TPM Vol. 32, No. S4, 2025
ISSN: 1972-6325
https://www.tpmap.org/

DEEP LEARNING-BASED FACE-IRIS RECOGNITION WITH CAPSULE NEURAL NETWORK (CAPSNET) FOR BIOMETRIC ATTENDANCE SYSTEM

SANGEETHA KARUNAKARAN[1], DR.A. AKILA[2]
[1]RESEARCH SCHOLAR, DEPARTMENT OF COMPUTER SCIENCE AND INFORMATION TECHNOLOGY, SCHOOL OF COMPUTING SCIENCES, VELS INSTITUTE OF SCIENCE TECHNOLOGY AND ADVANCED STUDIES (VISTAS), PALLAVARAM, CHENNAI, INDIA,
Email: sangitanu22@gmail.com
[2]ASSOCIATE PROFESSOR, DEPARTMENT OF COMPUTER SCIENCE AND INFORMATION TECHNOLOGY, SCHOOL OF COMPUTING SCIENCES, VELS INSTITUTE OF SCIENCE TECHNOLOGY AND ADVANCED STUDIES (VISTAS), PALLAVARAM, CHENNAI, INDIA,
Email: akila.scs@vistas.ac.in

Abstract*:* A model of biometric-based attendance system will be presented in this paper, which will utilize face recognition and iris recognition in order to make the attendance system more accurate and achieve greater level of security in the verification of the subject identity. Following the introduction of the proposed framework, early on, the acquisition of the CASIA-Iris-Distance Dataset is conducted, and subsequently, the basic pre-processing methods such as Hough Transform of Circles to segment the image, Min-Max normalization to scale the features, and Canny edge detection to visualize the iris pattern well is implemented. During the extraction of facial features where the size has to be reduced and the deep salient facial features have to be extracted, a Sparse Autoencoder (SAE) is used. These features extracted by the face and the iris modalities are then merged and placed into a Capsule Network, i.e., the Hyper Capsule Neural Network (HCNN), which maintains spatial hierarchies and shows a robust recognition performance regardless of small data changes. The various performance metrics are employed in determining that this system is workable and dependable in the real world. As a result of the combination of the recognition outputs, the system automatically predicts and records individual attendance. The proposed hybrid model (SAE+HCNN) through comparative analysis of performance is more precise and the accuracy of this proposed model is approximately 95% as compared to that of the SAE+CNN in which the accuracy is approximately 93-94%. The results provided above indicate that combination algorithm is very practical to reduce the risk of spoofing and boost the recognition accurateness in comparison to common single modal or multi-modal early fusion systems.

Keywords: Multimodal biometrics, Feature encoding, Sparse Autoencoder (SAE), Capsule Neural Network (CapsNet), Biometric attendance, Hough Transform, Minmax Normalization

1. INTRODUCTION

In contrast to the use of physical keys or passwords, biometrics technology holds considerable promise for bringing about a future in which identification and authentication procedures are not a conscious concern for everyone. With the recent developments in deep machine learning, facial recognition technology in particular is developing quite quickly in terms of identification accuracy and has garnered a lot of research interest as a potential technology that may provide both convenience and accuracy at the same time [1]. For the following reasons, the face and iris have been selected as the biometric features to be examined in this work. When compared to other biometrics, the human face is thought to be among the most practical. In addition, compared to other biometrics, face is unique in that it is inexpensive, contact-free, and very acceptable during acquisition. Additionally, on big datasets, the iris recognition systems produce low false matching rates and high matching rates [2]. The most popular biometric method for confirming an identity is face recognition (FR), which is utilized extensively in a variety of fields, including the military, banking, public safety, and daily life [3]. The paper presents a web-based attendance system using facial recognition and open-source pre-trained DL algorithms. The system consists of two core processes: documenting the face datasets and face matching to mark attendance. It combines web technologies and databases to control recognition procedures [4]. Face-Iris biometrics enjoy stable phenotype features, but a majority of the available databases are non-racially diverse, particularly African. To fill this gap, this paper presents CASIA-Iris-Africa, a large-scale collection consisting of 28,717 images of 1,023 subjects of African origin. It aids in the research into racial bias in iris recognition and makes demographically sensitive research possible. State-of-the-art baseline experiments show that existing systems exhibit race-based bias regarding performance diminution [5].

Objective

- To develop a hybrid biometric attendance system that incorporates a combination of face and iris recognition to enhance accuracy and security.
- To improve the quality of the image, use other advanced pre-processing algorithms, such as Circular Hough Transform to segment the iris, min max normalization, and edge direction analysis.
- To extract a deep facial feature with the assistance of Sparse Autoencoders (SAE) to effectively reduce dimensionality and feature representation.
- To combine face and iris features and categorize these features Capsule Networks to make robust recognition across variations in the input data.
- Assess the system performance in real-life environments to guarantee reliability, scalability, and resistance to spoofing in educational and corporate settings.

The remaining portion of the document is divided into significant sections, which are described as follows: Section II examines the current research efforts in Face-Iris Recognition with Capsule Neural Network used by different authors. Section III explains the workflow of the suggested approach in the Proposed Methodology. Section IV presents the findings analysis and performance data. Section V presents the conclusion.

2. RELATED WORK

B. U. Haq et al. (2023) The process consists of four separate stages: first registering the student's iris, then verifying their identification upon admission to the university, assessing each student's attendance at exams to determine their eligibility for, and keeping track of defaulters. Validation was carried out using real-time datasets comprising male and female respondents from different age groups, with a proven accuracy of 100%. Additionally, a user-friendly desktop application was developed to enhance end users' understanding and use.

Shashikala HK et al. (2020) Additionally, this initiative aims to provide students with the freedom to access their personal information, attendance history, teacher details, and schedule. Additionally, the teachers will have access to their daily agenda, all student information, and attendance status. The technology will help transform the conventional attendance management system into a precise and effective one once fully operational. We want to create an automatic attendance tracking system that uses iris recognition technology in the future. The Systems will decrease human labor and offer additional features like alarms, notifications, and information retrieval in addition to updating the attendance database.

Ennajar et al. (2024). According to a comparative analysis, our suggested ViT-L16 model is superior to previous approaches, particularly those that use a Vision Transformer with a Convolution Neural Network. The untried arrangement emphasizes assessments built on accuracy, loss, and Confusion Matrix and uses Jupiter Notebook, Python technology, Tensor Flow, and Keras. For improved performance and wider use in educational settings, future research should investigate incorporating other biometric modalities and improving the Vision Transformer design.

Orugba Kenneth Obokparo et al. (2024) One of the biometric identification methods is Iris recognition. Its algorithms allow for very transparent individual recognition. To monitor staff attendance at work and in class, iris recognition employs iris sensitivity to take a picture and compare it to a database. This paper introduces a technique for documenting attendance built on iris recognition. Compared to the manual, the antiquated technique of taking attendance at institutions, which is prone to mistakes and manipulation, is far superior.

