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A Novel Biometric Approach for Facial Image Recognition using Deep Learning Techniques

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ABSTRACT

In this paper, age and gender specific user identity recognition is implemented using facial features for biometric application. A novel approach has been developed by extracting Local Binary Pattern (LBP) and Gray Level Co-Occurrence Matrix (GLCM) image features which effectively represents facial and skin regions of user to classify facial images based on various age groups and gender. These extracted features are classified by Convolution Neural Network (CNN), Region-based CNN (RCNN) and Fast RCNN, namely three popular Deep Learning Classification techniques using IMDB wikicrop facial dataset. Experimentations using CNN classifier achieved best result of 96.4% accuracy in contrast to other two classifier results.

Key words: Classification, Biometric, Facial Images, Deep learning.

1. INTRODUCTION

Human age evaluation is basically the process of estimating an individual's precise age or age-range based on his/her portrait facial photo. Nowadays, personal verification and identification is widely employed in many security applications. There are lot of physiological and behavioral biometric traits commonly used for biometric person authentication like finger voice, speech, retinal movement, hand vein, gait , DNA, blood and so on [1]. These biometric traits are not user transferable and unique for each user which can't be hijacked, lost, stolen or broken [2-4]. Facial recognition involves identifying an individual faces as shown in Figure.1. There is the lot of research going on about automatic identification of age timeline and gender for human face images and it has lot of important applications, for example forensic application, banking system social surveillance etc. Many of the approaches established biometric classification systems primarily for age-range or gender assessment tasks [5][6] but only a few works on real-life faces snapped from the video, and they are designed for un-filtered and occluded faces.

Figure.1: Face aging of an individual at different ages

2. RELATED WORK

Estimating the person's approximate age and gender from an individual's facial representation, is a popular debate among various researchers/authors. Yunus Saatchi et al explained the recognition of gender category and face expressions using Appearance Model and cascade models. SVM classifier was employed to get better results of user's facial expression and emotion [1]. [2] Compares two age prediction WAS and AAS for predicting the undefined person's age from his social activities data captured from the public areas [3]. Aswathy et al described the age-gender detection by facial images using online websites and a dropout SVM to avoid overfitting [4-6].

3. MATERIALS AND METHODS

3.1 CNN classifier

CNN [17-20] is an example of deep learning based classifier which is prominently applied in data mining, bulk analysis, object recognition/classification and feature extraction, audio/image analysis. It has weight sharing property which employs less complex neural network structure with minimum number of weights. CNN architecture entails a sequence of layers such as convolution (ReLU), pooling (max, min, avg….), and fully connected (softmax).

Rectified Linear Units (ReLU), used as activation function in the hidden layer for training CNN, which thresholds the values at 0, and outputs a linear function when $x \geq 0$. Few fully connected layers are stacked at the end and also the last layer is soft-max having ReLU as classification function for obtaining the likelihoods of its input data. CNN parameters are trained by algorithm of Back Propagation like an conventional neural network.

4. PROPOSED WORK

In this paper, age-gender based classification system using facial images is implemented by extracting face and skin region, and later classified using deep neural network learning techniques. From the facial image, its skin region is separated by YCbCr color model and face regions are extracted using viola jones 'haar' algorithm. LBP and GLCM feature sets were extracted from those skin and face regions, which are classified later through CNN, RCNN and Faster RCNN techniques to facilitate age-gender detection.

