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Feature Vector Fusion for Image Based Human Age Estimation

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***Abstract*—**Human faces, as important visual signals, express a significant amount of nonverbal info for usage in human-to-human communication. Age, specifically, is more significant among these properties. Human age estimation using facial image analysis as an automated method which has numerous potential real-world applications. In this paper, an automated age estimation framework is presented. Support Vector Regression (SVR) strategy is utilized to investigate age prediction. This paper depicts a feature extraction taking into account Gray Level Co-occurrence Matrix (GLCM), which can be utilized for robust face recognition framework. It applies GLCM operation to remove the face's features images and Active Appearance Models (AAMs) to assess the human age based on image. A fused feature technique and SVR with GA optimization are proposed to lessen the error in age estimation.

***Keywords*—**Support vector regression, feature extraction, gray level co-occurrence matrix, active appearance models.

I. Introduction

INDIVIDUALS can easily extricate many kinds of helpful information from a face image; for example, identity, gender, expression, estimated age, and so forth. A human face image contains large information about personal qualities, including identity, emotional expression, gender, age and so forth. Normally, a human image can be thought as a complex signal of many facial traits, for example, skin color and geometric facial features. These characteristics assume a vital part in real applications of facial image analysis. In such applications, different qualities evaluated from a captured face image can infer further framework reactions. Age, specifically, is more significant among these characteristics. For instance, clients may require an age-specific human computer interaction framework that can gauge age for secure framework access control or intelligence gathering. Age is one of the important biometric qualities for reinforcing the identity authentication. The challenge of facial age estimation [1] mainly comes from two problems: 1) The wide differing qualities of visual appearance existing even within the same age gathering and 2) The less number of labeled face images in real cases.

Automatic human age estimation using facial image analysis has many potential real-world applications [2]. Compared with other facial variations, aging effects show three distinctive attributes:

1. The aging advancement is uncontrollable. No one can advance or postpone aging freely. The system of aging is not fast and irreversible.
2. Personalized aging patterns. Different individuals age in different ways. The aging pattern of every person is determined by his/her genes and also many external variables, for example, wellbeing, way of life, climate conditions, and so forth.
3. The aging patterns are temporal data. The aging advancement must comply with the order of time. The face status at a specific age will influence older face, yet will not affect those younger ones.

Each of these qualities contributes to the challenges of automatic age estimation. To start with, on the grounds that individuals cannot unreservedly control aging variation, the collection of sufficient training data for age estimation is to a great degree laborious. This trouble is now partially reduced because of public dissemination of the FG-NET Aging Database [3]. Nevertheless, every subject in this database only has face images at a couple ages, i.e., the dataset is highly incomplete in the perspective of aging patterns.

The age estimation issue is different from the issue of face recognition with age variation, where the objective is to gauge facial identities while no ages are evaluated from the input faces. The research efforts on age estimation may assist recognizing faces containing age variations. There are three main classifications that can arrange most existing image-based age estimation systems, for example, anthropometric model [4], [5], aging pattern subspace, and age regression. The changes of face shape and surface patterns identified with development are measured to sort a face into a numerous age groups. These techniques are suitable for coarse age estimation or modeling ages only for young individuals.

Visual data display numerous sorts of features that could be utilized to recognize or represent the information it uncovers. These features show both static and dynamic properties. Classification or recognizing a suitable feature depends on competent utilization of these features that give discriminative information helpful to high-level classification. Shape, color and texture features are prevalent features involved in numerous applications.

Normalization is especially valuable for classification algorithms involving neural networks, or distance measurements; for example, nearest neighbor classification and clustering. If utilizing the neural network back propagation algorithm for classification mining, normalizing the input values for every attribute measured in the training specimens will speed up the learning stage. There are many

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techniques for data normalization including min-max normalization, z-score normalization, and normalization by decimal scaling.

II. Related Works

Dibeklioglu et al. [6] proposed a system to extract and utilize dynamic features for age estimation, using a person's smile. It was tried on a huge, gender-balanced database with 400 subjects, with an age range between 8 and 76. Additionally, a new database on posed disgust expressions with 324 subjects in the same age range was used to assess the reliability of the proposed approach when utilized with another expression.

