Human Age Classification System Using K-NN Classifier

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Abstract. The age classification system is used to categorize age into various groups determined by facial features. Many researchers have used different techniques for the age classification system, namely Geometric Ratio, Wrinkle Ratio, Local Gabor Pattern, Histograms of Oriented Gradients, Adaptive Neuro-Fuzzy Inference system, Texture feature, Support Vector Machine and Artificial neural network. The current system does not give great precision in light of the fact that these strategies are wasteful for classification. The proposed work represents the classification of images depending on the groups. This work classifies the age into old, adult and child groups. This work completes in three steps, i.e., preprocessing, facial aging feature extraction and classification. In preprocessing, the RGB image is converted into a grayscale level image; the facial aging feature extraction is performed by skin texture feature extraction and wrinkle analysis. LGBPH and the density of wrinkles accomplished the wrinkle analysis. LGBPH is a histogram of LGBP which is calculated by LBP. The LGBP feature is not dynamic for features like rotation, alignment, and the illumination of the image. The proposed work selected three different skins for skin texture feature and five different skin textures for wrinkle investigation. This work uses K-NN classifier due to its fast processing; classifies the testing dataset from training dataset. The LGBPH provides better results and estimates the accuracy as compared to the previous technique used by the researcher. This classification is a triumphant work as it gives an efficient classification using facial aging feature extraction.

Keywords: Age classification system · Facial aging feature extraction · K- Nearest Neighbor (K-NN) · Local Gabor Binary Pattern Histogram (LGBPH) · Wrinkle analysis

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1 Introduction

Age is important as well as basic information about humans, which determines the age of a person. Human age is affected by internal and external factors. A person may live in different places having different environments. Therefore, environmental effects on human skin are noticeable. The skin texture of human varies from person to person. Numerous variables are influencing the age, for example, eating schedules, dietary patterns, a way of life, use of cosmetics and medical problems. This study proposed a structured age estimation framework. Presently, many researchers used distinctive databases to different age groups. The age determination is not easy by the human as well as by the machines. Age information can be beneficial for applications such as in the medical diagnosis, computer security; biometrics and video surveillance which are time-consuming and find difficulty in gaining better results in limited time. Many researchers give their contribution to the human age classification system. In computer vision, the classification of age system is a growing area in the research of the past decade [2, 11, 12, 14].

