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Enhancing Biometric Authentication: Deep Learning Models For Human Iris Recognition

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***Abstract*—An Iris biometrics has gained a lot of attention as of late. It happened because this quantifiable trait ensures a high level of efficiency and accuracy. Recently, iris recognition algorithms have shown outstanding identifying performance. There has been a rise in the use of iris recognition systems as an authentication method due to the fact that an individual's iris is a perfect biometric candidate due to its rich texture. This article details the methods used by the researchers at various points of the iris image recognition system. Additionally, the procedures linked to each stage were examined by the researchers. Seven phases comprise the recognition system: iris image acquisition; iris image quality improvement during the preprocessing phase; segmentation phase involving the separation of an iris region by an image background; normalisation phase involving a rectangle shaping of a segmented iris region; feature extraction phase encompassing an extraction of iris region features; and finalisation phase encompassing feature extraction. The comparative results have shown the Convolutional Neural Network (CNN) with Gaussian filter (GF) model obtained 99.99% accuracy that is higher than other models. This research endeavours to examine and delineate the phases of existing iris recognition systems.**

Keywords*—Biometric Authentication, Human Iris Recognition, Preprocessing, Segmentation, Normalization, Feature Extraction, Classification, Deep Learning.

I. INTRODUCTION

Computer vision is an important area of study that offers effective resolutions to numerous challenges. The primary application of pattern recognition is the automated identification of distinct entities within an image. Particular attention has been paid to computer vision in the security industry for identification purposes[1]. Automatic biometric systems employ quantifiable physiological or behavioural attributes to authenticate individuals' identities. Iris recognition is consequently gaining popularity within the security industry.

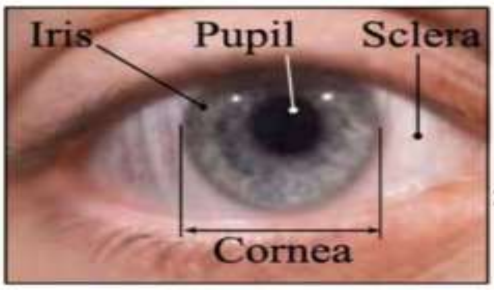

Fig. 1. The anatomy of the eye

The eye is made up of the iris, which is a thin annular structure. The amount and shape of light that reaches its retina are both regulated by it, together with the size of the pupil. As shown in Figure 1, it consists primarily of a limited number of components.

An annular, slender structure that composes the eye is the iris. In addition to controlling the size of the pupil, it also controls the amount and diameter of light that reaches the retina. It is primarily composed of a limited number of components, as illustrated in Figure 1. Iris recognition, fingerprint recognition, face recognition[2], retina recognition[3], and hand geometry recognition are all examples of physiological biometrics. Recognition of signatures, voices, and gait are all examples of biometric approaches used in behavioural models[4].

Iris recognition system (IRS) outperforms all other biometric recognition systems according to efficiency and reliability when it comes to verifying identity[5]. It is protected by a structure that can be accessed using a non-invasive technology and which change can have a positive or negative influence on health. It is an exciting future for the IRS for both large corporations and those in the security industry[6], because there are many applications and possibilities unlocked by this technology. The techniques employed for feature extraction, categorisation, and feature recognition determine a strength of a system, its requirements, and the speed and accuracy it can achieve[7]. Deep learning is capable of meeting these requirements. Several research has included deep learning as part of methodology since ML enables the system to automatically collect data, classify it, and detect patterns without explicit programming[8][9]. Recognition of faces and objects are two example of pattern recognition using deep learning[10]. The IRS also made use of deep learning, with several researchers using it to address recognition, segmentation, and classification issues. For instance, in the areas of identification, classification, and segmentation. The planned study will look at an iris identification system that uses a deep CNN.

