 | 53.3 | 46.7 | 33.3 | 62.2 |
| 0.35 | 68.3 | 56.7 | 43.3 | 31.7 | 64.4 |
| 0.5 | 73.3 | 63.3 | 36.7 | 26.7 | 70.0 |
| 0.76 | 78.3 | 73.3 | 26.7 | 21.7 | 76.7 |

Table 4: Results of LDA-BPNN system

| Threshold | RECALL | SPEC | FMR | FNMR | ACC |
|---|---|---|---|---|---|
| 0.22 | 68.3 | 56.7 | 43.3 | 31.7 | 64.4 |
| 0.35 | 71.7 | 60.0 | 40.0 | 28.3 | 67.8 |
| 0.5 | 76.7 | 66.7 | 33.3 | 23.3 | 73.3 |
| 0.76 | 80.0 | 76.7 | 23.3 | 20.0 | 78.9 |

The results obtained from the tables showed that maximum values were got at threshold of 0.76. The results obtained for in Table 3 Gabor filter at 0.76 threshold are Recall of 78.3% , SPEC of 73.3%, FMR of 26.7%, FNMR of 21.7% and ACC of 76.7%. The results obtained for in Table 2 for PCA at 0.76 threshold are REC of 75.0%, SPEC of 66.7%, FMR of 33.3%, FNMR of 25.0% and ACC of 72.2%. The results obtained for in Table 4 for LDA at 0.76 threshold are REC of 80.0%, SPEC of 76.7%, FMR of 23.3%, FNMR of 20.0% and ACC of 78.9%. The results obtained for in Table 1 for LBP at 0.76 threshold are REC of 88.3%, SPEC of 80.0%, FMR of 20.0%, FNMR of 11.7% and ACC of 85.6%.

Hence, it can be deduced that LBP performed the best among the four selected feature extraction techniques. The ROC graphs of Specificity vs thresholds, Recall vs thresholds, and Accuracy vs thresholds are shown in figure 6, 7 and 8 respectively.

