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Identifying Humans Based on Biometric Iris Recognition using an Interactive Transfer Learning Framework

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Abstract: Deep learning recently unveiled the most well-known methods for picture recognition. The most common method used for identification is human verification based on biometric samples. The prohibitive cost of creating, training, and using such models for the expansion of computer vision applications is the key barrier in such fields. To solve this issue, transfer learning provides flexible solutions to model the appropriate Convolutional Neural network (CNN) quickly and efficiently. In such a framework a previously trained CNN on a large dataset with a high number of classes is adapted to the at-hand taxonomizing problem. Iris is one of the most challenging biometric samples due to its nature besides having dual samples per person, meaning that a right and left iris samples. The transfer learning framework presented in this article relays on three well-known CNN models to model an iris based human recognition model. The selected MMU iris image database is analyzed and investigated using the most famous CNN models, which are Inception V3, Xceptions and InceptionResNetV2. The findings showed that the proposed framework is robust and reliable for the purpose of iris based human recognition with a high performance in the test stage, what proves our hypothesis applying proposed transfer learning framework.

Keywords: Recognition; Transfer; Learning; MMU database; Inception V3, Xception, InceptionResNetV2, Evaluation Measures.

1 Introduction

Recent years have seen the production of passports and biometric ID cards in several nations based on iris, facial recognition, and fingerprint technology to streamline airport security checks and facilitate passenger transit. In [1], In Australia and the UK, face recognition technology is being used to create biometric passports. Technology has been created to automatically take a person's picture and compare it to the pictures of biometric passports that are stored in a database. One of the biggest issues with secured access to data is user authentication. Using the distinctive characteristics of the iris, the iris can be used as a means of authentication and recognition. Other applications for it include ATMs and biometric recognition systems. This system often has several operating phases. Due to the iris dependability as a biometric sample, it turns out to be an extremely helpful strategy in most situations [2]. One biometric technology that makes use of the iris is the iris biometric. The iris is the spherical area of the eye that is surrounded on either side by the sclera (the white of the eye) and pupil. The sphincter and dilator muscles, which change the size of the pupil, work in conjunction with the iris to control how much light enters through the pupil. The pupil size ranges from 10% to 80% of the iris diameter, and the typical iris diameter is 12 mm (about 0.47 in) [3]. Iris recognition technology recently played a significant part in the safety and protection of areas that require high security precautions. There are numerous traditional stages in handcrafted techniques. The stages are iris localization, feature encoding, iris template matching, and ocular image acquisition. The second stage and bottleneck of an iris recognition system is iris localization. The subsequent phases won't be processed correctly if the iris in the eye image cannot be appropriately localized. Finding the iris requires processing a few difficulties. First off, a single static threshold cannot be used to threshold the gathered gray-scale eye images with various illuminations. The second factor that affects iris localization and reduces iris identification performance is iris occlusion brought on by eyelids and eyelashes. Thirdly, during picture capture, a bright spot-on pupil introduces some noise that

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messes up the iris localization procedure. Finally, the inability of the iris recognition system to localize the outer iris boundary may be caused by the low contrast between the iris and sclera. These problems emphasize the importance of choosing different threshold values for different pictures as well as the significance of increasing the iris boundary's contrast before localizing it. The Iris is a colorful, circular portion of the eye that is situated in the center. Each person's iris pattern is unique. The general procedure of identifying and validating a person is completed first, after which the iris picture is transmitted to data analysis for the extraction of features for each sample and is prepared for the authentication process [4,5,6].

