Research Article

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

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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. Squeeze net 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.

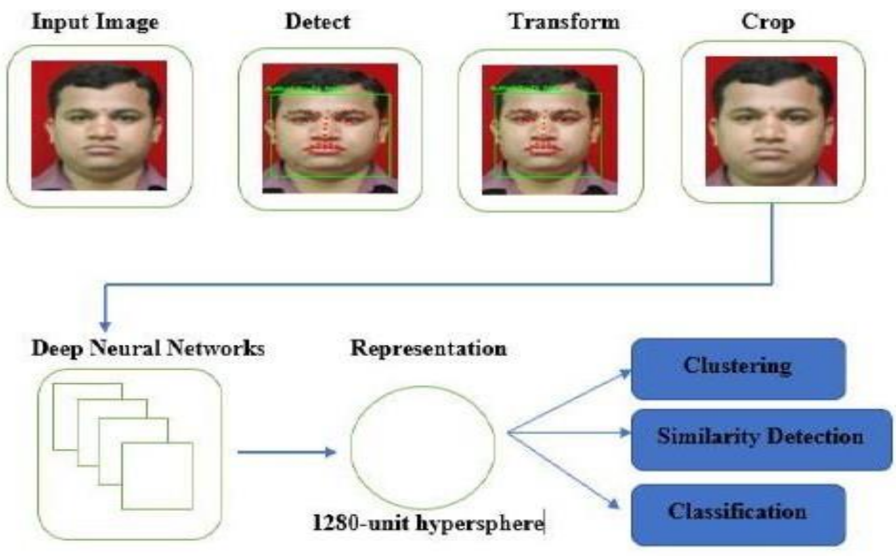

Figure 1. Overall architecture of the erected method with different phases of processing of input image

2. Background

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 Sqeeze 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.

$$S(v,h;\theta) = V_i - B_i - H_i \tag{1}$$

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 buy incorporating the formulation of eq (1) consisting of source image represented by $v_i$with respect to the target image indicated by h_j.

$$S(v,h;\theta) = -\sum_{i=1}^{N}\sum_{j=1}^{M} v_i W_{ij} h_j - \sum_{i=1}^{N} b_i v_i - \sum_{j=1}^{M} a_j h_j \tag{2}$$

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.

$$S(v,h;\theta) = -V^T W h - b^T V - a^T h \tag{3}$$

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.

$$S(v,h;\theta) = -\sum_{i}^{N}\sum_{j}^{M} \frac{v_i}{\sigma_i} W_{ij} h_j - \sum_{i=1}^{N} \frac{(v_i - b_i)^2}{2\sigma^2} - \sum_{j=1}^{M} a_j h_j \tag{4}$$

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)

$$S(v,h) = \frac{1}{Z} exp(-S(v,h;\theta)) \tag{5}$$

$$S(v) = \sum_{h} S(v,h) \tag{6}$$

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

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.

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.

Table 1. Comparison of Accuracies of contemporary methods with proposed approach

Year	Authors	Algorithms	Databases	Accuracy
2012	Kohli et al.	Self-similarity representation with weber faces	UB Kinface Database	69.67
	Guo et a	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
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
2014	Yan.et.al	Metric of Discriminative Learning	KinfaceW	72.01
	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
2019	**Proposed Method**	**Deep Features Learning for Facial Similarities Verification**	**KinfaceW,**	**96.31**
			UB Kinface,	**95.49**
			Cornell Kinface	**96.92**

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.

Graphical Results

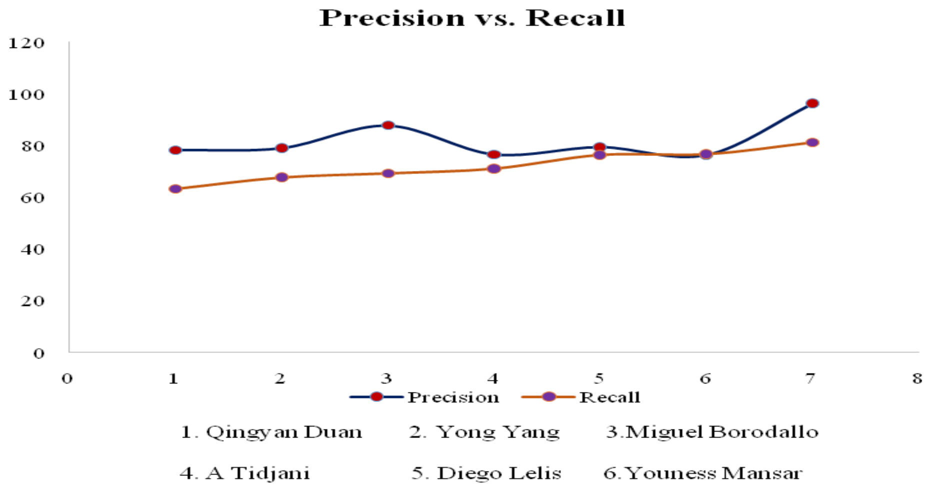

Figure 2. Comparison of precision vs. recall of different methods with respect to proposed Method

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.

$$Precision = \frac{TP}{TP + FP} \tag{7}$$

$$Recall = \frac{TP}{TP + FN} \tag{8}$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{9}$$

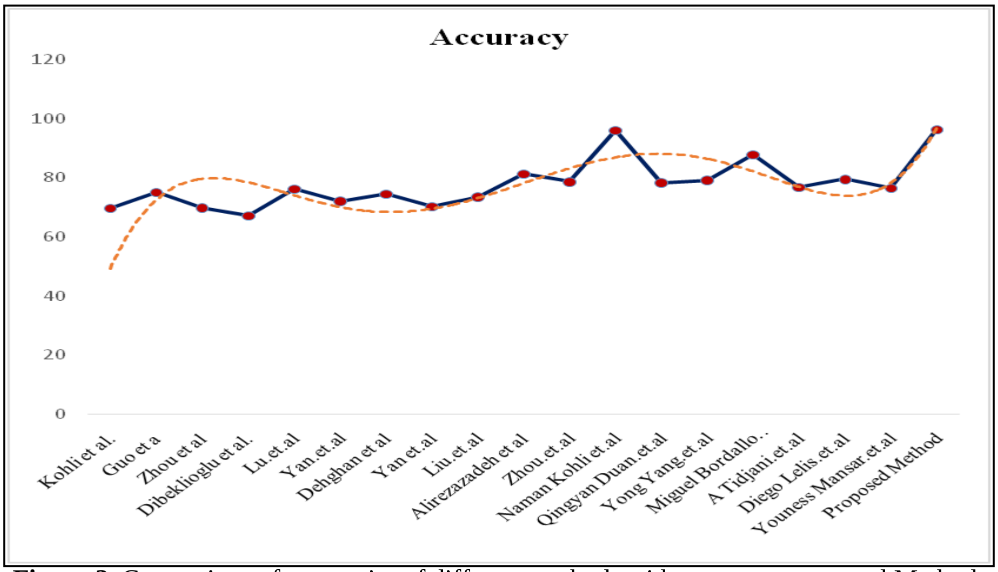

Figure 3. Comparison of accuracies of different methods with respect to proposed Method

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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