Journal of Advanced Research in Applied Sciences and Engineering Technology 54, Issue 2 (2025) 238-251

Journal of Advanced Research in Applied Sciences and Engineering Technology

Journal homepage:
https://semarakilmu.com.my/journals/index.php/applied_sciences_eng_tech/index
ISSN: 2462-1943

HDN-Net: A Hybrid Deep Neural Network to Improve Iris Recognition in Unconstrained Environments with Eyeglasses

Jasem Rahman Malgheet[1], Noridayu Manshor[1,*], Lilly Suriani Affendey[1], Alfian Abdul Halin[2], Mariam Raheem Mirza[3]

1 Department of Computer Science, Faculty of Computer Science and Information Technology, Universiti Putra Malaysia (UPM), 43000 Serdang, Selangor, Malaysia
2 Department of Multimedia, Faculty of Computer Science and Information Technology, Universiti Putra Malaysia (UPM) 43000 Serdang, Selangor, Malaysia
3 Department of Computer Science, College of Education, University of Al-Hamdaniya, Nineveh, Iraq

ABSTRACT

Recently, the use of iris recognition technology for biometric authentication has gained widespread acceptance due to the rich texture of the iris region, which provides a reliable standard for recognising individuals, as well as the non-intrusive nature of this method. However, the presence of eyeglasses poses a significant challenge to the accuracy of such systems. In unrestricted environments, current iris recognition techniques cannot effectively extract distinguishing features of the iris. Eyeglasses introduce scratches, specular reflections, dirt, blurriness, and other noise factors over the image of the iris, resulting in low recognition accuracy. To tackle this challenge, researchers have proposed the HDN-Net architecture. This architecture employs a multi-CNN model to combine the features of both the right and left iris images, extracting more distinguishing features to improve the accuracy of the classification task in the presence of challenges caused by eyeglasses. Experiment results show that the proposed iris recognition system achieves more promising performance compared to previous methods used in this field. The overall performance of our suggested HDN-Net method on the UBIRIS.V2 and CASIA-Iris.V4-1000 databases achieved 97.89% and 98.79% accuracy, respectively. Thus, the proposed HDN-Net method consistently outperforms other traditional and deep learning approaches and has the possibility to improve the accuracy of iris recognition systems (IRS) in real-world scenarios.

Keywords:

Iris recognition system (IRS); Deep learning (DL) techniques; Traditional techniques; Feature extraction; Feature classification; Residual network (ResNet); Convolutional neural network (CNN)

1. Introduction

1.1 Research Background

Security has become a major issue in our developed world. Biometric recognition system has been extensively researched in recent decades and is becoming increasingly relevant in fields such as personal identity and information security, among others. The need for secure, dependable, quick systems has given rise to the appearance of physiological and behavioural models in biometric

* *Corresponding author.*
E-mail address: ayu@upm.edu.my

https://doi.org/10.37934/araset.54.2.238251

systems. Both types of models effectively contribute to implementing security measures [1]. Physiological biometrics includes iris recognition [2], fingerprint recognition [3], face recognition [4], retina recognition, and hand geometry recognition [5]. The behavioural models comprise signature recognition, gait recognition, and voice recognition [6,7]. Out of all of these, the IRS has the highest efficiency and reliability for checking the authenticity of identities [8,9]. This is attributed to the consistent nature of human iris features, their enduring stability over time (i.e., remaining unaltered despite ageing), and their distinctiveness for each individual, including variations between twins and siblings [10]. Complex tissues of the iris region contain an abundance of specific features, such as bulges, grooves, loops, zigzags, and spots. It is protected by a structure that, if adjusted, could impact the health of a person. Moreover, the iris can be accessed by utilising a non-invasive machine [11]. Hence, business establishments, particularly within the security sector, are looking forward to the future of the IRS due to its possible applications, in view of the huge potential this technology offers.

Iris images are normally captured utilising operational systems within the near-infrared (NIR) spectrum, where the iris region appears more distinct compared to the visible (VIS) wavelength spectrum. Contemporary advancements in the field of IRS are directing their attention towards the difficulties posed by unconstrained environments, aiming to achieve higher recognition rates in more intricate scenarios, including off-angle, low resolution, rotated, distorted, cropped, scaled, occluded (by eyelash), low-quality, and off-focus images, as well as in images that contain noise from eyeglasses [12-19].

Eyeglasses are making the IRS more difficult as they can produce optical distortions, specular reflections, shadows, and dirt [19,20], thereby causing the performance of iris recognition systems to deteriorate [21-25]. Experiment results from previous studies showed that the error rate for iris images containing eyeglasses is twice that of iris images without eyeglasses [26]. The ISO/IEC 29794-6 biometrics sample quality standard mentioned in [26] specifically recommends instructing subjects to remove their eyeglasses before acquiring images of their iris. Due to the high prevalence of people with eyeglasses around the world, iris detection, iris segmentation (IS), and feature extraction are important elements to develop in order to improve IRS in unconstrained environments. To this end, the significance of this paper is its contribution to enhancing the accuracy of the IRS in the presence of the different types of noise caused by eyeglasses, such as dirt, scratches, specular reflections, blurriness, and other noise factors.

To tackle the challenges caused by eyeglasses, we propose a new HDN-Net architecture for the design of a robust and accurate IRS, in which a multi-CNN model is used to combine the features of both the right and left eye images, to extract more distinguishing features. The goal is to improve the accuracy of the classification task. HDN-Net combines unsupervised architectures, such as the Long Short-Term Memory (LSTM) and the idea of the Squeeze-and-Excitation Networks (SE-Net), with hybrid CNNs that in turn, combine the idea of both AlexNet and MobileNet with the idea of ResNet. The overall architecture of the suggested HDN-Net method is described in Figure 1, which consists of three primary parts: The Residual hybrid AlexNet-MobileNet (RHAM-Net) module, the Residual SE-LSTM module, and the fusion fully connected (FFC) module. The selection of Mobile-Net is motivated by its computational efficiency, making it suitable for lightweight computational devices and its compatibility with low-resolution images. The proposed HDN-Net module employs global hyperparameters based on Conv and DW-Conv to achieve a balance between accuracy and efficiency. The SE-Net technique is used to adaptively recalibrate responses of channel features by reweighting features and modelling the interdependencies among different channels. SE-Net enhances learning by selectively emphasizing important features and suppressing less useful ones. The objectives of incorporating the ResNet technique into our proposed HDN-Net method are to enhance the extraction and description of complex features in the iris tissue, particularly in the presence of challenges posed by eyeglasses. This inclusion aims to improve training process parameters, facilitate better propagation of features, enable feature reuse, and address the issue of gradient explosion resulting from the continuous increase in the number of layers in the HDN-Net network. HDN-Net network. The accuracy of the our proposed HDN-Net method was evaluated on the UBIRIS.V2 and CASIA-Iris.V4-1000 databases. Despite facing very difficult challenges during data collection, the experiment results showed that our proposed IRS achieved more promising results compared to the best methods currently used in this field.

