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Enhanced age prediction and gender classification (EAP-GC) framework using regression and SVM techniques

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ABSTRACT

In present scenario, biometric based applications are developing rapidly and plays vital role in various fields like military, crime investigations, VISA providing systems, etc. Based on that, the design of intelligent systems for human age and gender classification using face images has gained the interest of researchers and several studies has been done towards that. With that concern, this paper concentrates on developing a combined framework for age and gender classification in accurate and effective manner. Hence, an Enhanced Age Prediction and Gender Classification (EAP-GC) framework has been proposed by incorporating the Supervised Learning Model (SLM) that considers both the shape and texture changes over the learning process. Moreover, Partial Least-Square (PLS) technique is used for dimensionality reduction, thereby, increasing the prediction accuracy. For age determination, poly regression model is incorporated and the gender classification is accomplished using multi- Support Vector Machine (SVM) classification technique. The experimentation has been made with the widely available benchmark datasets, FG-NET and HQFaces, in MATLAB tool. The obtained results are then compared with some traditional classification models for providing evidence for the efficiency of the proposed mechanism. It is shown from the results that the EAP-GC model surpasses the other compared techniques in accurate age prediction and gender classification.

1. Introduction

In general, face is considered to be a munificent data source. Moreover, several informative data can be extracted from the facial images like emotion, age, gender, expressions, etc, for many applications. Several research works have been made regarding this in the domains of computer vision, image processing, biometric applications, multimedia and machine learning. Since, the people at different categories require distinctive preferences in factors such as consumption habit, linguistics, salutations and aesthetics. Age and gender determination plays a vital role in commercial communication services in present scenario.

Accordingly, for instance, an enquiry portal is broadly required by various applications, which selects the vocabulary, working interface and the services based on the consumer's age; a browser can find out whether the end-user comes under age classification to view the contents of particular web pages. Hence, the application oriented estimation of gender and age from human faces images is more required in commercial services. In particular, methodologies for age determination from facial images are regarded as age estimation, progression of age and AIFR [1]. From this, Age determination defines the automatic classification of similar age categories or exact ages of samples from the data acquired with their faces. And, Age evolution denotes the reformation of facial manifestation with some aging effects naturally. Finally, AIFR concentrates on developing the capability of automatic facial identification, without considering the aging effects.

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This paper focuses on both age prediction and gender classification by additionally allotting two classes such as male and female to the input images. Study results have exposed that human can categorize male and female with their faces with about 95% of precision rate. Conversely, the precision rate has become low, when it considers facial images of children. A significant process in age and gender determination is feature extraction, which helps in deriving key feature for efficient description. There are many feature extraction models have been developed and used by the research people, with no boundary to Local Binary Pattern [2], Neural Network Architectures [3] and Locality Preserving Projections (LPP) [4].

Moreover, it is to be stated that Active Appearance Model (AAM) [5] has become the maximum utilized feature extraction model, which focuses on both the shape and facial texture. The similar model has also been incorporated for gender classification, since it involves in dividing the facial texture into number of parameters, for making the evaluation convenient. The process has been worked by the inducement of principal component analysis, which is further a methodology for reducing dimensions by merging the shape and texture vectors of facial images. But, it considers only the facial data features rather providing significance to the parameters for age and gender classification. Hence, it is to be given that the AAM provides unsupervised principle, whereas the accurate classification of age and gender from human facial images requires supervised learning process. The Fig. 1 illustrates the generic operations involved in flow of age and gender classification.

With that note, the Enhanced Age Prediction and Gender Classification (EAP-GC) framework, proposed in this paper, improves the results of traditional AAM, by replacing Principal Component Analysis with Partial Least-Square (PLS) regression technique. PLS is a technique for dimensional reduction of input facial images by increasing the covariance value between the estimator and the response variable. Further, Supervised Learning Model (SLM) has also been incorporated for obtaining accurate classification outcomes. And, the performance valuation of the proposed methodology has been done with the benchmark databases FG-NET and HQFaces.

