



## Age Estimation Using Support Vector Machine

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### Abstract

Recently there has been an urgent need to identify the ages from personal images. This paper utilized machine learning technique to intelligent age estimation from facial images by support vector machine (SVM) with linear discriminate analysis (LDA) using FG\_NET dataset. The proposed work consists of three phases: the first phase is image preprocessing include four stages: grayscale image stage, histogram equalization stage, face detection stage has been carried out using viola jones algorithm, it comprises for four steps namely: Haar like Feature, integral image, Adaboost training, and cascading classifier, the last stage of image preprocessing phase is cropping and resize stage. The second phase is data mining include two stages: feature extraction stage using linear discriminate analysis and machine learning stage using support vector machine. The last phase is age estimation and evaluation. The FG-net dataset is used which divided into seven classes. After extracting the features from the seven classes. It has been found that some classes have the same number of features. Hence, the seven classes were combined into three classes depending on the number of features it contain, in order to become increased accuracy and reduce the execution time. The Experimental results display that the proposed system can grant high accuracy. The practical evaluation of the proposed system gives accuracy about 84%.

**Keywords:** Viola jones, linear discriminate analysis, machine learning, SVM classifier, Age estimation.

### تقدير العمر باستخدام تقنيات SVM

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### الخلاصة

في الآونة الأخيرة ، كانت هناك حاجة ملحة لتحديد الأعمار من صورهم الشخصية. استخدمت هذه الورقة تقنية التعلم الآلي لتقدير العمر من صور الوجه باستخدام SVM مع LDA على مجموعة البيانات FG\_NET. يتكون العمل المقترح من ثلاث مراحل: المرحلة الأولى هي معالجة الصور الأولية وتشمل أربع مراحل: مرحلة صورة التدرج الرمادي ، مرحلة معادلة المدرج التكراري ، تنفيذ مرحلة اكتشاف الوجه باستخدام خوارزمية فيولا جونز ، وهي تتألف من أربع خطوات وهي: Haar like Feature ، Integral Image ، Cascade classifier ، Adaboost Learning ، المرحلة الأخيرة من مرحلة معالجة الصور هي مرحلة القطع وتغيير الحجم. المرحلة الثانية من النظام المقترح تشمل استخراج البيانات لمرحلتين: مرحلة استخلاص الميزة باستخدام تحليل تمييزي خطي (LDA) ومرحلة تعلم الآلة باستخدام آلة متجه الدعم (SVM). المرحلة

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الأخيرة هي تقييم وتقدير العمر. تنقسم مجموعة البيانات FG-net إلى سبع فئات وبعد استخراج الملامح وجدنا بعض الفئات يملك نفس عدد الملامح لذلك تم الجمع بين الفئات السبع لتصبح ثلاث فئات اعتمادا على عدد من الميزات وذلك من أجل زيادة الدقة وتقليل وقت التنفيذ. وتظهر النتائج التجريبية أن النظام المقترح يمكن أن يمنح دقة عالية. والتقييم العملي للنظام المقترح يعطي دقة ٨٤٪.

## Introduction

Age estimation is one of the main approaches of facial image classification. It can be defined as determination of a human's age or age group from facial picture. In this work, an estimation and classification to the age from facial images has been implemented utilizing support vector machine (SVM) classifier. There has been several applications of age estimation which are: (I) Control of security: An automatic age estimation system can be utilized to prevent minors from purchasing alcohol or cigarette from sell machines or accessing inappropriate web site. (II) Interaction between Human and compute: The system can adjust the contents presented to a user based on his/her age. For example, a smart shopping chart can be designed to give recommendations according to the age of the customer. (III) Law enforcement: age estimation systems can help to locate the potential suspect's identification and suspect tracking (investigation) more efficiently and precisely by filtering the gallery database using the estimated age. However, in spite of advances in age estimation, it stills a difficult problem. This is because the face old age process can be determined not only by radical factors, e.g. genetic factors, but also by external factors, e.g. lifestyle, expression, and environment [1]. In this work, an estimation and classification to the age from facial face has been implemented using SVM classifier. The proposed system consists of three phases, image preprocessing phase, data mining phase and age estimation and evaluation phase. The image preprocessing phase includes four stages; gray image, histogram equalization, faces detection and (cropping and resize image stage). The data mining phase includes two stages; feature extraction stage which is use linear discriminant analysis (LDA) and classification stage which is use support vector machine (SVM), Finally; Age estimation and evaluation phase which includes two stages estimation and evaluation stages. The proposed system has been illustrated in Figure-1. SVM classifier has been used with LDA feature extractors which give accuracy rate of 84% as an average. SVM classifier has been used with principle component analysis (PCA) which gives accuracy rate of 75% as an average. SVM classifier has been used with local binary pattern (LBP) which gives accuracy rate of 82% as an average.

