International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 06 Issue: 08 | August - 2022 Impact Factor: 7.185 ISSN: 2582-3930

Iris Recognition

Rimple Dhamija,
Assistant Professor,
IMT, Faridabad
Rimpledhamija0403@gmail.com

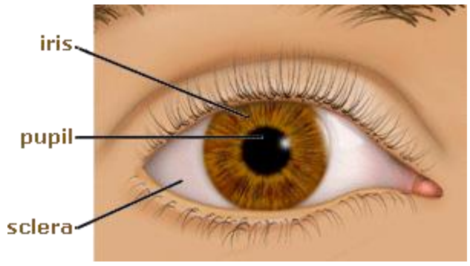
Abstract— This paper presents a review of literature related to biometric recognition system known as iris recognition system. Biometric authentication is an important security technology due to its properties of biometrics compared to other authentication methods. Since most of the observable characteristics of humans are unique, physiological features like fingerprints, iris color, face patterns and geometries considered as security passwords. Among those, iris gets the most attention in authentication because of its reliability. Even the iris textures being used in iris recognition are not similar in the left and right eyes of the same person. So, it is more secure than face/partial-face recognition. Goal of this paper is to explore recent work done in iris recognition systems and use of Deep learning techniques in Iris recognition. Deep learning can be used to efficiently and accurately analyze large quantities of data. Iris recognition leverages iris data analysis wherein efficient algorithms are used for identification and differentiation amongst individuals. In this review paper, we have reviewed various technologies in iris recognition. The final outcome of this paper clearly indicates that due to its success deep learning methods, especially, the convolutional neural networks, has a great future ahead.

Keywords— iris recognition, biometrics authentication, image processing, machine learning

I. INTRODUCTION

Iris recognition is an important area in security and authentication. Main challenge in biometric authentication is that how to apply biometric security solutions when biological characteristics of humans are rapidly changing. To tackle this problem, various mathematical and machine learning models are used. But one of the unusual features of iris is that it is stable in a person's life span. This has made iris recognition more popular in security industry.

Iris is a thin, circular structure in the eye, which actually controls the size of the pupil. It mainly consists of few components as shown in Fig.



Iris is pigmented muscular curtain which consists of unique patterns. Iris patterns can be read by automatic machines and step by step mechanism can be used to extract features for authentication purposes.

Deep learning uses Artificial Neural Networks (ANN), a layered structure of algorithms to provide the most successful machine learning methods for the feature selection and classifications. The ANNs are in general three-layered network consisting of input layer, hidden layer and output layer.

Deep learning is implemented using deep structure algorithms, hierarchical learning or deep machines learning and deep neural networks, learning techniques for features selection and transformations.

The deep learning inherits its principles mainly from conventional artificial neural networks. It is designed on the same principle of biological neural network of the human's brains. Both biological and artificial neurons are parallel processing units.

ANNs consists of two or more layers. Perceptron, a two layered ANN consist of two layers i.e., the input layer and the output layer. A multi-layer network has more than three layers - input layer, output layer along with one or more hidden layer(s).

Each progressive layer in the neural network gets the input from the previous layer.

The neural networks excel at classification tasks i.e. classification of dataset into unique classes. This classification method has the ability to recognize complex patterns for data of different types viz. signals, sounds, text, or images; and therefore, provide much better results for classification.

There are two learning techniques for this purpose - supervised and unsupervised learning.

In case of supervised learning, a set of positive and negative examples are used to train the system. The algorithms match the new set of data with the samples on which the system already been trained.

In case of unsupervised learning, data is processed using the intrinsic characteristics of this data.

This paper aims at exploring the latest researches in the area of iris images recognition.

II. LITERATURE REVIEW

In this section, we have reviewed most recent work done in the field of iris recognition using deep learning.

In [1], an innovative deep learning iris acknowledgement-based recognition technique is presented that can uses coordination between precision and speculation capacity. The basic point mentioned in this paper is that a deep learning-based iris acknowledgment structure can be used to address assorted organization conditions by applying on various data sets. It shows Another Extended Triplet Loss work for addressing idea of iris design for learning thorough iris highlights. Since then, a lot of advancement has been made to overcome the barriers between deep learning and iris recognizing.

