

LITERATURE REVIEW ON IRIS SEGMENTATION AND CLASSIFICATION BASED ON DEEP LEARNING

Sateesh Yaduwanshi*¹, Prof. Aditi Khemariya*²

*¹M.Tech Scholar, Department Of CSE MIST Indore, India.

*²HOD, CSE, Department Of CSE MIST Indore, India.

DOI : <https://www.doi.org/10.56726/IRJMETS29453>

ABSTRACT

Iris segmentation algorithms are a key part of full-fledged iris recognition systems and have a direct effect on the results of iris verification and recognition. But when standard iris segmentation algorithms are used on noisy iris databases that were recorded in unrestricted environments, they are not flexible enough and are not strong enough. Also, there aren't any big iris databases right now, so iris segmentation methods can't take full advantage of the benefits of convolution neural networks (CNNs). The problem of iris segmentation in handheld devices is then solved by making a deep learning scheme and coming up with a good way to improve it. Initial comparisons with iris segmentation algorithms that are available to the public show significant performance gains, especially on difficult image datasets that are meant to simulate the quality of images from a handheld device.

Keywords: Iris, Segmentation, Retinal Disorders, Machine Learning, Deep Learning.

I. INTRODUCTION

Iris texture is an important part of both the national defence and the security of the country because it is unique, can't be copied, doesn't require contact, and is stable. In general, an all-inclusive iris recognition system includes the following steps: At first, a device that can take pictures is used to take pictures of the iris. Then, techniques called "iris segmentation" are used to find the parts of the eye pictures that show the iris. After that, methods for "feature extraction" are used to get information about the iris. At last, the information about the iris is used in some kind of system for iris verification or recognition. With a few notable exceptions, iris images don't just show the iris, but also other parts of the eye, like the pupil, eyelid, eyelashes, and sclera [1]. Images of the iris don't just show the iris. The non-iris regions have a bad effect on how well iris segmentation works. Iris segmentation algorithms are made to get rid of the effects of areas that aren't the iris and accurately divide the iris into its parts based on images of the eye.

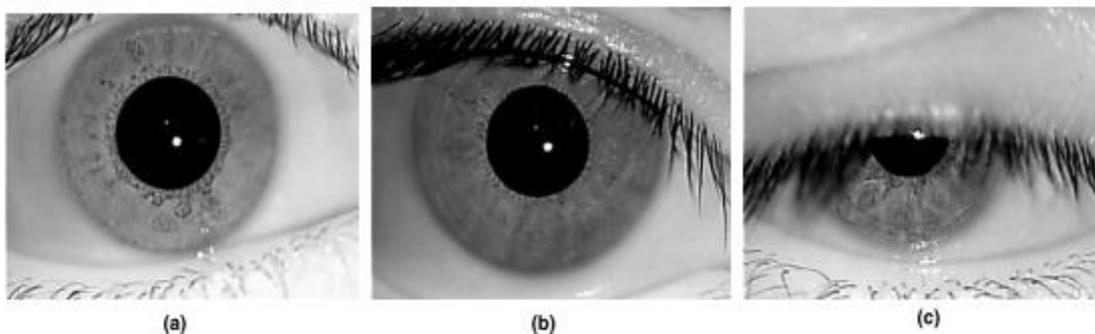


Figure 1. Samples of iris images under ideal and nonideal conditions. (a) Ideal iris images. (b) Iris images slightly occluded. (c) Iris images severely occluded.

In iris recognition systems, the algorithms used to divide the iris into different parts are very important. The next steps of iris extraction, verification, and recognition are directly affected by how well and how often the algorithms work [2].

Most of the iris segmentation algorithms that are currently available can accurately separate the different parts of the iris under ideal conditions. This means that the iris parts aren't covered by the eyelids or eyelashes, the iris images are clear, and the user is fully cooperative. But when conditions aren't perfect, it's hard to make strong algorithms for iris segmentation that can separate the different parts of the iris despite the effects of eyelids, eyelashes, light, and the user. This is because the iris is made up of many layers and has a complicated

structure.

