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Evaluating the Impact of Iris Image Preprocessing on CNN-Based Biometric Recognition Performance

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Abstract

Iris-based biometric recognition is a reliable identification technique because the iris pattern is unique and remains stable throughout an individual's lifetime. However, the quality of iris images significantly affects the accuracy of recognition systems, particularly when images are degraded by noise, uneven illumination, and occlusions caused by eyelashes and eyelids. This study investigates the impact of several image preprocessing techniques on the performance of an iris biometric recognition system. The preprocessing pipeline consists of image resizing, pixel value normalization, contrast enhancement using Contrast Limited Adaptive Histogram Equalization (CLAHE), and noise reduction through Gaussian filtering. The CASIA-IrisV1 dataset was employed for model development and evaluation, while a Convolutional Neural Network (CNN) was used as the classification model. Experimental results demonstrate that the proposed preprocessing pipeline improves the iris recognition accuracy from 91.2% to 96.4%. These findings indicate that image quality enhancement through appropriate preprocessing plays a crucial role in improving the robustness and accuracy of CNN-based iris biometric recognition systems.

Keywords: Iris recognition, Iris biometrics, Image preprocessing, Convolutional Neural Network (CNN), Recognition accuracy

1. Introduction

Biometric identification technologies have been increasingly adopted in various security applications due to their convenience, reliability, and high resistance to forgery compared with traditional authentication methods [1]. Biometric systems identify individuals based on unique physiological or behavioral characteristics, enabling more accurate and secure authentication than conventional approaches. Among the various biometric modalities, iris recognition has emerged as one of the most reliable techniques because the iris contains highly distinctive textural patterns that are unique to each individual and remain stable throughout a person's lifetime. Located in the anterior portion of the eye, the iris provides rich discriminative features that make it particularly suitable for high-security automatic identification and authentication systems [2]. Furthermore, iris patterns are relatively insensitive to aging and environmental changes, making them a robust biometric trait for long-term identity verification.

Despite its high reliability, the performance of iris recognition systems is strongly influenced by the quality of the acquired iris images. Images captured under practical conditions frequently suffer from several degradation factors, including digital noise, non-uniform illumination, reflections, and occlusions caused by eyelashes and eyelids [3]. These imperfections reduce the visibility of iris texture patterns, thereby degrading the effectiveness of feature extraction and ultimately lowering recognition accuracy. To mitigate these challenges, image preprocessing is commonly applied before feature extraction and classification. The primary objective of preprocessing is to enhance image quality by suppressing visual artifacts while standardizing image characteristics across the dataset. Effective preprocessing improves the visibility of iris texture details, allowing the recognition model to learn more discriminative features and consequently achieve better classification performance [4]. Several preprocessing techniques have been widely employed in iris recognition systems, including image resizing, pixel intensity normalization, contrast enhancement, and noise reduction. Among these methods, Contrast Limited Adaptive Histogram Equalization (CLAHE) has demonstrated considerable effectiveness in enhancing local image contrast, particularly under uneven illumination conditions, thereby revealing fine iris texture details that are essential for accurate recognition [5]. In addition, Gaussian filtering is frequently applied to suppress image noise while preserving the structural characteristics of the iris texture, leading to improved image quality without significant loss of discriminative information [6].

Besides preprocessing, the selection of an appropriate benchmark dataset is another critical factor affecting the performance and generalizability of iris recognition systems. The CASIA-IrisV1 dataset has become one of the most widely used public benchmarks in iris biometric research because it provides high-quality iris images with substantial inter-subject variability under different acquisition conditions [7]. Its diversity makes it suitable for evaluating the robustness and effectiveness of iris recognition algorithms. In this study, iris recognition performance is evaluated using a Convolutional Neural Network (CNN), a deep learning architecture that has achieved remarkable success in various computer vision applications due to its ability to automatically learn hierarchical feature representations directly from image data [8]. By integrating an effective image preprocessing pipeline with a reliable benchmark dataset and a CNN-based recognition model, this research aims to investigate the contribution of preprocessing techniques to improving the accuracy and robustness of iris biometric recognition systems.

2. Methods

The objective of this study is to evaluate the impact of iris image preprocessing on the accuracy of a CNN-based biometric recognition system. The proposed methodology consists of four main stages: iris image preprocessing, benchmark dataset preparation, CNN model architecture design and training, and performance evaluation using the testing dataset. This framework is intended to systematically assess the contribution of image preprocessing techniques to improving the accuracy and robustness of iris biometric recognition. Fig. 1 presents the proposed method.