The primary contributions of this article include:

i. Our proposed HDN-Net method addresses the challenges of IRS caused by eyeglasses, making iris recognition more reliable in unconstrained environments. The new HDN-Net is more accurate and efficient compared to current state-of-the-art iris recognition systems.
ii. Our proposed residual hybrid AlexNet-MobileNet (RHAM-Net) module, which combines the AlexNet and MobileNet techniques and exploits the idea of ResNet, is capable of extracting more distinguishing features. The purpose is to enhance the accuracy of IRS for subjects with eyeglasses by deepening the network and significantly decreasing the parameter count and reducing computational complexity.
iii. By selectively emphasising the important features and suppressing the less useful ones in the convolutional channels, our proposed ReSE-LSTM module makes the network more robust and more efficient at handling input images of arbitrary sizes. It also regulates the flow of information into and out of a memory cell.
iv. The accuracy of the suggested HDN-Net method has been evaluated on two publicly available databases of iris images, namely CASIA-Iris.V4-1000 and UBIRIS.V2.

The remainder of this paper is structured as follows: Subsection 1.2 describes a brief overview of related previous works of the IRS. Section 2 explains the architecture of the suggested HDN-Net framework in detail. The experiment setup of the suggested HDN-Net framework is described in section 3. The results of our experiment and a discussion of it are presented in Section 4. Finally, we introduce the conclusion of this paper in Section 5.

1.2 Literature Review

In this section, we review a number of significant contributions to the improvement of iris recognition systems. They are divided into two categories based on the level of innovation in the development procedures: traditional techniques and deep learning (DL) techniques.

1.2.1 Traditional techniques

Gad *et al.,* [27] had devised several multi-algorithmic approaches to iris recognition to improve its accuracy and robustness. These approaches are able to incorporate both feature extraction and matching algorithms, which can be selected based on their strengths and weaknesses for different aspects of the recognition process. However, one weakness of the multi-algorithmic approach is that it can increase computational complexity, which can be a challenge for resource-constrained devices in the CIoT framework. Barpanda *et al.,* [28] then proposed the tuneable filter bank-based feature that can be used in the feature extraction stage of the iris recognition process. The suggested filter bank provides an opportunity to optimise and tune the filter coefficients. However, a disadvantage of this approach is that it can be computationally expensive, requiring significant processing power and time. Additionally, there are other limitations to this method caused by several factors such as occlusion caused by eyelid and/or eyelash, blurring, poor/over-illumination, off-angles, and noise due to eyeglasses. Ahmadi *et al.,* [29] had proposed iris recognition techniques using a combination of two-dimensional Gabor kernel (2-DGK), step filtering (SF) [30], and polynomial filtering (PF) [31] for feature extraction and genetic algorithm (GA) [32] with hybrid radial basis function neural network (RBFNN) for the matching task. However, a drawback of this approach is that it requires a large dataset of labelled iris images for training, which can be time-consuming and expensive to obtain. Additionally, the model may not generalise well to new iris images outside of the training dataset, particularly in situations with significant variations in lighting, camera angle, or image quality. In conclusion, traditional approaches still leave much to desire due to their sensitivity to variations in lighting conditions, which can affect the quality of the iris images and result in false rejections or false acceptances.

1.2.2 Deep learning techniques

In the last years, deep learning (DL) techniques have shown remarkable performance in various computer vision tasks, including iris recognition. Wang *et al.,* [16] had proposed the MiCoRe-Net method for eye recognition, leveraging on a combination of mixed convolutional and residual network architectures to improve accuracy and efficiency. Such architecture is designed to capture both low-level and high-level features of the eye image, allowing for more robust and accurate identification. However, MiCoRe-Net unfortunately requires a large amount of training data to achieve optimal performance. Additionally, it is compromised by such visual challenges as occlusion due to eyelid and/or eyelash, blurring, poor/over-illumination, off-angles, and noise due to eyeglasses such as blurriness, scratches, specular reflections, dirt, and other factors. Subsequently, Lee *et al.,* [33] had suggested a method for ocular recognition using deep residual convolutional neural networks (CNNs) and a rough pupil detection algorithm for images captured by near-infrared (NIR) camera sensors. The rough pupil detection algorithm also helps reduce the computational complexity of the method. However, this paper does not provide a thorough analysis of the weaknesses or limitations of the method. In additional, the method is only evaluated on a limited dataset, and its performance on larger and more diverse datasets is unknown. Further research and testing are needed to validate the method's effectiveness and generalisability. Next, Zambrano *et al.,* [34] had proposed an iris recognition method that combines Low-Level CNN Layers Without Training and Single Matching. The proposed method is computationally efficient and does not require additional pre-processing. Single Matching also achieved high accuracy, using a single iris image without requiring a template database. However, it may not outperform other CNN-based methods, it's affected by the quality of the iris image and may not be suitable for large-scale iris recognition applications. Nguyen *et al.,* [35] then proposed the Complex-Valued Iris Recognition Network (CVIRN) that utilises complex-valued convolutional neural networks (CNNs) to extract features from iris images. Their method is designed to capture the complex-valued properties of iris images, which traditional methods cannot capture, thereby improving recognition accuracy. However, the method is computationally expensive and may require more resources than traditional methods, which can limit its practical application in some scenarios. Additionally, the performance of CVIRN may be affected by the quality of the iris image, such as image resolution and noise due to eyeglasses, which are blurriness, scratches, reflections, dirt, and other noise factors.

2. The Proposed HDN-Net Framework

The proposed HDN-Net architecture is made up of two main sections: The architecture of our suggested HDN-Net framework and Loss Functions.

2.1 Architecture of the HDN-Net Framework

In this section, we describe in detail an overview of the proposed HDN-Net framework based on the DL approach. A multi-CNN model combines the features of both the left and right iris images to enable the extraction of more distinguishing features. This gives better classification accuracy when faced with eyeglass challenges. The architecture of the suggested HDN-Net method combines unsupervised architectures, such as the Long Short-Term Memory (LSTM) as used in [36] and the idea of the Squeeze-and-Excitation Networks (SE-Net) [37,38] with hybrid CNNs that in turn, combine AlexNet [39,40] and MobileNet [41-43], with the idea of the residual network (ResNet) [44] to enhance the representation capacity of IRS by significantly decreasing the number of parameters and reducing its computational complexity.