## 2. Literature Survey

**Chao W. L.2012.** In this research, a new age estimation framework is proposed considering the essential factors of human ages. Relevant component analysis (RCA) is applied to realize a proper metric for neighbor searching. Locality preserving projection (LPP) is trained to decrease the feature dimensionality and learn the connections between features and aging labels. At last, an age-specific local regression algorithm called KNN-SVR is proposed to capture the complex human old age process. The simulation outcome performed on the widely-used FG-NET aging database shows that the system checks the lowest mean absolute error (MAE) versus the existing methods [2].

**Han H. in 2013.** Presented a hierarchical method for age estimation, and analyzed the influence of old age on individual facial elements using a component based representation. Human noticing ability to estimate age is evaluated using crowd sourced data obtained through the Amazon Mechanical Turk service, and matched with the performance of the proposed age estimation. Also illustrated that the performance of the proposed system is better than or similar to the age estimates applying by humans on FG-NET and a little subset of PCSO database [3].

**Gunay A. in 2015.** Presented a hierarchical age estimation way which is depending on decision level fusion of active appearance model (AAM), Gabor and local binary patterns (LBP) lineaments of facial images are supposed. Its main contribution is decision level fusion of global and local texture features of facial images. Locality is preserved by regional LBP histograms and Gabor filters. Furthermore, these local features are collective with global features of images extracted with AAMs. The proposed system used the FG-NET and PAL Aging [4].

**Liu K. H. in 2015.** Presented a multistep learning shape called grouping estimation fusion. Six different fusions used to enhance the performance. Extensive experiments conducted used datasets( FG-NET and MORPH-II), demonstrated the effectiveness of the proposed GEF as well as it is

possible to enhance the performance of the GEF methods to increase the diversity through decisions by containing other features or age grouping systems [5].

**Jain S.2016.** Age prediction model has been intended to predict the age from the input facial images. The system processes include preprocessing of input image, filtering, face and facial part detection, edge detection, features extraction, train the classifier by sending extracted features to the k-NN classifier and finally, testing is done for the test data by passing it to classifier in order to obtain the outcome[6]. From the experimental results achieved using the FG-NET aging database. The k-NN classifier can be showed produces better for the age-group prediction.

(Table-1) shows the summary of related works and the proposed system.

**Table 1-** related works summary

NO.	Name of authors	Details		
		The objective of works	Tools	dataset
1	Chao W.	Modern age evaluation method is proposed realize the essential factors of individual ages	K-Nearest Neighbor classifier support vector regression (k-NN-SVR)	FG-NET dataset
2	Han H.	Suggested a pyramid way for automatic age estimation.	(SVM-BDT)	FG-NET and a little set of PCSO database
3	Gunay A.	Modern pyramid age estimation method depends on decision level fusion of universal and regional features are suggested.	(AAM), local binary patterns (LBP)	FG-NET and PAL old age databases
4	Liu K. H.	Multistep learning system known GEF was suggested for human age evaluation Through facial images	Support vector machine (SVM), biologically inspired features (BIF),(HOG),(LBP)	FG-NET, MORPH-II dataset
5	Jain S.	age prediction model has been intended to predict the age from the input facial images	Used k-NN classifier	FG-NET dataset
6	The proposed system	Presents the application of machine learning techniques (SVM classifier) for the estimation of human age from facial images	Linear discriminant Analysis(LDA) and SVM classifier	FG-NET databases

### 3. The proposed system

The objective of the proposed system is to automatically estimate human ages based on face image. This system applied machine learning techniques to intelligently estimate age from facial images using support vector machine on FG-net dataset. After extracting the features by using linear discriminate analysis (LDA). The proposed system consists of three phases as shown in the following Figure-1.