2 Related Work and Organization of This Article

Demonstrating a deep learning-based multi-biometric iris identification system, authors [7] presented an original perspective on Multimodal biometric systems. Considering the widespread use of biometric systems for numerous applications throughout the world, the authors choose to concentrate on the multi-biometric Iris recognition system employing the deep learning approach. Iris then uses the different image templates that were gathered for segmentation. One of the most crucial stages of the entire procedure is this one. The feature extraction step is the third. The unnecessary characteristics and Iris image templates are eliminated, and the useful ones are extracted. This method has proven to be extremely helpful in the field of biometric recognition. Meanwhile authors in [8] present a Multitask CNN for Joint Detection of Presentation Attacks and Iris. The authors of this paper presented a method that combined PAD with iris detection using a CNN. It offered a fresh idea that might be applied broadly. It takes its cues from an object detection method that could omit variables essential to its proper operation. The sensing and recognition mechanisms are carried out using sensors. The categorization must be quite precise. The next phase is pattern matching. Another crucial component of the overall system is this. Many times, the facial features are complicated and detailed that the taxonomy and attribute extraction might fail to accurately, advocated employing segmentation methods derived from deep learning to improve iris authentication on mobile devices [9]. The authors of the research presented a unique strategy that would use deep learning segmentation techniques while simultaneously enhancing the Iris authentication technology used by mobile devices. Since iris segmentation and localization features are so common, suitable results are not produced. The number of frauds and unlawful and unauthorized efforts to infiltrate the systems is rising along with the number of users and data. Therefore, appropriate and efficient biometric authorization systems must be prepared to manage such situations. Therefore, this strategy was highly desired. Co-occurrence Features and a Neural Network Classification Approach for Iris Recognition were discussed by the [10]. A strategy for iris recognition based on co-occurrence characteristics and neural network classification was put forth in this paper. It was demonstrated that the suggested method of using grey co-occurrence features works very well to separate iris-based images. Based on classification accuracy, the proposed method's evaluation was examined. The MMU iris database was the one that was used. The proposed methodology has a best accuracy of 97.83 percent, which is comparable to state-of-the-art methods. ContlensNet: Robust Iris Contact Lens Detection Using Deep CNNs (Convolutional Neural Network) was presented by [11]. Contact lenses are a common last resort for many people. In these situations, the strategy to iris recognition needs to be slightly different. The genuine iris portion of the eye is covered by contact lenses, making it more challenging for the iris sensor to recognize it. The CNN technique is used in this work to offer a model of Contlens for efficient Iris contact lens detection. It has about 15 layers and an exceptionally reliable detection system in place. There are instances where many Iris images contain pixel properties and values that are comparable, and. Using fully convolutional networks, authors in [12] have demonstrated accurate iris segmentation in non-cooperative settings. The iris recognition techniques function in a specific way when the circumstances are right. It is a simple assignment with high user cooperation and a cooperative environment. In contrast, it becomes a challenging task in non-cooperative contexts when there is a high incidence of blur, disturbances, less user participation, and other unanticipated events. Therefore, the focus of this research is on reliable iris authentication in hostile circumstances. It makes use of the idea of neural networks that are completely conventional. Iris image noise is a significant issue. Additionally, those that are moving make a lot of movements. Such situations call for this strategy. Iris recognition using machine learning techniques: A survey is provided by [13]. Amazingly quickly, the techniques of machine learning are being used. Many job processes are being redesigned thanks to automation and artificial intelligence technology. Many different disciplines are using machine learning as a vast area of research. The study is used for recognition in their work. Research is done on the effects and applications of machine learning in recognition systems. It is considered how well the strategy handles the intricacy of the recognition technique. Therefore, the requirement of the hour is for a high-end system that can precisely pinpoint the specifics. A work employing SVM and ANN for iris identification was given by [14]. For iris recognition, this article employs the support vector machine and ANN methods. To separate the area for the iris segmentation, the Hough transform is also used. Based on the photographs that match and do not match, the Iris extracted images are categorized. Using this information, the system determines if the user has been authenticated or not. The categorization must be quite precise. The next phase is pattern matching. It functions effectively when the two approaches are combined. An experimental study of deep convolutional features for iris recognition is described [15]. A study on the Depp convolutional characteristics for iris detection was provided by the researchers. Regarding iris identification, the iris's characteristics are crucial. The iris of every individual varies in terms of some traits that are the same and others that are different. Therefore, a thorough investigation of the eye's iris is a difficult undertaking. In the past, many of these procedures required manual Laboure. The database needs to be comprehensive and accurate to contain every potential image of the iris and provide every form of user identification. The segmentation of the iris comes next. Iris's gathered image templates are employed for segmentation after that.

