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A Gender Recognition System Using Facial Images with High Dimensional Data

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Abstract

Gender recognition has been seen as an interesting research area that plays important roles in many fields of study. Studies from MIT and Microsoft clearly showed that the female gender was poorly recognized especially among dark-skinned nationals. The focus of this paper is to present a technique that categorise gender among dark-skinned people. The classification was done using SVM on sets of images gathered locally and publicly. Analysis includes; face detection using Viola-Jones algorithm, extraction of Histogram of Oriented Gradient and Rotation Invariant LBP (RILBP) features and trained with SVM classifier. PCA was performed on both the HOG and RILBP descriptors to extract high dimensional features. Various success rates were recorded, however, PCA on RILBP performed best with an accuracy of 99.6% and 99.8% respectively on the public and local datasets. This system will be of immense benefit in application areas like social interaction and targeted advertisement.

Keywords: Rotation Invariant Local Binary Pattern, Gender Recognition, Facial images, Histogram of Oriented Gradients, Principal Component Analysis

Introduction

Social interaction among people is always influenced by facial characteristics (Deokar, Patankar, & Kulkarni, 2018), with the changing world of visual technology, the challenge lies in the ability to automatically extract these facial features. Identifying human attributes such as gender, age, ethnicity is important and considered to be a challenging problem in many computer applications such as human-computer interaction (HCI), biometrics, surveillance, targeted advertisement, and demographic studies, gender recognition, etc. (Ng, Tay, & Goi, 2012).

Gender recognition plays important role in many fields and can be applied in a surveillance system, HCI, demographic research, commercial development, mobile application, and video games (Lin, Wu, Zhuang, Long, & Xu, 2015). For humans, it is quite easy and fast to identify and differentiate gender as we can easily tell by seeing a person's eye, mouth, ears, and nose whether that person is a female or male but this is a challenging task in computer vision. To solve this, a computer needs to be programmed in a way it can perform the task of recognition like a human.

The human brain has learned over the years from the environment, lessons learned from school, and even information acquired from books to mention but a few. Hence the need to train the machine to be as intelligent as the human brain. The human face can show many characteristics as gender, age and emotion, etc.

Gender classification aims to recognize the gender of an individual based on the characteristics that differentiate between masculinity and femininity (Lin et al., 2015). Facial analysis has recently been seen as a desirable area for research (Patel & Degadawala, 2020), especially in computer vision. The strong features of a human face make it a focus on gender classification (Mahmoud & Abdelrahman, 2019). Gender recognition methods can be divided into those that rely on handcrafted features and trainable (Foggia, Greco, Percannella, Vento, & Vigilante, 2019), features as color, texture, and shape and are identified as the main factors in distinguishing male and female. Detection of facial features such as mustache, earrings, make-up, eyes, and beards is very challenging due to variation in pose, illumination, occlusions, and facial expression(George Azzopardi, Greco, & Vento, 2016).

According to Wojcik and Remy (2019), a common limitation of most gender classification systems is the inability to account for individuals who are neither male nor female but beyond the limitations, training data used in training models are of great importance since they help in determining overall accuracy. A study from MIT and Microsoft researchers provides more evidence of exactly how bad facial-recognition is at accurately identifying dark-skinned faces especially when those faces belong to women (Josh, 2018). In a test to identify the gender of people from their faces, it was able to do so with more than 99% accuracy for light-skinned women and 65% accuracy for dark-skinned women. It was also reported that 1,270 faces were gathered, drawn from images of lawmakers in African countries, while three were Nordic countries. The researchers ran the images against facial recognition software from three providers and the results showed that darker-skinned females are the most misclassified group (with error rates of up to 34.7%). The maximum error rate for lighter-skinned males was 0.8%. The substantial disparities in the accuracy of classifying darker females, lighter females, darker males, and lighter males in gender classification systems require urgent attention if commercial companies are to build genuinely fair, transparent, and accountable facial analysis algorithms.

Most researchers perform gender and face recognition using facial analysis (Martins Ekata Irhebhude, Celestine, & Aget, 2019; Ng et al., 2012). Classifying selected facial images of Kaduna residence in northern Nigerian of varying age groups with challenging circumstances such as females wearing a scarf with or without makeup is the focus of this work. Datasets were gathered and used for the experiments. For classification, the Viola-Jones detection algorithm (Alionte & Lazar, 2015) was used for face detection while histogram oriented gradient (HOG) (Martins Ekata Irhebhude et al., 2019) and rotation invariant local binary pattern was used for feature extraction. The principal component analysis (PCA) was used for the discovery of high dimensional data from the selected features with a support vector machine (SVM) for the classification. Several classifiers have been used for gender recognition such as SVM, Neural Networks, Bayesian Classifiers, etc the SVM is the most widely used gender classifier (Ng et al., 2012), it works with the domain knowledge associated with facial features which distinguish male from females. Compared to another method of recognition such as the deep learning approach, SVM was chosen for this research because of the ease of use, less demand for computer resources, and compatibility with most system architectures.

There are different ways and traits which can help to differentiate among humans (Falohun, Fenw, & Ajala, 2016). Gender classification aims to recognize and identify a person's gender as either male or female. Several approaches including deep learning have been explored for gender recognition (Lawal, Akinrinmade, & Badejo, 2019).

Studies in (Abdullah, Rahman, Abas, & Saad, 2016; Falohun et al., 2016; Iloanusi & Ejiogu, 2020); Patel and Degadawala (2020); (Rekha, Gurupriya, Gayadhri, & Sowmya, 2019;

Wedpathak, Kadam, Kadam, Mhetre, & Jankar, 2018) used fingerprints and facial images as inputs for the classification of gender. Various success rates were recorded.

Authors in Mahmoud and Abdelrahman (2019) combined isolated and reliable facial components and contextual features such as hair (foggy face) and clothes. These features were trained with four datasets using deep CNN with AdaBoost-based fusion scorer to get the final classification decision.

