Age Detection based on Facial Image using Fusion Extreme Learning Machine Classifier

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ABSTRACT

Age Estimation from the human facial image is a very difficult process since age is influenced by many factors gender, life style, working environment, mental state of the person etc. For age estimation LBP (Local Binary Pattern) histogram are generated and wrinkle estimation is performed using the Gabor filter resulting with the Gabor feature vectors based on the wrinkle levels. Training and testing are done with Fusion Extreme Learning Classifier which is proposed. The proposed fusion classifiers combine the Gabor feature vectors and LBP histograms and estimates the age based on the classification results and manual voting results. The testing is performed with FG-Net database and achieves higher accuracy levels with ease of computation.

Keywords: Local Binary Pattern, Gabor Filter, Extreme Learning Machine, Wrinkle Estimation, Fusion Classifiers.

1 INTRODUCTION

Age estimation based on face images is difficult problem. First of all, there are many factors that affect face changes, including internal and external factors. Internal factors: Different people have different patterns of changes in age characteristics, and gender also has an impact on changes in age characteristics. External factors: acquired living conditions and working environment influences, such as extensive exposure to ultraviolet rays leading to skin aging; long-term consumption of tobacco and alcohol is also prone to aging; long-term unsatisfactory life, aging speed also accelerates. The acquired images often contain a lot of other information, such as lighting, posture, and expressions. Age changes are irreversible, data collection is difficult, and the lack of a suitable face image data set is an important factor in the difficulty of age estimation. In short, there are many potential applications for age estimation based on face images, but age estimation is a difficult problem, and there are still relatively few studies on this problem.

For face images, humans can easily obtain various information contained therein, such as identity, gender, race, approximate age, and facial expressions. It is quite difficult for a computer to reach the level of human recognition of human faces, especially the automatic estimation of the age of a human face. The reason is that compared to other facial changes, age changes have their own unique properties. First of all, people's age is uncontrollable and cannot be arbitrarily advanced or delayed. It is a slow and irreversible process; secondly, age has different patterns of change for different people, which is not only determined by internal factors such as genes, race, etc.Is also affected by external conditions such as health, lifestyle, climatic conditions, etc. The above-mentioned characteristics of age change not only make it extremely difficult to collect enough training data with age information, but it is also difficult to find accurate characteristics of age change. However, age estimation and face recognition with age changes have extremely wide applications, so it is increasingly important to seek solutions to such problems. The face image contains age information, but there is also a large amount of information that expresses the lighting conditions at the time of data collection, human expressions and postures, etc. This information is not only irrelevant to age, but also interferes with the estimation of age. Extracting features that can characterize age has become the key to problem solving. The application of age estimation based on face images is not limited to cross-age recognition. Age is an important biological characteristic of a person, and it can be applied to a variety of scenarios, such as age-based human-computer interaction systems, which provide different interactive interfaces according to different ages of users to better serve users; age-based access control, such as It is forbidden for minors to visit pornographic websites, purchase tobacco and alcohol, etc.; Personalized marketing in e-commerce, using different marketing methods for users of different age groups; Age filtering in criminal case investigation, etc.

Anthropometric mode [1], through the measurement of changes in the shape and texture of the face, roughly classifies the face into several age groups, but it is not suitable for more refined age division estimation. Age change mode subspace [2-3], collect face images of different ages of test subjects, it is necessary to know exactly the identity information of each face image in the training set. In many practical applications, the identity information of the face is incomplete, Lack of practical applicability. The age-change prevalence analysis method [4-5], through the popular learning algorithm to model an age-changing prevalence space, in this prevalence, a low-dimensional feature subpopulation is used as a feature description of the age change structure of the training sample, which can effectively reveal Popular structural features of face images, but still need to learn to establish the relationship between face age change information and low-dimensional features.

Age regression method [6-8], age regression method regards age estimation as a multi-linear regression problem, and the purpose is to find a suitable regression function to describe the connection between face image and age estimation. Because of its simplicity and efficiency, this method has been adopted by many face age estimation systems. The gradient histogram (HOG) and local binarization mode (LBP) proposed by the author are both statistical feature descriptors after the gray value difference of the face. They have the advantages of illumination and rotation invariance, and effectively suppress the image background information. Disturbance of age estimation. HOG and LBP histograms represent the characteristics of the age change of the face from the uniformity and consistency of the texture and the gradient direction histogram of the face gray value respectively, which provide a beneficial supplement to the information about the age change of the face. In view of the fusion of the shape features of the human face [9] and texture features, it has been proved by [8] that it can better describe the human age. The canonical correlation analysis (CCA) [10] method is used to fuse the local binary pattern (LBP) histogram and gradient histogram (HOG) as the feature descriptor of the face, and the support vector machine regression (SVR) combined with leave-one-out cross-validation method (The strategy of LOPO) has been trained and tested on the face age database FG-NET [11] of the University of Cyprus, and achieved satisfactory results.

