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Hybridized Feature Extraction for Facial Age Estimation using SVM

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Abstract: ***Forging of age is increasing dramatically these days, especially in areas such as military, industry, crime, processing of visa, job application, etc. One of the areas of human-PC-interaction is developing an application for the automated estimation of age using face pictures. Typically, an age estimation system consists of the extraction and classification of aging features; both of which are important to improve efficiency. For the ageing feature extraction, the hybrid features extraction, which are a mixture of Active Appearance Models (AAM), Local Binary Patterns (LBP) and Gabor filter is applied. As global facial features, the shape of human faces is extracted with AAM. The local facial features are the features of the skin textures extracted with LBP and wrinkle extracted with Gabor filter. An age classification utilizing Support Vector Machine (SVM) classifies age in groups. Eight age group class is used for the age estimation. The result is represented in Cumulative Score. The higher the Cumulative Score (CS) becomes, the age estimate becomes accurate as well. Our system is implemented using Object Oriented Programming (OOP) with the help of Open Computer Vision (OpenCV) library and private dataset from Department of Computer Science, Ignatius Ajuru University of Education (IAUE). The result shows 93% accuracy on age classification and age estimation from facial images which is better than the former method.***
Keywords: Hybrid feature extraction, Facial age estimation, AAM, LBP, Gabor filter, SVM, OOP, OpenCV

I. INTRODUCTION

Aging is an uncontrollable, unavoidable and irreversible procedure that cause variations in facial appearance, shape and texture. Facial appearance at one age is not the same as facial appearance of a similar individual at an alternate age. Age estimation has been considerably studied with the aim of locating out aging styles, pattern versions amongst individuals, factors that quicken facial maturing and how to nicely represent human face for automated age estimation. As one age, facial blemishes like wrinkles, freckles and age-spots appear. Underneath the pores and skin, melanin producing cells are damaged because of contact to suns' Ultra Violet (UV) rays. Freckles and age-spots shows up because of over manufacturing of melanin. Thus, light reflecting collagen diminishes as well as become nonuniformly circulated making facial skin tone non-uniform [1]. Areas that are badly influenced by sunbeams are upper cheek, nose, nostril-bridge and forehead. Facial aging is affected by numerous factors ranging from way of one's life, natural, career, psychological and environmental.

At present, the studies on age estimation with the use of face pictures is essential than ever, as it has many applications, including a web access control, underage cigarette-vending machine use, age-based recovery of face images, age prediction systems for locating lost young ones and face recognition robust age progression [2]. In addition, the estimated age of consumers who look at billboards is used in age specific goal advertising as consumer choices differ greatly by age. Age estimation systems are normally designed to use steps: an aging feature extraction and a features classification. Feature extraction could be very critical in age estimation, because the extracted features substantially have an effect on the classification performance. For this purpose, a great deal of effort has been directed towards the extraction of discriminative aging features. These features may be characterized into local features, global features and hybrid features.

Local features comprise of the quantity and intensity of wrinkles, skin aging with the use of patches and age spots, hair colour and the geometry of facial components that have been usually used to categorise human beings into age group including infants, teens and senior adult. The global facial features which include both the shape and appearance information of human faces. The local facial features are selected out with the aid of Gabor filters and local binary patterns (LBP). Due to the ability to assess the orientation and extent of wrinkles, Gabor filters have been used to detect wrinkles, edges and texture features [3]. Gabor filter has been viewed as the best texture descriptor in object recognition, segmentation, tracking of movement, and image registration. Since wrinkles seem as edge-like components with high rise frequency, Gabor edge evaluation method has been commonly used for

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wrinkle features extraction [4]. Local Binary patterns (LBP) is a texture description technique that can figure out microstructure patterns like spots, edges, lines and flat regions at the pores and skin [5].

The global features are generally used to estimate a detailed age and contain not only aging characteristics, but other individual characteristics. Global features are derived using active appearance models (AAM) as they provide more information about a face's appearance and shape. Due to the dimensional reduction of the principal component analysis (PCA), AAM features does not include extensive information on wrinkles and skin [6].

