Wrinkles Based Age Detection Using Adaptive Neuro Fuzzy Inference System

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Abstract *In the face-based analysis, wrinkles play a crucial role. They've been used in a variety of applications, including facial editing, facial expression detection, and estimating face age. Even though there has been some research carried out on the techniques for wrinkle analysis lately, inefficient detection lowers the accuracy and the worth of age estimation. Hence, an automatic wrinkle detection and age estimation method is important to keep up the consistency and decrease human errors. In this article, a scheme for the estimation of a person's age by analyzing the wrinkles found on face images is presented. As per this work, the wrinkle spots are identified from face image and the features values of Wrinkles are learned. On the basis of those features, the adaptive neural fuzzy reasoning method is used to determine the age. Experiment results demonstrate the effectiveness of the suggested model in terms of accuracy and SSIM measures.*

Keywords: Wrinkles, face-based analysis, Age Estimation and Adaptive Neuro Fuzzy Inference System.

1. Introduction

The biometric features of the human beings hold uniqueness. Detection and verification is emerging to be the field of study focus. Face recognition is one efficient technique for identifying any person using facial features [1]. Fingerprint, face, voice, iris, retina is extensively utilized such as that purpose of authenticating. Research work has been in vogue in these fields for quite some time. In past times, face recognition was considered for identifying the documents like land registration, in a high-security zone, a person's passport and documentation are required. [2,3].

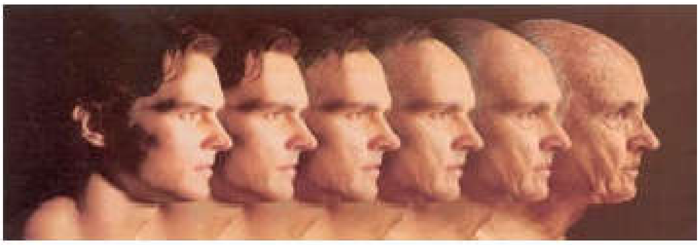

Fig.1.Age Progression of a Human

However, as a person ages, there is a change in facial features as illustrated in Fig. 1 and The database must be refreshed on a regular basis, which is quite cumbersome [4,5]. Therefore, it is critical to address the issue of face appearance and to seek out a solution, which helps in person identification despite the variations in facial image [6,7]. Age progression is typically specified in terms of the skin texture, structure of the face, skin colour. The facial features vary with the passing of age of a human being. In this article, a technique for the estimation of It is suggested to determine a person's true age by analysing wrinkled areas on face photos. This process includes wrinkle spots identification from face image and the features values of Wrinkles are learned. On the basis of those features, age is found with the help of adaptive neuro fuzzy inference system.

2. Literature Review

Ingole and Karande [2018] [8]Viola Jones Algorithm and Euclidean distance, as well as Support vector machine [SVM] for information collection and categorization applications, were used to establish a successful age estimate method. For age determination, a database of 90 photos (15 images per group) is used. The suggested method divides the input facial image into six age groups that are spaced apart by ten years. The reliability of this project's prediction is determined to be 98.89 percent. The proposed work is just about the steps performed sequentially in the age estimation system.

Grouping estimation fusion (GEF), a novel multiple step training approach for determining human age from facial photographs, was proposed by Liu et al [2015][9]. Age grouping, age estimation within age groups, and decision combining for final age estimation make up the three stages of the GEF. In the first stage, the faces are split into various age groups, each with a distinct age range. In the second phase, three methods are used to extract global features from the entire face and local features from individual facial characteristics (e.g., eyes, nose, and mouth). Each global or localized characteristic is used to determine the age of each cluster separately. In this way, numerous decisions (i.e., estimation outcomes) are produced. In the third phase, the numerous decisions made in the second phase are combined to provide the final estimated age. In the first stage, various age grouping systems are investigated for generating distinctive choices for the combination, with each system containing a variety of categories and flexible age ranges. Multiple decisions can be made as a consequence in the second stage, and they will be combined in the third step. Six different fusion methods are created and compared in total (intra-system fusion, inter-system fusion, intra-inter fusion, inter-intra fusion, maximum-diversity fusion, and composite fusion). Using the Face and Gesture Recognition Research Network and the MORPH-II databases, the GEF system's performance is assessed, and it significantly outperforms earlier state-of-the-art age estimating methods. Accordingly, the mean absolute age estimation errors on FG-NET have lowered from 4.48 to 2.81 years, and on MORPH-II, they have gone from 3.82 to 2.97 years.