Together with the rest of the human visual system, the eye is a big part of how information is processed so that we can understand it. In the past few years, ophthalmology has made a lot of progress, especially in the areas of early detection of retinal diseases, accurate diagnosis, spreading knowledge about eye health, automatic detection to prevent vision loss, and better treatment results. Image processing is becoming more and more important in the field of medicine, especially in ophthalmology, which is the study of eyes. If the disease is found the old way, it might not be possible to treat it until it has become more serious, and the process might take a long time. When the eye is checked manually, there are also times when the wrong diagnosis is made. If you don't want your vision to get worse, you need an accurate and automatic way to tell if you have a retinal illness. Some of the more serious problems that can happen to the retina are cataracts, glaucoma, diabetic retinopathy, macular degeneration, corneal scarring, floaters, and retinal detachment. Recent improvements in medical imaging techniques have led to some very exciting new developments in the field of automated disease detection. [3].

Glaucoma is the most common cause of blindness. During 2016, the World health organization estimated the number of loss of vision due to Glaucoma as 4.4 million worldwide. Glaucoma, a significant retinal disorder is characterized by raised Intraocular Pressure (IOP), cupping of the Optic Nerve Head (ONH) and visual field defects. It is a gradual, progressive and irreversible degeneration of optic nerve fibers leading to loss of vision. Statistical data provided by the Glaucoma Society indicates, among the retinal disorders Glaucoma affects 12.3% of the masses in India next to cataract as depicted in Figure 2.

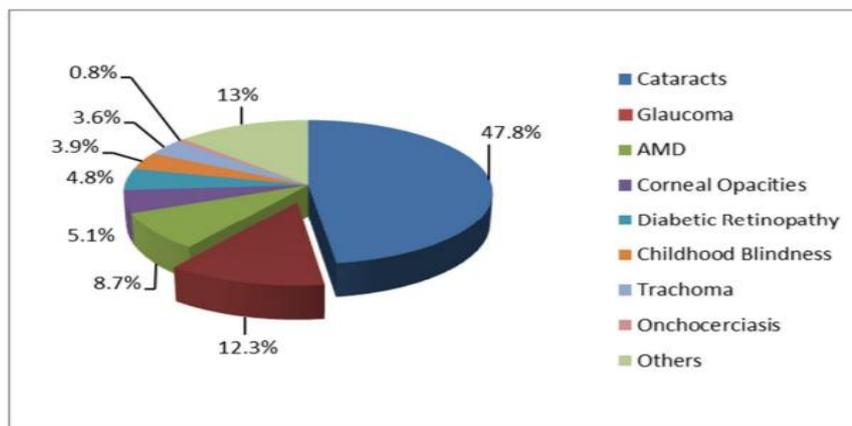


Figure 2. Statistics of Retinal disorders

Glaucoma affects an estimated 12 million individuals in India. By 2020, the number is projected to rise by 33%. (Rohit Saxena et al. 2013). The inability to diagnose Glaucoma has resulted in a significant incidence of blindness among the Indian people. The average number of patients seen by an ophthalmologist is believed to be between 2 and 3 lakh. In such circumstances, a lack of qualified technicians presents a significant problem. Even in a population receiving ocular examination, accurate diagnosis of Glaucoma remains a significant predictor of avoidable blindness. Glaucoma diagnosis and treatment are critical due to the asymptomatic nature of vision loss in the early stages and the irreversible nature of blindness in the later stages. A screening program for detection of Glaucoma involves manual examination of patients by an ophthalmologist. Glaucoma screening includes some techniques like Tonometry, Pachymetry, Gonioscopy, Perimetry, and Ophthalmoscopy. Among the stated techniques, Ophthalmoscopy plays a major role in the screening of Glaucoma. In order to help the ophthalmologist in handling more patients without compromising on the quality of examination, a new screening method is offered as an alternative to the manual procedure. A computer-aided diagnosis of the retinal disease is used in the new screening method. It improves both the quality and the efficiency of the work. Glaucoma detection using a computer-aided technique is based on retinal fundus image processing and aids in screening on a wider scale. It initially determines whether the patient is free from Glaucoma related abnormality and only the cases where the system suspects Glaucoma require guidance from an ophthalmologist. This way of screening reduces the workload of the medical experts, thereby improving the efficiency of screening done on a large scale. It also addresses the problem of lack of skilled personnel. This

thesis aims at developing a decision support system using the retinal image analysis building towards Computer-aided diagnosis-based screening for Glaucoma detection.

