Assessment of Facial Homogeneity with Regard to Genealogical Aspects Based on Deep Learning Approach

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Article History: Received: 10 November 2020; Revised: 12 January 2021; Accepted: 27 January 2021; Published online: 05 April 2021

Abstract: The current research work encompasses the assessment of similarity based facial features of images with erected method so as to determines the genealogical similarity. It is based on the principle of grouping the closer features, as compared to those which are away from the predefined threshold for a better ascertainment of the extracted features. The system developed is trained using deep learning-oriented architecture incorporating these closer features for a binary classification of the subjects considered into genealogic non-genealogic. The genealogic set of data is further used to calculate the percentage of similarity with erected methods. The present work considered XX datasets from XXXX source for the assessment of facial similarities. The results portrayed an accuracy of 96.3% for genealogic data, the salient among them being those of father-daughter (98.1%), father-son (98.3%), mother-daughter (96.6%), mother-son (96.1%) genealogy in case of the datasets from “kinface W-I”. Extending this work onto “kinface W-II” set of data, the results were promising with father-daughter (98.5%), father-son (96.7%), mother-daughter (93.4%) and mother-son (98.9%) genealogy. Such an approach could be further extended to larger database so as to assess the genealogical similarity with the aid of machine-learning algorithms.

Keywords: Computer Science, Features extraction, Features learning Clustering, Facial similarities, Classification

1. Introduction

Machine learning based approach is known to be successful in the assessment of facial similarities, verification and associated applications. Such features are often useful in the assessment of genealogical aspects with regard to the quantity of facial homogeneity in the subjects considered. The features extracted from the facial images are often subjected to novel assessment approaches so as to obtain the desired classification of the datasets considered. This approach has been extensively adopted in various image processing as well as in case of psychophysical applications with EEG[4]. The present work has been successful in the assessment of the genealogical aspects with regard to the facial homogeneity ascertained from the facial features. Similar features are brought closer to each other and the rest are pushed away from each other in the sample space. Squeezenet modules are used to train the system with images of size 127x127 being the basic structure. The resized images are then used for the learning module and feature extraction, which improves the accuracy of the system.

![Figure 1. Overall architecture of the erected method with different phases of processing of input image](image-url)
The discriminative subspaces of color components of Laiadi, Oualid et.al of [1] have been useful in extracting the facial features of images by analysing the color components in sub-spaces. However, the accuracy has been an issue due to the usage of image subspaces for the information calculations. Deep compact similarity metrics of Xiuzhuang Zhou et.al [2] has been more efficient due to the incorporation of the same. The drawbacks in this case have been mitigated with the erected method approach. Miguel Bordallo Lopez et.al of [3] determined the facial kinships by incorporating the hierarchical features representation learning. In further literatures pertaining to facial recognition, various approaches have been developed so as to ascertain the neural abilities of recognition. The present research work highlights the facial feature assessment for the genealogical identification.

3. Deep Learning Features For Facial Similarities Verification

The facial features of source image are compared with all other facial features of dataset by incorporating the designated Deep Learning facial features to make the system more expanded to combine the Existing Squeeze Net features. The features of facial images are cropped into 127x127 sizes before feeding the system with input images. The output of squeeze net is concatenated with Deep Learning Features Extraction (DLFE) that makes the system more efficient and yields good results.

The features extraction by Deep Learning concatenated with Squeeze Net features learning makes the system more efficient and robust by computing the information of facial features gathered from eq. (2), where eq. (1) is a generalized representation of the system.

\[ S(v, h; \theta) = V_i - B_i - H_i \]  

(1)

Weights \( W_{ij} \) of the proposed Deep Learning Features Extraction (DLFE) does the task of calculating the information of facial features of one photograph with target images by incorporating the formulation of eq (1) consisting of source image represented by \( v_i \) with respect to the target image indicated by \( h_j \).

\[ S(v, h; \theta) = -\sum_{i=1}^{N} \sum_{j=1}^{M} v_i W_{ij} h_j - \sum_{i=1}^{N} b_i v_i - \sum_{j=1}^{M} a_j h_j \]  

(2)

Eq.(3) measures the sequential information obtained from generalized Squeeze Net features with Deep Learning Features Extraction (DLFE) thereby the system increases the measure of features of one source image with target image.

\[ S(v, h; \theta) = -v^T W h - b^T V - a^T h \]  

(3)

This concatenated information is expanded into more statistical features learning that makes the system more suitable for measuring the information gathered from features of images to be compared with target images that makes the system more efficient.

\[ S(v, h; \theta) = -\sum_{i=1}^{N} \sum_{j=1}^{M} \frac{v_i}{\sigma_i} W_{ij} h_j - \sum_{i=1}^{N} \frac{(v_i - b_i)^2}{2\sigma^2} - \sum_{j=1}^{M} a_j h_j \]  

(4)

Statistical system of eq. (4) plays a significant role in measuring the features by deep neural information that makes the system and concatenates with measured weights to make the system more efficient and robust. The system has helped the proposed method with weights with exponential information obtained with weighted features learning as per eq. (5)

\[ S(v, h) = \frac{1}{Z} \exp(-S(v, h; \theta)) \]  

(5)

\[ S(v) = \sum_h S(v, h) \]  

(6)

Eq. (6) of the proposed method makes the system more efficient by concatenating with Squeeze Net features obtained from processing of images as per fig.1

3.1. Algorithm (DLFE)
Deep Learning Features Extraction (DLFE)

Begin

Step 1: Solve eq.(1)

Step 2: Solve eq. (2)

Step 2.1: Solve eq.(3)

Step 2.2: Solve eq.(4)

Step 2.3: Solve eq.(5) and concatenate eq (4)

Step 3:

Step 3.1: Compute eq. (6)

Step 3.2: Obtain facial similarity

End

Algorithm: Deep Learning Facial Features Learning

4. Results and Discussions

The results of the proposed method with respect to other contemporary efforts reported in different years is competitively good and has shown that the erected method based approach is most essential in applications that require to measure facial similarities.