Avantika Singh et al. (2020) If the original template is employed by storing the original IRIS template in the modified version, it can provide a cancellable iris bisexual authentication system that allows for different extensions and cancellations. In the first step, we have introduced a distinct deep architecture, which learns discriminatory iris properties as the aggregate. Unlike the more commonly applied quantitative indicators, this deep architecture adopts qualitative (ordinal) measures. This work's use of ordinal measurements makes it possible to encode unique iris traits effectively effectively.

Cassian Miron et al. (2022) This study presents an effective and light U-Net folding architecture of neural networks (CNNs) for iris segmentation of eye photographs. For all datasets investigated, the results of iris segmentation have become the latest and most recent criteria according to the traditional NICE1, F1, and MIOU accuracy criteria. Even though there exist a certain number of variations in the data records of such measurements, the Ubiris data records showed the lowest values of the parameter F1, MIOU, etc, 96.14% or 92.56%, although the values of such parameters by CAAT4 data records showed the lowest values of the parameter NICE1 0.38.

Shiv Kumar et al. (2021) Several biometric characteristics, such as face and iris, and their wide, unrestricted method of gathering data from subjects have created several difficulties in using biometrics. Periocular recognition has recently been shown to be a valuable characteristic for verification and authenticity. To evaluate the efficacy of different pattern recognition approaches in an unrestricted setting, we have given parameter analysis of periocular datasets in this study. This study's primary objective is to examine periocular biometrics methods in unrestricted settings to accomplish non-cooperative biometrics.

Rahmatallah Hossam Farouk et al. (2022) Using the three data records indicated above, a general modeling and simulation process has been used to validate the results of the suggested model. Also, the difference between the results obtained during the current experiment and the results of published data was made. Using CASIA HD, IITD CNN, and MMU CNN, the proposed biometric methods are 94.88%, 96.56%, or. 98.01%. The obtained accuracy showed that the classifier was superior to other classifiers used in published literature.

Ahmed Shamil Mustafa et al., Based on a review of the literature, this study proposes a decision fusion method that integrates fingerprint and iris biometrics without the need for any prior setup. The Gray-Level Co-occurrence Matrix with KNN is utilized for feature extraction when fingerprint and iris biometrics are coupled, and the AND gate is employed to determine the final decision. The suggested fusion approach outperformed single modality solutions in reaching final judgments for 20 test users with an efficiency level of 95%.

S. He et al. (2024). This paper presents an improved Enhance Deep Iris model-based iris recognition method to investigate iris recognition at a deeper level. The procedure initially extracts human iris properties using convolutional features. The sequential metric model is then shown to successfully recognize the iris and address the deformation issue brought on by the radial data of the iris texture.

Nalluri Prasanth et al. (2024) boost user authentication's precision and dependability. The study starts with the careful selection of a broad biometric dataset that includes periocular, iris, and face photos. A single CNN design enables the integration of multiple modalities, guaranteeing a thorough portrayal of the user's identity. The process of ideation, execution, and assessment has revealed a wealth of new techniques and technological developments that might completely alter the biometric security environment.

Camilo A. Ruiz-Beltran et al. (2023). To determine whether the network can distinguish this design from that connected to the out-of-focus eye picture, it will only be trained using properly focused eye images in this proposal. To process multi-channel input using the capacity of neuronal networks, CNN receives both grayscale images and highly pass-filtered versions that are often used to determine whether the iris is in focus. This work describes a sophisticated approach to properly focused eye recognition.

Young Won Lee et al. (2022) To address the issues that arise when low-resolution pictures are utilized for credit, we examined research that employed SR approaches and looked at iris and ocular identification methods based on high-resolution images. We also looked at the issues with each study. Accurately segmenting the flag region and extracting distinctive features from the iris data to identify each person are the two primary challenges in putting an iris identification system into practice.

E. Headley et al. (2024) In a traditional paradigm, this study investigates the effects of eyelid occlusion on off-angle iris identification. i) Assessing the overall impact of eye blinks on identification performance, ii) examining the effects on each specific angle, and iii) determining the level of occlusion required to maintain a good recognition performance in a traditional iris recognition pipeline are the main objectives. We modified the eyelid segmentation results to mimic eye blinking to generate different levels of eyelid occlusion because there aren't enough images of eye blinking in publicly available datasets.

Y. Moolla et al. (2021) This research Adults utilize biometric recognition extensively for various vocations requiring personal identification. New hardware and image processing software were developed especially for the fingerprint modality to gather newborn fingerprints and convert the images into a format for minutiae extraction and comparison that is backward compatible with current international standards. The advantages and disadvantages of using each sensory modality independently throughout the first year of life were investigated using quantitative performance evaluations and qualitative usage assessments. Instructions for using each modality were given, even though there was no one best way to do it.

Nada Alay et al. (2020) Based on a DL algorithm for people recognition using iris, vein, and finger biometric modalities, this work suggests a revolutionary multimodal biometric person identification method. The results showed that three biometric characteristics worked better than two or only one biometric feature in biometric identification systems. The results also demonstrated that our approach performed noticeably better than the state-of-the-art methods, achieving 99.39% accuracy with a feature-level fusion strategy and 100% accuracy with multiple score-level fusion strategies.

Farmanullah Jan et al. (2021) Iris segmentation, picture capture, feature extraction, and matching and identification modules are commonly found in iris biometric systems. Iris segmentation is crucial among these modules as it separates the legitimate iris portion of an input eye picture. Crude iris boundaries are corrected using the Fourier series, and the outer iris boundary is designated using the Circular Hough transform. Experimental findings are marginally superior when the proposed method is compared to numerous contemporary iris localization methods employing public iris datasets, including IITD V1.0, CASIA-Iris-Interval, and MMU V1.0.

Resend Tawfik Mohammed et al. (2022) This research One popular method for identifying obvious biometric identification methods that employ physical characteristics to identify people is iris recognition. Each person's iris has a unique structure and texture. Approaches are evaluated using other types of eye images, including those from the MMU IRIS database, CASIA V1, and MICHE I image from iPhones or Android phones. The aim of the present research plan is to use the proposed algorithm to achieve high performance in less-than-ideal situations.