The overall architecture of HDN-Net is illustrated in Figure 1. There are three main parts: The Residual hybrid AlexNet-MobileNet (RHAM-Net) module, the Residual SE-LSTM module, and the fusion fully connected (FFC) module. RHAM-Net comprises 4 residual blocks, each of which includes a 3x3 convolutional (3x3 Conv) layer, a Depthwise convolutions (DW-Conv) layer and a batch normalisation (BN) layer. Each residual block is followed by a 2×2 max-pooling layer as shown in Figure 1(a). The authors selected the MobileNet model because of its effectiveness in lightweight computational devices and because it can work with low-resolution images. The proposed module employs global hyperparameters based on Conv and DW-Conv to maintain a balance between accuracy and efficiency. Next, SE-LSTM consists of 2 residual blocks, the Residual SE-Net module (SE-Res) and the Residual LSTM module (LSTM-Res). Each of these residual blocks contains a 3x3 CONV, DW-Conv and BN layers as shown in Figure 1(b). The SE-Res and LSTM-Res blocks could be utilised to construct robust hybrid deep learning techniques that can deeply analyse complex patterns in huge and various data sets and to avoid exploding gradients and vanishing gradients due to the difficult challenge from eyeglasses in unconstrained environments.

Additionally, we utilise ResNet (direct connections blocks) as the basic unit in the network layer of our suggested method to improve the accuracy of the IRS with eyeglasses. Finally, FFC consists of the two flattened layers, followed by a fusion module and subsequent to that, three fully connected (FC) layers as shown in Figure 1(c). The fusion module is used to fuse the different features obtained from the Residual hybrid AlexNet-MobileNet module and the Residual SE-LSTM module, and each of the FC layers contains a ReLu activation function. The SoftMax technique is used after the third FC layer. To avoid gradient explosions, to do away with the need to determine the classification threshold for large-scale iris samples, to overcome the problem of insufficient discrimination of SoftMax, and to identify the appropriate hyperparameter, we suggested the HDN-Net method to enhance the accuracy of IRS for Eyeglasses, which optimises the original SoftMax classifier in modelling extreme or difficult samples due to eyeglasses. The reasons for adopting the ResNet technique [41,44,45] in our HDN-Net are to improve the task of extracting and describing the complex features of the iris tissue due to challenges from eyeglasses, to improve training process parameters, to better propagate of the features, to enable the reuse of the features, and to address the problem of gradient explosion caused by the continuous increase in the number of layers in our proposed HDN-Net network. The details of each one are explained below in separate sections.

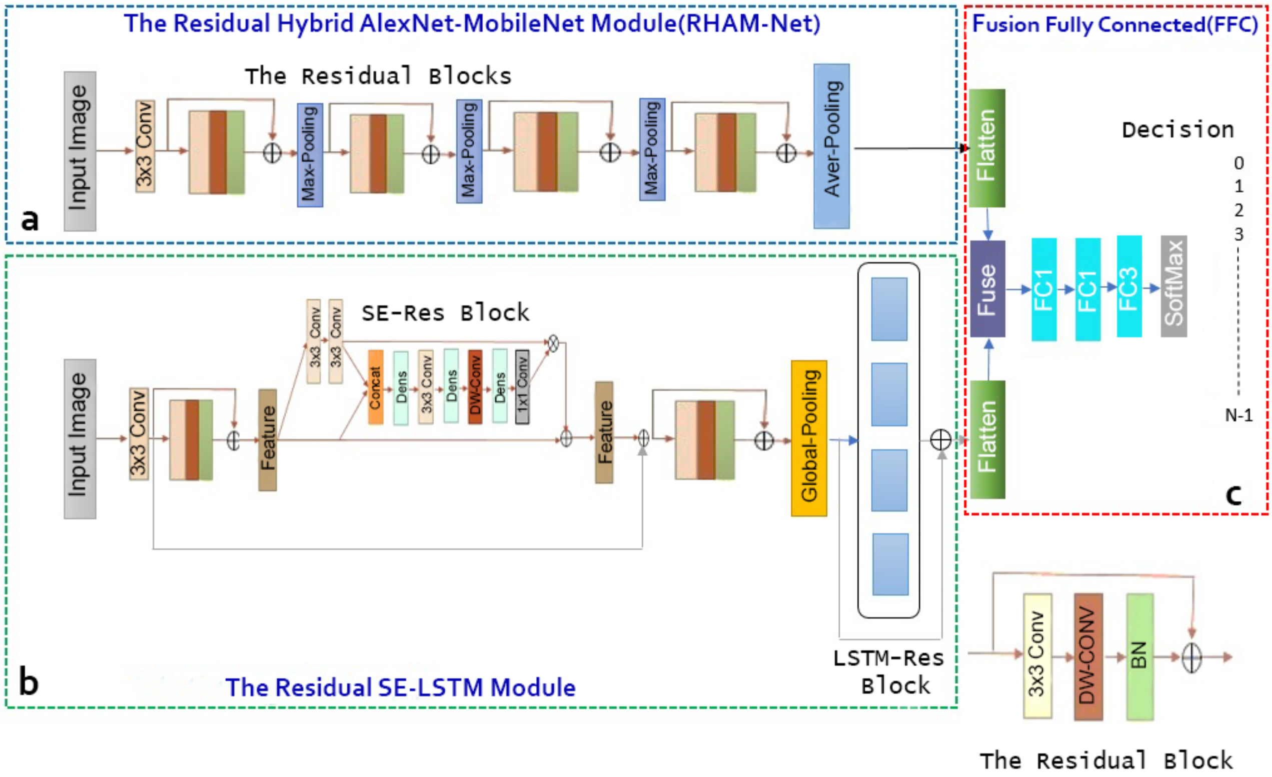


Fig. 1. The architecture of our suggested HDN-Net Framework for Feature Extraction and Classification

2.2 Loss Functions

In the training stage of the suggested HDN-Net method of the IRS, categorical cross-entropy was used for multiclass classification, where a unique integer value is set for each class from 0 to the class number –1 (K–1). Categorical cross-entropy calculates the average difference between the predicted and actual probability distributions for all classes in the problem, which is defined by the equation:

$$Loss\ Functions\ (LF_i) = -\sum_{i=1}^{J}[(M_i * log\ N_i)] \quad (1)$$

N_i is the output of the last layer of our framework (the probability for class i in the prediction), M_i is the probability for class i in the target (the probabilities for all classes), and J is the output size.

The target must be one-hot encoded in order for the categorical cross-entropy loss function to work properly with it. To predict the probability for each class, the output layer is set up using n nodes (one for each class). In this HDN-Net architecture, there are 128 nodes, with a "SoftMax" activation.

3. Experiment Setup

In this section, we briefly describe the databases we utilised to evaluate the architecture of our suggested HDN-Net Framework. We also present the implementation details. Finally, we explain the evaluation metrics used to evaluate performance accuracy of our suggested HDN-Net Framework.