2 Related Work

In the past, researchers have used different techniques and classifiers for feature extraction and classification of images. Kwon and Lobo [15] were the first investigators to work on the age classification system. Researchers have dealt with the problem of the small database which is insufficient for classification. Horng et al. [8] dealt with the problem of a relatively small database. However, the researcher faced the following three problems. First, estimation of age is not accurate for the system. Second, feature extractions depend on the size of the image which varies and change in the size of the image reduces the performance; and last, the unmanaged age groups. Kalamani et al. [13] used fuzzy lattice neural model for the age-related classification system. The researcher used various features that include wrinkle density, average skin variance, and wrinkle depth. The work of Kwon and Lobo [15] was the first in the area of the age-related classification problem. The researcher classified images into various age groups, namely adults, elderly and babies. This approach assessed on small sample size. It computes the mouth, virtual top of the head, eyes, chin, and nose as primary features. These feature ratios differentiate babies from the remaining age groups. The secondary feature was a wrinkle. These secondary feature ratios discriminate adults from the other categories. These classified categories had feature ratio and wrinkle analysis, and this was the first achievement to classify human age in different age groups. Horng et al. [8] are amongst the inventor to identify the age classification system. The inventor classified input images into four grayscale facial images age groups such as seniors, adults, young adults, babies, and middle-aged adults. Three steps follow the age-related classification procedure; the first step is localization, the second step is feature extraction, and the last step is age classification. The classification system uses neural networks. All categories are different from each other. The researcher used a private database. Kanno et al. [14] worked on age-related classification system. The authors used a private database to categorize 440 young male face images. The method used mosaic features and neural network. The age groups were showing 80% accuracy. Hayashi et al. [7] categorized human ages in a span of ten-year. The author used the histogram for equalization of the wrinkle and extraction of face wrinkles. Three hundred images database shows the accuracy of 27%. The age groups below 15 which have negligence changes, but have some recognizable changes in face done by analysis. Lanitis et al. [16] designed an age estimation algorithm. 0 to 35 years age estimation was taken. Above 35 years, the face did not provide better results. Iga et al. [9] used human and object interaction processing database which categorized 101 images into five different age groups. The information of skin, color, support vector machine and Gabor wavelet used with an accuracy of 58.4%. Takimoto et al. [20] used Human and Object Interaction Processing as the database. The author took images of different gender such as as 139 females and 113 males. The images categorized into six different age groups with the help of Principal Component Analysis neural network and Gabor wavelet which gained 54.7% and 57.3% accuracy for female and male facial images respectively. Ueki et al. [23] used WIT database for age classification. The method used a two-phase technique named 2DLDA and LDA. For feature extraction and description of a projection to maximize the proportion within the class and LDA did the segregation of the class. The accuracy rate o achieved for different range such as five years ranges, age group of 46.3% accuracy, ten years range age group of 76.8% accuracy and 15-year range age group accuracy of 78.1%. Yang and Ai [24] used different types of databases in an age classification system uses face recognition technology. The study had three thousand five hundred forty images. Six hundred ninety-six images are taken for study from Pose, Illumination, and Expression databases. These were three age groups in the database. This method used by Local Binary Pattern histogram technique. The accuracy was 92.12% for face recognition technology database and 87.5% Pose, Illumination and Expression database. Günay and Nabiyev [5] took a private database of 350 facial images and face recognition technology database. The method used Local Binary Pattern and Nearest Neighbor (KNN) classifier for classifying images into six age groups with 80% accuracy. Gao and Ai [4] used a fuzzy classifier, and Gabor features for grouping 6386 images in 4 different groups. The authors obtained 91% accuracy. Dehshibi and Bastanfard [2] proposed an age-related classification for four various age groups. The researcher used Iranian face Database (IFDB). The significant enhancement in the age-related classification achieved 86.64% accuracy. The researcher used 498 images for the age classification system. Tonchev et al. [21] developed an age group estimation system based on the subspace projection algorithm and vector classifier. Hajizadeh and Ebrahimnezhad [6] used Histograms on Probabilistic Neural Network and Oriented Gradients for analyzing 377 facial from the Iranian face database. Authors achieved 87.02% accuracy in categorizing images into age groups. Liu and Liu [18] designed an approach for the age-related classification system. The authors categorized images into five different age-groups. Support Vector Machine classifier used during the last stage [15]. Nithyashri et al. [19] used the Adaptive Resonance Theory Network (ART) method for classification. The author used the FG-NET database to categorize images into many different age groups such as senior adult, adult, young and child. Thukral et al. [22] used FG-NET database to classify images into several age groups. Fard et al. [3] classified 575 facial images into a different age group from the Productive Aging Lab face database.

Authors used Histogram of Local Binary Pattern, Oriented Gradients, and Adaptive Neuro-Fuzzy Inference methods and achieved 88.01% accuracy. Izadpanahi et al. [10] proposed a system of age classification for Iranian Face Database, Face and Gesture Recognition Research Network database and classified the face image into seven age groups. The feature used geometric ratios and wrinkle analysis. The classifier used Support Vector Classifier. The authors obtained accuracy at 92.62%. Lee et al. [17] classify images into different age groups based on local age group modeling. Kalansuriya et al. [12] classify facial images corresponding to gender and age. Images used by the author in the range of 8–63, 14–25, 26–45, 46–60 provide the gender classification of 100% and accuracy of age classification 90%, 50%, 40%, 90%. Jagtap and Kokare [11] classify input images into grayscale facial images age groups. The researchers used PAL face databases. The proposed system provided better accuracy of 93.75% for the age classification system.

3 Proposed Approach

Following points comprise the proposed age classification system.

3.1 Preprocessing

It is the first process of image processing considered as a general process. The objective of image preprocessing is to enhance and remove unwanted distortion, edges, some unnecessary information and remove changeable color quality. It provides the effect on the contrast of an image.

3.2 Facial Based Aging Feature Extraction

The facial aging feature extraction performed using skin texture feature extraction and wrinkle analysis. Skin texture features accomplished by local Gabor Binary Pattern Histogram (LGBPH) technique, and Wrinkle performs analysis of wrinkle features Extraction using LGBPH and wrinkle density.

3.2.1 Skin Textural Feature Extraction

The skin textural feature is extracted using LGBPH. LGBPH techniques are as follows.

3.2.1.1 Local Gabor Binary Pattern Histogram

LGBPH is a technique used for recognizing the face, which is first invented by Zhang et al. [25]. LGBPH is attained through applying Gabor filters of various orientations and frequencies, then using the LBP are applied over processing image and histograms are calculated. LGBP is a combination of Gabor feature and LBP feature.

