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A New Hybrid Model to Predict Human Age Estimation from Face Images Based on Supervised Machine Learning Algorithms

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Abstract**:** *Age estimation from face images is one of the significant topics in the field of machine vision, which is of great interest to controlling age access and targeted marketing. In this article, there are two main stages for human age estimation; the first stage consists of extracting features from the face areas by using Pseudo Zernike Moments* (*PZM*)*, Active Appearance Model* (*AAM*)*, and Bio-Inspired Features* (*BIF*)*. In the second step, Support Vector Machine* (*SVM*) *and Support Vector Regression* (*SVR*) *algorithms are used to predict the age range of face images. The proposed method has been assessed utilizing the renowned databases of IMDB-WIKI and WIT-DB. In general, from all results obtained in the experiments, we have concluded that the proposed method can be chosen as the best method for Age estimation from face images.*

Keywords**:** *Age estimation; Feature extraction; Feature selection; SVM; SVR.*

1. Introduction

Today, with the development of information technology and its spread among people, the need for a method to recognize the identity of people by machine instead of humans using biometric features has become a vital matter [1]. The basis of these methods is the uniqueness of some human characteristics such as the face, fingerprints, walking style, keyboard typing, DNA, and many other characteristics. However, the widespread use of face for identity recognition is because the needed data can be obtained easily much more than other methods, and face recognition methods generally have a relatively appropriate accuracy [2]. Age works a very important role in social communication and makes age estimation from face important in intelligent applications, including but not limited to access control, human-computer interaction, and marketing. For example, targeting the target audience based on age can play a vital role in marketing. Moreover, automatic age detection can be a great help in police and intelligence investigations. Determining age can be a challenging problem because the variance in each person's age depends on health, lifestyle, etc. Analyzing the human face using computer vision can help to estimate a person's age because the face contains important information. In the basic methods, key points of the face, e.g., nose, eyes, mouth, chin, etc., have been extracted and classified based on the size ratio between some of the extracted sizes of the face [3]. Many external and internal factors make it very difficult to predict accurately the age of human beings from their facial images. Internal factors include genetics, ethnicity, gender, as well as the uncontrollable nature of different patterns of maturation and aging process in humans; whereas external factors include makeup, facial hair, change of posture, posture, and lighting. According to research and works having been done infield, there are still problems with the accuracy criterion of people's age prediction. Compared to existing research, there are relatively few published works on age estimation, for three reasons [4, 5].

1. The task of estimating age cannot be deemed as a typical classification problem due to its varying treatment across different application contexts, it can be considered based on multiple classification and regression problems.

2. It is difficult for one person to collect a comprehensive and large database related to the aging process, especially for a collection of images with time comparison.

3. The contemporary approach to age estimation via facial images is typically comprised of two complementary components, namely, age image representation and age estimation technique. The following section presents the primary content of this article, which offers a comprehensive account of the proposed method alongside its experimental outcomes and analysis.

Age estimation based on facial image classification is automatically defined by considering the exact age or age group of people's faces [6].

A lot of efforts in the scientific and industrial sectors have been devoted to this issue during the last few decades. In this article, a system for estimating the age of people based on the fusion and integration of features with each other SVM and SVR algorithms is presented. In the proposed method, there are two main steps: The first step includes the extraction of features from the face areas and uses features of PZM, AMM, and BIF. The implementation results are seven different feature extraction modes, where three methods of extracting single features PZM, AMM, and BIF were have been evaluated, and then four methods through the fusion of features together and selection of suitable features from PZM-AMM, PZM-BIF, AMM-BIF, and PZM-AMM-BIF. Besides, using PCA, the length of feature vectors is reduced. In the second step, SVM and SVR algorithms are used to predict the age range of face images. Two famous databases IMDB-WIKI and WIT-DB have been used to evaluate the proposed method. Fig. 1 shows the general structure of the age estimation method.