Table 1: Comparative Analysis of Face and Iris Recognition

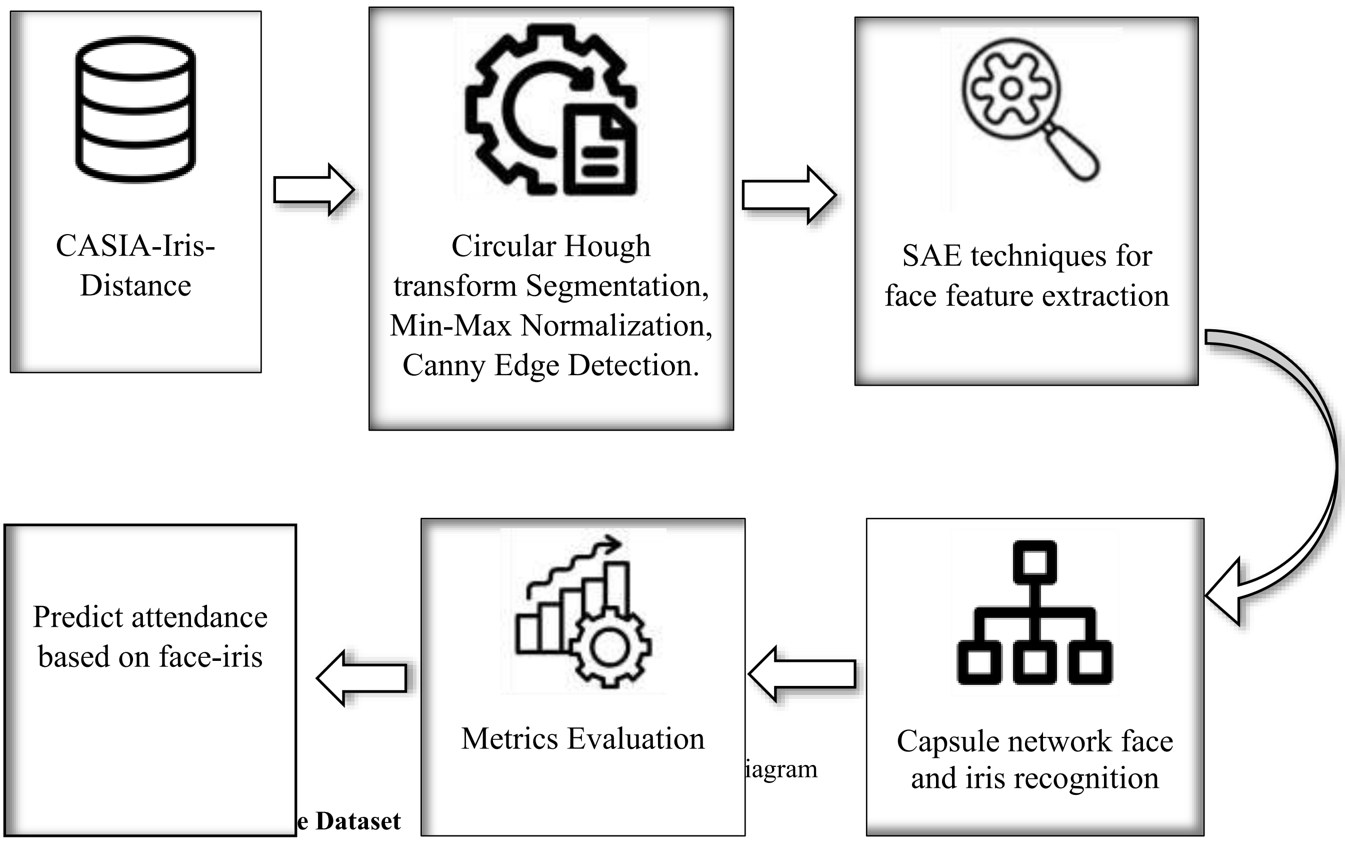
References. No	Dataset Names	Algorithm used	Result achieved
19	Multiple public iris datasets	Various traditional & DL methods	Survey: no specific results were reported
20	Off-angle iris datasets	Traditional iris recognition algorithms	Eyeblink reduced recognition performance significantly
21	Custom infant biometric dataset	Custom hardware + software	Feasibility of fingerprint, iris & ear recognition in infants
22	CASIA and IITD datasets	The deep learning-based fusion approach	Improved accuracy across all three modalities
23	CASIA-Iris, UBIRIS	Robust iris localization scheme	Improved segmentation under noise and blur
24	ECG & CASIA-Iris	Daugman's method	Good recognition accuracy on clean images
25	CASIA, IITD	Parallel localization + DL verification	High verification accuracy, efficient localization
26	Custom eye image dataset	BAT-optimized deep learning architecture	Accurate pupil detection with optimized performance
27	ECG & CASIA-Iris	Multimodal fusion algorithm	Reliable authentication with a low error rate

28	Synthetic iris dataset	Synthetic image generation techniques	Polar images yielded better visual quality for recognition tasks

The comparison table 1 shows an array of iris recognition research on various data sets, algorithms, and results. The findings are that the off-angle iris datasets that have eye blinking obstruct recognition performance when utilized with traditional algorithms. The paper examines the phenomenon of biometric recognition in infants on a designed dataset, proving that fingerprint, iris, and ear recognition exhibit a possibility.

3. PROPOSED METHODOLOGY

The suggested approach introduces a new approach of hybrid biometric based attendance system that is combined with face and iris recognition to provide an enhanced biometric based accuracy of identity verification and security. To start with, iris image input is obtained (CASIA-Iris-Distance). Preprocessing methods have been employed and among these is the Hough Transform to obtain precise iris segmentation, Min-Max normalizing of features to obtain corresponding proportions, and the Canny edge detection processing to outline elaborate iris patterns. In case of facial feature extraction, to achieve reduction in dimensionality and to capture the deep, meaningful facial features, Sparse Autoencoder (SAE) is used. Once features of the two modalities are extracted, the results are combined and fed into a Hyper Capsule Neural Network (HCNN). The HCNN also maintains the spatial hierarchies and is very effective in dealing with small differences of input image, yielding more dependable recognition outcomes. When both SAE and HCNN are used, the robustness and precision of the model is increased. Lastly, the system is trained and tested based on performance parameters and the systems marks attendance automatically by recognizing and matching real-time people inside the input expanded images.



iagram

e Dataset

Iris photos taken with our in-house long-range multi-modal biometric image collection and identification system Figure 2 are included in CASIA-Iris-Distance. By actively looking for iris, face, or palmprint patterns in the visible field using an intelligent multi-camera imaging system, the sophisticated biometric sensor can identify persons up to three meters away. By combining computer vision, human-computer interface, and multi-camera coordination technologies, the LMBS is human-centered and significantly enhances the usability of existing biometric systems. Dual-eye iris and face patterns are included in the picture region of interest as the CASIA-Iris-Distance iris images were taken using a high-resolution camera. Additionally, for multi-modal biometric information fusion, fine-grained face traits like skin pattern are evident.