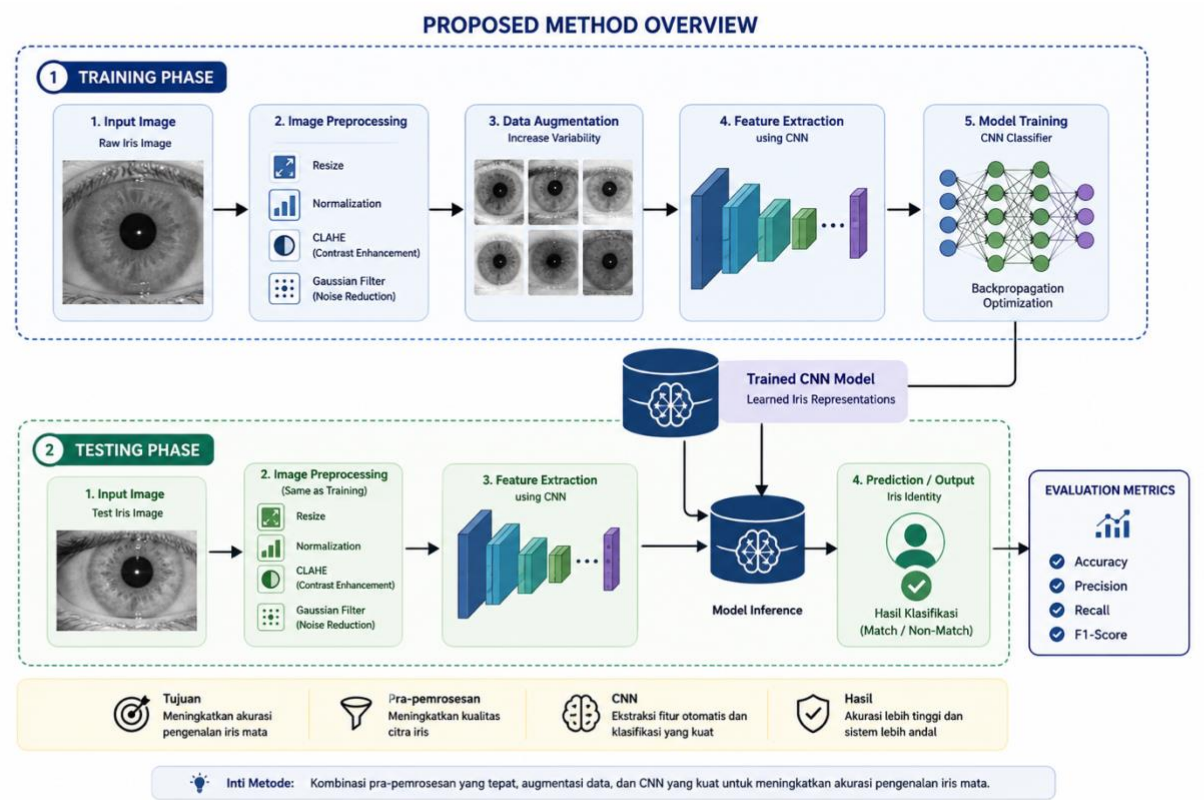


Figure 1. Proposed Mehod

2.1 Dataset

The CASIA-IrisV1 dataset, one of the most widely used benchmark datasets in iris biometric research, was employed in this study. Developed by the Institute of Automation, Chinese Academy of Sciences (CASIA), the dataset has been extensively utilized due to its consistent image quality and diverse iris pattern variations [9]. CASIA-IrisV1 contains 756 grayscale iris images collected from 108 individuals, with each subject contributing 14 images, comprising seven images of the left eye and seven images of the right eye [10]. All images were acquired using a near-infrared (NIR) imaging system, which minimizes the influence of ambient illumination and enhances the visibility of iris texture patterns. This imaging technique produces high contrast between the iris and surrounding ocular structures, thereby facilitating accurate iris segmentation and feature extraction [11]. Furthermore, the dataset incorporates natural variations in eye position, head orientation, and imaging conditions, making it suitable for evaluating the robustness of iris recognition algorithms.

Some images also contain realistic artifacts, including specular reflections on the corneal surface, eyelid occlusions, and eyelash interference, which increase the complexity of the recognition task. Consequently, the CASIA-IrisV1 dataset provides a challenging yet representative benchmark for assessing the performance of iris biometric recognition systems under real-world conditions [12]. For model development, the dataset was randomly divided into training and testing subsets while preserving a balanced distribution of subject identities. Specifically:

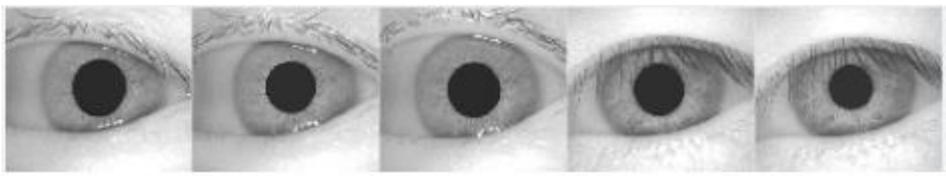
- 80% (604 images) were allocated for model training
- 20% (152 images) were reserved for model testing

