Comparative Study of Different Classifiers Based on Extracted Facial Features for Supervised Age Estimation

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Abstract: Estimating a person age is a major concern for many researchers due to his importance in many applications, whereas finding a person age is crucial in making specific decision. This paper conducts a comparative study between two classification-algorithms for age estimation which applied on extracted Local Binary Patterns (LBP). It was also divided dataset into 3 classes in order to improve results and increasing accuracy of system, Root Mean Squared Error, Mean Absolute Error and other parameters are used to measure the precision of the system. The proposed methodology of this work is divided into three phases. First phase consists pre-processing methods in which selected image is handled using color to gray scale image conversion and histogram equalization. Result image of which is manipulated by standard Viola-Jones algorithm to detect and crop face area from the whole image. While to ensure same size for all images, detected face image is resized to 256 × 256. Second phase tends to extract LBP features to be fed in the next classification phase. In third phase, two classifiers Logistic Model Tree (LMT) as well as Sequential Minimal Optimization (SMO) have been applied on the extracted features for age estimation.

Keywords: Viola Jones, Local binary patterns, machine learning, logistic model tree classifier, Age estimation.

1. Introduction
Age estimation is one of the main approaches of facial image classification due to several applications of age estimation [1]. One of the candidate applications is preventing teenagers from reaching age-restricted goods on automatic selling machines, accessing web pages with adult contents or entering some places that restricted to adults. It also provide an interface between Human and computers in online shopping when offered contents is adjusted based on costumer age. While in forensic applications, age estimation provides smart solution in estimating anonymous victim age [2]. It is also considered an age estimation from facial images is a challenging task if it compared with image classification and face recognition, because datasets of age estimation are limited whereas it is very hard to gather complete [3].

LBP features were used in several works of age estimation, in one of them, authors used histograms of Global and spatial LBP, each training image they assigned weights to each individual region image as an indication for the importance of contained information in them. Their experiments were trained and tested using Minimum Distance and K-Nearest Neighbors [4]. Their performance was restricted by the limitations of single-level LBP usage, and to overcome this limitation, the authors in [5] proposed adopting a multi-level LBP (MLBP) scheme for age estimation. Their experiments were classified using Support Vector
Regression (SVR), they paid less consideration for local features provided by the typical LBP. A new concept was adopted in [5] to combine between LBP and MLBP to pay more consideration to facial expressions that may affects facial features for age estimation. They also used SVR as feature classifier to increase results accuracy for age estimation.

In this paper, a proposed real-time age estimation scheme considers three steps, pre-processing, feature selection and classification. Standard Viola-Jones algorithm is adopted for detecting faces area from the images, in addition to color-to-gray conversion and histogram equalization to construct pre-processing stage. In features extraction stage, LBP algorithm is used to provide candidate features. While LMT and SMO classifiers are adopted estimate the age based on extracted features. Using C++ functions, face portion is detected from the input face image and extract features, and use java functions for classification.

2. Proposed Method

The proposed system adopted standard FG-NET face dataset for benchmarking with state of art in age estimation researches [6] [7]. Although it was firstly publish in 2004, it was released for public usage in 2006. FG-NET dataset is fully discussed in details in [8]. In first stage of this work, dataset images are firstly converted from RGB coloring system into gray in order to fit the requirements of extracted features which deal with such coloring system. Image quality is enhanced using histogram equalization algorithms. Then Region of Interest (ROI) that represents the face is detected using standard Viola-Jones algorithm [9], and then, face area is cropped from the image and resized to have one size for all studied images. Since pre-processing stage is not the main concern of this paper, standard published algorithms are used to accomplish required tasks [10]. Figure 1 represents the general steps for the proposed method execution:
2.1 Dataset

The data set used in this paper is divided into seven classes, each of them has its own age range as shown in table 1, the classification performance of each metric differs from one age group to another [11]. The estimation of age will referred to the output of each classification process done which will detect to which class this data belong.

Table 1: FG-NET dataset classes summarization.

| Class Number | Class Scope   |
|--------------|---------------|
| Class 1      | 3 to 7 years  |
| Class 2      | 8 to 13 years |
| Class 3      | 14 to 19 years|

Figure 1: Block diagram of proposed scheme for age estimation.
Features are extracted for each class and some classes are merged together since they have the same number of features, which leads to group the classes into three classes as shown in table 2.