The remaining sections of this article describe the proposed solution for a fast and accurate human identification based on biometric iris. In section 3, the CNN transfer learning-based framework is presented. Besides, a description of the MMU iris database in section 4. Meanwhile the study findings and results discussion with a conclusion is presented in sections 5, 6 and 7.

3 Proposed Transfer Learning Framework

In this study, we developed a model architecture based on three pre-trained models and a block with three different regularization layers for the generalization process to reduce the over-fitting of the classification of Iris images additionally, to avoid starting from scratch with training data and save training time, we used a transfer learning technique developed using ImageNet data. Tunable parameters include the number of layers in a CNN model and the number of components in each layer, which change depending on the operation to be done. One of the most important requirements for a neural network model to provide highly correct results is that it be trained with a large and diverse set of data. Much research employs ultramodern CNN models, which successfully classify 14 million images in the ImageNet dataset and produce high-accuracy results when applied to diverse disciplines. Five of these models, which are often used in academia, were utilized to classify the data in this investigation.

4 MIMU Iris Database

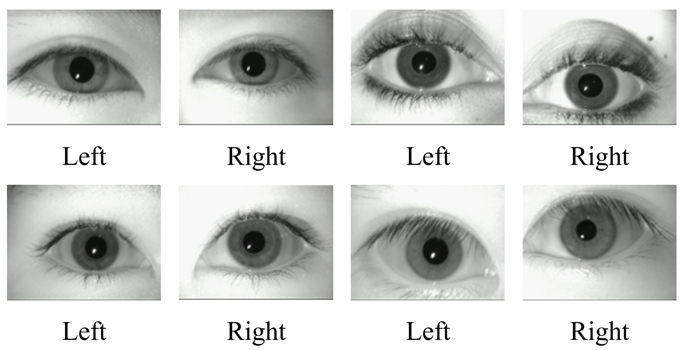

Fig. 1: Samples with a random selection through the MMU Iris Database for Human Biometric Verification.

MMU: A public database called Multimedia University (MMU1) contains eye images for training IRIS-based biometric attendance models. Each person's IRIS patterns for each Eye are distinctive, and thus makes it easier to recognize a certain person. This dataset includes 460 images in total, including 5 photographs of each left and right IRIS from 46 individuals. IRIS segmentation can be used to identify a specific person or classify an IRIS image using a database that has been saved. [16]. A sample of this database is presented in fig. 1.

5 Pre-trained CNN Models

Inception V3 [17] is a CNN trained on the ImageNet dataset, it has been proved to achieve an accuracy rate of more than 78.1 percent, making it a widely used image recognition model. This model is the confluence of many concepts that researchers have developed over time. A deep neural network with 42 layers makes up the Inception-v3. The inception-v3 model's building blocks include convolutions, max-pooling layers, average pooling, dropouts, and FC layers. L1, and L2 regularizes are used to improve the learning process, and weight regularizes are used to encourage the network to support small weights. It can be applied as a general strategy to decrease over-fitting during training and enhance the generalizability of the model. The addition of the batch normalization layer has a fundamental effect on network training. It considerably smooths out the terrain of the relevant optimization issue. This makes the gradients more predictable, enabling the adoption of a wider variety of learning rates and accelerating network convergence. Most large network architectures can be generalized using the dropout layer as a generalization technique. To reduce the risk of over-fitting, it is integrated into the model architecture. InceptionResNetV3 [18], a CNN model, came out on top in the ImageNet competition with an error rate of just 3.5 percent. InceptionResNetV3 structure is based on microarchitecture modules, in contrast to conventional sequential network models. Theoretically, success should rise with the number of layers in a model, but adding more parameters makes training and optimization more challenging. Low activity neurons in the neural network lose their effectiveness during training, and residues appear. Blocks that feed these residues to the following layers are added to build the InceptionResNetV3. There are multiple ResNet variations that use a varied number of weighted layers. By allowing the gradient to travel across this added shortcut gradient, InceptionResNetV3 lessens the issue of vanishing gradients. If the current layer is not needed, the InceptionResNetV3 model can skip the CNN weight layer thanks to identity mapping. This aids in preventing the over-fitting issue with the ResNet50 training sets 50 layers. The Xception [19] model was presented by Google. The input format for the Xception is a 299x299 RGB image. With 36 convolutional layers to extract features, it has a depth of 126. To reduce the number of parameters, the fully connected layer is swapped out for a global average pooling layer, and the prediction is generated using the SoftMax function. Except for the first and end modules, all the 14 modules composed of the 36 convolutional layers have linear skip connections surrounding them. Entry flow, middle flow, and exit flow are the three sections that form the 36 convolutional layers. The entry flow, the middle flow, which is repeated eight times, and the exit flow are all the steps that the data must initially go through. The middle flow is made up of 8*3=24 convolutional layers, the exit flow is made up of 4 convolutional layers, and the entering flow has 8 convolutional layers. The Xception model uses depth-wise separable convolution, which can cut down on the overall cost of convolution operations

