Improving Accuracy in Human Age Classification Using Ensemble Learning Techniques

Sreejit Panicker[1*], Smita Selot [1], Manisha Sharma[2]
[1]Department of Computer Applications, SSTC, CSVTU, Bhilai, India
[2]Department of Electronics & Telecommunications, BIT, CSVTU, Bhilai, India

Abstract

Age is a predominant parameter for arbitrating an individual, for security and access concerns of the data that exist in cyber space. Nowadays we find a rapid growth in unethical practices from youngsters as well as skilled cyber users. Facial image renders a variety of information that can be used, when processed to ascertain the age of individuals. In this paper, local facial features are considered to predict the age group, where local Binary Pattern (LBP) is extracted from four regions of facial images. The prominent areas where wrinkles are developed naturally in human as age increases are taken for feature extraction. Further these feature vectors are subjected to ensemble techniques that increases the accuracy of the model hence improving the efficiency in terms of MAE and performance parameters for age group classification. The proposed approach was evaluated on FG-NET facial aging dataset.

Keywords: Age estimation, Facial aging, LBP, Ensemble, Random forest.

1.Introduction

In the age of information processing the systems have reduced the complexity of Human – Machine interaction. Nowadays we have systems that generate age information using various aspects of human being, among those facial age classification still have its relevance in research. As security is a major concern in today's world, more accurate and reliable solutions are must in age estimation. Aging is visible from the age of twenty five onwards, a fine line that gradually gets converted into wrinkles over time, that happens due to a reduction in density and volume that makes it noticeable. The facial anatomy for aging can be described in terms of epidermis, dermis and subcutaneous layer that affects its structural form that consists of multiple layers of fat and muscle. Aging happens as skin changes its texture with reduction in collagen for various types of skin. We have considered features that have its relevance in skin aging; the extracted features are then trained to build a robust model that increases the accuracy of the system.

Every individual has their own aging pattern that makes the system difficult to get trained, the factors that determine one's aging pattern may be his/her living standard, fitness, sociality and working culture. Thus, wrinkles analyses at different facial locations contribute to a more robust model for age classification. Age estimation through facial images still has its relevance in computer vision and pattern recognition [1][2][3]. Major changes that happen in the human face in terms of aging is while transforming from youth to adulthood. The facial shape change has its importance in early childhood till he attains the age of twenty; thereafter it rarely has much significant changes in shape. Males and Females have different aging patterns, in females it may be external factors such as use of cosmetics and surgery.

Technological advancements have increased the need for age determination in cyber usage, as internet users and human machine interaction is increasing day by day, children's are most susceptible to its negative aspect. Thus a system to validate and give access to those applications that are to be use by children's will surely reduce its negative implications. The paper is divided into the following

*Email: sreejit.bhilai@gmail.com

sections: Section 2 we talk over research influence in the field of feature extraction and age classification. Section 3 is about the methodology used for wrinkle analysis using LBP and Ensemble techniques. Section 4 highlights the outcomes by applying the ensemble method and analysis of the results by applying different methods. Section 5 describes the summarization ofthe work done.

2. Related Work

Pontes., et, al, in 2016. Proposed an integrated framework using Active Appearance Model (AAM), Local Binary Patterns(LBP), Gabor Wavelets(GW) and Local Phase Optimization (LPQ) for achieving those features that discriminate efficiently in the shape, appearance, wrinkles, and skin spots. Furthermore, it proposes a new flexible approach to hierarchical age estimation using multiclass support vector machine (SVM) that can classify a person into age group followed by support vector regression (SVR) for evaluating specific age [4].

Dib., et, al, in 2011. Bio- Inspired Features (BIF) was used to examine different facial parts such as eye wrinkles, core face (without forehead area) and core face(with forehead area) having different outline points. The analysis shows that eye wrinkles covering 30% of the facial region covers the prominent aging characteristics compared to the entire face region [5].

Jana., et, al, in 2014 Proposed a system for estimating the real age of human's by examining the wrinkle area in facial image. Facial geographical parameters are detected and wrinkle characteristics are extracted, depending on the wrinkle characteristics each face is clustered using fluid c- means clustering algorithm. Age is estimated using the clustering value of each cluster and the average age in each cluster[6].

Yen., et, al, in 2002. Proposed a methodology that takes into consideration the edge density in a image distribution. In the pre-processing task an ellipse is calculated and apply genetic algorithm to find the best ellipse region. In the feature mining, the genetic algorithm is used to determine the facial characteristics, including eyes, nose and mouth, that were previously defined in sub regions [7].