- *Gabor Feature*

A collection of Gabor filter applied in image different frequencies and different orientation which extract feature, these features are called Gabor feature. A 2-D kernel is represented as follows:

Complex

$$g(x, y; \lambda, \theta, \varphi, \sigma, \gamma) = exp\left(-\frac{x'^2 + \gamma^2 y'^2}{2\sigma^2}\right) exp\left(i\left(2\pi\frac{x'}{\lambda} + \varphi\right)\right) \tag{1}$$

Real

$$g(x, y; \lambda, \theta, \varphi, \sigma, \gamma) = exp\left(-\frac{x'^2 + \gamma^2 y'^2}{2\sigma^2}\right) cos\left(2\pi\frac{x'}{\lambda} + \varphi\right) \tag{2}$$

Imaginary

$$g(x, y; \lambda, \theta, \varphi, \sigma, \gamma) = exp\left(-\frac{x'^2 + \gamma^2 y'^2}{2\sigma^2}\right) sin\left(2\pi\frac{x'}{\lambda} + \varphi\right) \tag{3}$$

Where,

$$x' = xcos\theta + ysin\theta \tag{4}$$

$$\sin\theta(1 + x)^n = 1 + \frac{nx}{1!} + \frac{n(n-1)x^2}{2!} + \ldots \tag{5}$$

$$y' = -xsin\theta + ycos\theta \tag{6}$$

In this equation λ represent the wavelength of the wave vector, θ describes the orientation of Gabor kernel φ the phase offset, σ is standard deviation of the Gaussian envelope and γ describes the spatial aspect ratio and specifies the ellipticity of the support of the Gabor function. Gabor filter bank of 40 filter made of five different scales, 0, 1, ……, 4, and eight orientation 0, 1…….. 8.

Gabor filter with convolution in image performed to extract the feature as the following equation

$$G(z) = \varphi_{\mu,v}(z) * J \tag{7}$$

Where,

G(z) = result of convolution
J(z) = input image
z = (x, y).

- *Local Binary Pattern*

LBP is a very easy and efficient method that related to texture. Because of computational simplicity and differential power, LBP technique is a very famous technique in many application areas. LBP has the ability to solve a computational problem that makes easy to examine images in real-world challenges. The LBP calls to non- uniform patterns that might be used to implement rotation-invariant descriptor and overcome the length of the feature vector. A pattern is said to be a uniform local binary pattern if the pattern takes no of transitions from 0 to 1 in bitwise or vice versa. If total no of the pattern is 256, then 58 patterns are used uniform pattern and 1 non-uniform pattern. The LBP feature vector created in the following way.

a. Partition the examined window into cells that each cell is having 16 × 16 pixels.
b. Consider the pixels along a circle, in which each pixel within a cell compares with its all pixel to 8 neighbors.
c. Value of the center pixel is more than the value of the neighbor pixel value. It means center pixel "1" neighbor's value is 0 otherwise, "1".

LBP are calculated by the following equation:

$$\mathrm{LBP}_{P,R} = \sum\nolimits_{j=0}^{P-1} s\left(g_p - g_c\right)2^p \tag{8}$$

where,

$$s(k) = \begin{Bmatrix} 1 & k \geq 0 \\ 0 & k < 0 \end{Bmatrix}$$

where,

g_p = pth pixel value
g_c = center pixel value
P = no of neighboring pixel
R = distance of neighboring pixels from center pixel.

3.2.2 Wrinkle Analysis

The wrinkle is a primary feature of the face used in the wrinkle analysis. As the age grows, the wrinkles are determined to face easily. A wrinkle shows that growing age progression. Wrinkle grows, according to the age progression. Wrinkles are inescapable information for a human being. The wrinkle analysis is calculated using LGBPH as a discussion in Sect. 3.2.1 and wrinkle density. Wrinkle helps in the age classification system. Wrinkle density is determined by

$$V_d = \frac{\boldsymbol{Wn}}{\boldsymbol{Tn}} \tag{9}$$

where,

V_d = wrinkle density
W_n = count the wrinkle pixel
T_n = total no of pixel in image.