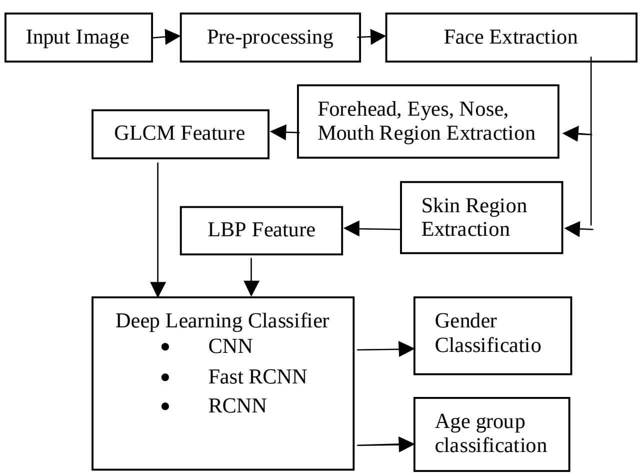

Figure 2: Overall flow diagram for age-gender detection

Algorithm

1. Facial images from the IMDb-crop dataset are uniformly resized to 512*512.
2. In preprocessing, the images are median filtered by 3*3 mask for smoothening.
3. Using Haar Cascade Classifier algorithm, the person's face is cropped form each image.
4. Again with Haar Cascade Classifier, four facial regions namely forehead, mouth, eyes and nose are extracted.
5. From the four facial regions 22 GLCM features for 2 offset directions 0◦ and 90◦ are extracted (22*2*4 = 176).
6. YCbCr color model, separates the skin region from the cropped facial images obtained in step 3.
7. From the skin region 16 bin LBP histogram features are extracted.
8. Totally 192 features extracted from different regions are given to RCNN, CNN and Fast RCNN for training the models for various age and gender categories.
9. The pertained classifier models are then tested and evaluated using the test dataset.

4.1 Dataset for Estimation of Age and Gender

IMDB-Wiki crop dataset is an online collection of popular actors, persons from wikipedia and Imdb movies website. It comprises of close up shots of people from various races, age group and ethnic groups like brown, black and white. It comprises of more than 10,000 images, out of them visually unclear, duplicate ones are truncated. Totally 2010 images from the dataset is selected for our proposed system.

Table 1: IMDB-Wiki crop dataset Separation

Gender	Age Group	Number of Training Images	Number of Testing Images
Female	18 to 35	252	159
	36 to 50	168	96
	51 to 65+	121	76
Male	18 to 35	330	181
	36 to 50	250	152
	51 to 65+	153	72
Total		1274	736

4.2 Preprocessing and Face Cropping

Each image is resized uniformly into 512 x 512 pixel size. Median Filtering is done to minimize the noise present on the input image, for enhancing the features or suppressing the image distortions for better processing. The face detection algorithm coined by Viola and Jones is used as the basis of the proposed design. The face detection and cropping is done with Haar Cascade Classifier algorithm.

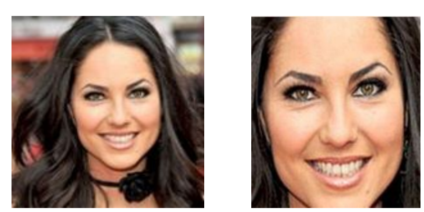

Figure 3: Face region extraction

4.3 Facial Feature Extraction

Eyes, nose, lips are the important key features of the face. It can be extracted using viola-jones algorithm again. But It sharply extracts the features. But key points to detect age and gender, bounding area of those features are not enough. Additional surrounding portion is necessary to extract the features. The wrinkles of the eye corner, mouth corner visualizes the aging factor. So calculation based eye region, mouth region and nose region has been calculated as shown in Figure.4

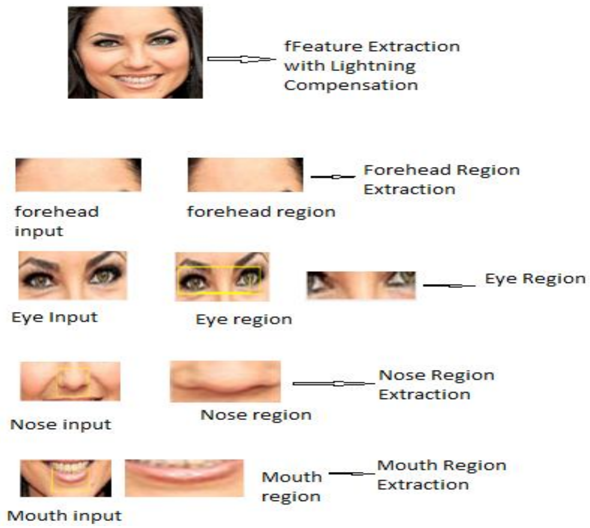

Figure 4: Haar Cascade Estimate the Facial region in Face Image

4.4 Skin Region Segmentation

It is proposed to extract the skin region from the user's cropped facial image as shown in Figure.5. During segmentation, colors in YCbCr color space are classified or grouped using a threshold value. Skin-color reference map for Cb is between 77 to 127 and Cr range is between 133 to 173, using which the human skin can be found for different races. Clustering the Cb and Cr components of the face region will retain the face's skin region and it also eliminates the background items like hairs, eyes, any scenery etc.