In [2], the researchers proposed a novel deep learning method for iris recognition wherein VGG and ResNet-50 organizations techniques were used for managing the pictures utilizing iris segmentation and standardization. In this method, the researchers leveraged a specific information increase method for iris images, on top of gaining from face space. They came up with two Convolutional Neural Network (CNN) models for face recognition that were later on utilized as iris detection. The observations clearly demonstrated that although the methodologies were using non-standardized and non-fragmented iris picture, it produced new best in class results for authority convention of the NICE.II rivalry.

In [3], The creators envisioned the up-and-coming age of wearable AR/VR show glasses and the challenges of individual verification. They chose iris verification as a biometric connection between the client and his information. However, due to the potential area of client-facing cameras, however, it is challenging to segment the iris precisely. A deep neural network is presented here to precisely segment contorted iris locations, as well as a suitable increasing strategy for constructing the constrained iris datasets that are utilized for the preparation from freely accessible front-facing iris datasets. That work was primarily centered around developing a deep learning process to partly resect mutilated iris pictures. The basic commitment was to create iris photographs using a n AR/VR head-mounted display mounted off-axis with off-pivot cameras. A subsequent expansion measure was applied to the mutilated iris pictures, adding contrast, obscuring, or shadows, representing the fluctuation of picture quality in real life.

In [4], researchers focused on the implementation of a deep learning procedure with the objective of improving segmentation performance on low-quality iris images. The purpose of this paper is to use particular information to prepare tests to simulate pictures taken with handheld cameras.

In this work, when preparing a deep neural network, dissemination of information plays a critical role in how this system functions and how it behaves in testing. The segmentation task is organized as a deep U-formed 13 layered network. It begins with 3x3 portions, planning the contribution to the first covered-up convolutional layer. In these investigations the pooling activity brings about undesirable noise at the final result of the network, The portions become bigger towards the focal point of the network, the greatest portion is 15x15. As we move away from the focal point of the networks, the piece size decreases toward the yield. The skip associations utilized in the organization help the yield with a remaining edge. It also results in a lower yield value. Based on the test results, low-quality outdoor photos shot without restriction showed significant improvements in segmentation.

Researchers attempted to use deep learning to improve off-point iris identification in [5]. Using iris/visual/periocular biometrics, the researchers evaluated the impact of look points. By utilizing convolutional neural networks, the accuracy of off-point iris recognition frameworks was improved.

Here, images of the iris are off-center, widened, and not ideal. Thus, the deep learning calculation was used in untraditional iris recognition systems to enhance the display of off-angle iris recognition. In this paper, convolutional neural networks (CNNs) are utilized with segmentation, standardization, and CNN-based encoding and coordinating to investigate the conventional iris recognition structure. For non-traditional structures, the researchers used iris images without segmentation.

Using deep convolutional neural networks, a procedure for iris gender classification was proposed in [6]. Using the diagram cut segmentation strategy, it fragments the iris from an original image. There are 16 convolutional layers in this model, divided into 3 convolutional layers used for extraction and variations in convolution window sizes. By using essentially retaining preparation information, the primary design can be made stronger and safer by surpassing the overfitting issue. Aside from providing 9,000 pictures for the preparation stage, 3,000 pictures for the testing stage, and

3,000 pictures for the check stage, the expansion cycle contributed to a huge increase in testing accuracy, the proposed method achieving 98.88%. A verification technique was used to assess the design's accuracy. This process involves using new increment strategies to evaluate the architecture of verified pictures. In its deteriorated scenario, the proposed method achieved a precision of 90.03%, demonstrating that it summarizes the information, rather than retaining it. It may reduce preparation time and contribute to higher test accuracy.

In [7], this researcher investigated iris recognition and filtering using residue convolution neural nets (CNNs), which could be learning from both representational features as well as performance features. An iris recognition framework is designed using the concept of transferred learning.

This was done by using the IIT Delhi's iris database, which had 2240 iris pictures of 224 different people, the resolution of which measured 320 by 240 pixels. In this work, the researchers concentrated on iris-recognition tasks. In this study, researchers used deep residue convolution networks to perform and identify images based on a transfer learning method using chosen datasets covering a wide range of topics. Using a previously trainable Res Net50 model, they trained an ImageNet dataset and fine-tuned it using training images.