3.3 Classification

K-Nearest Neighbor is very easy and straightforward to understand. It is a non - parametric method that applies to both classification and regression. In classification, an object is categorized from a majority vote of about their neighbors and using the object is allocated to class between k nearest neighbors (k is a small positive integer). In regression, the output is used for an object that is the average of their k-NN value [24, 26]. The feature vector space is part of the training and training sample of class labels. K-NN is to determine the numbers of k samples. The training has identified K samples. Categorization of samples that reused as test samples into a class. K-NN is used to categorize different age groups. It can be more efficient for large training data sets. The Euclidean distance D determined by

$$D = \sqrt{\sum\nolimits_{i=1}^{N} (x_i - y_i)^2} \tag{10}$$

where, x_i = element of X, y_i = element of Y.

4 Process Flow and Working of System

The process flow of age classification system s divided into three parts, i.e. preprocessing, skin aging feature extraction and classification. The Fig. 1 represent the process flow diagram of the age group classification system. The first process is preprocessing in which RGB image converted into the Grayscale image. The second process is facial aging feature extraction in which skin texture feature extracted using LGBPH and wrinkles are analyzed with the help of LGBPH and the density of wrinkle. The third process is a classification of images in the relevant age groups with the help of K-NN classifier.

4.1 Image Preprocessing

Image preprocessing is a critical and essential process in the image processing. It is an initial and primary step in any process of image processing. The objective of image preprocessing is to enhance and remove unwanted distortion, edges, some unnecessary information, and changeable color quality. Image preprocessing provides the effect on the contrast of an image. It gives a significant impact on image analysis and results. It converted RGB image into a grayscale level, crop facial area on gray scale level image and normalized as shown in Figs. 1, 2 and 3.

4.2 Facial Aging Feature Extraction

The second process is the facial aging feature extraction process for skin texture extraction. After that analysis of wrinkle is accomplished. A face has eight regions; used for facial aging feature extraction. There are three face regions; used for skin textural feature extraction. There are five face regions; used for wrinkle analysis. These are the particular areas of the face, which show identifiable age changes in Fig. 4.

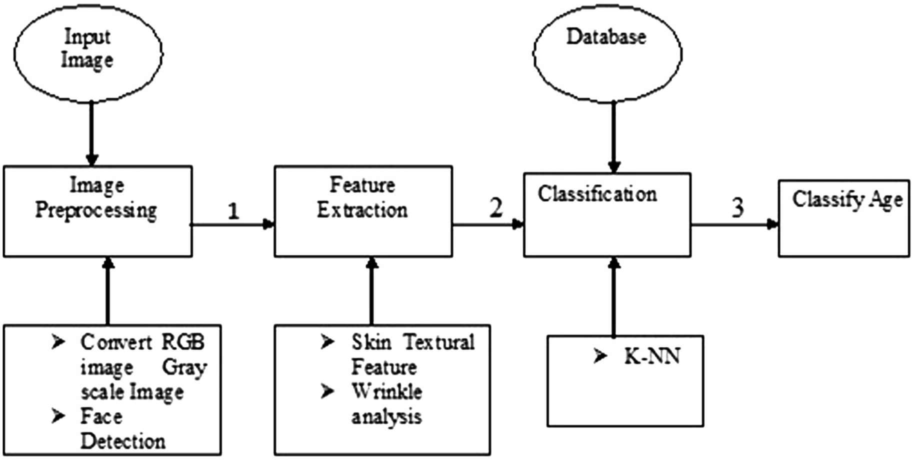

Fig. 1. Process flow of age group classification system

Fig. 2. RGB image

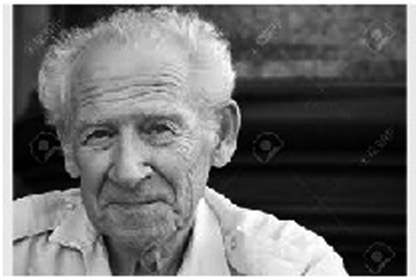

Fig. 3. Gray scale level image

Fig. 4. Cropped face area

4.2.1 Skin Textural Feature Extraction

For Skin textural features are extracted by LGBPH using the following steps.

Step (a): In the first step of skin texture feature extraction, proposed work builds a bank of 40 filters which used Gabor filter as shown in Fig. 5.

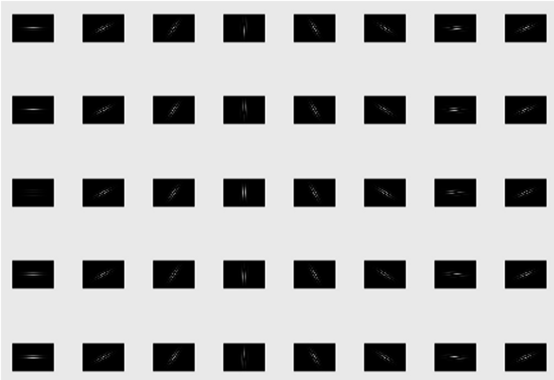

Fig. 5. Gabor filter bank used 40 filters with 5 scales and 8 orientations

Step (b): The used region is cropped from the grey level facial image.
Step (c): Calculate the convolution of the cropped region (Eq. 7) as shown in Fig. 6.