A. Contribution of this paper

Data about biometric identification systems that use the iris are included in this study. Additionally, it provides a detailed account of how each method performed and points out potential improvement areas for researchers who are interested. Using this performance study, iris-recognition system research may be enhanced. The following points provide the paper's contribution to this work:

- Focusing on iris identification approaches that integrate Convolutional Neural Networks (CNN) with Gaussian filters, the study mainly compares and contrasts these methods. Its primary goal is to evaluate various deep-learning methods using accuracy metrics. Goal is to help understand more fully a potential of DL algorithms in iris detection by offering insights into a strengths and shortcomings of each approach.
- The iris recognition system is comprised of six key processes, which are as follows: image capture, data preprocessing, feature extraction, segmentation, normalisation, and classification.
- For a purpose of ensuring that the iris images are right, the data preprocessing method includes image scaling, grayscale conversion, and histogram equalisation.
- To isolate the iris area, segmentation employs the Hough gradient approach. This method improves recognition accuracy by concentrating entirely on iris patterns that are unique to each individual.
- The normalisation procedure converts the segmented iris area into a rectangular representation, which improves the accuracy of template comparison.
- The research presents CNN for a purpose of iris identification, and it achieves an astonishing 99.99% accuracy rate of recognition. CNNs have the capacity to capture complicated iris patterns, as demonstrated by the fact that it outperforms other DL models like R-CNN, IRISNet, SVM, and PCA.

B. Organization of paper

The rest of the paper is organised as follows: Section II presents a summary of pertinent recent research; Section 3 explores three contemporary deep learning methodologies; Section 4 discusses the comparative results; and, finally, Section 5 concludes with recommendations for more research.

II. LITEARTURE REVIEW

This section briefly discusses some innovative iris-recognition work. Most methods of recognition utilise methodologies of deep learning. Upon studying these methods, it is easy to build own iris recognition architecture.

Khuzani et al., (2020), provide a four-step architecture for iris recognition that runs efficiently. Implementing an approach to iris segmentation that integrates relative total variation with coarse iris localisation; extracting features using Wavelet, GLCM, GLDM, Shape & density, and FFT; using Kernel-PCA to reduce features; and classifying 2000 iris photos from the CASIA-Iris-Interval dataset, which were acquired from 200 individuals, using a multi-layer neural network for classification. Verified by findings, a suggested scheme is capable of producing a trustworthy forecast with a precision level of up to 99.64%[11].

Liu et al., (2020), enhance the signal-to-noise ratios by applying triangle fuzzy median, triangular fuzzy average, and Gaussian preprocessing filters to the picture, which will fuzzify the area beyond the border. used the improved pictures processed by fuzzy operations to educate deep learning algorithms, which boosted recognition accuracy and accelerated convergence. The saliency maps demonstrate that deep learning finds more useful information in fuzzy pictures processed with filters. Numerous other DL applications for image processing, analysis, and prediction might gain from the proposed fuzzy operation of images [12].

Wang et al., (2020), introduces Iris ParseNet, a very efficient iris segmentation approach based on DL. Training and evaluating the proposed technique would require manually labelling three complex iris databases—CASIA.v4-distance, UBIRIS.v2, and MICHE-I—that include numerous illumination (VIS, NIR) and image sensors (long-range and mobile iris cameras), as well as diverse kinds of sounds[13].

Hsiao, Fan and Hwang, (2021), The cropped iris picture is classified using the EfficientNet model. The proposed DL iris identification system is able to attain recognition accuracies of up to 98% when trained on the CASIA v1 database. The proposed technique has better iris recognition accuracy than previous attempts, which may be useful for biometrics applications that employ iris data [14].

Hsiao, Fan and Hwang, (2021), An investigation of the most efficient architecture based on DL networks for iris biometric identification is conducted. A model based on VGG-16 is then used to categorise the iris picture. The proposed DL-based system, in conjunction with an independently developed near-infrared (NIR) database, is capable of attaining identification accuracies of up to 98% when dealing with intruders[15].

Hafeez et al., (2022), have thought of using the iris as a biometric verification source since it is a distinct feature of the eye that cannot be changed and stays the same from one person to the next. As an additional approach to iris identification, the PCA-based technique is suggested to use a similarity score independently. The first proposed technique enhanced accuracy to 99.73 percent and decreased calculation time to 6.56 seconds, according to experiments run on custom-built database; in comparison, the PCA-based method is less accurate[16].

Shanto, Ali and Ahsan, (2022), focus your efforts on teaching a CNN model to categorise all of the dataset's records. With test accuracy rates of 95.20% and 99.28%, respectively, in sessions 1 and 2, the suggested approach demonstrated encouraging results. This method has outperformed a number of the industry standard approaches. The primary public datasets used to evaluate the system are IITD Iris and Ubiris v1[17].