So as to take care of this issue, an age estimation technique based totally at the hybrid features extraction is proposed, and the defects found in every feature can then be compensated for by means of combining the global and local features. Therefore, hybrid features are suitable for the accurate estimation of age. When aging features are extracted and represented, then age classification is executed utilizing SVM classifier. Therefore, the hybrid features and the SVM classifier provide a very good overall performance for the estimation of age. Notwithstanding, they have been studied independently; studies of combining them has not been carried out in the previous works.

The department of computer science in Ignatius Ajuru University of Education Nigeria, has about 723 images in their database, which is employed as our dataset.

II. RELATED WORKS

There has been a great number of researches about how to accurately estimate ages from facial images using either publicly available dataset or private dataset or both public and private dataset. These age estimation methods were classified based on feature extraction and classification. In this section, previous works are described from these points of view.

A. Feature Extraction Techniques

The facial features used inside the preceding works are divided into 3 types: local features, global features and hybrid features. The local features which include wrinkles, pores and skin, hair and geometric features had been generally used to classify the age groups in lots of earlier research.

Age classification from facial pictures were introduced and facial pictures were labeled into three age groups: babies, teens and senior adults the use of the distance ratio of facial parts and the wrinkle. They extracted the distance ratios based totally on the anthropometry of the face as geometric features, which had been then used to differentiate babies from adults.

Wrinkle features were extracted via snakelets in the predesignated facial areas, and have been then used to categorize young and senior adults. The experimental outcomes had been said to illustrate its effectiveness. Although, this approach cannot be used for age modelling in adult and old age face images since there is no significant changes at this stage. This approach is restricted by the fact that it can only be tested on a small private dataset [7]. Jun-Da Xia and Chung-Lin Huang [8] proposed an age class method using wrinkle features extracted through the Sobel filter together with the hair coloration features. The regions for extraction of features were selected based on the AAM's detected facial landmarks.

The connection between age and features was reviewed as quadratic aging functions and then the facial age was calculated using characteristics of aging. In their work, instead of obtaining a specific age, they were able to classify age group for age estimation. Using AAM and regression methods, the first age estimation set of rules was proposed by [9].

Lanitis et al. [2] utilized the AAM features to think about various classifiers for age estimation. The error rates in the extended techniques reduced although evaluations were done on small datasets.

Geng et al. [10], [11] proposed a method called AGing pattErn Subspace (AGES) which uses the sequence of an individual’s facial images arranged in chronological order to model the aging process. The features of face images are extracted with AAM. PCA is then used to learn for each human ageing subspace. Their methodology was able to compensate missing ages by learning a subspace representation of one's pictures when displaying a sequence of a subject's growing old face. To estimate age, check image is positioned at every conceivable area within the aging pattern to discover a point that can best reconstruct it. Gathering face dataset with people's face pictures at several ages with some picture quality may not be viable since its features do exclude data about wrinkles and skin, due to the dimensional decrease done by the PCA.

The simple idea is to display the aging sample, which is characterized as the series of a specific individual' s face pictures arranged in order of time, through making an illustrative subspace. The right aging pattern for a previously unseen face picture is decided by way of the projection inside the subspace that can reproduce the face picture with minimum reconstruction error, while the location of the face picture in that aging sample will at that point suggest its age.

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In the study, AGES and its variations are in comparison with the restrained existing age estimation methods (WAS and AAS) and some techniques (kNN, BP, C4.5, and SVM). Also, an examination with human recognition capacity on age is directed. It is intriguing to take note of that the performance of AGES isn't just notably higher than that of all the other algorithms, but also to that of the human observers [11]. Gunay and Nabiyev [12] displayed an Automatic age class with Local Binary Pattern (LBP). In their investigation, they characterized the FERET pictures as per their ages with 10 years interval. The faces have been divided into small regions from which the LBP histograms have been extracted and linked into feature vector to be utilized as a proficient face descriptor. For each new face supplied to the system, spatial LBP histograms were delivered and used to characterize the picture into one of the age classes. In the classification phase, minimum distance, nearest neighbor and k-nearest neighbor classifiers were used. The experimental results were shown that system performance is 80% for age estimation. But their approach deals poorly with noisy images.