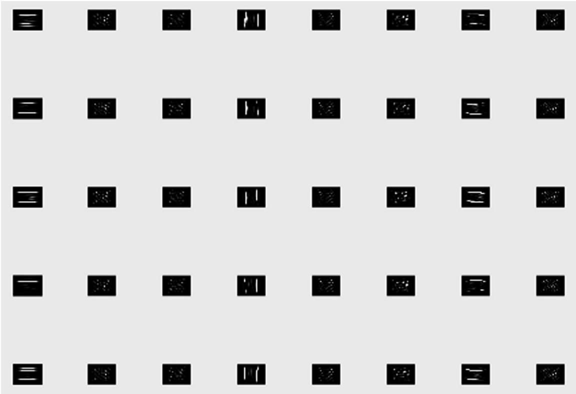

Fig. 6. Convolution of crop region with 40 Gabor filter bank

Step (d): This cropped region proposed system used Gabor filter bank with convolution to determine the Gabor feature. Local binary pattern technique is used along Gabor filter to calculate local gabor binary pattern as shown in Fig. 7.

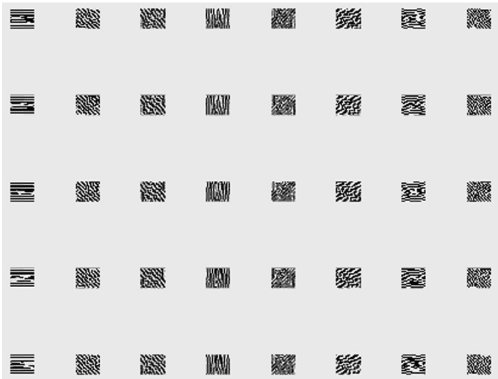

Fig. 7. LBP over Gabor features to create LGBP.

Step (e): Evaluate the histogram of LGBP which is referred LGBPH as shown in Fig. 8.

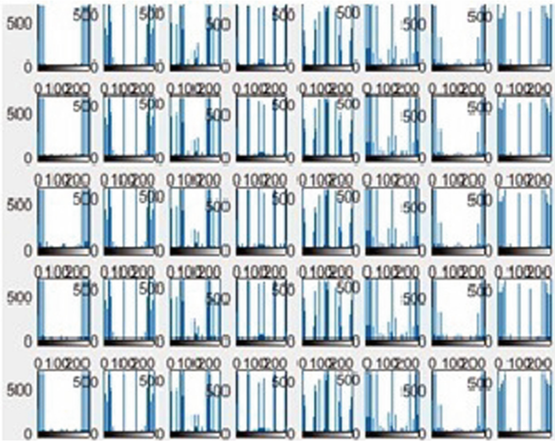

Fig. 8. Histogram of LGBP

4.2.2 Wrinkle Analysis

The wrinkle analysis evaluates wrinkle density and LGBPH.

(A) The following steps calculate the LGBPH for wrinkle analysis as shown in Fig. 12.

Step (a): Build a bank of 40 filters which use Gabor filter.
Step (b): The cropped region is used from grey level face images.
Step (c): Calculate convolution of crop image through 40 filter bank for extracting Gabor feature.

Step (d): Determine the magnitude of every Gabor features.
Step (e): This step Take the first 12 features of Gabor and applying LBP for evaluation of LGBP.
Step (f): Evaluate the histogram of LGBP which referred LGBPH.

(B) The following steps is performed for the detection of wrinkle.

Step (a): Firstly cropped the region of interest used for wrinkle analysis and used a Gaussian filter to remove noise from an image as shown in Fig. 9.
Step (b): This step performed the canny operator to edge detection of an image and performed the morphological operation for reducing unnecessary edges as shown in Figs. 10 and 11.

LGPBH is used differently for wrinkle analysis and skin textural feature extraction. This study applies the LBP on 40 Gabor features for skin texture feature extraction Whereas 12 Gabor features applied to wrinkle analysis with a large amount of amplification and highest correlation using input image.