Torrisi et al [2015] [10] suggested a technique for choosing the most unique CLBP patterns for describing the faces during age classification. The studies demonstrate that the suggested strategy improves age classification accuracy while reducing computational time and space requirements.

A system for determining age based on the shape and textural intensity of grey levels in facial images was presented by Ouloul et al [2016] [11]. The most important result of this study is the invention of a new description, Local Matched Filter Binary Pattern, which facilitates the identification and encoding of wrinkled facial regions. This descriptor, when combined with variables derived from the active appearance model, makes it easier to create a really unique age. Investigations using the FG-net database, as well as comparative results, show that this descriptor is useful in estimating age.

3. Proposed Methodology

The recommended solution is presented in this section Wrinkles on face based age estimation model is discussed extensively. Thismodel learns the features of the input face wrinkles and age is found on the basis of those features applying adaptive neuro fuzzy inference system. The proposed model's general structure is depicted in Figure 1.

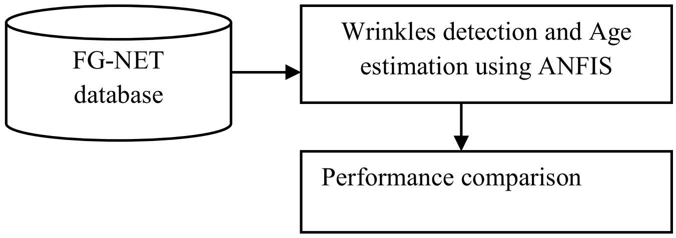

Figure.2. Overall architecture of the proposed model

3.1. Wrinkles detection and Age estimation using Adaptive Neuro Fuzzy Inference System (ANFIS)

ANFIS will be provided with the face images as the input. The ANFIS network is a kind of neural network and it works just like the neuro fuzzy network. Figure.3 illustrates the ANFIS structure for implementing these two rules.

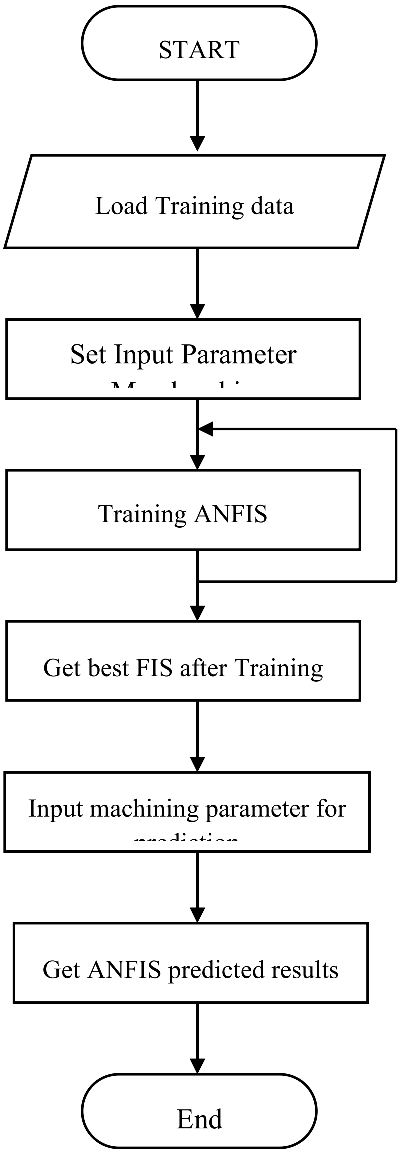

Figure: 3. Flowchart for ANFIS

All of the nodes in the first layer are adaptable elements. The fuzzy association class of the data is formed by the outputs from layer 1, which are stated as:

$$O_i^1 = \mu_{A_i}(x)\ for\ i = 1,2 \quad (1)$$

Where *x* and *y* represent the input nodes, *A* and *B* indicate the linguistic labels, (*x*) and (*y*) signify the membership functions which often take up a bell shape using the maximum and minimum values equivalent to 1 and 0, respectively [12].

$$\mu(x) = \frac{1}{1+\left(\frac{x-c_i}{a_i}\right)^{2b_i}} \quad (2)$$

Where , a_i, b_i, and $c_i$refer to the premise parameters set.