Guo et al. [13] used a large database to study automatic age estimation with the influence of gender on age estimation based on facial representations combining biologically inspired features (BIF) with manifold learning techniques They also used smaller gender and age groups rather than all ages to study age estimation. There have been reductions in error in both cases. Based on these results, they designed three frameworks for automatic age estimation that exhibits high performance. Unlike previous methods involving manual separation of men and women before calculation of age. Furthermore, a data fusion approach was proposed using one of the frameworks, which gives an age estimation error reduction of MAE: 4.77. However, their techniques have computational complexity. A deep Convolutional Neural Networks (CNN) technique that was prepared on a database for face recognition assignment is used to estimate the age data at the Adience database. Their approach stated 3 large contributions, namely:

1) It proves that a CNN model, which became skilled for face recognition task, may be utilized for age estimation to improve overall performance.
2) Over fitting issue may be conquered by way of employing a pretrained CNN on a huge database for face recognition job.
3) Not just the quantity of preparing pictures and the number subjects in a training database affects the overall performance of the age estimation model, but also the pre-training project of the CNN determines the model's performance. But has a few demanding situations on picture type, mainly photos with low resolution, pose, blur, poor lightning and facial appearance [14].

From all the stated literature survey, it is understood and clear that it's far necessary to increase a hybrid method to estimate the age. An age estimator facilitates in labelling the faces based at the extracted features of the facial pictures.

The age group of equal face range are similar in shape, texture and in appearance. Most of the existing age estimators attempts to concentrate on facial textures and shapes which are not static whilst aging process. Hence, there is a necessity to get information on wrinkles features and skin features for better age estimation accuracy.

B. Age Estimation Algorithm

Once ageing characteristics are extracted and represented, the subsequent stage is age estimation. Age estimation is a unique pattern recognition project wherein age labels may be considered as a class or a set of sequential value. Age estimation is approached as a class problem while age labels are regarded as sequential chronological collection.

In order to decide the classifier, Support Vector Machine (SVM), LDA, distance measure and neural networks had been used in the previous works. Dehshibi and Bastanfard [15] exhibited distance ratios among landmarks to classify human faces in numerous age groups. They categorized face pictures into 4 age-groups under 15, 16-30, 31-50 and over 50 years on a private dataset using back propagation neural network with distance ratios as inputs. They showed an accuracy of 86%.

Thukral et al. [16] used geometric features and choice fusion for age-group estimation. They completed 70% usual overall performance for 0 to 15, 15-30 and above 30 years age-group. Gunay and Nabiyev [12] proposed programmed age classification with LBP. They used spatial LBP histograms to categorise faces into six age-groups. Using nearest neighbour classifiers, they carried out accuracy of eighty percentage on age-groups 10-15, 20-25, 30-35, 40-45, 50-55 and 60-65.

Hajizadeh and Ebrahimnezhad [17] represented facial features with the use of Histogram of Oriented Gradients (HOG). Using probabilistic neural network (PNN) to classify HOG functions derived from multiple areas, 87 percent accuracy was achieved in the classification of face images into four groups. Liu et al. [18] supplied age group classification through structured fusion of uncertainty-driven shape features and selected surface features.

It was additionally discovered that the general performance of age-estimation diminishes as the quantity of age-group increases. Sai et al. [19] proposed LBP, Gabor and Biologically Inspired Features for face illustration. They utilized Extreme Learning Machines (ELM) for age group estimation. Their method carried out accuracy of approximately 70%.

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Hu et al. [20] presented Kullback-Leibler / raw facial representation intensities before using the Convolutional Neural Network (CNN) to determine age. Their approach demonstrates that deep learning (Deep Neural Networks or CNN) achieves better Mean Absolute Error (MAE) compared to traditional classification methods. Moreover, better accuracies can be achieved where age groups have wide ranges and hence not applicable in a narrow-range age group estimation.

