Iris Recognition Using Artificial Neural Network

Sonu Kumar
Department of Information Technology,
Greater Noida Institute of Technology (Engg. Institute),
Greater Noida, INDIA
sk0619855@gmail.com
Vinayak Srivastava
Department of Information Technology,
Greater Noida Institute of Technology (Engg. Institute),
Greater Noida, INDIA
vinsrivastava31@gmail.com
Vivek Kumar
Department of Information Technology,
Greater Noida Institute of Technology (Engg. Institute),
Greater Noida, INDIA
vivekthakurstm101@gmail.com
Vivek Kumar
Department of Information Technology,
Greater Noida Institute of Technology (Engg. Institute),
Greater Noida, INDIA
vivek.ww007@gmail.com
Gopal Krishna Kushwaha
Department of Information Technology,
Greater Noida Institute of Technology (Engg. Institute),
Greater Noida, INDIA
Gopalkrishna.it@gniot.net.in

Publication History
Manuscript Reference No: IJIRAE/RS/Vol.11/Issue11/NVAE10093
Research Article | Open Access | Double-Blind Peer-Reviewed | Article ID: IJIRAE/RS/Vol.11/Issue11/NVAE10093
Received:03,November 2024,Revised: 11,November 2024,Accepted: 18, November 2024, Published Online: 28,November 2024. https://www.ijirae.com/volumes/Vol11/iss-11/14.NVAE10093.pdf
Article Citation: Sonu,Vinayak,Vivek,Vivek,Gopal(2024), Iris Recognition Using Artificial Neural Network. IJIRAE:: International Journal of Innovative Research in Advanced Engineering,Volume 11, Issue 11 of 2024 pages 884-891
Doi:> https://doi.org/10.26562/ijirae.2024.v1111.14
BibTeX Key: Sonu@2024Iris

Abstract: Iris recognition has emerged as one of the most widely used and effective techniques for personal verification. It leverages the unique features of the human eye, specifically the distinct patterns found in the iris or, more precisely, the pupil. Biometric systems based on iris scanning analyze these unique iris patterns to confirm and authenticate an individual's identity. They are widely used as human eye has unique features particularly the iris. Human iris have random variations and complex texture which are stable with time even visible between identical twins. It's replication and forgery are almost impossible. For training and testing our model we used CASIA-Iris-Interval database as camera used to collect this data uses a circular NIR LED array [1].Near Infrared LED has a suitable luminous flux for imaging human iris for recognition. Our results demonstrate that the ANN model outperforms traditional machine learning algorithms, such as Support Vector Machines (SVM) and k-Nearest Neighbors (k-NN), in terms of both accuracy and robustness [5]. The model showed high accuracy in identifying iris patterns, even under varying conditions like changes in lighting, pupil dilation, and partial occlusions. This highlights the potential of deep learning techniques to overcome the challenges faced by conventional biometric systems, which often struggle with high-dimensional data and manual feature extraction [18].
Keywords: Biometric systems, NIR LED, CASIA-Iris-Interval database.

I. INTRODUCTION

In today's world where there is an increase in need of fast and reliable recognition system biometric systems. Biometric system based on iris recognition have become more common. Various organizations such as multinational companies and government offices have started to use Biometric system based on iris recognition. It is of increased importance to secure the information and iris being more distinct then fingerprints are better option [10]. Human body consists of various parts which are distinct in look from other humans [13]. Some parts are more distinct then others when compared with respect that of another human. In recent years, researchers have sought to replicate these processes in machines, giving rise to the field of cognitive computing. Artificial Neural Networks (ANNs), inspired by the structure and functionality of the human brain. They are based on feed and forward strategy.