The random data partitioning strategy was designed to maintain proportional representation of all subjects while preventing information leakage between the training and testing sets, thereby reducing the risk of overfitting [13]. Since the dataset consists of 108 unique identities, the proposed CNN-based recognition system is required to accurately distinguish highly similar iris patterns despite variations in acquisition conditions, visual noise, and viewpoint differences. This evaluation protocol provides a reliable assessment of the system's generalization capability for practical biometric recognition applications. Examples of iris images from the CASIA-IrisV1 dataset are illustrated in Fig. 2.

a. ID001

b. ID002

c. ID003



d. ID004

Figure 2. Contoh Citra Iris dari Dataset CASIA-IrisV1

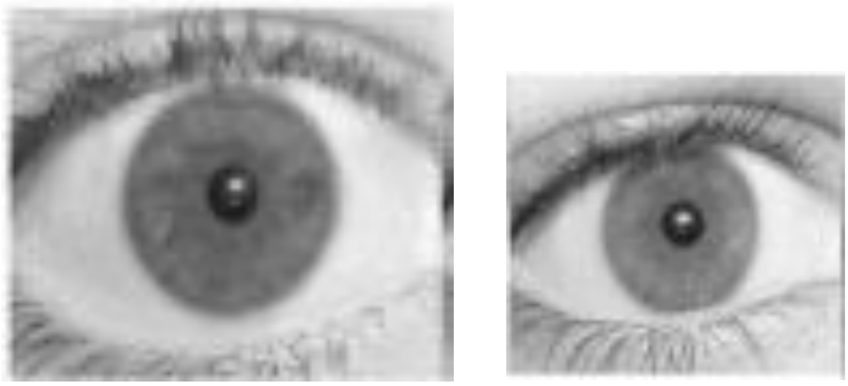
2.2 Image Preprocessing

To enhance the quality of iris images prior to feature learning, a comprehensive preprocessing pipeline was applied to the CASIA-IrisV1 dataset. The primary objective of preprocessing was to improve the visibility of iris texture while reducing image artifacts that could negatively affect the performance of the Convolutional Neural Network (CNN). A consistent preprocessing procedure was applied to all images to ensure uniform image quality throughout the training and testing stages. High-quality input images enable the CNN to learn more discriminative iris features, thereby improving the accuracy and robustness of the biometric recognition system. The preprocessing pipeline consisted of four sequential operations: image resizing, pixel intensity normalization, contrast enhancement using Contrast Limited Adaptive Histogram Equalization (CLAHE), and noise reduction using a Gaussian filter [14].

CLAHE was employed to enhance local image contrast and emphasize fine iris texture details, particularly in regions affected by non-uniform illumination. Subsequently, Gaussian filtering was applied to suppress high-frequency noise while preserving the structural characteristics of the iris pattern, resulting in smoother and more visually consistent images.

- Image Resizing

  Since the original images in the CASIA-IrisV1 dataset have varying dimensions, image resizing was performed as the first preprocessing step to standardize the input size required by the CNN model. In this study, every iris image was resized to 128 × 128 pixels, providing a uniform input representation for all samples. Standardizing image dimensions offers several advantages [15]. It reduces computational complexity during model training, minimizes memory consumption, and prevents geometric distortions that could alter the discriminative iris texture patterns. Furthermore, using a fixed input size allows the CNN architecture to process images consistently, thereby improving training efficiency and facilitating stable feature extraction across the entire dataset. Fig. 3 illustrates the image resizing process.



a. Before Resize b. After Resize

Figure 3. Example of an iris image before and after the resizing process.

- Image Rescaling (Normalization)

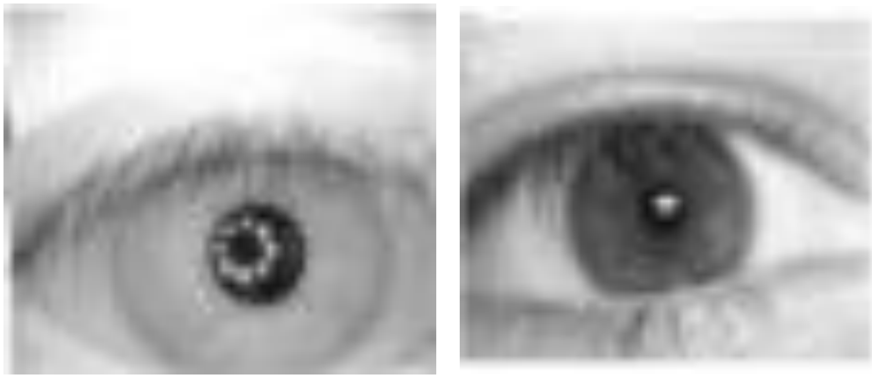
  Following the image resizing step, pixel intensity normalization was performed by rescaling the pixel values from the original range of 0–255 to a normalized range of 0–1. This normalization process aims to reduce the influence of illumination variations while providing a consistent input distribution for the CNN model. Normalizing pixel intensities improves the stability of the training process by ensuring that all input features are represented within a uniform numerical range. Consequently, the neural network can update its weights more efficiently, resulting in faster convergence during optimization. Moreover, normalization prevents certain high-intensity pixel values from dominating the learning process, thereby promoting balanced feature learning and improving the overall generalization capability of the model [16]. Fig. 4 presents an example of an iris image before and after the normalization process.

