IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)
An International Open Access, Peer-reviewed, Refereed Journal

FACIAL FEATURE DISCOVERY FOR ETHNICITY RECOGNITION USING CNN ALGORITHM

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Abstract: The facial feature discovery is a very essential task in ethnical group face recognition. In this paper, we have found ethnical group face dataset which includes Asian, Black, Indian, Latin. We used real time face image to recognize the ethnicity group. Every ethnicity group has their own characteristics and facial features. Therefore, we considered the particularly four ethnical groups in that we intended to find the similar characterizations in some of the ethnical groups. According to the geographical location human facial information will vary, so we have collected data from various regions and that helps to give us the exact result. In this report we exploit the range information of human faces for ethnicity identification using Deep learning. This project is proposed to understand and analyses the relation between the ethnicity and ethnical groups, by combining registered range and intensity images. We trained images and we managed to give a precise result. This work helps to analyses the facial features evolution in anthropology (the study of human societies and cultures and their development.) the proposed integration scheme outperforms each individual ethnicity.

Keywords: Facial feature, Ethnicity detection, Anthropology research, Image processing, Convolutional Neural Network

I INTRODUCTION

A facial recognition system is a technology that is capable of identifying or verifying a person from a digital image. By using this technology, we understand the various range of ethnical groups and that helps to analyze the person's ethnicity [1]. In recent days facial recognition is widely used in security and various applications. Now a day’s face recognition are widely used and it is very used to identify the ethnicity face recognition does the major role border control, customs check, and public security. Also, it performs the very important part in physical anthropology [2]. Usually, facial features are influenced by genes, environment, society, and other factors Anyway, genes have a very important role in ethnical groups. It is hardly unique and it includes various genes and it's very hard to analyze it from other ethnical groups. The only possible way is by understanding the various gene systems and processes among it. Which lead to the similarities of facial features and its several ethnicities, and it analyze the facial features by computing AI. This paper helpful to anthropology (the study of human societies and cultures and their development) as it may indicate the facial features evolution [3].

II LITERATURE SURVEY

The study [4] proposed that analyzing the face region in T-region that includes (eyes, nose, forehead, lips and jaw line) using KNN(k-nearestneighbors).,weshow thattheeffectivesparsesensingapproachtogeneral facerecognition is not working anymore for ethnical group facial recognition if the features based on whole face image are used. The proposed three “T” regions are evaluated on the Olivetti research laboratory face dataset, and the results show that the constructed “T” regions for ethnicity recognition are not suitable for general face recognition.

This paper [5] LBPH as a distribution description of given local texture patch, and partition the feature domain of Chi square distance between this histogram and a reference histogram to form a LUT (look up table) basedweakclassifier.Withinthesetofallpromisinglocalpatches,realAdaBoost is used to select the best ones and construct a strong classifier.

This paper [6] explores the appearance-based scheme which has demonstrated its power in image-based face recognition.

The main contributions of this work [7] is analysis of the effectiveness of a purely facial- structure-based distance function for gender and ethnicity classification, (2) a training scheme which is agnostic of the underlying facial distance function, and (3) a resulting fully-automatic system which achieves accuracy of ∼ 99% for race and ∼ 94% for gender on a public benchmark dataset.

This study [8] Raw image based approaches consider the entire raw face image (generally frontal) as the input and employ dimensionality red auction techniques (down-sampling or subspaces) to process the facial image to finally feed the classifier. A classification accuracy of 96.3% was achieved on a union database containing 2630 samples of 263subjects.

The system presented in this paper [9] consists of three modules, Gabor filtering, Adaboost learning and SVM classifier. shows the system flow chart based on our method. In recent years, Gabor, Adaboost and SVMs have been successfully applied to various tasks in computational face-processing. These include face detection, face expression recognition. In this paper, we have applied the novel combination to a new face retrieved task.