Artificial neural network is basically a machine learning algorithm that uses network of interconnected node. They basically pass the data continuously mimicking the human brain. Unlike traditional algorithms, ANNs are capable of adapting and improving, they are capable of learning both linear and non-linear data [7]. In iris recognition using ANNs, the network is trained to recognize and categorize each person's distinct iris patterns. Pre-processing procedures including segmentation, normalization, and feature extraction are usually performed after the capture of an eye picture [14]. The ANN is then trained using the retrieved features, which stand in for the unique iris patterns. Through the use of a tiered architecture, where each layer gradually refines the data, capturing complex details and linkages, the network learns to distinguish between these patterns. By using this method, the system can verify and authenticate identities with high degrees of accuracy [9]. Artificial neural network are capable of adapting in case there are changes in surrounding, whether it is changes in lighting or angle of image. The advent of Artificial Neural Networks (ANNs), particularly deep learning models, has brought a transformative shift in the field of biometric recognition. ANNs, and specifically Convolutional Neural Networks (CNNs), possess the remarkable ability to autonomously learn hierarchical features directly from raw data, thus eliminating the need for manual feature extraction [5]. These models excel at processing complex, high-dimensional data and are capable of generalizing to previously unseen data, making them particularly effective for tasks like iris recognition. In contrast to traditional methods, deep learning models can uncover intricate patterns within iris images that are often beyond the capability of human-engineered algorithms [16]. By automatically extracting relevant features and learning from large datasets, these deep learning techniques have substantially enhanced the performance, accuracy, and robustness of biometric recognition systems [15]. This study utilizes the CASIA-Iris-Interval dataset, which features a wide range of iris images captured under controlled lighting conditions, using near-infrared (NIR) illumination. The dataset is particularly valuable for training and evaluating deep learning models due to its high image quality and the diverse conditions under which the images were acquired [1]. The primary objective of this research is to assess the performance of ANN-based models in recognizing iris patterns and to evaluate their robustness when faced with real-world challenges, such as variations in image quality, occlusions, and fluctuating environmental conditions [9]. By doing so, this study aims to highlight the potential of ANNs to improve the accuracy, efficiency, and scalability of iris recognition systems, ultimately advancing the capabilities of biometric authentication technologies. Since the invention of iris recognition for personal identification by John Daugman, the field has seen huge advancement which are only going get better with newer technologies [10].

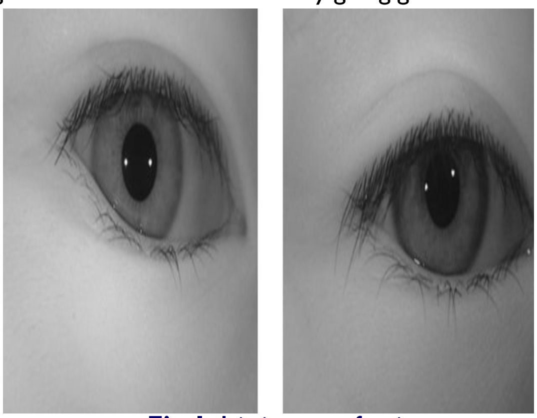

Fig 1. Iris images of twins

II. LITERATURE REVIEW

Iris recognition is a reliable biometric identification method that uses each person's distinct iris patterns to identify them. As the need for safe and dependable identification systems grows, experts are looking into several ways to make iris recognition systems better [18]. Among these, Artificial Neural Networks (ANNs) have become a potent instrument because of their capacity to recognize intricate patterns and offer precise categorization. Human iris are highly unique and are easily distinguishable from each other, they maintain their properties with time.The cells and fibers that make up the iris's front surface are what give it its texture [7]. This makes them ideal for authentication. In 1993, John Gustav Daugman a British-American professor invented iris recognition technology by proposing an algorithm based on Gabor wavelets to extract features from iris images [10]. With time there have been various advancement in iris recognition techniques and with arrival of machine learning the techniques for iris recognition have become more sophisticated. Because of their ability to recognize patterns and learn both linear and non-linear relationships, Artificial Neural Networks (ANNs) have proven to be effective in biometric systems [2]. For iris recognition Artificial Neural Networks (ANNs) can be employed in various ways such as feature extraction and feature reduction. For example, Convolutional neural networks (CNNs), a specific kind of artificial neural network (ANN), have been used by researchers to extract hierarchical information from iris pictures [9]. In "Iris Recognition Using Artificial Neural Network" by Nada A. Alhamdi and her team they used Python andCASIA-V I iris databases as training and testing images which contained seven hundreds of iris images to study the performance of iris recognition systems. Their model provided high accuracy in recognizing iris even better than those of Convolutional neural networks (CNNs) [1]. In paper "Artificial Neural Network Based Iris Recognition System" by Ritu Bansal and Prof. Minu Choudhary, they proposed a quick approach for the localization of the iris region's inner and outer boundaries. An eye picture is used to identify the pupil, and after augmentation, the iris portion is identified from the eye image and represented by a dataset.