a. Before Rescaling b. After Rescaling

Figure 4. presents an example of an iris image before and after the normalization process

- Contrast Enhancement

  To improve the visibility of iris texture patterns, Contrast Limited Adaptive Histogram Equalization (CLAHE) was employed as the contrast enhancement technique. Unlike conventional histogram equalization, CLAHE enhances local image contrast while limiting excessive amplification of noise, making it particularly suitable for iris images with non-uniform illumination. The application of CLAHE highlights discriminative iris features, such as radial furrows, concentric rings, and fine texture patterns, which are essential for accurate biometric recognition. This enhancement is especially beneficial for the CASIA-IrisV1 dataset, whose near-infrared (NIR) images may exhibit variations in local illumination despite controlled acquisition conditions. By improving the contrast of subtle iris structures, CLAHE enables the CNN model to extract more informative and discriminative features, thereby enhancing classification performance and overall recognition accuracy. Fig. 5 presents an example of an iris image before and after the application of CLAHE.



a. Before contrast enhancement   b. After contrast enhancement

Figure 5. Comparison of an iris image before and after contrast enhancement using CLAHE

- Image Augmentation
  Following the preprocessing stage, image augmentation was applied to increase the diversity of the training data while preserving the intrinsic characteristics of the iris texture. Data augmentation is an effective strategy for improving the generalization capability of deep learning models, particularly when the available training dataset is relatively limited.

(a) original   (b) Rotation +10°   (c) Rotation -10°

(d) Translation   (e) Zoom   (f) Contrast Adjusment

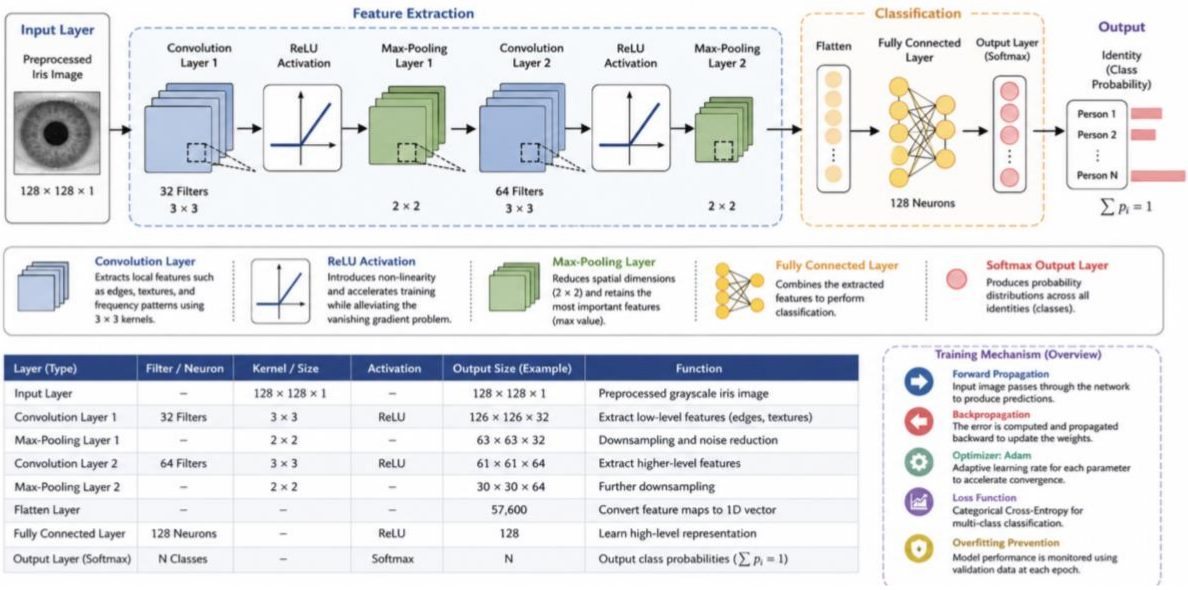
Fig. 6 Iris images before and after the image augmentation process.

In this study, augmentation techniques were carefully designed to generate realistic variations without altering the discriminative iris patterns that are essential for biometric recognition. The augmented images retained the structural integrity of the iris while introducing natural variations that may occur during image acquisition. This approach enables the CNN model to become more robust to changes in imaging conditions and reduces the risk of overfitting.