3.1 Datasets

In this study, the UBIRIS.V2 and CASIA-Iris.V4-1000 databases were utilised to evaluate the performance accuracy of the suggested technique in the iris classification task and the IRS. Figure 2 illustrates samples of iris images sourced from these databases and used in our experiments. Detailed information of the two databases is given below.

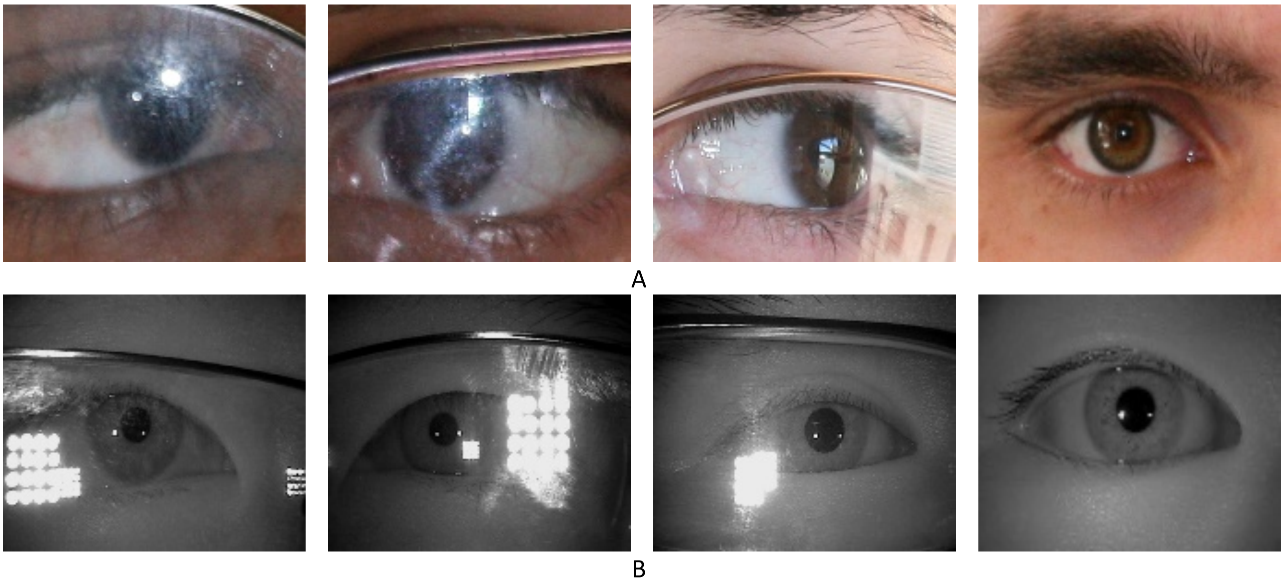


Fig. 2. Some samples of iris images from the two publicly available databases were used in our experiments. (a) The UBIRIS.V2 database. (b) The CASIA-Iris.V4-1000 database

3.1.1 CASIA-Iris.V4-1000

CASIA-Iris.V4-1000 constitutes a subset of CASIA-Iris.V4 [46], which has been introduced available by the Centre for Biometrics and Security Research (CBSR). The dataset encompasses 20,000 NIR iris images that have been acquired from 1,000 subjects. The images include both right and left eyes, with each subject having between 1 to 10 samples. All the images share a resolution of 640×480 and were captured using an IKEMB-100 camera and saved in the .jpeg format. The database consists of 5,320 eye images with eyeglasses and 14,668 eye images without eyeglasses. The eyeglass samples include those with reflections. For individuals who wear eyeglasses, the database has their images without and with eyeglasses, to establish a standard for performance evaluation. From this database, a subset encompassing 60% of the iris images was selected for training, 20% for validation, and the remaining 20% for testing purposes.

3.1.2 UBIRIS.V2

UBIRIS.V2 [47] contains images of the iris captured in non-ideal (unconstrained) environments in visible (VIS) light. The images were acquired in 2 sessions from 261 subjects (right and left eyes), giving a total of 522 different items. In total, there are 11,102 samples, acquired utilising a Canon EOS DSLR camera featuring a 400 mm focal range, an exposure duration of 1/200 s, and an ISO setting of 1600. All the eye images are saved in the (.tiff) format. The dataset comprises 2,209 eye images taken when subjects wearing eyeglasses and 8,893 eye images without eyeglasses. Each image has a resolution of 800×600 pixels. For model training, 60% of the images were utilized, 20% were allocated for validation, and the remaining 20% were reserved for testing purposes.

3.2 Implementation Details

We used PyCharm as the simulation platform for our experiments, using TensorFlow backend with Keras, and run on a laptop with an Intel (R) Core (TM) i7-9750H processor. The laptop is equipped with a Nvidia GeForce GTX 1660Ti GPU (6GB-GDDR6), accompanied by 32GB DDR4 RAM. Storage is facilitated by a 512GB NVMe SSD, and the laptop operates on a 64-bit Windows 10 Home system. The HDN-Net framework was trained using the CASIA-Iris.V4-1000 and UBIRIS.V2 databases. The training involved 500 epochs, each with 10 steps, for both the UBIRIS.V2 and CASIA-Iris.V4-1000 databases. Augmentation techniques were not applied during training. The optimization process utilized Adam with a learning rate of 10^{-4}. Our proposed HDN-Net method was tested on two types of images of the iris, without and with eyeglasses. The iris images with eyeglasses pose such challenges as reflections, blurriness, scratches, dirt, shadows, and other issues.

3.3 Evaluation Metrics

The performance of our proposed HDN-Net method was evaluated according to five metrics, which are: Accuracy (ACC), as defined in Eq. (2) and having a value within the range of 0 to 1; Equal Error Rate (EER), computed through Eq. (3) and falling between 0 and 1; Precision (Pr), calculated using Eq. (4); Recall (Sensitivity), denoted as (Rec) and determined by Eq. (5); and F-Measure (FM), calculated using Eq. (6). These calculations involve the utilization of true negative (TN), true positive (TP), false negative (FN), and false positive (FP) values.