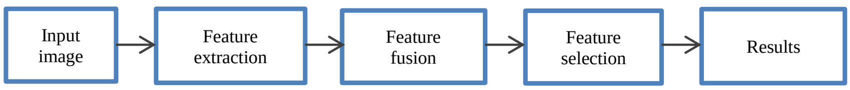

Fig. 1. System overview

Table 1. Abbreviations and acronyms list

Pseudo Zernike Moments –	PZM	Multilayer Perceptron Neural Network –	MLPNN
Active Appearance Model –	AAM	Mean Absolute Error –	MAE
Bio-Inspired Features –	BIF	Principal Component Analysis –	PCA
Support Vector Machine –	SVM	Local Binary Pattern –	LBP
Support Vector Regression –	SVR	Radial Basis Function –	RBF

2. Related work

Age estimation is a process in which the image of a person's face is processed by a computer and his/her age is estimated based on the criteria of years. The first human age estimation method has been presented in 1994, based on the biological view of the face. In a two-step process, this method has divided the face images into three categories: child, young and old. The first stage uses the calculation of the distance rate at different points of the face, with the help of face anthropometry, the images of adults and immature people have been separated. In the second step, the analysis of facial wrinkles has been used to divide the images of adults into two groups, young and old. This method is sensitive to the direction and angle of the image [7].

In the article [8], a system for estimating the age of people based on their faces and the genetic algorithm is presented. In the proposed method, there are four main steps. The first stage is pre-processing which includes image contrast improvement, face recognition, and image resizing; the second stage includes the extraction of folds and creases, which form the input features of the next stage. In the third step, the genetic algorithm is used and performed with the feature selection operation while the length of the feature vector is reduced. Finally, in the fourth stage, the selected features are classified into four age groups using the SVM and SVR classifiers to estimate the age of people. The recognition rate of the system on the FG-NET standard data set has been 74.35% based on the Mean Absolute Error (MAE) criterion of 4.29 years, it has a higher performance and accuracy than similar methods.

In [9], to extract features, filters have been applied to different parameters at different levels in the hierarchical model. Such a system has achieved an average absolute error of 5.97 years on the FG-NET database using an MLPNN neural network and an average absolute error of 4.68 years on another database.

A method for estimating the age group using facial features is presented by [10], which includes pre-processing, feature extraction and classification, and geometric features of faces such as wrinkles, facial angles, and distance between eyes. Then, the classification uses the k-Means clustering algorithm, and the age range has been dynamically determined for the groups. This method could be used for gender classification, too.

Estimating the age of people based on tissue is presented by [11]. The method uses the LBP and k-Means of the closest class. The proposed work has been evaluated on the FERET database. Images or data have been divided into five groups: An image has been received from the input, pre-processing operations, such as resizing, smoothing, etc., have been performed, and then its features have been extracted for machine learning and classification methods. It is measured with the database and the age group of the corresponding photo has been displayed.

In the article [12], the problem of age estimation is usually challenging. Because the issue of age depends on many factors, the aging process, such as smoking, multiple genes, emotional stress, weight changes, etc., is increased. Graphic features, such as human faces, are suitable for age estimation change with the change of pose, lighting, imaging conditions, and glasses. Male and female people might be seen with different separation features in the image due to reasons such as jewelry, beauty treatments, and hairstyles.

The pattern method for age estimation is used by [13]. The main idea of Peary's pattern model is a sequence of classified and ordered images in a unit of time that makes up space. This method determines face images with minimum reconstruction errors by using projection in space.

3. The proposed method

Typically, the age estimation process comprises two key components, namely feature extraction, and classification. This scholarly article postulates that the enhancement of the precision of automated age estimation systems is contingent upon the amalgamation and consolidation of features. The proposed system is depicted in Fig. 2 through a block diagram.