Another classification work was done with Autonomous robots designed by authors in Foggia et al. (2019) to interact with and recognize the gender of customers in shopping centers.

A face-based gender analysis recognition system was developed by authors in Lawal et al. (2019) using a dataset consisting of over 6000 images of Nigerian faces from different tribes and under varying conditions. Standard CNN architecture was used for both extraction and classification in other to achieve 98.72% validation accuracy in gender classification. The methodical approach adopted by the authors was not clear and the result presentation was very poor. The methodology adopted was vague and irreplicable, hence this study.

According to Guangjun, Wei, and Yaoxin (2016) proposed use of facial measurements for gender recognition combining depth gradient with a distance of facial features. The recognition model was trained using a random forest algorithm and evaluated on a public face database. Although the algorithm proposed was not ideal for changing face pose, they recommended future research to correct the changes and reduce the effect of occlusion.

Studies in Linder, Wehner, and Arras (2015) proposed a real-time full-body tessellation learning approach for gender classification in 3D data achieving 91% accuracy for people standing and 87% with people walking. The authors were able to solve the problem associated with difficulty in recognizing gender from side and back view.

A survey of methods used in gender classification in still images and video using computer techniques was carried out by authors in Ng et al. (2012) focusing on observable characteristics of humans. In tackling challenges faced in terms of clothing, accessories, and hairstyles they suggested using classifiers that are robust to variation, pose, articulation, and occlusion of the body. The authors concluded that in cases where facial analysis is not suitable, the whole-body image can be used.

According to studies in Dhomne, Kumar, and Bhan (2018), authors proposed an efficient technique to speed up the recognition process in real-time gender recognition using the D-CNN method, the authors used the VGGNet with celebrity dataset to obtain an improved overall accuracy of 95% in gender prediction.

According to Wojcik and Remy (2019), trained models on diverse sets of data to classify images of people as men or women based on their outward physical appearances achieving 87% accuracy result.

Authors in Kumar, Singh, and Kumar (2019) proposed a new algorithm for automatic live gender recognition based on facial images. In the paper, SVM was used for the classification and Scale-Invariant Fourier Transform (SIFT) descriptor for feature extraction. The implementation of the result was tested on the FEI dataset. Combination Of Shifted Filter Responses (COSFIRE) was used for keypoint detection and pattern recognition by G Azzopardi and Petkov (2013).

Studies in George Azzopardi et al. (2016) proposed a method that combines domain-specific and trainable features to recognize gender using face images. Viola-Jones algorithm was applied to the input image, the COSFIRE and SURF based descriptors find and extract different features and properties in the human face and use these features to distinguish between faces of men and women. The recognition rate of 94.7% and 99.4% were achieved on the GENDER FERET and LFW dataset used for the experiment. The authors also evaluated the method on new datasets of live scenarios achieving a high accuracy rate of 91.5%, in comparison to the SURF method the COSFIRE filters are the most effective and can be applied in any visual pattern recognition problem.

Authors in Nguyen and Park (2016) used HOG and weighted HOG to classify the gender of people using visible and thermal images as input. This study used the full body of a human as input to classify gender. Accuracies obtained were not up to a 90% recognition rate even when PCA was applied on the extracted features. This may not be unconnected with the fact that human structure alone cannot help determine the gender of a person.

Studies in Shervan (2019) showed that improved local binary patterns (LBP) texture descriptors helped enhance the accuracy obtained for gender recognition. Issues such as noise sensitivity, rotation sensitivity, and low discrimination were handled by improved LBP. Five (5) different classifiers were used for the experiment with a k-nearest neighbor (KNN) giving the highest recognition accuracy of 94.17%.

In Lian and Lu (2006) authors presented a novel multi-view gender classification approach with LBP texture as features and SVM as classifier. LBP histogram was extracted from the divided face area of the selected face and concatenated to form the feature vector. Results obtained showed that the proposed technique recorded an accuracy of 96.75%.

According to a study conducted in Annalakshmi, Roomi, and Naveedh (2019), researchers proposed a spatially enhanced LBP and HOG as feature techniques for the recognition of gender in varying challenging circumstances using an SVM classifier. Authors combined SLBP and HOG as a hybrid feature to show the effectiveness of combining texture and local shape features to adequately represent the human face for gender categorization. Good recognition rates of 99.1% and 95.7% were obtained from two publicly available datasets of FERET and LFW respectively.

Authors in Vandna, Vinod, and Bhupendra (2013) compared the performance of LBP and HOG feature extraction algorithms on Indian faces. Results obtained using the SVM classifier showed that HOG performed better than LBP when used as features for gender classification with a recognition accuracy of 95.56%.

From the reviewed literature, not known work has been done on facial images with occlusion, people using a scarf, young and old faces among dark-skinned people within the northern region of Nigeria. Also, most studies focused on classification without necessarily looking at the impact of the skin color of the human face under consideration. The proposed method focused on classifying dark and light-skinned faces and determine the impact principal component analysis (PCA) plays on the selected features in the classification of the human face into male or female respectively.

Methodology

The methodology contains the standard gender classification system, the proposed methodology, datasets used for the experiments, and detailed descriptions of the methods adopted for the study.

Figure 1 shows the general classification framework for gender recognition (Lin et al., 2015) consisting of five blocks including sensing, data preprocessing, feature extraction, gender classification, and performance evaluation.

Figure 1: General classification Framework

Sensing: this is the first step in gender recognition, it involves obtaining raw data using specific sensors including cameras.

Data preprocessing: preprocessing is a process done to improve the quality of raw data, it includes extraction of information needed, face detection, removal of noise and unwanted information from raw data which leads to improvement in recognition result.

Feature Extraction: this block minimizes the data and extracts necessary features from the preprocessed results which would be used for classification.

Gender Classification: classification is done with the help of patterns extracted from the facial images(Martins Ekata Irhebhude et al., 2019), after which they are classified as male or female. Several types of classifiers can be used for gender recognition such as SVM, K-nearest neighbors (KNN) (Peterson, 2009).