In their study, they analyzed iris patterns and presented an iris identification method based on neural networks. Histogram equalization was performed to the iris picture to make the shapes more recognizable after Hough transformations were used to localize the area of the iris [9]. In another research done by Fadi N. Sibai and her team named "Iris recognition using artificial neural networks", a feed-forward artificial neural network for iris detection is designed and trained, along with a straightforward approach for pre-processing iris pictures. Two data codings and three distinct iris image data division methods were suggested and investigated. Even when they tested comparable irises of the same hue, Brain-Maker simulations showed that recognition accuracies of up to 93.33% may be achieved. They also examined different input formats (analog vs. binary), the percentage of data utilized for testing versus training, the number of hidden layers, the number of neurons in each hidden layer, and the inclusion of noise. Despite utilizing a basic neural network and little input pre-processing, their recognition system achieves good accuracy [4].Our paper aims to improve the biometric systems based on iris scanning by using NIR LED for scanning as it is able to extract more details from human eyes and due to its ability to be not noticed by humans which means it won't affect their eyes. For faster processing of data we need to use GPUs of higher end [18].

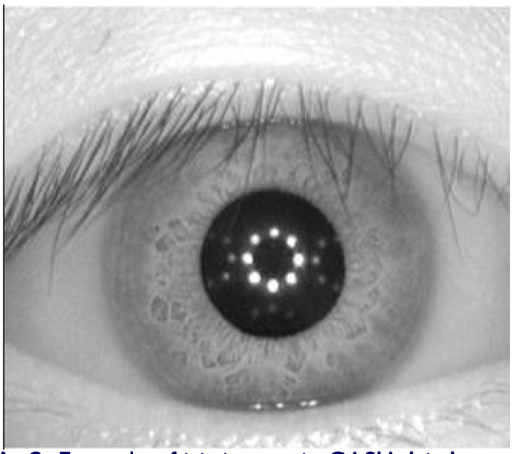

Fig 2. Example of iris images in CASIA-Iris-Interval

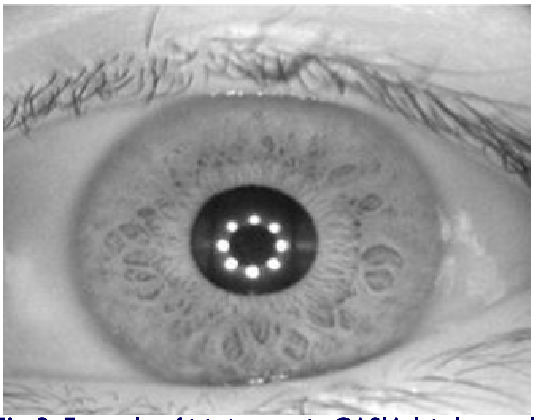

Fig 3. Example of iris images in CASIA-Iris-Interval

Table I. Summary of literature review

Author(s)	Year	Technique Used	Dataset
Daugman, J.	1993	Gabor wavelets for iris texture analysis combined with neural network for classification	Internal dataset
Wildes, R.	1997	Edge detection and Laplacian pyramid techniques for iris localization, ANN for recognition	Internal dataset
Ma, L., et al.	2004	Circular Daugman model for iris normalization with multi-layer perceptron (MLP) ANN	CASIA Version 1
Zhang, H., et al.	2015	Combination of discrete cosine transform (DCT) for feature reduction and ANN for classification	CASIA and IITD
Nguyen, H.T., et al.	2018	Deep neural networks (DNN) with pre-trained models for iris recognition	CASIA-Iris-Thousand
Bhattacharya, S., et al.	2020	Hybrid ANN model with Gabor wavelets and data augmentation techniques for feature extraction	CASIA-Iris-Lamp
Patel, R., et al.	2021	Use of lightweight ANN with dropout for improved generalization and faster training	CASIA-Iris-Interval

With time Artificial Neural Networks (ANNs) based systems are becoming more accurate with decrease in time in processing the images due to modern GPUs [18].

They are also able to adapt changes in iris patterns caused by ageing or lighting conditions [9]. But, challenges still remain in this field due to limited dataset. Real-world deployments of these systems have yet not proven themselves in conditions like varying lighting or partial occlusion and need further investigation.