Localization of Optic Disc Region-The amount of resources needed for displaying the fundus picture is reduced when glaucoma diagnosis is based on feature extraction. The suggested approach minimises superfluous data, unlike current methods that extract characteristics from the full fundus picture. For improved diagnostic accuracy, features from the Glaucoma informative areas are taken into account. The feature derived from the fundus picture's limited optic disc area is more discriminative for Glaucoma diagnosis than the whole fundus image; As a result, in the identification and study of retinal structures, the optic disc area is regarded as an essential landmark.

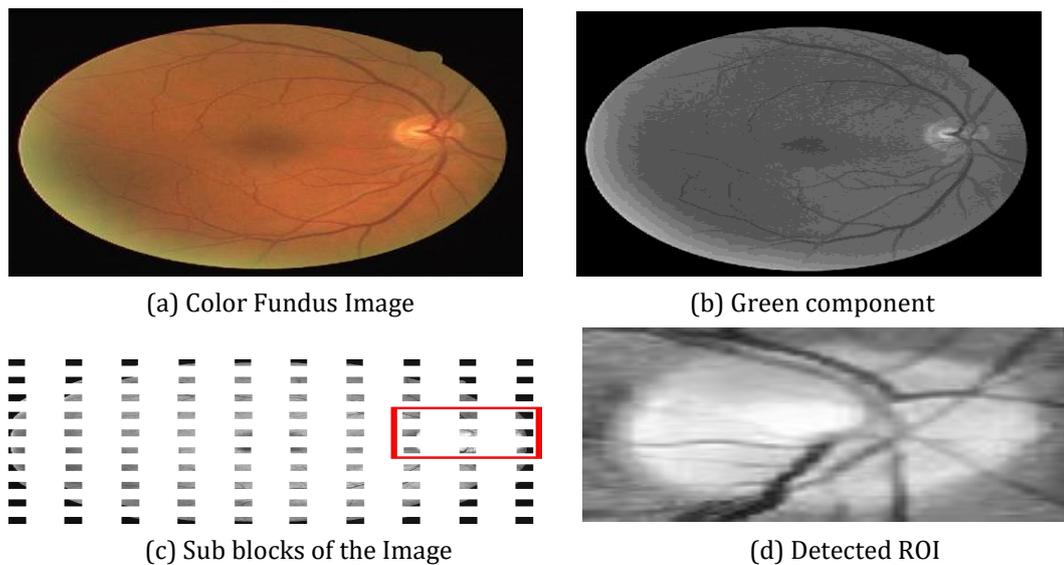


Figure 3. Localization of Optic Disc Region

Increased IOP, which is the primary cause of Glaucoma, causes morphological abnormalities in the cup and disc area. As a result, precise localization and identification of the Optic disc area are important in the Glaucoma detection analysis process. On the nasal side of the optic disc, the brightness is lower than on the temporal side. The whole optic disc shines brighter than the surrounding region, giving it the appearance of a hollow ring (Yogita Vaidya et al. 2014). The optic disc's size, shape, and colour, as well as blood vessel kinking from the optic disc, aid in the identification and localisation of the ROI (Wong Wing Kee Damon et al. 2012). The optic disc's size and form may also vary significantly. The brightest pixel area, gradient direction variety, and blood vessel convergence are all factors that go into detecting the optic disc region. Because the green component of the colour fundus picture has greater contrast than the red and blue components, it is used for optic disc localization. The seed point in the input fundus picture is a high-intensity area inside the green component. The seed point is found by splitting the green component of the retinal fundus picture into 32x32 sub-blocks and scanning each block for the brightest pixel area, as shown in Figure 3. (c). The ROI encompasses the area around the seed point. Figure 3 depicts the brightest sub block in the input retinal picture, which includes the whole optic disc encircled by blood vessels (e). On the publicly accessible datasets Drishti-GS1 and FAU, the optic disc area localization and detection techniques are evaluated. The accuracy of the localization is reported in Table 2.2, which compares the proposed method's localization and detection of the optic disc area to the ground truth given with the dataset.

