Northern Nigeria Human Age Estimation From Facial Images Using Rotation Invariant Local Binary Pattern Features with Principal Component Analysis

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Abstract

In predicting human age, several approaches have been used and tested on different datasets, in this paper, we implemented an age estimation system from facial images using Rotation Invariant Local Binary Pattern Descriptor (RILBD) feature, this was combined with Principal Component Analysis (PCA) for feature high dimensional data and the Support Vector Machine (SVM) algorithm was used for classification. The facial images were grouped into four classes namely; class1 (0-10 years), class 2 (11-20 years), class 3 (21-35 years), and class 4 (above 35 years). To test the performance of the proposed method, experiments were carried out on the Local dataset captured within Kaduna metropolis in the Northern part of Nigeria and the FGNET dataset which is publicly available online. The system achieved an overall accuracy result of 95.0% and 95.7% on the two datasets. This system will be of immense benefit to law enforcement systems (to levy underage drivers), age-specific Human-Computer Interaction (HCI), age-specific access control systems, etc.

Keywords: *Age Estimation, Rotation Invariant Local Binary Pattern, Feature Extraction, Facial Features, Machine Learning, Artificial Intelligence*

1. Introduction

Facial recognition is a process that involves studying the characteristics of a face [1] for application in different research areas such as; gender, emotion, ethnicity, age, security control, the interaction between computers and humans, etc. Estimating age from facial images is a challenging task for computer vision systems while humans find it easy to accomplish [2]. The use of computerized systems and algorithms that can recognize features from facial images and estimating ages based can improve the way machines communicate with humans especially in real-life situations.

Age estimation is a process of determining a person's age or age group, this can be done in many ways like using biometric features [3]; it involves labeling a face image with the exact year and age group of an individual [4]. Human age varies for many reasons such as lifestyle, genetics, drugs, etc. the accuracy of age classification is a huge challenge due to the aging pattern of human [3]. Age estimation tries to use an algorithm to classify age based on features extracted from facial images. In this work, estimation of age has been implemented using Support Vector Machine (SVM) classifier for classification of black faces from facial images from the northern part of Nigeria with varying conditions such as faces with make-up, facial marks, minima occlusion and headscarves into four different age groups. Black faces are considered due to the ageing process difference within different races [5], the need to have a database of black facial images was also a factor considered.

The aging process affects the appearance and structure of a person, this process is related to morphology and face texture [6]. We considered four age group categorizations, infant (0-10 years), teenagers (11-20years), young adults (21-35 years), and adults (above 35 years).

The rest of the paper is organized as follows: section 2 is the literature review, section 3 gives key concepts, a review of texture descriptors used in the paper and a proposed methodology based on the PCA computed on RILBD. Section 4 presents experimental results and the final section presents the conclusion and future work.

2. Literature Review

Age estimation is a technical area that has not been popularly researched on unlike other aspects of face recognition [7]. Facial appearances vary for different people, it can be affected by different factors which cause variation in faces, age is a factor that causes constant and permanent changes to facial appearance [8]. Automatic facial age recognition aims to use algorithms that allow estimation of a person's age based on features derived from facial images [9].

Authors in [5] proposed a fully automatic age estimation that can extract face aging features automatically in real-time using a cascaded AdaBoost algorithm for face detection. A combination of Gabor wavelets and Orthogonal Locality Preserving Projection (OLPP) were used for feature extraction and reduction, age estimation from the features was done with an SVM classifier. The face and gesture network (FGNET) database [10] was used for the experiment, the performance was measured with Mean Absolute Error (MAE) and Cumulative Score (CS), the experiment produced MAE of 8.43 and 5.71 using KNN and SVM respectively. The authors reported that there was still no efficient automatic method of aligning feature points quickly and correctly and concluded data reduction methods makes it easier and convenient to select target features and that the OLPP gives the lowest dimensionality of feature vectors. The MAE is expressed in years and is computed as the average of absolute error between the predicted ages and the ground-truth ones while the CS is equal to the percentage of tested images for which the age error is less than the given threshold [11].

Onifade and Akinyemi [12] proposed a Group-Wise (GW) ranking approach to age estimation from facial images, in this approach, specific information from an age group is used to determine other subjects belonging to that age group before predicting the actual age of the subject. The publicly available FGNET aging database [10] and FAGE dataset which consists of black faces locally sourced by the authors were used for the experiment, authors chose to apply the model on age range 13 to 40 years for training and testing due to their observation of these age groups belonging to the most active period of human life. The result showed a Mean Absolute Error (MAE) of 1.32 when experimented with a combination of the FGNET and FAGE dataset indicating the approach can be used across different ethnicities.

Reade and Viriri [13] proposed a hybrid age estimation system that compares the performance of different algorithms on age estimation, they classified face images into three age groups; child, adult, and senior. Using the FGNET database for the experiment, Local Binary Pattern (LBP), Active Shape Models (ASM), and Histogram of Oriented Gradient (HOG) were used for feature extraction. Features extracted from the facial images were classified using SVM, K-nearest neighbor (KNN), and Gradient Boosting Tree (GBT). With an 82% success rate, the GBT performed better than other classifiers. The authors recommended further investigation of the effect of their approach on more age groups.

Rahman, et al. [14] developed a database which they called BUET facial database for age estimation, consisting of 244 images of male and 157 females within the age range of 16 to 50 years, the proposed algorithm was tested on the BUET database and Adience database by Eidinger, et al. [15]. The image processing method used compares some features extracted from facial images by using edge detection procedures, creation of binary masks, and estimation of wrinkle densities. The viola Jones algorithm was to get the approximate position of the cheeks and forehead which were their region of interest. The result of the experiment showed a better age performance result on their BUET database achieving an accuracy result of 58.7% while using the same methodology, the experiment yielded a low accuracy result of 45.1% on the Adience database. Further investigation of other important features is recommended for age estimation, it was also noted that lighting plays important role in the accuracy of expected results, and the publicly used images produced more error due to diverse light conditions.

