Facial Features Extraction for Age Estimation Based on a Neural Network

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Abstract: The determination of a person’s age using computer-based programming relies on biometric features such as facial features and fingerprints. These technologies, which require the intense study of age progression mechanisms in the human face and the factors that influence face aging patterns, have increasingly attracted attention due to their various real-world applications. In this paper, a feature selection method (FSM) has been adopted to identify the most suitable local binary pattern (LBP) features for age estimation. The selected features were then classified using a back-propagation neural network (BPNN). Extracted features were classified using a MATLAB-based artificial neural network (ANN), in which a back-propagation network (BPN) was used. The proposed BPN network contains four layers of neurons: an input layer, two hidden layers, and an output layer. Each layer contains nine neurons in addition to the bias. Experiments in this work were conducted using three types of image datasets: standard FG-NET, privately-collected, and real-time captured image dataset. Experimental results demonstrate the significant role of using a back-propagation neural network (BPNN) with FSM, which produced an estimation accuracy of up to 93.22% after two rounds, while without FMS, estimation accuracy reached 82.966% at most, depending on the original LBP features. However, the accuracy using the images captured by the connected camera reached no more than 71%.

Keywords: Local binary pattern, feature selection method, age estimation, back-propagation neural network.

1. Introduction
Age estimation was recently considered as a widely required application in classification issues regarding facial images, which is defined as the determination of a person’s age from an image by analyzing his or her biometric features. Guessing the estimated age of an individual via studying or looking at his face image is a challenging role in common. It is a challenging task even using the vision system of human eyes [1]. Age evaluation is not a new concept, but the new digital technologies surrounding the practice have attracted increasing amounts of attention due to their many real-world applications. For example, teenagers could one day be prevented from buying alcohol or cigarettes from automatic machines with this technology, and minors could be blocked from webpages meant for adults using age estimation systems [2, 3].

The aging process is not universal and different individuals may age in different ways [4]. Different internal and external factors determine the aging patterns of a specific person. Such factors may contain genetic factors, health conditions, living style, in addition to different conditions of weather [5]. To achieve successful results in applications like age estimation or age classification, this study uses the standard FG-NET dataset to train algorithms that consider all of these factors. In addition, a dataset privately collected by the author and real-time captured images using a connected camera was also considered in this work. For feature extraction, a local binary pattern (LBP) was selected to identify signs of facial aging, and a back-propagation neural network (BPNN) was chosen to classify extracted features for age estimation. This work adopted a feature selection method (FSM) to select the best possible set of features among all produced LBP values.
2. Related Work

Over the past two decades, several works have been produced on age estimation. Many researchers have used local binary patterns (LBP) to extract features. ANN has garnered attention from a considerable number of researchers because of its classification efficient [6], which has led to usage in many applications. Oladele et al. (2016) proposed using a developed classification scheme for age estimation, where the authors adopted a Back- Propagation Neural Network (BPNN) to assign each face image to one of eight different age groups. They adopted the standard Principal Component Analysis (PCA) for extracting age-progression features from face image to be used by BPNN as classification features. The developed system was tested with the FG-NET database. Their experimental results consumed 110.914 seconds for training time. They had an error rate (MAE) of about 3.88 years to yield an overall classification accuracy of 82.2% [7].

Noor et al. (2020) presented comparing between two standard classifiers for a comparative study about age estimation. The authors extracted LBP’s as candidate features to represent face texture. Their adopted dataset was the standard FG- NET face image set, where they depended on the length of features number to divide the dataset into three classes or age groups. Their proposed methodology consisted of three main phases: pre-processing, feature extraction (LBP), and age classification. Standard Logistic Model Tree (LMT) and Sequential Minimal Optimization (SMO) were adopted as classifiers to estimate the required age. LMT achieved better results than the SMO classifier for two out of three of the classes. They provided considerable precisions for LMT were about 96.4% and 78.6%, against achieved results by SMO classifier (93.4% and 31.05%) respectively [8].

In 2015, Kuan et al. [9] proposed a new algorithm using the standard multi-step learning technique for estimation fusion. The authors conducted extensive experiments on the two standard datasets FG-NET and MORPH-II. They achieved less MAE value, which was reduced from a previous (4.48) to be (2.81) using FG-NET and from (3.82) to (2.97) using MORPH-II datasets.