Tharwat et al. [7] designed three different classifiers in view of KNN classifier's concept for facial age estimation and created to accomplish high efficiency calculation of facial age estimation. Initially, KNN-distance methodology computes minimum distance amid test face image and every instance belonging to the class, which has the highest number of nearest samples. Secondly, a modified KNN version was proposed and the classifier scoring results interpolated to ascertain the definite age estimation. Finally, KNN-regression classifier is used as third classifier which combines the classification and regression approaches to increase the accuracy of the age estimation system. Results conducted using FG-NET Database demonstrates the effectiveness of the proposed approach.

Chen and Hsu [8] explored the age ranking by an arrangement of ranking features lying on a low-dimensional space. A basic and adaptable subspace to learn strategy was proposed to overcome constrained optimization issues. Proposed system includes more accessible data to enhance the feature discriminability. SVR was proposed with ranking features to learn age estimators. The outcomes on the age estimation demonstrate that proposed system beats exemplary subspace learning methodologies, and the semi-administered learning effectively incorporates the age ranks from unlabeled data under different scales and wellsprings of data set.

Zhang and Yeung [9] proposed a novel way to deal with age estimation by formulating the issue as a multi-assignment learning issue. A variant of the Gaussian Process (GP) called Warped Gaussian Process (WGP), a multi-undertaking extension called MulTi-errand Warped Gaussian Process (MTWGP) was proposed. Age estimation is planned as a multi-assignment regression issue in which every learning errand alludes to estimation of the age function for every person. While MTWGP model's common features are shared by different persons, it likewise permits person-particular features to be learned naturally. Experiments were conducted using FG-NET and MORPH age databases which demonstrate that MTWGP compares positively with best in class age estimation strategies.

Liu et al. [10] presented a novel multistage learning framework, called Grouping Estimation Fusion (GEF), for human age estimation by means of facial images. The GEF consists of three stages: Age grouping; age estimation within age gatherings; and decision fusion for final age estimation. Altogether, six fusion plans (i.e., intra-framework fusion, inter-framework fusion, intra-inter fusion, inter-intra fusion, most extreme differing qualities fusion, and composite fusion) were produced and compared. The performance of the GEF framework was assessed on the Face and Gesture Recognition Research Network and the MORPH-II databases, and it outflanks the existing cutting edge age estimation techniques by a significant margin. Mean outright mistakes of age estimation were decreased from 3.82 to 2.97 years on MORPH-II and 4.48 to 2.81 years on FG-NET.

Guo and Wang [11] concentrated on human age estimation in face images under significant expression changes. A down to earth and strong age estimation framework was created that does not require clients to pose in neutral expression. Two databases originally gathered in the Psychology community were used to assess the proposed structure and corresponding strategies for cross-expression age estimation.

Lanitis [12] presented a system for age estimation taking head movements into account. The attainability of the proposed system has been assessed using a committed experimental technique where the performance of age estimation was compared using head movements against age estimation taking into account mouse movements and age estimation in view of face images. Preliminary results demonstrate the potential of using head motion as the premise for estimating the age of clients.

Li et al. [13] proposed a novel and efficient facial age estimation algorithm which chooses human age in various leveled structure. Since the face appearance of people in the same age gathering or even of the same age has a few likenesses in common, precise age estimation within the age stage is comprehended by Sparse Representation-based Classification (SRC) in final step. Then again, SRC obliges sufficient training examples in every class but this assumption often is not true, making the performance of age estimation unreliable. Thought of Ordinal Hyperplanes Ranker (OH Rank) and weights of tests' numbers in every class have been utilized to take care of the aforementioned issue, improving the age estimation results. Aftereffects of experiments conducted on the FG-NET Database demonstrate the effectiveness of proposed strategy.

Guo and Zhang [14] considered the issue of cross-population age estimation. A novel routine is proposed for cross-population age estimation with a decent performance which depended on projecting the diverse aging patterns into a similar space where the aging patterns can be interrelated even if they come from different populations. The projections were likewise discriminative between age classes because of the traditional integration discriminant analysis technique. Likewise, the amount of data needed was examined in the objective population to learn a cross-population age estimator. Finally, the achievability of multi-source cross-population age estimation was examined. Experiments were conducted on a vast database of more than 21, 000 face images chosen from the MORPH.

Choi et al. [15] made a comparison on the performances of Sobel filter, Ideal High Pass Filter (IHPF), difference image between original and smoothed image, Haar and Daubechies Discrete Wavelet Transform (DWT), Gaussian High Pass Filter (GHPF), for extracting neighborhood features in age estimation. The extracted were classified by SVR. BERC and PAL aging database were used for evaluation and results demonstrate that GHPF gives a superior performance than different strategies.