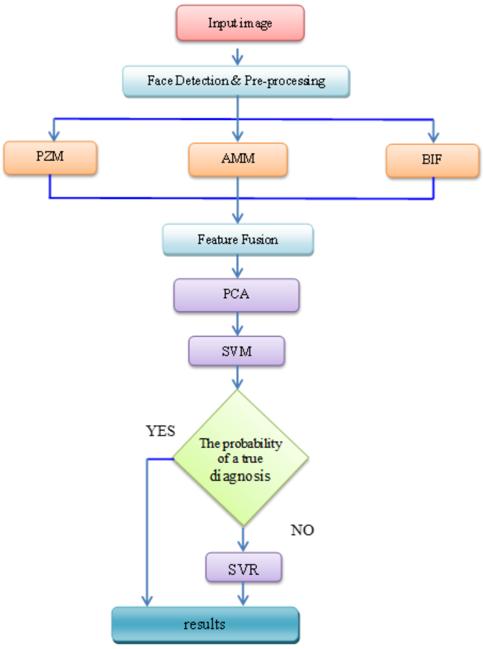

Fig. 2. The proposed method's flowchart for the face-based age estimation

Step 1. Receiving images from their normalizing database, the process consists of dividing the pixels of the image by two and placing the brightness values in the range [0, 1]. To normalize the number of brightness pixels on the total number, the pixels of the image will be divided while the normalization will make the values between 1 and 0.

Step 2. Place the features in seven groups, which include three individual and four integrated methods. In the first step, PZM, AAM, and BIF features are extracted, and in the second step combined fusions of features PZM+AMM, PZM+BIF, AMM+BIF, and PZM+AMM+BIF and then select suitable features.

Step 3. By using PCA, the length of the feature vectors is reduced.

Step 4. SVM and SVR classification methods on the test and training data of the previous step are used to classify the data.

Step 5. To check the efficiency of the methods and compare them, the criterion of the number of correct predictions has been used.

To evaluate the quality of the results and compare it with other methods, the average absolute error evaluation criterion has been used and calculated by the next formula:

$$\text{MAE} = \frac{\sum_{i=0}^{n} |E_{Ai} - R_{Ai}|}{n}, \tag{1}$$

where E_{Ai} is the estimated age and R_{Ai} is the actual age of the sample out of n tested samples.

3.1. Age estimation database

It is very important to collect data to combine real images of age and accurate age estimation. However, it is very difficult to collect the large size of age databases especially when we want to collect a collection of images from a person in chronological order. In this paper, two popular databases IMDB-WIKI and WIT-DB have been used [14].

3.1.1. IMDB-WIKI dataset

Since most of the databases in this field have a small number of images, this database has been prepared to provide an acceptable collection. It has been created by collecting face images from IMDB and Wikipedia and then using face detection and recognition software to automatically detect and recognize faces and assign age and gender labels to them. The IMDB-WIKI dataset contains more than 500,000 face images of celebrities and ordinary people, with age labels ranging from 0 to 100 years old. The age labels have been obtained by using the year of birth and the date when the image was taken, assuming that the age at the time the photo was taken is the difference between the two. The age classes on this website are divided into 6 classes (0 to 15, 16 to 25, 26 to 35, 36 to 45, 46 to 60, and 61 to 100 years) [15].

3.1.2. WIT-DB database

The WIT-DB contains images of approximately 5500 people from various regions of Japan, with roughly equal numbers of men and women. Each person has between 1 and 14 images in the database, and there are a total of 12,008 images of female faces and 14,214 images of male faces. The images are unobstructed views from the front, with neutral expressions and varying lighting conditions. The age labels for each image range from 3 to 85 years [16].

3.2. Pre-processing

At this stage, using the Viola-Jones algorithm, face recognition is done in the input images. As can be seen in Fig. 3, there are additional areas in the input image, and these areas cause incorrect features to be extracted and disrupt the system's performance. For this purpose, first, the face areas in the input images are identified and cut. Five areas of the face image including the eyes, nose, and two areas around the lips are extracted. Then the face regions are resized to a fixed size and the extra regions in the input images that do not contain faces are removed. After the face recognition stage, due to the difference in the size of different faces and cropped areas, all face images are resized to 128×128 pixels. After performing pre-processing on the input images, the images enter the next stage, which is the stage of feature extraction. Fig. 3 shows an example of the output of the face recognition stage in the input images and the cropped area of the face [17, 18].