Fig. 9. Forehead region

Fig. 10. Edge detection by canny operator

Fig. 11. Wrinkle detection

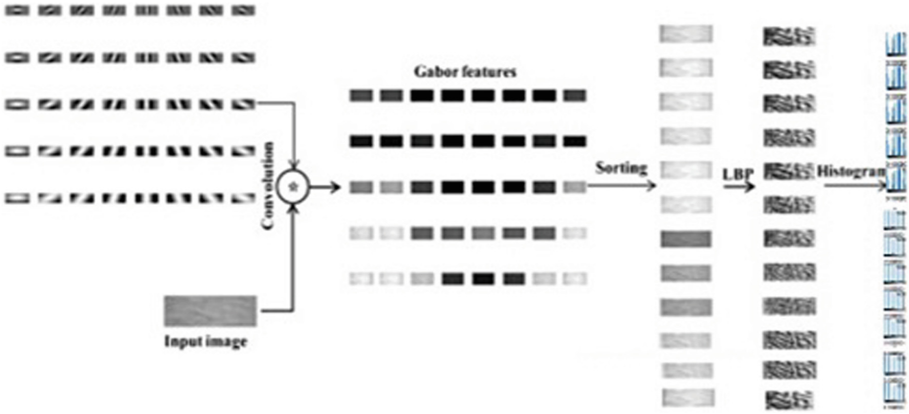

Fig. 12. LGBPH evaluation analysis of wrinkle

Gabor filter's response shows the highest amount of correlation using the input image to match the orientation of the face wrinkle to the orientation of its answers. There are following steps which used to extract facial aging feature extraction.

i. Crop the three regions of skin texture namely nose, left cheek below eyes, right cheek below eyes, according to dimension mention as [5, 5, 0.33, 0.4], [5, 5, 0.33, 0.3], [5, 5, 0.33, 0.3] pixels as shown in Fig. 13.
ii. Calculate the LGBPH of three skin textural region of the face image.
iii. Concatenate LGBPH of three skin textural regions of face area which stored in the following vector

$$V = [v_1, v_2, v_3] \tag{11}$$

Where
V = skin textural feature matrix

iv. Crop the five regions of skin texture namely left eye's corner, right eye's corner, forehead, left below eyes, right below eyes, according to dimension mention as [5, 4, 0.11, 0.25], [10, 4, 0.11, 0.25], [3, 3, 1, 0.25], [10, 7, 0.33, 0.166], [10, 7, 0.33, 0.166] pixels as shown in Fig. 14.
v. Determine the wrinkle analysis by calculating LGBPH and wrinkle density for each particular five regions.
vi. Concatenate LGBPH of five skin textural regions of face area which stored in the following vector

$$Wa = [w_1, w_2, w_3, w_4, w_5] \tag{12}$$

Where
Wa = LGBPH of wrinkle analysis feature matrix

vii. Concatenate same for wrinkle density and stored in the following vector

$$V_d = [wd_1, wd_2, wd_3, wd_4, wd_5] \tag{13}$$

Where
V_d = Wrinkle density feature vector

viii. Combine the LGBPH of these three regions of the face area and LGBPH of the wrinkle analysis feature vector

$$Vc = [V, Wa] \tag{14}$$

ix. After the feature extraction, reduce dimension due to large matrix size. For dimension reduction, Principle Component Analysis (PCA) used as named Vp.

x. Before combining wrinkle density and LGBPH feature concatenation, normalization performed by the following equation

$$F(i) = \frac{F_{ki} - \min(F_k)}{\max(F_k) - \min(F_k)} \tag{15}$$

After normalization, both features are fusioned.

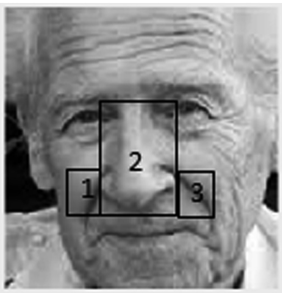

Fig. 13. Regions used for skin textural feature extraction

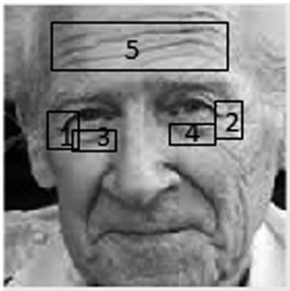

Fig. 14. Regions used for wrinkle analysis

4.3 Classification

The last process is classifications which are very important to categorize input face images into age groups. A training dataset comprised the feature extracted from the face and labeled to the data set pair; forms a model. The testing dataset obtained these feature in the same fashion. The extracted feature with its age group applied to classify which determine the age group. K-NN is an easy and fast way to implement, and its nearest k neighbors classify the subject. After that last feature classifies the input image into the relating age group. The model has been used these features to categorize the age groups. K-NN classifier categorizes the testing dataset images in which it belongs to one of the age groups such as young, adult and old [1].