Depending on the membership rank, the face's wrinkles are identified The second layer's nodes are fixed nodes. They are identified as a basic multiplier by the letter M on its label. The results of this layer can be summed up as follows:

$$O_i^2 = w_i = \mu_{A_i}(x)\mu_{B_i}(y),\ i = 1,2 \quad (3)$$

The output $w_i$represents the firing strength of a rule. The results attained from each node specifies the rule's firing strength.

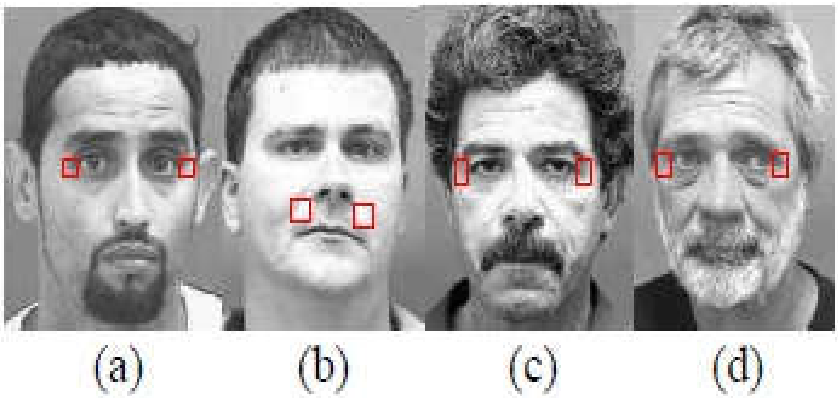

Figure: 4. Various poses of diverse people. (a), (c) and (d)illustrate that wrinkle's look will be unique owing to higher pose angle. (b) indicates that appearance of wrinkle isdissimilar due to expression.

The third layer also contains fixed nodes, and this step learns the features of wrinkles. They bear the label "N," denoting normalisation of the firing intensity from the preceding layer. The outputs of this layer can be shown as follows:

$$O_i^3 = w_i = \frac{w_1}{w_1+w_2},\ i = 1,2 \quad (4)$$

These outcomes are referred to as the normalised firing strengths.

Nodes, that are adaptable nodes, are found in the fourth layer [13]. The output of each node in this layer is the product of the standard fire intensity and a first order polynomial (for a first order Sugeno model). Consequently, the outputs of this layer are represented by

$$O_i^4 = w_i f_i = w_i(p_i x + q_i y + r_i) \quad (5)$$

Where w indicates the output of layer 3, and $\{p_i, q_i, r_i\}$ represents the parameter set. These parameters are called as the resultant parameters

There is only one fixed node that is designated with a S in the fifth tier. This node adds up all of the input signals. At this step, theage of a specific human face image is found [14].

Thus, the model's entire output is represented as:

$$O_i^5 = \sum_{i=1} w_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{6}$$

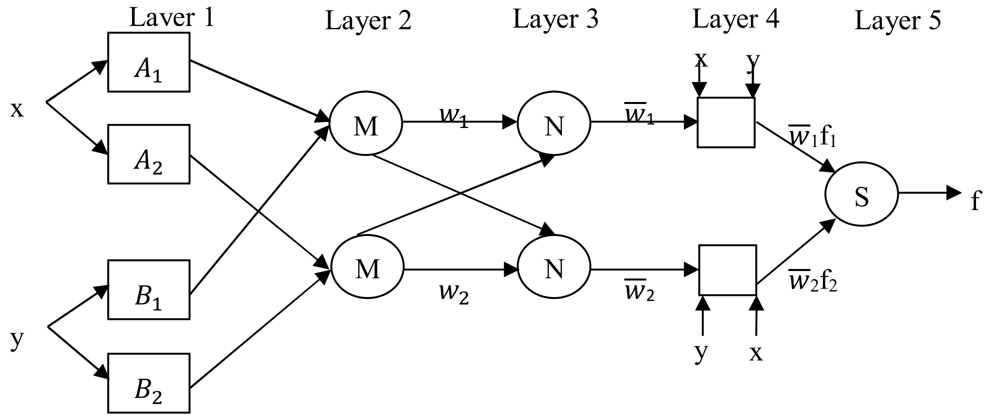

Figure.5. ANFIS architecture

4. Results and Discussion

This chapter describes the suggested model's actual outcomes. MATLAB 2013 is used to implement the given model. The FG-NET ageing dataset can be found at https://yanweifu.github.io/FG NET data, the suggested ANFIS model is compared to the current SVM method in aspects of correctness and SSIM. The FG-NET ageing dataset contains 1002 photos of 82 individuals (6-18 images per person) whose age range between 0 and 69 years (FG-NET ageing dataset, taken on September 2012). A total of 68 landmark traits were manually recognized on all of the facial photos in the sample. In addition, all of the photographs in the collection have the following meta-data: Size, age, gender, spectacles, headgear, moustache, beard, horizontal attitude, and vertical position are all factors to consider. The facial images have all the probable versions, which include lighting, position, emotion, beards, moustaches, spectacles, etc., since they were collected from real-life albums on different themes.