By exposing the model to a wider range of realistic image variations during training, image augmentation enhances the CNN's ability to learn invariant iris features, ultimately improving the accuracy and reliability of the biometric recognition system. Fig. 6 illustrates examples of iris images before and after the image augmentation process.

2.3 Convolutional Neural Network (CNN)

A Convolutional Neural Network (CNN) was employed as the classification model in this study due to its capability to automatically learn discriminative iris texture patterns from preprocessed image data. CNNs are particularly effective in capturing the unique characteristics of iris textures, including circular structures, intensity variations, spatial frequency, and orientation information. These distinctive features are difficult to extract using conventional handcrafted feature extraction methods. Consequently, the use of CNN significantly enhances the accuracy and robustness of iris identification systems by enabling automatic hierarchical feature learning.In this study, the preprocessed iris images were used as input to the CNN model for identity classification. The CNN architecture was selected because of its proven effectiveness in iris recognition tasks, particularly under challenging imaging conditions such as noise, rotational variations, and illumination changes. Furthermore, CNNs demonstrate strong robustness in extracting invariant and discriminative features from iris images, making them well suited for the CASIA-IrisV1 dataset, which contains variations in lighting conditions as well as partial occlusions caused by eyelids. These capabilities enable the model to maintain reliable recognition performance even when the input images exhibit suboptimal visual quality.



Layer (Type)	Filter / Neuron	Kernel / Size	Activation	Output Size (Example)	Function
Input Layer	–	128 × 128 × 1	–	128 × 128 × 1	Preprocessed grayscale iris image
Convolution Layer 1	32 Filters	3 × 3	ReLU	126 × 126 × 32	Extract low-level features (edges, textures)
Max-Pooling Layer 1	–	2 × 2	–	63 × 63 × 32	Downsampling and noise reduction
Convolution Layer 2	64 Filters	3 × 3	ReLU	61 × 61 × 64	Extract higher-level features
Max-Pooling Layer 2	–	2 × 2	–	30 × 30 × 64	Further downsampling
Flatten Layer	–	–	–	57,600	Convert feature maps to 1D vector
Fully Connected Layer	128 Neurons	–	ReLU	128	Learn high-level representation
Output Layer (Softmax)	N Classes	–	Softmax	N	Output class probabilities ($\sum p_i = 1$)

Figure 7. The Architecture of the CNN Used in This Study

2.3.1 CNN Architecture

The Convolutional Neural Network (CNN) architecture employed in this study consists of several fundamental layers designed to progressively extract discriminative iris features and perform identity classification. The overall architecture comprises convolutional layers, Rectified Linear Unit (ReLU) activation functions, max-pooling layers, a fully connected layer, and a softmax output layer. The arcitecure of CNN used in this study show in Fig. 7.

a. Convolution Layer
The convolution layer is responsible for extracting local discriminative features from iris images, including circular and radial texture patterns that are unique to each individual. In this study, 3 × 3 convolution kernels are employed to capture edges, texture details, and low- to high-frequency spatial information. Each convolution kernel generates a feature map representing different visual characteristics of the iris image, enabling the network to learn increasingly complex feature representations.

b. Activation Function (ReLU)
Following each convolution operation, the Rectified Linear Unit (ReLU) activation function is applied to introduce non-linearity into the network. ReLU enhances the model's capability to learn complex feature representations while accelerating the training process and mitigating the vanishing gradient problem commonly encountered in deep neural networks.

c. Pooling Layer
A 2 × 2 max-pooling layer is employed after the activation function to reduce the spatial dimensions of the feature maps while preserving the most informative features. This operation decreases computational

complexity, improves translation invariance, and enables the CNN to focus on the most discriminative iris patterns, thereby enhancing the robustness of the classification model.

d. Fully Connected Layer
The extracted feature maps are subsequently flattened into a one-dimensional feature vector and passed to the fully connected layer for classification. This layer integrates the learned high-level features to determine the identity of the iris. Finally, a softmax activation function is applied in the output layer to generate the probability distribution over all identity classes.

2.3.2 CNN Learning Mechanism

During training, the CNN performs forward propagation to generate prediction outputs from the input iris images, whereas backpropagation is employed to update the network weights by minimizing the prediction error. The Adaptive Moment Estimation (Adam) optimizer is adopted because of its ability to adaptively adjust the learning rate for each model parameter, resulting in faster convergence and more stable optimization. The categorical cross-entropy loss function is utilized, as it is well suited for multi-class classification problems.To improve the model's generalization capability and prevent overfitting, the classification performance is evaluated on the validation dataset after each training epoch. Furthermore, the preprocessing techniques, including image normalization, Contrast Limited Adaptive Histogram Equalization (CLAHE), and Gaussian filtering, provide enhanced image quality and facilitate the extraction of more discriminative iris features. Consequently, these preprocessing steps contribute significantly to improving the overall classification accuracy of the CNN model.