$$ACC = \frac{TP+TN}{TP+FP+TN+FN} \tag{2}$$

$$EER = \frac{FP+FN}{TP+FP+TN+FN} \tag{3}$$

$$Pr = \frac{TP}{TP+FP} \tag{4}$$

$$Rec = \frac{TP}{TP+FN} \tag{5}$$

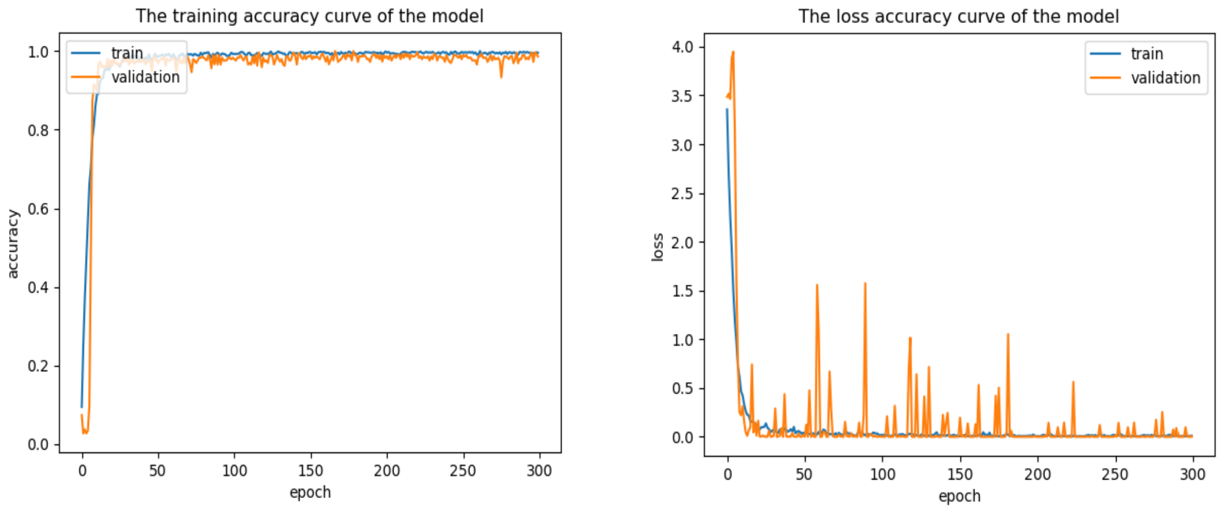
$$FM = \frac{2*Pr*Rec}{Pr+Rec} \tag{6}$$

4. Experiment Results

In this section, two subsections have been introduced to evaluate the performance accuracy of the proposed MMPDN-Net method: to evaluate and analyse its performance accuracy during the training and validation phases, and to evaluate and compare its performance accuracy with state-of-the-art methods during the testing phase. This is done to substantiate the claim regarding the appropriateness of the proposed HDN-Net method.

4.1 Training and Validation Phase

Figure 3 (a) and (b) illustrate the differences in training and validation for both the accuracy and loss curves of the proposed method, respectively. In these curves, the left figure represents training accuracy, while the right figure represents training loss. The x-axis denotes the epoch number, and the y-axis represents the loss and accuracy during the training phase per batch of epochs from 0 to 500. The high-frequency tops in the accuracy and loss curves indicate significantly higher accuracy and loss values for those specific batches during training for both training and validation. Comparing the training and validation curves for accuracy and loss of our proposed HDN-Net method, it is evident that the performance of HDN-Net converges faster to the highest accuracy and the lowest loss between training and validation curves.



(a) Accuracy curve of training and validation (b) Loss curve of the training and validation

Fig. 3. Performance of the proposed HDN-Net method (a) Accuracy curve of training and validation (b) Loss curve of the training and validation

4.2 Testing Phase

The iris region extraction process was initiated using our proposed segmentation method as a pre-processing phase on the iris images. Our multi-segmentation network, MS-Net, as introduced in [55], was employed for the initial segmentation. This network relies on a deep learning approach designed to capture high-level semantic features while preserving spatial information, thereby enhancing the accuracy of iris segmentation. It is essential to note that all the algorithms discussed and compared with our proposed method in this paper were applied to the same test sets. The subsequent section evaluates the results obtained from the proposed HDN-Net method in the test phase, utilizing five metrics and two available databases to assess performance accuracy. The five-evaluation metrics used during the testing phase, which are Accuracy (ACC), Equal Error Rate (EER), Precision (Pr), Recall (Rec), and F-Measure (FM), provide a quantitative measure of the system's performance and help in comparing it with other existing IRS.

The two purposes of this evaluation are to measure the inter- and intra-database accuracies of the proposed HDN-Net and some previous state-of-the-art techniques of the IRS.

4.2.1 Inter-database performance of HDN-Net

In this research, we tested the accuracy of HDN-Net Framework using five metrics on three different categories of data taken from the two public databases (CASIA-Iris.V4-1000 and UBIRIS.V2) of iris images. The three categories measured are without eyeglasses, with eyeglasses, and overall. The results are displayed in Table 1. For images without eyeglasses, HDN-Net achieved a score of more than 0.98 and 0.99 on UBIRIS.V2 and CASIA-Iris.V4-1000 databases, respectively, for four of the metrics (ACC, Pr, Rec, FM) and its EER values were less than 0.0026 and 0.011 on CASIA-Iris.V4-1000 and UBIRIS.V2, respectively. The performance of HDN-Net was affected for images with eyeglasses. Its accuracy was higher than 97% and 96% for four of the metrics (ACC, Pr, Rec, FM) and its EER values were 0.031 and 0.021 on UBIRIS.V2 and CASIA-Iris.V4-1000 databases, respectively. It is important to note that the generally poorer performance on UBIRIS.V2 database is due to the high noise content from eyeglasses, which reduces the clarity of the iris features. Furthermore, it can be observed that HDN-Net achieved more than 97% and 98% accuracies for four of the metrics (ACC, Pr, Rec, FM) in the overall category (with and without eyeglasses) on UBIRIS.V2 and CASIA-Iris.V4-1000 databases, respectively, and its EER values were less than 0.021 and 0.012 on UBIRIS.V2 and CASIA-Iris.V4-1000 databases, respectively.

Table 1
A comparison of the performance of the proposed HDN-Net method with/without eyeglasses on the UBIRIS.V2 and CASIA-Iris.V4-1000 databases

Database	Category	Pr	Rec	FM	EER	ACC
CASIA- Iris.V4-1000	Without eyeglasses	0.99765	0.99739	0.99752	0.00256	0.99744
	With eyeglasses	0.97958	0.97818	0.97855	0.02168	0.97832
	With & Without eyeglasses (Overall)	0.98862	0.98779	0.98804	0.01212	0.98788
UBIRIS.v2	Without eyeglasses	0.98937	0.98895	0.98921	0.01093	0.98907
	With eyeglasses	0.97126	0.96828	0.97003	0.03136	0.96864
	With & Without eyeglasses (Overall)	0.98031	0.97862	0.97962	0.02115	0.97885

4.2.2 Intra-database performance of HDN-Net and other state-of-the-art methods

Figure 4 shows the performance of the proposed HDN-Net method within a database compared with some previous state-of-the-art techniques of the IRS, using the metric ACC (Accuracy) to perform the evaluation on CASIA-Iris.V4-1000. The x-axis in Figure 4 represents the different methods being compared, while the y-axis represents the performance value of each method. Overall, the results show that the suggested HDN-Net technique outperforms other techniques of iris recognition, has a higher ACC and a lower EER than the other methods in the comparison, on the UBIRIS.V2 and CASIA-Iris.V4-1000 databases. This indicates that the efficiency of HDN-Net is generally the best.