Hasa and Mahdi [16] adopted the local Binary pattern (LBP) algorithm as a face descriptor to extract features from facial images. Also, Feature Selection Method (FSM) technology was used to further identify the best features among all the features provided by the LBP and also to improve accuracy in age classification. After that, the SVM classifier was applied to classify the test images and assign a person to a particular related age. Evaluation of the system gave an accuracy of 93.81% with the FSM technique and 81.6% without applying the technique, with the removal of damaged images from the database the accuracy was increased to 94.57%.

Atallah, et al. [17] reviewed the different state of the art techniques for age estimation using facial images, the authors compared techniques from different scholarly papers from 2010 to 2017, the SVM, Local Binary Pattern (LBP), and Grayscale Arranging Pairs (GAP) had the highest detection accuracies of 99.8%, 98.7% and 99.85% respectively about 23 databases have been used by different scholars which showed that different techniques can be effectively applied to particular scenarios. Their study opened up new trends for further research in predicting the effect of aging as it varies from one individual to another.

Janaa, et al. [18] proposed a method using extracted wrinkle features from facial images to estimate the real age of humans, this involved four stages; pre-processing, facial feature extraction, classification, and age estimation. A fuzzy C-means clustering algorithm was used for classification, for the age estimation, the average age was calculated using training face images. A Total of 75 face images were used for the experiment, obtaining a remarkable and significant result showing information from wrinkle feature is important for age classification as it gave better results when compared to other features. The wrinkle feature was calculated using the forehead portion, the upper portion of cheeks, eyelids region, and eye corner regions. The use of more facial features was recommended to improve the accuracy of the algorithm.

A strategy for estimating age groups were looked into by Kumar, et al. [1], the process used are in three phases; position, extraction of characteristics, and classification. Components such as wrinkle features (the study of wrinkle patterns) and geometric features (distance between different parts of the face) were used for the feature extraction phase. The classification was done with the use of the k-means clustering algorithm. They were able to establish wrinkle features as the best result in measuring human age and concluded that the topography of wrinkles was the best strategy in determining age group.

The self-organizing feature map (SOFM) algorithm was used by Oladele, et al. [2] to estimate the age group from facial features. The authors used the extracted facial features to classify input face images into eight age groups. For feature extraction PCA was used, an accuracy of 92.2% was obtained when the experiment was carried out with 450 training samples and test samples of 180 images. The authors further tested the system on black faces resulting in performance not as perfect as that of white faces in the FG-NET database used for their experiment, they attributed this to skin textures and illumination, they recommended training the system with black faces.

The FGNET dataset was also used by Abbas and Kareem [19] for age estimation, they proposed a system which was implemented in three phases; image preprocessing, data mining, and age estimation. For feature extraction, Linear discriminate analysis (LDA) was applied on the FGNET dataset which the authors divided into seven class division; (3-7 years, 8-13, 14-19, 20-25, 26-30, 31-40 and 41-50 years). After extraction, the classes were further combined into three classes as the authors discovered some classes had a similar number of features; hence they further reduced the number of classes from seven to three by combining similar classes that contain the same features together which resulted in having three new classes; the first with age group between (3-7 and 26-30 years), the second had groups (8-13,14-19 20-25 years) and the third class (31 - 40 and 41-50 years). SVM was applied on feature extracted with PCA, LDA, and LBP to give accuracies of 75%, 84%, and 82% respectively.

Ahmed and Viriri [3] reviewed different existing and recent state-of-art research on age estimation from facial images. According to the authors, several models for extracting features for age estimation exists such as the Anthropometric model [6] which measures the size and proportion of human faces it performs better in classifying younger people than adults; Aging Pattern Subspace (AGES) model [20] uses facial images to the model aging process, Aging manifold [21] learns the pattern of age for each individual in different images for a single age or age group, and Active Appearance Model (AAM) uses the statistical model for facial image representation.

Challenges such as having the forehead covered with hair leads to system failure, sometimes producing wrong estimated age results as such hair is been perceived as wrinkles [22] although the use of wrinkles still increases the performance of the system, datasets consisting of a large number of facial images of people at different age gives a good system performance. Biometrics ratios and wrinkle analysis were used by these authors to define features of faces for classifying age into three different groups; 10-30, 30-50 50, and above. Three classifiers were also used KNN, decision tree classifier, and Naïve Bayesian classifier, these classifiers were judged by precision and recall rate of each class. The Naïve Bayesian had the best result of 72.48% and 77.78% in recognizing group 10-30, the KNN failed in identifying the elderly. From the results of their experiment, the authors discovered predicting lower age group was easier than older groups, they recommended adding a pitch of face in biometric ratio calculation to increase performance accuracy.

The performance of deep learning is good with estimation but when a new and unseen database is used for a pre-trained deep neural network it can impact negatively on the output of the age estimation system Dornaika, et al. [11], with retraining or fine-tuning process the problem can be solved although they require large data and powerful computational facilities. The Local binary pattern (LBP), HOG, and Binarized statistical Image features (BSIF) were methods used by Liao, et al. [23] to extract facial features, the authors proposed a divide-and-rule algorithm strategy for age estimation. Factor Analysis model (FAM) was used for feature reduction because it uses the category information of the age groups and age estimation was carried out using the divide-and-rule method and obtaining MAE of 4.32 and 4.02 based on an experiment carried out on the FGNET dataset

Dong, et al. [24] proposed a Deep Convolutional Neural Networks (Deep ConvNets) structure for age classification tasks, the Deep ConvNets is trained with Image of groups datasets [25] for face identification and age classification, the ages in the dataset were assigned, seven classes. From the experiment, the result showed the Deep ConvNets was able to extract high level discriminative facial features from images, and extract age related features from the dataset.

Dornaika, et al. [11] adopted transfer learning with the use of a pre-trained deep convolutional neural network (DCNN) as a feature extractor which enables the DCNN knowledge to be transferred to new datasets instead of retraining the whole DCNN on new images. The authors also made a comparative study on age estimation based on hand-crafted (LBP, HOG, and BDIF) and deep features, the hand-crafted features need to focus on the face region only and concluded deep features gave better results. The need to also focus on execution time and computational complexity for age estimation system was emphasized and not for authors to only focus on improving the accuracy of a system.