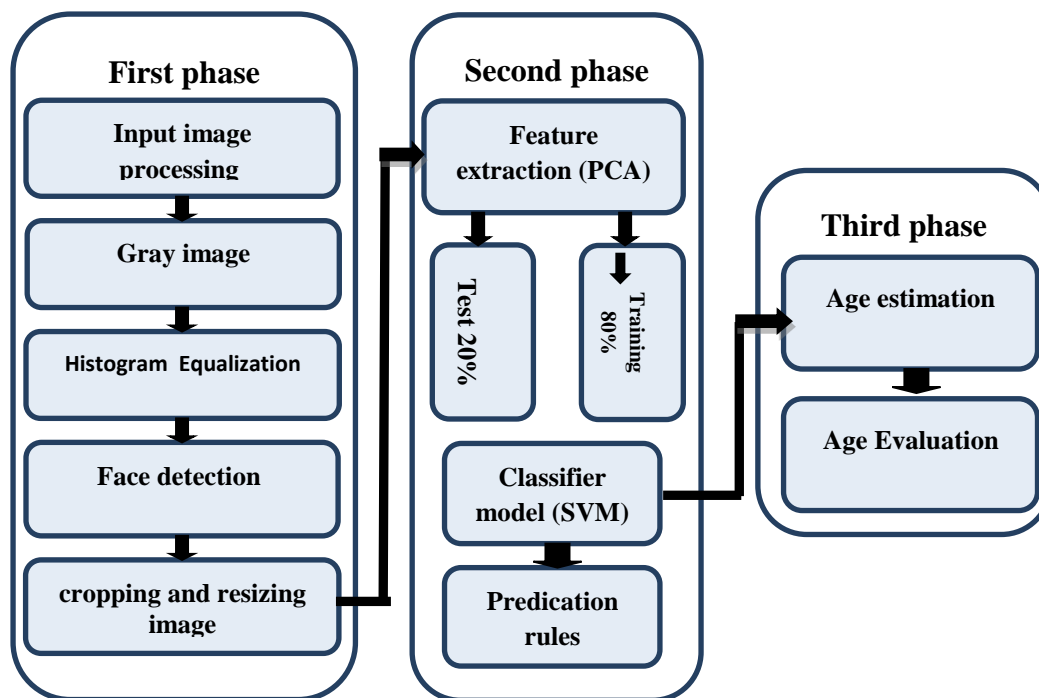


Figure 1- Block Diagram of the Proposed System

The proposed system used FG-NET [7] dataset which consists of 890 frontal face images of 82 different individuals, 12 images per subject. The scope of the age from 3 year to 50 years. In this work, it has been proposed to divide the FG\_net dataset into seven classes. The first class represents 3-7 years, the second class represents 8-13 years, the third class represents (14-19) years, the fourth class represents 20-25 years, the fifth class represents 26-30 years, the sixth class represents 31-40 years and the last class represents 41-50 years. After extracting the features from the seven classes. It has been found that some classes have the same number of features. Hence, the seven classes were combined into three classes depending on the number of features it contain. The first new class had four features only which included ages from 3-7 and 26-30 years. The second new class had five features only which included ages from 8-13, 14-19 and 20-25 years. The third new class had nine features which included ages from 31- 40 and 41-50 years. The proposed system implements three phases:

**3. 1 Image preprocessing phase**

The first phase is an image preprocessing phase includes four stages as follows:

**3. 1. 1 gray image process**

Conversion of color images to grayscale image requires more knowledge about the color image. In this stage use the main three steep operations[8]., Get the RGB values of a pixel, perform mathematics for turning these numbers to one grey value, change the original RGB values with the new grey value by using equation (1).

$$\text{Grayscale image} = 0.33 \text{ Red} + 0.56 \text{ Green} + 0.11 \text{ Blue} \dots\dots\dots (1)$$

**3. 1. 2 Histogram Equalization**

Equalization of histogram is a process in image preprocessing disparity modification depending on the picture histogram. The stages for execution of this algorithm, the first step is getting size of grayscale pictures, second step divided the total number of pixel normalization the values from step 1, third step maximum grayscale level value and round multiplied by the value from step 2, the last step by using a one-to-one correspondence, the results from step 3 are mapped to the gray level value.[9].