2 LITERATURE SURVEY

Kwon and Horng [12,13] The method based on the anthropometric model measures and extracts the changes in the growth of the head from a baby to an adult, and calculates the six geometric ratios between the eyes, nose and mouth, and extracts the eyes by using the edge detection of the Sobel operator. Calculate the ratio of the distance between the two organs on the basis of the position of the nose and the mouth as the input of the BP neural network training to distinguish infants and adults; distinguish young and old by extracting wrinkle features in the frontal area of the face and the lower eyelid pouch area People ; by locating eyes, nose, mouth, chin, face .Dehshibim and Bastanfard[14] The 6 feature points of the forehead and the forehead are extracted, and the 7 ratios between them are extracted as the training parameters of the BP neural network; and the Canny operator edge detection method is used to extract the wrinkle features of the forehead, the tail of the eye and the cheek in the face. The wrinkle density is used as the training parameter of the BP neural network. Finally, a 4-layer BP neural network is trained as a classifier to classify the age stages of 15 years old and below, 16-30 years old, 31-50 years old, 50 years old and above, and obtain 86.64% average classification accuracy rate.Hayashij[15] The method based on the appearance model The method based on the appearance model is mainly for modeling human skin color, hair color and wrinkle distribution. Edge detection is performed by Sobel operator, local texture features are extracted and their density is calculated.Nakona et al[16]Principal component analysis (PCA) and multivariate discriminant analysis (MDA) are used to reduce the dimensionality of gray histograms to obtain color features . Txiajd andHuangcl[17]The support vector machine (SVM) is used in 20~30 years old, 31~40 years old, 41 years old. The four age groups of ~50 years old and 51~60 years old achieved an average classification accuracy of 72.52% .Guoget.al[18] Using Gabor filter to extract the skin texture features of faces of different ages more finely, the age estimation in the YGA age database has obtained the average absolute error of 3.47a for men and 3.91a for the average absolute error of women. On the FGGNET age database Achieved an average absolute error of 4.77. Feature-based modeling methodsZhangy and Zhouzh[19]The main representative models based on feature modeling methods are: from the perspective of regression and classification, the age estimation problem is handled separately based on canonical correlation analysis and cost-sensitive learning, and the two types of Combining the results of the method, the average absolute error of 3.4863a is obtained.Yu and Du[20] Through the improved non-negative matrix factorization (NMF), a subspace with age representation is established to represent the original image, and the radial basis function neural network (RBF) is used for training and prediction, and an average of 6.23a is obtained. Absolute error Du et aland Geng et.al[21,22]; The face images of the same object at different ages are arranged in chronological order to form the age pattern of the object.PCA is used to reduce the dimensionality of the face image of the age pattern of different objects, and it is obtained by extracting the feature vector Age pattern subspace (AGingpattErn Subspace, AGES), and estimate its age through positioning, obtained an average absolute error of 6.22a on the FGGNET age database, and an average absolute error of 8.83a on the MORPH age database. Methods based on deep learning With the great success of deep learning in the field of image processing, after 2015, research on age estimation methods has made breakthrough progress driven by deep learning algorithms. Levi et al. [23] used 1947 photos The social photo trains a network structure composed of 3 convolutional layers and 2 fully connected layers, which are between 0-2 years old, 4-6 years old, 8-13 years old, 15-20 years old, 25~32 years old, and 38 years old. Eight age groups of ~43 years old, 48-53 years old, and 60 years old and above have obtained an average accuracy rate of (50.7±5.1)% and 1Goff (84.7±2.2)%. Yi et al. [24] used face images of different sizes to train a convolutional neural network and obtained an average absolute error of 3.63a. In the ChaLearnLAP 2015 apparent age estimation competition,Rothe et al. [25] first used 20 VGGG16 structures The ImageNet dataset is pre-trained, and then fine-tuned on the IMDBGWIKI and LAP datasets, and finally the final output is determined by the average of 20 VGGG16 networks. With the average absolute error of 3.221a, it won the ChaLearnLAP2015 apparent age estimation competition. Liu et al. [26] proposed an age estimation structure called AgeNeg, which was pre-trained using CASIAGWebFace data set, and fine-tuned on CACD, MorphGII and WebFaceAge data sets, and finally obtained with the average absolute error of 3.345a Won the second place in the ChaLearnLAP 2015 apparent age estimation contest.Antipov et al. [27] trained 14 VGGG16 structures, of which 3 VGGG16 networks are only responsible for identifying children aged 0-12, and the remaining 11 networks are used for recognition of 0-99 years old. With the results of εGscore 0.24111, they obtained the ChaLearnLAP2016 appearance. First place in the age estimation contest.