The remainder of the paper is framed as follows: Section 2 deliberates the related works based on Age Estimation and Gender Classification. Section 3 presents the working process of Enhanced Age Prediction and Gender Classification (EAP-GC) framework. The evaluated results and discussions with performance comparison are provided in the section 4 and finally, section 5contains the conclusion with some key points for future enhancement.

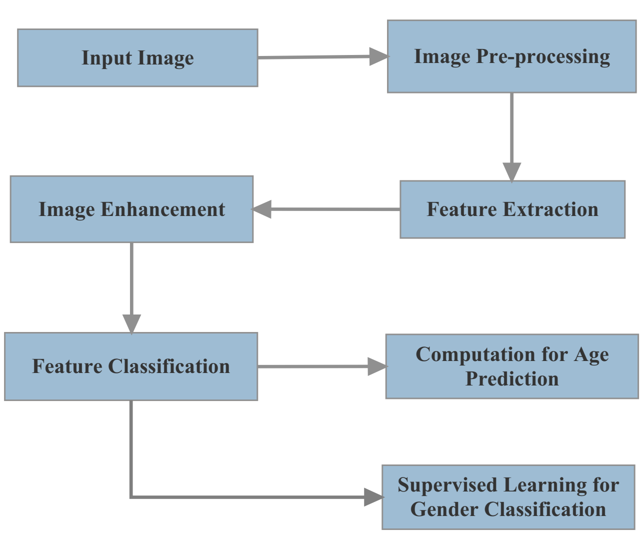

Fig. 1. Generic operations involved in the workflow.

2. Related works

2.1. Existing feature extraction techniques

In general, the feature extraction techniques for facial images are categorized as local and holistic. The local approach based feature extraction can also be termed as part-based approach, focuses on prominent facial parts like wrinkles on face. Using this local feature based extraction, the authors [6], have classified the 2D inputs into three age classes: 1. Babies, 2. Youngsters and 3. Senior Citizens. It is also given in the paper that the face is termed as the ratios between feature peak lengths and the wrinkles are mentioned using snakelet transform. The ratio determination has been used for differentiating babies and young adults, whereas snakelets are used for finding the difference between young and senior adults. More approaches based on sobel edge detection [7], Gabor Filters and Robinson compass Mask using Rank based Edge Texture Unit (RETU) [8] for appropriate wrinkle definition along with facial textures. But, the techniques based on local features are not suitable for specific age determination, since it defines about the shape changes.

Further, the global features called holistic feature extraction concerns the whole face for feature extraction. The methodologies include LPP [9], AAM, and Marginal Fisher Analysis (MFA) [10], etc. The model concentrates on both the shape and texture changes of input facial images. Further, Biologically Inspired Features (BIF) has been used in [11] for providing appropriate estimation.

2.2. Techniques for age determination

The issues on extraction of age based elements from human face images have gained growing attention in present decade and many approaches have been put forth. An informative survey has been demonstrated in [12]. In [13], an age progression model has been developed for analyzing the features of 18 years old adults. The model needs proper localization of facial attributes, but the process was not suitable for wild images that have been acquired from social platforms. In a different way, age determination based on subspace transformations to reduce dimensions [14]. But, the well-allied and near frontal input requirement has been the major disadvantage of those models.

Further, in [15], facial patches distribution has been done with Gaussian Mixture Model (GMM). Another work in [16], Local Binary Patterns (LBP) based hierarchical age classification has been used for accurate age determination. The models presented in [17–19] discussed about gender prediction, age grouping and classification. A novel model for Age Classification based on CLBP is given in [18]. In that, the dataset images are analyzed based on the Correlation, Contrast, Energy co-efficient and Homogeneity. Fibonacci Weighted Neighbourhood Pattern (FWNP) was given in [19] for age grouping in which Motif Shape Primitives was considered. But, the specific age determination based on the arithmetic features of the facial images was the limitation that is notices in that.