An approximation of the age range was provided with four predefined groups. We used a fast and efficient method of machine learning: extreme learning machine to solve the problem of age categorization. Local Gabor Binary Patterns, Biologically Inspired Function and Gabor were adopted to represent the face picture. Three specific aging datasets were used to estimate age and experimental results were recorded to be robust and effective [19].

Rampay and Satyanarayana [21] proposed a methodology for automatic age estimation based on Local Binary Pattern (LBP) and Grey Level Co- Occurrence Matrix (GLCM). Using LBP and GLCM, the local facial features are extracted and these characteristics are given as inputs for age calculation to the SVM. The research was performed using the FG-NET database on their system. Ultimately, their approach revealed the 88% accuracy of the classification

III.METHODOLOGY

A. Analysis of the Existing System

In an attempt to support research activities related to facial aging, the FG-NET aging database was launched in 2004. Since then, a group of researchers have used the dataset to conduct research in different facial aging fields and it is available to the public.

Rampay and Satyanarayana proposed a methodology for automatic age estimation based on Local Binary Pattern (LBP) and Grey Level Co- Occurrence Matrix (GLCM). The local facial characteristics are extracted using LBP and GLCM and these characteristics are given as inputs for age estimation to the Support Vector Machine. The experimentation on their method was carried out using FG-NET database. Finally, their system demonstrated the classification accuracy of 88%. The architecture of the existing system is depicted in Fig. 1.

1) *Image Input*: Images were gotten from FG-NET dataset which is publicly available for researchers. And then inputted into Matlab for image preprocessing.
2) *Image Pre-Processing*: Image preprocessing step is performed to extract only the facial regions and to adjust the size and the orientation of the faces. Image preprocessing helps in image enhancement, noise reduction and edge detection by converting the image from color image to gray scale.
3) *Feature Extraction*: Each of the preprocessed image is considered and LBP features and GLCM features are extracted. Local Binary Pattern (LBP) is used for classification in computer vision. For texture classification LBP is widely used and in combination with Histogram of oriented Gradient (HOG) gives improved performance. Gray Level Co-occurrence Matrix (GLCM) is well familiar method for texture analysis and it is also known as Grey Level Spatial Dependency Matrix. It estimates image possessions collectively which are related to second order statistics. The functions of GLCM specifies the texture of an image by estimating probability of pixel's pairs with specific values and approaches towards special relationship happens in an image then producing statistical measures from this matrix.
4) *Age Classification:* In the age classification module, the subject is classified into one of the age groups using SVM classifier. SVM is a supervised learning method which uses support vectors to build a classification or regression model.

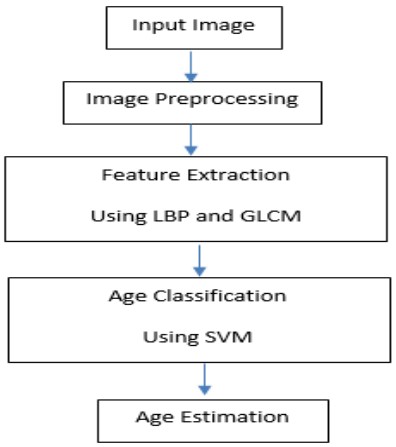


Fig. 1 Architecture of the existing system

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B. Analysis of the Proposed Method

The proposed age estimation method consists of image input, image preprocessing, Active Appearance Model (AAM), Local Binary Pattern (LBP), Gabor, and age classification using SVM which is implemented using OOP in OpenCV library, as depicted in Fig. 2.