3 Proposed Research Methodology

3.1.Feature Extraction:

Select the LBP feature description of the face image to start, then use PCA to extract the features, fuse the extracted features, and finally select the classifier to learn the age regression model, and use the model to predict the age.

Age change feature extraction, the general principle of image feature selection is that the difference between images of the same class is small (smaller intra-class distance), and images of different classes have larger differences (larger class distance), that is, the most distinguishable The characteristics of force. At the same time, the computational complexity of feature extraction is minimized. With the increase of age, the most prominent changes in the face are reflected in local areas, such as the corners of the eyes, the corners of the mouth, etc. The local binary pattern (LBP) for face images that are closely related to age changes. Difference statistics of gray value.. Normalize the face image into an 80×64 grayscale image, and divide it into a grid containing 80 8×8 windows, then extract the histograms of LBP for each small window, and finally connect the histograms separately A sequence of histograms is formed as the LBP feature vector of the face.

3.2 Local Binary Pattern

The LBP operator binarizes each pixel in the face image according to the central gray value of the 3×3 domain pixel relative to the central pixel: each pixel uses its gray value fc as the threshold, if the surrounding pixels gray If the value fp is greater than or equal to the gray value, the point is set to 1, otherwise it is 0. Perform 0/1 encoding on its 8 neighborhoods to obtain a binary string with a length of 8, and use the binary string as the encoding of the pixel, as in formula (1)

$$\text{LPB}_{P,R} = \sum_{p=0}^{p-1} s(fp - fc).2^{p} \qquad (1)$$

Where $s(fp - fc) = \begin{cases} 1 & fc \geq fp \\ 0 & fc < fp \end{cases}$, f_c = The gray value of the center pixel , f_p(p=0,1,2,…,N): The gray value of the pixel sampling point in the center pixel area.

Each sampling point in the field is assigned a sampling point according to a different weighting coefficient 2p, and the sum is finally summed. And rotate counterclockwise p times in sequence, with the minimum value as the final LBP value of the center pixel to ensure that the rotation does not change. As shown in formula (2)

$$LPB_{P,R} = \min\{ROR(LBP_{P,R}, i) \quad i = 0,1,\ldots P-1\} \qquad (2)$$

The LBP feature is used to estimate the age of the face, as shown in the grid face gray map shown in Figure 2, the LBP feature extraction is performed on these 80 small regions, and the histogram of each region is calculated. Finally, the The histograms are connected as a representation of the human face.. Use uniform uniform mode LBPP, Rriu2, where P=8, R=1, u2 refers to uniform uniform mode, that is, the number of transitions of 0 and 1 in the binary code is not allowed to exceed 2 times, as shown in formula (3) , LBPP, Rriu2 mode local area histogram vector length is 59.

As the first attribute parameter, the local binary pattern (LBP) histogram values were examined among the data in order to examine the situation of similar facial structures within the same age groups, as well as detailed classification of wrinkles. Histogram is the classification of the values in a data set and their representation with a created column chart. In the histogram, the columns on his graph do not represent a single data, as in a normal column graph, but a multiple group. Hence the naming of the columns is done with the range values.