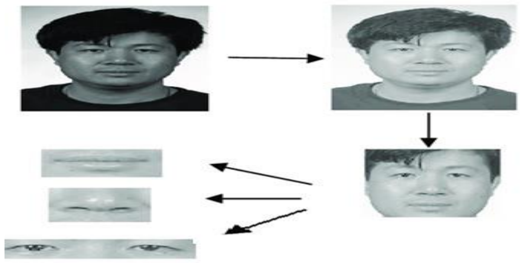

Fig. 3. A view of the pre-processing process

3.3. Feature extraction

The first step in the age estimation process is to describe the face by choosing the appropriate features. These features should contain information that, in addition to creating the most distinguishing features are not sensitive to changes such as rotation and scale. In this article, to obtain a suitable description of the face, the proposed method is used, where the feature vectors are extracted from the face images. Features of PZM, AMM, and BIF Filters have been used, and then merging it for choosing the appropriate features as suggested. Thereafter, to reduce the dimensions of the input vector and create vectors containing features with the highest resolution, we applied the PCA dimension reduction method to the features obtained from the proposed method [19].

3.3.1. PZM

The PZM is one of the important methods for extracting the feature. The PZM is a two-dimensional mapping function on a complex and orthogonal basis $\{V_{nm}(x, y)\}$. The polynomials $\{V_{nm}(x, y)\}$ are defined as follows [20]:

(2) $$V_{nm}(x, y) = R_{nm}(x, y) \exp\left(j_m \tan^{-1}\left(\frac{y}{x}\right)\right),$$

$Rnm\ (x, y)$ is a radial polynomial defined as follows [21]:

(3) $$R_{nm}(x, y) = \sum_{s=0}^{n-|m|} D_{n,|m|,s}(x^2 + y^2)^{\frac{n-s}{2}},$$

(4) $$D_{n,|m|,s} = (-1)^s = \frac{(2n+2-s)!}{s!(n-|m|-s)!(n-|m|-s+1)}.$$

Based on the above functions, $R_{n,-m}(x, y) = R_{nm}(x, y)$, $V_{nm}(x, y)=V^*_{nm}(x, y)$. The PZM is the image of a two-dimensional function on these basis functions. PZM is an order n and a frequency m for the discrete and two-dimensional function $f(x, y)$, which has zero value outside the circle, it is calculated as follows:

(5) $$\mathrm{PZM}_{nm} = \frac{n+1}{n} \sum_x \sum_y f(x, y)\, V^*_{nm}(x, y).$$

PZM can be calculated in two methods: the first method is a direct calculation of relation (5) based on the model, while the second method uses central and radial geometric moments. Therefore, PZM can be defined as follows:

(6) $$\mathrm{PZM}_{nm} = \\ = \frac{n+1}{n} \sum_{(n-m-s)even,s=0}^{\mathrm{n}-|m|} D_{n,|m|,s} \sum_{a=0}^{k} \sum_{b=0}^{m} \binom{k}{a} \binom{m}{b} (-j)^b . \mathrm{CM}_{2k+m-2a-b,2a+b} + \\ + \frac{n+1}{\pi} \sum_{(n-m-s)odd,s=0}^{\mathrm{n}-|m|} D_{n,|m|,s} \sum_{a=0}^{d} \sum_{b=0}^{m} \binom{d}{a} \binom{m}{b} (-j)^b . \mathrm{CM}_{2d+m-2a-b,2a+b.}$$

where $d=k=((n–s–m)/2$, $\mathrm{CM}_{i,j}$ is the central geometric moment, and $\mathrm{RM}_{i,j}$ is the radial geometric moment. In this part, the calculated PZM is divided by the PZM_{00} moment, which represents the area of the pattern, which causes the moments to be scaled. In this way, PZM_{00} will be equal to one for all patterns. On the other hand, because $\mathrm{PZM}_{nm}=\mathrm{PZM}^*_{n,-m}$ the PZM is calculated only for positive m [20].