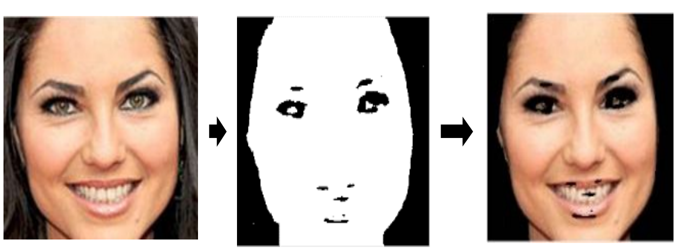

Figure 5: Skin Region Identification from Face Extraction with lighting compensation

4.5 LBP Feature Extraction

In this feature extraction stage, 16 LBP features are extracted using the below steps from the facial skin regions:

a. Facial skin region is divided into 20x20 pixel cells.
b. Equate every pixel to its eight neighboring pixels.
c. An 8-digit binary number is obtained by assigning "1" when the processing middle pixels is lesser or equal to the neighboring pixel, and "0" otherwise as shown in Figure. 6

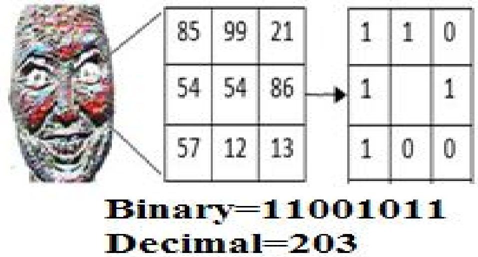

Figure 6: Value extraction using LBP Encoding

d. Now for finding each number's frequency, a histogram is computed over the cell, which results in 256-dimensional feature vector as shown in Figure. 7

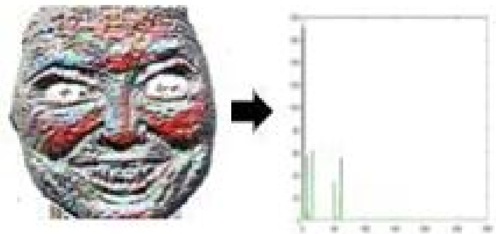

Figure 7: LBP Matrix is converted into LBP Histogram

e. Concatenation the histograms of the cells into 16 bins (normalized), which gives a 16-dimension feature vector for the entire image.

4.6 GLCM Feature Extraction

GLCM represents spatial distribution and frequency of the image's intensity values along specified distance and angles. It depicts the pattern of occurrence of each gray level pixel i neighboring with other gray level pixel j considering the distance d at angle θ. In 1973, [12] introduced 14 statistical texture features namely Angular second moment, correlation, contrast, sum of squares, inverse difference variance, sum average, sum entropy, sum variance, entropy, different variance, different entropy, Information measures of correlation and auto correlation coefficient [15]. Later [12] suggested two alternate versions of correlation and homogeneity. Six shift invariant grey level statistics features namely cluster prominence, dissimilarity, cluster shade, maximum probability, normalized inverse difference and its moment is employed. Thus, a total of 22 features [16] are computed along two offset direction 0◦ and 90◦ per region for the given image.

4.7 Classification

CNN is traditionally made up of high level feature analysis and classification stages. In proposed method, in spite of directly giving image as input, GLCM+LBP combined feature vector is passed for representing the image to improve the classification accuracy. Therefore, the CNN architecture consists of [INPUT - CONV - RELU - FC] as in Figure 8 and Figure.9 which is implemented in Matlab using the MatConvNet toolbox.

- INPUT [22x9x1] - 22 GLCM features in two offsets from four regions (forehead, eyes, nose, mouth) along with 16 LBP features from skin region with zero padding along the last row.
- CONV layer - convolution layer result in [22x9x8] size for 8 filters.
- RELU layer - activation function.
- Three fully-connected (FC) layers with 384 neurons and 6 softmax output neurons to find category scores.

Table 2: Input data for fully connected layer

f_1^1	f_1^2	-	f_1^{22}	22 GLCM for offset direction 0◦ from forehead
f_2^1	f_2^2	-	f_2^{22}	22 GLCM for offset direction 90◦ from forehead
f_3^1	f_3^2	-	f_3^{22}	22 GLCM for offset direction 0◦ from eye
f_4^1	f_4^2	-	f_4^{22}	22 GLCM for offset direction 90◦ from eye
f_5^1	f_5^2	-	f_5^{22}	22 GLCM for offset direction 0◦ from nose
f_6^1	f_6^2	-	f_6^{22}	22 GLCM for offset direction 90◦ from nose
f_7^1	f_7^2	-	f_7^{22}	22 GLCM for offset direction 0◦ from mouth
f_8^1	f_8^2	-	f_8^{22}	22 GLCM for offset direction 90◦ from mouth
f_9^1	f_9^2	-	f_9^{22}	16 LBP with needed zero padding