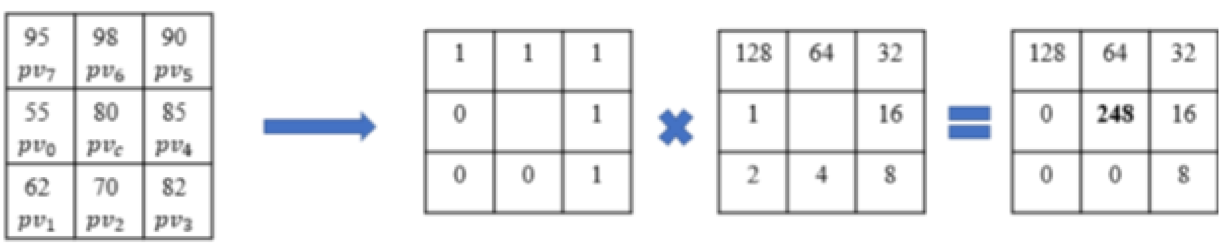

Figure 1: Sample LBP application

Here, a test was made for 8 neighbors of the central matrix over the threshold value selected for the matrix amplitude, and the 0 and 1 values were placed in the indices. Subsequently, the binary coefficients on the neighborhood numbers of the matrices were calculated and assigned to the indices. LBP histogram matrix values are created by assigning the sum of the neighboring index values to the central index in a new picture matrix. This process is completed by sliding the LBP frame over the entire picture.

3.3 Wrinkles estimation

Facial creases: Facial wrinkles are deep, shallow wrinkles caused by changes in the structural integrity of the skin. It occurs due to loss of skin and muscle flexibility resulting from repetitive facial movements and changes in skin expressions. In clinical areas, terms such as line, groove and sulcus are used.Mentolabial wrinkles (or grooves): Mentolabial wrinkles are one or more horizontal wrinkles that appear between the lower lip and chin (mentum). These wrinkles extend between the orbicularis oris muscle and the mentalis muscle.

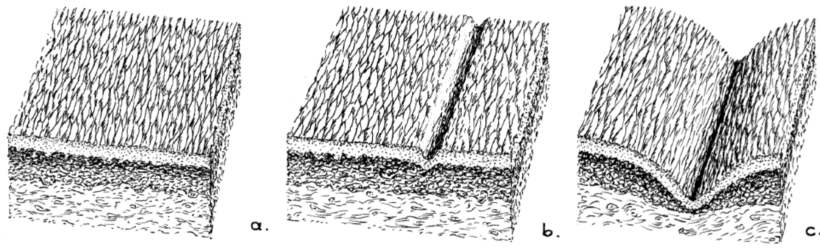

Figure 2: Textural changes in the skin: (a) wrinkles, (b) mimetic wrinkles and (c) grooves

3.4 Gabor filter and image attributes

Facial wrinkles are 3D features of the skin and appear as fine discontinuities or stretch marks in the surrounding skin tissue. However, facial wrinkles can be easily masked by lighting / acquisition conditions in 2D images due to the peculiar nature of the skin surface texture and its reflective properties**.**In applications based on image-based analysis of aging skin, wrinkles are analyzed more like texture rather than curvilinear discontinuity / crack features. It has been seen in the literature that the image features based on the Gabor filter bank to emphasize the fine curvilinear discontinuities in the skin tissue caused by wrinkles are effective features in classification. The real Gabor filter core function directed to the angle α is given in equation 3:

$$g(x_1.x_2) = \frac{1}{2\pi\sigma_{x_1}\sigma x_2} \exp\left[\frac{-1}{2}\left(\frac{x_1^2}{\sigma_{x_1}^2} + \frac{\gamma^2 x_2^2}{\sigma_{x^2}^2}\right)\right]\cos(2\pi f x_1) \quad (3)$$

Here, the parameters $\sigma x1$ and $\sigma x2$ indicate the scale of the 2D Gaussian envelope. It represents the frequency of the isosoid. gives the spatial aspect ratio that defines the ellipticity or elongation of the Gabor function. For $x1$ and $x2$, the values are as follows:

$$\begin{bmatrix} x_1' \\ x_2' \end{bmatrix} = \begin{bmatrix} \cos\alpha & \sin\alpha \\ -\sin\alpha & \cos\alpha \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \begin{bmatrix} \cos\alpha & \sin\alpha \\ -sin\beta & \cos\alpha \end{bmatrix} \quad (4)$$

$\{gk\ (x1,\ x2),\ k = 0,\ldots,\ K - 1\}$ series $ak = -\pi/2 + \pi k/K$ It symbolizes Gabor filters directed to their angles. Here K represents the total number of equally spaced filters in the angle range $[-\pi/2, \pi/2]$. If the filter in question is applied to the input picture, the corresponding maximum amplitude among filtered responses is calculated by Equation 5.

$$I'(x1,x2)=maxk(IkF(x1,x2)) \quad (5)$$

The maximum amplitude response is normalized to the range [0,1]. Subsequently, the pixels where the points where the Gabor filter generates high response are marked. As can be understood from here, the controlled output values are average amplitude and root mean square energy. Amplitude and phase outputs of sample data passing through Gabor filter are given in Figure 3.