The literature on iris recognition shows significant advancements but also reveals certain gaps. Traditional feature extraction and dimensionality reduction methods, while achieving high precision, may limit adaptability to diverse datasets. Improved preprocessing techniques and advanced segmentation methods have been developed but lack integration with cutting-edge deep learning architectures. Various deep learning models have been utilised, yet comprehensive comparisons with other advanced models are scarce. Some methods, like PCA-based techniques, show efficiency but fall short in accuracy compared to more sophisticated approaches. High accuracy with CNN models suggests potential, but combining CNN with other techniques remains underexplored. Additionally, studies on real-time applications and broader dataset validation are limited. Advanced techniques combining deep learning with optimisation algorithms need further comparative analysis to establish superiority. Future research should focus on integrative and comparative approaches and address real-time application challenges in diverse environments.

III. METHODOLOGY FOR IRIS RECOGNITION

When considering the FAR and FRR, iris recognition stands head and shoulders above the other biometric modalities. A significant quantity of intricate texture information is accessible for identification when using iris as a biometric approach. The goal of this research is to create a biometric identification that leverages the iris's texture, namely an iris recognition system. Capturing the iris picture, preprocessing it, segmenting its boundaries, normalising it, extracting features, and finally classifying it are the six basic steps of a standard iris recognition system, as displayed in Figure 2.

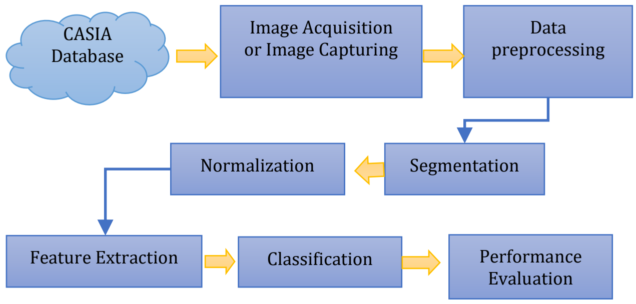

Fig. 2. Human Iris recognition system

A. *Image Acquisition or Image Capturing*

The process of acquiring or capturing an image is the first stage in iris recognition. This is a challenging stage since people's irises vary greatly in size and colour. The CASIA database is used to collect iris pictures for this research.

B. *Data Preprocessing*

Acquiring a precise iris image for input requires thorough preprocessing. Iris images are taken using a specialised camera in certain lighting circumstances as one of the many processes in data preparation. The approach primarily consists of three steps: resizing the image, greyscale conversion, and histogram equalisation. All of the steps are outlined in great detail below:

- **Image-Resizing:** Images are adjusted to remove the issue of varied resolutions in order to resolve the issue of varying iris sizes in a same database. This strategy makes it easier to get the same characteristics on all the images. Here, the image is shrunk down to 256 × 256 pixels. The 320x280 pixel main image and the 256×256 pixel scaled image of the CASIA database are shown in the figures below.
- **Gray-Scale Conversion:** The term "grey-scale" describes a broad category of colourless grayscale tones. One generalisation is that white is the lightest colour and black is the darkest. If an image is grayscale, then it contains only one colour channel. Any image that is already grayscale is preserved, whereas any image that is coloured is transformed to grayscale. There are three colours that make up an image pixel: red, green, and blue. In order to transform a colour image into a grayscale one, the values of the RGB colour space, which include 24 bits, are quantised to 8 bits.
- **Histogram Equalisation:** A approach that falls under the umbrella of Histogram modelling is histogram equalisation. Changing the intensity distribution of the histogram allows one to alter the picture's contrast and dynamics. When applied to a picture, this technique produces a linear trend in the cumulative probability function. Consequently, the image's contrast and quality are both improved by this method.

C. *Segmentation*

Iris identification relies on segmentation, a process of separating an iris area by a remainder of tanhe eye picture. Here, the pupil and sclera form an outline around an iris in an iris image. A removal of a pupil allowed for a direct examination of the iris, the only part of the eye that displays the unique patterns used for identification [18]. Hough gradient approach was used for segmentation. The smart edge detector, an edge detection technique, is used by this approach to determine the iris's borders. The device can precisely locate the iris boundary by analysing its outline.