**3. 1. 3 face detection process**

The face detection is the necessary processes because all of the following processes will depend on it. In this research, one strategy has viola jones to face recognition which applied for this goal [10]. This method consists of four steps as follow:

**A. Haar-Like Features**

Voila jones have used features instead of using pixel directly because the can encode ad-hoc field knowledge and applied features instead of pixel would raise the fast of system. In addition haar like features are strong effective in facial detecting. As seen in Figure-2 every one of the haar features has a value computed via taking the area of every rectangle, multiplying every one of them by their respective weight, and after that adding up results [11].

**B. Integral Image**

The second step of voila jones face detecting algorithm is an integral image. It's known as a summed region table.is a process of fast and efficient calculating the addition of value in rectangle subset of pixel grid, as seen in Figure-3. The value at any index (x, y) of the integral image is the summation of the image pixels above and to the left of index (x, y)[12]. Figures-4 represents the generation of the integral image.

**C. Adaboost Learning Method**

It's a mechanical learning method when a selected a few instead of the weak classifier everyone is indicated with at exact one Haar-like feature and connect them to shape a strong classifier. The aim of Adaboost process it is to choose the best feature such as polarity and threshold. To final the best execution feature voila jones have submitted a strong simple process to locate each new weak classifier by estimation each feature of all in training examples done to finding the better execution feature[13].

**D. Cascade**

A series of strong classifiers are formed in order to quickly discard unpromising regions of the image by using cascaded architectures of classifiers and arranged in the ascending order of complexity for the strong classifiers in the cascade. This process performs an elimination of face candidates quickly using a cascade of stages, which eliminates candidates via making stricter requirements in each stage with later stages being much more difficult for a candidate to pass [14]. Candidates exit the cascade if they pass all stages or fail any stage. A face is detected if a candidate passes all stages.as seen in Figure-5.



Figure 2-Examples of Haar properties

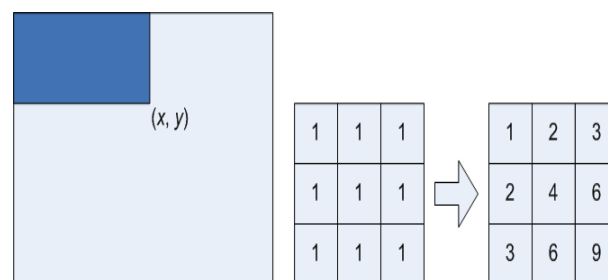


Figure 3- Integral image generations

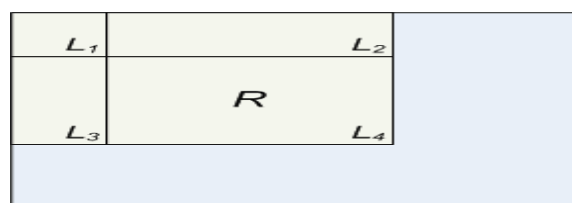


Figure 4- a computing the area R is performed with the use of the corner of the rectangle locations of the integral image  $R = L4 - L3 - L2 + L1$

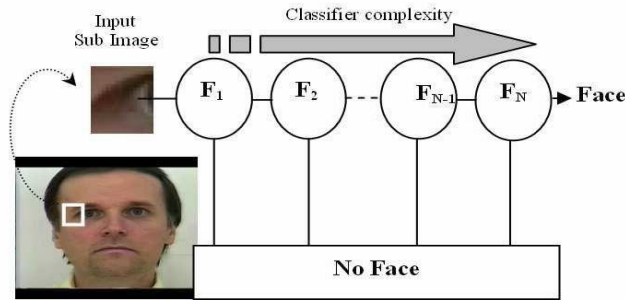


Figure 5- cascade classifier

**3. 1. 4 Cropping and resizing stage**

After face detection stage, the next stage is cropping and resizing stage. This stage removes outside components of a picture in order of developing the form. The process of resizing will change the size of the input image to 200 \* 200 pixels in dimension that will be used for the feature extractive.