1) *Image input:* Images were gotten from a private dataset of Department of Computer Science, Ignatius Ajuru University of Education.
2) *Pre-processing of image*: The orientation and scale of the original images are different. Thus, the preprocessing step of the image is performed to extract only the facial regions and to adjust the facial size and orientation. Image preprocessing helps to improve image, reduce noise and detect edges by converting the image from color image to gray scale using the support of the OpenCV library with OOP.
3) *Feature Extraction:* The extraction feature consists of global extraction of features using AAM and local extraction of features using Gabor filters and LBP. The AAM's appearance and shape parameters are derived using PCA as global features. The features of the wrinkle and texture were extracted as local features using Gabor filter and LBP respectively.
4) *Age classification:* In the age classification module, the subject is classified into one of the age groups using SVM classifier. SVM is a supervised learning method which uses support vectors to build a classification or regression model.

C. Algorithm of the Proposed Method

1) *Step 1:* Convert color or gray scale images into gray scale images.
2) *Step 2:* Then use Histogram equalization and frequency normalization techniques to pre-process the images.
3) *Step 3:* Extract the face of the image using Object Oriented Programming in OpenCV library
4) *Step 4:* Pre-processing and feature extraction with AAM, LBP and Gabor.
5) *Step 5:* Use the SVM classifier to create a model.
6) *Step 6:* Classify and estimate the age group with the aid Trained Model.

Table 1, shows the number of images in database of Department of Computer Science, Ignatius Ajuru University of Education (IAUE), Nigeria. There are 723 images in the database and total of 15 images were tested.

Table I. Dataset of Department of Computer Science, IAUE

Age Group	Training Set	Test Set
0-2	0	0
4-6	0	0
8-12	0	0
15-20	300	2
25-32	300	10
38-43	100	3
48-53	20	0
60-100	3	0
Total	723	15

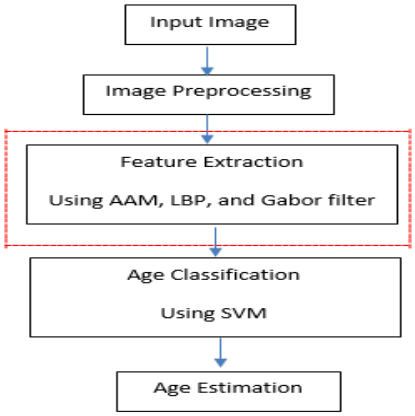


Fig. 2 Architecture of the propose system

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IV. EXPERIMENT AND RESULT

The image was gotten from a private dataset of Department of Computer Science, IAUE. An image is an object and is reloaded in diverse method as two-dimensional matrix or grid of pixels, where pixels are the rudiments of a digital picture with a certain brightness quality corresponding to the object's reflected light. There are two kinds of pictures, for example gray scale and colored images where gray scale picture are 2D matrix of pixels every pixel having some brightness value and coloured pictures also are 2D matrix of pixels in which every pixel have three intensity values each for a primary color i.e. red, green, blue (R,G,B). A digital image is made up of pixels that can be considered on the screen as small dots. A standard size of a picture is 512-by-512 pixels. In the general case we state that a picture is of size m-by-n in the event that it is made out of m pixels in the vertical axis and n pixels in the horizontal axis.

Fig. 3 shows some colored images from private database, of Department of Computer Science, Ignatius Ajuru University, Port Harcourt, Nigeria.



Fig. 3 Color images from IAUE private database

Gray scale A gray scale (or gray level) image is simply an image in which the only colors are shades of gray. The cause why these images are distinguished from any other color image is that less data needs to be provided for each pixel. In fact, a ' gray ' color is one in which the red, green and blue elements all have the same frequency in RGB space, and it is therefore necessary to specify only one intensity value for each pixel as opposed to the three intensities required to specify each pixel in full color images. The gray intensity of the scale is often located as an 8-bit integer that gives 256 possible shades of gray from black to white.

A gray scale shows the number of intensity values that can be used to represent an image. Most of the images are of 8 bit, so there are 256 intensity values in its gray scale where 0 frequency value represent black, 256 frequency value represent white color and all values between 0 and 256 are intermediate gray brightness.