2.3.3 Advantages of CNN

The application of CNN in this study offers several important advantages. CNN automatically learns hierarchical feature representations directly from preprocessed iris images without requiring handcrafted feature extraction. The extracted features exhibit strong robustness against variations in iris rotation, image noise, and corneal reflections, resulting in more reliable recognition performance. The CNN effectively captures subtle discriminative iris texture patterns after image enhancement, thereby improving classification accuracy and overall recognition performance. Experimental results demonstrate that the proposed CNN model achieves reliable iris recognition performance even under challenging imaging conditions, including noise contamination and illumination variations.

2.4 Training Process

The training process is a crucial stage in enabling the CNN model to effectively learn discriminative iris texture patterns. After completing the preprocessing stage for all images in the CASIA-IrisV1 dataset, the dataset was divided into training and testing subsets using an 80:20 ratio. The model was implemented using a Python-based deep learning framework, with hyperparameters specifically configured for iris recognition. The objective of the training process is to optimize the network parameters to accurately classify iris identities while ensuring good generalization performance on unseen data.

2.4.1 Data Partitioning

The CASIA-IrisV1 dataset, consisting of 756 iris images, was partitioned into two subsets:

- Training set: 604 images (80%)
- Testing set: 152 images (20%)

The data partitioning was performed while maintaining a balanced distribution of subject identities across both subsets to minimize class imbalance and reduce potential model bias.

2.4.2 Training Configuration

The CNN model was trained using the hyperparameter shown in Table 1.

Table 1. The hyperparameter of CNN used

Parameter	Value
Optimizer	Adam

Learning Rate	0.001
Batch Size	32
Number of Epochs	50
Loss Function	Categorical Cross-Entropy
Evaluation Metrics	Accuracy and Loss

The Adam optimizer was selected because it adaptively adjusts the learning rate for each trainable parameter, resulting in faster convergence, improved training stability, and more efficient optimization than conventional stochastic gradient descent methods.

2.4.3 Forward and Backpropagation Process

During the training phase, the CNN model performs four sequential learning stages.

- Forward Propagation
  Each preprocessed iris image is propagated through the CNN architecture to generate an initial prediction based on the current network weights. During this stage, the network progressively learns discriminative iris characteristics, including furrows, crypts, concentric rings, radial streaks, and other distinctive texture patterns.
- Loss Computation
  The prediction error is quantified using the categorical cross-entropy loss function, which measures the discrepancy between the predicted class probabilities and the corresponding ground-truth labels.
- Backpropagation
  The computed loss is propagated backward through the network to update the weights of each layer using the Adam optimization algorithm. This iterative optimization process is performed for every mini-batch until the model converges toward an optimal solution.
- Validation
  At the end of each training epoch, the model is evaluated using the validation dataset to monitor classification performance, assess learning progress, and detect potential overfitting. The validation results are subsequently used to determine whether further training improves the model's generalization capability.

2.4.4 Overfitting Prevention

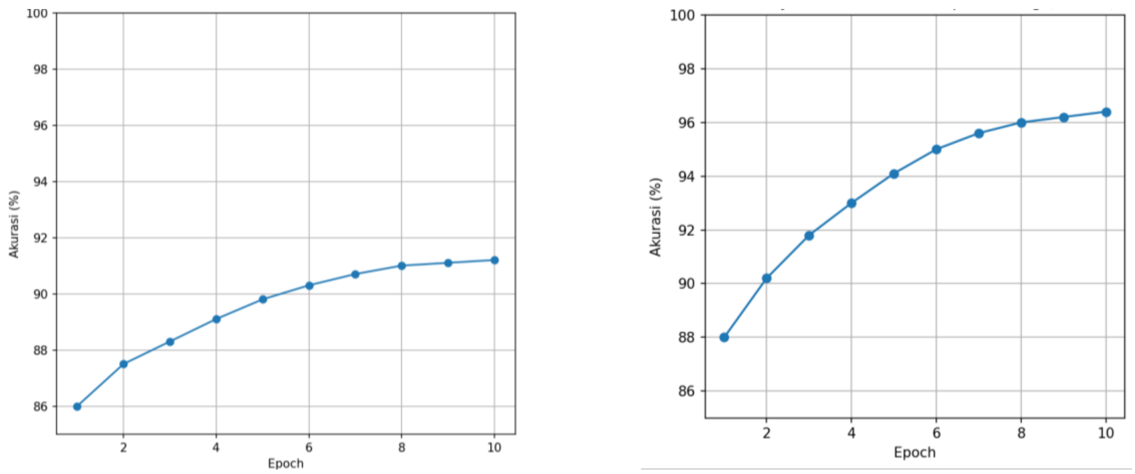
Several regularization strategies were employed to prevent the model from memorizing the training data and to improve its generalization performance. A Dropout layer with a dropout rate of 0.3 was incorporated to reduce neuron co-adaptation and minimize overfitting. Data augmentation techniques, including random rotation and translation, were applied to increase the diversity of the training samples without altering the intrinsic iris characteristics. Early stopping was implemented to terminate the training process when the validation accuracy failed to improve for several consecutive epochs, thereby preventing unnecessary training and reducing the risk of overfitting. These strategies collectively improve the robustness and generalization capability of the proposed CNN model when recognizing previously unseen iris images.