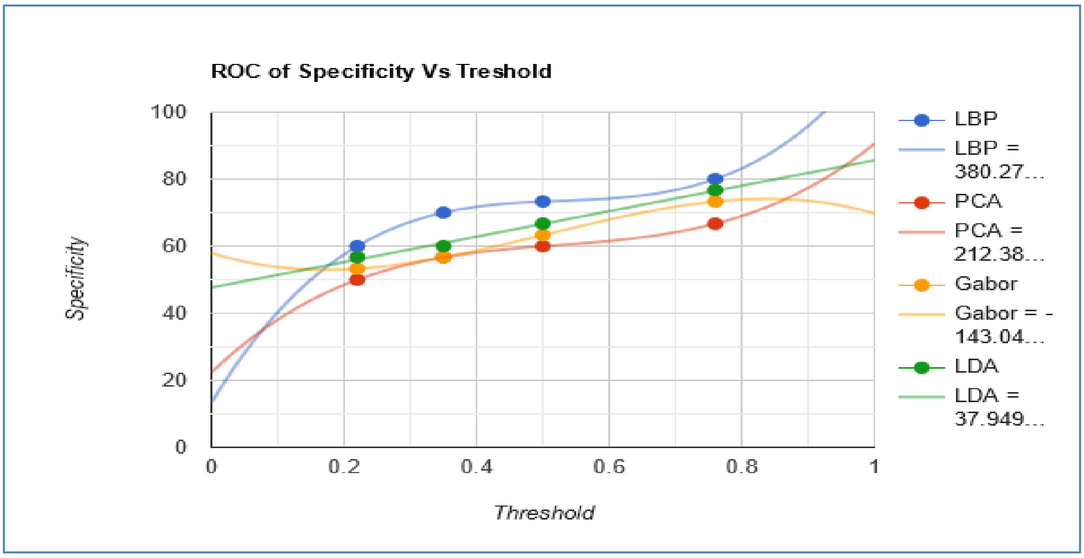


Fig. 6: ROC graph of Specificity vs Thresholds

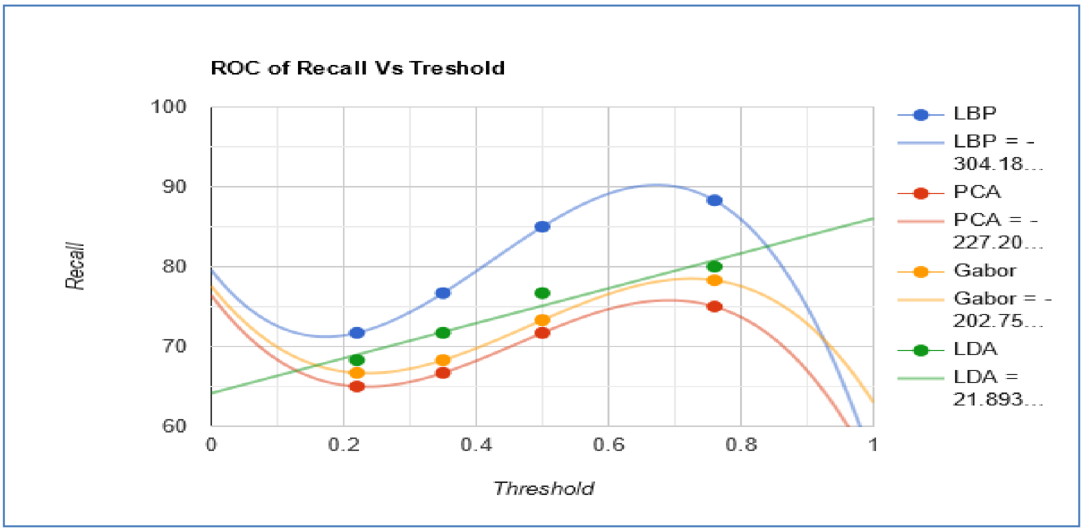


Fig. 7: ROC graph of Recall vs Thresholds

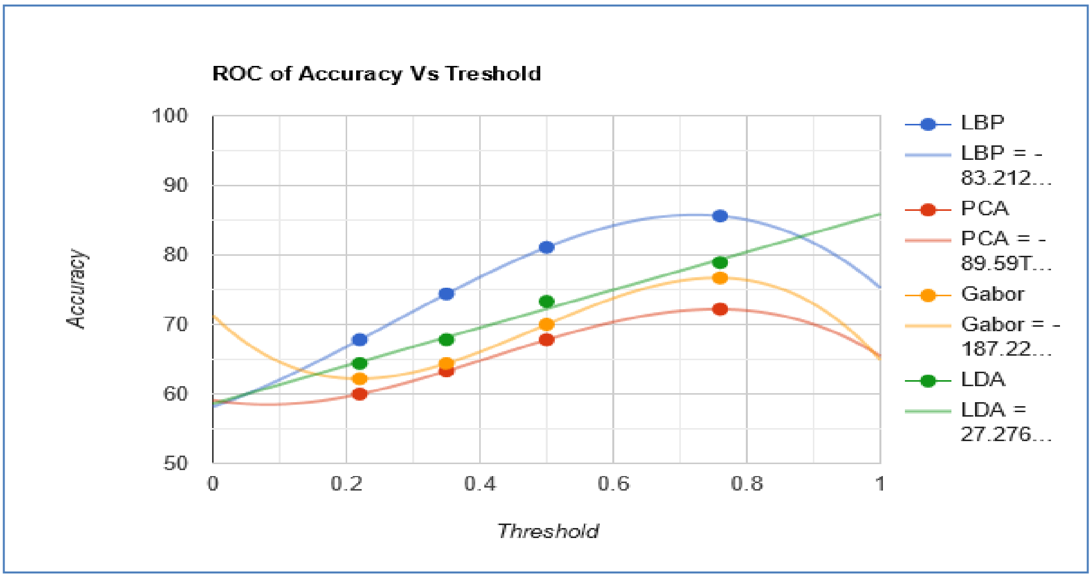


Fig. 8: ROC graph of Accuracy vs Thresholds

## VI. CONCLUSION

This paper presented an evaluation of performances of four selected feature extraction techniques viz LBP, PCA, Gabor filter and LDA). These techniques were selected based on their notable performances in image classification problems. The evaluation procedure employed four stages which are image collection, pre-processing, feature extraction and images matching. The face images were first pre-processed and then subjected to selected feature extraction techniques (LBP, PCA, Gabor filter and LDA). The extracted features were then matched with BPNN. The results of recognition accuracy produced by Gabor filter, PCA, LDA and LBP at 0.76 threshold are 76.7%, 72.2%. 78.9% and 85.6%. Hence, it can be deduced that LBP performed the best among the four selected feature extraction techniques. However, this work can be improved on by considering other notable feature extraction techniques for evaluation and also possibly improve the efficiency of any of these techniques through cascade or optimization methods.

## ACKNOWLEDGEMENT

I appreciate TETFUND for her financial support toward the successful completion of this project.