**3. 2 Data mining phase:**

The proposed data mining phase consists of two stages as follows:

**3. 2. 1 Feature extraction stage:**

The first stage in the data mining phase is feature extraction. Feature extraction is corresponding to reduction dimensionality. Identifying a group of the primary features is named feature selection. In this work, linear discriminate Analysis (LDA) [15] has been used to extract features from facial image, LDA is a technique that takes a collection of data and transforms it such that the new data has given statistical properties. Datasets can be converted, tested and vectors can be assorted in the converting space by two different methods [16]. First is class-dependent transformation: This kind of method includes increasing the ratio of between class differences to within class differences. Second is class-independent transformation: This method includes increasing the ratio of total difference within class difference. Linear discriminate Analysis (LDA) is used to decrease the dimensional representation of face image, mainly Eigen face is the Eigenvector selected from LDA Eigen faces. In age classification, each training face image is transformed into a vector. The covariance matrix is computed by multiply variance image by variance image transform. Eigen faces (Eigenvectors associated with Eigenvalues) are constructed, which represent various features face image as shown in Algorithm 1 [16].

In this first stage, calculation of the average vectors  $m_i$  using equation (2), ( $i=1, 2, 3$ ) classes:

$$m_i = \begin{bmatrix} \mu_{\omega i}(\text{sepal length}) \\ \mu_{\omega i}(\text{sepal width}) \\ \mu_{\omega i}(\text{sepal length}) \\ \mu_{\omega i}(\text{sepal width}) \end{bmatrix}, \text{with } i=1,2,3 \text{ vector}$$

$$m_i = \frac{1}{n} \sum_{i=1}^n x_i \dots\dots\dots(2)$$

The next stage compute the scatter matrix includes within-class scatter matrix Eq. (3), class-covariance matrices Eq. (4), and between-class scatter matrix Eq. (5).

$$SW = \sum_{i=1}^c (N - 1) \frac{1}{N-1} \sum_{x \in D_i} (x - m_i)(x - m_i)^T \dots\dots\dots(3)$$

$$\sum_{i=1}^c \frac{1}{N-1} \sum_{x \in D_i} (x - m_i)(x - m_i)^T \dots\dots\dots(4)$$

$$SB = \sum_i^c N_i(m_i - m)(m_i - m)^T \dots\dots\dots(5)$$

where  $m$  is the total average,  $c$  no. of class,  $m_i$  and  $N_i$  are the sample average and sizes of the respective classes. Solving the generalized eigenvalue problem for the matrix  $Sw^{-1}SB$ , then check that the eigenvector-eigenvalue calculation

$$Av = \lambda v \dots\dots\dots(6)$$

Where  $A = Sw^{-1}SB$ ,  $v$ =Eigenvector,  $\lambda$ =Eigenvalue. the last stage, has been used the  $4 \times 2D$  matrix  $W$ , which just calculated for transforming the samples to the new sub-space using the formula.

$$Y = X * W \dots\dots\dots(7)$$

The LDA is performed by calling LDA –Fisher Faces Feature algorithm 1.

<b>Algorithm 1 : LDA –Fisher Faces Feature [16]</b>
<b>Input:</b> Crop and resize face image
<b>Output:</b> Fisher face feature vectors(average from 4 to 9)
<b>Begin</b>
<b>Step 1:</b> Read transform face images
<b>Step 2:</b> Store transform face image in matrix.
<b>Step 3:</b> compute the d-dimensional mean vectors by using Equation (.3)
<b>Step 4:</b> Compute the scatter matrices.
Compute within –class scatter matrix (SW) by using Equation (.4).
Compute the class-covariance. by using Equation (.5)
Compute between –class scatter matrix (SB) by using Equation (.6).
<b>Step 5:</b> Solving the generalized eigenvalue problem for matrix by Equation (.7).
<b>Step 6:</b> Choosing linear discriminates for the new property sub-space.
Sorting the eigen-vectors via decreasing eigen-values.
Selecting $k$ eigen-vectors with the biggest eigen-values.
<b>Step 7:</b> Transforming the samples to the new sub-space by using Equation (.8).
<b>Step 8:</b> Return feature vectors.
<b>End</b>

