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Gender Classification from Eye Images by Using Pretrained Convolutional Neural Networks

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Abstract: Automatic gender classification from face images has been a popular topic among researchers for a decade. Feature extraction and classification methods are very important to create a successful automatic classification system. Due to the richness of face image datasets today, many successful machine learning and deep learning methods has been implemented. It is very critical to extract accurate features from the datasets to achieve promising classification scores when traditional machine learning methods are used. However, deep learning models have been designed to extract the features automatically from the raw data directly. This also automatize the feature extraction process besides classification. The hidden and unpredictable feature sets can be explored by the deep neural networks which can increase the classification performance comparing to traditional machine learning methods. Convolutional Neural Networks (CNN) as one of the effective classes of deep models have been adopted by many scientists for solving the gender classification problem. It can solve the problem of the fact that facial cues can change from origin to origin which makes the accurate feature extraction harder. There are several state-of-the art pretrained CNN structures which are very successful for image classification problems. The performance of CNNs is generally higher when the number of the input data is high. However, in this study, the success of the pretrained CNN models is investigated when the data is limited. Considering this fact, in this study, rather than using complete face images, only the one eye image regions with eyebrows are used for the gender classification. The performance results present that the best CNN models are NASNetLarge and Xception models.

Keywords: Eye region, facial data, Classification with CNN, Layer structure

Introduction

Today, artificial intelligence solves many problems related to human recognition. For instance, the face, fingerprint (Cimtay et al., 2021), speech, iris are some of the human data to be used by artificial intelligence models. Human gender recognition from face data is also a challenging topic today due to the rapid change of human face. The performance of the methods may easily decline by the change of the face like with/without moustache, beard or with aging. It can also be affected by the orientation of the head. In literature, many methods and models have been developed by researchers to solve those kinds of problems and provide accurate results (Danisman et al., 2015).

Deep learning has gained much more interests in the application areas of automatic feature extraction, object recognition, classification, etc. Especially, more complex and deep convolutional neural networks perform high accuracy. By drawing inspiration from various areas, deep learning has been also applied for gender classification from face images. The study in (Janahiraman et. al., 2019) creates a dataset which is composed of the facial images of Caucasian and Malaysians people and applies various Convolutional Neural Network

(CNN) architectures to conduct a gender classification. It reports 88%, 85% and 49% accuracy by using VGG-16, ResNet-50 and MobileNet models respectively. The study conducted by (Akbulut et al., 2017) applies CNN and Local Recipient Areas Excessive Learning Machine (LRA-ELM) methods on Adience dataset (Eidinger et al., 2014) and achieves 80% and 87.13% for LRA-ELM and CNN, respectively. The study in (Arora et. al., 2018), approximately uses 1500 face images where most of them were chosen from CASIA dataset (Dong et al., 2011). It develops a CNN and achieves 98.5% gender classification accuracy. The study conducted by (Raza et al., 2018) develops a deep learning method for classifying pedestrian gender. The pedestrian was segmented from the picture using a preprocessing step. Then, for classification, stacked auto encoders with a softmax classifier were utilized. It achieves accuracy rates of 82.9%, 81.8%, and 82.4% percent in the front, posterior, and mixed views, respectively on MIT dataset (*Pedestrian Data*, *2021*), and about 91.5% in the PETA dataset (Deng et al., 2014). In (Gündüz et. al., 2019), a comparative analysis is performed between the CNN models: Proposed CNN, AlexNet and VGG-16. 72.20%, 65.63% and 99.41% accuracies have been obtained respectively. Another study in (Levi et. al., 2019) proposes a simple CNN to improve the performance of gender classification. Promising accuracy results have been obtained on Adience dataset. A Resnet-101 CNN based method called Hyperface is proposed in (Ranjan et al., 2017). This method increases the gender recognition rate and speed.

The study in (Abdalrady et. al., 2020) reports the interchange of traditional CNN models with the PCANet model for gender categorization. In addition, by using PCANet, it is able to decrease the size of the network design in complicated CNN models. For gender categorization, this technique has an accuracy of 89.65%. In (Yu et al., 2017) researchers proposes a CNN with reduced number of layers. By applying the method on a dataset composed of 1496 body images, it achieves 91.5% accuracy.

In this study, gender classification from facial images is reduced to gender classification from eye images. Therefore the dataset and region of interest is narrowed. Since, pretrained CNN models perform very promising scores on image classification problems, in this study, several state-of-the-art CNN models which have not been applied on that specific classification problem, are employed on a well-structured eye images dataset. The rest of the paper is organized as follows. Section II provides some information about the dataset used in this study and provides the details of our methodology. In Section IV, the classification results are presented. Finally, the paper is completed with concluding remarks.

Materials and Methods

Figure 1. Selected female eye images from the dataset

Figure 2. Selected male eye images from the dataset

Datasets

There are many face datasets such as Adience, FERET (*color-feret-database*, 2021), Gallagher's dataset (Gallagher et. al., 2008), LFW (Huang et al., 2007) which have been used for gender classification in the literature. However, they all provide the whole face imagery and segmentation of eye is an additional work for the researchers. Since this study conducts a comparative analysis between state-of-the-art CNN models only by using the eye images, we use the dataset named "Female and Male" which is referenced in (*eyes-rtte*, 2021). This dataset includes only the eye images which are extracted from whole face images. Note that it usually includes either complete or some part of eyebrows also. Moreover, it includes 5202 female and 6323 male eye images. Figure 1 and 2 show female and male eye image examples from this dataset.