Fu et al. [16] overviewed the complete cutting edge techniques in the face image-based age synthesis and estimation themes. Existing models, mainstream algorithms, framework performances, technical challenges, prevalent face aging databases, evaluation protocols, and promising future directions were given precise discussions.

Tokola et al. [17] introduced a novel way to deal with estimating age from a single "wild" image, where posture, illumination, expression, face size, and face occlusions were not managed. Proposed strategy lessens the impacts of variations that as of now exist within in image. Using posture particular projections, image features were mapped into a latent space that is stance insensitive and age-discriminative. Age estimation was then performed using a multi-class SVM.

Li et al. [18] presented a new system for facial age estimation in light of ordinal discriminative feature learning. Considering the temporally ordinal and continuous normal for aging process, the proposed strategy not only goes for preserving the neighborhood manifold structure of facial images, it wants to keep the ordinal information among aging faces. Additionally, redundant information was removed from both the region information and ordinal information based on minimizing nonlinear correlation and rank correlation. The experiments were conducted on Groups dataset and the FG-NET dataset, and the experimental results demonstrate the effectiveness of the proposed system against the best in class routines.

III. METHODOLOGY

AAMs, GLCM, SVR and Genetic Algorithm advanced Support Vector Regression (GA-SVR) were proposed.

A. FG-NET Dataset

FG-NET was funded by the European Union within the fifth Framework Program, Information Society Technologies (IST) in the class of initiative Support Measures – Networks of Excellence and Working Groups. One of the real points of the undertaking was to encourage research technology development in the region of face and gesture recognition by specifying and supplying suitable image sets [19].

For every subject in the FG-NET Aging Database, 10 sets of face images are randomly chosen; the first as "gallery" face and the second one as "test" face. Typically, there is surprising age difference between them.

B. AAMs

AAMs [21] are the closely connected to the concepts of Active Blobs [22], and Morphable Models. These are parametric models, non-linear, and generative of a certain visual phenomenon. Face modeling has been the most frequent application of AAMs.

In a characteristic application, the first step is to fit AAM to an input image, i.e. model parameters are formed to amplify the "match" between the model instance and the input image. The model parameters are then utilized as a part of whatever the application is.

Fitting an AAM to an image is a non-linear optimization issue. The typical methodology is to iteratively tackle for incremental added substance redesigns to the parameters (the shape and appearance coefficients. Given the current appraisals of the shape parameters, it is conceivable to twist the input image onto the model coordinate edge and then compute a lapse image between the current model instance and the image that the AAM is being fit to. In many past algorithms, it is just accepted that there is a constant linear relationship between this lapse image and the added substance incremental redesigns to the parameters. The constant coefficients in this linear relationship can then be found either by linear regression or by other numerical systems [23].

AAMs are only one instance in a large class of firmly related to linear shape and appearance models and their related fitting algorithms. This class includes AAMs, Shape AAMs, Direct AMs, Active Blobs, and Morphable Models, and in addition potentially others. Many models were proposed independently in 1997-1998.

C. GLCM

The definition of GLCM's is as follows [24]: Suppose, an image to be evaluated is rectangular, and has N_x columns and N_y rows and the gray level at each pixel is quantized to N_g levels. Let $L_x = \{1, 2, ..., N_x\}$ be columns, $L_y = \{1, 2, ..., N_y\}$ be rows, and $G_x = \{0, 1, 2, ..., N_g - 1\}$ be set of N_g quantized gray levels. Set $L_y \times L_x$ is set of pixels of the image ordered by their row–column designations. The image I can be characterized as a function which assigns some gray level in G to every pixel or pair of coordinates in $L_y \times L_x; L_y \times L_x \to G$. The texture-context information is specified by the matrix of relative frequencies P_{ij} with 2 neighboring pixels divided by distance d occur on the image, one with gray level I and the other with gray level. Such matrices of gray-level co-occurrence frequencies are a function of the angular relationship and distance between the neighboring pixels. Formally, for angles quantized to 45^0 intervals, the un-normalized frequencies are defined as shown in the equations. The equations define the features. Let $p(i, j)$ be the (i, j)th entry in a normalized GLCM. The mean and standard deviations for the rows and columns of the matrix are

$$\mu_x = \sum_i \sum_j i.p(i,j),$$
$$\mu_y = \sum_i \sum_j j.p(i,j),$$
$$\sigma_x = \sum_i \sum_j (i-\mu_x)^2.p(i,j),$$
$$\sigma_y = \sum_i \sum_j (\mathrm{j}-\mu_y)^2.p(i,j), \tag{1}$$

The features are as.