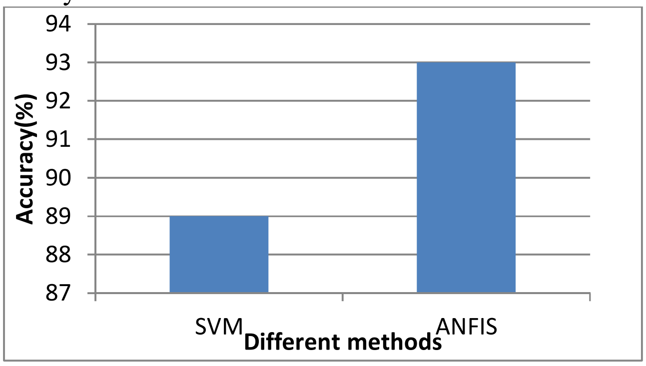

Figure: 6. Accuracy results of different methods

The above chart shows a comparative evaluation of Efficiency measures with the current classification SVM and the new ANFIS system. ANFIS uses a participation functional for feature learning in the suggested work, which improves the reliability of the ANFIS. Various approaches are depicted on the X-axis, and reliability levels are shown on the Y-axis in the graph above. As can be seen from the findings, the newly proposed ANFIS model yielded greater reliability outcomes of 93 percent, whereas the existing SVM method yielded just 89 percent.

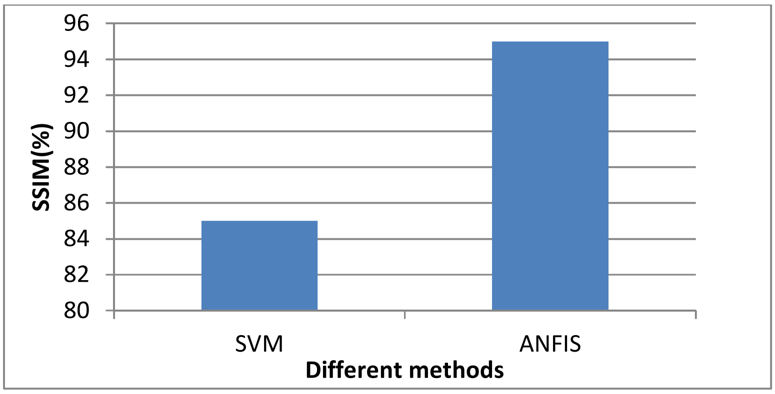

Figure: 7. SSIM results of different methods

The performance comparison between the suggested ANFIS technique and the modern classifier SVM using SSIM measures is shown in the above picture. Various methods are plotted along the X-axis of the graph above, while SSIM values are plotted along the Y-axis. It can be inferred from the results that the proposed ANFIS model yields improved SSIM values of 96%whereas the SVM approach attains just85% correspondingly.

5. Conclusion and Future Work

This research recommends a revolutionary method for estimating a person's age. The proposed technique introduces are liable methodology which helps in the estimation of the age of an individual using a collection of facial images in multiple age groups. In compared to the other characteristics, the wrinkle area feature produces the best results for determining a person's age. Therefore, wrinkle area analysis is a very effective process for the estimation of the real age of an individual. In this research work, the wrinkle spots are identified from facial image and the features values of Wrinkles are learned. Age is found applying adaptive neuro fuzzy inference system. The results achieved are substantial and excellent. It is confirmed from the results of the experiments that the proposed model yields increased accuracy of 93% and it is more than other techniques. Spectacled faces impose hurdles in proper identification of the eye and eyeball. Anterior aspect images are required and every part of the face must have even brightness. Images must have one human face only and there should not be any hair along the forehead. Therefore, this work requires further research, where additional facial feature will be considered for improving the assessment of age precision. This study could be useful helpful in the estimation of future faces.

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