Oladipo, et al. [7] carried out research reviewing commonly used techniques and approaches for facial recognition. The authors also determined the use of face recognition techniques in age estimation. It was discovered that most data used for age estimation were captured in a controlled or semi-controlled environment where illuminations were uneven, also images used were mostly static and not tested in areas that capture real-time situation and challenges. The authors noted the practical applications of age estimation in areas such as; law enforcement systems (to levy underage drivers), age-specific Human-Computer Interaction (HCI), age-specific access control, etc. For future research, a recommendation was made on the use of data with complicated pose and illumination environment for age detection.

Authors in [26] proposed a ResNet50 CNN based predictor with a focus to reduce the Mean Absolute Error (MAE) using fewer training facial images to predict the age of faces. Results obtained showed comparable results with state-of-the-art with lower MAE.

In [27], authors proposed a two-level CNN architechture to predict age and gender of unfiltered human faces. Authors pre-trained their network using two public datasets before adopting it on self captured data. Authors reported an accuracy of 83.1%.

In [28], authors proposed lightweight CNN (MA-SFV2: Mixed Attention-ShuffleNetV2) by transforming the output layer that is merging the classification and regression age estimation methods thereby highlighting important features through preprocessing and augmentation. Authors presented results using cumulative score and MAE, obtaining state-of-the-art performance.

Authors in [29] reported studies on gender classification and age estimation using neural network. Authors reported eight (8) evaluation metrics using eleven (11) neural networks.

Texture feature extraction is important in applications such as face detection. Several methods have been used for feature extraction in applications like face detection [30], such methods include Local Binary Pattern [31], Gabor filter and wavelet transfer[32], co-occurrence matrices, etc. The LBP unifies the traditional texture analysis model and there have been several modifications of this model to improve its performance in specific applications such as; texture classification, face recognition, object detection [33]. Due to its sensitivity to image rotations, LBP results are affected in some applications and are not applicable in databases with large variations such as face recognition, texture classification, and scene classification [34], to resolve the limitation Rotation-Invariant Local Binary Descriptor (RILBD) was proposed by Mehta and Egiazarian [35], their framework incorporates structure extracted from LBP. The RILBD is computed by shifting the binary code at each location based on the dominant direction.

From reviewed literature, it is observed most researchers used public databases like FGNET in implementing age estimation systems. The FGNET is scarce of black faces and estimating age is particularly challenging especially among dark skin make-up (this can cover wrinkles) and young age faces. There is therefore the need to have a robust black-face database for local testing and implementation among the African population [7]. Similarly, machine learning compared to other method of recognition such as the deep learning approach, was adopted because of the ease of use, less demand for computer resource and compatibility with most system architectures. In this paper, the authors proposed feature sets of PCA computed on RILBD due to its robustness and efficiency for classification of age into four groups. The proposed technique is compared to other state of art technique where Gabor features were used as a descriptor.

Table 1 shows an overview on the reported literatures, highlighting the characteristics, advantages and disadvantages.

Table 1: Comparative Study on Age Estimation

Authors	Characteristics	Advantages	Disadvantages
Lin et al. [5]	Proposed a fully automatic age estimation using a cascaded AdaBoost algorithm for face detection. Gabor wavelets for feature extraction, Orthogonal Locality Preserving Projection (OLPP) for dimension reduction with an SVM classifier.	Authors obtained 90% accuracy and MAE of 8.43 and 5.71 using two classifiers	Authors obtained 90% accuracy; which leaves room for improvement.
Reade and Viriri [13]	Proposed a hybrid age estimation system that compares the performance of different algorithms on age estimation, they classified face images into three age groups; child, adult, and senior. Using the FGNET database for the experiment, Local Binary Pattern (LBP), Active Shape Models (ASM), and Histogram of Oriented Gradient (HOG) were used for feature extraction.	Authors obtained 82% accuracy.	Authors obtained 82% accuracy, which leaves room for improvement. Dataset was grouped into child, adult and senior.
Rahman, et al. [14]	Authors extracted features from facial images using edge detection procedures, creation of binary masks, and estimation of wrinkle densities.	The result of the experiment showed an accuracy result of 58.7% and 45.1% on the BUET and Adience databases.	Algorithm obtained a very poor accuracy of 58.7% and 45.1% using two datasets, which leaves room for improvement
Hasa and Mahdi [16]	Adopted the LBP algorithm to extract features from facial images with a Feature Selection Method (FSM) technology was used to further identify the best features. SVM classifier was applied to classify the test images and assign a person to a particular related age.	Evaluation of the technique gave an accuracy of 93.81% with the FSM technique and 81.6% without applying the technique,	Result obtained without feature selection gave 81.6% accuracy and 93.81% when FSM was applied, which leaves room for improvement

Follow Table 1: Comparative Study on Age Estimation

Authors	Characteristics	Advantages	Disadvantages
Oladele, et al. [2]	Proposed self-organizing feature map (SOFM) algorithm to estimate the age group from facial features. Authors used the extracted facial features to classify input face images into eight age groups. For feature extraction PCA was used	An accuracy of 92.2% was obtained when the experiment was carried out with 450 training samples and test samples of 180 images.	The authors grouped faces into eight categories; which seem unrealistic. They also recommended training the system with black faces.
Abbas and Kareem [19]	Proposed a system which was implemented in three phases; image preprocessing, data mining, and age estimation. For feature extraction, Linear discriminate analysis (LDA) was applied on the FGNET dataset which the authors divided into seven class division; (3-7 years, 8-13, 14-19, 20-25, 26-30, 31-40 and 41-50 years). After extraction, authors reduced the number of classes from seven to three the first with age group between (3-7 and 26-30 years), the second had groups (8-13,14-19 20-25 years) and the third class (31 - 40 and 41-50 years). SVM was applied on feature extracted with PCA, LDA, and LBP.	Accuracies of 75%, 84%, and 82% was obtained.	Accuracies obtained were 75%, 84% and 82%, which leaves room for more improvement
Ali et al.[22]	Challenges such as having the forehead covered with hair leads to system failure, sometimes producing wrong estimated age results as such hair is been perceived as wrinkles. Biometrics ratios and wrinkle analysis were used by these authors to define features of faces for classifying age into three different groups; 10-30, 30-50, 50 and above. Three classifiers were also used KNN, decision tree classifier, and Naïve Bayesian classifier,	The Naïve Bayesian had the best result of 72.48% and 77.78% in recognizing group 10-30, the KNN failed in identifying the elderly.	Results obtained were not so good, hence the need to improve on the accuracies
Liao, et al. [23]	Proposed LBP, HOG, and Binarized statistical Image features (BSIF) as features and a divide-and-rule algorithm strategy for age estimation. Factor Analysis model (FAM) was used for feature reduction	Obtained MAE of 4.32 and 4.02 on the FGNET dataset	FGNET dataset is void of black faces.
Agbo-Ajala and Viriri [27]	Authors proposed a two-level CNN architechture to predict age and gender of unfiltered human faces. Authors pre-trained their network using two public datasets before adopting it on self captured data	Authors reported an accuracy of 83.1%.	Accuracy of 83.1%, which leaves room for improvement

