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ScienceDirect

Procedia Computer Science 00 (2022) 000–000

Procedia Computer Science

www.elsevier.com/locate/procedia

Face and Iris Recognition using CNN models: An analytical study

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Abstract

Two of the most common biometrics features that are widely used are face and iris. Facial and Iris recognition plays a major role where very high security is demanded to overcome the limitations like copying token-based passwords, some sort of key, or even fingerprints. In this work, we have analysed face and iris recognition using different CNN architectures. Yale dataset and UBIRIS datasets are used for face and iris respectively. Facial features like the spacing of eyes, bridge of the nose, ears, chin, etc. are extracted for the face while around 240 biometric features are extracted the for iris. The experiment results show accuracy equal to 94.73% (Vgg16), 85.42% (Densenet201), and 82.94% (Xception) for face, and similarly for iris accuracy was equal to 90.16%(Vgg16), 83.60%(Densenet201), and 80.32%(Xception). This analysis shows that Vgg16 performs superior to the rest of the architectures that were experimented on in this paper.

Keywords

Biometric Recognition, CNN, Iris Recognition, Face Recognition, Authentication.

I. Introduction

Security has been a major point of discussion since the very beginning. People by default are protective of their belonging, and we have managed to come far in terms of our progress in the security field. Earlier we used token-based features like some sort of key or id for security purposes, but the issue with this approach is that it can easily be lost or counterfeited. Then we started using knowledge-based features like passwords or answers to security questions. Even though this seemed pretty good, it was still not safe for the public cause you could forget your password or the answer you choose someone may end up guessing it right [1].

These issues made people think that what we can use to improve our security even further. The first person to ever use biometrics features was Alphonse Bertillon in France where he used measurement of the body to keep records of criminals which help in identifying them later. Even though this approach had many flaws, this sparked the beginning of using biometrics features for security purposes. Unlike token-based features, these can't be lost and unlike knowledge-based features, these can't be forgotten, these were the major benefits biometrics had over others [2].

Biometrics recognition is using any part of your body as a feature to recognize you. It can be the face, finger veins, palm, iris, ear, or voice. These are becoming more common is day to day life as you can see in your phones which have at least 3 of the below mentioned, either it is voice, face, or fingerprint. Biometric recognition had a surge of usage lately as soon as they released it for common people like in phones, houses, or other places that are easy to access for anybody. It was used a lot in offices or other industrial places since long before it became available for everyone but slowly it was popularized and now it can be found everywhere. We here are using Facial recognition and Iris recognition. Our proposed system is using 3 different pre-trained models and running a one data set each for iris and facial and then comparing results that we are getting for iris and facial. The three pre trained models we are using are VGG16, Densenet201, Xception. The purpose of our proposed system is to compare and analyse the result of different models and see which model is performing better for us in different scenario and overall which model works best to use it for major projects. This helps to reduce the time it takes to check which model is working best for any project by running multiple models at the same time [3] [4]. Shown below are samples from the dataset we used. Figure 1 shows sample from facial dataset and Figure 2 shows sample from iris dataset.

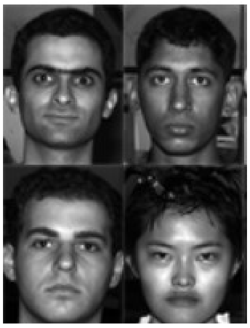

Figure 1 Sample of our facial dataset

Figure 2 Sample of our iris dataset

Our contribution: In this research paper, we have analyzed the performance of VGG16, DenseNet201, and Xception CNN models on two different datasets, the Yale Extended B dataset, and the Ubiris dataset. To evaluate the performance of the CNN models, we have calculated performance metrics like the Cohen kappa score, sensitivity, Matthew's correlation coefficient, and accuracy, these are explained in detail in section 4.2 of the research paper.

The rest of the paper is organized as follows. Section 2 of the research paper includes some of the leading research published on biometric recognition and most of them include the use of pre-trained CNN models. Section 3 explains the algorithm used for training and the performance evaluation of CNN models for both face and iris recognition. Section 4 explains the performance metrics used and shows the performance of the CNN models in tabular form. The work done in the research paper is finally concluded in Section 5.