2.3. Models for gender Classification:

A comprehensive survey on gender classification methodologies has been discussed in [20]. A SVM based gender classification model has been demonstrated in [21] for analyzing the intensities of the images, and in various image processing applications [22,23] Further, SVM classifier is replaced with AdaBoost in [24]. A combined model for age determination and gender classification has been given in [25], using arbitrary viewpoints and under occlusion. Most of the models for age determination and gender classification have been proposed for gray scale images, for dealing with color images, in [26], the quaternion type moments has been used to preserve the global features of PCA. It was designed to handle with complex type features of color images. But, it is to be stated that the work processed in unsupervised manner.

3. Proposed framework

The proposed Enhanced Age Prediction and Gender Classification (EAP-GC) framework incorporates Partial Least-Squares (PLS) regression for replacing Principal Component Analysis to diminish dimensions. The process of feature extraction has been done with the shape and texture determination of images. Moreover, Supervised Learning Model (SLM) has been developed for accurate age estimation and gender prediction by considering the shape and texture determination of input images.

3.1. Incorporation of Partial Least-Square (PLS) regression for dimensional reduction

PLS regression technique is mainly use for reducing dimensionalities by increasing the value of covariance between the Predictor Variable (PV) and the response variable (RV). From that, latent grades will be produced that comprises the reduced rate of dimensions and the higher prediction rate. The technique has been termed as a statistical process, in which latent grades are generated through the linear combinations of the PV and RV. It normalizes and combined parameters from several regressions. Hence, concurrently, the regression and dimensional reduction have been accomplished. The PLS involves in elements search that have the ability to collect the directions of greatest variance in PV and the direction of best relation or covariance between PV and RV. Thereby, it is performing variable decomposition in supervised manner.

Let predictor variable, $PV_0 \in \mathbb{R}^N$ represent $I \times N$ matrix, where 'I' is the number of input samples and 'N' is the dimensional attribute of each sample and the response variable RV_0 be in $I \times M$ matrix, where 'M' states the number of attributes belongs to response variable. Perhaps, in most of the times the value of 'M' is 1. The decomposition has been done as,

$$PV_0 = XA^T + T, RV_0 = YB^T + Q \tag{1}$$

Where X and Y are $I \times K$ matrices of 'K' number of latent grades from the derived vectors, the matrices A and B are inputs having $N \times K$ and $M \times K$ elements, respectively. Then, $I \times N$ matrix T and $I \times M$ matrix Q are considered to be the matrix residuals. Further, the latent score 'X' can be evaluated from the mean centred attribute set calledPV_0.

$$X = PV_0 WT, PV_0 = PV - \overline{PV} \tag{2}$$

From the above equation (2), PV denotes the predictor variables set and $\overline{PV}$ is the mean of PV has equal dimension with zero mean PV called PV_0. Correspondingly, RV and RV_0 are having same dimensions and RV_0 represents the zero mean RV. The weights of the matrix is given as WT={wt_1, wt_2, ... wt_k} is evaluated by resolving the optimization problem. Moreover, the computation of 'k' the direction of dimension vector is given as,

$$\widehat{WT}_K = argmax_r PV_0^T RV RV^T PV_0 wt \tag{3}$$

From that, WT^T WT = 1 and $PV_0^T PV_0 wt_i = 0$, for i = 1.........K-1. Based on the equation, it is possible to redefine the original content from the latent grade by the WT matrix inversion as WT^{-1}, which is given as P. And, here 'P' is given as projection coefficient. When there are mean centered training set PV_{tr} and their labels are given as RV_{tr}, the test samples are termed as PV_{ts}, whose class labels are to be determined. Here, PLS has been used for reducing dimensions by test sample projection based on their weights (denoting matrix WT). Therefore, the latent grades matrix X_{ts} for test sample is determined as follows,

$$X_{ts} = PV_{ts} WT \tag{4}$$

The proposed model determines shape definition and texture differences from the dataset images.