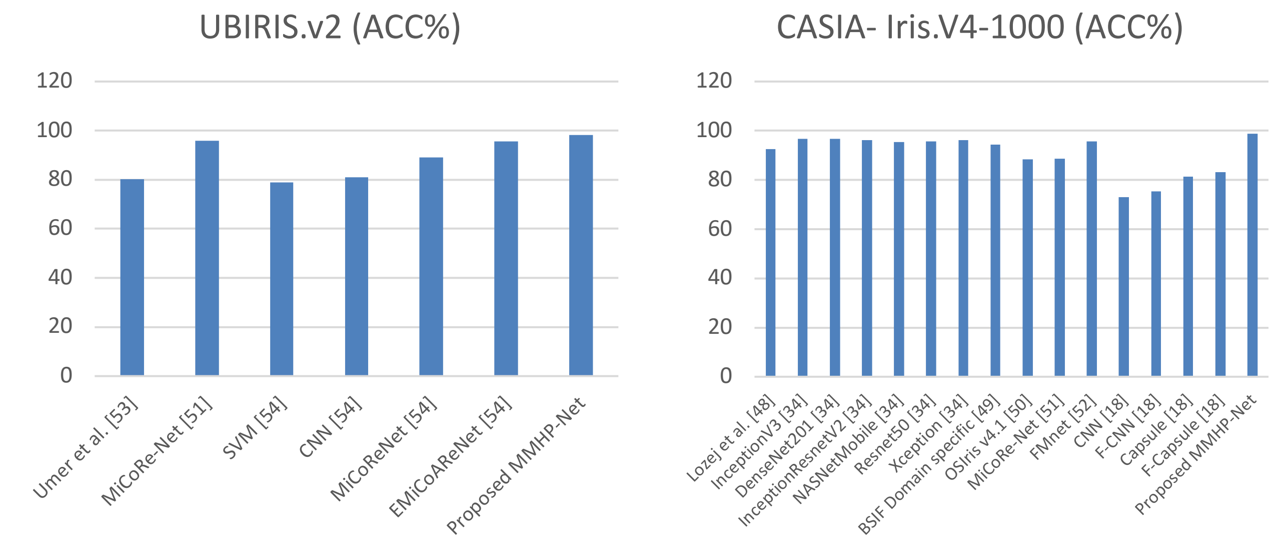


Fig. 4. Comparison of the ACC results (%) of our suggested HDN-Net and some state-of-the-Art techniques of the IRS on the UBIRIS.V2 and CASIA-Iris.V4-1000 databases

5. Conclusion

Iris recognition systems (IRS) are acknowledged to be highly effective in biometric identification and authentication, but they can face significant challenges in accuracy when processing images with eyeglasses. Eyeglasses can cause a variety of distortions and occlusions such as scratches, specular reflections, dirt, blurriness, and other noise factors that make it difficult for iris recognition systems to identify an individual's unique iris pattern accurately. To address this challenge, researchers have proposed the HDN-Net architecture, which uses a multi-CNN model to combine the features of both the left and right iris images in order to extract more distinguishing features, thus improving the accuracy of classification when faced with challenges due to eyeglasses. The overarching structure of the suggested HDN-Net framework comprises three major parts: the RHAM-Net module, the Residual SE-LSTM module, and the FFC module. The accuracy of the proposed iris recognition system was evaluated on the UBIRIS.V2 and CASIA-Iris.V4-1000 databases. The experiment results explain that our proposed iris recognition system achieves more promising results in terms of robustness and recognition accuracy compared to previous methods used in this field.

Acknowledgement
The authors acknowledge the financial support from the Putra Grant (Cost Centre: 9693600) funded by Universiti Putra Malaysia (UPM).

References
[1] Bowyer, Kevin W., Karen P. Hollingsworth, and Patrick J. Flynn. "A survey of iris biometrics research: 2008–2010." *Handbook of iris recognition* (2016): 23-61. https://doi.org/10.1007/978-1-4471-6784-6_2
[2] Viriri, Serestina, and Jules R. Tapamo. "Integrating iris and signature traits for personal authentication using user-specific weighting." *Sensors* 12, no. 4 (2012): 4324-4338. https://doi.org/10.3390/s120404324
[3] Jain, Anil K., Sunpreet S. Arora, Kai Cao, Lacey Best-Rowden, and Anjoo Bhatnagar. "Fingerprint recognition of young children." *IEEE Transactions on Information Forensics and Security* 12, no. 7 (2016): 1501-1514. https://doi.org/10.1109/TIFS.2016.2639346
[4] Bonnen, Kathryn, Brendan F. Klare, and Anil K. Jain. "Component-based representation in automated face recognition." *IEEE Transactions on Information Forensics and Security* 8, no. 1 (2012): 239-253. https://doi.org/10.1109/TIFS.2012.2226580