Histogram Equalization of Gray Scale Image, we have used histogram equalization to enhance the image. Equalization of the histogram extends object frequency values over a wider range. This is used because it eliminates the effect of various conditions in imaging. When evaluating faces, it is essential to have as little variation as possible due to external pressures (such as condition of an image) to make the variations between the faces more visible. The histogram equalization of gray scale image during the image preprocessing.

A. Shape and appearance feature extraction

shape vectors S_i, for i= 1, …, n

$$S = S_0 + \sum_{i=1}^{n} P_i \, S_i \qquad (1)$$

Equation 1, shows that , for I = 1,…, n are the shape parameters. In order to obtain the appearance model, the shape of an image is normalized by warping it to the mean shape , The facial appearance, A(x) is expressed by a linear combination of the mean appearance A0 and the m appearance images Ai (x).

$$A(x) = A_0 + \sum_{i=1}^{m} \Lambda_i \, Al\,(x) \qquad \forall x \in S_0 \qquad (2)$$

Equation 2, shows that is the appearance parameter. The shape parameter and the appearance parameter are utilized as facial global features for age estimation. Furthermore, certain critical aging features such as wrinkles and skin textures are removed from the AAM features in the PCA's dimension reduction process. However, the appearance parameter of the AAM does not sufficiently represent facial aging, so extra local characteristics are expected for age estimation.

B. Wrinkles feature extraction

A Gabor filter with various parameters according to the position and frequency of the selected face area was used to examine facial wrinkles with directional characteristics. The Gabor filter extracts the facial wrinkles, which have different attributes, such as deep and fine wrinkles, using different frequencies. The Gabor filter is widely used for identification and segmentation of texture, image analysis, motion detection. The two dimensional Gabor filter in the spatial domain is defined in equation 3.

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$$G, \Lambda, \Theta, \gamma, \phi, \sigma\ (x,y) = A = exp\left(\frac{-x'^2+\gamma^2y'^2}{2\sigma^2}\right) \cos\left(2\pi \frac{x'}{\Lambda}+\phi\right) \quad (3)$$

Where;

x'= x cosΘ + y sinΘ and y'= -x sinΘ + y cosΘ

Wavelength (Λ) is ≥ 2 for real numbers

Orientation (Θ) = Real numbers between 0 and 360 degrees

Phase offset (ϕ) = Real numbers between -180 and 180, 0 and 180 for center symmetric, -90 and 90 for anti-symmetric function.

Aspect ratio (ɣ) = spatial aspect ratio.

For ɣ = 1, the support is circular

For ɣ < 1, the support is elongated in orientation parallel stripes

For ɣ = 0.5, default value

Sigma/Standard deviation (σ) = Guassian envelope

C. Skin features extraction

As a person grows older, facial defects like freckles, lentigines (age spots) and fine wrinkles on the flesh are increasing. The skin characteristics are extracted using the method of Local Binary Pattern (LBP), which identifies microstructures such as borders, spots and flat areas. However, the LBP has the benefit of simplicity in computing. The LBP operator is used to define texture, facial image processing, gender and age detection. The LBP's basic concept is to allocate each pixel a code that compares it with its corresponding pixels. The creation of the LBP code is given in equation 4.

$$LBP_{P,R} = \sum_{p=1}^{p-1} S(g_p - g_c)\, 2^p \text{, where } S(x) = \begin{cases} 1, x \geq 0 \\ 0, x < 0 \end{cases} \quad (4)$$

Where P is the amount of corresponding pixels, R is the distance from the center to the corresponding pixels. g_c Links to the gray value of the center pixel, g_p(P= 1, …, P-1) links to the gray values of the P equally spaced pixels on the circle of radius R (R > 0) that forms a circularly symmetric neighbor set, and S is the threshold function of x.