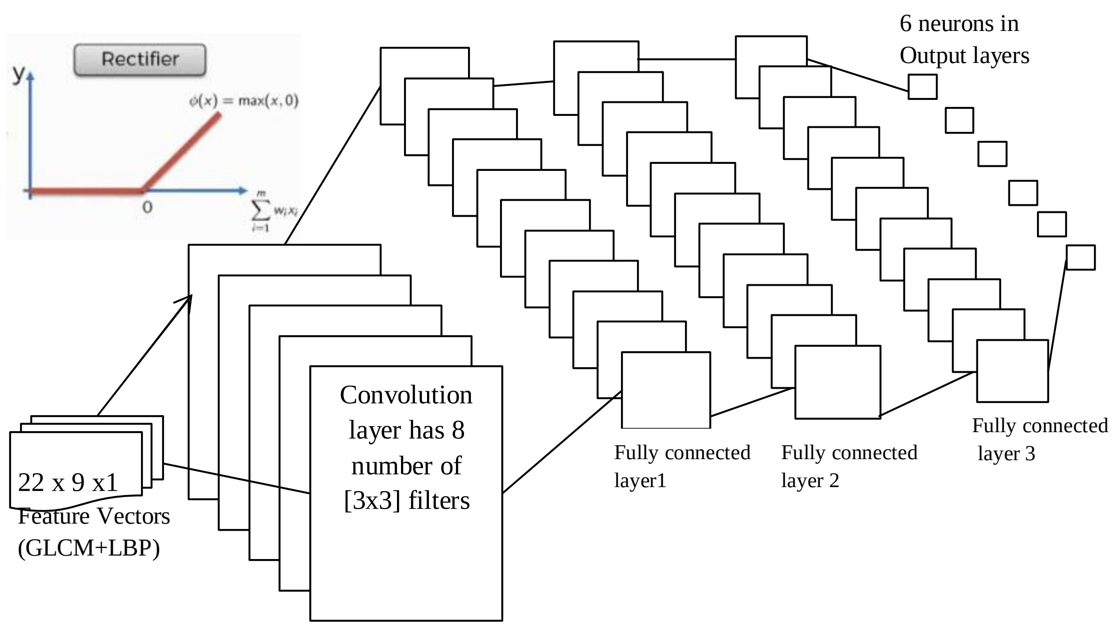

Figure 8: Processing with fully connected layers in CNN

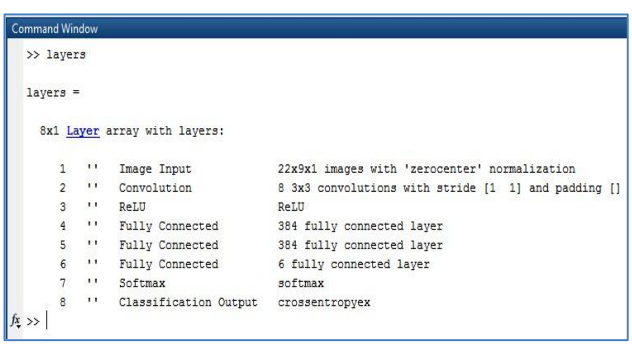

Figure 9: CNN Classifier output obtained in Matlab

5. EXPERIMENTAL RESULTS AND DISCUSSIONS

Table 3: Experimental results from CNN classifier

Gender	Age Group	Precision	Recall	F-measure
Female	18 to 35	84.67	92.42	88.37
	36 to 50	82.12	90.45	86.08
	51 to 65+	79.51	89.32	84.13
Male	18 to 35	87.61	92.25	90.85
	36 to 50	97.93	94.35	96.10
	51 to 65+	98.95	93.45	96.59

Table 4: Experimental results from Fast RCNN classifier

Gender	Age Group	Precision	Recall	F-measure
Female	18 to 35	84.67	89.42	86.98
	36 to 50	80.83	90.45	85.37
	51 to 65+	86.70	90.32	88.47
Male	18 to 35	87.61	82.35	84.90
	36 to 50	96.93	92.35	94.58
	51 to 65+	98.95	91.35	95.00

Table 5: Experimental results from RCNN classifier

Gender	Age Group	Precision	Recall	F-measure
Female	18 to 35	84.67	92.42	88.37
	36 to 50	79.45	90.45	84.59
	51 to 65+	82.32	89.32	85.67
Male	18 to 35	87.61	82.35	84.90
	36 to 50	96.93	84.35	90.20
	51 to 65+	98.95	89.35	93.90

Table 3-5 tabulated the results with different deep classifiers for each category individually. Their results clearly show that all three classifiers have been showing better results for old age categories and results are also comparatively higher for male than the female gender. Despite a lower F-measure of 84.13% for Female 51 to 65+ age group, CNN outputs optimum results for all other groups with F-measure higher than 86% and in nutshell these tables clearly states that CNN is best suited for age and gender prediction.