1) Energy: $f_1 = \sum_i \sum_j p(i,j)^2$
2) Contrast: $f_2 = \sum_{n=0}^{N_g-1} n^2 \left\{ \sum_{i=1}^{N_g} \sum_{j=1}^{N_g} p(i,j) \,\|\, \mathrm{i-j} |= \mathrm{n} \right\}$
3) Correlation: $f_3 = \dfrac{\sum_i \sum_j (i,j)\,\mathrm{p(i,j)} - \mu_x \mu_y}{\sigma_x \sigma_y}$
4) Homogeneity: $f_4 = \sum_i \sum_j \dfrac{1}{1+(i-j)^2}\, p(i,j)$
5) Entropy: $f_5 = -\sum_i \sum_j p(i,j) \log(p(i,j))$
6) Autocorrelation: $f_6 = \sum_i \sum_j (ij)\, p(i,j)$
7) Dissimilarity: $f_7 = \sum_i \sum_j |\, i-j \,| .p(i,j)$
8) Cluster Shade: $f_8 = \sum_i \sum_j (i+j-\mu_x-\mu_y)^3\, p(i,j)$
9) Cluster Prominence: $f_9 = \sum_i \sum_j (i+j-\mu_x-\mu_y)^4\, p(i,j)$
10) Maximum Probability: $f_{10} = \underset{i,j}{MAX}\, p(i,j)$

The important parameters considered when designing a GLCM, are:

1) Region size,
2) Quantization levels,
3) Displacement value, and
4) Orientation value.

The region size gives the region's dimensions of which GLCM is computed. In [25], [26], the region sizes of 32 x 32 and 64 x 64 were utilized to perform dynamic nearby thresholding on SAR ocean ice imagery effectively. So as to catch ocean ice textural contexts, the bigger region size is considered and set it to 64 x 64 during experiments with GLCM.

D.Fused Features with Z Score Normalization

In z-score normalization, the qualities for and trait '*A*' are normalized taking into account the mean and standard deviation of '*A*'. A quality '*v*' of '*A*' is normalized to '*v*'' by computing: $v' = ((v-\overline{A})/\sigma_A)$ where $\overline{A}$ and σ_A are the mean and the standard deviation separately of property '*A*'. This system for normalization is valuable when the real minimum and most extreme of property '*A*' are unknown [20].

E. SVRs

SVR is a modification of machine-learning-theory-based classification called support vector machine. Machine learning techniques have been connected for assigning trading signal. Many studies utilized support vector machine for determining whether a case contains specific class [27], [28]. Yet, the shortcoming only manages discrete class marks, while trading signal continuum data sort on the grounds that a weight of signal can take a purchase or offer force. Grounded in measurable learning theory, SVR is fit to foresee the continuous trading signal while as yet benefiting from the robustness of SVM.

Because of its prediction capacity, SVR has been utilized for predictions as a part of many fields [34], [35]. In view of the computation of a linear regression function in a high-dimensional feature space, the inputs for SVR are mapped by means of a nonlinear function. The modeling of SVR can be depicted as takes after. Assume $f(x) = (\mathrm{w}\,.\Phi(\mathrm{x})) + \mathrm{b}$ where w is the weight vector, x represents the model inputs, b is a bias, and $\Phi(x)$ stands for a kernel function which utilizes a nonlinear function to transform the nonlinear input to be linear mode in a high-dimensional feature space. Typically, the regression modeling obtains the coefficients through minimizing the square lapse, which can be considered as empirical risk based on loss function. The ε- insensitivity loss function was introduced [29], and it can be portrayed as takes after:

$$L_\varepsilon(f(x),y) = \begin{cases} |\, f(x)-y \,| - \varepsilon, & \text{if} |\, f(x)-y \,| \geq \varepsilon, \\ 0, & \text{otherwise}, \end{cases}$$

where y is the objective yields; ε defines the region of ε-insensitivity. When the predicted value falls into the band zone, the loss is zero. Though, when the predicted value falls outside the band region, the loss is explained as the difference between the predicted value and the margin. When empirical risk and structure risk are both considered, the SVR can be set up to minimize the following quadratic programming issue:

Minimize:

$$\frac{1}{2}\|\, w \,\|^2 + C \sum_{i=1}^{n} (\xi_i + \xi_i^*)$$

Subject to

$$(y_i - (w.\Phi(x_i)) - b \leq \varepsilon + \xi_i (w.\Phi(x_i)) + b - y_i \leq \varepsilon + \xi_i^*$$
$$\xi_i, \xi_i^* \geq 0, \text{ for i=1,2,...,n}$$

where i=1,2,...,n is the number of training data, $(\xi_i + \xi_i^*)$ represents the empirical risk, $(1/2)\|w\|^2$ stands for the structure risk preventing overlearning and absence of connected universality, and C is a modifying coefficient representing the exchange off between exact hazard and structure hazard. With a proper modifying coefficient C, band region width ε, and kernel function, the ideal estimation of every parameter can be fathomed by Lagrange technique. The SVR-based regression function can be portrayed as takes after [30]:

$$f(x,w) = f(x,r,r^*) = \sum_{i=1}^{N} (r_i - r_i^*)\Phi(x,x_i) + b$$

where r_i *and* r_i^* are Lagrangian multipliers and satisfy the equality $r_i r_i^* = 0$.

F. Genetic Algorithm (GA)

The GA proposed by Holland [31] is inspired by the living natural evolution strategy. GA is a worldwide optimization system that imitates the natural evolution mechanisms, including survival of the fittest, crossover, and mutation. It performs well in complex optimization issues given its effortlessness and robustness, and it has been effectively connected in different forecasting fields. To adequately scan for the optimal solution, attention ought to be centered on the selection of population size, crossover rate, and mutation rate. More points of interest of GA can be found somewhere else [32], [33].

The essential optimization methodology is depicted as takes after:

Step1. Randomly initialize a gathering of chromosomes. The chromosomes correspond to the solutions in an optimization issue.

Step2. Assess the candidate's fitness chromosomes. The chromosomes with littler fitness will probably survive.

Step3. Produce a new generation according to the proportionate. The chromosomes with higher fitness will probably be chosen.

Step4. Perform a crossover or mutation operation to generate new candidate chromosomes.

Step5. Return the solution if the optimal solution has been accomplished or return to Step2 until a certain number of iterations has been come to.

G. GA-SVR

The training parameters C, σ and ε incredibly influence the forecasting performance of SVR. In any case, the proper selection of these SVR parameters is extremely troublesome. In this research, GA is utilized to streamline the training parameters. GA has strong worldwide inquiry capacity, which can get optimal solution in brief time [34], [35]. So GA is utilized to hunt down better combinations of the parameters in SVR. After a progression of iterative computations, GA can obtain the optimal solution. The strategies and process of optimizing the SVR parameters with genetic algorithm is depicted as takes after:

Initial Value of SVR Parameters: In presented GA-SVR model, the training parameters C, σ and ε of SVR are dynamically enhanced by implementing the evolutionary process with a randomly generated initial population of chromosomes, and the SVR demonstrate then performs the prediction errand using these optimal qualities. Presented approach simultaneously determines the fitting kind of kernel function and optimal kernel parameter values for optimizing the SVR model. The process of optimizing the SVR parameters with genetic algorithm is shown in Fig. 1.