II. Literature review

In biometrics, the individual biological characteristics of each person are stored in a template and then the template is presented in the identification process which then is compared to the template stored before that. Therefore, not every biological measure is a biometric measure unless it contains some important properties such as universality (UV), uniqueness (UQ), permanence (PM), and vulnerability. Universality factor (UV) means that this can be applied to everyone. Uniqueness factor (UQ) means that any two people cannot have or possess the same patterns for these biometric measurements. Permanence factor (PM) means that these patterns are unique to each person, and these don't change overtime. Hair colour or body weight are biological measures, but problem with this is they can change overtime hence they are not reliable [5], [6]. The importance of each of the above-mentioned traits in each iris and face recognition method is shown in

Table 1.

Table 1 Importance of various factors

Factors	Face	Iris
UV	H	H
UQ	H	H
PM	L	H
Accuracy	M	H
Vulnerability	M	L
Security	M	H

In [1], the authors developed a multimodal biometric model for user identification. This system employed the CNN deep learning algorithm. One of the models they used was VGG16 and the data set they used was SDUMLA-HMT. They worked on three different biometrics traits in this system namely iris face and finger veins. Since they were using three traits their accuracy was upwards of 99.39%.

In [7] , the authors discussed background information on the anatomy of an iris, a detailed history of how iris became one of the traits of the recognition system, and a general framework of iris recognition in use currently. They also studied various publicly available iris databases. Some of the datasets they studied were Ubiris both versions (1 and 2), and every cassia-iris dataset available (interval, lamp, twins, etc.)

In [8], the authors reviewed different algorithms used in iris recognition. They first showed the stages of the iris recognition algorithm which were: iris image capture, image pre-processing, feature extraction, template matching, and then finally result. Then they explained algorithms for every step mentioned above some of them are Hough transform, Integro-Differential operator, Bisection method, Black Hole search method, etc.

In [9], the authors showed the basic structure and principles of CNN. This paper elaborated on the CNN model by layering the sampling layers and convolutional together. Model they used, contains two sampling and convolution layers, a Softmax layer after a fully connected layer.

III. **Proposed Method**

3.1 Facial Recognition

In this section, we use the Yale B dataset and run it in three different pre-trained models mentioned below and then compare the results we get from them to others. The process of facial recognition starts from the model using a haar cascade classifier for facial detection then the facial images are cropped accordingly. The dataset is then converted into a NumPy dataset for facial classification where we run them in below mentioned pre-trained model, we do this in all three models then we compare their results.[10]. The algorithm we used in our proposed method is shown below in Figure 3

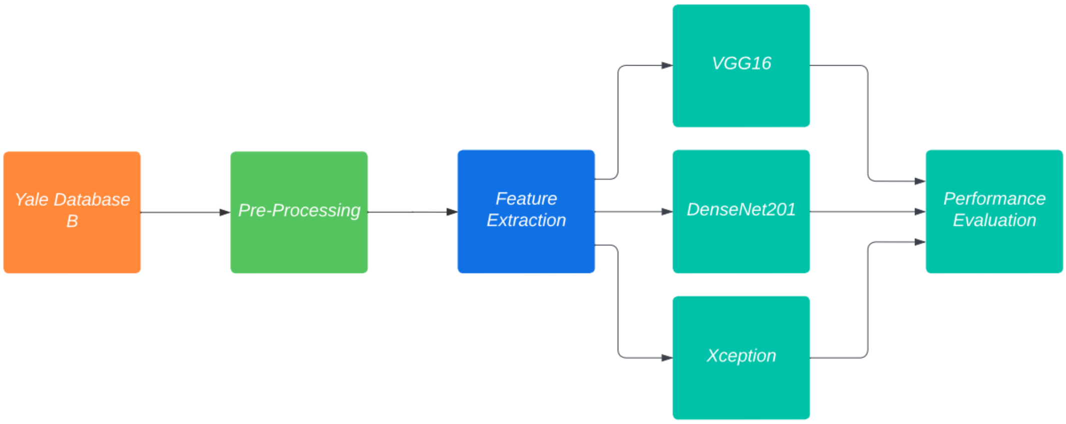

Figure 3 algorithm for facial recognition

3.1.1 Dataset

For the process of face recognition, we use the extended Yale B dataset for classification. This database contains 2414 pictures of 38 subjects. There are close to 64 pictures per subject, with some of the features used that are mentioned below:

Center-focused, happy, sad, sleepy, surprise, wink, left-right etc [11].

A sample of the Yale B face dataset is shown in

.