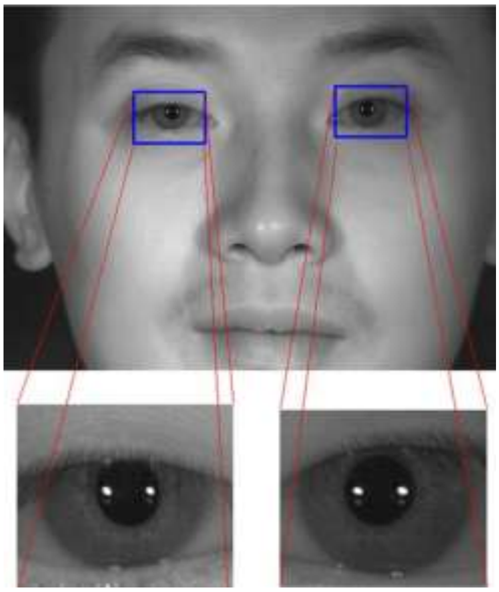


Figure 2 The biometric sensor used for collection of CASIA-Iris-Distance

3.2 Pre-processing

3.2.1 Circular Hough Transform Segmentation

The circular Hough transform is used to determine the pupil and iris segmentation margins. Its output includes the iris and pupil centers' coordinates. It also supplies the pupil's radius and iris. The CHT in Figure 3 shows the pupil border that was discovered following the use of the Hough transform.

$$(x-a)^2+(y-b)^2=r^2 \quad (1)$$

Where a, b Center of the detected circle, r Radius of the circle, Edge points that satisfy this Equation contribute votes in Hough space for candidate circles.

$$x=a+rcos(\theta) \quad (2)$$

$$y=b+rsin(\theta) \quad (3)$$

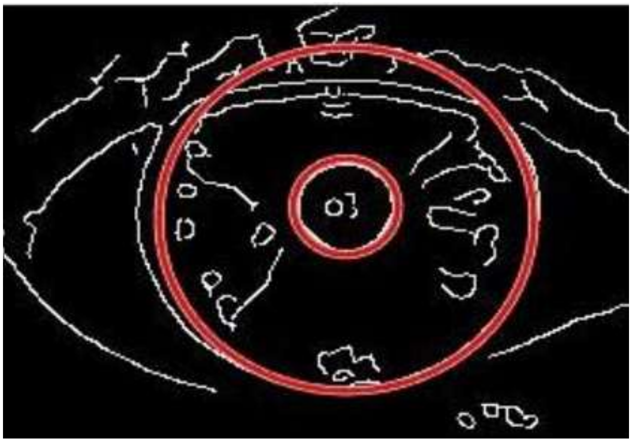


Figure 3 Pupil boundary detection using circular Hough transform

3.2.2 Normalization

Min-Max The process of normalization involves bringing each pixel's intensity level within the specified range, which is typically zero to one. The method works by taking the value of each individual pixel and normalizing it based on the image's greatest and lowest intensity levels.

$$I_{norm} = \frac{I - I_{min}}{I_{max} - I_{min}} \quad (4)$$

Where I is the original pixel value, I_{min} is the minimum pixel intensity in the image, and I_{max} is the maximum. This transformation will make sure that all pixel values are rescaled proportionally where the darkest pixel is zero, and the lightest pixel is 1.

3.2.3 Edge direction

Edge detection occurs in image processing, and seeks out abrupt changes in image intensity that usually represent the boundaries, features, or contours of objects in an image. In iris recognition Edge detection is used to identify some of the major structures in the iris such as the boundary of the iris, pupil edges, and eyelids by identifying changes in between the parts of the eye shown in figure 4.

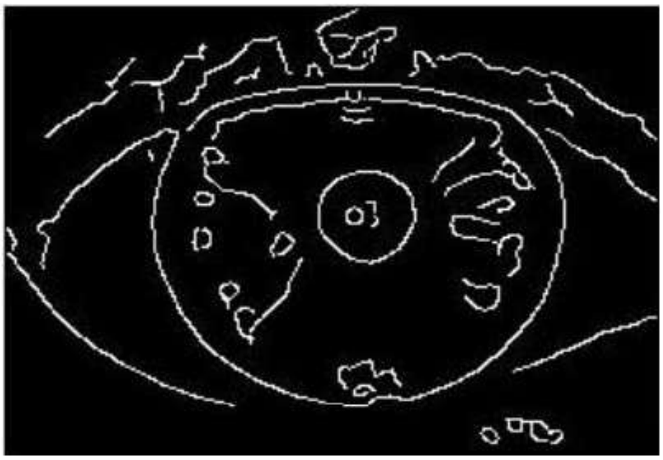


Figure 4 Edge image from edge detection

3.3 Sparse Autoencoder techniques for face feature extraction

Deep characteristics of face and iris pictures are extracted using Sparse Autoencoder (SAE) techniques in the face-iris recognition system. As unsupervised systems, SAEs manage to obtain compact, discriminative representations by compressing and reversing input data along with multiple layers of hidden units. In the retrieval of face features, the SAE retrieves critical face features like contours, textures, and spatial relationships, and in iris images, complex features like iris patterns and texture are retrieved. The latter part, the encoder, will decrease the dimensionality of the input; thus, the model can be concentrated with the most relevant information, and the latter part, the decoder, also makes sure that learned features are representative.

Equation (5) may be used to express auto encoders A with input I= $\{x1, x2, \ldots, x\sim n\}$, hidden representation Rg= $\{h1, h2, \ldots, hi\}$, and output Rf= $\{x\sim 1, x\sim 2, \ldots, x\sim n\}$.

$$x_{\tilde{\imath}} = f(g(x_i)) \quad (5)$$

Using Equation (6), the encoder function g converts $xi \in I$ to $hi \in Rg$.

$$h_i = g(x_i) \quad (6)$$

The decoder function f transfers $hi \in Rg$ to $xi \in I$, as explained by equation (7).

$$x_{\tilde{\imath}} = f(h_i) \quad (7)$$

Reducing Δ, or the difference between the auto-encoder's input and output, as shown by Equation (8), is the aim of auto-encoder training.

$$\min\,(f.g) < \Delta(x_i, x_{\bar{i}}) > \quad (8)$$

The mathematical formulation of DWT for a signal $x(t)$ is expressed as:

$$DWT(a,b) = \frac{1}{\sqrt{|a|}}\int_{-\infty}^{\infty} x(t)\psi\left(\frac{t-b}{a}\right)dt \quad (9)$$

Where:

- $\psi(t)$ is the wavelet function (mother wavelet).
- A represents a scale (frequency analysis).
- b denotes translation (time/position).
- $x(t)$ is the input signal or image data.