**3. 2. Machine learning stage:** The machine learning algorithm was used the SVM classifier, the objective of image classification is to categorize all pixels in the image into classes. Classification analysis the numerical properties of various image features and organizes data into categories. Classification is a form of data analysis that can be utilized to predict future data trends or to extract models describing important data classes. SVM are popular in many pattern recognition problems in most of classification technique, including texture classification. SVM designed to maximize the marginal distance between classes with decision boundaries drawn by using different kernels. This is done by maximizing the margin from the hyper-plane to the more classes. The samples closest to the margin that were selected to determine the hyper-plane is known as support vectors. SVM is today not only the major trend in texture classification, it is also generally a very popular classifier in various pattern-recognition problems, including face recognition and detection problems [17].SVM has been performed by calling The proposed SVM classifier-RBF Algorithm 2.

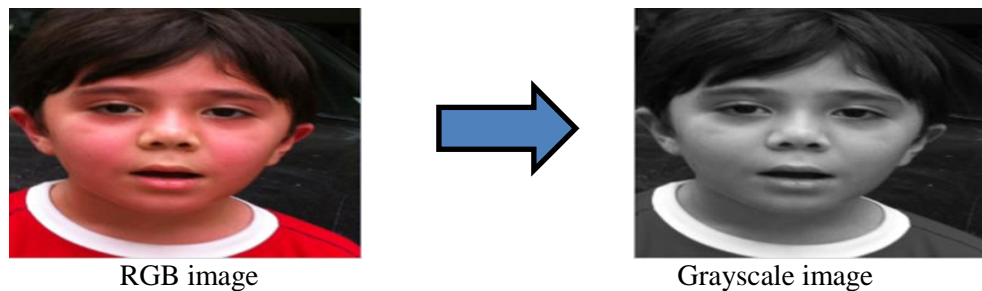
<b>Algorithm 2: The proposed SVM classifier-RBF [18]</b>
<b>Input:</b> Feature vector for of all training images, feature vector for Testing images M: n-classes, attributes
<b>Output:</b> class test
<b>Begin</b>
<b>Step 1:</b> Read feature vector for of all training images, with M attributes and feature vector for Testing images.
<b>Step 2:</b> Obtain the weight $w$ and kernel $K$ using the classical adaptive scaling SVM.
<b>Step 3:</b> Initialize all data into an entire dataset.
<b>Step 4:</b> Use random forest algorithm to rank the features.
<b>Step 5:</b> Update working dataset by removing less important features. Until the number of feature are small.
<b>Step 6:</b> Apply SVM with RBF kernel into the reduce features.
Minimize ( $\frac{1}{2} \ w\ ^2 + C \sum_{i=1}^m \xi$ )
Subject to: $Y_i (W^T x_i + b) \geq 1 - \xi_i$ , $\xi_i \geq 0$ , $i = 1, 2, \dots, m$
Where $Y_i$ is the class label of support vector $x_i$ , $w$ is a weight vector ,b is bias and variables $\xi$ is positive slack which is necessary to allow miss classification
<b>Step 7:</b> Consider parameter C seeks to decision error when searching for the maximum marginal hyperplane.
Maximize [ $\sum_{i=1}^l \alpha_i - \frac{1}{2} \sum_{i=1}^l \sum_{j=1}^l \alpha_i \alpha_j y_i y_j K(x_i, x_j)$ ]
Subject to: $0 \leq \alpha_i \leq C$ , $\mathbf{1} \leq i \leq l$ , $\sum_{i=1}^l \alpha_i y_i = 0$ , where indicates the overall inputs. Where $x$ is a training sample and $k$ is the radial basis function is given by $K(x_i, x_j) = \exp(-\gamma \ x_j - x_i\ ^2)$
<b>Step 8:</b> Choose the best parameter for create as a classification model.
<b>End</b>

#### 4. Experimental results and evaluation

Experiments are performed on age estimation by applying SVM classifier with linear discriminate analysis LDA. The designing process of the proposed system had used three phases which were image preprocessing, data mining and age estimation and evaluation (prediction). Each phase will be explained in detailed with example and obtained results.