II. LITERATURE REVIEW

A lot of research has been done and is still being done to get iris image segmentation to work well. In this section, we give a brief summary of the research documents that were mentioned earlier and that worked on different ways to divide up an iris picture.

Caiyong Wang et.al (2020) Iris images taken in non-argument environments are often unfavorable to challenge many existing IRIS segmentation methods. To resolve this issue, this article proposes a deep segment method of the learning process, called IrisParsenet. In contrast to many earlier IRIS segmentation methods,

wherein the prediction of the exact iris masks predict with the usual semantic segment frames, the proposed approach is an IRIS segmentation solution, ie the IRIS mask and the iris limits inside and the external parameters are performed positively Model them into a uniform multitasking network. In addition, an attention module is upgraded to improve segment performance. To train and evaluate the proposed method, we manually mark three representative and demanding databases Iris, ie casia.v4distance, ubiris.v2 and Michei, with many lighting sensors (NIR, VIS) and image sensor (Longgrange and Mobile Iris Camera), Together with many types of noises. In addition, some uniform evaluation protocols are set up to compare fairly. Extended experiments are made in these newly commented databases and the results showed that the proposed approach has achieved advanced performance on different benchmarks. In addition, the proposed IRIS segment method can be used as a general drip change for each IRIS identification method and will significantly improve the performance of non-production iris recognition.

Chengshun Hsiao et.al (2021) This article develops an effective deep learning method for ironic biometric authentication. First, based on the UnEAT model, the proposed system uses the semantic segmentation technology to locate and extract in Iris' ROI). After the Roi of Iris revealed in an eye picture, eyes expects to cut small eyes in small eyes with the canceled ROI. Thereafter, the IRIS features of the cut Eye image are improved by balancing the adaptation diagram or the Gabor filter process. Finally, the IRIS sectional image is effectively categorized by the model. According to the Database of Automation Science (Casia) of the Chinese Science Institute, the IRIS identification program is based on the proposed deep learning to identify identity accuracy of up to 98%. Compared to previous works, the proposed technology can provide an effective accuracy of IRIS for biometric applications with IRIS information.

Chia-Wei Chuang et.al (2020) In this research project, a YOLOv3 tiny-based deep learning inference network that is both effective and easy to use is being looked into for use in biometric authentication. First, photos of the eye are sorted by how much of the iris and sclera they show. This is done so that the YOLOv3 tiny-based classifier, which will be explained in the next paragraph, can correctly figure out who each person is. The YOLOv3 tiny-based inference model used by the UBIRIS database can get an average mean accuracy (mAP) of up to 99.92% with just one anchor box. The suggested low-complexity design doesn't need to separate the iris and the sclera. This makes it more accurate than earlier ocular biometric studies that used information from the iris or the sclera.

Shabab Bazrafkan et.al (2018) This research looks at how important correct iris segmentation is for implementing embedded authentication workflows based on iris authentication. This is important because biometric authentication is becoming more common in portable devices. In the next section, we'll talk about iris segmentation on portable devices using a deep learning method and a good extension method. Since the first published comparison of iris segmentation algorithms, there have been many improvements, especially on hard picture datasets meant to match the quality of images from handheld devices.