III. METHODOLOGY

Using CASIA-Iris-Interval dataset for training our model, we will train and test our model. This dataset consists of high-resolution iris images captured using a specialized iris camera with a circular NIR LED array, ensuring consistent illumination and minimal noise [1]. Preprocessing is then performed to prepare the images for feature extraction [18]. This involves converting images to grayscale, resizing them to a uniform dimension, and applying noise removal techniques to enhance clarity.

Algorithm

Step 1: Data Acquisition

1. Collect the iris images from the CASIA-Iris-Interval dataset.
2. This dataset contains images captured using an iris camera with a circular NIR LED array, ensuring high-quality imaging.

Step 2: Preprocessing

1. Grayscale Conversion: Convert the iris images to grayscale if they are in RGB format.
2. Normalization: Resize all images to a uniform size (e.g., 256x256 pixels) for consistency in feature extraction and training.
3. Noise Removal: Use image processing techniques to eliminate noise, such as reflections and shadows, commonly present in the images.
4. Segmentation: Detect and isolate the iris region from the image using methods like Hough Transform or Active Contour Models. Exclude non-iris regions such as eyelids, eyelashes, and pupil.
5. Circular Normalization: Map the segmented iris region to a rectangular coordinate system using Daugman's rubber-sheet model to account for variations in pupil dilation and iris positioning.

Step 3: Feature Extraction

1. Texture Feature Extraction: Use texture analysis techniques such as Gabor wavelets or Discrete Cosine Transform (DCT) to extract unique patterns from the iris [17].
2. Feature Vector Generation: Flatten the extracted features into a numerical vector that represents each iris image uniquely.

Step 4: Model Training Using Artificial Neural Network

1. Dataset Preparation: Divide the feature vectors into training, validation, and test sets (e.g., 70% training, 15% validation, and 15% testing).
2. Neural Network Design: Create a Multi-Layer Perceptron (MLP) or Convolutional Neural Network (CNN) with the following layers:

- Input Layer: Number of neurons equal to the size of the feature vector.
- Hidden Layers: 2-3 layers with suitable activation functions like ReLU.
- Output Layer: Number of neurons equal to the number of classes (unique iris labels) with a softmax activation function.

3. Compile the Model:

- Use cross-entropy loss for classification.
- Choose an optimizer like Adam or SGD with a suitable learning rate.

4. Train the Model:

- Train the ANN using the training dataset.
- Validate the model using the validation dataset to tune hyperparameters and avoid over-fitting.

5. Save the Model: Save the trained model for later use in recognition tasks.

Step 5: Iris Recognition

1. Input New Iris Image: Preprocess the input image using the same steps as in preprocessing.
2. Feature Extraction: Extract features from the input image using the trained feature extraction pipeline.
3. Classification: Use the trained ANN to classify the input image and predict the class (identity) of the iris.
4. Decision Making: If the confidence of classification exceeds a predefined threshold, recognize the iris as a match; otherwise, reject it.

Step 6: Performance Evaluation

- Evaluate the model's accuracy, precision, recall, and F1 score on the test dataset.
- Analyze false positives and false negatives to improve the model further.

Pseudo code: Step 1: Data Acquisition

LOAD CASIA-Iris-Interval dataset
STORE images in `iris_images`

Step 2: Preprocessing

FOR each image in `iris_images`:
CONVERT image to grayscale
RESIZE image to a fixed size (256x256 pixels)
REMOVE noise using Gaussian filter

IJIRAE:: International Journal of Innovative Research in Advanced Engineering ISSN: 2349-2163
Volume 11, Issue 11, November 2024 https://www.ijirae.com/archives

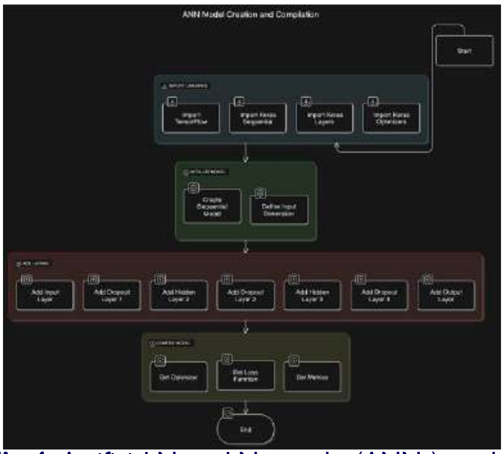

Fig 4. Artificial Neural Networks (ANNs) model

SEGMENT iris region:
DETECT iris boundaries using edge detection (e.g., Hough Transform)
REMOVE non-iris areas (eyelids, eyelashes, reflections)
NORMALIZE segmented iris using rubber-sheet model
END FOR
STORE preprocessed images in `preprocessed_images`