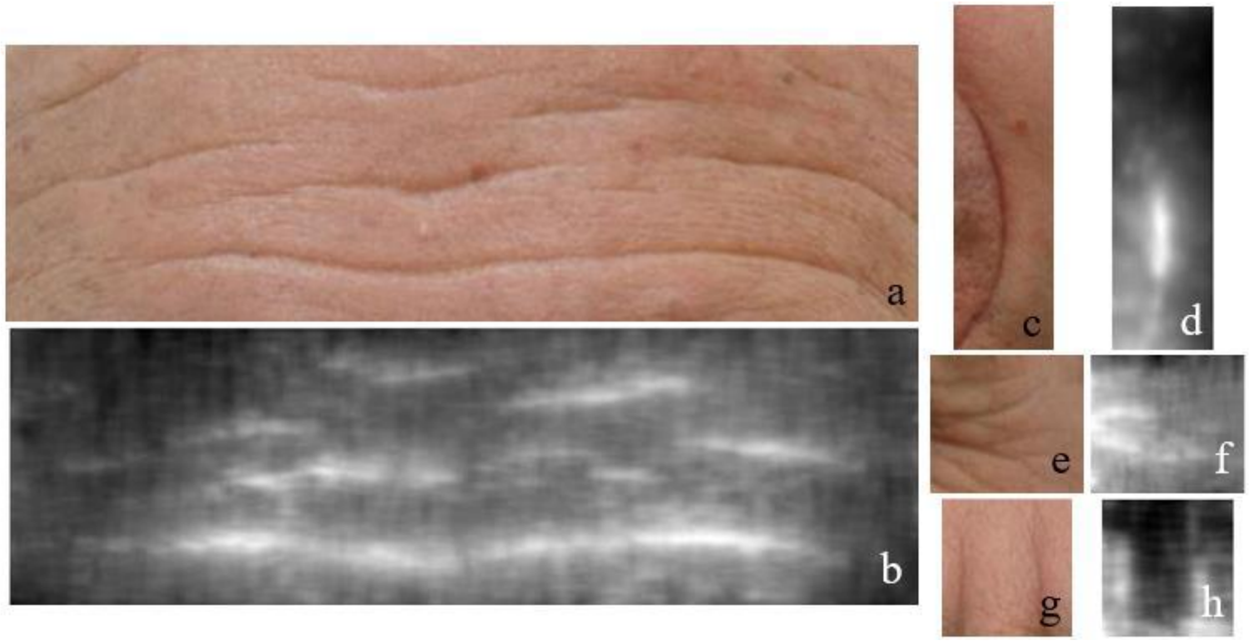

Figure 3: Gabor outputs for wrinkle areas a) forehead b) filtered forehead c) nasolabial groove d) filtered nasolabial groove e) crow's feet f) filtered crow's feet g) brow h) filtered inter-eyebrow area

3.5 Wrinkle index

The depth and height values of the lines and grooves seen in the wrinkle areas provide important information to the physician about the skin age of the person. The number of these wrinkles are features that affect the elongation, length and age class. With these values obtained from the wrinkles in question, an index was proposed to assign an age tag to people. In order to localize the wrinkles seen on the face, a study was carried out on the length and depth values of the wrinkles in the relevant region by taking derivatives of the images from the 1st degree, then passing through the Gabor filter. Wrinkle length 1 is calculated by Equation 6 as the ratio of wrinkle circumference lpi to wrinkle area s for each local area.

$$l = lpi / s \quad (6)$$

Wrinkles seen in wrinkle areas are labeled and evaluated by physicians according to height and depth values. The level diagram used for this labeling is given in Figure 4.4. Scoring levels made on this diagram are given in Table 1.

Table 1: Wrinkle scoring levels

Level 0	No wrinkles
Level 1	Detectable wrinkle only
Level 2	Shallow wrinkles

Level 3	Moderately deep wrinkle
Level 4	Deep wrinkle, well defined edges
Level 5	Too deep wrinkle, excessive folding

The wrinkle index calculated over the wrinkle length and depth calculation is weighted according to the effect levels in relation to the age. The wrinkle index values obtained were labeled at 6 levels in total according to the labeling given in Table 1.