Mousumi Sardar et.al (2020) Biomass depends a lot on iris segmentation that is done automatically. In particular, machine learning and deep learning have been very important to these automated representation systems. This is a good plan, but it has some problems, like the need for a lot of computing power and the lack of large training data sets. Interactive learning is less expensive and takes less time than traditional lectures in this case. We introduce a UNet interactive transform for iris segmentation. Using the Squeeze Expand module, the number of important parameters is cut down, and training time is cut down as well. With the help of the interactive part, datasets that don't have enough annotation samples can be used to build ground truths. ISqEUNet works better than three public iris datasets and state-of-the-art methods that are already in use.

GürkanŞahinet.al (2019) Iris sclera Biometric User Recognition and Vitality Detection System is one of the features to realize high precision. In this study, the segmentation process is considered as the first step in the iris sclera user validation system. Existing convolutional neural network-based deep learning methods have been used for segmentation of the iris. The performance of the investigated method is being tested on two sets of eye image data (UBIRIS and magnetic acquisition data). Our experimental results show that the deep learning-based segmentation method is better than the conventional method in terms of dice scores for both datasets.

Ehsaneddin Jalilian et.al (2020) while deep learning techniques become increasingly becoming a selected tool for the IRIS segment, there is no comprehensive recognition framework for IRIS identification for such modules. In this work, we study the effects of various gas already based on CNN and their identity performance offering an improvement program to balance segment due to additional deformations. In addition, we propose a loose parameter algorithm to recall the page image into the front view. Take advantage of these things, we continue to examine whether: (i) segmented outputs and / or repair of IRIS images before or after the segment the remuneration of waste or (ii) improves the general ability of the network to improve training It on the iris image of different gas fields. In each test step, segment accuracy and identification performance are evaluated and the results are analyzed and compared.

Ananya Zabin et.al (2020) an effective identification algorithm of IRIS sensor identification can be used in certain legal applications, ie the detection of the IRIS is violated on IRIS records. This knowledge is likely to increase the accuracy of the overall IRIS identification system of IRIS identification by providing optional operators that correspond to the IRIS image of Samesensor or Crosssensor. In both cases, the knowledge of the origin of the sensor is used to collect this data if not available or corrected that the wrong data does not lead to the accuracy of higher iris accuracy. Another advantage of the identification of the iris is that it can support the improvement of the Faker-IRIS data acquisition, ie. If I know the IRIS sensor, we can better use suitable models in order to identify falsely for a specific iris. In this article, we suggest an effective identification algorithm to learn deep that sensors are interactive. Our approach uses a moderate amount of data and the ability to adapt to learning speed variants as well as variants of data used for exercising in each class. Our proposed approach uses a number of IRIS records, including the IRIS images recorded in different Deadlock distances. We use duplicate images, original dual or membrane form instead of Iris, after detection, segment and normalization of iris. Therefore, the algorithm is effective, fast and less dependent on additional algorithms can add computational complexity. Our proposal process involves transferring transfer with the use of IRIS images with a higher quality by using a set of image quality data and tightly reached a hundred accuracy percentage after cross Validation.

Luiz A. ZanLorssensi et.al (2018) the use of IRIS as a biometric feature is widely used due to its difference and uniqueness. Today, one of the most important research challenges is based on the detection of IRIS images obtained in the visible spectrum in an unlimited environment. In this case, the determined IRIS is influenced by the distance from shooting, turning, blur, mat, low contrast and special reflections, creating sounds to disturb the IRIS identification systems. In addition to identifying the IRIS areas, pretreatment techniques such as normalization and loud iris images are used to minimize these problems. However, these techniques are definitely going into some mistakes. In this context, we propose the use of profound, more specific services, architectures based on VGG and Resnet50 networks to handle images with segments and standardize the IRIS (and not). We use learning transfers from the Face domain and also suggest a certain increase in data technology for IRIS images. Our results show that the approach to the use of IRIS images is not natural and only pictures Iris reach a new art status in an official protocol of Nice. II Competition, a subset of the Uiris database, one of the most difficult databases for the environment is not bound, with the average error rate (EER) is 13.98%, which represents the absolute reduction, is about 5%.