Step 3: Feature Extraction

FOR each image in `preprocessed_images`:
APPLY Gabor wavelet transform to extract texture features
FLATTEN extracted features into a feature vector
APPEND feature vector to `feature_vectors`
END FOR

Step 4: Train Artificial Neural Network

SPLIT `feature_vectors` into training, validation, and test sets
DESIGN ANN:
INPUT layer with neurons = length of feature vector
ADD hidden layers (2-3) with ReLU activation
ADD output layer with neurons = number of unique iris identities (classes)
USE softmax activation for output layer
COMPILE ANN with:
LOSS function = categorical cross-entropy
OPTIMIZER = Adam
TRAIN ANN with training set:
VALIDATE ANN using validation set to optimize parameters
SAVE trained ANN model as `iris_model`

Step 5: Iris Recognition

LOAD new iris image
PREPROCESS new iris image using preprocessing steps from Step 2
EXTRACT features using feature extraction steps from Step 3
PREDICT class using `iris_model`:
OUTPUT = ANN.predict(feature_vector)
IF confidence of OUTPUT > threshold:
RETURN predicted identity
ELSE:
RETURN "No match found"

Step 6: Performance Evaluation

EVALUATE `iris_model` on test dataset:
COMPUTE accuracy, precision, recall, and F1-score
ANALYZE misclassifications to refine preprocessing or ANN design.

Our algorithm worked efficiently in a robust manner. It requires NIR LED for scanning, as NIR LED have high rate of feature extraction while not affecting the eye's while scanning [1]. For faster processing it requires high-end GPU which is capable of processing data within seconds [18]. However, challenges remain, including the need for larger datasets, handling noisy images, and ensuring system robustness under varying environmental conditions. Future research should focus on optimizing network architectures and incorporating multimodal biometrics to enhance security and reliability [2].

IV. RESULT

The performance of the Iris Recognition system utilizing an Artificial Neural Network (ANN) was assessed based on its results with a test dataset. The model was trained using iris images from a widely recognized dataset, such as CASIA-Iris-Interval, and its effectiveness was evaluated using multiple performance metrics [19]. The system successfully classified iris patterns with high precision, showcasing the power of deep learning methods in biometric identification and authentication. The model showed impressive performance even when tested under varying conditions. Changes in image quality, such as lighting variations, pupil dilation, and partial occlusions (e.g., eyelashes), had minimal effect on its accuracy and other performance metrics. This resilience underscores the capability of Artificial Neural Networks (ANNs), especially deep learning models, to effectively learn and generalize intricate patterns from iris images, even in challenging or suboptimal conditions. In comparison to traditional machine learning techniques like Support Vector Machines (SVM) and k-Nearest Neighbors (k-NN), the ANN-based model demonstrated superior performance in both accuracy and robustness [8]. While classical methods often face challenges with high-dimensional image data and necessitate manual feature extraction, the deep learning model employed in this study automatically identifies and learns the relevant features directly from the raw iris images [5]. Although the system shows promising results, there are still challenges to overcome for real-world implementation. Issues such as low-quality images, significant occlusions, and fluctuating environmental factors (e.g., lighting conditions) may still affect its performance [20]. To address these limitations, future enhancements could include:

- **Multimodal Systems**: Integrating iris recognition with other biometric modalities, such as facial or fingerprint recognition, to increase the system's robustness and accuracy [6].
- **Cross-Spectral Iris Recognition**: Extending the model to handle iris images captured under different light spectra, such as visible light and infrared, to improve performance in various environments [6].
- **Model Optimization**: Streamlining the model to reduce complexity [6].