## REFERENCES

[1]. S. Akanksha, A. Saloni. S. Pushkar. M. Ankush, (2015). “Indian Sign Language Gesture Classification as Single or Double Handed Gestures”, International Conference on Image Information Processing, 2015.
[2]. R. Abbassi, A. Abbassi, A. Heidari., S. Mirjalili, (2019). An efficient salp swarm-inspired Algorithm for parameters identification of photovoltaic cell models. Energy Convers Manag 179:362–372.
[3]. E. Alpaydin, (2010). Introduction to Machine Learning. London: The MIT Press.
[4]. T. Ahonen, et al., (2004)."Face recognition with local binary patterns," Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), vol. 3021, 469-481.
[5]. A. Bansal et al., (2012). "Face Recognition Using PCA and LDA Algorithm," in Second International Conference on advanced Computing & Communication Technologies (ACCT), 2012, 251-254.
[6]. S. Balakrishnama and A. Ganapathiraju (1998). Linear discriminant analysis-a brief tutorial. Institute for Signal and information Processing.
[7]. D. Coomans,, Massart D., and Kaufman. L. (1979). Optimization by statistical linear discriminant analysis in analytical chemistry. Analytica Chimica Acta, 112(2), 97–122..
[8]. J. Cui and Y.Xu.. (2011). Three dimensional palmprint recognition using linear discriminant analysis method. In Proceedings of the second International Conference on Innovations in Bioinspired Computing and Applications (IBICA),, 107–111
[9]. R. Deepesh (2011). A Realtime Face Recognition system using PCA and various Distance Classifiers, Computer vision and processing. 5(3), 15-22.
[10]. F. Ehsan et al., (2004). "Robust Face Recognition through Local GraphMatching," Journal of Multimedia, vol. 2, 31-37.
[11]. H. R. Ekenel and R. Stiefelhagen (2006) "Analysis of Local Appearance-BasedFace Recognition: Effects of Feature Selection and Feature Normalization,"in Conference on Computer Vision and Pattern Recognition Workshop,CVPRW,, 34-34.
[12]. P. Franti, (2001). Digital Image Processing, Univ. of Joensuu, Dept. of Computer Science, Lecture notes
[13]. T. Feng .and G. Wu. (2014) A theoretical contribution to the fast implementation of null linear discriminant analysis method using random matrix multiplication with scatter matrices. arXiv preprint arXiv:1409.2579.
[14]. T. Huawei, W. Rugang and Li Z. (2016). An Enhanced Local Binary Pattern for Texture Classification, *Advances in Computer Science Research, volume 58,* Modeling, Simulation and Optimization Technologies and Applications (MSOTA 2016).
[15]. S. Hassanipour, H. Ghaem, M. Arab-Zozani, M. Seif,, Fararouei, M., Abdzadeh, E., Paydar, S. (2019). Comparison of artificial neural network and logistic regression models for prediction of outcomes in trauma patients: A systematic review and meta-analysis. *Injury*, *50*(2), 244–250. http://doi.org/10.1016/j.injury.2019.01.007.
[16]. F. M Ismaila. (2022). Hybridized Local Binay Pattern-Levyflight Firefly Algorithm based Human face Recognition Access Control System, PhD Thesis, Unpublished, Ladoke Akintola University of Technology, Nigeria.
[17]. W. O. Ismaila, A . Adetunji, A. Falohun and Iwashokun G. B. (2012). A Study of Features Extraction Algorithms for Human Face Recognition. Transnational Journal of Science and Technology, 2(6), 14-22.
[18]. S. Karamizadeh, S, Abdullah, A. Manaf., Mazdak Z., Hooman A. (2013). An Overview of Principal Component Analysis, *Journal of Signal and Information Processing*, 2013, 4, 173-175
[19]. H. E. Kim,. M. Ahn, M. Shin, and S.-H. Sim. (2019). Crack and non crack classification from concrete surface images using machine learning. *Structural Health Monitoring*, 18(3), 725–738.
[20]. C. Ki-Chung., et al., (1999). "Face recognition using principal component analysis of Gabor filter responses," in International Workshop on Recognition, Analysis, and Tracking of Faces and Gestures in Real-Time Systems, Proceedings, 53-57.
[21]. P. Lo (2007). "Dynamic local feature analysis," *Biometric Technology Today*, vol. 15, 8-8.
[22]. J. Lu,, K. Plataniotis. and Venetsanopoulos. A. N. (2003). Face recognition using lda-based algorithms. IEEE Transactions on Neural Networks, 14(1):195–200.

[23]. J. A. Mohamed (2016). Classification Using Two Layer Neural Network Back Propagation Algorithm, Circuits and Systems, 7, 1207-1212.

[24]. D. Murugan, *et al. (*2010) "Performance Evaluation of Face Recognition UsingGabor Filter, Log Gabor filter and Discrete Wavelet Transform,"*International Journal of Computer Science & Information Technology,* vol. 2, pp. 125-133.

[25]. A. Majumder, Chowdhury S, Sil J. (2015).Gabor Filter Based Face Recognition Using Non-frontal Face Images, Conference Paper · August 2015, WCI '15, August 10 - 13, 2015, Kochi, India. 419-425.

[26]. D. .Murugan *et al. (*2010) "Performance Evaluation of Face Recognition UsingGabor Filter, Log Gabor filter and Discrete Wavelet Transform,"*International Journal of Computer Science &* Information Technology, vol. 2, 125-133.