Performance Evaluation: in evaluation, the system measures items such as accuracy. Accuracy is the most important standard; it refers to the probability of correct recognition as either male or female.

The block diagram of the proposed system is shown in figure 2. This proposed system follows the standard gender classification framework in figure 1. In implementing the gender recognition system, a database of facial images was captured. Methodological steps are capture image, face detection, and image cropping, feature extraction, and classification.

Two different sets of face datasets were used in this study: Images of Groups Dataset (IOG) (Gallagher & Chen, 2009) and self-captured (LocalDataset) dataset.

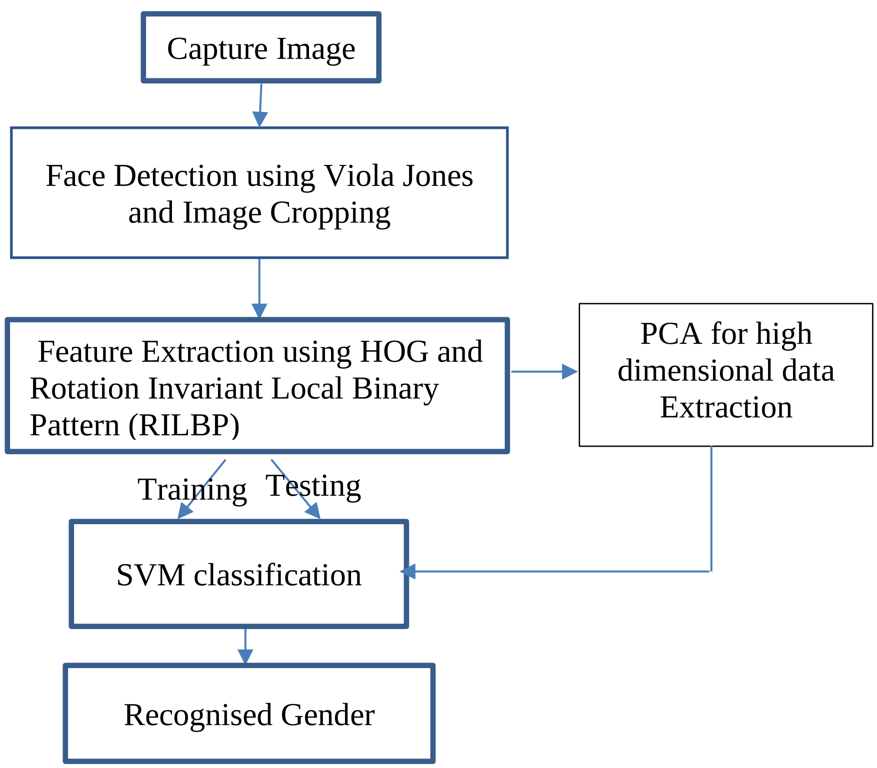


Figure 2: Proposed Methodology

IOG Dataset

The IOG dataset consists of different data-files with 28,231 images, for our experiment we 1344 images. The images consist of a group of people in a family portrait, group portrait, group photo, wedding groom, and bride portrait. The images had different varieties with some people sitting, lying, standing on elevated surfaces and some have dark glasses, unusual facial expressions, and face occlusions. Figure 3 shows sample images used for the experiment from the IOG dataset.

Figure 3: Random sample images from the IOG dataset

LocalDataset

The Local Dataset consists of collections of 305 images of individuals in passport-sized photographs and 299 images from groups of people in a birthday party locally captured from Kaduna residents in the northern part of Nigeria. The images have a unique mix of the age range (infants to adulthood) and positioning with some of the people with scarfs, caps, makeup, and unusual facial expressions. Figure 4 shows some sample images from the LocalDataset used for the experiment.

Figure 4(a): Random sample images of LocalDataset selected from passport sized photographs

Figure 4(b): Random sample images of LocalDataset selected from Birthday Party

Face Detection

This is the first step in the classification and recognition system, the captured image serves as raw input data. Face detection is important in other to identify the human face from the images, using the Viola-Jones algorithm (Alionte & Lazar, 2015) for face detection, the MATLAB cascade objector detector is applied on the input images this creates the detector that detects the face from the raw input image the following command is used:

faceDetectorVariable = vision.CascadeObjectDetector

After the detector is created the next step is defining the bounding box around the detected objects, this is done by the following syntax:

BoundingBoxVariable = step (faceDetectorVariable, image_input_varableName)

This command returns the BoundingBox Variable containing the regions of detected faces in the image. The detected faces were cropped and resized so that they have the same dimension to use the result to experiment. See Figures 5 and 6 for samples of detected and cropped faces