6 Results and Discussion

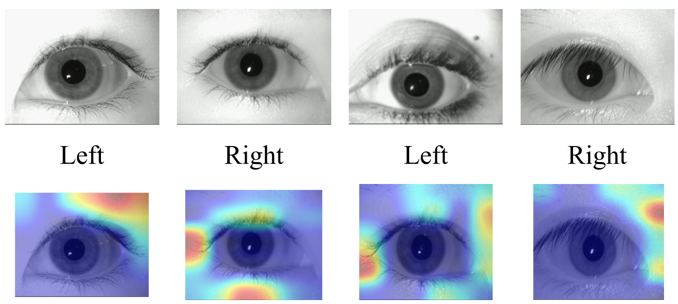

Fig. 2: Raw input samples important features of the MMU Iris Database for Human Biometric Verification.

It is essential to measure classification effectiveness in image classification research to scientifically validate the study's findings. Image categorization research has made use of performance assessment measures. These metrics are also utilized in this research to assess the accuracy and reliability of the classification phase. The model's effectiveness is determined by several characteristics, including accuracy, Error, sensitivity, specificity, error rate, precision, F1-Score, MCC, and Kappa statistical coefficient. These are accuracy, specificity, sensitivity, and precision. When the data in the classes is unbalanced, the MCC metric is a beneficial measure. Equations (1-8) show related formulations for each of these measures based on True Positive Rate (TPR), True Negative Rate (TNR), False Positive Rate (FPR), and False Negative Rate (FNR) outcomes.

$$Accuracy(Acc) = \frac{TNR + TPR}{TPR + FNR + FPR + TNR} \tag{1}$$

$$Error_{Rate} = 1 - \frac{TNR + TPR}{TPR + FNR + FPR + TNR} \tag{2}$$

$$Precision = \frac{TPR}{TPR + FPR} \tag{4}$$

$$Sensitivity = \frac{TPR}{TPR + FNR} \tag{5}$$

$$F1_{Score} = 2 \times \frac{Sensitivity \times Precision}{Sensitivity + Precision} \tag{6}$$

$$MCC = \frac{TPR \times TNR - FPR \times FNR}{\sqrt{(TPR + FPR) + (TPR + FNR) + (TNR + FPR) + (TNR + FNR)}} \tag{7}$$

The kappa statistic is a chance-corrected measure of agreement instead of correlation. Kappa eq. is described as follows:

$$Kappa = \frac{(\text{þ} - \text{ғ})}{(\eta - \text{ғ})} \tag{8}$$

Where þ is the real percentage of agreements among raters, ғ is the predicted percentage of agreements, and η is the overall count of observations. The performance results for the testing data based on three models, Inception V3, Xception, and InceptionResNetV3 are shown in figs. 3,4,5,6,7,8.

Table 1: Evaluation of model inference with TOP in performance rates marked in bold.

Measure	InceptionV3	XceptionNet	InceptionResNetV2
Accuracy	0.9603	0.9499	0.9367
Error Rate	0.0397	0.0501	0.0633
Sensetivity	0.9690	0.9624	0.9446
Specifity	0.9842	0.9802	0.9957
Precesion	0.9614	0.9776	0.9915
FPR	0.0158	0.0198	0.0243
F1 Score	0.9650	0.9546	0.9377
MCC	0.9493	0.5949	0.9134
Kappa	0.8941	0.8664	0.8311

Average metrics results are collected to get the actual predictions for all classes. Metrics such as accuracy, Sensitivity, specificity, error rate, precision, F1-Score, confusion matrix, FPR, MCC, and Kappa have been measured to assess the performance of all the models. Three models' accuracy scores show that CNN architectures can reliably diagnose Iris conditions. For Iris instances, InceptionResNetV2 outperforms the other two models with the all-metrics measures.