Lozej et.al (2019) Even though deep learning is becoming more popular in many areas of computer vision and image processing, it hasn't helped iris identification much so far. Most of the time and energy spent on deep iris identification research has gone into making new models for identifying and strongly identifying iris representations. Since it doesn't deal with iris recognition from start to finish, the proposed model uses intelligent iris (and removal wrapping) strategies to give deep learning models normalised inputs. Concerns are clear when it comes to complex data distributions and changes in non-linear data. When it comes to deep learning, the traditional ways of segmenting are essential. This study looks at how iris division affects the performance of deep learning models. It does this by using a simple two-stage pipeline of division and recognition. Analyze how the accuracy of splits affects the performance of recognition and decide if splitting is needed. We use the CASIA Thousand and SBVPI datasets in our tests to find out some interesting things.

Caiyong Wang et.al (2020) this paper proposes a new deep optical convolution neural network specially designed for iris segmentation of noise images acquired from mobile devices. Unlike previous studies that focused solely on improving the accuracy of split masks using popular CNN technology, our method is a

complete end-to-end iris split solution. CNN-based iris segmentation that applies to all common iris recognition systems. By introducing an intermediate pictorial boundary representation, the prediction of the iris boundary and segmentation mask jointly formed a multi-label semantic segmentation problem. This can be sufficiently addressed through a carefully fitted network of stacked hourglasses. Experimental results demonstrate that our method achieves competitive or best performance in both iris segmentation and localization in two challenging mobile iris databases.

Daniel Kerrigan et.al (2019) this paper presents three new open-source deep learning-based iris segmentation methods and methods for using irregular segmentation masks in conventional Gabor wavelet-based iris recognition. For training and validation of the method, we used a variety of publicly available iris images acquired by different teams and different sensors, including CASIAIrisIntervalv4, BioSec, NDIris0405, UBIRIS, Warsaw BioBase Post MortemIris v2.0 (post iris images) data acquired from NDTWINS20092010. (Iris images acquired from identical twins). These various training materials will improve the generalization ability of the proposed segmentation technique. In database isolation training and testing, we found that deep learning-based segmentation in terms of Intersection over Union calculated between the results obtained and the manually annotated groundtruth surpassed existing (OSIRIS) segmentation. Indicates to do. Interestingly, go-based iris matching is not always better when using deep learning-based segmentation and is equivalent to using Daugman-based segmentation.

ERVIEW OF DEEP NEURAL NETWORKS Some of the most popular deep learning architectures used in computer vision today are convolutional neural networks (CNNs), recurrent neural networks (RNNs), long short term memory (LSTMs), encoder-decoders, and generative adversarial networks (GANs). Because deep learning has become so popular recently, we won't talk about many other ways to make deep neural networks, like transformers, capsule networks, gated recurrent units, and spatial transformer networks. Transfer learning can be used to train DL models from scratch on new applications or datasets when there isn't enough labelled data. This is possible when there is enough data that has been labelled, but this isn't always the case. Transfer learning is the process of using a model that was trained for one job to do something similar but different. A model for classifying images that was trained on ImageNet could be used for other things, like recognising faces. For example If you're doing image segmentation, you're probably using an encoder part of the network that was trained on ImageNet (a much larger dataset than most image segmentation datasets) and retraining your model with those initial weights. Since these models have already been trained, it is assumed that they can learn from images with fewer labels, which makes it easier to train their models.

Convolutional Neural Networks (CNNs)

Convolutional neural networks (CNNs) are among the most effective and widely used models in deep learning, especially for computer vision problems. CNNs were first proposed by Fukushima in his seminal paper on the "Neocognitron" [17], which was based on the Hubel and Wiesel hierarchical receptive field model of the visual cortex. These models served as the basis for Fukushima's concept for CNNs. Then, for the purpose of identifying phonemes, [18] proposed CNNs with weights distributed over temporal receptive fields and backpropagation training, whereas [13] created CNN architecture. These two developments were from the field of computer vision (Figure 2). Pooling a Convolution In convolution pooling, there is complete connection between the output and the input.