For shape determination PLS model is used and the shape of each input facial image from the training database is mentioned by a list of 2D landmarks, which are ordered to develop a vector 'v' is given as,

$$v = (x_1, x_2, \cdots, x_n, y_1, y_2, \cdots, y_n)^T \tag{5}$$

Further, the rotational and scaling variations are eliminated from the 2D landmarks by proper shape alignment. Following, the supervised learning model has been designed based on the description in section 3.1. The shape matrix 'V' is framed as V={v_i} and the class labels are stored in the response variable vector 'RV'. And, 'v' is computed as follows,

$$v = \overline{v} + G_v P_v \tag{6}$$

Here, $\overline{v}$ is the mean of shapes, G_v denotes the latent grades of 'v' and P_v represents the projection coefficient of 'v'. Each 'v' of image pixel textures is translated to vector 'w'. By employing the PLS derivation to the matrix W={w_i}. Moreover, a linear image texture form is attained as,

$$w = \overline{w} + G_w P_w \tag{7}$$

Where, $\overline{w}$ denotes the gray level texture G_w is the vector of latent grades for image texture 'w' and P_w represents the projection coefficient of image intensities.

3.2. Supervised learning model (SLM)

For framing the SLM, all input facial images are encapsulated to the mean value as $\overline{v}$, this is accomplished to compare the control points of the images at training dataset to a defined shape. The translational variations are generalized by employing the offset and scaling values to the encapsulated images.

By concatenating the 'G_v' and G_w, combined model of shape of the input sample and texture can be derived as,

$$G_c = (G_v G_w) \tag{8}$$

Further, the correlation between the shape and texture of the obtained image is eliminated by applying the 'G_c' to PLS computations, by considering both $G_v and G_w$ has '0' mean values. Hence, the SLM based facial image of each face can be represented by the following equation,

$$G_c = LC_c, C_c = (C_v C_w) \tag{9}$$

From the above equation, L is the latent grade vector denoting both the shape and image intensities of specific input sample and C_c is the combined model based projection coefficient. 'C_v' is the G_v oriented coefficient and C_w is the G_w oriented coefficient respectively. Therefore, the linear based SLM denotes both the shape and texture based on the vector 'L' is given as,

$$v = \bar{v} + LC_v P_v \; and \; w = \bar{w} + LC_w P_w \tag{10}$$

From the appropriate definition of shape and image textures, the problems on age and gender determination can be effectively resolved.

3.3. EAP-GC framework

The overall framework of the proposed EAP-GC model is presented in the Fig. 2. Moreover, the proposed model works in two