In another work [10], the authors compared three models of classification, where the used LBP features. They extracted their features form gradient histogram and they adopted a deep-learning network for classification training. Three standard classifiers were applied in their work such as ANN, SVM and decision trees, where such classifiers assign each set of features to the related age. A freely available dataset (KIMIA Path960) was used offering 960 different images. Dataset images were provided using 20 different scans of tissue to measure classification accuracy and to test followed models in feature extractions. Results accuracy achieved by SVM was up to 90.52% stating the highest accuracy using LBP features which, while classification accuracy achieved using deep-learning features was (81.14%).

In this work, the original LBP algorithm was adopted for feature production, and FSM was used to choose the best possible set of features. For classification, BPNN was used to assign each set of features to an approximate age group. A classification accuracy (CA) score was used to evaluate results.

3. Methodology

This work applied the standard FG-NET face dataset as a base to benchmark our progress relative to other age estimation research using the same dataset [11]. The proposed scheme for age estimation consists of four main stages: pre-processing, face extraction, extracting face feature, and the final classification stage. In the pre-processing stage, the goal is to enhance and process studied images into suitable forms to produce age progression features. Then, the features are extracted using standard LBP, where the most efficient set of features is selected using FSM. For age estimation, selected features are classified using BPNN to assign them to their appropriate ages as Figure 1.
The proposed system uses FG-NET containing 1002 of faces from 82 different persons describing an age range from 0 to 69 [12], which can be subdivided into 10-year age class ranges. Cross-validation techniques for dataset splitting are used in most age estimation research, and as a result, they are adopted in this study to split the dataset images into training and testing sets. 70% of dataset images were allocated to the training set and 30% comprise the designated testing set, as shown in Figure 2.

**Figure 1:** Block diagram of the proposed scheme for age estimation.

**Algorithm 1:** Practical steps of the proposed age estimation scheme
1: Load the image.
2: Convert image colours into gray scale.
3: Enhance image details using Histogram Equalization.
4: Extract face area from the image using Viola-Jones algorithm.
5: Resize all images to 512×512.
6: Compute LBP values for extracted image.
7: Measure feature changes intra-class and inter-class.
8: Select features with high inter-class changes and low intra-class changes using FSM algorithm.
9: Divide the dataset into 70% training and 30% testing.
10: Classify extracted features using training and testing of BPNN algorithm.
11: Record estimated age.
12: Evaluate the results using CA measure.

**Figure 2:** Dataset splitting into training and testing sets.
3.1 Pre-processing
The MATLAB function rgb2gray was used for grayscale conversion. Grayscale images are preferable to color images, as they result in two-dimensional matrices that reduce processing times [13]. Secondly, the grayscale images are enhanced using histogram equalization to optimize the contrast of the images [14], as shown in Figure 3 (a, b, & c).

3.2 Face extraction
In this phase, the facial area was extracted from the entire image. First, face image is detected using the standard Viola-Jones (V&J) algorithm to the gray images. V&J consists of four elements: Haar-like features, integral images, the AdaBoost learning method, and cascaded classifiers [15]. Then, the detected face areas were cropped to reduce the data size. After that, the cropped images were resized for consistency, as shown in Figure 3 (d & e).

![Figure 3: Pre-processing and face extraction results.](image)

3.3 Feature extraction
This stage describes the process of extracting the relevant data from a facial image, where such data must have significant representation for the related image in the classification process with an acceptable error rate. The feature extraction stage consists of two main steps: feature production and feature selection.

3.3.1 Feature production
An LBP algorithm was used to produce image features. This algorithm handles images by extracting 3×3 windows, where each window has 1 center pixel and 8 neighbors. Each neighbor pixel was converted to (1) if it was bigger than the central pixel; otherwise, the neighbor was converted to (0) [16]. Resulting binary bits were transformed into a byte by connecting these bits in a circular path starting from a specific corner, and the resulting byte was converted into a decimal assigned to the central pixel. After finding this point, a histogram was calculated and normalized. The normalized histogram represents the features obtained from this algorithm [17, 18], as shown in Figure 4.