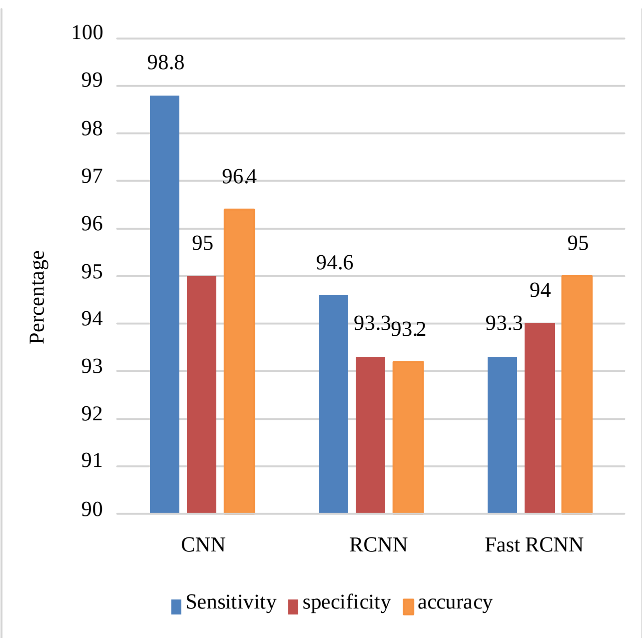

Figure 10: Performance measures from CNN, RCNN and Fast RCNN

Figure 10 plots the sensitivity, specificity, and accuracy measures for each classifier with combined LBP+GLCM feature set. The graph clearly reveals that CNN outperforms both RCNN and Fast RCNN. CNN accuracy is 96.4% which is very promising when matched with other classifiers whose accuracy is only around 93-95%.

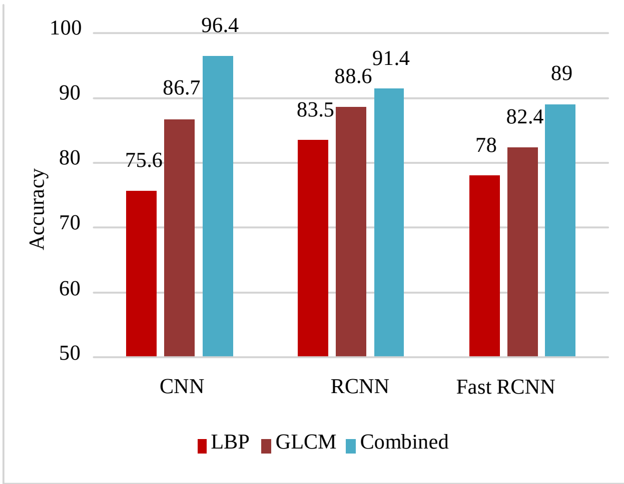

Figure 11: Performance measures from various combinations of classifiers and features

In figure 11 individual LBP, individual GLCM and combined LBP+GLCM feature set are tested with different classifiers and their corresponding accuracy is recorded. CNN provided an optimum as well as maximum accuracy of 96.4% with combined LBP+GLCM feature set when matched with by RCNN and Fast RCNN resulting 91.4% and 89% respectively.

6. CONCLUSION

In this research, a new approach is proposed/build for automatic age, gender recognition on facial feature. This approach extracts totally 2 different features from the face image. The first feature extracted is LBP, which is forms the skin facial textures and the second feature extracted is GLCM, which is from the Landmark points of the face image. And the recognition stage is developed in 3 different frameworks. The first framework contains LBP and GLCM features with CNN classification, the second framework includes features with R-CNN classification, and the third framework respectively deal the features for classification of Fast R-CNN. In this facial recognition system, both texture and geometrical information along with different Deep learning classification makes the proposed method more powerful as well as efficient. When compared with three deep learning classifier CNN obtained the better accuracy 96% respectively.

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