3. Methodology

The proposed methodology for the age estimation is shown in the block diagram in Figure 1 and the steps involved are briefly discussed in subsequent subsections.

3.1 Dataset

Two datasets were used for the experiment; the FGNET dataset [10] which is publicly available online consists of 1002 images of individuals with different age categories, and the local dataset was captured using a high-definition camera. The local dataset (Local Dataset) consists of 663 images of black individuals in various sizes from randomly selected people at a social gathering, within the Kaduna metropolis in the northern part of Nigeria. The two datasets contained a unique mix of age range from infant to adulthood and was been divided into four groups, the first group represents 0-10 years, the second 11-20 years while the third and fourth groups represented 21-35 years, and Above 35 years respectively.

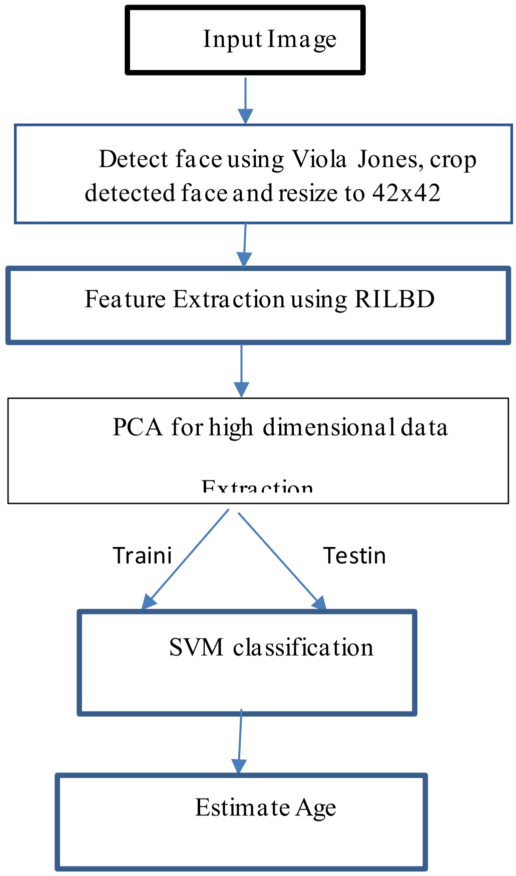


Figure 1: Proposed Methodology

(a)

(b)

Figure 2: Sample images of detected faces in different age groups from (a) Local Dataset and (b) FGNET dataset

Figure 2 show some samples of detected facial images in the different age group categories from the Local Dataset and FGNET datasets. It can be seen that the dataset for local images contained detected faces with poor image quality and partially occluded face.

3.2 Facial Image Detection

For the implementation of the system, the first phase is face detection, this is essential in face recognition as it is used to detect faces in images. Faces were detected from the input images of the local datasets shown in figure 2. The purpose of face detection is to localize the faces in images [5, 36] and detect human faces in images. After face detection, the next stage is cropping and resizing. The detected faces were resized to 42×42 pixels in dimension before feature extraction. The Viola-Jones algorithm was used due to its robustness, extensive use, and successes recorded in face detection.

3.3 Feature Extraction

Several Texture based descriptors are used for face classification, the LBP is popular due to its good performance and simplicity [37], the LBP is not invariant to image rotations hence the incorporation of rotation invariance property. Rotation invariant texture analysis provides texture features that are invariant to the rotation angle of input texture image [38]. In this paper, the RILBD is computed on facial images after which the PCA is computed on the extracted RILBD for high dimensionality data. PCA is a dimensionality reduction method used to reduce the dimensionality of large datasets by transforming them into smaller values that still contains most of the information in the larger dataset, The following steps were involved in the PCA algorithm used: [39, 40]

Step 1: Standardization this is done mathematically by subtracting the mean and divide by the standard deviation of each variable. This is shown in equation 1.

$$Z = \frac{value - mean}{standard\ deviation} \quad (1)$$

Step 2: Covariance matrix computation- this step shows how variables of input data are varying from the mean to see if there exists a relationship between them. The covariance matrix for 3-dimensional data with variables x, y, z is shown in equation 2.

$$\begin{bmatrix} cov\ (x,x) & cov(x,y) & cov\ (x,z) \\ cov\ (y,x) & cov\ (y,y) & cov\ (y,z) \\ cov\ (z,x) & cov\ (z,y) & cov\ (z,z) \end{bmatrix} \quad (2)$$

Step 3: Compute the eigenvectors and eigenvalues of the covariance matrix to identify the principal components, the eigenvectors of the covariance matrix are the directions of the axes where there is more information which is called the principal component, eigenvalues are the coefficients attached to the eigenvectors this gives the amount of covariance carried in each principal component.

Step 4: Feature vector- in this step, the decision is made to keep all components or discard those with low eigenvalues and form a matrix of vectors called the Feature vector

3.4 Support Vector Machine Classification

SVM was used for classification, SVM is a technique used to train classifiers, regressors, and probability densities, it can be used for both binary and multi-classification tasks [41]. For training and testing images 70% and 30% were used on the two descriptors. Ages were classified into four groups 0-10, 11-20, 21-35, and Above 35 years respectively.

4. Experimental Result

Experiments were conducted on the FGNET and Local Dataset to show the performance of the proposed feature technique, evaluation of the system was done using Receiver Operating Characteristic (ROC) curve and confusion matrix.