3.3.2. AAM

In the AAM method, two series of expansions must be calculated, the first is the expansion of the figure according to the base figure and special features, and the second is the expansion of the base figure based on the base appearance and special features, as shown in the figure [21].

Next, the following tasks are performed on the obtained model: minimizing the error between the input image $I(x)$ and $A(x) = M (W(x; p))$ if x is the pixels of the base shape S0, the corresponding values of the input image I will be $W(x; p)$. In Pixel x, the AAM model will have the following appearance.

(7) $$A(X) = A_0(x) + \sum_{i=1}^{M} \lambda_i A_I(x).$$

In pixel $W(x; p)$ the input image has brightness $I(W(x; p))$. Finally, we minimize the least squares differences between the brightness of the input image and the estimated appearance of the shape [22, 23].

(8) $$\sum_{u \in s_0} [A_0(x) + \sum_{i=1}^{m} \lambda_i A_i(X) - I\,(W(x;c))]^2.$$

3.3.3. BIF

The BIF feature extraction method is derived from visual processing in the eye cortex. In this method, similar to the structure of the eye cortex, a model is introduced which consists of several alternating layers called simple (S) and complex (C). These layers model the increasing complexity of cellular units from the primary visual cortex to the inferior cortex of the eye. The first layer (simple layer S1) is created by applying the Gabor filter on the input image, and the second layer (complex layer C1) is created by applying the maximum operator on the first layer. To use the BIF feature extraction method in age estimation, it is enough to use these two layers [24, 25].

3.4. Fusion and feature selection

Feature extraction refers to the systematic technique of identifying and selecting pertinent attributes from the raw data and converting them into a meaningful set of features that are appropriate for representation and analysis of the data. A feature extraction algorithm typically involves several steps, including pre-processing, normalization, and selection of appropriate fusion functions. The length of the vectors used to represent the features is also an important consideration.

In this method, placing features in seven groups using three individual and four integrated methods is implemented. In the first step, PZM, AAM, and BIF features are extracted, and the second step fuses feature PZM-AMM, PZM-BIF, AMM-BIF, and PZM-, AMM-BIF, then selecting the suitable features from them. It has been shown that feature fusion can effectively achieve better age estimation than single-feature representation alone [26].

3.5. Reducing the dimensions of features

This method is categorized as a feature-dimension reduction method and a principal component analysis method. In PCA, new features obtained could have the best description of the desired data. The principal component analysis includes an analysis of the eigenvalues of the covariance matrix. It applies a mapping to the features to depict them in line with the best descriptors of that data. As a result, the best descriptors are those features that have the highest variance; it means that the dispersion of the data is the highest in their direction. The purpose of PCA is to find vectors that do the best possible job of identifying the subspace and defining the space of the face [27].

Fig. 4 shows two-dimensional data of PCA.