The authors [10] describes a system which automatically detects faces, tracks the macros time, and classifies them as either male/female and Asian/non-Asian . Each of the components of this system has been tested on a difficult dataset of faces from the World Wide Web. The best published technique for gender classification is an SVM, which when tested on rectified FERET data yields an error rate of 3%. When trained and tested on a set of faces detected by our system, the SVM system yields an error rate of 23% and requires over 3000 support vectors (much of the increase can be attributed to the lack of rectification).

In this paper [11] accuracy achieved in ANN was 82.4% and in CNN was 98.6%. The results obtained using Artificial Neural Network was better than the results achieved in. And the significant improvement is achieved with convolutional neural networks. But the cost of CNN is much more than ANN in terms of time required for feature extraction and training that network.

III METHODOLOGY

Convolutional Neural Network

Convolutional Neural Networks are a category of **Neural Networks** which proven very effective in areas such as image recognition and classification. CNN consists of a input layer and output layer and it has many hidden layer submerged in it, and is specialized in the linear operation. ConvNets have been successful in identifying faces, objects and traffic signs apart from powering vision in robots and self-driving cars.

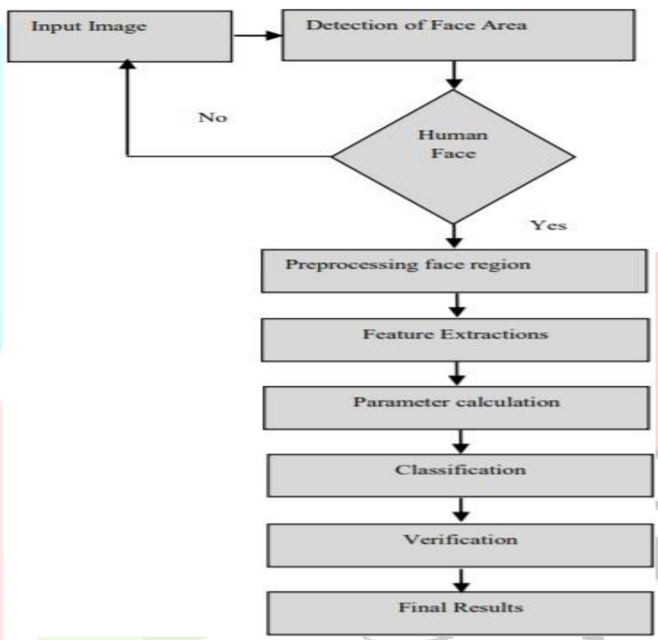

Fig.1. Proposed methodology

Ethnicity distribution

Number of races in each dataset are ordered below in FairFace dataset.

race	file
Black	14.102416
East Asian	14.164668
Indian	14.201559
Latino_Hispanic	15.409711
Middle Eastern	10.624366
Southeast Asian	12.444665
White	19.052615

Fig.2. Number of races in the dataset

I’ve merged two Asian races into a single Asian race. Thus, distribution becomes as illustrated below after data manipulations.

race	file
Asian	26.609333
Black	14.102416
Indian	14.201559
Latino_Hispanic	15.409711
Middle Eastern	10.624366
White	19.052615

Fig.3. Race distribution after data manipulation

Reading image pixels

These datasets just include basic names and their races so we have to read the image pixels on the file name.

	file	race
0	FairFace/train/1.jpg	East Asian
1	FairFace/train/2.jpg	Indian
2	FairFace/train/3.jpg	Black
3	FairFace/train/4.jpg	Indian
4	FairFace/train/5.jpg	Indian

Fig.4. Image names with their corresponding race

We will read image pixels based on the file names. Now, images pixels are stored as a column

	file	race	pixels
0	FairFace/train/1.jpg	Asian	[8.0, 8.0, 10.0, 9.0, 9.0, 11.0, 10.0, 8.0, 11...
1	FairFace/train/2.jpg	Indian	[129.0, 127.0, 104.0, 127.0, 125.0, 102.0, 123...
2	FairFace/train/3.jpg	Black	[216.0, 171.0, 174.0, 212.0, 167.0, 170.0, 206...
3	FairFace/train/4.jpg	Indian	[42.0, 47.0, 50.0, 42.0, 47.0, 50.0, 41.0, 46....
4	FairFace/train/5.jpg	Indian	[44.0, 39.0, 35.0, 44.0, 39.0, 35.0, 43.0, 40....