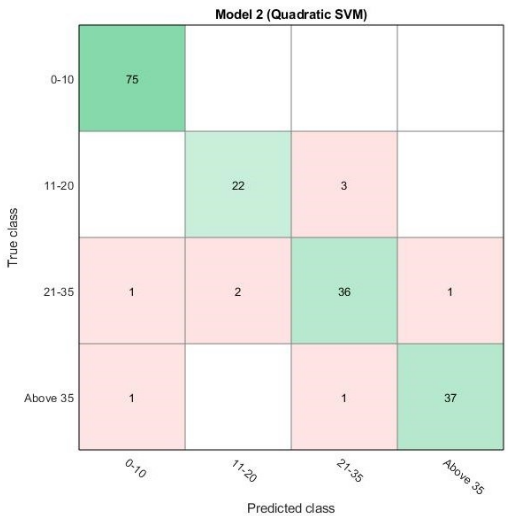
4.1 Performance Measure

The performance of age estimation in this paper was tested using classification accuracy, true positive rate (TPR), Positive predictive value (PPV), false discovery rate (FDR), confusion matrix, and ROC curve.

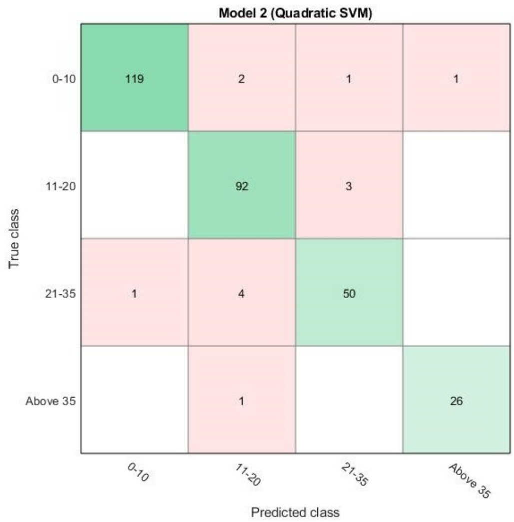
To evaluate the performance of the proposed technique for age estimation, experiments were performed on the FGNET and Local Dataset by using an SVM classifier on the extracted features. The classification accuracy of the model is discussed in subsequent paragraphs.

This model had an accuracy of 95.0% and 95.7% for LocalDataset and FGNET datasets. The performance of the model is shown in the confusion matrix and ROC curve in figures 3, 4, 5, and 6.

Figure 3 shows the confusion matrix of the number of observations obtained after age classification using PCA on RILBD with 30% held out for testing. The diagonal cells in green, shows that the classifier performed well. Figure 3(a) shows the result for the LocalDataset with 75, 22, 36, 37 images correctly classified as age groups 0-10, 11-20, 21-35, and above 35 years respectively. In the age group 0-10, no image were incorrectly classified. for the 11-20 age group, 3 were classified incorrectly. Similarly, for 21-35 and above 35 age groups, a total of 6 images were incorrectly classified to other age groups. Similarly, Figure 3(b) shows the result for the FGNET dataset with 119, 92, 50, 26 images correctly classified to belong to 0-10, 11-20, 21-35 and above 35 age groups, with 4, 3, 5 and 1 wrongly classified. The green diagonal cells in the figure showed that the classifier performed well.



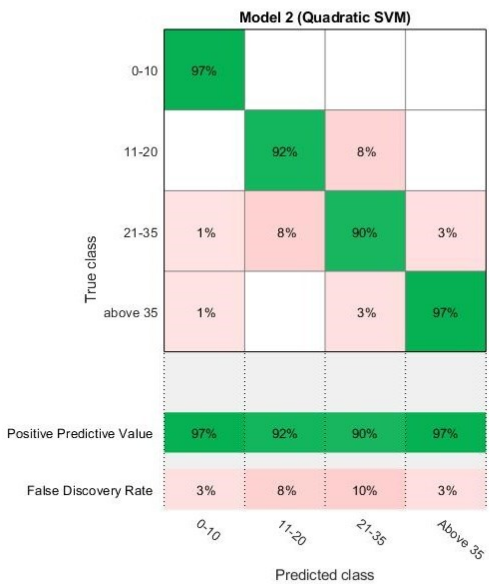
(a) Local Dataset



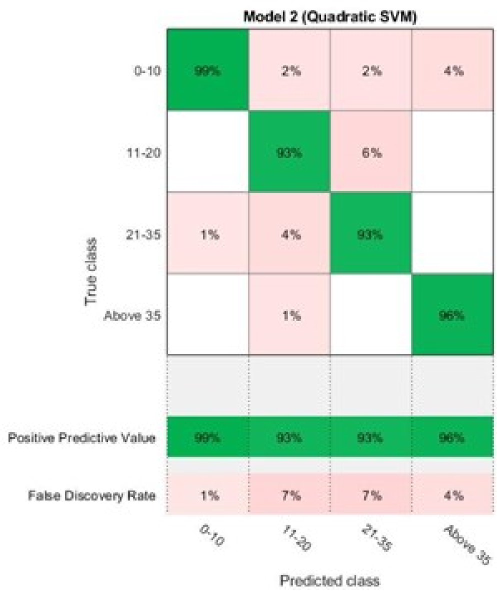
(b) FGNET Dataset

Figure 3: Confusion matrix showing Number of Observation RILBD

Figure 4 show the confusion matrix performance of the classifier indicating PPV, FDR for Local Dataset and FGNET datasets. From Figure 4(a) the results showed the percentage of all ages for the Local Dataset with true class while the column shows the predicted class, the PPV shows the percentage of the correctly classified images as 97%, 92%, 90%, 97% according to their various age groups which are in the green colored cell. The FDR showed the percentage of misclassified images as 3%, 8%, 10%, 3%. Similarly, in Figure 4(b), 99%, 93%, 93% and 96% were the PPV for each age group, the FDR values were 1%, 7%, 7%, 4% for each age group for the FGNET dataset. The results show good classification performances.