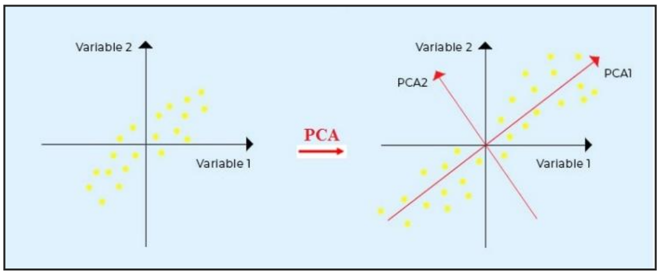

Fig. 4. Data distribution in the algorithm

3.6. Classifications

In the stage of classification, age estimation is generally followed by two single-stage and hierarchical approaches. The single-stage approach deals with finding the age tag among others [28]. However, in the hierarchical approach, the images are divided into age groups, gender, etc. and then the age tag is searched in a smaller range [29]. Due to the wide range of ages, finding the exact age tag by a single-step approach is difficult as it has a high error. In the hierarchical approach, complexity increases due to the existence of groups, e.g., age, gender, etc., groups need to train a separate model for each group, which causes decreasing the popularity of these methods. In this step, the feature vectors obtained from the previous step are estimated by the trained classifier and the age of people. According to the scope of this article and the age range of people, SVM and SVR methods have been used to classify and estimate the age of people.

SVM and SVR are powerful machine-learning algorithms for classification and regression tasks, respectively. Both of these algorithms use a nonlinear kernel function to map the input data to a higher dimensional space where it is easier to separate or regress the data.

In the following, the SVM method and the SVR method used in the article are explained.

3.6.1. SVM

SVM is a new learning method that is often used for binary classification. By introducing a feature space result from the use of kernel functions, the support vector machine takes the input data to a space with higher dimensions and increases the separation of data that are not separated linearly [30]. Typically, this task, i.e., taking the input vectors to higher dimensional spaces, is associated with an increase in the computational complexity and overlap problem. Nonetheless, support vector machines are not directly related to a higher dimensional space and only need internal multiplication relations in space [31].

Suppose we have n training samples in a real space with dimensions P and two classes. We want to find a plane that separates the points of class $c_i = 1$ from the points of class $c_i = -1$. The equation of this plane is $wx_i - b = 0$ is written, where w is the normal vector and perpendicular to the plane and the parameter b/w specifies the distance of the plane from the origin of the normal vector. For each sample, if $wx_i - b \geq 1$ then sample x_i belongs to the first class; otherwise, if $wx_i - b \leq -1$ then sample x_i belongs to the second class. The values of b and w should be chosen in such a way that the condition of the maximum distance is satisfied. The kernel function is a weight function used in non-parametric forecasting techniques and has two conditions. This category is one of the most popular fields in biometrics, identity verification, access control, and video surveillance. However, SVMs have the following properties [32-34]:

1. Classifier is designed with a maximum generalization
2. Automatic determination of the optimal structure and topology.
3. Modelling nonlinear differentiation functions using nonlinear kernels and the concept of inner multiplication.

Fig. 5 shows the SVM work method.

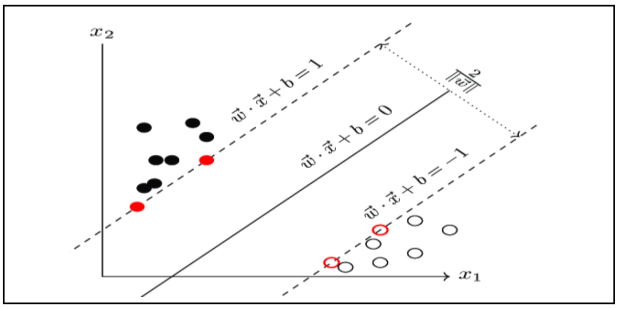

Fig. 5. SVM classification

3.6.2. SVR

SVR is a machine learning technique that is used to predict continuous target variables. It is a type of SVM algorithm that is modified to perform regression instead of classification. In SVR, the purpose is to minimize the error between the predicted values and the actual values while maintaining a balance between the complexity of the model and the degree of error. The error is typically measured using the MAE. SVR uses a kernel function to map the input data into a higher dimensional space. The most commonly used kernel functions are linear, polynomial, RBF, and sigmoid. The main advantage of SVR over traditional regression techniques is that it can handle nonlinear data more effectively. Additionally, it is less sensitive to outliers compared to other regression algorithms [35, 36].

4. Experimental results

This section examines the implementation results of the proposed algorithm and compares its results with classical feature extraction and classification algorithms. Different algorithms have been assessed with MATLAB software version R2020a, and it has been deployed on a laptop with Dell 8th Gen Intel Core i5-8250U specifications.