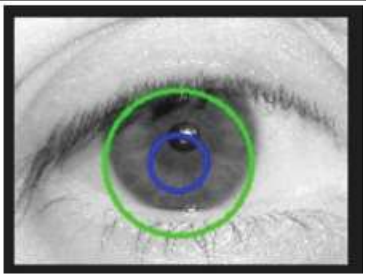

Fig. 3. Unsegmented iris image

An unsegmented image of the iris is shown in Figure 3. Iris area has not been separated from the whole image yet. When iris images are not properly segmented, it might lead to issues with the iris identification system. Findings are inaccurate.

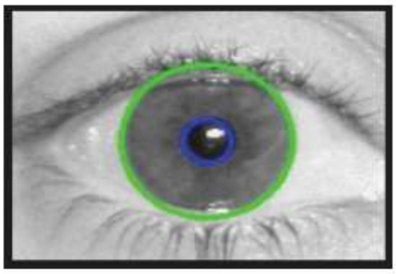

Fig. 4. Segmented iris image

The image that depicts the segmented iris is displayed in Figure 4. It is a cutaway and extracted section of the original image. A number of image processing techniques have successfully separated an iris area from the rest of an eye, including the lids and lashes.

D. *Normalization*

Another important stage in iris recognition is normalisation. They made a rectangular depiction of the segmented iris area. This improves the ability to compare and match iris templates. To accomplish this change, they have utilised a rubber sheet normalisation method. An iris image is converted into a specific format by using a standardisation technique that eliminates size and rotation inconsistencies. Here is how iris patterns are obtained. They may compare and match features in an iris recognition system with the use of these patterns.

E. *Feature extraction*

A feature extraction process is utilised to a normalised image after a normalisation step. An essential part of iris identification is feature extraction, which involves taking an image of the iris and then extracting its distinct patterns. To achieve the texture complexity of iris, the Gaussian filter (GF) was implemented. Therefore, the template implies a vital part of the identification and matching process.

Fig. 5. Iris template obtained from the feature extraction technique

Figure 5 was generated using the feature extraction method. Many iris templates have been compiled for a purpose of matching.

Using the feature extraction method, they were able to get the iris templates. This process of finding a match between the test data and these templates is called feature matching. In order to find out how similar two images are, feature matching compares the extracted iris template to another image's template. A distance measure, such the hamming distance, is usually computed among the two templates to do this. The hamming distance has been used to assess the degree of resemblance or dissimilarity across iris templates.

F. *CNN in Iris Recognition*

Iris identification models based on CNNs have attracted a lot of interest from researchers as improve upon traditional image processing methods while also removing limitations [19]. Using convolutional layers, pooling layers, and fully connected layers—repetitive blocks of neurons—CNN is able to obtain feature representations from images and performs better than many traditional hand-crafted feature approaches. A common CNN design, as shown in Figure 6, was used in this investigation (CNN's-GF[20]).

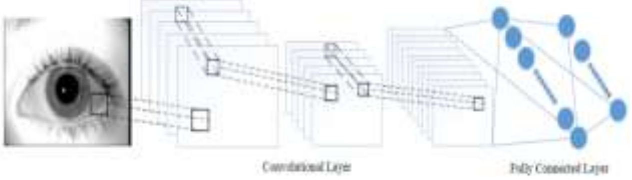

Fig. 6. CNN architecture for Iris recognition[21]

1) *Convolution layers*

In order to extract features from an input image, convolution layers are essential. To execute the convolution process, a back-propagation technique is utilised to update a value of randomly generated kernels/filters. Here is what a typical convolution layer does as follows Equ. 1:

$$x_j^l = f\left[\sum_{i\epsilon m_j} x_j^{l-1} * wx_{ij}^l + b_j^l\right] \tag{1}$$

where x_j^{l-1} and x_j^l are i^{th} input by $(l-1)^{th}$ layer, and a j^{th} output to a L layer, respectively. An operation * shows a convolution operation and w_{ij}^l denotes a weight for a kernel. b_j^l represents a bias term of a j^{th} output in a L layer. f (.) is an activation function.

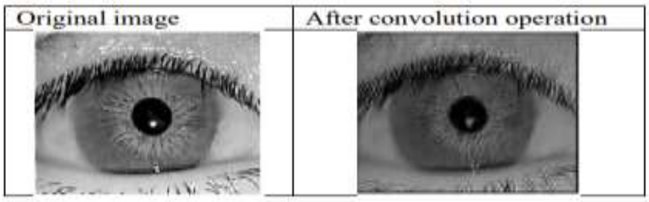

Fig. 7. Before and after convolution operation input image

Figure 7 shows the subsequent outcomes of implementing 2-D filtering with a 5 x 5 mask.