5 Results

The proposed system used a private database which has 270 images having testing and training data set. Three regions of an image, namely nose, left cheek below eyes, right cheek below the eyes for skin texture feature extraction uses LGBPH. The skin texture LGBPH features stored in matrix named as V. For wrinkle analysis firstly LGBPH calculates the five regions namely left eye's corner, right eye's corner, forehead, left below eyes, right below the eyes is used. Then calculates wrinkle density. The LGBPH feature of wrinkle analysis stored in matrix named as Wa and the length of wrinkle density feature stored in a vector named as Vd. Skin texture LGBPH features stored in a matrix called as V and LGBPH feature of wrinkle analysis stored in matrix named as Wa. Both matrices are combined and stored in a matrix named as Vc. The size of both feature matrixes is large; therefore PCA applied for reducing a dimension of a matrix to store in a vector named as Vp. The reduced vector is normalized as the feature lies in range 0 to 1, used in the classification. The whole mechanism used in both training and testing stages. The proposed system takes 180 images to use for training datasets, and 90 images choose to apply for testing datasets. The last feature classifies the input image to the relevant age group. The model used these features to categorize into different age groups. K-NN classifier categorized the testing dataset images into groups young, adult and old.

- *Recognition Results*

As shown in Table 1, there are three groups, namely child, adult and old. The total numbers of the testing dataset have 90 images having 30 images of each group, 28 images from child group matched accurately. The recognition rate of the child group obtained is 93.3% Twenty-nine images are matched accurately from the adult group. The recognition rate of the adult group obtained is 96.6%. Thirty images are matched accurately from the adult group. The recognition rate of the old group obtained is 100%. The average recognition rate of proposed system which is obtained by K-NN classifier = (93.3 + 96.6 + 100)/3 = 96.6%. Figure 15 shows the accuracy of child, adult and old groups. The x-axis denotes the groups, and Y-axis denotes accuracy of different groups. The accuracy of child, adult and old represented in the graph is 93.3%, 96.6%, and 100% respectively.

Table 1. Recognition rate of input image

Groups	Recognition results			
	Child	Adult	Old	Recognition rate
Child	28	0	2	93.3%
Adult	0	29	1	96.6%
Old	0	0	30	100%

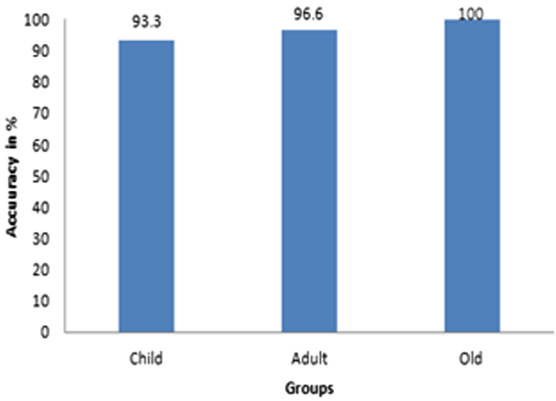

Fig. 15. Accuracy of groups

- *Comparison with Existing Techniques and Classifiers*

Table 2. Comparison of existing techniques and classifier

Author's name	Features	Tools of classification	Accuracy in %
Kwon and Lobo [15]	Geometric ratio and wrinkle analysis	Similarity measures	100
Kanno et al. [14]	Mosaic feature	ANN classifier	80
Horng et al. [8]	Geometric ratio and wrinkle analysis	ANN classifier	81
Iga et al. [9]	Gabor feature	SVM classifier	58.4
Gao and Ai [4]	LBP feature	FUZZY LDA classifier	91
Dehshibi and Bastanfard [2]	Geometric ratio and wrinkle analysis	ANN classifier	86.64
Hajizadeh and Ebrahimnezhad [6]	Histogram of Oriented Gradient	PNN classifier	86.64
Fard et al. [3]	LBP and HoG features	ANFIS classifier	88.01
Izapandhi and Toygar [10]	Geometric ratio and wrinkle analysis	SVC classifier	92.62
Kalansuriya and Dharmaratne [12]	Geometric ratio and parameter calculation	ANN classifier	90
Solanki and Priyadarshni (Proposed method)	Facial aging feature	K-NN classifier	96.6