3. Result and Discussions

The training results demonstrate that the proposed preprocessing pipeline substantially improves the performance of the CNN-based iris recognition model. After applying image normalization, Contrast Limited Adaptive Histogram Equalization (CLAHE), and Gaussian filtering, the model achieved a significant increase in classification accuracy.

- Accuracy before preprocessing: 91.2%
- Accuracy after preprocessing: 96.4%

These findings indicate that the preprocessing techniques effectively enhance iris image quality and facilitate the extraction of more discriminative texture features, thereby enabling the CNN model to achieve higher recognition accuracy and improved classification performance.



a. Before Preprocessing   b. After Processing

Figure 8. The training accuracy curves obtained before and after image preprocessing

Fig. 8 illustrates the training accuracy curves obtained before and after image preprocessing. The model trained on the original iris images achieved a relatively stable classification accuracy of approximately 91.2%, suggesting that insufficient image contrast limited the CNN's ability to learn highly discriminative iris texture features. Following the application of Contrast Limited Adaptive Histogram Equalization (CLAHE), the training accuracy increased markedly to 96.4%, representing an absolute improvement of 5.2 percentage points. The enhanced performance indicates that CLAHE effectively improves local image contrast and reveals fine iris texture details, enabling the CNN to extract more representative and discriminative features. These findings confirm that image contrast enhancement plays a crucial role in improving the robustness and classification performance of CNN-based iris recognition systems.

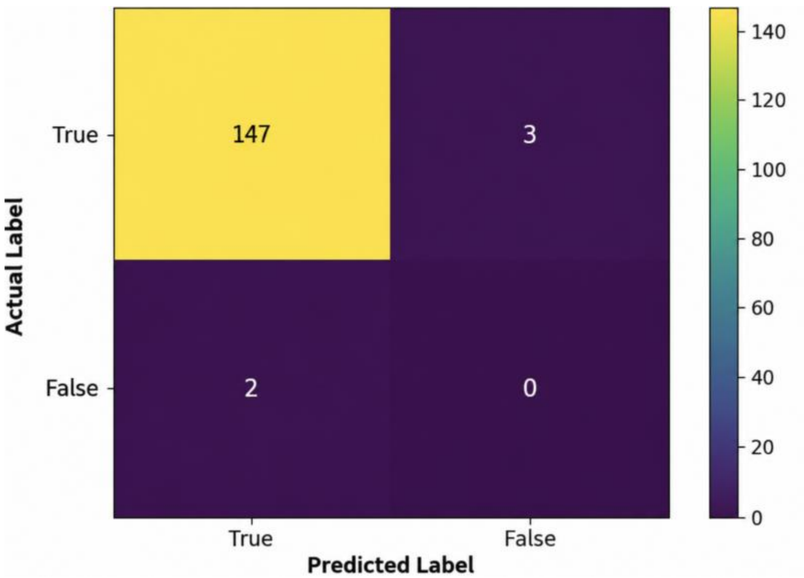


Figure 9. Confusion Matrix Results

a. Confusion Matrix

Based on the confusion matrix shown in Fig. 9, it can be observed that out of the 152 iris images in the testing dataset, 147 were correctly classified by the proposed CNN model, while only five images were misclassified. The high proportion of correctly classified samples demonstrates the model's strong capability to accurately recognize and distinguish discriminative iris texture patterns after the application of the proposed preprocessing pipeline. The small number of misclassified samples may be attributed to several factors, including suboptimal image quality, residual noise, or similarities in iris texture patterns among certain individuals. Nevertheless, these misclassifications are minimal and do not substantially affect the overall performance of the recognition system.

The confusion matrix results are consistent with the overall classification accuracy of 96.4%, which represents a considerable improvement over the performance achieved before image preprocessing. This finding confirms that the preprocessing stages, including image resizing, intensity normalization, contrast enhancement using Contrast Limited Adaptive Histogram Equalization (CLAHE), and noise reduction through Gaussian filtering, play a critical role in improving iris image quality. These techniques enhance local texture details while suppressing image artifacts, enabling the CNN to learn more discriminative feature representations and perform more accurate classification. Consequently, the confusion matrix provides strong evidence that the proposed preprocessing framework significantly enhances the effectiveness, robustness, and reliability of the CNN-based biometric iris recognition system.

b. Accuracy

Fig. 10 presents the training and testing accuracy curves of the proposed CNN model over 50 training epochs. Both curves show a steady increase throughout the training process, indicating that the network progressively learns increasingly discriminative iris texture representations. Minor fluctuations are observed during the early training epochs, particularly in the testing accuracy, which can be attributed to the model's initial adaptation and parameter optimization. As training continues, the two curves gradually stabilize and converge, demonstrating effective learning and consistent optimization. Notably, the difference between the training and testing accuracy remains relatively small across all epochs, indicating that the model achieves good generalization without exhibiting substantial overfitting. This behavior confirms that the combination of image preprocessing techniques—including normalization, Contrast Limited Adaptive Histogram Equalization (CLAHE), and Gaussian filtering—and the proposed CNN architecture enables the extraction of robust and discriminative iris features. Consequently, the model achieves stable learning, high classification accuracy, and reliable performance on unseen iris images.