Fig.5.Pixels information of files

Input features

Pixels are stored as a list. We need to reshape each line to (224, 224, 3). Besides, inputs should be normalized in neural networks because of activation functions. This is going to be an input feature we will pass to the network as input.

Target

To predict the target value which is race column. So, the network will have 6 output (outputs are the number of races in dataset) which are races which one hot encoding. The outputs are the races mentioned in the dataset.

Train and validation split

Test and train sets are separate. To avoid the over floating we apply early stopping because, to avoid over fitting we have split train and validation.

Base Model

We will use VGG-Face for transfer learning. Let’s construct it first.

Transfer Learning

Some facial patterns can be discovered in early layers. We don’t need to train it from scratch.

We expect the last layer to learn something that is layer 7

We just need 6 output but the original VGG-Face network has 2335 outputs so we change and customize the VGG-Face dataset.

Training

Instead of feeding all train data, I prefer to feed it as batches. I got the best result for16.384 (2^14) batch size. I feed randomly selected16Kinstances in every epoch. If validation loss would not decrease for 50 rounds, then training should be terminated to avoid over fitting.

Loss

Thebestepochwas29.Wetrained thenet work for 80 roundsbuttrain loss decreased while validation loss increased when epoch > 30 in the following steps. That's exactly over fitting.

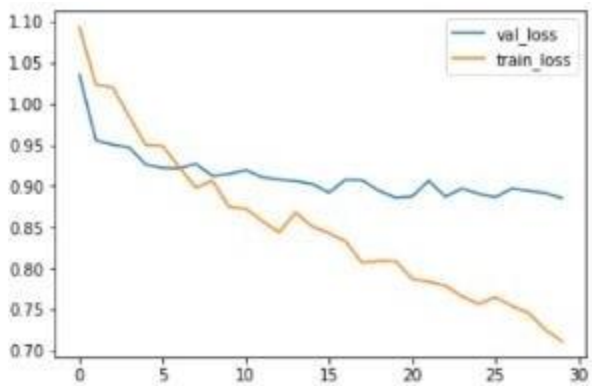

Fig.6. Train and validation loss

Evaluation

We train the network with train data set and use validation set to apply early stop. Epoch is the best iteration for a validation set actually. However, the network could memorize the validation set and it could still be overfitted. That's why we haven't fed the test set to the network yet. We expect that test and validation loss should be close if the model is robust.

The both test and validation loss are 0.88 and accuracy are 68%. We can say that the model is robust.

Prediction

We can make predictions for the test set. Also, we can print prediction and actual values and plot the original image as well.

Fig.7. Predictions for randomly selected instances in the test set

Heat map

The following heat map explains everything.

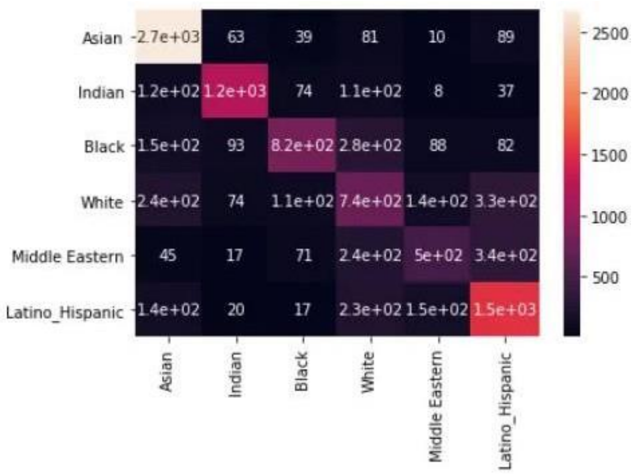

Fig.8. Heat map

Predicting custom images

We can predict the ethnicity for custom images as well. We applied prediction for the characters of Silicon Valley. Results are really satisfactory.