3.4 Capsule network face and iris recognition

The multimodal biometric identification system utilizes face and iris characteristics and employs a Capsule Network (CapsNet). As features, the Capsule Networks attempt to maintain the spatial hierarchy of features and, therefore, are ideal for recognizing the complex patterns in face and iris images. Compared to classical convolutional neural networks (CNNs), CapsNets carry out dynamic routing to identify pose and texture differences and help in improving recognition precision, particularly where there are demanding situations like occlusion or off-angle alignment. Combining the fusion of face and iris modes creates an opportunity to exploit the robustness of both face features, ease of use, and the high level of uniqueness of iris patterns to result in an increase in robustness and a decrease in error rates in the system shown in Figure 5.

$$Z_{ij,k} = \sum_{1=1}^{L} W_{i,j,k,1}X_{i,j,k,1} + b_{i,j,k} \quad (10)$$

Where $Z_{ij,k}$ is the activation of the k^{th} feature map at position (i,j) in the output $W_{i,j,k,1}$ is the weight associated with the i^{th} input channel at position (i,j) in the filter of the k^{th} feature map $X_{i,j,1}$ is the activation of the i^{th} input channel at position (i,j) in the input and $b_{i,j,k}$ is term associated with the k^{th} feature map at position (i,j).

$$V_{i,j,k} = Squash\left(\sum_{1=1}^{L'} W_{i,j,k,1}U_{i,j,1}\right) \quad (11)$$

$$S_j = \sum_i C_{ij}\hat{u}_{j|i} \quad (12)$$

Where Sj is the higher-level capsule's output, $\hat{u}\ j|i$ is the forecast of the output vector that the higher-level capsule provides according to the input of the primary capsule, and ci, j is the coupling coefficient.

$$y_k = squash(S_jSK) \quad (13)$$

Where yk represents the kth capsule's output vector, and sk represents the input vector linked to the kth capsule.

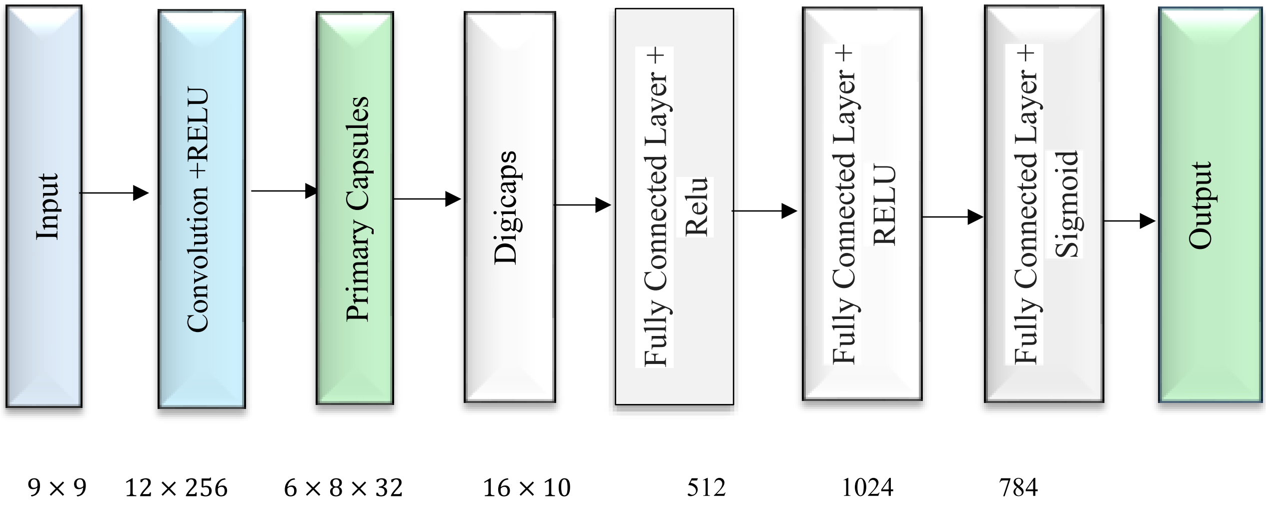


Figure 5 Capsule network architecture in face and iris

Table 2 Workflow of the Proposed Face-Iris Recognition Model

Begin
Step 1: Import Libraries: For image processing, machine learning, and evaluation. **Step 2: Define Functions:** ▪ Apply_ SAE: Extract wavelet features. ▪ Preprocess_ face-iris image: Segment, normalize, enhance, and extract features from face-iris images. ▪ preprocess_dataset: Loop through dataset, preprocess images, resize, normalize, and save. **Step 3: Build Mode:** ▪ Combine CapsNet for spatial features and Transformer for sequence analysis. ▪ Add dense layers and softmax for classification. **Step 4: Prepare Data**: ▪ Load and preprocess images. ▪ Split data into training and validation sets. ▪ One-hot encode labels. **Step 5: Train Model**: ▪ Compile with Adam optimizer and train using training data. ▪ Save the trained model. **Step 6: Evaluate Model**: ▪ Predict classes on validation data. ▪ Compute metrics: Accuracy, Precision, Recall, F1 Score. ▪ Display confusion matrix. **Step 7: End**

The steps and the working flow of the proposed face-iris recognition model are provided in the table 2. It begins with an import of the library, data preprocessing and the construction of a hybrid model with CapsNet and Transformer. Training and assessment of the result and saving the output has concluded the process.

4. RESULT AND DISCUSSION

The paper performs trials on both the sparse feature extraction approach utilising SAE and the face and iris detection method based on hyper capsule network, respectively, to confirm their superiority and efficacy. Both comparison and ablation trials are among the primary experiments. The environment setup and parameter combinations for the experiment are shown in Table 3.

Table 3 Experiments Parameter details

Configuration item	**Details**
Framework	Python 3.8
CPU	Intel
System	Windows10
Optimizer	Adam Optimizer
Memory	32GB
Total Training Epochs	100 epochs
Batch size	16
Initial Learning rate	0.01
Learning rate adjustment	Reduce Learning rate by 10 times at the 45th and 60th epochs

The study separates the CASIA Iris image database into training and test sets in a 7:3 ratio based on Table 3. It is important to note that every experiment in the study is done at least ten times, and different random initialization or cross-validation techniques are used to guarantee the stability and dependability of the findings.