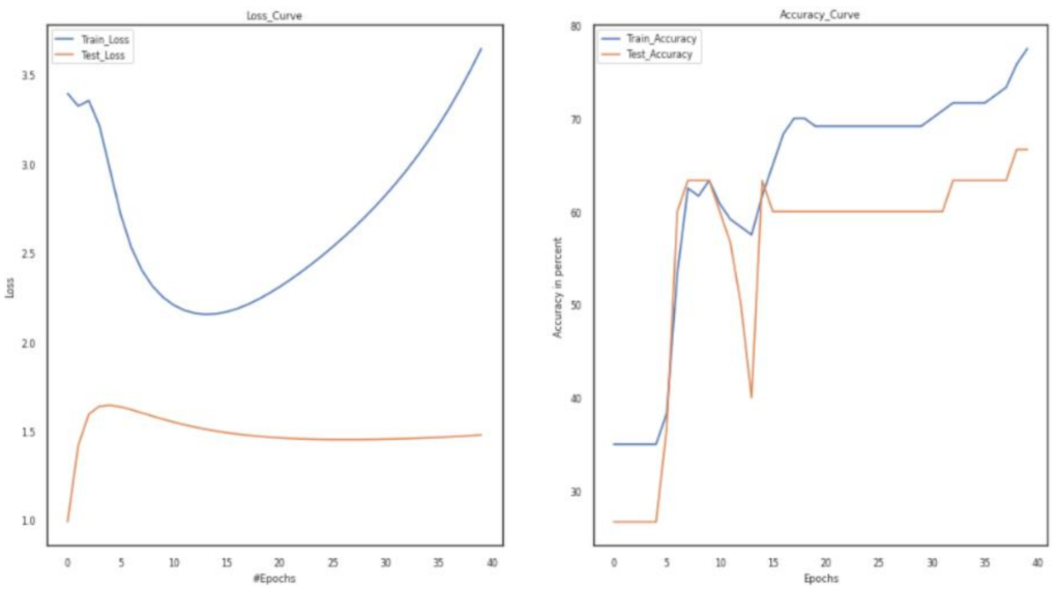


Fig. 10 presents the training and testing accuracy curves of the proposed CNN

4. Conclusion

Although the proposed approach achieved a substantial improvement in classification accuracy, this study is limited to a single dataset, indicating the need for further validation using additional publicly available iris datasets to evaluate the model's generalization capability. This study employed the CASIA-IrisV1 dataset, which consists of 756 iris images collected from 108 individuals. The dataset was divided into training and testing subsets using an 80:20 ratio. The iris images exhibit various challenges, including image noise, uneven illumination, and partial occlusions caused by eyelids and eyelashes, necessitating an effective preprocessing pipeline prior to classification. The proposed preprocessing pipeline consisted of image resizing, pixel value normalization (rescaling), contrast enhancement using Contrast Limited Adaptive Histogram Equalization (CLAHE), and noise reduction through Gaussian filtering. These preprocessing techniques effectively improved the visual quality of the iris images by enhancing local texture details and suppressing image artifacts that could interfere with feature extraction. Consequently, the improved image quality enabled the Convolutional Neural Network (CNN) to learn more discriminative iris texture representations. Experimental results demonstrated that the proposed preprocessing framework significantly improved the performance of the iris recognition system, increasing the classification accuracy from 91.2% before preprocessing to 96.4% after preprocessing. Furthermore, the confusion matrix revealed that the majority of testing samples were correctly classified, as evidenced by the dominant values along the main diagonal and the relatively small number of misclassified samples. These findings indicate that the CNN model effectively distinguishes iris patterns from different individuals when trained using high-quality preprocessed images. Overall, this study confirms that image quality is a critical factor in CNN-based biometric iris recognition systems. Rather than serving merely as a preliminary step, image preprocessing constitutes an essential component of the recognition pipeline by enhancing feature discriminability, improving classification accuracy, and increasing the robustness of the recognition system. The findings of this study provide a valuable reference for the development of more reliable iris recognition systems, particularly those that emphasize effective image preprocessing techniques. Future research should investigate the proposed preprocessing framework using larger and more diverse iris datasets and evaluate its performance with advanced deep learning architectures to further improve recognition accuracy and model generalization.

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