2) *Pooling layers*

For convolutional layers to provide more efficient computations, this layer's principal role is to decrease a size of feature maps and enhance a valuable features shown by filters during image convolution. The standard method of pooling data is either getting an average value $f_{avg}(x) = \frac{1}{N}\sum_{i=1}^{N} x_i$ or a maximum operation $f_{max}(x) = \max_i x_i$, where x is a vector containing an activation values by a local pooling area of N pixels in the picture.

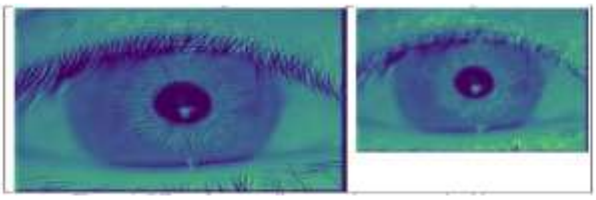

Fig. 8. Effect of max pooling operation on convolved image

Maximising the pooling process on the convolved image yields the result shown in Figure 8.

3) *Fully Connected Layers*

A common way for CNN pipelines to end is with fully connected layers. For N-dimensional vectors x, Softmax is an enhancement of the Sigmoid function that "squashes" them into Sigmoid(x), with each output being a number between 0 and 1. Many different multi-class classification algorithms make use of the softmax function, CNNs in particular. A number of classes in a dataset being examined (Nc) is represented by the dimension of the vector that the softmax layer acts on; in this example, it is positioned at the end of the network. Accordingly, the softmax predicts the likelihood of each class based on data supplied by a final fully connected layer. A softmax function is defined as follows Equ. 2:

$$f_j(z) = \frac{e^{z_j}}{\sum_{j=1}^{N_c} e^{z_j}} \tag{2}$$

where z is the score from the fully connected layer.

IV. Results Analysis And Discussion

An efficient Iris Recognition System using a DL method for authentication verification is shown in this presentation. Using the CASIA dataset, they compare the CNN system's performance to previous studies and provide findings. With the help of the SGDM optimiser, the CNN architecture is trained. Additionally, the dataset is divided as follows: 70% for training and 15% for validation and testing. Fifty iterations make up the training phase. There are 32 items in each batch. Figures ten and eleven show the proposed CNN for Dataset CASIA, together with its training and validation accuracy plots and loss function plots.

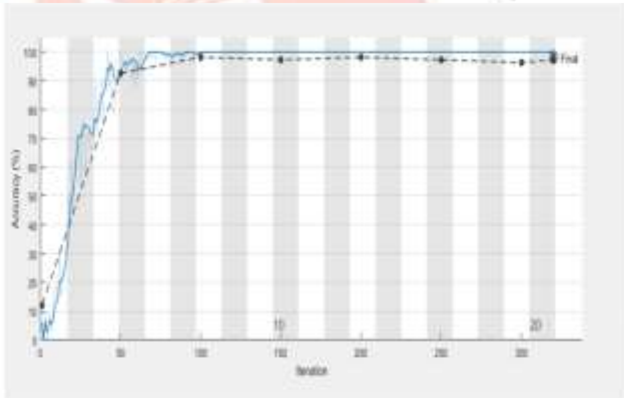

Fig. 9. CNN training and validation accuracy over the iterations

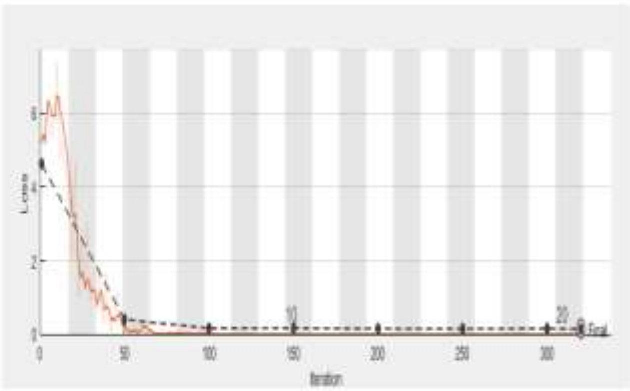

Fig. 10. Loss Function over the iteration

Figures 9 and 10 show the CNN model's loss and accuracy curves, respectively. The accuracy and loss curve are shown on the y-axis, while the total number of epochs is shown on the x-axis. The model's accuracy levels are 96.44% during training and 99.99% during validation; the training loss is 0.1978%, and the validation loss is 99.99%.