Figure 5(a): Sample of detected faces from IOG dataset

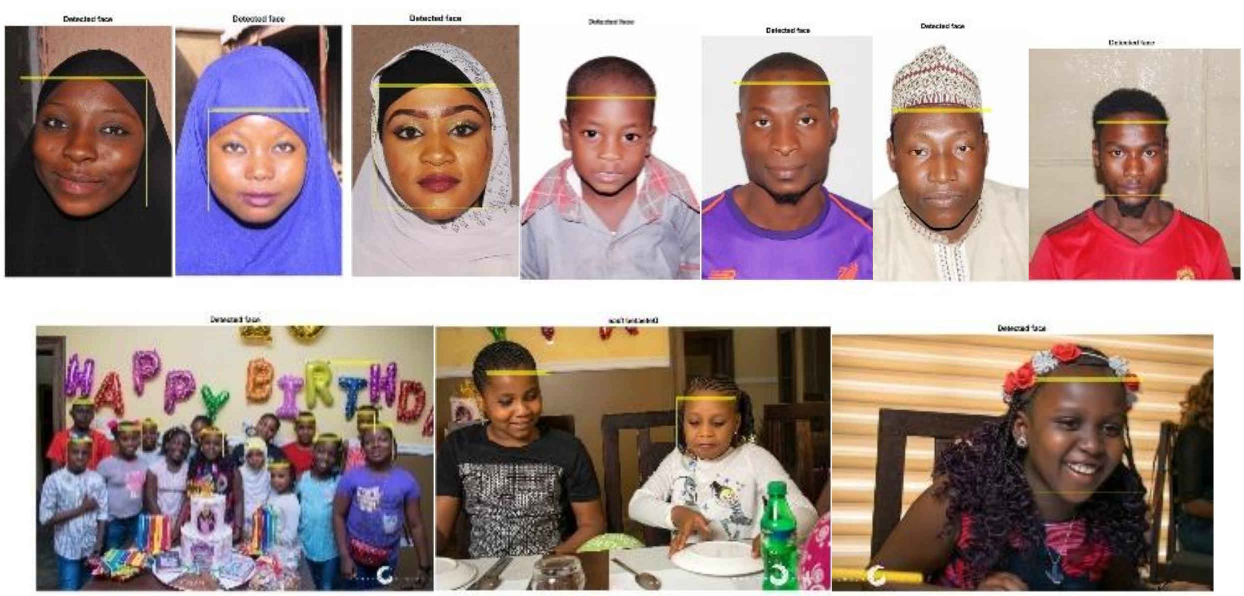


Figure 5(b): Sample detected faces from Local dataset

Figure 6(a): Cropped male and female sample faces from IOG dataset

Figure 6(b): Cropped male and female sample faces from LocalDataset

Feature Extraction

The feature extraction process transforms the raw images of the detected faces into numerical features. The features were extracted from the cropped detected faces. This process is performed to store discriminative information about each face in a compact feature vector. Mostly used features for gender recognition are pixel intensity values also known as raw features, Local Binary Pattern (LBP)(Lian & Lu, 2006) descriptor, fiducial distance (George Azzopardi et al., 2016), and Histogram of Oriented Gradient (HOG) (Annalakshmi et al., 2019; Nguyen & Park, 2016; Vandna et al., 2013). Because of popularity and efficiency, two descriptors were used as features for gender recognition in this study; Histogram of Oriented Gradient (HOG) (Dalal & Triggs, 2005) and Rotation Invariant Local Binary Pattern (RILBP) (Shervan, 2019).

Rotation Invariant Local Binary Pattern (RILBP)

As reported by Ahonen, Matas, He, and Pietikainen (2009), the LBP operator is a texture descriptor that labels image pixels by 3×3-neighborhood threshold with center value summed by powers of two.

RILBP is the extension of LBP through the use of different neighborhood sizes (see figure 7). This is achieved by a circular neighborhood denoted by (P, R), where *P* is the number of points sampled and *R* is the radius of the neighborhood. These points *P* lie at coordinates (x, y); such that

$$(x_P, y_P) = (x + Rcos\left(\frac{2\pi p}{P}\right), y - Rsin\left(\frac{2\pi p}{P}\right)) \tag{1}$$

If the point does not fall at coordinates, the pixel value is bilinearly inserted.
LBP label for the center pixel (x, y) of image $f(x, y)$ is obtained through:

$$LBP_{P,R}(x, y) = \sum_{p=0}^{P-1} s\big(f(x, y) - f(x_P, y_P)\big)2^P \tag{2}$$

where $s(t)$ is the thresholding function

$$s(t) = \begin{cases} 1, t \geq 0 \\ 0, t < 0 \end{cases} \tag{3}$$

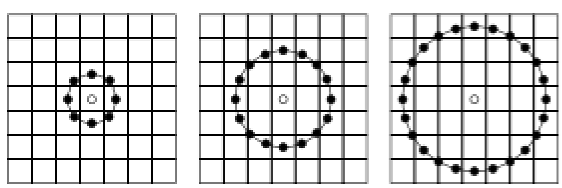


Figure 7: Three circular neighborhoods: (8,1), (16,2), (24,3) (Ahonen et al., 2009)

Histogram Oriented Gradient (HOG)

As reported in Martins Ekata Irhebhude et al. (2019), HOG features represent the structure of an object. HOG is used as a feature extraction technique that expresses information about the direction of curvatures of an image. It captures information about the local edge and gradient structures and maintains invariance in illumination, shadowing, and rotation. HOG is implemented by dividing the image into smaller regions named cells and accumulating each local cell's $1 - D$ histogram of gradient directions over each pixel. It works by counting the occurrences of gradient orientation in the localized portion of the image window. HOG features capture object appearance and shape through the capturing of the distribution of local intensity gradients (Martins Ekata Irhebhude, 2015).

The local edge and gradient structures form a representation that is contrast normalized to ensure illumination invariance. The gradient is calculated by applying a $[-1; 0; 1]$ and $[-1; 0; 1]^T$ in horizontal and vertical directions of the image. The gradient information is collected from each local cell's histogram using tri-linear interpolation. On the overlapping blocks composed of neighboring cells, as shown in figure 8.

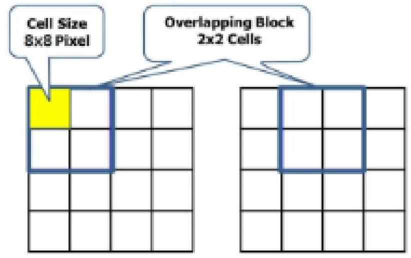


Figure 8: Cells and Overlapping Blocks

Support Vector Machine (SVM)

In Martins Ekata Irhebhude et al. (2019), SVM is described as a discriminative classifier defined by a separating hyperplane. It is a supervised learning algorithm that outputs an optimal hyperplane that categorizes new examples. SVM builds a supervised learning algorithm that is used for classification and regression analysis. SVM builds a hyperplane that has *n*-dimensional parameters *w* and *b*, which are used for classification. SVM can be used for both binary and multi-classification.