Selected areas and extracted features in the face region are given in Table 2. The attributes in question were obtained by using the necessary image processing algorithms and applying the relevant mathematical operations to the data sets in the Matlab environment, and the necessary feature vectors for each data were extracted. In the next section, the classifiers required to develop a prediction algorithm using these feature vectors are explained.

Table 2: Regions used for classification and extracted features

Face Areas Used	**Extracted Attributes**
Groove Area (Right and Left)	Wrinkle length
Chin Area	Wrinkle Depth
Edge of Mouth(Right and Left)	Wrinkle Index
Under Eye Bags(Right and Left)	LBP Histogram
Between Eyebrows	Gabor Filter average amplitude value

4. CLASSIFICATION METHOD USED

Classification is also a very effective application for the age estimation problem addressed in the thesis study. Fusion Extreme Learning machine is used for examining the classification performances individually, experiments were made for the fusion classifier test by using the voting logic used on the basis of the k-nearest neighbor algorithm.

Extreme learning machines are typical single hidden layer feedforward neural networks (SLFNs), which are widely used in classification and regression problems. Unlike traditional neural network models, the ELM algorithm can adaptively set the number of hidden layer nodes and randomly Assign the input weight and the number of hidden layer nodes, and then use the least square algorithm to solve the output weight. The training process does not require iteration, so the training speed is significantly improved compared to the traditional BP algorithm and Support Vector Machine (SVM) algorithm.

ELM Steps involved

- Assign random input of (weights, biases) Arbitrary hidden layer input weight $\boldsymbol{w}_{\mathbf{i}}$, Arbitrary hidden layer Bias$\boldsymbol{b}_i$

- Calculate the hidden layer output matrix ***H*** by applying X over all m number of hidden neurons with activation function g(W X +b).
- Calculate the hidden layer output weight **β** where **$\beta = H^{+}T$, Where, $H^{\dagger} = (H^{T} H)^{-1} H^{T}$, T=**output layer where $\mathbf{H}^{+}$ is Moore Penrose generalized inverse of **H.**

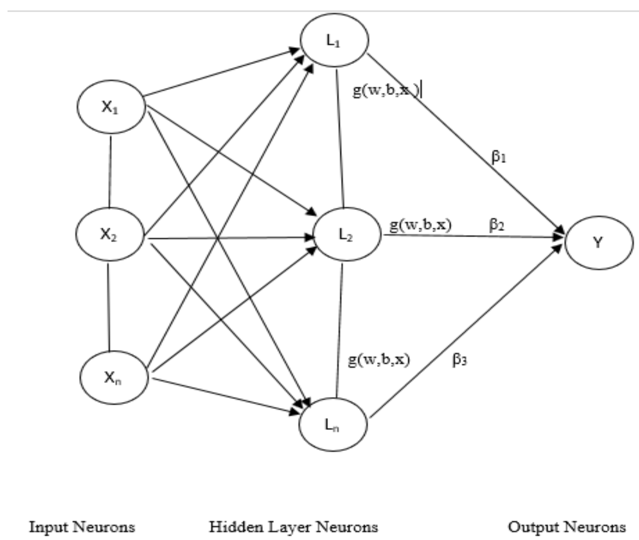

Figure 4: Extreme Learning Machine

$$\beta^{T} H = T$$

$$H = \begin{bmatrix} f(w_1 \cdot q_1 + b_1) & \cdots & f(w_1 \cdot q_N + b_1) \\ f(w_2 \cdot q_1 + b_2) & \cdots & f(w_2 \cdot q_N + b_2) \\ \vdots & \vdots & \vdots \\ f(w_K \cdot q_1 + b_K) & \cdots & f(w_K \cdot q_N + b_K) \end{bmatrix}_{K \times N}$$

$$\beta = \begin{bmatrix} \beta_1^{T} \\ \beta_2^{T} \\ \vdots \\ \beta_K^{T} \end{bmatrix}_{K \times m}, T = [\, t_1, t_2, \cdots, t_N \,]_{m \times N}$$