To test the proposed method and to determine its superiority over similar methods, the images of IMDB-WIKI and WIT-DB databases have been used. When using each of these two databases, we considered 20% of the data for training and 80% for test data. All the images used to perform each of the stages of training and testing the model have been first converted to a gray model and prevent the creation of computational overhead by other additional information in the image such as the border and background, as well as to speed up the processing time. The inner part of the face is separated from the image in the size of 128×128. In this experiment, first of all, we have placed the features in seven groups including three individual methods and four integrated methods. The PZM, AAM, and BIF features are extracted, and then features PZM+AMM, PZM+BIF, AMM+BIF, and PZM+AMM+BIF have been blended to select the best features. Then, the length of the features' vectors has been reduced using PCA. Thereafter, SVM and SVR classification methods on the test and training data in the previous step have been used to classify the data. The average absolute error evaluation criterion has been used to evaluate the quality of the results and compare it with other methods, which were explained previously. Tables 2 and 3 show the accuracy results for the various features along with SVM and SVR classifications on the IMDB-WIKI dataset. As shown in Tables 2 and 3 the human age estimation from facial images based on the combined feature fusion PZM+AMM+BIF is the best feature. Besides, the fusion features PZM+AMM work together and work well; whereas, BIF works with lower performance than other features. Fig. (6) shows the best results that have been obtained in a database IMDB-WIKI for different age groups.

Tables 4 and 5 show the accuracy results of the various features mentioned previously with SVM and SVR classifications on the WIT-DB dataset. Tables 4 and 5 show the human age estimation from facial images based on the PZM+AMM+BIF features fusion which is the better feature. Also, the fusion feature of PZM+AMM and the PZM both work well whilst, BIF works with lower performance than other features. Fig. 7 shows the best results that have been obtained in a database WIT-DB for different age groups. According to the above tables, it is clear that the SVM method is more successful than the SVR method.

Table 2. Percentage accuracy in three age groups with SVM classification and IMDB-WIKI age database

Age groups	PZM	AMM	BIF	PZM+AMM	PZM+BIF	AMM+ BIF	PZM+AMM+BIF
0-15	93.8	93.1	84.4	96.3	94.8	94.1	99.1
16-25	94.3	92.7	85.2	97.8	93.4	93.7	98.8
26-35	94,1	91.5	84.8	97.2	93.9	93.9	98.9
35-45	93.6	91.6	87.8	97.3	94.4	92,2	98.3
46-60	94,1	91.5	84.8	97.2	93.9	93.9	98.9
61-100	93.6	91.6	87.8	97.3	94.4	92,2	99.3

Table 3. Percentage accuracy in three age groups with SVR classification and IMDB-WIKI age database

Age groups	PZM	AMM	BIF	PZM+AMM	PZM+BIF	AMM+ BIF	PZM+AMM+BIF
0-15	96.8	94.1	91.4	96.3	94.8	93.1	98.6
16-25	95.3	95.7	91.2	97.8	93.4	92.7	98.4
26-35	95,1	94.5	89.8	96.2	94.9	94.9	97.3
36-45	96.6	95.6	91.8	96.9	95.4	93,2	97.5
46-60	94,1	91.5	84.8	97.2	93.9	93.9	98.2
61-100	93.6	91.6	87.8	97.3	94.4	92,2	98.6