Iqbal., et, al, in 2017. Directional Age Primitive Pattern (DAPP), a local face descriptor was proposed , that inherits divergent cue info and is functionally more strong and biased than existing local descriptors. DAPP was used for separate age group recognition and age approximation tasks [8].

Hu., et, al, in 2017. A new learning system was proposed that uses the inadequately labelled data through deep convolutional neural networks. Kullback–Leibler divergence is used to insert the age difference information for each pair of images. The entropy and cross-entropy losses are modified to each image to generate a single highest value for the distribution. The losses are combined to design a neural network for understanding the age through age difference information [9].

Liu., et, al, in 2015. Proposed a process for estimating human age through facial image called as Grouping Estimation Fusion(GEF) using a multistage learning system. There are three stages in GEF namely, age grouping, age estimation in age groups and decision fusion to find the facial age. In the first stage, facial images are classified in different age groups, further three methods are implemented to extract global characteristics from the face and local characteristics from facial components (e.g. eyes, nose and mouth). In the third stage individual global and local features are used for estimating the age of each group. As a result we have several decisions (e.g. estimated results) that are fused to find out the final age of the facial image [10].

Chang., et, al, in 2015. The proposed method uses relative order information for rank prediction amid age labels. In this approach, the age range is achieved by accumulating a series of binary classification outcomes, in which cost sensitivities are introduced within labels to improve aggregate performance efficient descriptor, a dispersing transform that disperses the Gabor coefficients and combines Gaussian smoothing in multiple layers, is assessed for the extraction of facial features. It shows the descriptor generalization of bio-inspired characteristics[11].

Jana., et, al, in 2013. proposed a system for calculating the age of humans by exploring the facial image area of the wrinkle. Wrinkle features are noticed and features from facial images are extracted. The facial image is clustered with a fuzzy c-means clustering algorithm, depending on the features of the wrinkle [12].

Andreas Lanitis., et, al, in 2004. proposed a face-like model using statistical approaches. It was also used as the basis to generate a set of parametric face images. Based on the model classifiers, the form of illustration given for the image was accepted and an estimate of the age for the face image was calculated. In the given training set, classifiers for each age group were used to assess age on the basis

of different image clusters. Therefore, the most appropriate classifier was selected as given requisite in terms of age range, in order to calculate the exact age estimate [13].

Ramesha., et, al, **in 2010** projected an algorithm for age classification with mined features using small training sets, giving better results even if one image per person is accessible. This is a three-stage process involving pre-processing, extraction and classification of features. The facial characteristics are acknowledged by the canny edge operator to detect facial parts for the extraction of features and are classified using the Artificial Neural Network [14].

3 Methodology

Facial images are subjected to wrinkle analysis using extracted features of facial regions that are predominant for age classification. The LBP operator is applied to extracted facial regions and computed values are stored as training dataset for learning. Age classification by facial wrinkle analysis using ensemble techniques that improve the accuracy of the proposed system, due to its technique of combining more than one base model that generates the best predictive model and in this way increases the accuracy. Applying the pre-processing and performing classification using different classifiers individually gives less accuracy as compared to performing ensemble.

A.Random Forest

The random forest classifier is a Meta learner classifier that consists of more than one individual learner. The learners (trees) combined to form random forest that votes on a certain outcome. Each vote in random forest algorithm is given equal weight. The classification is done based on the maximum votes generated.

B. Bagging

In ensemble technique we apply bootstrap aggregation generally known by Bagging, in which we create models. The generated models use the same algorithm with random sub samples of the dataset generated from the initial dataset with sampling method. In this type of sampling some original feature values are present more than once and some may not be present in the sample. It depends on the dataset samples required that is followed n times. In the next step we aggregate the generated models by voting and averaging techniques used for the same.

3.1 Local feature Extraction

The input facial image is subjected to cropping after normalization in the predefined area of interest. The identified areas are those where wrinkle are prominent and visible during the aging phenomenon. The areas are a) Forehead b) Corner Right end of eye c) Corner Left end of eye d) Lower chin. Once the areas are cropped, the cropped images are pre-processed for uniformity in size. Further, the images are given for feature extraction using Local Binary Pattern. The local binary pattern operator is an operator which describes the pixel environment by generating a bit code from a pixel's binary derivatives. The operator is normally used for gray images and intensity derivatives. The LBP operator [15] works with eight neighbors of a pixel, the center pixel value is taken as threshold. The neighbor pixels are compared with the value of this center pixel , if it has a higher gray value or same value then one is assigned to that pixel, otherwise zero.