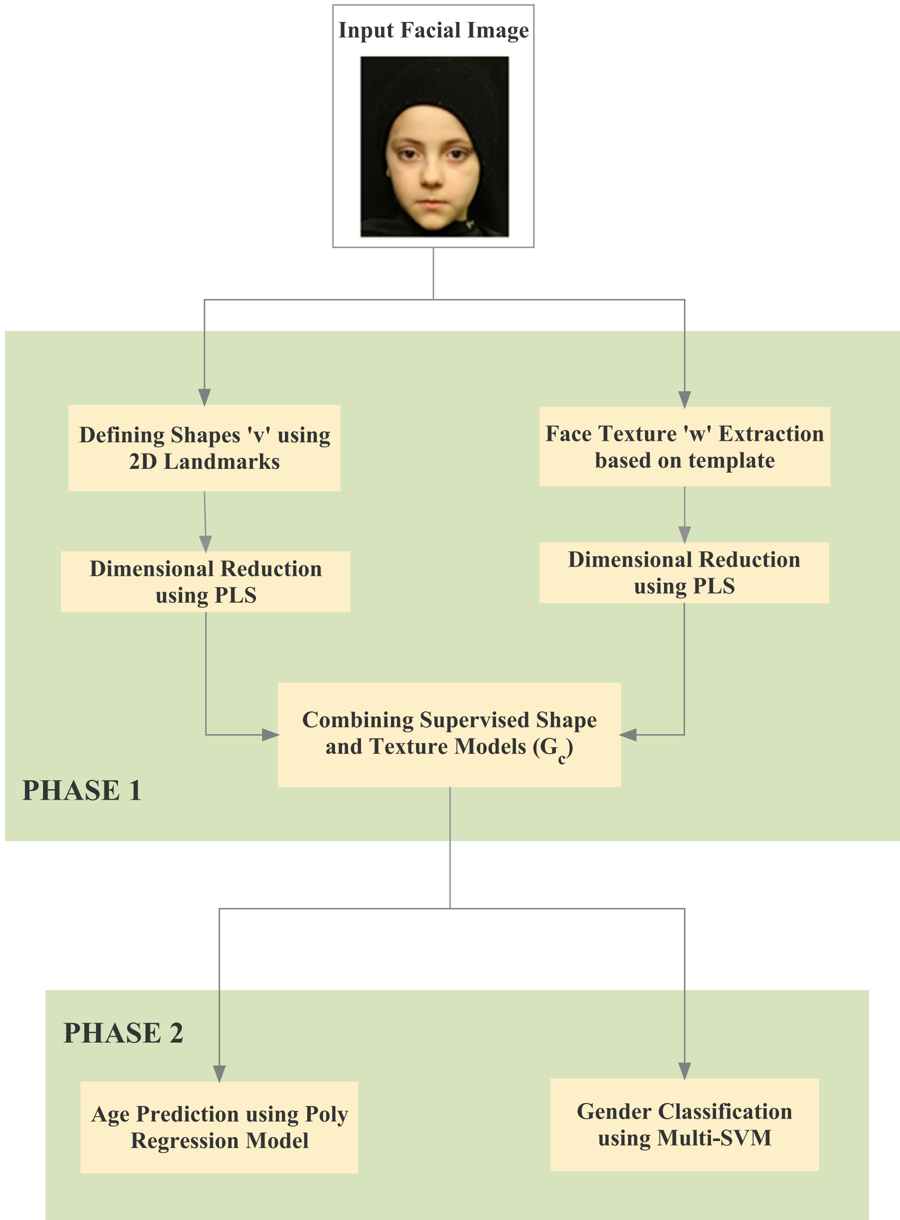

Fig. 2. Pictorial representation of enhanced age prediction and gender classification (EAP-GC) framework.

phases. In phase 1, the facial shape and texture extraction of the input image is carried out using the methodologies such as PLS and SLM, explained in previous sections 3.1 and 3.2. Following that, the phase 2 of the work involves in the process of age determination using poly regression technique and classifying gender using Multi-SVM model.

The model contains elements for determining both the age and gender using shape and texture of sample images. For framing the aging pattern and prediction of exact age, poly regression model is used here. Therefore, Aging Function (AF) of facial images are given as,

$$AgingFunction = AF(L) \tag{11}$$

Where, L is the aging vector for all the instances in the facial database and L is the set, which is given as L={l_1,l_2,...l_m}, in which 'm' is the number of instances.

Then, for each facial instance from database, the age function is determined from the aging vector using the following equation.

$$AF = \delta + \rho^T l \tag{12}$$

$$AF = \delta + \rho_1^T l + \rho_2^T l^2, \cdots \rho_m^T l^{m-1} \tag{13}$$

From the above equations (12) and (13), the offset value is mentioned as 'δ' and the poly regression coefficients are given as $\rho_1^T$and ρ_2^T. Using these equations of Ordinary Least Square and Quadriatic functions, the age of the facial images are classified accurately.

The secondary part of the proposed model is to classify the gender of the input image using the classification model for categorizing the results under male or female classes. Assuming that the training dataset as (U_i, V_i) for i = 1 to m with $U_i \in \mathbb{R}^N$ and $V_i \in \{-1, 1\}$ and the classifier function (CF)Vis determined as follows,

$$CF(U_i)\begin{cases} \geq 0 V_i = 1 \\ < 0 V_i = -1 \end{cases} \tag{14}$$

Based on the above equation, the class results 1 is considered as male and −1 is taken as female. Moreover, in this gender classification process, SVM classification technique is used, since it provides better results in binary classifications.

3.3.1. Work flow of the enhanced age prediction and gender classification model

The Fig. 3 presented below describes the work flow of the proposed EAP-GC Model. The input images are acquired from the benchmark datasets and the texture is obtained with poly regression. The evaluation results and the comparative study aregiven in the subsequent section 4. From the dataset images, the shape and texture are determined from the equations presented in section 3.1 and Latent vector 'L' is determined using (9). The value of 'L' is noted as single parameter, which denotes both the definition of shape and texture resembles single face. Then, it is given for testing with phase 1 and phase 2 of proposed model, from which the age and gender is determined respectively.