In the 2015 ImageNet visual recognition campaign, ResNet was the winning method. Using ResNet produces simpler gradient flows for more efficient learning. Identity shortcut connections are at the core of Res Net, allowing one or more layers to be omitted. By allowing immediate access to early layers in the networks, the slope value for those layers can become a lot simpler. Using Nvidia Tesla GPU, the researchers designed the model for 100 iterations using a cluster size of 24 computers, and Adam-streamlining agents are used to improve losses work, with a learning rate of 0.0002. Before feeding to the neural net, all images are downsized to 224x224.

An iris recognition technique using both edge-based calculations and learning-based calculations was proposed in [8]. In order to find and group the eyes, they used a 6-layer R-CNN. A Gaussian combination model with bouncing boxes was applied to approximate the pupillary region. Five key limit points determined the pupillary circle limit. In order to find the limit points of the limbus, a limit point determination technique was used, and the limit of the limbus was constructed based on these limit points.

In [9], the researchers examined how iris recognition and detection frameworks affect iris recognition. In this study, a deep neural network model CNN was used for encoding and analyzing the surface of the iris, as well as evaluating the impact of the methodology on the iris identification system. Using CNN-based segmentation models, the researchers produced segmentation segments and explained ground truth segments.

Due to the fact that deep learning models can explain nonlinear information changes, the researchers were able to explain how an extremely serious exhibition is still possible even when the iris surface is not normalized. Testing consisted of incorporating the results of standard (heuristic) segmentation techniques alongside the opening up of the iris. As a side result of the study using the CASIA-thousand (NIR) and SBVPI (VIS) datasets, it has been revealed that a different CNN-based recognition model can be used to encode heterogeneous iris surfaces captured in a wide spectrum of EM images.

In this paper, the importance of image segmentation for data related to the iris was demonstrated, and the results from the proposed method were the best compared to other methods of segmentation.

Additionally, segmentation, which is specifically designed for deep learning, cleans up the data. When segmentation is used during model preparation, the model can unite accurately (for example, to a sufficiently high degree), when the larger datasets are used. In the situation where the information pictures are immediately prepared, the model unites at a low level of exactness (10%-20%). In this manner, for this specific scenario, the segmentation also eased the difficulty of the issue by guiding the recognition model to a discriminative domain, making the preparation simpler. This review concluded more exploration was needed to determine whether iris standardization has an impact.

In [10], there are two sections: a Fully Convolutional Encoder-Decoder Network fitting with consideration modules to generate different likelihood maps using more discriminative highlighting. The second part is a powerful post-processing strategy which included edge denoising, Viterbi-based identification of coarse forms, and least-squares circle fitting to limit the iris pixels.

Three delegate iris datasets and the place of the student were chosen to represent the inward/outward boundary of each iris image. Furthermore, entire assessment conventions were formulated for calculating restrictions and assessing iris segmentation.

[11], In this paper, the researchers describe a technique for more precise iris recognition. The methodology they use attempts to solve this issue by fusing the widened convolutional bit with the remaining learning in our system to achieve more accurate iris coordinating. Using such a technique also improved deep neural organization and made it more effective. The trial results, using within database and cross-database execution assessment, on three diverse public iris pictures data sets demonstrate superior results and validate the effectiveness of this methodology. Images of the iris are naturally represented as visual data and can be consolidated within the deep neural network to additionally enhance their details, which is beneficial for future research as well. This methodology used the MaskNet, which was independently developed. The improvement of an all-inclusive engineering approach that includes both concealed

pieces as well as the preparation of MaskNets is deeply intriguing and part of the work in this area to come.

Pre-processing the images with a Gaussian, triangle fuzzy mean, and triangle fuzzy medium smooth filter is done in [12] by fuzzifying the regions behind the boundaries. Fuzzy operations yield a modified image, which was then used for the training phase of a deep learning algorithm, which maximizes recognition accuracy and the convergence process.

Fuzzification is found to improve the performance of training on raw images over training on raw images. Comparatively to traditional methods of data augmentation, the fuzzified picture filters used have increased the signal-to-noise ratios by a greater margin. Furthermore, the accuracy has improved, and convergence has also sped up. F-CNN and F-Capsules are more accurate and robust compared to CNN and Capsules. In addition to improved test results, this model performed better in comparison to the conventional crisp model of sets used in the same CNN neural network when the Gaussian method of triangular fuzzy membership is used.