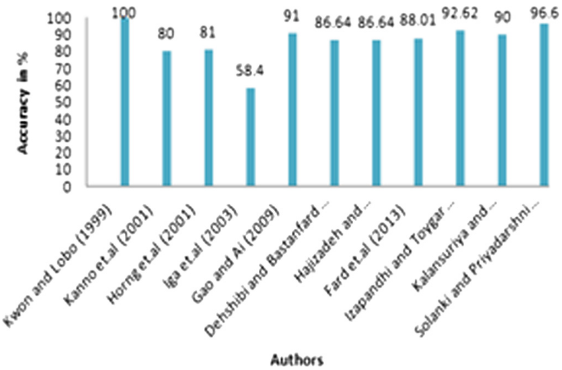

Fig. 16. Comparison of accuracy achieved by authors

Many researchers worked on the age classification system. The researchers used many techniques of classification. The work of Kwon and Lobo [15] was first in the area of age-related classification problem which used geometric ratio, wrinkle analysis feature and similarity measures as a tool of classification. The researcher classified images into various age groups namely adult, seniors and babies with 100% accuracy. Kannoet al. [14] used mosaic features and neural network for the age classification system. The accuracy obtained with four age groups with 80% accuracy. Horng et al. [8] classify input images into four grayscale facial images with ANN classifier having 81% accuracy. Iga et al. [9] used a Gabor filter for extracting the feature and SVM as a tool of classification. Images divide into five different age groups. The analysis was done [4] with an accuracy of 58.4%. Gao and Ai used a fuzzy classifier, and Gabor features for grouping images in 4 different groups. The accuracy obtained 91%. Hajizadeh and Ebrahimnezhad [6] used Histograms of Probabilistic Neural Network and Oriented Gradients for analysis with 86.64% accuracy [14]. Fard et al. classified facial images in a different age group. Izadpanahet al. [10] classify face image into seven age groups using Support Vector Classifier. Analysis obtained accuracy 92.62%. Kalansuriya and Dharmaratne classify facial images using geometric ratio, wrinkle analysis and ANN classifiers to corresponding to gender and age. Images used by the author in the range of 8–63, 14–25, 26–45, 46–60 which provide the gender classification of 100% and accuracy of age classification 90%, 50%, 40%, 90%. Figure 16 represents the comparison of accuracy by various authors. Proposed work provides better results and estimates the accuracy as compared to the previous technique used by the different researcher in Table 2.

6 Conclusion

Human face provides adequate information that is easily recognizable by a human. The human face also provides expression, moods, and state of action. As a human grows, noticeable change perceives in age progression. The age classification is also challenging for the machine to categorize face images in age groups. In this work, the age-group classification system has been classified age into three different groups which include a child, adult and old. A method is used to solve the age classification related problem. The proposed work is completed in three stages, namely preprocessing, facial aging feature extraction and classification. Preprocessing is an important and essential stage that RGB image converted into the grayscale image because it removes unwanted distortion, edges, some unnecessary information, and changeable color quality. Facial aging feature extracted by skin textural feature extraction with the help of LGBPH and Wrinkle analysis method. For skin, texture feature used three regions (nose, left cheek below eyes, right cheek below eyes) and for wrinkle analysis used five regions (left eye's corner, right eye's corner, forehead, left below eyes, right below eyes). LGBPH accomplishes skin texture feature extraction, and Wrinkle analysis is performed using LGBPH and wrinkle detection. LGPBH is handled differently for wrinkle analysis and skin textural feature extraction. LBP applied on 40 Gabor features for skin texture feature extraction whereas 12 Gabor features applied to wrinkle analysis with a large amount of amplification and highest correlation using the input image. Gabor filter's response shows the highest amount of correlation using the input image to match the orientation of the face wrinkle to the orientation of its answers. LGBPH is unvarying for rotation illumination and translation. The facial aging features which used the region of interest from face images to categorize into different age groups. K-NN classifier is a fast learning classifier, used in the proposed work. The proposed system classified into three groups namely child, adult and old which obtained accuracy 93.3%, 96.6% and 100% respectively. The overall accuracy of the proposed system is 96.6%. The proposed methods provide a better result and improve existing age classification system. LGBPH give a better result and estimate the accuracy as compared to the previous technique used by the researcher. This classification is successful work which provides an efficient classification using facial aging feature extraction. The Proposed system provides a better result and improves existing age classification system. In the future, for an age classification system used the most extensive database for improving the real-time system.

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