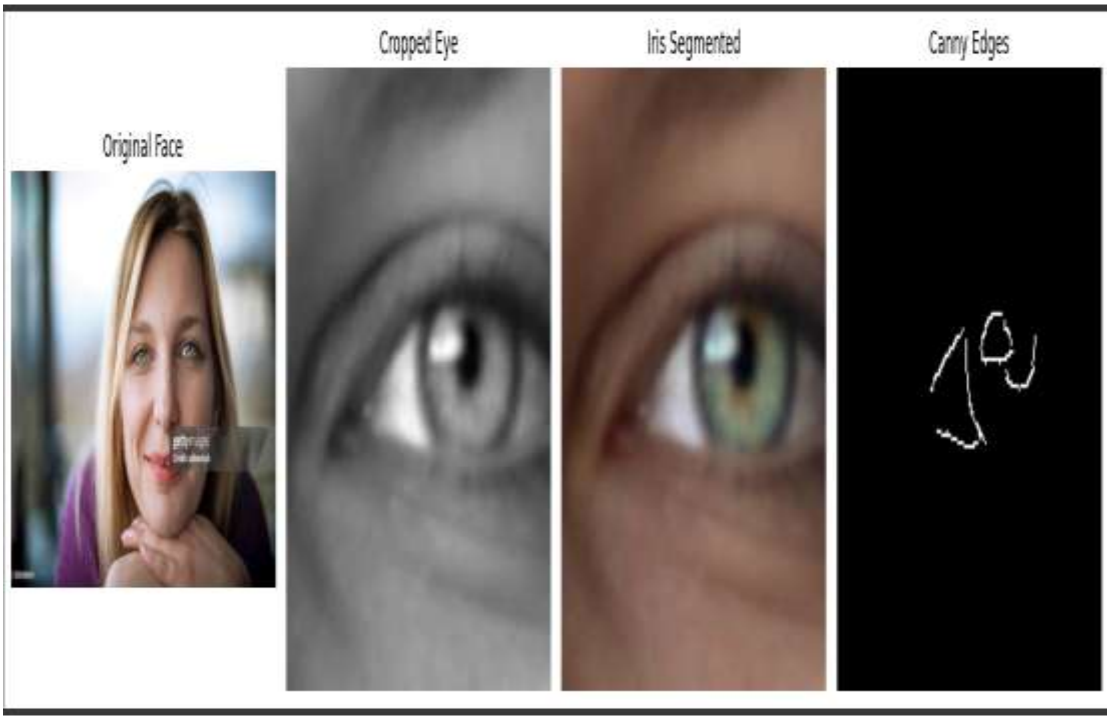


Figure 6 Preprocessing the input image using circular Hough Transform.

Figure 6 above shows the preprocessing and segmentation process for the original facial image. The cropped eye image was taken from the original input image and scaled using the normalizing technique. The circular Hough transform (CHT) was used to extract the iris from the cropped eye image. Canny edge detection is used to identify the iris pattern in the segmented picture.

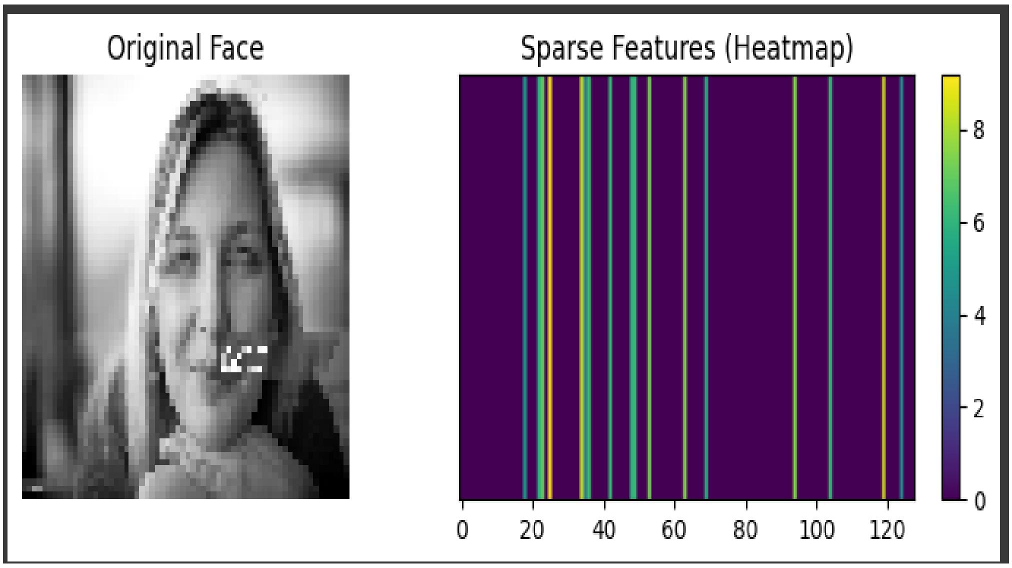


Figure 7 Heatmap of feature extraction using Sparse AutoEncoder

Figure 7 provides a visual comparison between a segmented image from the original image and its corresponding sparse feature representation. The heatmap shows the sparse features extracted from this image using a Sparse Autoencoder. In this heatmap, each vertical line represents the activation of a specific neuron in the encoding layer, where the color intensity reflects the magnitude of the activation. Most of the area remains dark purple, indicating that many features are inactive or close to zero, which is a characteristic of sparse representations. Only a few features show strong activations (highlighted in brighter colors), meaning that the model has learned to represent the face using a minimal but highly informative subset of features.

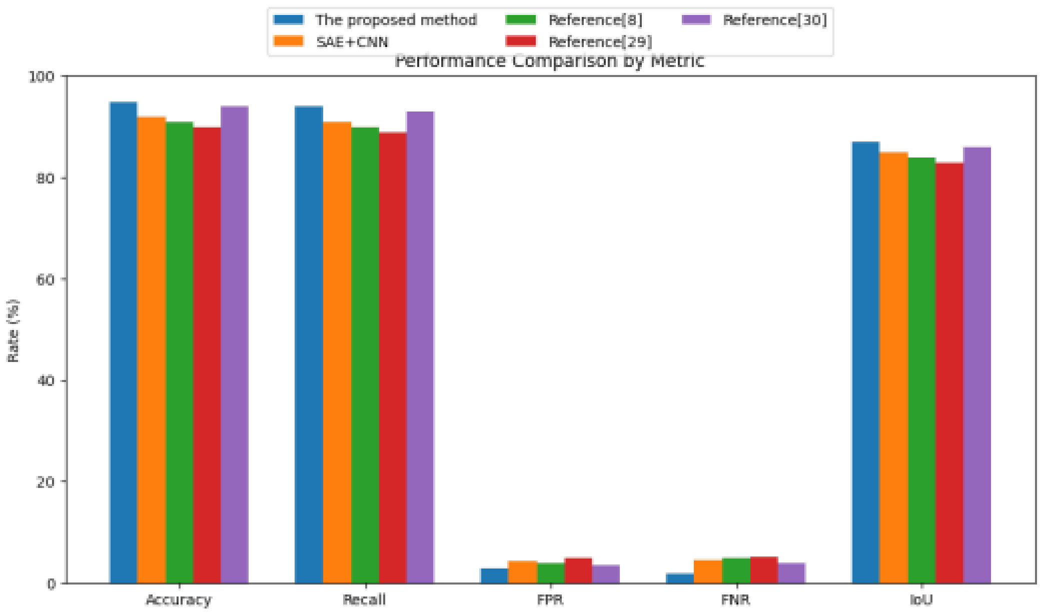


Figure 8 Performance comparison of the proposed model with a reference model

As seen in Figure 8, performance metrics including accuracy, recall, false positive rate, false negative rate, and intersection over union are used to evaluate the reference model with the proposed hyper capsule neural network model.The hyper capsule neural network performs better than the other methods assessed on every criterion. The best accuracy and recall are obtained by the suggested method, demonstrating its efficacy in generating accurate predictions and detecting real positive situations. It also has the lowest FPR and FNR, demonstrating its capacity to reduce missed detections as well as false alarms.