![Figure 4: General process of computing LBP features.](image)
3.3.2 Feature selection
Some of the features extracted using the LBP algorithm were weak, resulting in diminished age estimation accuracy. Thus, in this work, FSM was used to reduce the number of weak features and select the best. A high-performing feature must yield high discrepancies between different ages (inter-class) and low discrepancies between different individuals of the same age (intra-class). This work adopts the statistical form of standard deviation (SD) to measure feature significance intra-class and inter-class. Thus, a ratio of these two SD measures was used to produce a single metric that represents feature performance. A high value indicates a high performance of the studied feature and vice versa. This metric can be computed using equation (1).

$$\text{performance} = \frac{SD_{\text{age}}}{SD_{\text{person}}}$$  

Table 1 contains three columns representing three ages. A fifth column ($\mu_i$) represents the computation of average feature values for each individual over age progression. Similarly, the seventh row ($\mu_j$) represents the computation of average feature values within the same age class. Accordingly, the sixth column (SD$_i$) and eighth row (SD$_j$) have been added to represent the dispersion of different ages and different individuals to demonstrate interclass feature differences.

To produce the final value of FSM, the ratio of inter-class changes (0.158) was divided by intra-class changes (0.183), yielding an FSM of 0.863.

| Data Samples | Age1 | Age2 | Age3 | $\mu_i$ | SD$_i$ | Interclass |
|--------------|------|------|------|---------|-------|------------|
| Person1      | 0.71 | 0.87 | 0.59 | 0.72    | 0.11  |            |
| Person2      | 0.28 | 0.63 | 0.51 | 0.47    | 0.15  |            |
| Person3      | 0.24 | 0.17 | 0.82 | 0.41    | 0.29  |            |
| Person4      | 0.33 | 0.79 | 0.64 | 0.59    | 0.19  | 0.158      |
| Person5      | 0.58 | 0.48 | 0.48 | 0.51    | 0.05  |            |
| $\mu_j$      | 0.43 | 0.59 | 0.61 |         |       |            |
| SD$_j$       | 0.18 | 0.25 | 0.12 |         |       |            |
| Intra-class  | 0.183|      |      |         | FSM= 0.863|            |

3.4 Classification
The classification stage provides the final product of the proposed age estimation system, in which, BPNN is adopted as a standard classifier. As mentioned previously, the standard FG-NET database for face images is adopted to provide training and testing images. Due to the requirements of BPNN, the FG-NET database was divided into training (70% of dataset images) and testing (30% of dataset images) sets. The adopted classifier trains and tests extracted LBP features to assign each image to the corresponding age group. In this work, the adopted BPNN contained four layers of neurons: an input layer (9 neurons + bias), two hidden layers (9 neurons + bias), and an output layer, as shown in Figure 5.
Figure 5: The structure of BPN with the number of layers and neurons.

The BPNN works as follows:
1. Extracted features are fed into the input layer using input neurons.
2. Neurons of the input layer are modeled with the weights \( w \), which are selected randomly.
3. The output of each layer neuron is calculated to be handled as inputs for next layer.
4. Errors in the outputs are calculated, as per equation (2).
   \[ \text{Error} = \text{Actual Output} - \text{Desired Output} \]  
5. Adjust weights by spreading back from the output layer to the input layer through hidden ones to minimize the error rate. Keep re-doing the whole process until reaching the desired output. The results of the developed system were evaluated using mean absolute error (MAE) as in equation (3), and classification accuracy (CA) as in equation (4)
   \[ \text{MAE} = \frac{\sum_{i=1}^{n}|EA_i - RA_i|}{n} \]  
   \[ \text{Accuracy} = \frac{\text{Number of correctly classified samples}}{\text{Total number of samples}} \]  
   Where \( EA_i \) is the estimated age for the \( i \)th of \( n \) tested samples, \( RA_i \) is the real age for the \( i \)th of \( n \) tested samples, and \( n \) is the number of samples.

4. **Age estimation using real-time captured images**
   A real-time approach is also included in this paper to estimate the required ages of people automatically by capturing facial images with a camera. The dataset used within this system was collected by the authors of this study. In order to test the system online, a camera was connected to acquire facial images. Captured images were then passed through all stages of the proposed age estimation scheme, as shown in Figure 6. Due to the absence of a training image set for the camera-captured images, the system was trained using the standard FG-NET database.
5. Results
This section analyzes and discusses the results achieved through the experiments conducted in this work. Due to the sizable amount of handled images contained in the FG-NET database, which enabled a greater number of images to be trained and tested, the proposed age estimation scheme achieved a higher CA value using FG-NET images than with the private collection and camera images. Experimental results demonstrate the significant role of the feature selection method through the significant differences in the CA values when applying the estimation scheme with and without the use of FSM. Table 2 illustrates achieved CA results according to FSM usage and the differences between FG-NET, private, and camera images.