D. Classification using Support Vector Machine

SVM are a useful technique for data classification. A conventional SVM is designed for class problems by selecting the optimal linear decision hyper-plane. SVM classifier is a prevalent machine learning method; it can be used for domain classification and regression analysis, such as computer vision, content restoration, clustering and classification, data analysis, etc. SVM's main goal is to train the classifier using training data and to create a model that predicts class labels for test data when the input is only test data. For the training set is linearly non-separable then it is mapped to high-dimensional feature space. This projection into high dimensional feature space is efficiently performed by using kernels

Typically, on the output gray scale image, we perform the pre-processing operations first. These operations are equalization of histograms, normalization of intensities. Histogram equalization and intensity normalization are performed on the image due to different lighting which facilitate the image contrast and then the front of the image is extracted with the help of the OpenCV library using OOP. A training dataset is created by extracting the features from the faces using AAM, LBP and Gabor. A classifier will then be equipped with the function and the marked data set pair will form the model. For test image, the features are extracted in the same way. The model uses these features to classify the age group of the person, and the sample of our age group classification for age estimation is shown in Fig. 4 and Fig. 5. In Fig. 4, the three faces displayed are correctly classified to their age group. Whereas, in Fig. 5, only two out of three faces were correct. One of the faces gave a poor age group estimation because of his spectacles. The system cannot accurately estimate the age of someone with spectacle.

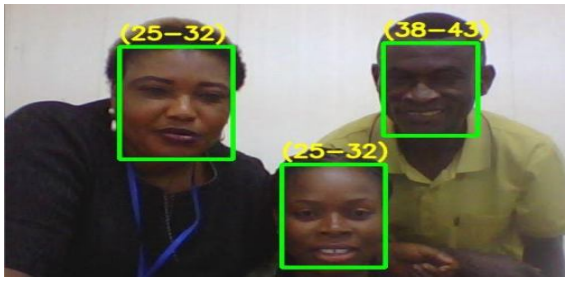


Fig. 4 Accurate age group classification for age estimation

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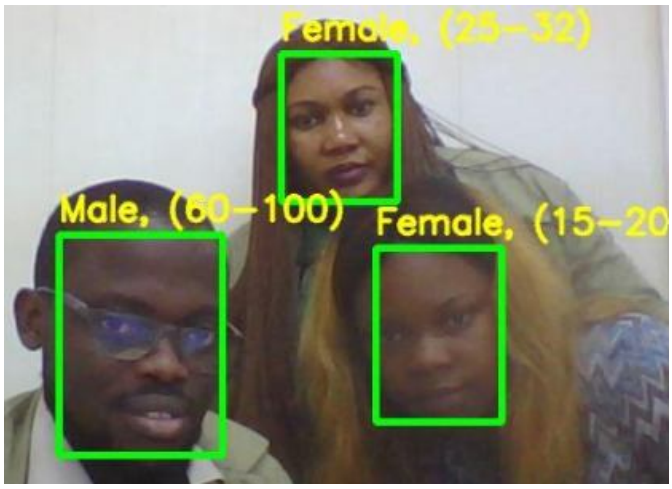


Fig. 5 Poor age group classification for age estimation

The cumulative score (CS) is defined as the ratio of the number of data whose errors are lower than a threshold value to the total number of data. It is expressed by equation 5.

$$CS(th) = N_{e \leq th} / N\ (100\%) \qquad (5)$$

where $N_{e \leq th}$ is the number of data whose estimation error (e) is lower than threshold (th), N is the number of total data.

The total testing set of the proposed system is 15, and 14 out of the total number of the test set is correct. Therefore, the accuracy of the performance which is also the Cumulative Score (CS) is;

From equation 5, $CS(th) = N_{e \leq th} / N\ (100\%)$

Therefore, CS(th) = 14/15 = 0.93 x 100 = 93%

The Cumulative Score is 93% which shows the accuracy performance of the proposed system. The higher the Cumulative Score (CS) the better the overall performance. Hence, the result shows that the proposed facial age estimation based on AAM, LBP and Gabor filter using SVM performed better than the existing method of age estimation.

V. CONCLUSION

Using SVM, AAM, LBP and Gabor filter can be employed to estimate age more accurately from face image since they give information on shape, texture and wrinkle features of the face respectively. Although, the proposed system does not accurately estimate the age of anyone with eyeglass, since wrinkles, edge and texture of the skin cannot be extracted with spectacles. Therefore, the proposed system performs better age estimation accuracy than using only LBP and GLCM with SVM which gives information on shape and texture features alone.