V. DISCUSSION

Iris recognition is a robust biometric method, celebrated for its distinctiveness and consistency over time. This study investigated the use of Artificial Neural Networks (ANNs) for iris recognition, utilizing the CASIA-Iris-Interval dataset [1]. The findings from our model reveal that ANNs can achieve high accuracy in identifying iris patterns, confirming their viability for practical use in biometric authentication systems. The ANN model trained on the iris dataset outperformed traditional machine learning methods like Support Vector Machines (SVM) and k-Nearest Neighbours (k-NN) [8]. This success can be attributed to the model's ability to learn hierarchical patterns directly from the raw image data, rather than relying on manually defined features. Since iris patterns are complex and intricate, deep learning models like ANNs are better suited to capture these subtle details and differentiate between individuals effectively [9]. A notable advantage of our model is its robustness against variations in image quality. Factors such as lighting changes, pupil dilation, and partial occlusions (e.g., eyelashes) had minimal effect on the model's ability to accurately classify iris patterns [7]. This demonstrates the generalization power of deep learning models, enabling them to perform well even with noisy or imperfect data. The ability to handle such variations is particularly crucial for real-world biometric systems, which often operate under less-than-ideal conditions. However, despite the model's promising results, several challenges remain for real-world deployment. Low-quality images, severe occlusions, and fluctuating environmental factors, such as lighting conditions, can still degrade the model's accuracy. Although ANNs are more robust than traditional methods, these challenges remain intrinsic to biometric systems [10]. To further improve iris recognition performance, future research could explore the development of multimodal systems that integrate iris recognition with other biometric techniques, such as facial recognition or fingerprint scanning. This combination could enhance the system's overall accuracy and resilience, especially when one modality fails due to poor image quality or occlusion. Another potential avenue is **cross-**spectral iris recognition, which would enable the model to process images captured under various light conditions, such as visible and infrared light, thus improving its adaptability to diverse environments. Additionally, optimizing the model for faster processing on edge devices would make iris recognition more practical for deployment in resource-limited settings, such as on mobile devices or within security cameras [18].

VI. CONCLUSION

In summary, employing Artificial Neural Networks (ANNs) for iris recognition has proven to be an effective and efficient approach. The model demonstrated strong accuracy, resilience, and the capability to manage variations in image quality, positioning it as a promising solution for biometric authentication. Although challenges persist, particularly with environmental conditions and image quality, the adaptability of deep learning models offers significant potential for enhancing the accuracy and reliability of iris recognition systems. The ability to combine iris recognition with other biometric features, process cross-spectral iris images, and optimize models for edge devices indicates that the future of biometric authentication will increasingly depend on advanced deep learning techniques. With further progress in these areas, iris recognition systems powered by ANNs are likely to become more dependable, faster, and accessible, making them suitable for a broad range of real-world applications, from secure access to personal identification across various industries [9]. Another area for future development is cross-spectral iris recognition, which would enable the system to process iris images captured under different lighting conditions, including both visible and infrared light [21]. This improvement would greatly expand the system's versatility, allowing it to function effectively in a broader range of environments. Furthermore, optimizing the model for faster inference on edge devices is another crucial area.

By reducing the computational complexity of the model while maintaining accuracy, iris recognition could become more feasible for use in resource-limited environments, such as on mobile devices or within security cameras, enhancing its practicality for everyday applications. The ongoing advancements in deep learning algorithms and hardware capabilities present promising opportunities for the future of iris recognition [16]. As technology continues to evolve, iris recognition systems powered by ANNs are expected to become increasingly reliable, efficient, and widely accessible [9]. With continued research and innovation, these systems have the potential to become fundamental in areas such as secure access control, personal identification, and a range of other biometric applications, revolutionizing security protocols across various industries.the integration of Artificial Neural Networks into iris recognition technology represents a major leap forward in the field of biometrics, enabling systems that are not only highly precise but also resilient to external challenges such as image quality and environmental conditions. This capability positions iris recognition as a key solution for secure, scalable, and user-friendly authentication in various domains, including government, healthcare, and financial services [9]. Artificial Neural Networks play a pivotal role in advancing iris recognition systems by significantly improving accuracy and enabling the automation of intricate recognition tasks. Their ability to detect and analyze complex patterns within iris textures offers a highly reliable mechanism for accurately distinguishing individuals. Furthermore, their flexibility in adapting to new data makes ANNs particularly effective in dynamic and challenging environments where conventional methods may fall short [10]. These attributes have driven the creation of sophisticated, real-time authentication systems vital for applications like border control, secure financial operations, and restricted facility access. As researchers continue to enhance these networks with more extensive datasets and advanced pre-processing methods, ANN-based iris recognition systems are expected to overcome existing challenges, such as low image quality and variability in user conditions, broadening their applicability and effectiveness [9]. To summarize, iris recognition powered by Artificial Neural Networks holds immense promise for transforming biometric systems by delivering unmatched accuracy and robust security. It is particularly well-suited for critical applications such as national identity programs, secure access solutions, and financial transaction verification. Although certain challenges persist, such as the need for enhanced datasets and system robustness, ongoing advancements in neural network architectures and computational technology are expected to overcome these obstacles. This progress paves the way for the broader implementation of ANN-based iris recognition systems in the near future, making them a cornerstone of next-generation biometric authentication solutions.