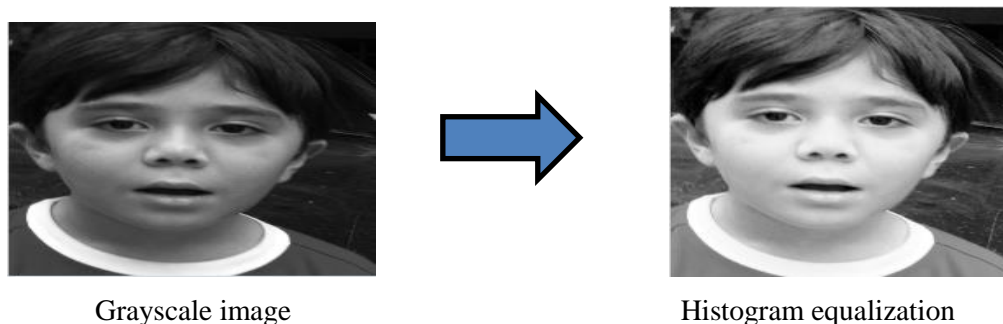
**4.1 Image Preprocessing Phase:** This phase consists of four stages:

**4.1.1 Grayscale Image:** this stage was converting the input image from RGB (color image) to grayscale image, shows Figure-6 below.



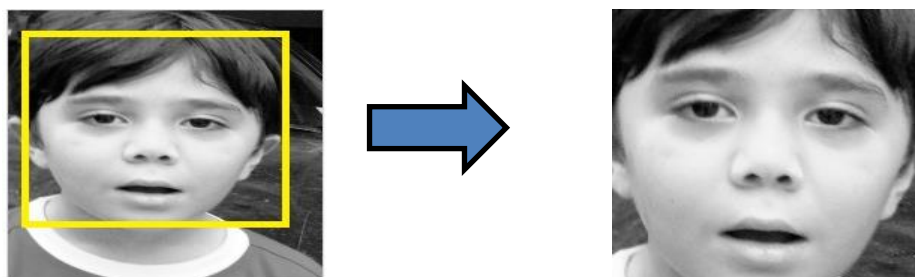
**Figure 6-**Represents RGB image converted to grayscale image

**4.1.2 Histogram Equalization:** After converting color image into grayscale image, the second stage will apply the histogram equalization Algorithm, as shown in Figure-7 for same class mentioned above.



**Figure 7-**Represents grayscale image converted to histogram equalization

**4.1.3 Face detection phase:** when the grayscale image and histogram equalization are implementation in first and second stage, the face detection will implemented in third stage by crossing the image through four step which were Haar lick feature, integral image, Adaboost learning and cascade classifier. After that, the face detection is obtained as shown in Figure-8 for same class mentioned above.



Draw yellow rectangle  
on the histogram equalization

Face detection results

**Figure 8-** Represents face detection results by using Viola Jones algorithm



**4.1.4 Cropping and resizing stage:** the last stage was done by cropping process and all images were resize with 200 \* 200 dimensions as shown in Figure-9 for same class mentioned above.



**Figure 9-**Represents Cropping and resizing process

**4.2 Data Mining Phase:** in data mining phase there were two stages where first stage was a feature extraction and second stage was machine learning. Each of which has used certain Algorithm.

**4.2.1 Feature Extraction:** in this stage, where the Algorithm of feature extraction was used linear discriminate analysis Algorithm.

**4.2.2 Machine learning stage:** in this stage, where the Algorithm of machine learning technique was used SVM classifier for features with LDA feature extraction. That accuracy of LDA is shown in Table-2 while the accuracy of PCA, LBP as shows in Tables-(3, 4).

**Table 2-**Accuracy of SVM – LDA

class representation	No. of training	No. of testing	SVM-LDA	Accuracy of LDA
(3-7)(26-30)	215	79	64	81%
(8-13)(14-19) (20-25)	409	81	71	88%
(31-40)(41-50)	96	10	8	80%
Average	<b>720</b>	<b>170</b>	<b>143</b>	<b>84%</b>

**Table 3-**Accuracy of SVM – PCA

Class Representation	No. of training	No. of testing	SVM-PCA	Accuracy of PCA
(3-7)(26-30)	215	79	56	71%
(8-13)(14-19) (20-25)	409	81	65	80%
(31-40)(41-50)	96	10	6	60%
Average	<b>720</b>	<b>170</b>	<b>127</b>	<b>75%</b>