In the InceptionResNetV2 and Xception models, the TNR, which measures the model's capacity to prevent false alarms, is greater than 93.6 %. However, only InceptionResNetV2 is determined to have excellent Error Rate, and Sensitivity which measures a model's ability to recognize positive cases. Although the InceptionResNetV3 model is like Xception it cannot be regarded as a robust model because of its lower accuracy and precision rate.

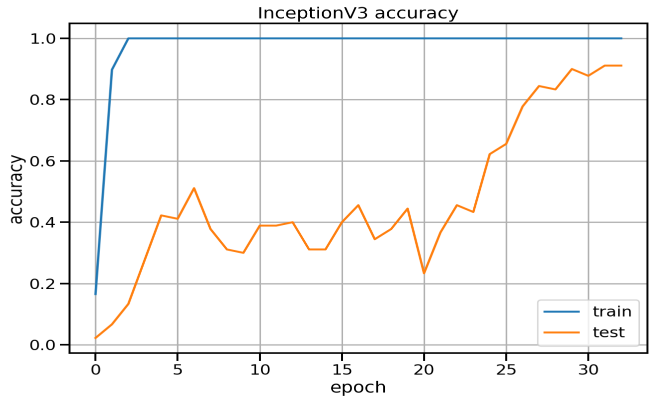

Fig. 3: Inception V3 transfer learning performance over 33 epochs of learning, learning rate=0.0001 and a batch of size 8 images per iteration.

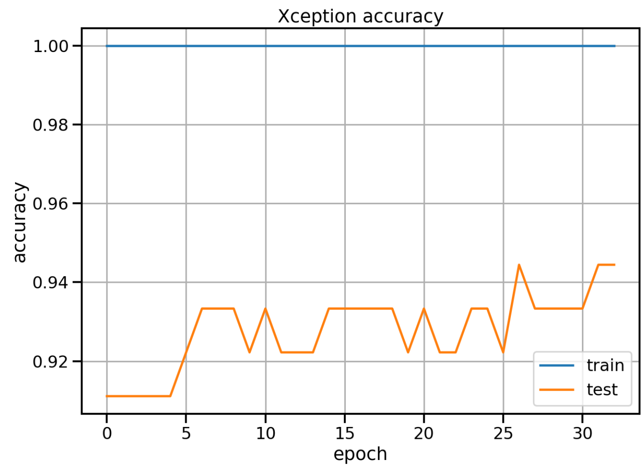

Fig. 4: Xception transfer learning performance over 33 epochs of learning, learning rate=0.0001 and a batch of size 8 images per iteration.

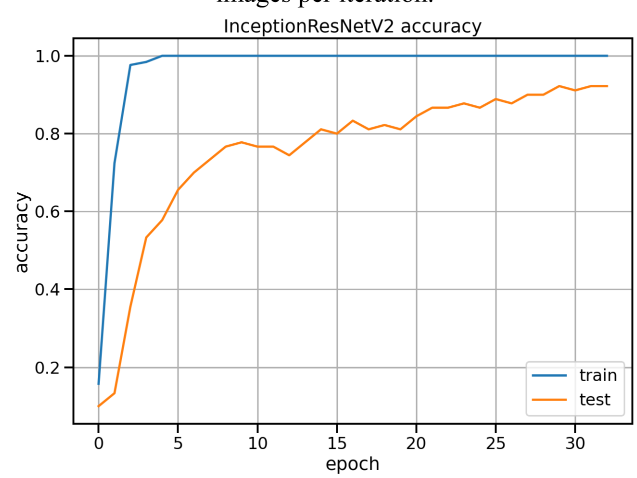

Fig. 5: InceptionResNetV2 transfer learning performance over 33 epochs of learning, learning rate=0.0001 and a batch of size 8 images per iteration.