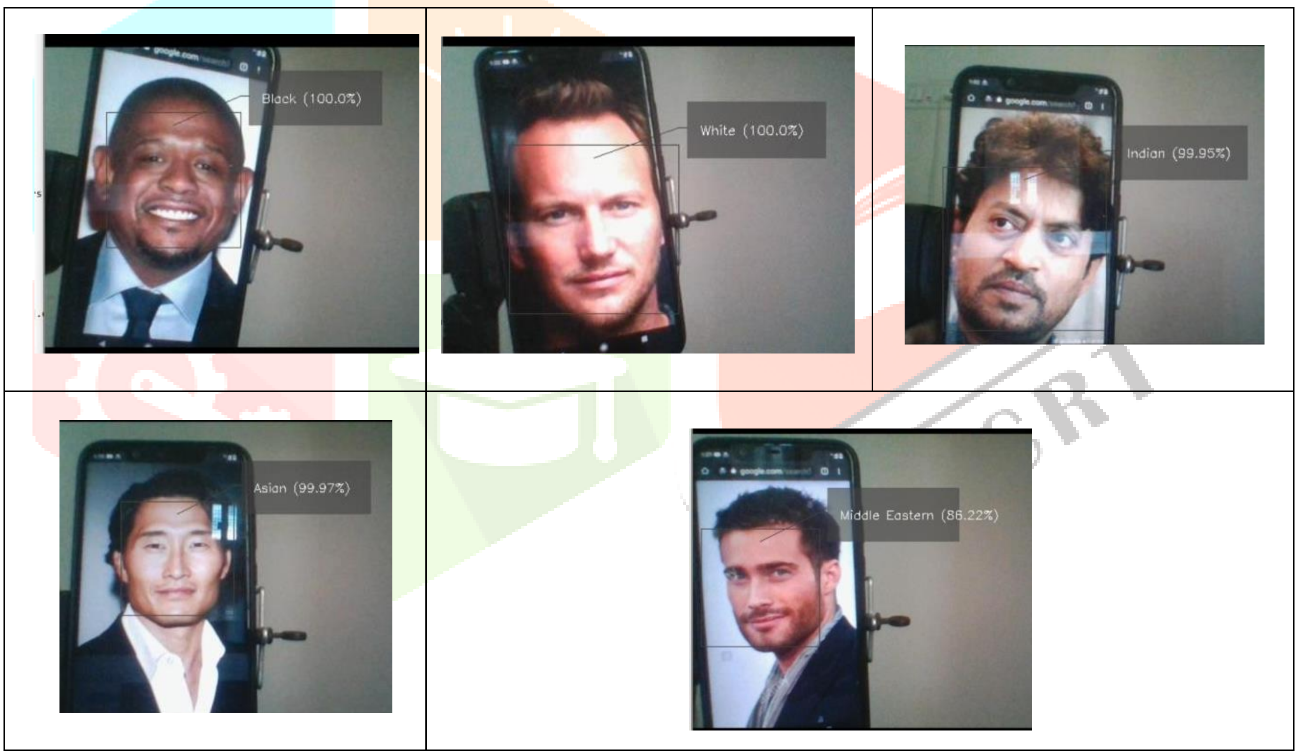

Fig.9. Predictions

CONCLUSION AND FUTURE WORK

This paper mainly focuses on extract the facial features by using deep learning for ethnicity recognition. Feature based Methods is implemented to extract the facial features which helps to find the ethical groups and our accuracy is very precise by comparing to other papers. This is because of the good dataset. This work detects hundreds of facial feature landmarks to construct features for ethnicity representation according to anthropometry.

In future we are using better data set to increase the accuracy for detecting the Ethnicity by facial features. Our project might helpful for missing children, search investigations, refugee crisis.

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