According to Lian and Lu (2006), given a labeled set of *M* training samples (f_i, l_i) where $f_i \in R^N$ and l_i is the associated label ($l_i \in \{-1,1\}$), a SVM classifier finds the optimal hyperplane that correctly separates the training data while maximizing the margin. A discriminant hyperplane is defined thus:

$$d(x) = \sum_{i=1}^{M} l_i \alpha_i . k(f, f_i) + b$$

where $k(.,.)$ is a kernel function, *b* is a bias and the sign of $d(x)$ determines the class membership of f. To construct an optimal hyperplane is equivalent to finding all the nonzero α_i and is formulated as a quadratic programming problem with constraints.

For a linear SVM, the kernel function is a dot product in the input space while nonlinear projects to higher dimensional feature space using mapping function $\phi: R^N \to F^M$, where $M \gg N,$ and then constructs a hyperplane in *F*. As reported in Lian and Lu (2006), Mercer's theorem can simplify the projected higher dimensional samples using the function $k(f, f_i) = \phi(f).\phi(x_i)$, where ϕ is the nonlinear projection function. Kernel functions such as polynomials and radial basis functions satisfy Mercer's theorem and have been used successfully in nonlinear SVMs:

$$k(f, f_i) = ((f . f_i) + 1)^d$$
$$k(f, f_i) = exp(-\gamma|f - f_i|)^2$$

where d is the degree in a polynomial kernel and γ is the spread of a Gaussian cluster.

Principal Component Analysis (PCA)

To reduce feature space, the cropped images were reduced to 42×42 image sizes before HOG features were extracted, resulting in a total of 576 feature dimensions. Rotation Invariant Local Binary pattern (RILBP) (Ahonen et al., 2009) is a way of texture description, it is applied on the entire image and compares the intensity value of each center pixel with 3×3 block neighborhood. Similar to the HOG descriptor, the RILBP features were extracted from the input image and trained with the SVM classifier to obtain recognition accuracy results.

To improve classification accuracy, the Principal Component Analysis (PCA) was applied to extract the high dimensional features, it linearly transforms predictors to remove redundant dimensions, and generates a new set of variables called principal components. The PCA was applied on both the HOG and RILBP descriptor and also trained with the SVM classifier to obtain the accurate result. The following PCA algorithm was applied on the extracted HOG and RILBP features.

PCA Algorithm:

Subtract mean from feature data.
Calculate the covariance matrix.
Compute eigenvectors of the covariance matrix.
Sort eigenvectors by corresponding eigenvalues.
Sorts the vectors.
Captured variance is given by eigenvalues.
Sorted eigenvectors = principal components (PCs)
Project data onto space spanned by PCs.
Matrix containing eigenvectors
Multiplication with feature data matrix.

Results and Discussion

Our technique was evaluated using two datasets; LocalDataset and IOG datasets. For classification SVM classifier was used. SVM is a technique used to train classifiers, regressors, and probability densities, it can be used for both binary and multi-classification tasks (Martins E. Irhebhude, Odion, & Chinyio, 2016). SVM builds a supervised learning algorithm that is used for classification and regression analysis. For training and testing, 70% and 30% were used for all four descriptors; RILBP, PCA on HOG, PCA on RILBP, and HOG, also known as models 1, 2, 3, and 4 respectively. The following parameters were used for training the classifier: preset: Quadratic SVM, kernel function: Quadratic, kernel scale: Automatic, Box Constraint level: 1, Multiclass method: one-vs-one, and standardized data: true.

Experiments were conducted on the IOG and LocalDataset datasets to evaluate the performance of the proposed technique. To evaluate the technique, confusion matrix, and Receiver Operating Curve (ROC), True positive Rate (TPR), False-negative Rate (FNR) were used.

Given a classifier and an instance, there are four possible outcomes. If the instance is positive and it is classified as positive, it is counted as a True Positive (TP); if it is classified as negative, it is counted as a False Negative (FN). If the instance is negative and it is classified as negative, it is counted as a True Negative (TN); if it is classified as positive, it is counted as a false positive (FP)

ROC Curve: The ROC curve is plotted with TPR against the FPR where TPR is on the y-axis and FPR is on the x-axis. It tells how much the model is capable of distinguishing between classes (Narkhede, 2018). The range is usually between 0 and 1. The closer the value is to 1 the better.

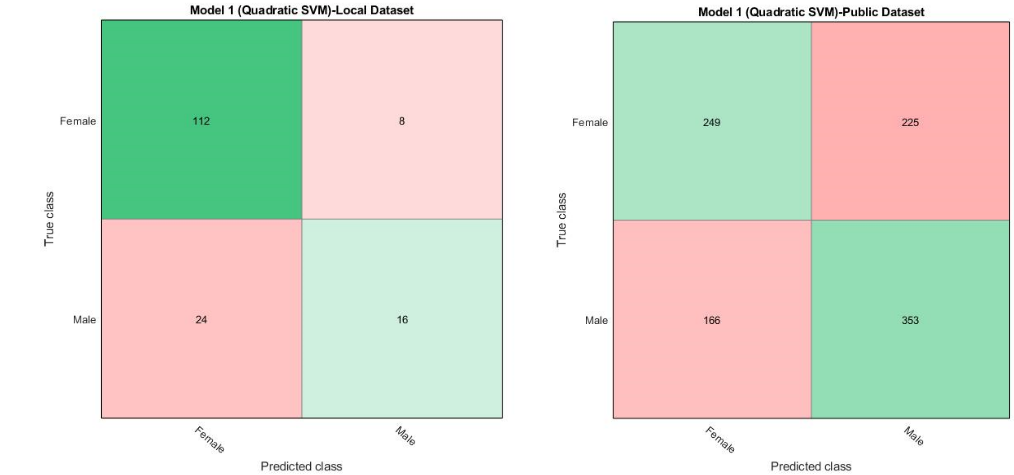
True Positive Rate: TPR is the proportion of all negatives that still yield positive test outcomes, TPR is also called hit rate and recall (Fawcett, 2006). The closer the value is to 1 the better. TPR is given as in equation 4

$$TPR = \frac{TP}{(TP+FN)} \quad (4)$$

False Negative Rate: FNR is the proportion of positives that yield negative test outcomes with the test. The closer the value is to zero the better. FNR is given as in equation 5.