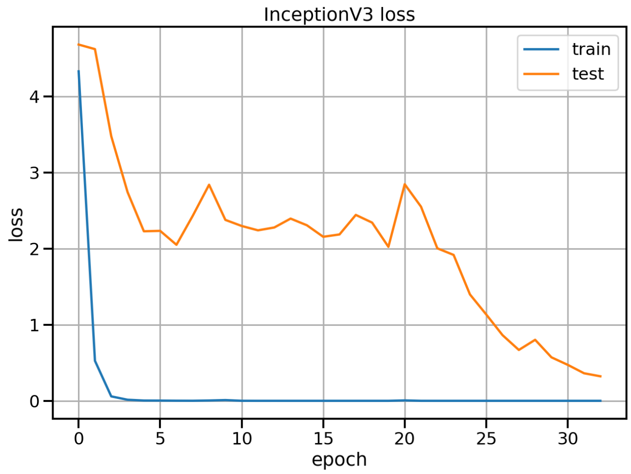

Fig. 6: Inception V3 transfer learning loss over 33 epochs of learning, learning rate=0.0001 and a batch of size 8 images per iteration.

Fig. 7: Xception model transfer learning loss over 33 epochs of learning, learning rate=0.0001 and a batch of size 8 images per iteration.

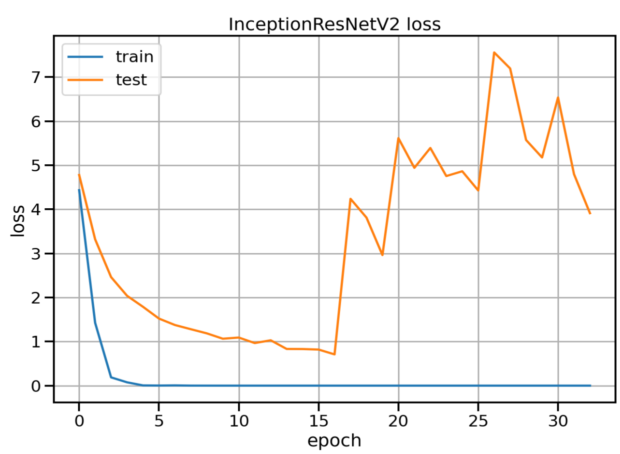

Fig. 8: InceptionResNetV2 model transfer learning loss over 33 epochs of learning, learning rate=0.0001 and a batch of size 8 images per iteration.

7 Conclusion and Future Scope

In this study, we developed a CNN model based on iris images to supply a quick and precise solution to the Iris detection issue. The primary innovation was the addition of regularization block layers between the network's CNNs. Three different deep CNN architectures were tested on imagery for Iris patient diagnostic suggestion in this study. During the study, all networks had pre-trained parameters that helped them transfer their prior experience to the dataset. These models were pre-trained using the ImageNet database as the model's foundation. The TP findings of the InceptionResNetV2 model are the best of all models. Regularization-based architectures can be capable of supplying a reliable Iris condition diagnosis. Increased detection precision requires transfer learning. Fine-tuning these models could improve their accuracy.

Other pre-trained algorithms could be investigated for the purpose of developing a recommendation system. In the future, researchers will be able to evaluate multi-modal datasets that combine coughing sounds and scan image information to show Iris patients. Even though a single iris scan can be used to find multiple iris problems at once, the current work can be made better by adding iris images as a diagnostic tool for multi-label modeling. As a challenge, there is frequently an enormous daily bulk release of iris image datasets.

We need autonomous data techniques to be ready for production. The real-time reliability hypothesis is satisfied due to the findings in table 1, with a sufficient defense against the statistical significance in results. CNN modeling targeting transfer learning methods provided such an accelerating plus robustness to the human identification problem of iris-based authentication. The MMU V1 database presents a great challenge in state-of-the-art biometric applications. The findings of the presented framework are evaluated individually using a set of statistical measures to guarantee the significance of our results. The presented approach is proven to be reliable in real-time applications for iris-based human identification with significant accuracy according to either the optimal individual measure or from performance generalization perspective.

Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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