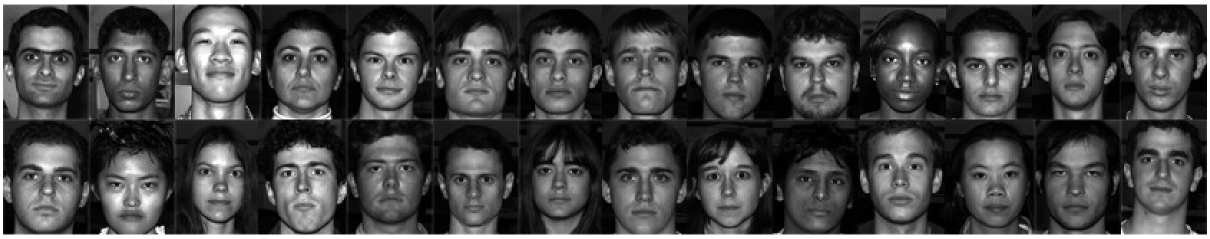

Figure 4 Yale extended

3.2 Iris Recognition

The process of iris recognition can be divided into 4 steps, eye detection, iris detection, iris segmentation, and iris classification. We used the ubiris dataset for iris recognition. The model uses haar cascade classifiers to detect eyes. Then Hough transform is applied to the images for iris detection and the images are sent for iris segmentation. After iris segmentation, the iris classification phase starts, and we use the pre-trained models mentioned below for classification [12]. The algorithm we used for iris recognition is show in Figure 5.

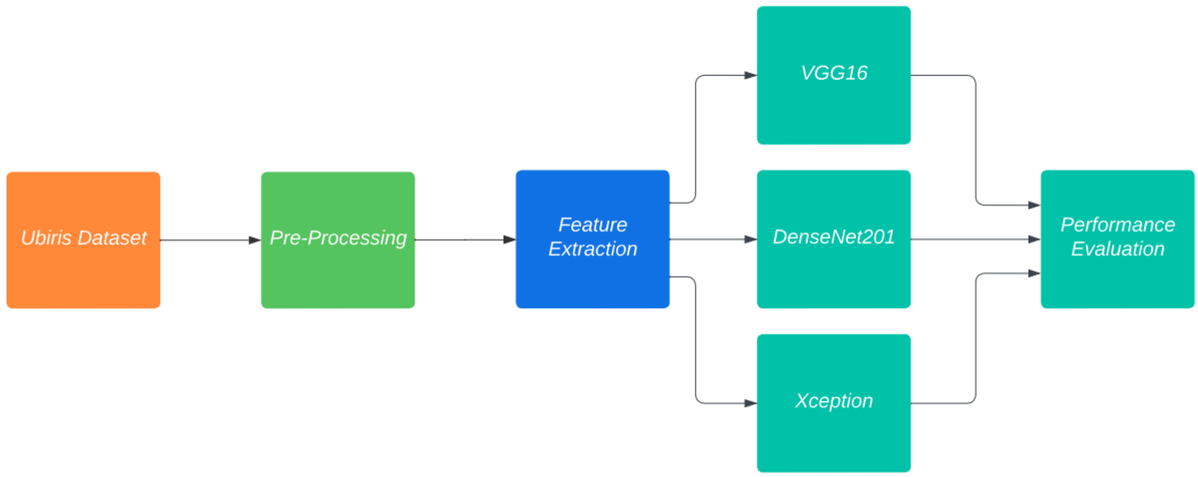

Figure 5 algorithm for iris recognition

3.2.1 Dataset

The UBIRIS dataset contains images of 241 persons and a total of 1877 images. This dataset contains images with several noise factors that better evaluate the iris recognition methods. The images have been captured in two sessions.

The first session minimized the noise factor-like reflections, luminosity, and contrast by setting up the framework in a dark room.

In the second session, the picture capture location was changed to the natural brightness factor. This promotes the appearance of heterogeneous images dealing with problems of reflection, contrast, brightness, and concentration [13].

IV. Results and discussion

4.1 Experimental Setup

The only way to check if the results are reliable enough is first going through which system they were running on. If the system is not powerful enough then people will question the reliability, accuracy, and efficiency of the work we have done. We applied different matching algorithms and feature processing to our proposed system. Experiments are performed on windows 11, processor ryzen 7 4800h with 8 cores, and 16GB ram to gain high accuracy and performance. For facial recognition, we used the yale B dataset which has 2414 images of 38 subjects (11 photos each). And for iris recognition, we used the ubiris dataset which has 1877 images from 241 persons which are in JPEG format[5].