The value of the LBP code of a pixel (x_c, y_c) is produced by applying a binomial weight 2^p to each S (g_P - g_c). These binomial weights are summed to get:

$$LBP_{P,R}(x_c, y_c) = \sum_{P=0}^{P-1} S(g_P - g_C) 2^P \tag{1}$$

Where P is the sampling points on a circle of radius R and g_c is the grey value of the center pixel and g_0 to g_{P-1} corresponds to the P number of neighbours.

S(x) =   1, if x ≥ 0;
         0, Otherwise

The LBP features for the individual cropped images comprise of 59 feature vector values that are combined together with other feature values, these values are then normalized, standardized and then resampled to perform the ensemble techniques to improve the accuracy of the proposed model for age classification. Normalization is done to numeric values by scaling and translation parameters in the given dataset and standardization is done to numeric attributes to have zero mean and unit variance.The feature set is combined, and the new dataset is trained to generate an appropriate model

for our approach. (Figure-1,2) shows the facial model in our approach uses four areas identified for feature extraction, used further for analysis using different classifiers.
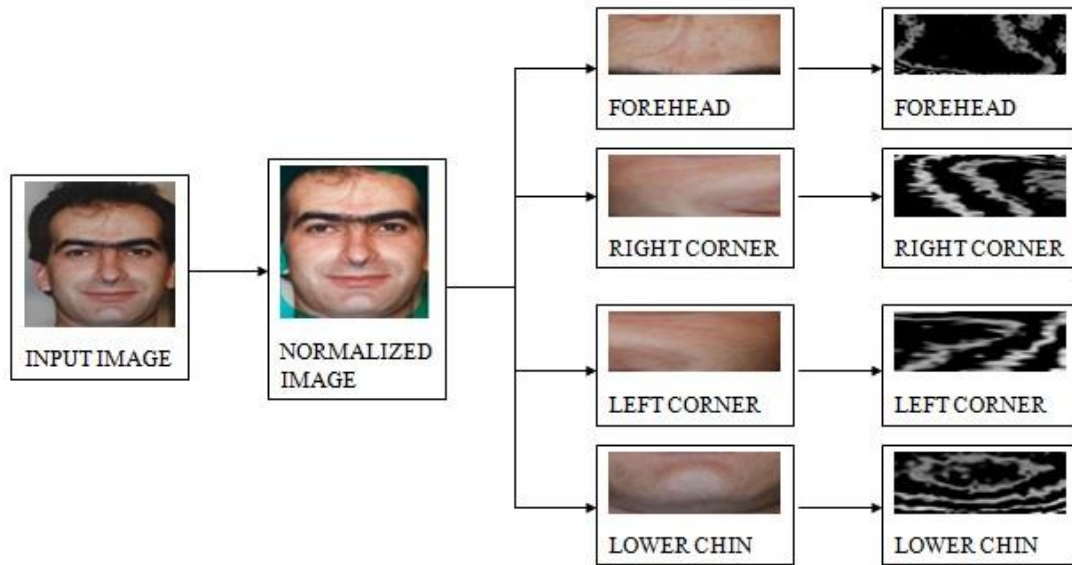

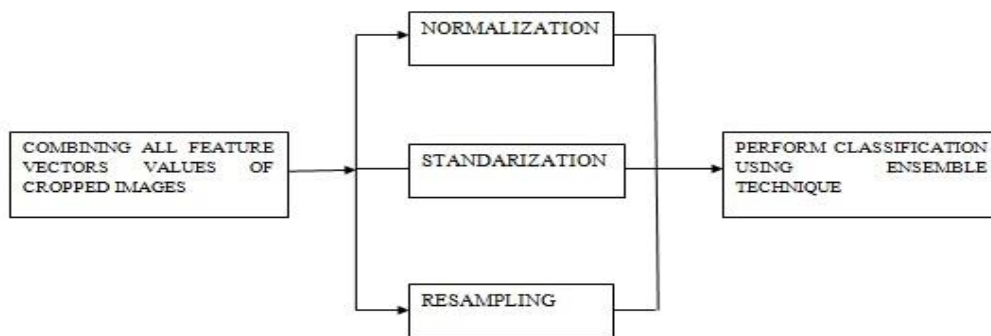**Figure 1**- Methodology applied for feature extraction

Figure 2- Application of ensemble technique to the feature set values.