[13] proposes a Self-Learning computationally intelligent system. Using Gabor channels, the researcher made highlight vectors based on iris highlights. The methodology used in this work involved utilizing a managed neural network that was first created with various contributions from various iris include vectors, and then recognition was targeted. Following the discovery of edge pictures from dim scale iris images and the discovery of Hough changes from edge pictures, the centroid of the inward circle of the student for the indicated sweep was determined. Among the most noteworthy pixel positions is the middle mark of the understudy's inner circle. With the pointless parts eliminated, the iris ring from the picture is retrieved. The iris ring was then framed into a picture of 64x512 pixels in the square shape. Afterwards a low-pass Gaussian channel was applied to eliminate commotion. It is characterized by high recurrence, which is called normalization. Twenty Gabor channels were acquired and applied to eight sub-pictures for a total of 160 sifted sub-pictures. From each sifted sub-picture, the normal total deviation (AAD) was calculated. Creating an element vector of 160x1 from AAD esteems. A single-dimensional cluster was applied to the refined neural organization for evaluating yield as a certified client or not: if a client is a real one, the organization gives yield as an individual's file number. The proposed calculation distinguished comprehensive from restricted information of the iris. Based on the results of the execution, it appears that this calculation can correctly identify individuals based on their iris.

[14] suggests a UNet for iris segmentation. In that work, the Squeeze Expand modules were used to reduce preparation time. Using the minimization of boundaries contained within, this would simultaneously improve capacity efficiency. For datasets with insufficient clarified examples, the intelligent part helped to produce the ground truth. It can be viewed as a classification-based model that combines the prospects and advances of deep learning; in that paper, it was discovered that using the less unpredictable model reduced over-fitting while allowing easier access to the more modest datasets of iris recognition. The model can treat huge setting variations among different pictures vigorously using picture explicit data. Using intuitive and robotized ground truths has helped in reducing the time spent by specialists while creating precise segmentation.

An efficient deep learning-based approach to segmenting the iris was described in [15]. In contrast to the previous CNN-based iris segmentation strategies, this approach represents the final segmentation of the iris system, i.e., the masks and the defined inward and external limits of the iris are displayed effectively into a unity to prepare it to perform multiple tasks.

MICHE-I dataset was utilized to develop and evaluate the proposed approach. Furthermore, reasonable examinations were created using a few standard assessment conventions. Several benchmarks showed that this methodology achieved best-in-class performance. Furthermore, the iris segmentation strategy proposed here can also be applied to any iris recognition approach.

Table 1: Literature Review Summary

Id	Methodology	Data	Accuracy
[1]	Fully Convolutional Neural Network	ND-IRIS-0405 Iris network (FCN) Image Dataset (ICE 2006)	Better performance using FCN
]2]	VGG and ResNet-50 networks	UBIRIS dataset	The ResNet-50 achieved good results when non-segmented images were used.
[3]	Deep neural networks	The CASIA Thousand and Bath 800	Bath 800(99.12%) CASIA Thousand (99.34%)
[4]	Deep Learning	The CASIA Thousand and Bath 800	Bath 800(98.5%) CASIA Thousand (99.7%)
[5]	Convolutional Neural Network	Iris dataset with an off-angle	Cropped pictures with visible iris

International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 06 Issue: 08 | August - 2022 Impact Factor: 7.185 ISSN: 2582-3930

		view.	texture yield better results
[6]	Deep Learning Convolutional Neural Network	The original dataset contains 3,000 photos, 1500 of males and 1500 of women.	98.88% accuracy achieved
[7]	Deep learning using Convolutional Neural Network	IIT Delhi Iris Database	95.5% accuracy
[8]	Deep learning using R-CNN	CASIA Thousand	95.49% accuracy
[9]	Segmentation using CNN	CASIA Thousand	82.87% accuracy
[10]	Fully Convolutional Encoder-Decoder Network	CASIA Thousand and MICHE-I	CASIA Thousand(94.3%)
[11]	Residual network learning with dilated convolutional layer	ND-IRIS, (ICE2006), CASIA V4-distance	Better precision results as compared to other Iris recognition methods
[12]	Fuzzy Pre-processing with deep learning	CASIA and VISTA	CASIA (82.87%) VISTA (88.4%)
[13]	Self-Learning computationally intelligent system	CASIA	99.9%
[14]	Deep learning using CNN	CASIA	Superior precision and improved performance
[15]	Deep learning using CNN	CASIA, MICHE-I	Performance of Iris recognition improved in non-cooperative environment