Table 2: Effect of the dataset type on system accuracy.

| Dataset Type        | FG-NET with FSM | FG-NET without FSM | Private own dataset | Private image from camera |
|---------------------|------------------|---------------------|---------------------|---------------------------|
| 93.22%              | 82.966%          | 75.15%              | 71%                 |

Notably, the private dataset and camera images achieved significantly lower CA values than FG-NET images. These discrepancies can be attributed to the differences in the sizes of training image sets. Table 3 illustrates the effects of varying dataset sizes on CA values during different stages of the private dataset construction.

Table 3: The effects of different dataset sizes on CA value.

| Private dataset size | 100    | 200    | 300    | 400    |
|----------------------|--------|--------|--------|--------|
| CA Value             | 52.52% | 61.85% | 63.79% | 75.15% |

In addition to the size of training datasets, Figure 7 displays the effects of image quality on estimated ages using the private dataset.

Figure 6: Steps of real-time age estimation system.

Figure 7: The effects of image quality on estimated age using a real-time.
To benchmark this study using state-of-the-art age estimation techniques, Table 4 provides a comparison of accuracy achieved through this work’s proposed age estimation scheme and other recently-published works in the field of age estimation. As one can observe, the use of LBP to identify features combined with two rounds of FSM produces CA and MAE values that noticeably exceed those produced in other works.

Table 4: Proposed estimation scheme versus other methods of feature selection.

| Research               | Features                  | Features Selection       | Classifier                          | MAE  | CA (%) |
|------------------------|---------------------------|--------------------------|-------------------------------------|------|--------|
| Chao et al., 2013 [18] | Face Landmarks            | Active Appearance Model (AAM) | K-Nearest Neighbour (KNN) Support Vector Regression (SVR) | 4.38 | N/A    |
| Han et al, 2013 [19]   | Biologically Inspired Model (BIM) | N/A                      | Support Vector Machine (SVM)     | 4.7  | N/A    |
| Chen and Hsu, 2013 [20]| Gaussian Mixture Model (GMM) Hidden Markov Model (HMM) | AAM                      | SVR                               | 4.56 | N/A    |
| Han and Jain, 2014[21] | Face Landmarks            | N/A                      | SVM                               | N/A  | 87.15  |
| Kumar et al., 2014[22] | Face Landmarks And Wrinkles features | AAM                      | Non Overlapped Generalized Exemplar (NNge) | N/A  | 93.01  |
| Liu et al., 2014 [23]  | Face Landmarks            | Principal Component Analysis (PCA) | SVR                               | 5.28 | N/A    |
| Proposed Method        | LBP                       | FSM                      | BPNN                               | 4.51 | 93.81  |

Although many age estimation researchers accept a margin of error of ±2 years from real ages as correctly-classified ages [24], this metric does not indicate how near or far misclassified ages are from the correct age. In this work, age dispersion was measured to show the deviation of estimated ages from real. Figure 8 demonstrates that all estimated ages are distributed not far from the real ages. Exact age classification yielded an encouraging ratio, while recorded age estimations in this work were distributed in such a manner that 95.4% of age estimations were no more than ±4 years apart from the real ages.
6. Conclusions
A back-propagation neural network (BPNN) containing three types of layers—input, hidden, and output layers—was adopted in this work as a classifier. The input layer contained nine neurons, and the hidden layer contained two sub-layers with nine neurons each. This work adopted a feature selection method (FSM) to select the best possible set of features among all local binary pattern (LBP) produced features. The proposed estimation scheme achieved an increased classification accuracy (CA) value (93.22%). The use of FSM enhanced the achieved accuracy; without the use of FSM, a CA of only 82.96% was achieved. Three types of face datasets were used in this study: the FG-NET database containing 1,002 images, a private dataset containing 400 images, and real-time captured images using a connected camera. The private dataset achieved only 75.15% accuracy.

7. References
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