$$FNR = \frac{FN}{(TP+FN)} \quad (5)$$

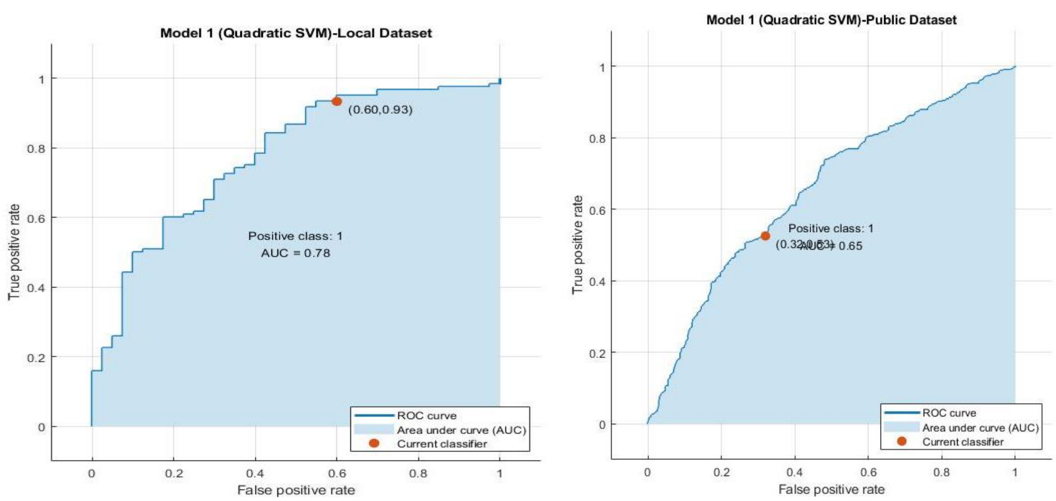
Model 1: RILBP Features– The model had an overall recognition accuracy rate of 79.4% and 60.6% for LocalDataset and IOG Datasets, figures 9 and 10 shows result for confusion matrix and ROC curves respectively.



(a) LocalDataset (b) IOG Dataset

Figure 9: Confusion matrix per number of observations for Recognition using RILBP Features

Figure 9 is the confusion matrix indicating the number of observations in recognition performance when RILBP was used as features, in each cell (figure 9a), 112 females and 16 males' observations were correctly predicted with 32 wrongly predicted cases, while 249 females and 353 males (figure 9b) observations were correctly predicted with 391 wrongly predicted cases.

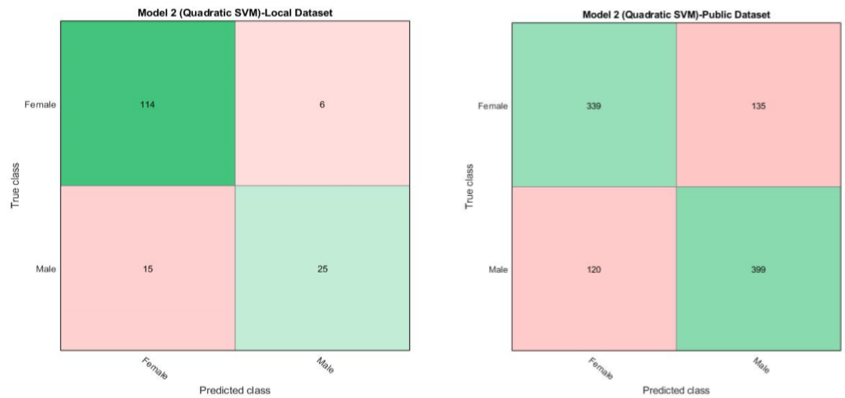


(a) LocalDataset (b) IOG Dataset

Figure 10: ROC Curves for Recognition Performance using RILBP Features

Figure 10 shows the ROC curves for recognition performance on LocalDataset (figure 10a) and IOG dataset (figure 10b) when RILBP was used as features. The curve is plotted as TPR versus FPR, the Area Under Curve (AUC) is a measure of the overall performance of the classifier. It can be seen that AUC is 0.78 showing the overall performance of the SVM classifier on RILPB faces at 78%, which indicates good performance. FPR and TPR of 0.60 and 0.93 shows that 60% of observation was assigned incorrectly to the female class while 93% of observation is classified correctly to the female class (figure 10a). Similarly, an AUC of 0.65 indicated a 65% performance rate. FPR and TPR of 0.32 and 0.53. showed that 32% of observation was assigned incorrectly to the female class while 53% of observation was classified correctly to the female class (figure 10b)

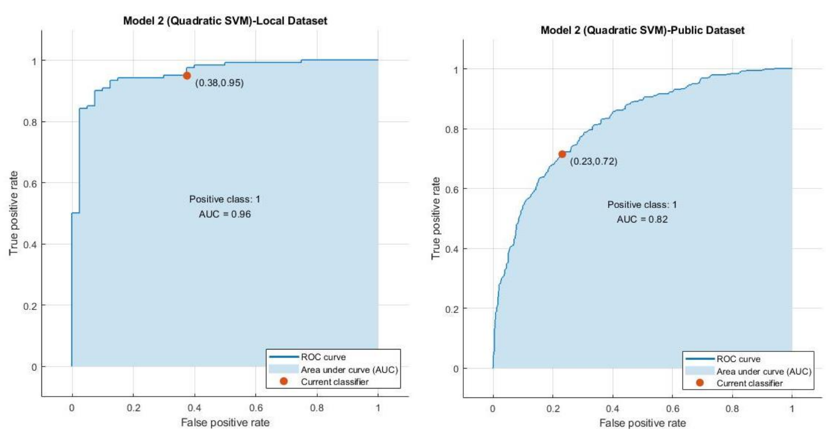
Model 2: PCA on HOG - the PCA on HOG had an overall recognition accuracy of 75.2% and 74.3% for LocalDataset and IOG Datasets, with results for confusion matrix and ROC curve shown in figures, 11 and 12 respectively.