4.2 Evaluation Criteria

After running yale B and ubiris in those pre-trained models mentioned below we noted down the results which are shown in table no. 3 and 4. Some of the key points used in the table are explained below:

- Accuracy: Accuracy mentioned below can be defined as which model is best at identifying patterns between databases based and the input data. Formula for accuracy is shown in Equation 1.

$$Accuracy = \frac{TN+TP}{TP+FP+FN+TN} * 100 \quad (1)$$

- Loss: it can be defined as the penalty for a bad prediction i.e., a number indicating how bad the model's prediction is in that instance.

- Sensitivity: It is basically a measure of a model on how well it can detect positive instances. It is also known as true positive rate (TPR). Formula for sensitivity is shown in Equation 2

$$sensitivity = \frac{TP}{TP+FN} \quad (2)$$

- Cohen's Kappa: Cohen's kappa statistics are used to measure the degree of agreement between two evaluators or judges. Each evaluator or judge classifies items into mutually exclusive categories. Formula for Cohen's Kappa is shown below in Equation 3.

$$k = \frac{P_{observed}-P_{chance}}{1-P_{chance}} \quad (3)$$

- MCC: Matthews correlation coefficient (MCC) can be defined as a metric that we can use to assess the performance of a classification model. Formula for MCC is shown below in Equation 4.

$$MCC = \frac{TP*TN-FP*FN}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}} \quad (4)$$

4.3 Performance evaluation of proposed work

Facial Recognition:

In this proposed method three different models for comparison study were used (i.e., Vgg16, Densenet201, Xception). During our study we found out that Vgg16 had an Accuracy of 94.73%, Loss of 0.61, Sensitivity of 0.89, Cohen's Kappa 0.88 and MCC of 0.89. Densenet had an Accuracy of 85.42%, Loss of 0.79, Sensitivity of 0.84, Cohen's Kappa 0.83 and MCC of 0.83. Xception had an Accuracy of 82.94%, Loss of 0.78, Sensitivity of 0.79, Cohen's Kappa 0.77 and MCC of 0.78. From what we have seen from our results it shows that Vgg16 is best suited for Yale-B dataset we used. Details of our result is shown below in Table 2

Table 2 result of facial recognition

S.No.	Model	Accuracy	Loss	Sensitivity	Cohen's Kappa	MCC
1	Vgg16	94.73	0.61	0.89	0.88	0.89
2	Densenet201	85.42	0.79	0.84	0.83	0.83
3	Xception	82.94	0.78	0.79	0.77	0.78

Iris Recognition:

In this proposed method three different models for comparison study were used (i.e., Vgg16, Densenet201, Xception). During our study we found out that Vgg16 had an Accuracy of 90.16%, Loss of 0.78, Sensitivity of 0.87, Cohen's Kappa 0.86 and MCC of 0.85. Densenet had an Accuracy of 83.60%, Loss of 1.03, Sensitivity of 0.82, Cohen's Kappa 0.80 and MCC of 0.81. Xception had an Accuracy of 80.32%, Loss of 5.16, Sensitivity of 0.79, Cohen's Kappa 0.79 and MCC of 0.79. From what we have seen from our results it shows that Vgg16 is best suited for Ubiris dataset we used. Results of this dataset were somewhat inferior to what we have seen in facial recognition is due to the fact that data set we used for iris had a lot of noise in it which was not the case in facial recognition. Details of our result is shown below in Table 3

Table 3 result of iris recognition

S.No.	Model	Accuracy	Loss	Sensitivity	Cohen's Kappa	MCC
1	Vgg16	90.16	0.78	0.87	0.86	0.85
2	Densenet201	83.60	1.03	0.82	0.80	0.81
3	Xception	80.32	5.16	0.79	0.79	0.79

V. Conclusion

In this article, a smart multimodal comparison system for comparing results of different models on a single dataset is proposed in which we extract different features and then compare to the ones we have already stored. The proposed system will help in identifying the unique patterns of iris and face features for each individual and then compare results we get from different models we used to check which works best for our dataset and then use that model for our further research. This proposed system helps in identifying the best model that works for our data set by using multiple models at a time by doing so we reduce the time it takes to compare result by three folds as we are using three models at a time which cannot be achieved by a single model system. Several runs were performed on a dataset containing 38 subjects for face and 241 subjects for iris to measure the accuracy between the three used models. The results of the proposed system showcased that Vgg16 was our best performing model among its piers and the accuracy it gave is 94.73% with a loss of 0.61% along with sensitivity of 0.89, Cohen's kappa of 0.88 and mcc of 0.89and for iris recognition Vgg16 was best performing model with an accuracy of 90.16% with a loss of 0.78% along with sensitivity of 0.87, Cohen's kappa of 0.86 and mcc of 0.85.

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