Huang et al. pointed out that if the number of hidden nodes is sufficient, the activation effect is infinitely different, and all network parameters do not need to be adjusted. In the training phase, the input weight and the deviation of the hidden layer node are obtained by the SLFN algorithm, according to the parameters and input The sample can calculate the input weight and output matrix connected to the hidden node. Once the input weight wj and the hidden layer deviation bj are randomly determined, the hidden layer output matrix H is uniquely determined, and the output weight β is obtained by the following formula:

$$\beta = \arg\min \| \beta^T H - T \|^2 = H^{\dagger} T$$

5 EXPERIMENTAL RESULTS

Through the fusion ELM, individuals were classified over a total of 7 age classes: 18-25 years old, 26-33 years old, 34-41 years old, 42-49 years old, 50-57 years old, 58-65 years old and over 65 years old.In the methodology, it is recommended to use a reference test with known sensitivity and specificity or predictable from other studies to analyze the accuracy levels of the diagnostic test. In order to carry out the said analyzes, the separation of the available data through the test algorithm and the distribution of their real situations with respect to each other is examined. The confusion matrix given in Table 3 is used in the representation of this distribution. Confusion matrix is also called error matrix in machine learning and classification problems.

Table 3: Confusion matrix

CONFUSION MATRIX	**Real Situation**	
	Positive	**Negative**
Positive	Correct Positive	False Positive (FP)
Negative	False Negative (FN)	True Negative (DN)
Total	Total Positive (P)	Total Negative (N)

The calculation of the parameters required to analyze the test performance is performed over this matrix. Details of the data contained in the confusion matrix are explained below. To analyze test performance, parameters such as sensitivity, specificity, accuracy and precision need to be calculated.

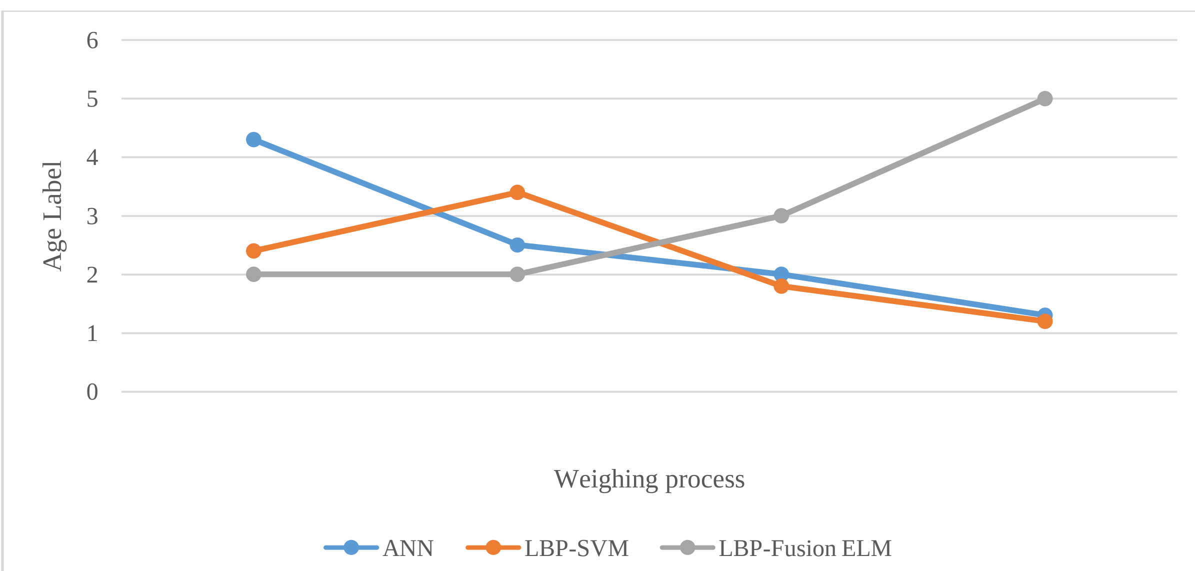

Figure 5:Sample estimation results for fusion classifier application

The said fusion classifier was created over the four classifier methods described above. The weighing process has been applied to the algorithms with the highest accuracy percentage obtained for each method in individual classifiers. Age labeling over this weighing process is shown in Figure 5.

6 CONCLUSION

The research method extracts the local statistical features, LBP features and Gabor values from wrinkle estimation. Finally, the FG-NET face database is trained and tested by the Fusion Extreme Learning Machine.Initially wrinkle estimation is performed then LBP histograms are generated. Fusion classifier categorizes the facial images based on previously classified age groups. Test parameters are calculated and the results falls in any of the categorized ages.

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