**Table 4-**Accuracy of SVM –LBP

Class Representation	No. of training	No. of testing	SVM-LBP	Accuracy of LBP
(3-7)(26-30)	215	79	58	73.5%
(8-13)(14-19) (20-25)	409	81	72	89%
(31-40)(41-50)	96	10	9	90%
Average	<b>720</b>	<b>170</b>	<b>139</b>	<b>82%</b>

The above Table-2 shows the accuracy of the three classes and by applying SVM classifier with feature extraction (LDA).The first class represented 3-7 and 26-30 years contains 215 training images and 79 testing images. The ages 64 images has been estimated successfully which gives accuracy of 81.0126%. The Second class represented 8-13, 14-19 and 20-25 years contains 409 training images and 81 testing images. The ages 71 images has been estimated successfully which gives accuracy of 87.6543%. The last class represented 31-40 and 41-50 years and contains 96 training images and 10 testing images. The ages 8 images has been estimated successfully which gives accuracy of 80%. Hence, the total number of the training images is 720 images, while the number of testing images is 170 images, applying the SVM classifier with LDA gives an accuracy rate of 84%, applying the SVM classifier with PCA gives an accuracy rate of 75% and applying the SVM classifier with LBP gives an accuracy rate of 82%. As seen in Table-5 below.

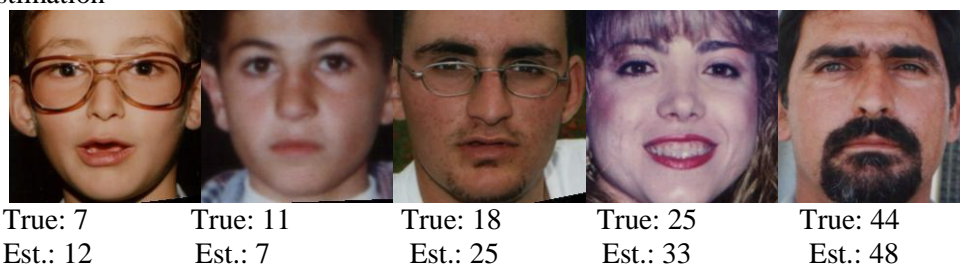
**Table 5-**Comparison of accuracy between SVM-LDA, SVM-PCA and SVM-LBP

class representation	No. of Training	No. of Testing	SVM-LDA	SVM-PCA	SVM-LBP
(3-7) (26-30)	215	79	64	56	58
(8-13) (14-19) (20-25)	409	81	71	65	72
(31-40) (41-50)	96	10	8	6	9
Average	720	170	143	127	139
<b>Accuracy</b>			<b>84 %</b>	<b>75 %</b>	<b>82 %</b>

SVM classifier with LDA was selected of the accuracy. So, the SVM classifier was the best way to be implemented. To illustrated the application of the SVM classifier Show Figure-10.



**a:** good estimation



**b:** poor estimation

**Figure 10-**Examples of age estimation using the proposed system **a:** Good age estimates; **b:** poor age estimation.

**5. Conclusion**

Age estimation is an important activity in facial image classification. Age estimation is defined as age of a person based on his or hers biometric features that extraction from face, exactly on the basis of two-dimensional facial images. Facial characteristic points can be defined as a standard reference points on human face used by scientists in order to recognize a person’s face, or to estimate the age of a person. In this work, support vector machine (SVM) classifier has been used with the FG\_NET

dataset and gives a high precision result. FG-NET dataset is divided into seven classes; class one represents 3-7 years, class two represents 8-13 years, class three represents 14-19 years, class four represents 20-25 years, class five represents 26-30 years, class six represents 31-40 years and class seven represents 41-50 years. After extracting the features from the seven classes. It has been found that some classes have the same number of feature. Hence, the seven classes are combined into three classes depending on the number of features. SVM classifier gives accuracy is 84%. From Table-5 can be observed that the greater the number of instance in the class the greater the accuracy. In addition to, the type of dataset used to estimate the age, images number and images quality, to ensure that the estimate of age is right.

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