4. Evaluation results and discussions:

For the evaluations of the proposed model, images from FG-NET [27] and HQFaces [28] are used. The simulation tool used here is MATLAB. And, the prediction results are evaluated with the previous models such as Rank based Edge Texture Unit (RETU) and Marginal Fisher Analysis (MFA). Moreover, the information about the datasets is provided below. It is also to significant to compare results obtained from age determination the work with previous works such as FIDRSP, CLBP and FWNP Pattern.

5. FGNET dataset

In FGNET, the database for age determination comprises about 1000 samples from 82 objects and the aging variation of data in the database is from 0 to 69. Therefore, each single object contains several image samples. The distribution of aging in the samples are not uniform, makes the dataset more challenging. Moreover, the dataset also contains samples from gray-scale images to fully colored images with varieties of expressions on faces. The images for gender classification in FGNET comprises images for about 571×431 instances from 34 females and 40 males respectively.

6. Hqfaces dataset

The images of HQFaces dataset are collected from Politecnico di Torino, Italy. It contains 184 HD imges with the resolution of 4256×2832. Moreover, the database contains 57% of male images and all the images are subjected to capture under same lightings.

Based on the computations provided in Section 3, the vector 'V' denotes the class banes that comprises the specific ages of the training data. On the other hand, for gender classification, value 1 represents male and −1 as female face. Further, in order to examine with the accuracy of the obtained results, cross validations are used here. The sample of a single person is used for testing and trained the classified with the rest of the instances. This develops a real-time testing case, in which the image that is under test is completely new to the model. In such manner, the results are validated for its accuracy and precision. The Figs. 4(a) and (b) contains the images that are obtained from FGNET and HQFaces datasets, respectively.

6.1. Factors involved for performance evaluation

The performance evaluation factors for age determination are Mean Absolute Error (MAE), which is defined as the mean of all absolute error and Cumulative Score (CS).

$$MAE = \sum_{i=1}^{S_n} |TA - DA| / S_n \tag{15}$$

Where, S_n is the number of sample images that are undergone for testing, 'TA' is the Threshold Age and 'DA' is the Determined Age. As mentioned above, another significant factor involve in evaluation is Cumulative Score and it is computed as in (16).

$$CS(k) = N_{err\leq k} / S_n \times 100 \tag{16}$$

Where, $N_{err\leq k}$ states that the number of samples on the model produce absolute error not greater than 'k' years.

Accuracy of gender classification is determined by the factor called Precision Rate and the equation is given as follow,

$$PR = \frac{\sum AccurateDetections}{\sum Numberofsamples} \times 100 \tag{17}$$