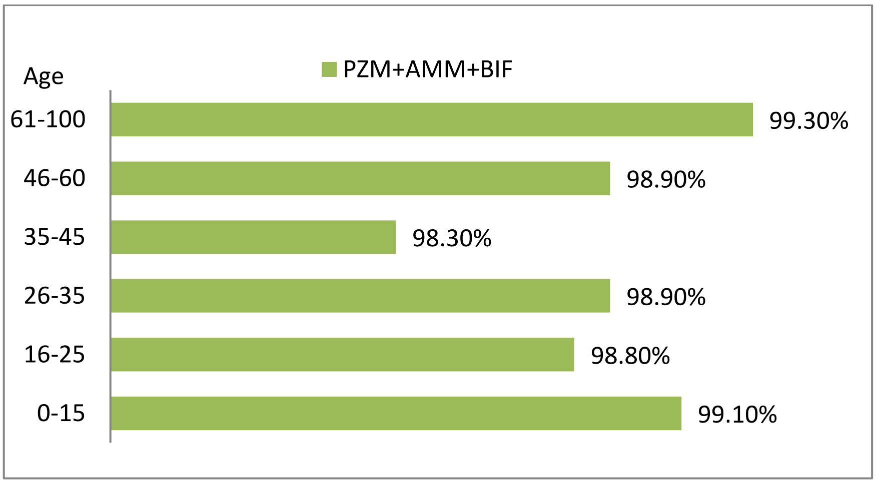

Fig. 6. The best results with the database IMDB-WIKI and for different age groups

Table 4. Percentage accuracy in three age groups with SVM classification and WIT-DB age database

Age groups	PZM	AMM	BIF	PZM+AMM	PZM+BIF	AMM+ BIF	PZM+AMM+BIF
3-20	96.8	95.9	86.7	98.2	95.3	93.9	99.2
21-40	94.6	93.8	86.4	97.o	93.6	94.7	98.6
41-60	96,9	96.2	87.8	97.8	94.9	94.8	98.4
61-85	95.9	96.4	85.7	97.9	96.8	94,8	99.4

Table 5. Percentage accuracy in three age groups with SVR classification and WIT-DB age database

Age groups	PZM	AMM	BIF	PZM+AMM	PZM+BIF	AMM+ BIF	PZM+AMM+BIF
3-20	93.8	94.1	94.4	96.3	96.8	95.1	98.7
21-40	93.3	93.7	94.2	95.8	96.4	95.7	98.4
41-60	93,1	94.5	95.8	95.2	96.9	94.9	97.5
61-85	93.6	93.6	94.8	95.3	97.4	95,2	98.1

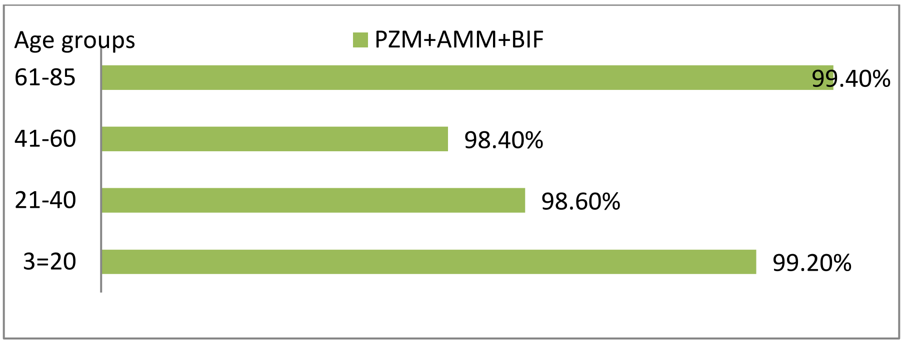

Fig. 7. The best results with the database WIT-DB and for different age groups

5. Conclusion

The purpose of this article is to find an ideal and effective method to detect people's chronological age from facial photos. To achieve this aim, firstly, we have defined the facial features of people imposed for this purpose, and secondly, we implemented the proposed features to achieve the best performance. PZM, AMM, and BIF have been selected and combined to detect the appropriate features from them. It is necessary to reduce the dimensions of the features appropriately for this purpose. Reducing the dimensions of the problem and improving the classification accuracy of the algorithm analysis has been carried out for the extracted features using PCA. Finally, we have used the appropriate and robust classifiers, SVM and SVR in the human age estimation. In general, we have found this method to have the least errors for human age estimation from all the results obtained in the experiments.

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