(a) LocalDataset (b) IOG Dataset

Figure 11: Confusion matrix per number of observations for Recognition using PCA on HOG Features

Figure 11a shows a confusion matrix with the number of observations indicated in each cell for the experiment conducted when PCA was performed on HOG extracted features, 114 females and 25 male observation were predicted correct, while 15 out of the 40 males were predicted as female and 6 out of the 120 females were predicted as males (figure 11a). On the IOG Dataset, 339 females and 399 male observations were predicted correct, while 120 out of the 510 males were predicted as female and 135 out of the 474 females were predicted as males (figure 11b). The results showed that the classifier had a good performance.

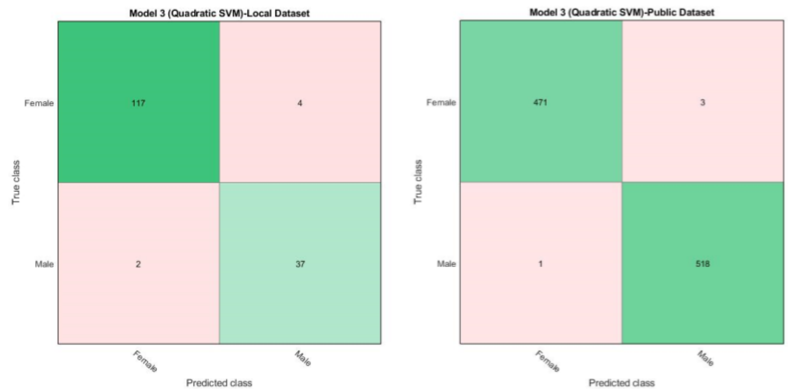


(a) LocalDataset (b) IOG Dataset

Figure 12: ROC Curves for Recognition Performance using PCA on HOG Features

Figure 12 shows the ROC curves for LocalDataset and IOG Datasets experimental performance when PCA was computed on HOG and used as features. It can be seen that AUC is 0.96 showing the overall performance of the SVM classifier on PCA on HOG faces at 96%, which indicated an excellent performance. FPR and TPR of 0.38 and 0.95 showed that 38% observation was assigned incorrectly to the female class while 95% observation is classified correctly to the female class (figure 12a). Similarly, figure 12b AUC is 0.82 showing the overall performance of the SVM classifier on PCA on HOG faces at 82%, which indicated an excellent performance. FPR and TPR of 0.23 and 0.72 showed that 23% observation was assigned incorrectly to the female class while 72% observation is classified correctly to the female class.

Model 3: PCA on RILBP - the PCA on RILBP had an overall recognition accuracy of 99.8% and 99.6% for LocalDataset and IOG Datasets, with results for confusion matrix and ROC curve shown in figures, 13 and 14 respectively.

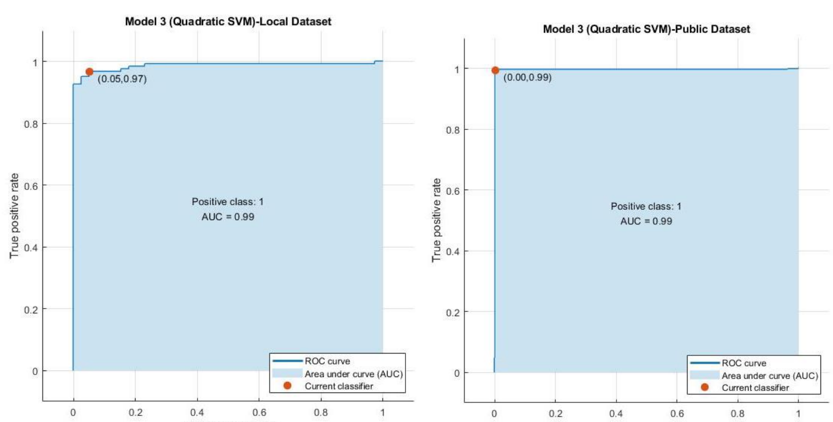


(a) LocalDataset (b) IOG Dataset

Figure 13: Confusion matrix per number of observations for Recognition using PCA on RILBP Features

Figure 13 shows a confusion matrix with the number of observations indicated in each cell for an experiment conducted when PCA was performed on RILBP extracted features, 117 females and 37 male's observation were predicted correct, while 2 and 6 were wrongly predicted as females and males respectively (figure 14a). Similarly, 471 females and 518 male observations were predicted correctly, while 1 and 3 were wrongly predicted as females and males respectively (figure 14b). The results showed that the classifier had an excellent performance.

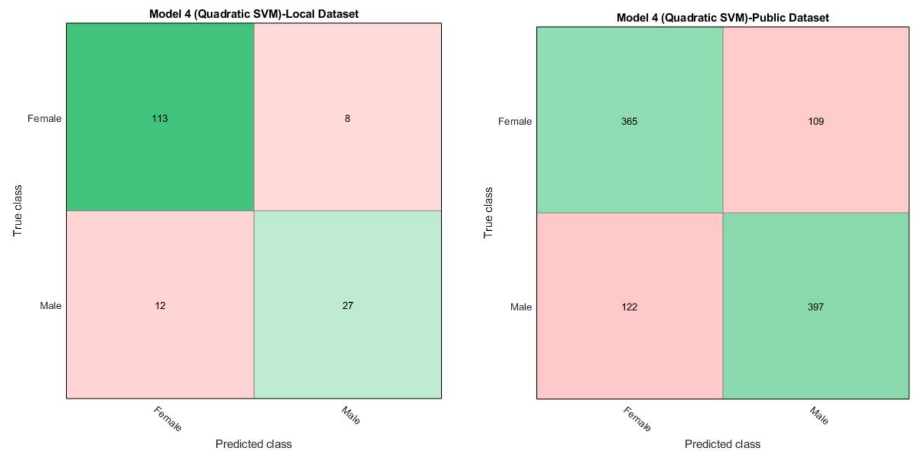
Figure 14 shows the ROC curve for LocalDataset and IOG Dataset classification performance when PCA was computed on RILBP and used as features. It can be seen that AUC is 0.99 showing the overall performance of the SVM classifier on PCA on RILBP faces at 99%, which meant an excellent classification performance. FPR and TPR of 0.05 and 0.97 with 0.00 and 0.99 showed that 5% observation was assigned incorrectly to the female class while 97% observation is classified correctly to the female class in figure 14a.