3.2 Ensemble Technique

It's a machine learning technique that combines several base models in order to produce one optimal predictive model. Ensemble methods give better predictive performance because it uses multiple learning algorithms, compared to performance of any constituent learning algorithms alone. Ensemble learning algorithms requires more computation than evaluating the prediction of a single model.

Ensemble methods that we have applied are Bagging, Random Forest, Stacking. The details of extracted features that are cropped from the given facial image is given in Table-1.

Table 1- Details regarding facial features in the Model

Feature Id	Feature parameter
F1	Forehead
F2	Right corner of eye
F3	Left corner of eye
F4	Lower portion of chin

These facial features are used to compute the Local Binary pattern for the cropped regions of the images from FG-NET facial aging database. The computed values are then labelled accordingly as we use FG-NET aging database for age classification in different age groups learning purpose.

3.3 Facial aging Dataset

The Network for Face and Gesture Recognition (FG-NET) is a database of face images of people of different ages. FG-NET is widely preferred for age-related research, as it contains 1,002 color or gray-scale high-resolution images for different tasks. The age of people in the database varies between 0 and 69 years in chronological order. It consists of 82 multiple race pictures with different lights, poses and expressions. The main effort to develop such a database was to help researchers performing various facial imaging operations to investigate the effects of aging. The database is freely available for research purposes.

4. Experimental Outcomes

4.1 Training with FGNET dataset

In training images of different persons with varying ages, in all age groups are measured. Four groups are categorized as Child(C), Young (Y), Middle Aged (M) and Older (O). The extracted features are provided to Weka tool for machine learning. The pre-processed training dataset is trained using multiple classifier. The result of ensemble technique on dataset is shown in Table-2. Further the saved model is used to perform classification using the same classifier for the test dataset.

Table 2- Result for Ensemble Techniques applied on feature dataset.

Classifier/Performance Parameter	Percent correct	MAE	IR Precision	IR Recall	F-Measure	True Positive rate	False Positive rate
Random Forest	89.85	0.07	0.93	0.99	0.95	0.99	0.40
Random Tree	87.50	0.05	0.92	0.91	0.92	0.91	0.50
Bagging (Random Forest) Iterations 10	90.35	0.10	0.95	1.0	0.96	1.0	0.30
Bagging(Random Forest)Iterations 50	90.60	0.10	0.95	1.0	0.97	1.0	0.30
SMO	89.10	0.25	0.95	1.0	0.96	1.0	0.30
Lazy(IBk)	90.60	0.06	0.90	1.0	0.94	1.0	0.06
Lazy(KStar)	88.25	0.05	0.94	0.93	0.96	0.93	0.03
Lazy(LWL)	89.10	0.05	0.94	1.0	0.96	1.0	0.04
Bagging(REPTree)	82.60	0.12	0.90	0.96	0.91	0.96	0.07
Stacking(Logistics)	84.65	0.06	0.88	0.85	0.87	0.85	0.07
Tree (J48)	81.70	0.08	0.91	0.92	0.91	0.92	0.06
Rules(Decision Table)	77.35	0.22	0.88	0.84	0.88	0.84	0.09

The graph plotted describes the test dataset, that successfully classified for the four age groups. Figure-3 shows the corresponding graph for the performance parameter per cent correct against the various ensemble classifiers.
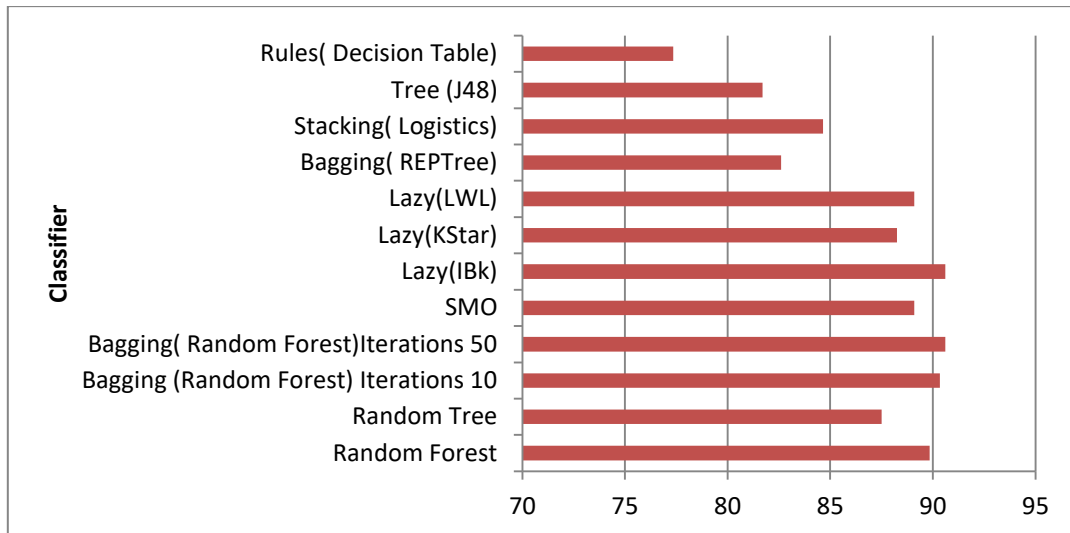
Figure 3- Performnce graph showing Classifiers verses Correctly classified (in percent).