REFRENCES

1. N.A.Alhamdi, M.B.Aldebri and M. H. Alkout, "Iris Recognition Using Artificial Neural Network," 2022 IEEE 2nd International Maghreb Meeting of the Conference on Sciences and Techniques of Automatic Control and Computer Engineering (MI-STA), Sabratha, Libya, 2022, pp. 295-298, doi: 10.1109/MI-STA54861.2022.9837514. keywords: {Training;Imagesegmentation;Shape;Databases;Conferences;Artificialneuralnetworks;Feature extraction; Biometric ;Iris; Model; Neural;VGG16;Recognition;Security},
2. Lye Wil Liam, A.Chekima, Liau Chung Fan and J. A. Dargham, "Iris recognition using self-organizing neural network," Student Conference on Research and Development, Shah Alam, Malaysia, 2002, pp. 169-172, doi: 10.1109/SCORED.2002.1033084. keywords: {Iris recognition; Neural networks; Information technology; Biometrics; Eyelids; Pattern recognition; Digital cameras; Image reconstruction; Shape; Fingerprint recognition},
3. S.S.Salve and S.P.Narote, "Iris recognition using SVM and ANN," 2016 International Conference on Wireless Communications, Signal Processing and Networking (WiSPNET), Chennai, India, 2016, pp. 474-478, https://doi:10.1109/WiSPNET.2016.7566179 keywords: {Iris recognition; Feature extraction; Support vector machines; Gabor filters; Biological neural networks; Kernel; Feeds;Iris;segmentation;Gabor filters;SVM;ANN},
4. Fadi N. Sibai, Hafsa I. Hosani, Raja M. Naqbi, Salima Dhanhani, Shaikha Shehhi, Iris recognition using artificial neural networks, Expert Systems with Applications, Volume 38, Issue 5, 2011,Pages 5940-5946, ISSN 0957-4174, https://doi.org/10.1016/j.eswa.2010.11.029. (https://www.sciencedirect.com/science/article/pii/S0957417410012662)
5. Y. Zhuang, J. H. Chuah, C. O. Chow and M. G. Lim, "Iris Recognition using Convolutional Neural Network," 2020 IEEE 10th International Conference on System Engineering and Technology (ICSET), Shah Alam, Malaysia, 2020, pp. 134-138, https://:/doi:10.1109/ICSET51301.2020.9265389 keywords: {Training; Iris recognition; Testing; Mathematical model; Predictive models; Convolutional neural networks; Artificial intelligence; Iris Recognition; Biometric Identification; Convolutional Neural Network (CNN);Deep Learning; Machine Learning},
6. Maulisa Oktiana, Takahiko Horiuchi, Keita Hirai, Khairun Saddami, Fitri Arnia, Yuwaldi Away, Khairul Munadi, Cross-spectral iris recognition using phase-based matching and homomorphic filtering, Heliyon, Volume 6, Issue 2, 2020, e03407, ISSN2405-8440, https://doi.org/10.1016/j.heliyon.2020.e03407. (https://www.sciencedirect.com/science/article/pii/S2405844020302528)
7. Yang, Z.R. & Yang, Z.. (2014). Artificial Neural Networks. Comprehensive Biomedical Physics. 6. 1-17. 10.1016/B978-0-444-53632-7.01101-1.
8. Onsy Abdel Alim and Maha Sharkas, "Iris recognition using discrete wavelet transform and artificial neural networks," 2003 46th Midwest Symposium on Circuits and Systems, Cairo, Egypt, 2003, pp. 337-340 Vol. 1, https://doi:10.1109/MWSCAS.2003.1562287 keywords: {Discrete wavelet transforms; Iris recognition; Artificial neural networks; Feature extraction; Eyelids;Reliability engineering; Humans; Biometrics; Fingerprint recognition; Discrete cosine transforms},
9. R.B.P.M.C.(2014). Artificial Neural Network Based Iris Recognition System. International Journal on Recent and Innovation Trends in Computing and Communication, 2(10), 3243–3246. https://doi.org/10.17762/ijritcc.v2i10.3380