(a) LocalDataset (b) IOG Dataset

Figure 14: ROC Curves for Recognition Performance using PCA on RILBP features

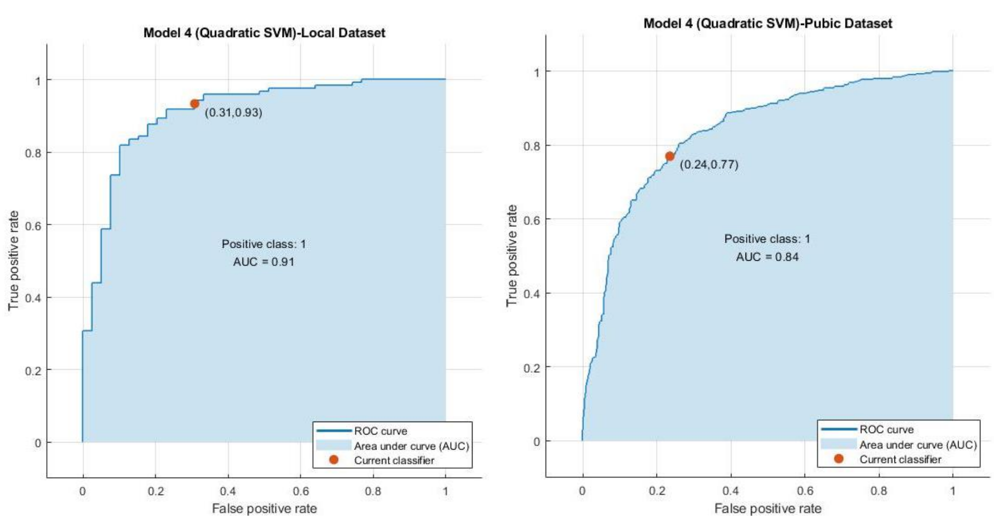
Model 4: HOG - the HOG experiment had an overall recognition accuracy of 74.3% and 76.7% for LocalDataset and IOG Datasets, with results for confusion matrix and ROC curve shown in figures, 15 and 16 respectively.



(a) LocalDataset (b) IOG Dataset

Figure 15: Confusion matrix per number of observations for Recognition using HOG features

Figure 15 shows a confusion matrix with the number of observations indicated in each cell for an experiment conducted when HOG was extracted and used as features, 113 females and 27 male's observation were predicted correct, while 12 and 8 were wrongly predicted as females and males respectively (figure 15a). Similarly, 365 females and 397 male observations were predicted correctly, while 122 and 109 were wrongly predicted as females and males respectively. The results showed that the classifier had a good performance.



(a) LocalDataset (b) IOG Dataset

Figure 16: ROC Curves for Recognition Performance using HOG features

Figure 16 shows the ROC curve for LocalDataset and IOG Datasets classification performance when HOG was used as features. It can be seen that AUC is 0.91 showing the overall performance of the SVM classifier on HOG faces at 91%, which meant an excellent classification performance. FPR and TPR of 0.31 and 0.93 showed that 31% observation was assigned incorrectly to the female class while 93% observation were classified correctly to the female class (figure 16a).

Figure 16b shows the AUC is 0.84 showing the overall performance of the SVM classifier on HOG faces at 84%, which meant an excellent classification performance. FPR and TPR of 0.24 and 0.77 showed that 24% observation was assigned incorrectly to the female class while 77% observation were classified correctly to the female class.

Table 1: Comparative Results Analysis of LocalDataset and IOG Datasets

	Dataset		Overall Accuracy (%)	TPR (%)	FNR (%)	AUC (%)
Model 1	IOG	Female	60.6	53	47	65
		Male		68	32	
	Local	Female	79.4	93	7	78
		Male		40	6	
Model 2	IOG	Female	74.3	72	28	82
		Male		77	23	
	Local	Female	75.2	95	5	96
		Male		63	38	
Model 3	IOG	Female	99.6	99	1	99
		Male		>99	<1	
	Local	Female	99.8	97	3	99
		Male		95	5	
Model 4	IOG	Female	76.7	77	23	84
		Male		76	24	
	Local	Female	74.3	93	7	91
		Male		69	31	

Although existing studies (Vandna et al., 2013) reported that HOG performed better than LBP. This study has shown that when PCA is applied on HOG and RILBP, PCA on RILBP gave an improved recognition rate that is almost 100%. From the results obtained in table 1, Model 3 had the best classification performance in all experiments conducted.

Conclusion

This paper proposed gender classification from facial images with different challenging circumstances. Face detection was carried out from the raw input images using the Viola-Jones algorithm. This was done to identify and separate human faces from the images. HOG and RILBP descriptors were used, features were extracted and the descriptors were trained with an SVM classifier.

PCA was applied to the descriptors to further improve the classification accuracy. RILBP, PCA on HOG, PCA on RILBP, and HOG were trained with the SVM classifier on the IOG and LocalDatsets obtaining the highest accuracy of 99.6% and 99.8% (Model 3) respectively. Future work would look into generating more local data and have a wider mix among Nigerians.

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