Method

In this study, authors aim to investigate the success of different state-of-the art pretrained deep learning models on gender classification from eye images. For that purpose, InceptionV3, InceptionResnetV2, Xception, NASNetLarge models are used as the base model. The base model is supported with GlobalAveragePooling, Dropout and Dense layers. Dropout layer is used to prevent the network from a possible overfitting problem.

In this study, to remove the effect of different lighting conditions, each eye image in the dataset is normalized. We use 4-fold cross validation to train and test the deep models. Image dataset is first shuffled and then randomly divided into 4-folds. Therefore, for each fold, 75% of eye images are assigned as training set and 25% is assigned as test set. The training is implemented by using Keras on Python environment. The image sizes are adjusted as 75x75. The designed layer structures are given in Table 1.

Table 1. Layer description of CNN models

Layer number	Layer Type	Output shape
1	InceptionV3 InceptionResnetV2 Xception NASNetLarge	(None, 75, 75, 3)
2	InceptionV3 InceptionResnetV2 Xception NASNetLarge (functions)	(None, 8, 8, 2048)
3	GlobalAveragePooling2D	(None, 2048)
4	Dropout	(None, 2048)
5	Dense	(None, 2)

The training parameters of CNNs are given in Table 2.

Table 2. Training parameters of CNN models

Parameter	Value
optimizer	Adam
loss	categorical_crossentropy
shuffle	True
Number of epochs	30
batch_size	64

Table 3. Keras models

Model	Size (MB)	Top-1 Accuracy	Top-5 Accuracy	Parameters	Depth	Time (ms) per inference step (CPU)	Time (ms) per inference step (GPU)
InceptionV3	92	0.779	0.937	23,851,784	159	42.25	6.86
InceptionResNetV2	215	0.803	0.953	55,873,736	572	130.19	10.02
Xception	88	0.790	0.945	22,910,480	126	109.42	8.06
NASNetLarge	343	0.825	0.960	88,949,818	-	344.51	19.96

The model's size, accuracy, number of parameters, depth and time inference steps for CPU and GPU are given in Table 3 (*Keras applications*, 2021). NASNetLarge model has a huge number of parameters however the maximum top-1 and top-5 accuracy.

Results and Discussion

In this study, authors aim to investigate the use of pretrained deep models on gender classification from eye images. The most successful pretrained deep models namely InceptionV3, InceptionResnetV2, Xception and NasNetLarge are used. The mean confusion matrixes for different deep models are given in Tables 4-7. The right bottom corner of each table provides the general mean accuracy and standard deviation which is calculated from the accuracy scores of the folds. Furthermore, the mean Recall, Precision and F1 scores are also presented. As it can be obtained from the tables, very promising classification performances are handled.

Table 4. Confusion matrix for InceptionV3 model

	Model : InceptionV3			Recall	Precision	F1
Target class	Female	1251	50	96.19	95.20	95.69
	Male	63	1518	96.01	96.84	96.42
		Female	Male			
		Predicted class		Accuracy : 96.09±0.3		

Table 5. Confusion matrix for InceptionResnetV2 model

	Model: InceptionResnetV2			Recall	Precision	F1
Target class	Female	1246	55	95.79	95.13	95.45
	Male	64	1517	95.96	96.51	96.23
		Female	Male			
	precision	Predicted class		Accuracy: 95.88±0.6		

Table 6. Confusion matrix for Xception model

	Model: Xception			Recall	Precision	F1
Target class	Female	1251	49	96.21	97.09	96.64
	Male	38	1544	97.62	96.90	97.25
		Female	Male			
		Predicted class		Accuracy: 96.98±0.2		

Table 7. Confusion matrix for NasNetLarge model

	Model: NasNetLarge			Recall	Precision	F1
Target class	Female	1256	44	96.57	94.36	95.45
	Male	75	1506	95.25	97.12	96.17
		Female	Male			
		Predicted class		Accuracy: 95.85±0.8		

Although all of the models used in this study achieves very good results, the best model according to Recall, Precision and F1 scores are given in Table 8. As can be observed from the table, Xception and NASNetLarge deep CNN models are determined as the best ones.

Table 8. Best models for recall, precision and F1 scores

Criteria	Best Model
Mean Accuracy	Xception
Male Recall	Xception
Female Recall	NASNetLarge
Male Precision	NASNetLarge
Female Precision	Xception
Male_F1	Xception
Female_F1	Xception

Conclusion

This study presents the classification performance of state-of-the-art deep CNN models: InceptionV3, InceptionResnetV2, Xception and NASNetLarge on gender classification from eye images. These models have been trained with "Female and Male" dataset. Results have shown that although the facial data is limited to the single eye region, the accuracy, recall, precision and F1 scores are still very high. This shows that the feature points on the eye region are determinative on gender classification. This is due to the physical differences between male and female eyes like the shape and slant, and also the shape and smoothness of eye brows. The employed models are all very successful, however according to the scores, NASNetLarge and Xception models are the best ones.

Scientific Ethics Declaration

The authors declare that the scientific ethical and legal responsibility of this article published in EPSTEM journal belongs to the authors.

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