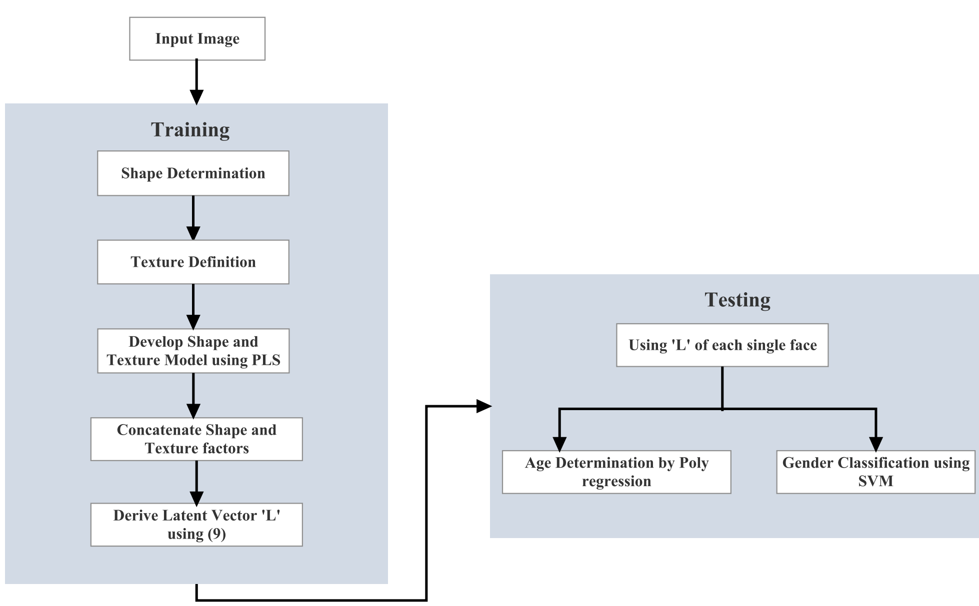

Fig. 3. Work flow of EAP-GC Model.

(a)

Fig. 4a. Images obtained from FGNET.

(b)

Fig. 4b. Images from HQFaces.

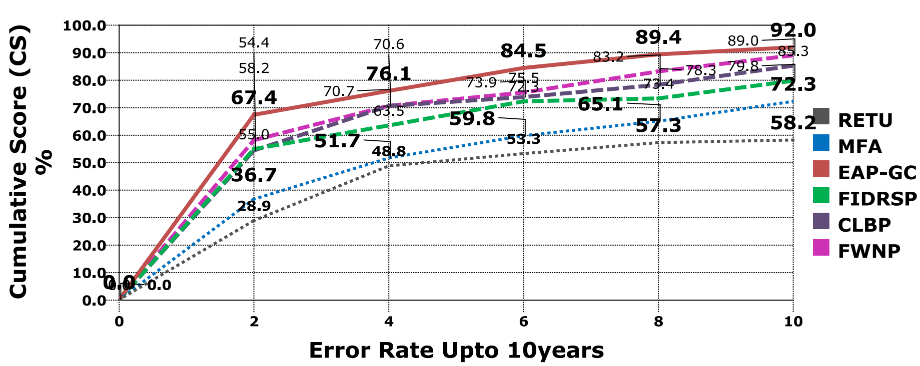

Fig. 5. Results on analysis with FGNET dataset.

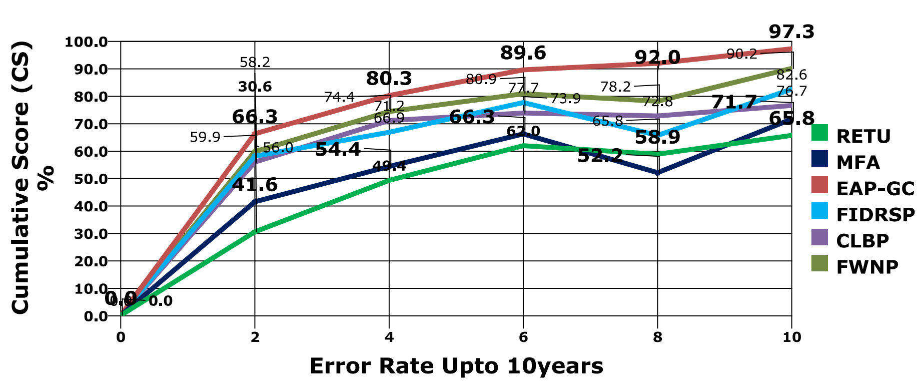

Fig. 6. Results on analysis with HQFaces dataset.

Table 1
MAE and CS Obtained with FGNET Dataset.

Models	MAE	CS (%)
RETU	7.32	63.8
MFA	6.51	72.3
FIDRSP	6.43	76.1
CLBP	5.64	89.6
FWNP	5.87	80.3
EAP-GC	4.26	92.0

Table 2
MAE and CS Obtained with HQFaces Dataset.