III. CONCLUSION

Deep learning-based iris recognition is one of the most active research areas these days. There are many applications that can utilize iris recognition where biometric authentication is required. The process of iris recognition involves examining the random patterns on a person's iris in order to identify them. Iris is a pigmented or colored circle on the surface of the eye, usually brown or blue. This technology is considered one of the fastest, most accurate, and safest methods of biometric identification.

In this review, we discuss the most recent publications in iris recognition that utilize deep learning techniques.

Deep learning has proven most successful for iris recognition, but we can conduct more research to determine and compare different deep learning neural network structures.

The conclusion also states that the iris does not have any real characteristics that can be utilized as references to make categorization decisions in the future.

In the end, we conclude that directed edge detection algorithms such as Canny and Hough are practically always required for any IRS described in the literature.

IV. REFERENCES

“[1] Zhao, Zijing, and Ajay Kumar. "Towards more accurate iris recognition using deeply learned spatially corresponding features." Proceedings of the IEEE International Conference on Computer Vision. 2017.

[2] Zanlorensi, Luiz A., et al. "The impact of preprocessing on deep representations for iris recognition on unconstrained environments." 2018 31st SIBGRAPI Conference on Graphics, Patterns and Images (SIBGRAPI). IEEE, 2018.

[3] Varkarakis, Viktor, Shabab Bazrafkan, and Peter Corcoran. "A deep learning approach to segmentation of distorted iris regions in head-mounted displays." 2018 IEEE Games, Entertainment, Media Conference (GEM). IEEE, 2018.

[4] Bazrafkan, Shabab, and Peter Corcoran. "Enhancing iris authentication on handheld devices using deep learning derived segmentation techniques." 2018 IEEE international conference on consumer electronics (ICCE). IEEE, 2018.

[5] Karakaya, Mahmut. "Deep Learning Frameworks for Off-Angle Iris Recognition." 2018 IEEE 9th International Conference on Biometrics Theory, Applications and Systems (BTAS). IEEE, 2018.

[6] Khalifa, Nour Eldeen M., et al. "Deep iris: deep learning for gender classification through iris patterns." Acta Informatica Medica 27.2 (2019): 96.

[7] Minaee, Shervin, and Amirali Abdolrashidi. "Deepiris: Iris recognition using a deep learning approach." arXiv preprint arXiv:1907.09380 (2019).

[8] Li, Yung-Hui, Po-Jen Huang, and Yun Juan. "An efficient and robust iris segmentation algorithm using deep learning." Mobile Information Systems 2019 (2019).

[9] Lozej, Juš, et al. "Influence of segmentation on deep iris recognition performance." 2019 7th International Workshop on Biometrics and Forensics (IWBF). IEEE, 2019.

[10] Wang, Caiyong, et al. "Joint iris segmentation and localization using deep multi-task learning framework." arXiv preprint arXiv:1901.11195 (2019).

[11] Wang, Kuo, and Ajay Kumar. "Toward more accurate iris recognition using dilated residual features." IEEE Transactions on Information Forensics and Security 14.12 (2019): 3233-3245.

[12] Liu, Ming, et al. "Fuzzified image enhancement for deep learning in iris recognition." IEEE Transactions on Fuzzy Systems 28.1 (2019): 92-99.

[13] Thakkar, Sejal, and Chirag Patel. "Iris Recognition Supported best Gabor Filters and Deep learning CNN Options." 2020 International Conference on Industry 4.0 Technology (I4Tech). IEEE, 2020.

[14] Sardar, Mousumi, Subhashis Banerjee, and Sushmita Mitra. "Iris Segmentation Using Interactive Deep Learning." IEEE Access 8 (2020): 219322-219330.

[15] Wang, Caiyong, et al. "Towards complete and accurate iris segmentation using deep multi-task attention network for non- cooperative iris recognition." IEEE Transactions on information forensics and security 15 (2020): 2944-2959."