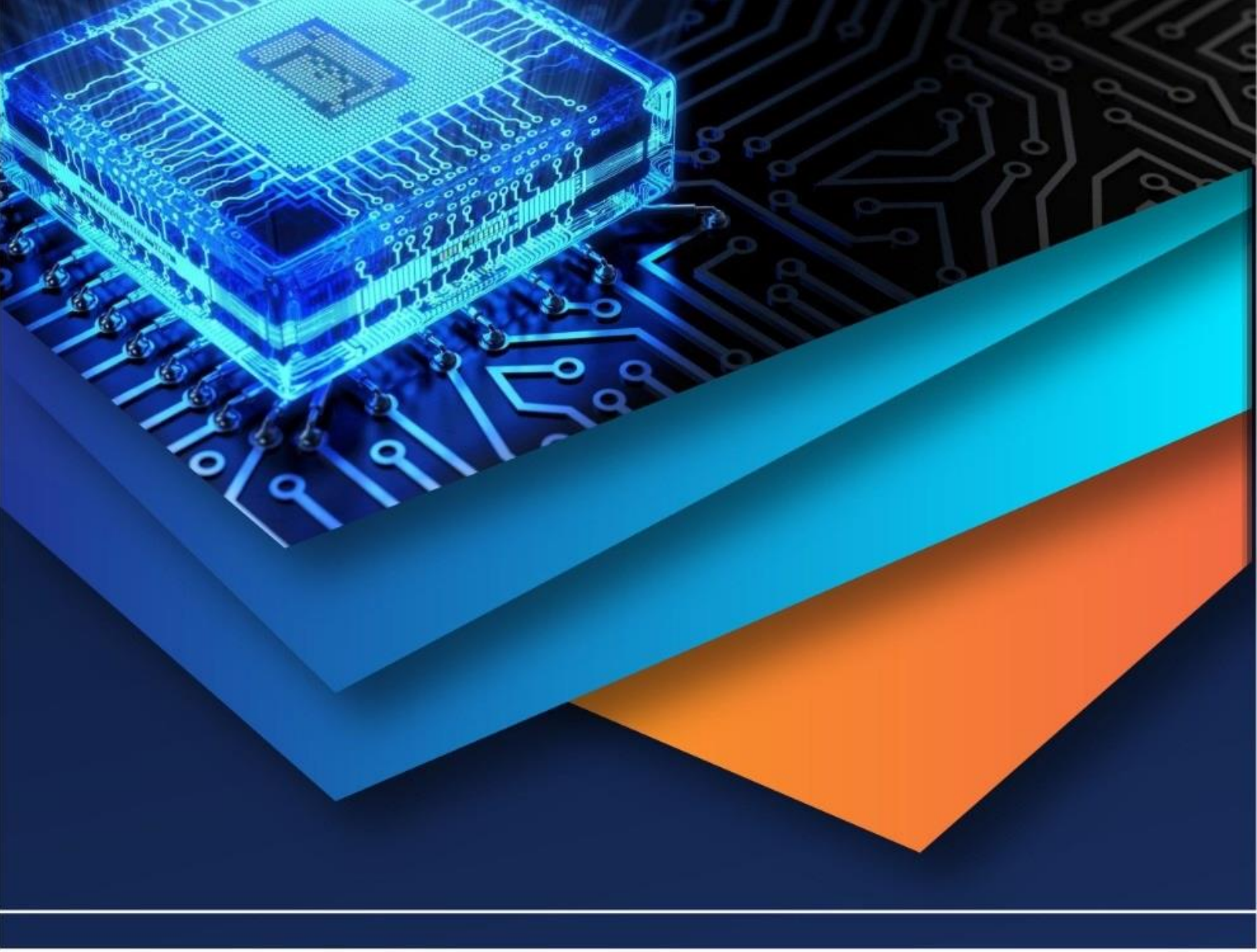
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