### Table 2: FG-NET dataset classes summarization.

| Class Number | Class Scope         |
|--------------|---------------------|
| Class 1      | 3-7 and 26-30 years |
| Class 2      | 8-19 and 20-25 years|
| Class 3      | 31- 40 and 41-50 years|

#### 2.2 Feature Extraction using Local Binary Patterns (LBP)

Extracting LBP features from face image is applied to the extracted face image, from which, a mask of (3×3) size and its center pixel is concerning one. Each neighboring pixel of this mask is assigned to 0 if it is smaller than the center and assigned 1 if it is greater or equal to center pixel, and by tracing neighboring pixels in circular manner, resultant stream of bits are converted to a decimal number. The original center pixel is replaced by the output decimal number as shown in Figure 2 [12].

![Figure 2: Block diagram of replacing decimal number.](image)

#### 2.3 Classifications

Two methods are used for feature classification, whereas dataset images are divided into training and test subsets. Depending on classified features, each image is assigned to the expected age, and the results of the two classifiers are analyzed for comparison purpose.

##### 2.3.1 Logistic Model Tree (LMT) Classification

This algorithm is a supervised training algorithm that combines Logistic Regression (LR) and Decision Tree Learning, which has been used to train the system for classification stage that assign obtained features to the related age class. The classification of the features obtained from image used to predict the estimated age of human as shown in Figures 3. In which (a) is concerning with assigning each image to the related class, while (b) concerns with estimating the specific age.
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Figure 3: (a) Face image classification using LMT, (b) Face Image age Estimation and classification using LMT.

2.3.2 Sequential Minimal Optimization (SMO) Classification

This algorithm is a supervised training algorithm that used for settling the quadratic programming (QP) issue that emerges during the training of support-vector machines (SVM). Where the classification of the data that is used to train the system to compare the features obtained from the feature extraction phase to reveal the class of features to which it belongs. After that, the age stage is predicted according to the feature extracted. Figure 4 shows the classification of the features obtained using SMO.

Figure 4: (a) Face image classification, (b) Face image age estimation and classification using SMO.

3. Experimental Results

Evaluation of the used algorithm was done and calculated as which is shown in tables 3 and belong to the essential questions from (1) to (6).

True Positive rate = \( \frac{\text{diagonal element}}{\text{summation of relevant row}} \) \hspace{1cm} (1)

True negative rate = \( \frac{\text{non – diagonal element}}{\text{summation of relevant row}} \) \hspace{1cm} (2)

Precision = \( \frac{TP}{TP + FP} \) \hspace{1cm} (3)

Recall = \( \frac{TP}{TP + FN} \) \hspace{1cm} (4)

Error rate (Err) = \( \frac{FP + FN}{TP + FP + TN + FN} \) \hspace{1cm} (5)

Accuracy = (correctly classified / all images) \hspace{1cm} (6)
Where, TP: True Positive rate, TN: True Negative rate, FP: False Positive rate, FN: False Negative rate.

Table 3: Comparison between Classifications Algorithm Results Part.

| Algorithm | Class no. | True Positive Rate | True Negative Rate | Precision  | Recall    | Mean Absolute Error | Root Mean Squared Error |
|-----------|-----------|--------------------|-------------------|------------|-----------|--------------------|------------------------|
| LMT       | Class 1   | 96.279             | 99.358            | 96.473     | 96.279    | 1.201              | 8.392                  |
|           | Class 2   | 80.208             | 98.765            | 78.614     | 80.208    | 2.333              | 12.435                 |
|           | Class 3   | 96.088             | 99.653            | 96.353     | 96.088    | 1.228              | 6.008                  |
| SMO       | Class 1   | 92.09              | 98.64             | 93.43      | 92.09     | 16.04              | 27.29                  |
|           | Class 2   | 44.79              | 94.26             | 31.05      | 44.79     | 9.20               | 21.32                  |
|           | Class 3   | 79.06              | 99.77             | 97.28      | 97.06     | 9.88               | 21.79                  |

Through the results shown in the Table 4, which compares two classifications based on the division of ages represented into classes. It shows that the LMT classifier is more accurate than the SMO classifier in most classes. Whereas the precisions are 96.4%, 78.6% and 96.3% for classes 1, 2, and 3 respectively comparing to 93.4%, 31% and 97% for SMO classifier. These results have an effect on the values of mean absolute error which shows that the lowest precision was the highest ratio compared to the rest.

4. Conclusion

The dataset dividing was utilized where FG-NET dataset is divided into three classes or groups depending on the length of features number and applied the work on the intended class in order to make the comparison easier, hence increasing the accuracy. LMT and SMO classifiers has been implemented for age estimation. Where, LMT is better than SMO classifier for classes 1 and 2 with their precision about 96.4% and 78.6% compared with 93.4% and 31.05% for SMO classifier. While, the precision for SMO classifier (class 3) about 97.28% is higher rate than the LMT classifier which is about 96.353. This difference is the result of facial characteristics of different ages.

5. References

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