[5] Nazmdeh, Vahid, Shaghayegh Mortazavi, Daniel Tajeddin, Hossein Nazmdeh, and Morteza Modarresi Asem. "Iris recognition; from classic to modern approaches." In *2019 IEEE 9th Annual Computing and Communication Workshop and Conference (CCWC)*, pp. 0981-0988. IEEE, 2019. https://doi.org/10.1109/CCWC.2019.8666516
[6] Devi, R., and Pothula Sujatha. "A study on biometric and multi-modal biometric system modules, applications, techniques and challenges." In *2017 Conference on Emerging Devices and Smart Systems (ICEDSS)*, pp. 267-271. IEEE, 2017. https://doi.org/10.1109/ICEDSS.2017.8073691
[7] Bazrafkan, Shabab, Shejin Thavalengal, and Peter Corcoran. "An end to end deep neural network for iris segmentation in unconstrained scenarios." *Neural Networks* 106 (2018): 79-95. https://doi.org/10.1016/j.neunet.2018.06.011
[8] Li, Stan Z. *Encyclopedia of Biometrics: I-Z*. Vol. 1. Springer Science & Business Media, 2009.
[9] Szewczyk, Robert, Kamil Grabowski, Malgorzata Napieralska, Wojciech Sankowski, Mariusz Zubert, and Andrzej Napieralski. "A reliable iris recognition algorithm based on reverse biorthogonal wavelet transform." *Pattern Recognition Letters* 33, no. 8 (2012): 1019-1026. https://doi.org/10.1016/j.patrec.2011.08.018
[10] Flom, Leonard, and Aran Safir. "Iris recognition system." U.S. Patent 4,641,349, issued February 3, 1987.
[11] Alvarez-Betancourt, Yuniol, and Miguel Garcia-Silvente. "An overview of iris recognition: a bibliometric analysis of the period 2000–2012." *Scientometrics* 101 (2014): 2003-2033. https://doi.org/10.1007/s11192-014-1336-1
[12] Zainal, Nasharuddin, Abduljalil Radman, Mahamod Ismail, and Md Jan Nordin. "Iris segmentation for non-ideal images." *Jurnal Teknologi* 74, no. 3 (2015): 39-43. https://doi.org/10.11113/jt.v74.4549
[13] Alvarez-Betancourt, Yuniol, and Miguel Garcia-Silvente. "A keypoints-based feature extraction method for iris recognition under variable image quality conditions." *Knowledge-Based Systems* 92 (2016): 169-182. https://doi.org/10.1016/j.knosys.2015.10.024
[14] Nguyen, Kien, Clinton Fookes, Raghavender Jillela, Sridha Sridharan, and Arun Ross. "Long range iris recognition: A survey." *Pattern Recognition* 72 (2017): 123-143. https://doi.org/10.1016/j.patcog.2017.05.021
[15] Jung, Yujin, Dongik Kim, Byungjun Son, and Jaihie Kim. "An eye detection method robust to eyeglasses for mobile iris recognition." *Expert Systems with Applications* 67 (2017): 178-188. https://doi.org/10.1016/j.eswa.2016.09.036
[16] Wang, Zi, Chengcheng Li, Huiru Shao, and Jiande Sun. "Eye recognition with mixed convolutional and residual network (MiCoRe-Net)." *IEEE Access* 6 (2018): 17905-17912. https://doi.org/10.1109/ACCESS.2018.2812208
[17] Winston, J. Jenkin, and D. Jude Hemanth. "A comprehensive review on iris image-based biometric system." *Soft Computing* 23 (2019): 9361-9384. https://doi.org/10.1007/s00500-018-3497-y
[18] Liu, Ming, Zhiqian Zhou, Penghui Shang, and Dong Xu. "Fuzzified image enhancement for deep learning in iris recognition." *IEEE Transactions on Fuzzy Systems* 28, no. 1 (2019): 92-99. https://doi.org/10.1109/TFUZZ.2019.2912576
[19] Malgheet, Jasem Rahman, Noridayu Bt Manshor, Lilly Suriani Affendey, and Alfian Bin Abdul Halin. "Iris recognition development techniques: a comprehensive review." *Complexity* 2021 (2021): 1-32. https://doi.org/10.1155/2021/6641247
[20] Jung, Yujin, Dongik Kim, Byungjun Son, and Jaihie Kim. "An eye detection method robust to eyeglasses for mobile iris recognition." *Expert Systems with Applications* 67 (2017): 178-188. https://doi.org/10.1016/j.eswa.2016.09.036
[21] Lu, Weihua, and Jean-François Petiot. "Affective design of products using an audio-based protocol: Application to eyeglass frame." *International Journal of Industrial Ergonomics* 44, no. 3 (2014): 383-394. https://doi.org/10.1016/j.ergon.2014.01.004
[22] Bowyer, Kevin W., Karen Hollingsworth, and Patrick J. Flynn. "Image understanding for iris biometrics: A survey." *Computer vision and image understanding* 110, no. 2 (2008): 281-307. https://doi.org/10.1016/j.cviu.2007.08.005
[23] Proença, Hugo, and Luís A. Alexandre. "Iris recognition: Analysis of the error rates regarding the accuracy of the segmentation stage." *Image and vision computing* 28, no. 1 (2010): 202-206. https://doi.org/10.1016/j.imavis.2009.03.003
[24] Bharadwaj, Samarth, Himanshu S. Bhatt, Mayank Vatsa, and Richa Singh. "Periocular biometrics: When iris recognition fails." In *2010 fourth IEEE international conference on Biometrics: Theory, Applications and Systems (BTAS)*, pp. 1-6. IEEE, 2010. https://doi.org/10.1109/BTAS.2010.5634498
[25] Raffei, Anis Farihan Mat, Hishammuddin Asmuni, Rohayanti Hassan, and Razib M. Othman. "Frame detection using gradients fuzzy logic and morphological processing for distant color eye images in an intelligent iris recognition system." *Applied Soft Computing* 37 (2015): 363-381. https://doi.org/10.1016/j.asoc.2015.08.035
[26] Drozdowski, Pawel, Florian Struck, Christian Rathgeb, and Christoph Busch. "Detection of glasses in near-infrared ocular images." In *2018 International Conference on Biometrics (ICB)*, pp. 202-208. IEEE, 2018. https://doi.org/10.1109/ICB2018.2018.00039
[27] Gad, Ramadan, Muhammad Talha, Ahmed A. Abd El-Latif, Mohamed Zorkany, EL-SAYED Ayman, EL-Fishawy Nawal, and Ghulam Muhammad. "Iris recognition using multi-algorithmic approaches for cognitive internet of things (CIoT)

framework." *Future Generation Computer Systems* 89 (2018): 178-191. https://doi.org/10.1016/j.future.2018.06.020

[28] Barpanda, Soubhagya Sankar, Pankaj K. Sa, Oge Marques, Banshidhar Majhi, and Sambit Bakshi. "Iris recognition with tunable filter bank based feature." *Multimedia Tools and Applications* 77, no. 6 (2018): 7637-7674. https://doi.org/10.1007/s11042-017-4668-z

[29] Ahmadi, Neda, Mehrbakhsh Nilashi, Sarminah Samad, Tarik A. Rashid, and Hossein Ahmadi. "An intelligent method for iris recognition using supervised machine learning techniques." *Optics & Laser Technology* 120 (2019): 105701. https://doi.org/10.1016/j.optlastec.2019.105701

[30] Ashbourn, Julian. *Biometrics in the new world: The cloud, Mobile technology and Pervasive identity*. Springer Science & Business Media, 2014. https://doi.org/10.1007/978-3-319-04159-9

[31] Bhateja, Vikrant, Mukul Misra, Shabana Urooj, and Aimé Lay-Ekuakille. "A robust polynomial filtering framework for mammographic image enhancement from biomedical sensors." *IEEE Sensors Journal* 13, no. 11 (2013): 4147-4156. https://doi.org/10.1109/JSEN.2013.2279003

[32] Bhateja, Ashok K., Shikhar Sharma, Santanu Chaudhury, and Nitin Agrawal. "Iris recognition based on sparse representation and k-nearest subspace with genetic algorithm." *Pattern Recognition Letters* 73 (2016): 13-18. https://doi.org/10.1016/j.patrec.2015.12.009