Figure-4 shows the performance of various classifiers using ensemble technique is shown in the graph with performance parameters namely Precision, Recall and F-Measure classification and prediction.
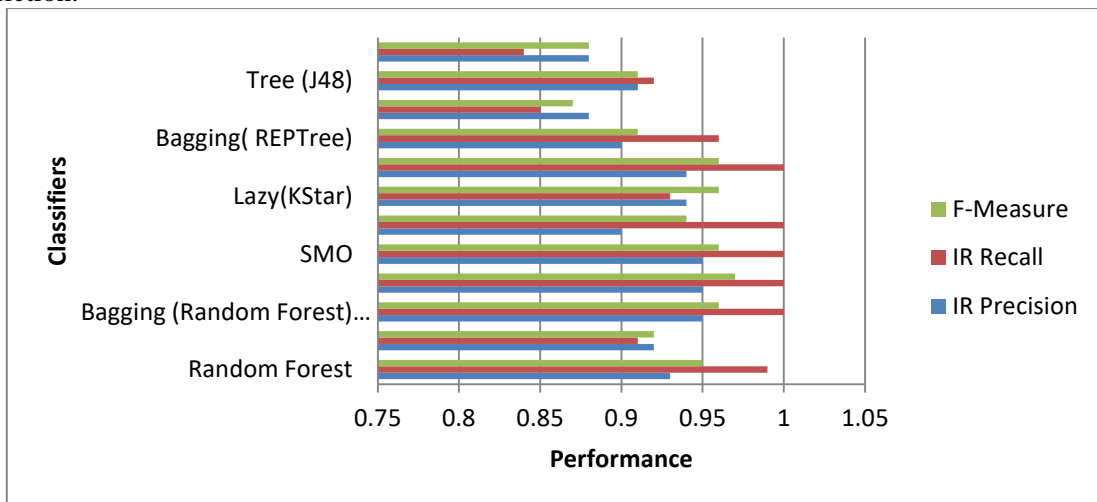

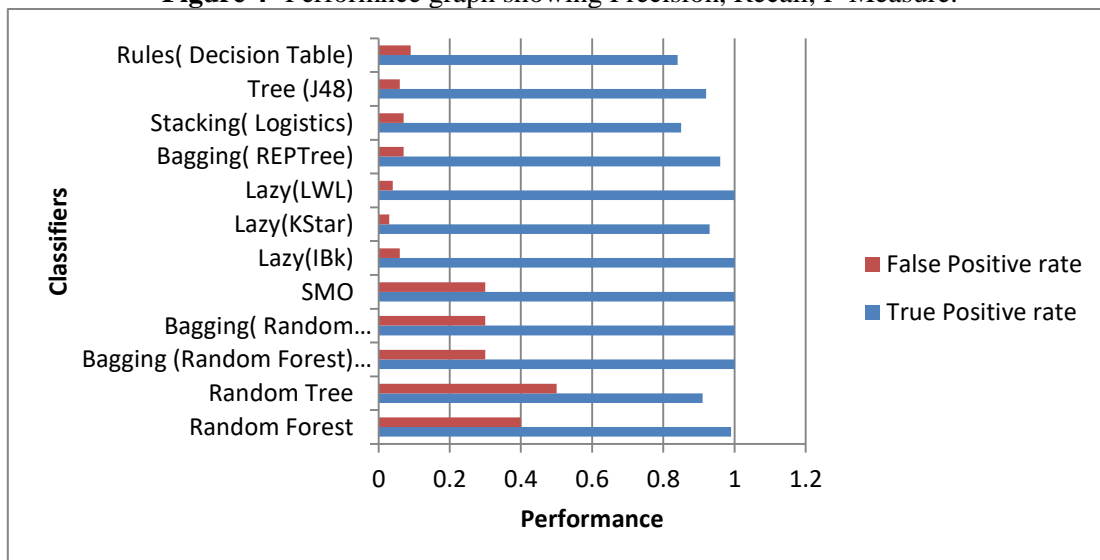**Figure 4-** Performnce graph showing Precision, Recall, F-Measure.