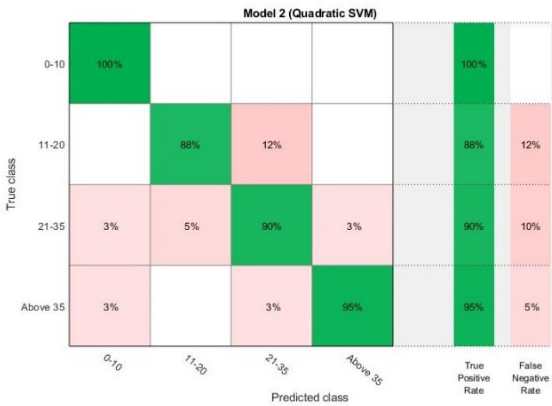


(a) LocalDataset

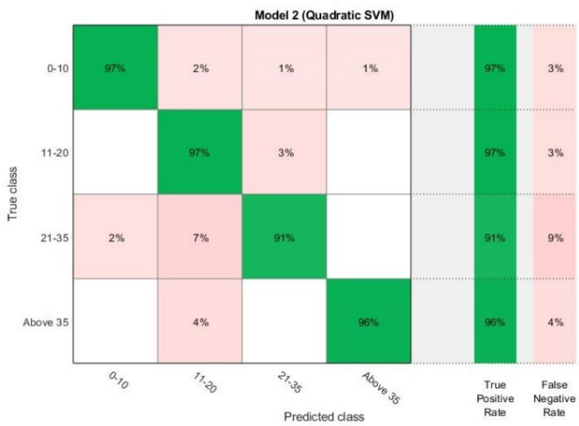


(b)FGNET Dataset

Figure 4: Confusion matrix showing Positive Predictive Value False Discovery Rate



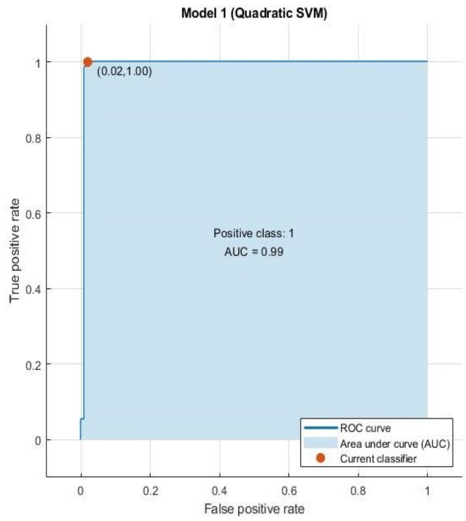
(a) Local Dataset



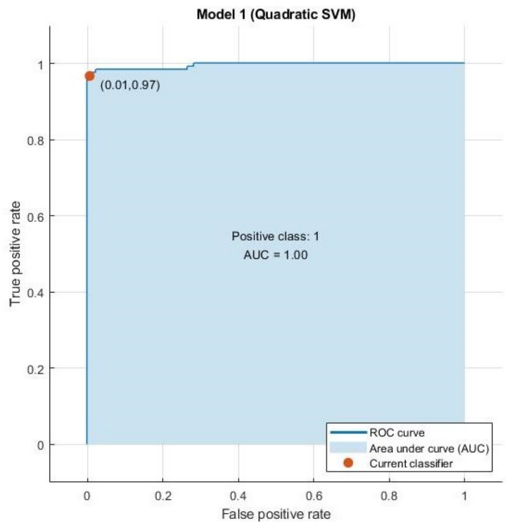
(b) FGNET Dataset

Figure 5: Confusion matrix of True Positive Rate False Negative Rate

Figure 5 shows the confusion matrix for the performance of the SVM classifier indicating the TPR, FNR for the LocalDataset and FGNET datasets. Results in Figure 5(a) shows 100%, 88%, 90% and 95% as TPR while 0%, 12%, 10% and 5% as FNR for the LocalDataset. Similarly, in Figure 5(b), the TPR read 97%, 97%, 91%, 96%. This percentage rates shows the TPRs that are true for the age groups 0-10, 11-20, 21-35, and above 35 respectively on FGNET dataset. The classifier predicted FNR values of 3%, 3%, 9%, 4% indicates the percentages of falsely predicted instances in the various age groups. Results showed good classification performance.



(a) **Local Dataset**



(b) FGNET Dataset

Figure 6: ROC curve for Age classification using PCA on RILBD

Figure 6 shows ROC curve performance on the Local Dataset and FGNET dataset when PCA was computed on RILBD and used as features and classified using SVM. Results showed the TPR and FPR, the marker shows the values of the TPR and FPR. In Figure 6(a) TPR and FPR have values of 1.00 and 0.02 which indicate the classifier assigned 2% of the observation incorrectly to the positive class while the TPR of 1.00 indicates 100% were correctly assigned to the positive class. The Area Under curve (AUC) of 0.99 indicates the overall quality of the classifier as 99% which is an excellent performance. Similarly, from Figure 6(b), the TPR and FPR values show 0.97 and 0.01 which indicates 1% of the observation were incorrectly assigned to the positive class while 97% were correctly assigned to the positive class, AUC of 1.00 shows 100% excellent performance.

4.2 Comparison with State-of-Art-Algorithm

The result of the proposed method was compared to state of art method by Pirozmand, et al. [42], the authors using Gabor wavelet as features achieved an overall performance accuracy of 90% while the proposed method gave an accuracy of 95.0% on the Local Dataset and 95.7% on FGNET dataset indicating that the proposed method had a better classification performance. The authors classified the images into three groups namely; Group1 (0 to 3 years), Group2 (5 to 10 years), and Group3 (20 to 80 years) while the proposed method classified facial images into a more realistic four groups; (0-10 years), (11-20 years), (21-35 years) and above 35 years. In another study, authors in [27] reported 83.1% accuracy using CNN classification as against over 95% reported in the proposed technique.