4.1. Comparison of Results

The Deep Learning Facial features learning concatenation with Squeeze Net facial features learning phases have been assessed in the present work. The Concatenation of Processing with Squeeze Net facial features with Deep Neural Networks has made the system more efficient, the results of comparison of erected method with other contemporary methods mentioned in table 1 presents the comparison done by the proposed system with other methods.

Table1. Comparison of Accuracies of contemporary methods with proposed approach

| Year | Authors   | Algorithms                                                      | Databases           | Accuracy |
|------|-----------|-----------------------------------------------------------------|---------------------|----------|
| 2012 | Guo et al | Prod of likelihood ratio on salient features                    | Customized Database | 75.01    |
|      | Zhou et al| Pyramid of Gabor based gradient oriented features               | Customized Database | 69.75    |
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| Year | Authors                        | Method                                                                 | Dataset           | Accuracy |
|------|--------------------------------|------------------------------------------------------------------------|-------------------|----------|
| 2013 | Dibeklioglu et al.             | Spatial features with temporal                                         | Uva-NEMO SMILE    | 67.11    |
|      | Lu et al.                      | Neighborhood repulsed learning with Multi-view                        | KinfaceW          | 76.1     |
|      | Yan et al.                     | Metric of Discriminative Learning                                     | KinfaceW          | 72.01    |
| 2014 | Dehghan et al                  | Auto-encoders with discrimination                                      | KinfaceW          | 74.51    |
|      | Yan et al.                     | Prototype discriminative feature learning                             | KinfaceW          | 70.11    |
|      | Liu et al.                     | Kinship verification with Inheritable Fisher Vector                    | KinfaceW          | 73.45    |
| 2015 | Alirezazadeh et al             | Kinship Verification with Genetic Algorithm for feature selection     | KinfaceW          | 81.31    |
|      | Zhou et al.                    | Similarity Learning with Ensemble Method                               | KinfaceW          | 78.61    |
| 2016 | Naman Kohli et al              | Representation learning for Kinship Verification (KVRL-fcDBN)         | KinfaceW          | 96.1     |
|      | Qingyan Duan et al             | Face Verification with Kinship Verification                           | KinfaceW          | 73.84    |
| 2017 | Yong Yang et al                | Kinship Verification Based on Transfer Learning and Feature of Non-linear Mapping | KinfaceW          | 78.46    |
|      | Miguel Bordallo Lopez et al    | Transfer Learning with Feature of Non-linear Mapping                   | Uva-NEMO SMILE    | 87.8     |
| 2018 | A Tidjani et al                | Kinship Verification with Deep Learning Features                      | KinfaceW          | 76.65    |
|      | Diego Lelis et al              | Deep Learning for Kinship Verification                               | KinfaceW          | 79.48    |
| 2019 | Youness Mansar et al           | Kinship prediction with Deep Neural Networks                           | KinfaceW          | 76.42    |
|      | **Proposed Method**            | **Deep Features Learning for Facial Similarities Verification**        |                   | **96.31**|

The present research work has focused more towards identifying the facial similarities among relatives as well as the quantification of the similarity in terms of percentage values with various datasets such as KinfaceW, UB Kinface and Cornell Kinface.

#### 4.2. Graphical Results
It is clear from the above fig.2 that precision vs. recall of the erected method is comparatively better than other contemporary methods. The significance of the erected methods is very good to identify the facial similarities among different people presented in the dataset KinfaceW and UBKinface.

\[
\text{Precision} = \frac{TP}{TP + FP} \tag{7}
\]

\[
\text{Recall} = \frac{TP}{TP + FN} \tag{8}
\]

\[
\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{9}
\]

The above fig.3 presents the accuracy of the erected method with reference to other contemporary methods. The accuracy criteria is measured by analysing the True positivity obtained from the erected method with false positivity and false negativity of the proposed method determines the accurate classification of facial features into different classes of facial features represented in terms of performance metrics like Precision, Recall, Accuracy of the proposed method as per eq. (7), eq. (8), eq. (9) respectively.

5. Conclusion
The Deep Neural Network based facial features learning has contributed the performance of the proposed method by analysing and understanding the facial features of the dataset Kinface W and UB Kinface. The facial features of these dataset have been subjected to processing by deep neural network-based features learning and have yielded a good classification accuracy of 96.3% with respect to Father-Daughter, 96.1% with respect to Father-Son, 97.4% with respect to Mother-Daughter, and 96.5% with respect to Mother-Son relationships of images of KinfaceW-I and KinfaceW-II and UB Kinface datasets. The research work has focused its attention by contributing good classification accuracy with machine learning tasks for genealogical similarity.

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