[27]. S., Muhammad et al (2007)., "Face Recognition using Gabor Filters," Journal of Applied Computer Science & Mathematics, vol. 5, 53-57..

[28]. J. Mazanec, *et al.*, (2008). "Support vector machines, PCA and LDA in face recognition," *Journal of electrical engineering -electrotechnickycasopis,* vol. 59, pp. 203-209.

[29]. J. Mazanec *et al.*, (2008). "Support vector machines, PCA and LDA in face recognition," *Journal of electrical engineering -electrotechnickycasopis,* vol. 59, pp. 203-209.

[30]. A. Martinez . and A. Kak (2001). "PCA versus LDA," *Pattern Analysis and Machine Intelligence, IEEE Transactions on,* vol. 23, pp. 228-233.

[31]. T. Ojala, M. Pietikainen and Harwood D., (1996). "A comparative study of texture measures with classification based on feature distributions" Pattern Recognition vol. 29, 1996.

[32]. F. Pan,, Song, G. Gan, X. and Gu. Q. (2014). Consistent feature selection and its application to face recognition. Journal of Intelligent Information Systems, 43(2):307–321.

[33]. P. B. Purwanta, Adi C. K., Dewi N. P.(2020). Backpropagation Neural Network for Book Classification Using the Image Cover, International Journal of Applied Sciences and Smart Technologies, 2(2), 179–196.

[34]. S. M. Prakash. and Kalpna C. J., (2011). "Face Recognition Using PCA," International Journal of Artificial Intelligence & Knowledge Discovery, vol. 1, pp. 25-28.

[35]. P. J. Phillips*., et al.*, (1998). "The FERET database and evaluation procedure for face recognitionalgorithms," *Image and Vision Computing,* vol. 16, pp. 295-306.

[36]. C. Ruchi (2015). Facial Expression Recognition Using Facial Movement Features, Coputer Science & Engineering, India, vol. 4 Issue 4, 2318 – 2324

[37]. M. Remzi, T. Anagnostou, V. Ravery, Zlotta, A., Stephan, C., and Marberger, M. (2003). An artificial neural network to predict the outcome of repeat prostate biopsies. Urology, 62(3), 456–460. http://doi.org/10.1016/s0090-4295(03)00409-6.

[38]. M. Shen, et al., (2012). "Independent component analysis for face recognition basedon two dimension symmetrical image matrix," in 24th Chines Control and Decision Conference (CCDC, pp. 4145-4149.

[39]. P. B. Saurabh. and D. S. Chaudhari (2012). "Principal Component Analysis for Face Recognition," International Journal of Engineering and Advanced Technology, vol. 1, pp. 91-94.

[40]. A.Singh, N. Thakur, and A. Sharma. (2016). A review of supervised machine learning algorithms. In: *3rd International Conference on Computing for Sustainable Global Development (INDIACom),* 1310–1315. New Delhi, India.

[41]. Sarangi, S, Sahidullah, M,; Saha, G. (2020). "Optimization of data-driven filterbank for automatic speaker verification". Digital Signal Processing. 104. arXiv:2007.10729. doi:10.1016/j.dsp.2020.10279 5.

[42]. P.Sharma, P. Hans, and S. C. Gupta. (2020). Classification of plant leaf diseases using machine learning and image preprocessing techniques. In: *10th International Conference on Cloud Computing, Data Science Engineering (Confluence)*, 480–484. Noida, India.

[43]. M. Ture, I. Kurt, Turhan Kürüm, A., and Ozdamar, K. (2005). Comparing classification techniques for predicting essential hypertension. Expert Systems with Applications, 29(3), 583–588. http://doi.org/10.1016/j.eswa.2005.04.014.

[44]. V. Tyagi (2013). Understanding Digital Image Processing, CRC Press Taylor & Francis Group,.

[45]. L. Wiskott, et al (1997). "Face recognition by elastic bunch graph matching,"Pattern Analysis and Machine ntelligence, IEEE Transactions on, vol. 19, 775-779.

[46]. Wu, M. C, Zhang, L., Wang, Z.,. Christiani, D. C and Lin. X. (2009). Sparse linear discriminant analysis for simultaneous testing for the significance of a gene set/pathway and gene selection.Bioinformatics, 25(9):1145–1151.

[47]. N. Yassin, S.. Omran, E. El Houby, and H. Allam. (2017). Machine learning techniques for breast cancer computer aided diagnosis using different image modalities: A systematic review. *Computer Methods and Programs in Biomedicine*, 156, 25–45.

[48]. Viszlay, M. Lojka, and Juh´ar J. (2014). . Class-dependent two dimensional linear discriminant analysis using two-pass recognition strategy. In Proceedings of the 22nd European Signal Processing Conference (EUSIPCO), 1796–1800. IEEE.