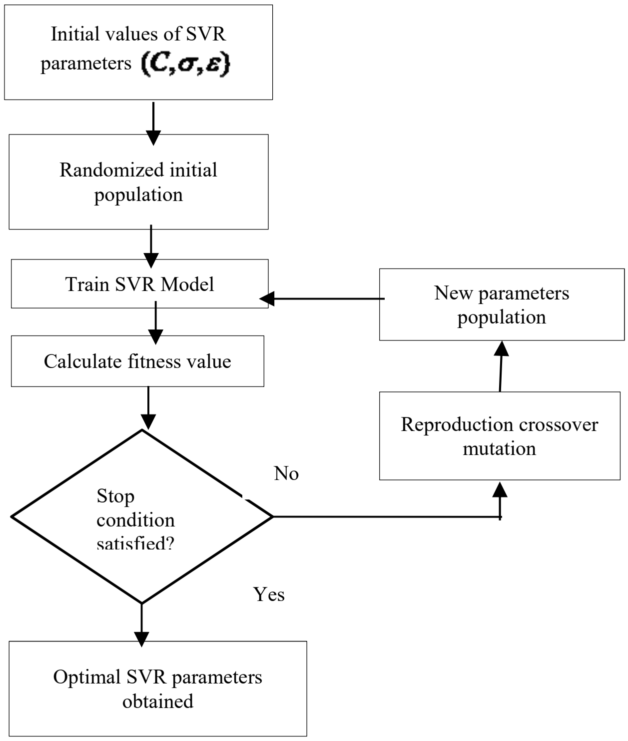

Fig. 1 The process of SVR parameters optimized by genetic algorithm

"Selection" administrator: Selection is performed to choose chromosomes to reproduce. In light of fitness function, chromosomes with higher fitness will probably produce offspring in the next generation by means of the roulette wheel or tournament system to choose whether or not a chromosome can survive into the next generation. The chromosomes that survive into the next generation are then set in a mating pool for the crossover and mutation operations. Once a couple of chromosomes have been chosen for crossover, one or all the more randomly chosen positions are assigned into the to-be-crossed chromosomes.

"Crossover" administrator: Crossover is performed randomly to exchange genes between two chromosomes.

"Mutation" administrator: The mutation operation takes after the crossover to determine regardless of whether a chromosome ought to mutate to the next generation.

IV. Experimental Results

Tables I-IV show the Cumulative Score for GLCM, AAM and Fused, Mean Absolute Error, Cumulative Score for GLCM, AAM and Fused for SVR with GA parameter optimization and Mean Absolute Error for SVR with GA parameter optimization respectively. Figs. 2-5 show the same.

It is observed from Table I and Fig. 2 that the cumulative score level of fused features gets increased than GLCM and AAM techniques. The average value of fused technique increased by 10.01% than GLCM and by 10.59% than AAM Techniques.

TABLE I
CUMULATIVE SCORE FOR GLCM, AAM AND FUSED

Error Level	GLCM	AAM	Fused
0	9	10	11
1	23	27	32
2	32	36	43
3	47	50	54
4	51	57	61
5	55	60	68
6	62	65	72
7	68	74	79
8	71	76	82
9	73	79	84

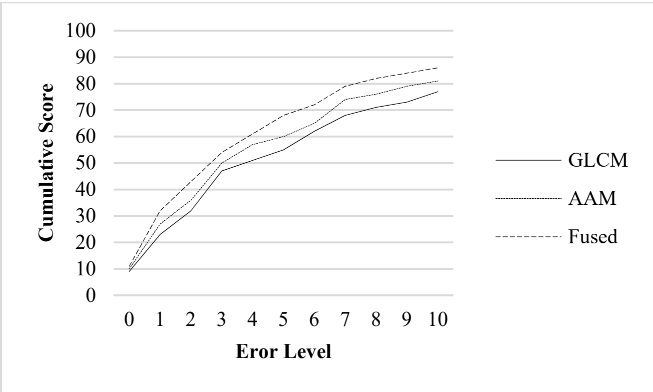

Fig. 2 Cumulative Score for GLCM, AAM and Fused

TABLE II
MEAN ABSOLUTE ERROR

	Mean Absolute Error
GLCM	6.7
AAM	6.1
Fused	5.3

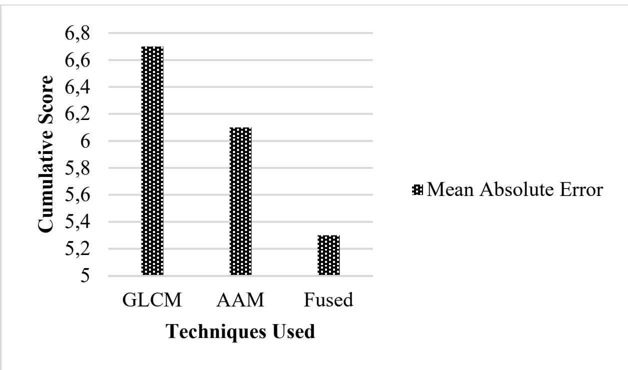

Fig. 3 Mean Absolute Error

It is observed from Table II and Fig. 3 that the mean absolute error gets reduced for fused techniques than GCLM and AAM by 23.33% and 14.04% respectively.