Figure 5- Performance parameters showing True Positive and False Positive rate.

5. Conclusion

The proposed approach using ensemble technique for improving the accuracy of the model is applied to the feature set comprising facial texture. The four prominent areas where wrinkles are noticeable in early aging are considered. The features are extracted using the Local Binary Pattern, the extracted features are then applied to classification in different age groups. Among the various models applied the result shows Bagging (Random Forest) exhibits the best in all performance criteria as compared with accuracy of 89.13% for J48 classifier [16] to our approach that gives an accuracy of 95 % by applying ensemble technique using bagging for Random forest classifier. The prediction accuracy in terms of true positive rate is better as compared to other researchers.

6. References

1. .Hua, Gu., Guangda, Su.and Cheng, Du. **2003**. Feature Points Extraction from Faces. *Image and Vision Computing*, Palmerston North, pp: 154-158.
2. Hewahi, N., Olwan, A., Tubeel, N., Asar, S. E. and Sultan, Z. A. **2010** .Age Estimation based on Neural Networks using Face Features. *Journal of Emerging Trends in Computing and Information Sciences*. **1**(2): 61-67.
3. Panicker, S., Smita Selot and Manisha Sharma. **2014**. Human Age Estimation Through Face Synthesis: A Survey. *i-manager's Journal on Pattern Recognition*, **1**(2): 1-6.
4. Pontes, Britto, Fookes, and koerich. **2016**. A flexible hierarchical approach for facial age estimation based on multiple features, Pattern Recognition, Elsevier 54, pp: 34-51.
5. Mohamed, Y. El Dib. and Hoda M. Onsi. **2011**. Human age estimation framework using different facial parts. *Egyptian Informatics Journal,* Elsevier, **12**: 53-59.
6. Jana, D. and Rituparna, S. **2014**. Age Estimation from Face Image using Wrinkle Features (ICICT), *Elsevier Procedia Computer Science*, **46**: 1754 – 1761.
7. Yen. G. G. and Nithianandan. N. **2002**. Facial Feature Extraction using Genetic Algorithm. Congress on evolutionary computation, Honolulu, pp: 1895-1900.
8. Iqbal, Shoyaib, Ryu, Wadud and Chae. **2017**. Directional Age-Primitive Pattern (DAPP) for Human Age Group Recognition and Age Estimation. *IEEE Transactions On Information Forensics And Security,* **12**(11): 2505 – 2517.
9. Hu. Z., Wen. Y., Wang. J., Hong. R. and Yan. S. **2017**. Facial Age Estimation With Age Difference. *IEEE Transactions On Image Processing,* **26** (7): 3087 -3097.
10. Liu. K., Yan. S. and Kuo, C. **2015**. Age Estimation via Grouping and Decision Fusion. *IEEE Transactions On Information Forensics And Security.* **10**(11): 2408 – 2423.
11. Chang. K. and Chen. C. **2015**. A Learning Framework for Age Rank Estimation Based on Face Images With Scattering Transform. *IEEE Transactions On Image Processing,* **24**(3): 785.
12. Jana, D. and S. **2013**. Age Group Estimation using Face Features. *International Journal of Engineering and Innovative Technology (IJEIT),* **3**(2): 130-134.
13. Lanitis. A.*,* Draganova. C. and Christodoulou. C. **2004**.Comparing Different Classifiers for Automatic Age Estimation, *IEEE Transactions on Systems, Man, And Cybernetics—Part B: Cybernetics*, **34**(1): 621-628.
14. Ramesha. K., Raja.K.B., Venugopal. K. R. and Patnaik L.M. **2010**. Feature Extraction based Face Recognition, Gender and Age Classification. *International Journal on Computer Science and Engineering,* **02**(01): 14-23.
15. Ojala. T., Pietik¨ainen. M. and Harwood. D. **1996**. "A comparative study of texture measures with classification based on feature distributions" *Pattern Recognition*, **29**: 51-59.
16. Abbas. A.R. and Kareem, A.R. **2018**. Intelligent Age Estimation From Facial Images Using Machine Learning Techniques. *Iraqi Journal of Science*, **59**(2A): 724-732.