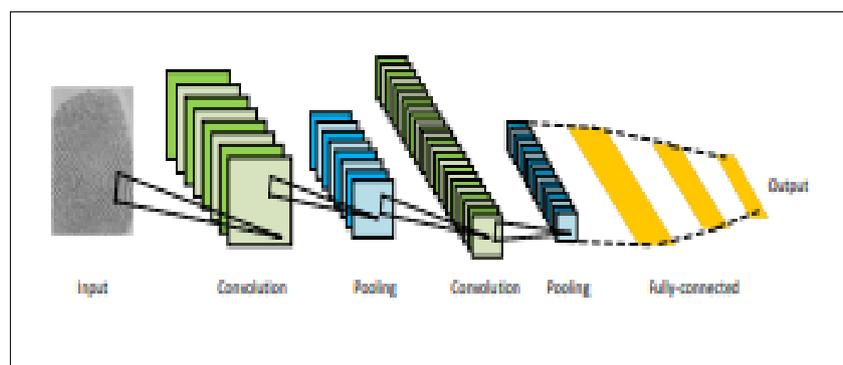


Figure 4. Architecture of convolutional neural networks. From [13].

CNNs are mostly made up of three different kinds of layers: i) convolutional layers, which use a kernel (or filter) of weights to extract features; ii) nonlinear layers, which use an activation function on feature maps (usually elementwise) to allow the network to model nonlinear functions; and iii) pooling layers, which replace a small area of a feature map with some statistical information (mean, standard deviation, etc.). Each unit in a layer is connected locally to the units in the layer below it. This means that each unit gets weighted information from a small group of units in the layer below it. This group of units is called the receptive field. When you stack layers to make a multi-resolution pyramid, the higher-level layers are able to learn features from receptive fields that get wider as the pyramid gets taller. The main advantage of CNNs from a computational point of view is that all of the receptive fields in a layer share the same weights. Compared to fully-connected neural networks, this means that there are a lot less parameters. Some of the most well-known CNN architectures are AlexNet [19], VGGNet, ResNet, GoogleNet, MobileNet, and DenseNet. CNN also mentions DenseNet. [20]

III. CONCLUSION

Iris texture is important to the defence and security of the country because it is unique, noncontact, nondestructive, and hard to fake. In general, an all-inclusive iris recognition system includes the following steps: At first, a device that can take pictures is used to take pictures of the iris. Then, techniques called "iris segmentation" are used to find the parts of the eye pictures that show the iris. After that, methods for "feature extraction" are used to get information about the iris. At last, the information about the iris is used in some kind of system for iris verification or recognition. A Most iris recognition systems have five main parts: iris image acquisition, iris boundary segmentation, iris feature extraction, iris matching verification or identification, and iris matching verification or identification. In order for the iris recognition process to work, the iris needs to be segmented correctly. If we choose the right part of the image of the iris, we can get the useful information out of it. This lets us make the system for identifying people by their eyes even more accurate. In this study, we look at how artificial iris segmentation methods have been studied in the past.