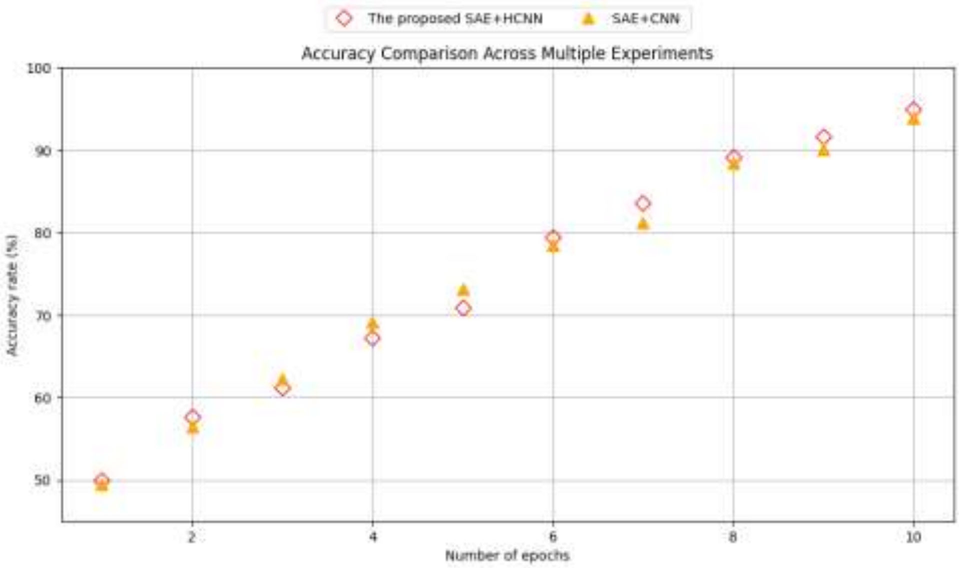


Figure 9 Proposed model's accuracy comparison over 10 epoch steps

The figure 9 illustrates the comparison of accuracy rates between two model- Saarse Autoencoder combined with hyper capsule neural network and sparse autoencoder with convolutional neural network across 10 epochs. The proposed model displays the linear improvement in accuracy as number of epochs. In initial epochs, the performance of both model is relatively similar. At 10 th epochs, SAE+HCNN model consistently outperforms the SAE+CNN model. The proposed model achieves a higher accuracy rate, reaching approximately 95 %, while SAE+CNN levels off at around 93-94%.

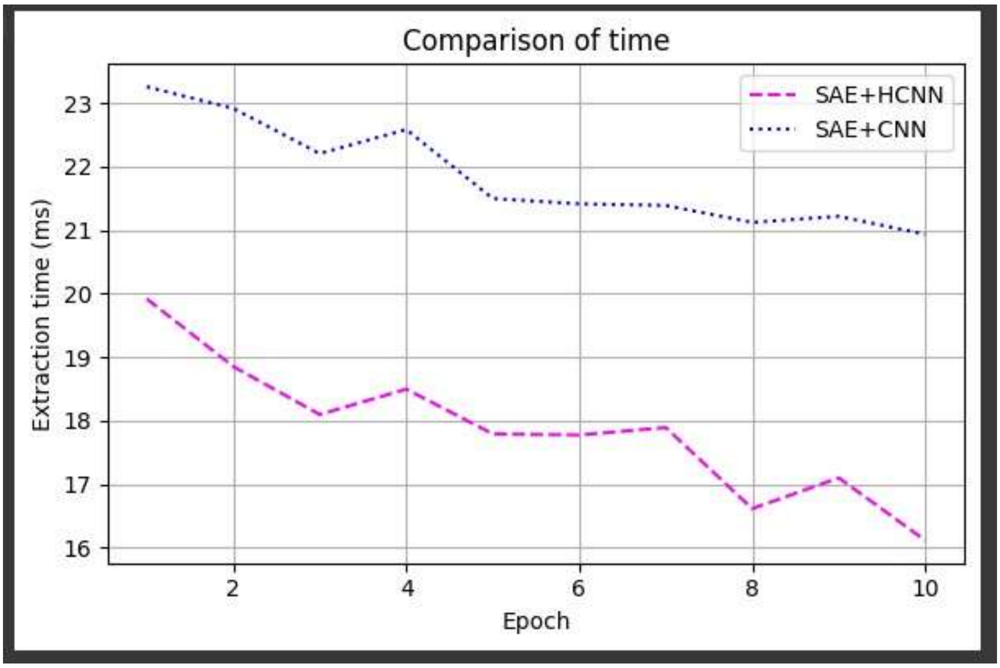


Figure 10 Comparison of Extraction Model

Figure 10 shows how the model execution time of SAE+HCNN steadily drops from 23 ms to around 10 ms throughout training, whereas that of SAE+HCNN is almost 25 ms dropping to around 27 ms. The SAE feature extraction time, on the other hand, is the shortest of the entire process; it starts at around 25 ms and steadily drops to around 5 ms. Consequently, SAE is a more effective choice for the benchmark network.

Table 4 Performance Comparison of Iris Recognition Methods Using Different Datasets

Dataset used	Accuracy (%)
CASIA-Iris databases [15]	Accuracy rate achieves 95%
ND-IRIS-0405 and CASIA-Lamp datasets [16]	The method's accuracy rate was 89.77%.
Biometric Dataset [17]	Accuracy- 94.2%
Proposed model (CASIA-Iris-Distance)	HCNN+SAE model accuracy 95%

The table 4 was part of a comparative study of accuracies of the face-iris recognition in various benchmark datasets and methods. The CASIA-Iris database attained 95% of accuracy, whereas the ND-IRIS-0405 and the CASIA-Lamp databases had a lower accuracy rate of 89.77%. In the same way, the Biometric Dataset had 94.2% accuracy. On the contrary, the same accuracy can be observed using the proposed model based on the work with CASIA-Iris-Distance dataset and using the hybrid HCNN and SAE method (95%). This is in spite of a performance of 95% recorded by CASIA baseline, but our study model encapsulates powerful deep learning mechanisms that provide better feature extraction and robustness. This proves that our suggested system competes or even better than current methodologies in the area of face- iris recognition.