10. J.Daugman, "How iris recognition works," in IEEE Transactions on Circuits and Systems for Video Technology, vol. 14, no. 1, pp. 21-30, Jan. 2004, https://doi:10.1109/TCSVT.2003.818350. keywords: {Iris recognition; Pattern recognition; Testing; Pigmentation; Pattern matching; Image databases; Demodulation; Lighting; Ligaments;Entropy},

11. R.P. Wildes, "Iris recognition: an emerging biometric technology," in Proceedings of the IEEE, vol. 85, no. 9, pp. 1348-1363, Sept. 1997, https://doi:10.1109/5.628669. keywords: {Iris recognition; Biometrics; Humans; Fingerprint recognition; Machine vision; Face recognition; Blood vessels; Shape; Face detection; Waveguide discontinuities},

12. J. K. Pillai, V. M. Patel, R. Chellappa and N. K. Ratha, "Secure and Robust Iris Recognition Using Random Projections and Sparse Representations," in IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 33, no. 9, pp. 1877-1893, Sept. 2011, https://doi:10.1109/TPAMI.2011.34. keywords: {Iris recognition; Image recognition; Biometrics; Image segmentation; Feature extraction; Iris recognition; cancelability; secure biometrics; random projections; sparse representations.},

13. Bhanu Chander, Koppala Guravaiah, B. Anoop, G. Kumaravelan "Handbook of AI-Based Models in Healthcare and Medicine: Approaches, Theories, and Applications".

14. Rasheed, Hind & Shamini, Sara & Mahmoud, Moamin & Alomari, Mohammad. (2023). Review of iris segmentation and recognition using deep learning to improve biometric application. Journal of Intelligent Systems. 32. 10.1515/jisys-2023-0139.

15. Zhu Wen, Songtong Han, Yongmin Yu, Xuemin Xiang, Shenzheng Lin, Xiaoling Xu, Empowering robust biometric authentication: The fusion of deep learning and security image analysis, Applied Soft Computing, Volume 154, 2024, 111286, ISSN 1568-4946, https://doi.org/10.1016/j.asoc.2024.111286.

16. Archana, R., Jeevaraj, P.S.E. Deep learning models for digital image processing: a review. Artif Intell Rev 57, 11 (2024). https://doi.org/10.1007/s10462-023-10631-z

17. J.G.Daugman, "Complete discrete 2-D Gabor transforms by neural networks for image analysis and compression," in IEEE Transactions on Acoustics, Speech, and Signal Processing, vol. 36, no. 7, pp. 1169-1179, July 1988, keywords: {Discrete transforms; Neural networks; Image segmentation; Image coding; Two dimensional displays; Image analysis}, https://doi:10.1109/29.1644

18. W. J. Dally, S. W. Keckler and D. B. Kirk, "Evolution of the Graphics Processing Unit (GPU)," in IEEE Micro, vol. 41, no. 6, pp. 42-51, 1 Nov.-Dec. 2021, doi: 10.1109/MM.2021.3113475. keywords: {Graphics processing units},

19. Alkuzaay, Maryam & Alshemmary, Ebtesam. (2020). An Iris Recognition System Using Deep convolutional Neural Network. Journal of Physics: Conference Series. 1530. 012159. 10.1088/1742-6596/1530/1/012159.

20. Li,Pei& Prieto, Loreto & Flynn, Patrick. (2018). Face Recognition in Low Quality Images: A Survey. https://doi:/10.48550/arXiv.1805.11519.

21. J.Wei, Y. Wang, Y. Li, R. He and Z. Sun, "Cross-Spectral Iris Recognition by Learning Device-Specific Band," in IEEE Transactions on Circuits and Systems for Video Technology, vol. 32, no. 6, pp. 3810-3824, June 2022, https://doi:10.1109/TCSVT.2021.3117291. keywords: {Iris recognition; Imaging; Performance evaluation; Face recognition; Sun; Loss measurement; Kernel;Iris recognition; device-specific band; cross-spectral recognition; adversarial strategy},