TABLE III
CUMULATIVE SCORE FOR GLCM, AAM AND FUSED FOR SVR WITH GA PARAMETER OPTIMIZATION

Error Level	GLCM	AAM	Fused
0	9	10	11
1	24	28	33
2	34	37	44
3	49	51	55
4	52	59	64
5	57	63	71
6	63	67	75
7	70	76	81
8	73	78	84
9	75	79	86

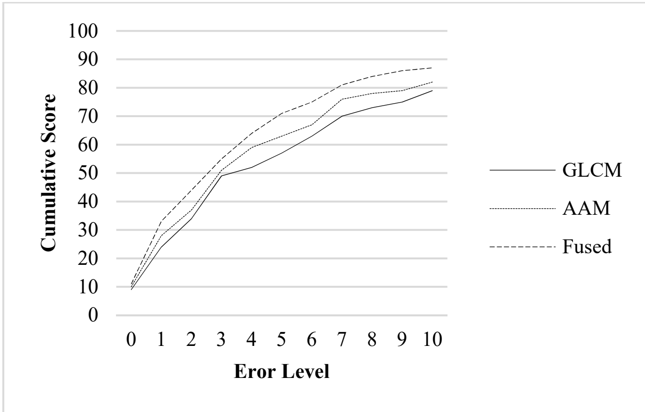

Fig. 4 Cumulative Score for GLCM, AAM and Fused for SVR with GA parameter optimization

It is observed from Table III and Fig. 4 that the cumulative score level of fused features for SVR with GA parameter optimization gets increased than GLCM and AAM techniques. The average value of fused technique increased by 10.42% than GLCM and by 10.57% than AAM Techniques.

TABLE IV
MEAN ABSOLUTE ERROR FOR SVR WITH GA PARAMETER OPTIMIZATION

	Mean Absolute Error
LCM	6.2
AAM	5.9
Fused	5.1

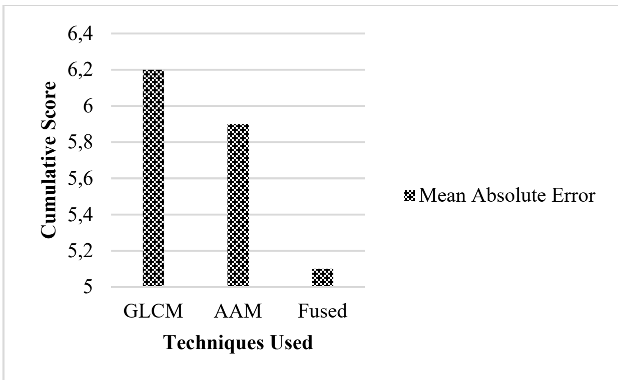

Fig. 5 Mean Absolute Error for SVR with GA parameter optimization

It is observed from Table IV and Fig. 5 that the mean absolute error gets reduced for fused techniques of SVR with GA parameter optimization than GCLM and AAM by 19.47% and 14.55% respectively.

V. Conclusion

Estimating human age naturally by means of facial image analysis has loads of potential true applications, for example, human computer interaction and sight and sound communication. Nonetheless, it is still a challenging issue for the existing computer vision frameworks to naturally and positively assess human ages. The aging manner is found by not only the person's gene, additionally many external elements, for example, wellbeing, living style, living location, and climate conditions. Males and females might likewise age in a different way. The current age estimation is still not adequate for reasonable utilization and more exertion must be put into this research direction. In this paper, a programmed age estimation structure is presented. An intertwined feature technique and SVR with GA optimization is presented to diminish the blunder in age estimation. FG-NET dataset is utilized for experiments. Results demonstrates that combined score level of melded features gets increased than GLCM and AAM techniques. The average estimation of intertwined technique, 10.01% increase over GLCM and by 10.59% over AAM Techniques. Likewise, the mean supreme slip gets lessened for intertwined techniques than GCLM and AAM by 23.33% and 14.04% individually. Be that as it may, SVR with GA parameter optimization is connected which performs better comparing to existing algorithm which demonstrates the outcomes in a superior manner. That is aggregate score level of melded features for SVR with GA parameter optimization gets increased than GLCM and AAM techniques. The average estimation of melded technique increased by 10.42% than GLCM and by 10.57% than AAM Techniques and mean outright blunder gets lessened for intertwined techniques of SVR with GA parameter optimization than GCLM and AAM by 19.47% and 14.

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