[33] Lee, Young Won, Ki Wan Kim, Toan Minh Hoang, Muhammad Arsalan, and Kang Ryoung Park. "Deep residual CNN-based ocular recognition based on rough pupil detection in the images by NIR camera sensor." *Sensors* 19, no. 4 (2019): 842. https://doi.org/10.3390/s19040842

[34] Zambrano, Jorge E., Daniel P. Benalcazar, Claudio A. Perez, and Kevin W. Bowyer. "Iris recognition using low-level CNN layers without training and single matching." *IEEE Access* 10 (2022): 41276-41286. https://doi.org/10.1109/ACCESS.2022.3166910

[35] Nguyen, Kien, Clinton Fookes, Sridha Sridharan, and Arun Ross. "Complex-valued iris recognition network." *IEEE Transactions on Pattern Analysis and Machine Intelligence* 45, no. 1 (2022): 182-196. https://doi.org/10.1109/TPAMI.2022.3152857

[36] Bhunia, Ankan Kumar, Aishik Konwer, Ayan Kumar Bhunia, Abir Bhowmick, Partha P. Roy, and Umapada Pal. "Script identification in natural scene image and video frames using an attention based convolutional-LSTM network." *Pattern Recognition* 85 (2019): 172-184. https://doi.org/10.1016/j.patcog.2018.07.034

[37] Hu, Jie, Li Shen, and Gang Sun. "Squeeze-and-excitation networks." In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 7132-7141. 2018. https://doi.org/10.1109/CVPR.2018.00745

[38] Hu, Yang, Guihua Wen, Mingnan Luo, Dan Dai, Jiajiong Ma, and Zhiwen Yu. "Competitive inner-imaging squeeze and excitation for residual network." *arXiv preprint arXiv:1807.08920* (2018).

[39] Krizhevsky, Alex, Ilya Sutskever, and Geoffrey E. Hinton. "Imagenet classification with deep convolutional neural networks." *Advances in neural information processing systems* 25 (2012).

[40] Lu, Siyuan, Shui-Hua Wang, and Yu-Dong Zhang. "Detection of abnormal brain in MRI via improved AlexNet and ELM optimized by chaotic bat algorithm." *Neural Computing and Applications* 33, no. 17 (2021): 10799-10811. https://doi.org/10.1007/s00521-020-05082-4

[41] Pan, Haihong, Zaijun Pang, Yaowei Wang, Yijue Wang, and Lin Chen. "A new image recognition and classification method combining transfer learning algorithm and mobilenet model for welding defects." *Ieee Access* 8 (2020): 119951-119960. https://doi.org/10.1109/ACCESS.2020.3005450

[42] Velasco, Jessica, Cherry Pascion, Jean Wilmar Alberio, Jonathan Apuang, John Stephen Cruz, Mark Angelo Gomez, Benjamin Molina Jr, Lyndon Tuala, August Thio-ac, and Romeo Jorda Jr. "A smartphone-based skin disease classification using mobilenet cnn." *arXiv preprint arXiv:1911.07929* (2019). https://doi.org/10.30534/ijatcse/2019/116852019

[43] Wang, Wei, Yiyang Hu, Ting Zou, Hongmei Liu, Jin Wang, and Xin Wang. "A new image classification approach via improved MobileNet models with local receptive field expansion in shallow layers." *Computational Intelligence and Neuroscience* 2020 (2020). https://doi.org/10.1155/2020/8817849

[44] He, Kaiming, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. "Deep residual learning for image recognition." In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 770-778. 2016. https://doi.org/10.1109/CVPR.2016.90

[45] Wang, Wei, Yutao Li, Ting Zou, Xin Wang, Jieyu You, and Yanhong Luo. "A novel image classification approach via dense-MobileNet models." *Mobile Information Systems* 2020 (2020). https://doi.org/10.1155/2020/7602384

[46] Drozdowski, Pawel, Florian Struck, Christian Rathgeb, and Christoph Busch. "Detection of glasses in near-infrared ocular images." In *2018 International Conference on Biometrics (ICB)*, pp. 202-208. IEEE, 2018. https://doi.org/10.1109/ICB2018.2018.00039

[47] Proença, Hugo, Silvio Filipe, Ricardo Santos, Joao Oliveira, and Luis A. Alexandre. "The UBIRIS. v2: A database of visible wavelength iris images captured on-the-move and at-a-distance." *IEEE Transactions on Pattern Analysis and Machine Intelligence* 32, no. 8 (2009): 1529-1535. https://doi.org/10.1109/TPAMI.2009.66

[48] Lozej, Juš, Dejan Štepec, Vitomir Štruc, and Peter Peer. "Influence of segmentation on deep iris recognition performance." In *2019 7th International Workshop on Biometrics and Forensics (IWBF)*, pp. 1-6. IEEE, 2019. https://doi.org/10.1109/IWBF.2019.8739225

[49] Czajka, Adam, Daniel Moreira, Kevin Bowyer, and Patrick Flynn. "Domain-specific human-inspired binarized statistical image features for iris recognition." In *2019 IEEE Winter Conference on Applications of Computer Vision (WACV)*, pp. 959-967. IEEE, 2019. https://doi.org/10.1109/WACV.2019.00107

[50] Othman, Nadia, Bernadette Dorizzi, and Sonia Garcia-Salicetti. "OSIRIS: An open source iris recognition software." *Pattern recognition letters* 82 (2016): 124-131. https://doi.org/10.1016/j.patrec.2015.09.002

[51] Wang, Zi, Chengcheng Li, Huiru Shao, and Jiande Sun. "Eye recognition with mixed convolutional and residual network (MiCoRe-Net)." *IEEE Access* 6 (2018): 17905-17912. https://doi.org/10.1109/ACCESS.2018.2812208

[52] Tobji, Rachida, Wu Di, and Naeem Ayoub. "FM net: Iris segmentation and recognition by using fully and multi-scale CNN for biometric security." *Applied Sciences* 9, no. 10 (2019): 2042. https://doi.org/10.3390/app9102042

[53] Umer, Saiyed, Bibhas Chandra Dhara, and Bhabatosh Chanda. "NIR and VW iris image recognition using ensemble of patch statistics features." *The Visual Computer* 35 (2019): 1327-1344. https://doi.org/10.1007/s00371-018-1544-4

[54] Shanbagavalli, T. R. "EMiCoAReNet: An Effective Iris Recognition Using Emerging Mixed Convolutional and Adaptive Residual Network Approach." *Turkish Journal of Computer and Mathematics Education (TURCOMAT)* 12, no. 7 (2021): 2242-2255.

[55] Malgheet, Jasem Rahman, Noridayu Bt Manshor, Lilly Suriani Affendey, and Alfian Bin Abdul Halin. "MS-net: Multi-segmentation network for the iris region using deep learning in an unconstrained environment." *IEEE Access* (2023). https://doi.org/10.1109/ACCESS.2023.3282547