IV. REFERENCES

- [1] Caiyong Wang;Jawad Muhammad;Yunlong Wang;Zhaofeng He;Zhenan Sun Towards Complete and Accurate Iris Segmentation Using Deep Multi-Task Attention Network for Non-Cooperative Iris Recognition IEEE Transactions on Information Forensics and Security Year: 2020
- [2] Cheng-Shun Hsiao;Chih-Peng Fan;Yin-Tsung Hwang Design and Analysis of Deep-Learning Based Iris Recognition Technologies by Combination of U-Net and EfficientNet 2021 9th International Conference on Information and Education Technology (ICIET) Year: 2021
- [3] Chia-Wei Chuang;Chih-Peng Fan;Robert Chen-Hao Chang Design of Low-Complexity YOLOv3-Based Deep-Learning Networks with Joint Iris and Sclera Messages for Biometric Recognition Application 2020 IEEE 9th Global Conference on Consumer Electronics (GCCE) Year: 2020
- [4] Shabab Bazrafkan;Peter Corcoran Enhancing iris authentication on handheld devices using deep learning derived segmentation techniques 2018 IEEE International Conference on Consumer Electronics (ICCE) Year: 2018
- [5] Mousumi Sardar;Subhashis Banerjee;Sushmita Mitra Iris Segmentation Using Interactive Deep Learning IEEE Access Year: 2020
- [6] Gürkan Şahin;Orkun Susuz Encoder-Decoder Convolutional Neural Network Based Iris-Sclera Segmentation 2019 27th Signal Processing and Communications Applications Conference (SIU) Year: 2019
- [7] Ehsaneddin Jalilian;Mahmut Karakaya;Andreas Uhl End-to-end Off-angle Iris Recognition Using CNN Based Iris Segmentation 2020 International Conference of the Biometrics Special Interest Group (BIOSIG) Year: 2020
- [8] Ananya Zabin;Thirimachos Bourlai A Deep Learning Based Approach to Iris Sensor Identification 2020 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM) Year: 2020
- [9] Luiz A. Zanolensi;Eduardo Luz;Rayson Laroca;Alceu S. Britto;Luiz S. Oliveira;David Menotti The Impact of Preprocessing on Deep Representations for Iris Recognition on Unconstrained Environments 2018 31st SIBGRAPI Conference on Graphics, Patterns and Images (SIBGRAPI) Year: 2018

-
- [10] Lozej;Dejan Štepec;Vitimir Štruc;Peter Peer Influence of segmentation on deep iris recognition performance 2019 7th International Workshop on Biometrics and Forensics (IWBF) Year: 2019
- [11] Caiyong Wang;Yunlong Wang;Boqiang Xu;Yong He;Zhiwei Dong;Zhenan Sun A Lightweight Multi-Label Segmentation Network for Mobile Iris Biometrics ICASSP 2020 - 2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP) Year: 2020
- [12] Daniel Kerrigan;Mateusz Trokielewicz;Adam Czajka;Kevin W. Bowyer Iris Recognition with Image Segmentation Employing Retrained Off-the-Shelf Deep Neural Networks 2019 International Conference on Biometrics (ICB) Year: 2019
- [13] Hugo Proença;João C. Neves Segmentation-Less and Non-Holistic Deep-Learning Frameworks for Iris Recognition 2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW) Year: 2019
- [14] Yuting Yang;Peisong Shen;Chi Chen A Robust Iris Segmentation Using Fully Convolutional Network with Dilated Convolutions 2018 IEEE International Symposium on Multimedia (ISM) Year: 2018
- [15] Viktor Varkarakis;Shabab Bazrafkan;Peter Corcoran A Deep Learning Approach to Segmentation of Distorted Iris Regions in Head-Mounted Displays 2018 IEEE Games, Entertainment, Media Conference (GEM) Year: 2018
- [16] Mahmut Karakaya Deep Learning Frameworks for Off-Angle Iris Recognition 2018 IEEE 9th International Conference on Biometrics Theory, Applications and Systems (BTAS) Year: 2018
- [17] Juš Lozej;Blaž Meden;Vitimir Štruc;Peter Peer End-to-End Iris Segmentation Using U-Net 2018 IEEE International Work Conference on Bioinspired Intelligence (IWOB) Year: 2018
- [18] Hugo Proença;João C. Neves Deep-PRWIS: Periocular Recognition Without the Iris and Sclera Using Deep Learning Frameworks IEEE Transactions on Information Forensics and Security Year: 2018
- [19] Yang Meng;Run Wang;Juan Wang;Jie Yang;Guan Gui IRIS: Smart Phone Aided Intelligent Reimbursement System Using Deep Learning IEEE Access Year: 2019
- [20] Aidan Boyd;Adam Czajka;Kevin Bowyer Learning-Based Feature Extraction in Iris Recognition: Use Existing Models, Fine-tune or Train From Scratch? 2019 IEEE 10th International Conference on Biometrics Theory, Applications and Systems (BTAS) Year: 2019