Table 2: Age Estimation Classification using Proposed and State-of-art technique in [5, 42]

Parameters	Proposed Methodology		PCA on Gabor	
	Local Dataset	**FGNET**	**Local Dataset**	**FGNET**
Overall Accuracy	95.0%	95.7%	73.2%	67.0%
TPR	1.00	0.97	0.88	0.92
FPR	0.02	0.01	0.08	0.12
FNR	0%,12%,10%,5%	3%,3%,9%,4%	8%,75%,32%,56%	3%,3%,9%,4%
FDR	3%,8%,10%, 3%	1%,7%,7%,4%	11%,39%,40%, 34%	15%,60%,49%, 41%
PPV	97%, 92%, 90%, 97%	99%,93%,93%,96 %	89%,61%,60%,66 %	85%,40%,51%,9%
AUC	**0.99**	**1.00**	**0.97**	**0.94**

Table 2 shows a comparison of results obtained on the Local Dataset and FGNET using the proposed method and other techniques. Results showed in all cases that the proposed technique performed better than state-of-art technique. From the table, we can see that the proposed technique gave at least 95% accuracy as against the techniques in [5, 42] which had 73.2% and 67.0% for local and FGNET datasets respectively. The TPR and FPR rates were excellent using the proposed technique. The results obtained were all better using the proposed technique in all cases under consideration.

5. Conclusion

This paper successfully created an age estimation system from facial images with different challenging circumstances among northern Kaduna residence of Nigeria. The images used were taken from the FGNET dataset and the Locally gathered dataset, the RILBD was adopted for feature extraction with PCA applied on the descriptor to further give an improved accuracy result. The PCA on RILBD were trained with an SVM classifier and the system was able to achieve excellent accuracy result of 95.0% and 95.7%. Future work will look into working with more datasets among black races with varying illuminating conditions.

References

[1]. R. Kumar, A. K. Srivastava, and D. K. Agarwal, "Estimation of Age Groups based on Facial Features," *International Journal of Engineering Research & Technology (IJERT),* vol. 7, no. 7, 2018.

[2]. M. O. Oladele, E. Omidiora, and T. M. Adepoju, "An Unsupervised Neural Network Method for Age Group Estimation using Facial Features," *Transactions on Machine Learning and Artificial Intelligence,* vol. 3, no. 6, pp. 34-41, 01/03 2016, doi: 10.14738/tmlai.36.1689.

[3]. M. Ahmed and S. Viriri, "Age Estimation using Facial Images: A Survey of the State-of-the-art," presented at the Sudan Conference on Computer Science and Information Technology (SCCSIT), Elnihood, Sudan 2017.

[4]. A. S. AL-Shannaq and L. A. Elrefaei, "Comprehensive Analysis of the Literature for Age Estimation From Facial Images," *IEEE Access,* vol. 7, pp. 93229-93249, 2019, doi: 10.1109/ACCESS.2019.2927825.

[5]. C.-T. Lin, D.-L. Li, J.-H. Lai, M.-F. Han, and J.-Y. Chang, "Automatic Age Estimation System for Face Images," *International Journal of Advanced Robotic Systems,* vol. 9, no. 5, pp. 1-9, 2012, doi: 10.5772/52862.

[6]. P. Grd, "Introduction to Human Age Estimation Using Face Images," *Research Papers Faculty of Materials Science and Technology Slovak University of Technology,* vol. 21 pp. 21-30, 2013, doi: 10.2478/rput-2013-0005.

[7]. O. Oladipo *et al.*, "Face-Age Modeling: A Pattern Recognition Analysis for Age Estimation," presented at the IEEE International Conference on Bioinformatics and Biomedicine (BIBM), 2019.

[8]. R. Angulu, J. R. Tapamo, and A. O. Adewumi, "Age estimation via face images: a survey," *EURASIP Journal on Image and Video,* pp. 1-35, 2018, doi: 10.1186/s13640-018-0278-6.

[9]. A. Lanitis, "Facial Age Estimation," *Scholarpedia,* vol. 5, no. 1, p. 9701, 2010, doi: 10.4249/scholarpedia.9701.

[10]. Y. Fu. FG-NET Dataset [Online] Available: https://yanweifu.github.io/FG_NET_data/

[11]. F. Dornaika, I. Arganda-Carreras, and C. Belver, "Age Estimation in Facial Images Through Transfer Learning," 2018, doi: 10.1007/s00138-018-0976-.

[12]. O. F. W. Onifade and J. D. Akinyemi, "A GW Ranking Approach for Facial Age Estimation," *Egyptian Computer Science Journal,* vol. 38, no. 3, pp. 63-74, 2014.

[13]. S. Reade and S. Viriri, "Hybrid Age Estimation Using Facial Images," presented at the International Conference Image Analysis and Recognition, 2015.

[14]. S. T. Rahman, A. Arefeen, S. S. Mridul, A. I. Khan, and S. Subrina, "Human Age and Gender Estimation using Facial Image Processing," presented at the IEEE Region 10 Symposium, 2020.

[15]. E. Eidinger, R. Enbar, and T. Hassner, "Age and Gender Estimation of Unfiltered Faces," *IEEE TRANSACTIONS ON INFORMATION FORENSICS AND SECURITY,,* vol. 9, pp. 2170-2179, 2014, doi: 10.6084/m9.figshare.12444272.v1.

[16]. N. F. Hasa and S. Q. Mahdi, "Facial Features Extraction Using LBP for Human Age Estimation Based on SVM Classifier," presented at the International Conference on Computer Science and Software Engineering (CSASE), Duhok, Kurdistan Region – Iraq, 2020.

[17]. R. Atallah, A. Kamsin, M. A. Ismail, S. Abdelrahman, and S. Zerdoumi, "Face Recognition and Age Estimation Implications of Changes in Facial Features: A Critical Review Study," *IEEE Access,* 2018, doi: 10.1109/ACCESS.2018.2836924

[18]. R. Janaa, D. Dattaa, and R. Saha, "Age Estimation from Face Image using Wrinkle Features," presented at the International Conference on Information and Communication Technologies (ICICT 2014), 2014.

[19]. A. R. Abbas and A. R. Kareem, "Age Estimation Using Support Vector Machine," *Iraqi Journal of Science,* vol. 59, no. 3c, pp. 1746-1756, 2018, doi: 10.24996/ijs.2018.59.3C.19.