A. System Evaluation

The effectiveness of this classification strategy can only be determined by comparing the class to the baseline. Effective categorisation depends on a number of conditions being satisfied. In order to carry out the experiments that are dependent on the dataset, the ground truth is used.

Accuracy is defined as the percentage of accurate predictions relative to all valid guesses in the dataset. Accuracy levels range from 0.0 (very low) to 1.0 (very high). In Equation (3), "accuracy" refers to the percentage of correct predictions.

$$Accuracy = \frac{\mathrm{TP + TN}}{\mathrm{TP + TN + FN + FP}} \quad (3)$$

A true positive (TP) is the result of a classifier correctly labelling a negative tuple as a true negative (TN). False positives (FP) occur when there is an error in the marking of negative tuples. Negative results that are really recorded as negative are called false negatives (FN).

A following table I offers an accuracy comparison different DL models R-CNN[22], IRISNet [23], SVM[24], PCA[16] and CNN's-GF for Iris Recognition.

TABLE I. COMPARISON BETWEEN DIFFERENT DEEP LEARNING MODELS FOR IRIS RECOGNITION

Models	Accuracy
R-CNN[22]	95.49
IRISNet [23]	97.32
Support Vector Machine[24]	98
PCA[16]	99.73
CNN-GF	99.99

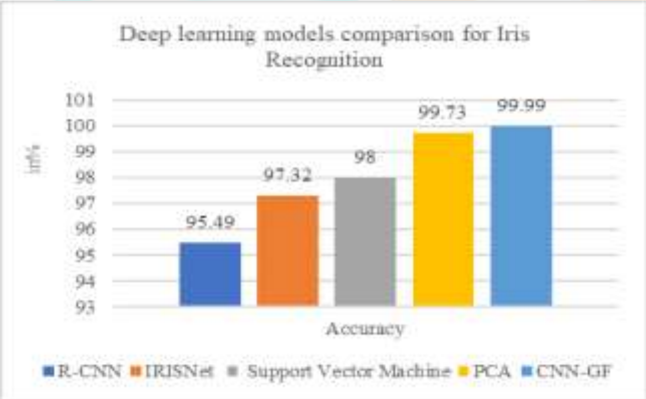

Fig. 11. Comparative bar graph of deep learning models comparison with accuracy measure for Iris Recognition

The comparison of multiple DL models for iris identification reveals varying levels of accuracy, as shown in Figure 11. Notably, PCA achieves an incredible 99.73% accuracy, demonstrating the efficacy of its dimensionality reduction method. CNN's-GF outperforms all other models with an astounding 99.99% accuracy, demonstrating the potential of convolutional neural networks in capturing complex iris patterns. Support Vector Machine likewise performs well at 98%, while IRISNet and R-CNN attain accuracies of 97.32% and 95.49%, respectively. This comparison research highlights the various capabilities of deep learning models in iris detection, with CNN's-GF outperforming the other techniques.

V. Conclusion And Future Work

Using a chronological approach, they explored several methods for iris detection in this study. Theft of personal information has grown in importance in the realm of security applications in the last several years. To make sure the individual's identity is recognised and to make the identification procedures more successful, these recognition models are studied and researched extensively. Each of these approaches is beneficial for iris recognition, as stated in the paper. Modern advancements in unique iris recognition technology guarantee that the fast and safe traditional identifying method maintains a remarkable recognition rate. Proposed iris recognition systems, which provide iris recognition algorithms beyond neural networks, have raised the security of an individual's identity recently. Every technology has benefits and drawbacks, which has led to the evolution of creative technologies. This survey study may be used to help new researchers in research by looking for better iris-recognition systems.

This design may be altered in the future to make use of coloured iris images, which will enhance the accuracy of iris boundary identification. The effectiveness of the existing IrisConvNet model in addressing the heterogeneous iris detection problem might be investigated. Future work could involve using deep learning techniques like CNNs and RNNs for improved pattern recognition, expanding datasets for better generalizability, and enhancing real-time processing for mobile and IoT integration. Additionally, focusing on privacy and security in voice data handling will be crucial for practical and ethical deployment in biometric authentication systems.

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