5. CONCLUSION

Finally, the paper can provide a comprehensive biometric-based attendance system that considers face and iris recognition to increase verification accuracy and enhance security. The system processes the CASIA-Iris-Distance data set, and pre-processing entails segmentation using the Hough Transform method, scaling using Min-Max, and edge detection techniques to highlight the patterns in irises that use Canny. A Sparse Autoencoder (SAE) is used to complete dimensionality reduction and the collection of deep facial characteristics. A combination of these two sets of features of the face and the iris is combined and processed through a Hyper Capsule Neural Network (HCNN), whereby spatial relationships are preserved and the reliability of recognition is enhanced. The performance analysis indicates that the accuracy of the proposed hybrid model (SAE+HCNN) is about 95% compared to the SAE+CNN model (93-94%). It demonstrates that using deep learning-based feature extraction and advanced neural architecture is productive.

REFERENCES

1. Imaoka, Hitoshi, Koichi Takahashi, Akinori F. Ebihara, Jianquan Liu, Akihiro Hayasaka, Yusuke Morishita, and Kazuyuki Sakurai. "The future of biometrics technology: from face recognition to related applications." APSIPA transactions on signal and information processing 10, 2021.
2. Abdellatef, Essam, Eman M. Omran, Nabil A. Ismail, Salah ES Abd Elrahman, Khalid N. Ismail, Mohamed Rihan, Mohamed Amin, Ayman A. Eisa, and Fathi E. Abd El-Samie. "Cancelable face and iris recognition system based on deep learning." Optical and Quantum Electronics 54, no. 11,2022.
3. Wang, Mei, and Weihong Deng. "Deep face recognition: A survey." Neurocomputing, Vol. 429, 2021.
4. Ismail, Nor Azman, Cheah Wen Chai, Hussein Samma, Md Sah Salam, Layla Hasan, Nur Haliza Abdul Wahab, Farhan Mohamed, Wong Yee Leng, and Mohd Foad Rohani. "Web-based university classroom attendance system based on deep learning face recognition." KSII Transactions on Internet and Information Systems,16, no. 2022.
5. Muhammad, Junxing Hu, Kunbo Zhang, and Zhenan Sun. "CASIA-iris-africa: A large-scale african iris image database." Machine Intelligence Research, Vol.21, no. 2, 2024.
6. B. U. Haq, and M. Saqlain, "Iris detection for attendance monitoring in educational institutes amidst a pandemic: A machine learning approach," J. Ind Intell., vol. 1, no. 3,2023.
7. Shashikala HK1, Pooja Panjiyar, Abhinav Singh Upreti, Shaik Dadapeer Software, "Survey on Iris Based Recognition Systems," International Journal of & Hardware Research in Engineering,2020.
8. Ennajar, Slimane et al.,"Monitoring Student Attendance Through Vision Transformer-based Iris Recognition," International Journal of Advanced Computer Science & Applications, 2024.
9. Orugba Kenneth Obokparo and Imianvan Anthon, "Attendance System Using Iris Recognition," Journal of Science and Environment, 2024.
10. Anie Rose Irawati, Yohana Tri Utami ,Rahman Taufik "An Exploration of Tensor Flow-Enabled Convolutional Neural Network Model Development for Facial Recognition: Advancements in Student Attendance System", Scientific Journal of Informatics, 2024 .

11. Avantika Singh, Aditya Nigam, "Cancelable Iris template generation by aggregating patch level ordinal relations with its holistically extended performance and security analysis," Elsevier, 2020.
12. Cassian Miron, Alexandru Pasarica, Vasile Manta & Radu Timofte, "Efficient and robust eye images iris segmentation using a lightweight U-net convolutional network," Springer Nature, 2022.
13. Shiv Kumar, "Analysis for Iris and Periocular Recognition in Unconstraint Biometrics," International Journal of Advance Research in Science and Engineering, ISSN: 2319-8346, 2021.
14. Rahmatallah Hossam Farouk,Yasser M. Abd El-Latif, "A Proposed Biometric Technique for Improving Iris Recognition," International Journal of Computational Intelligence Systems, 2022.
15. Ahmed Shamil Mustafa and Abdullah Khalid, "Multimodal Biometric System Iris and Fingerprint Recognition Based on Fusion Technique," International Journal of Advanced Science and Technology,2020.
16. S. He and X. Li, "Enhance Deep Iris Model for Iris Recognition Applications," IEEE Access, vol. 12, 2024.
17. Nalluri Prasanth, Trishitha Ketineni, Uday Sai Kiran Chilukuri, "Convolutional Tri Biometrics: A Unified Approach for Iris, Periocular, And Facial Authentication," JTAIT, Vol.102. No. 10, 2024.
18. Camilo A. and Antonio Bandera, "FPGA-Based CNN for Eye Detection in an Iris Recognition at a Distance System," Electronics, Vol.1, 2023.
19. Young Won Lee and Kang Young Park, "Recent Iris and Ocular Recognition Methods in High- and Low-Resolution Images: A Survey," Mathematics, Vol.10, No.12,2022.
20. E. Headley, D. Tebor and M. Karakaya, "How Eye Blink Affects the Recognition Performance of Traditional Off-Angle Iris Images," SoutheastCon, pp. 1243-1249, 2024.
21. Y. Moolla, C. S. Ntshangase, N. Nelufule and P. Khanyile, "Biometric Recognition of Infants using Fingerprint, Iris, and Ear Biometrics," in IEEE Access, vol. 9, 2021.
22. Nada Alay and Heyam H. Al-Baity, "Deep Learning Approach for Multimodal Biometric Recognition System Based on Fusion of Iris, Face, and Finger Vein Traits," Sensors, 2020.
23. Farmanullah Jan, Irfanullah Khan, "A robust iris localization scheme for the iris recognition," 2021.
24. Resend Tawfik, Harleen Kaur, Bhavya Alankar, Ritu Chauhan, "Recognition of human Iris for biometric identification using Daugman's method," Biometrics, May 2022.
25. Yinyin Wei et al., "Iris Recognition Method Based on Parallel Iris Localization Algorithm and Deep Learning Iris Verification," Sensors, Vol.22, 2022.
26. S. Navaneethan, S. Padmakala, and C. Senthilkumar, "The Human Eye Pupil Detection System Using BAT Optimized Deep Learning Architecture," Computer Systems Science & Engineering, 2023.
27. K. Ashwini, G. N. Keshava Murthy, S. Raviraja, G. A. Srinidhi, "A Novel Multimodal Biometric Person Authentication System Based on ECG and Iris Data" Biomed Research International, 2024.
28. Adrian Korda, Bartuzi-Trokielewicz Michał Ołowski and Mateusz Trokielewicz, "Synthetic Iris Images: A Comparative Analysis between Cartesian and Polar Representation," Sensors, Vol. 24, No.7, 2024.
29. Muhammad J, Wang C, Zhang K, Sun Z. CASIA-Face-Africa: A Large-Scale African Face Image Database. IEEE TransInformForensic Secur. 2021; 16:3634–46.
30. Kim H-I, Yun K, Ro YM. Face Shape-Guided Deep Feature Alignment for Face Recognition Robust to Face Misalignment. IEEE Trans Biom Behav Identity Sci. 2022.