[20]. X. Geng, Z.-H. Zhou, and K. Smith-Miles, "Automatic Age Estimation Based on Facial Aging Patterns," *IEEE TRANSACTIONS ON PATTERN ANALYSIS AND MACHINE INTELLIGENCE,* vol. 29, no. 12, pp. 2234-2240, 2007, doi: 10.1109/TPAMI.2007.70733.

[21]. Y. Fu, G. Guo, and H. T., " Age Synthesis and Estimation via Faces: A Survey," *IEEE Transactions on Pattern Analysis and Machine Intelligence,,* vol. 32, 2010, doi: :10.1109/TPAMI.2010.36.

[22]. S. M. Ali, Z. A. Darbar, and K. N. Junejo, "Age Estimation from Facial Images Using Biometric Ratios and Wrinkle Analysis " 2015.

[23]. H. Liao, Y. Yan, W. Dai, and P. Fan, "Age Estimation of Face Images Based on CNN and Divide-and-Rule Strategy," *Mathematical Problems in Engineering,* vol. 2018, pp. 1-8, 2018, doi: 10.1155/2018/1712686.

[24]. Y. Dong, Y. Liu, and S. Lian, "Automatic Age Estimation Based on Deep Learning Algorithm," *Neurocomputing,* vol. 187, pp. 4-10, 2016, doi: 10.1016/j.neucom.2015.09.115.

[25]. A. Gallagher and T. Chen, " Understanding Images of Groups of People," presented at the IEEE Conference on Computer Vision and Pattern Recognition. , 2009.

[26]. M. Sadia, A. Md. Mahfujul, and H. T. Kamrul, "Age Estimation From Facial Image Using Convolutional Neural Network(CNN)," presented at the 2019 International Conference on Computer, Communication, Chemical, Materials and Electronic Engineering (IC4ME2), Rajshahi, Bangladesh, Bangladesh, 11-12 July 2019, 2019.

[27]. O. Agbo-Ajala and S. Viriri, "Deeply Learned Classifiers for Age and Gender Predictions of Unfiltered Faces," *The Scientific World Journal,* vol. 2020, p. 1289408, 2020/04/21 2020, doi: 10.1155/2020/1289408.

[28]. X. Liu, Y. Zou, H. Kuang, and X. Ma, "Face Image Age Estimation Based on Data Augmentation and Lightweight Convolutional Neural Network," *Symmetry,* vol. 12, no. 1, p. 146, 2020. [Online]. Available: https://www.mdpi.com/2073-8994/12/1/146.

[29]. T. Gangesh and N. P. Nitin, "Gender Classification and Age Estimation using Neural Networks: A Survey," *International Journal of Computer Applications* vol. 176, no. 23, pp. 34-41, May 2020 2020, doi: 10.5120/ijca2020920251.

[30]. F. Yuan, "Rotation And Scale Invariant Local Binary Pattern Based On High Order Directional Derivatives For Texture Classification," *Digital Signal Processing,* vol. 26, pp. 142-152, 2014, doi: 10.1016/j.dsp.2013.12.005.

[31]. Y. Feiniu, "Video-based smoke detection with histogram sequence of LBP and LBPV pyramids " vol. 46, no. 3, pp. 132-139, 2011, doi: 10.1016/j.firesaf.2011.01.001.

[32]. C. Liu, "Gabor Feature Based Classification Using the Enhanced Fisher Linear Discriminant Model for Face Recognition," *IEEE TRANSACTIONS ON IMAGE PROCESSING,* vol. 11, pp. 467-476, 2002.

[33]. P. G. Freitas, L. P. Da Eira, S. S. Santos, and M. C. Q. De Farias, "On the Application LBP Texture Descriptors and Its Variants for No-Reference Image Quality Assessment," *Journal of Imaging,* vol. 4, no. 10, pp. 1-41, 2018, doi: 10.3390/jimaging4100114.

[34]. D. Yueqi, J. Lu, J. Feng, and J. Zhou, "Learning Rotation-Invariant Local Binary Descriptor. ," *IEEE Transactions on Image Processing.,* pp. 1-15, 2017, doi: 10.1109/TIP.2017.2704661.

[35]. R. Mehta and K. Egiazarian, "Rotated Local Binary Pattern (RLBP): Rotation Invariant Texture Descriptor," presented at the 2nd International Conference on Pattern Recognition Applications and Methods, ICPRAM, 2013.

[36]. E. Alionte and C. Lazar, "A Practical Implementation of Face Detection by Using Matlab Cascade Object Detector," presented at the 19th International Conference on System Theory, Control and Computing (ICSTCC), Cheile Gradistei, Romania, 2015.

[37]. T. Ojala and M. Pietikaeinen, "Multiresolution Gray-Scale and Rotation Invariant Texture Classification with Local Binary Patterns," *IEEE TRANSACTIONS ON PATTERN ANALYSIS AND MACHINE INTELLIGENCE,* vol. 24, no. 7, pp. 971-987, 2002.

[38]. T. Ahonen, J. Matas, C. He, and M. Pietikainen, "Rotation Invariant Image Description with Local Binary Pattern Histogram Fourier Features," presented at the Scandinavian Conference on Image Analysis, 2009.

[39]. T. Malathi and M. K. Bhuyan, "Local Gabor Wavelet-Based Feature Extraction and Evaluation," in *Proceedings of 3rd International Conference on Advanced Computing, Networking and Informatics* 2015, vol. 43: Springer, New Delhi, pp. 181-189, doi: 10.1007/978-81-322-2538-6_19.

[40]. Z. Jaadi. "A Step By Step Explanation Of Principal Component Analysis." https://builtin.com/data-science/step-step-explanation-principal-component-analysis (accessed.

[41]. M. E. Irhebhude, P. O. Odion, and D. T. Chinyio, "Centrog Feature Technique For Vehicle Type Recognition At Day And Night Times," *International Journal of Artificial Intelligence and Applications (IJAIA),* vol. 7, no. 6, pp. 43-56, 2016, doi: 10.5121/ijaia.2016.7604.

[42]. P. Pirozmand, M. F. Amiri, F. Kashanchi, and N. Y. Layne, "Age Estimation, A Gabor PCA-LDA Approach," *The Journal of Mathematics and Computer Science* vol. 2, no. 2, pp. 233-240, 2011, doi: 10.22436/jmcs.002.02.03.