Models	MAE	CS (%)
RETU	8.01	65.9
MFA	6.51	72.1
FIDRSP	5.43	82.6
CLBP	5.14	760.6
FWNP	4.87	90.3
EAP-GC	3.32	97.2

The experimentation is initially done with FGNET dataset and then with the images obtained from HQFaces. Moreover, the estimated results are compared with the existing models. The Fig. 5 and Fig. 6 depict the evaluation results on age prediction phase of the proposed model with respect to the cumulative score. The Fig. 5 presents the results obtained with the experimentation on FGNET dataset. It is clearly observed from the figure that the proposed model attains higher value of cumulative score, hence, prediction rate is very accurate in EAP-GC model. For the evaluations with FGNET, it produced about 92% of CS and for HGFaces dataset, the proposed model shows 97% of score, which is the greater value than others. It is also to be given that the CS is determined here based on the error rates up to 10 years of age. Further, the Table 1 and Table 2 depict the MAE and CS values obtained on analysis.

Another factor to be evaluated for testing the Gender classification is precision rate and the results are given in Fig. 7 and Fig. 8 for FGNET and HQFaces Dataset, respectively. It is very obvious from the figures that the proposed model attains higher rate of accuracy than other models.

7. Conclusion

This paper develops a novel model called Enhanced Age Prediction and Gender Classification framework for accurately detect the age and gender of the person from input images. The phase 1 of this model works to determine the age of a person using PLS regression for clear definition of shape and texture of facial images. Following, the phase 2 works on gender classification using the Supervised Learning Model (SLM). The integration of algorithms produces the results more efficient and précised. Moreover, the images from the benchmark datasets such as FGNET and HQFaces are used for evaluating the proposed model, and, the obtained results are also provided. When compared the results with the existing works, the EAP-GC model provides better accuracy in both Age prediction and Gender classification.

As future enhancement, the work can be improved in such a manner to implement of detecting age and gender from images obtained with surveillance systems instead of still images. This would help in solving several security issues in various applications.

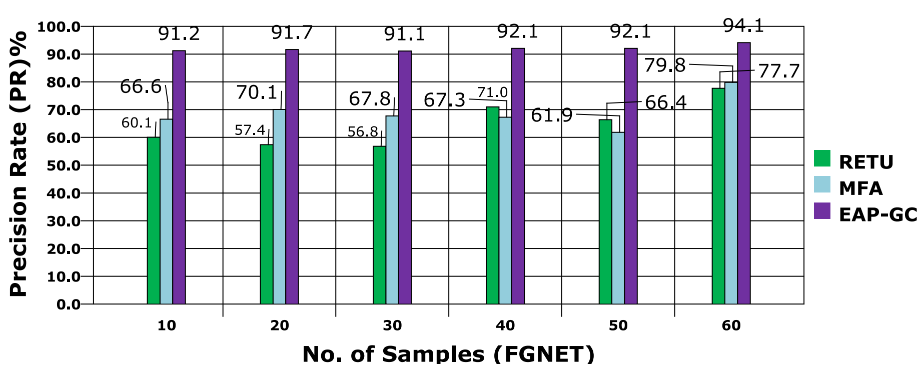

Fig. 7. Evaluation for gender classification accuracy with FGNET.

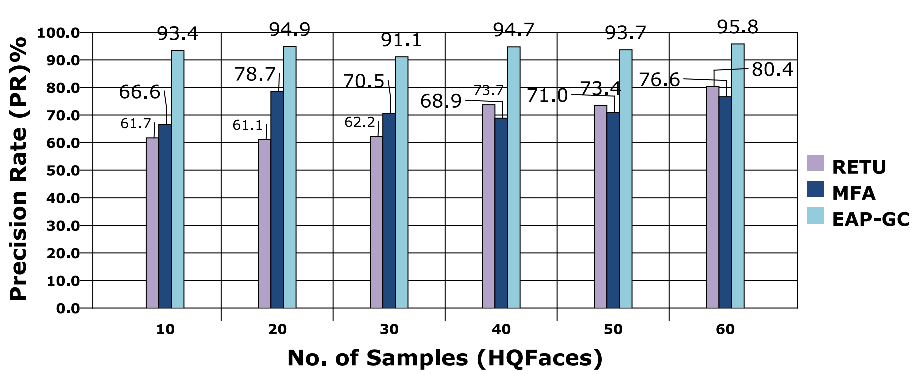

Fig. 8. Evaluation for gender classification accuracy with images from HQFaces.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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