Iris Recognition in Low-Light and Non-Ideal Conditions

Project Final Reports

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Abstract

This project aims to improve the performance of iris recognition systems under challenging conditions such as low light and natural lighting. UBIRIS V1, which has challenges such as focus problems and low light conditions, was selected as the dataset.

In this project, various preprocessing, segmentation, and feature extraction methods were tested. This report includes a detailed description of all the techniques used to achieve the model with the highest accuracy, as well as an in-depth analysis of the model's performance and results.

The highest performance was observed when preprocessing was applied using CLAHE, Gaussian Blur, and Morphological Operation techniques, segmentation was performed with Canny Edge Detection and Circular Hough Transformation, and the iris area was cropped. Additionally, this performance was enhanced by developing the system with our custom Convolutional Neural Network (CNN) model. As a result of training, it was observed that this model achieved an accuracy of 70%.

Although this research did not contribute significantly to the effectiveness of deep learning-based iris recognition systems under low-quality and challenging conditions, it also analyzes the advantages of deep learning models compared to traditional methods in the literature. It enables the examination of how changes implemented in the project to improve test accuracy impact performance on small datasets.

1. Introduction

The iris recognition project aims to design and implement advanced biometric systems that utilize the unique and intricate patterns found in the human iris to achieve high accuracy and reliability in identification and authentication [1]. Iris recognition biometric systems operate based on the analysis of detailed and complex patterns in the human iris [2]. The iris, a part of the human eye structure, forms the colored portion of the eye and gains a unique structure as a result of the combination of genetic factors and environmental influences. This uniqueness is not only evident between individuals but also differs between the two eyes of the same person. Iris recognition systems capture high-resolution images to convert the intricate patterns of the iris into a digital format and compare these patterns with a reference database. These systems stand out due to the stability of iris structures throughout a person's lifetime, their contactless nature, and their lower susceptibility to fraud compared to other biometric methods. Moreover, iris recognition technology provides a highly reliable solution for identity verification by maintaining high accuracy rates while remaining unaffected by light reflections and environmental factors.

The project's primary objective is to compare the performance of CNN-based models with iris recognition projects using the same dataset. The second objective is to observe the effects of different preprocessing, segmentation and feature extraction methods on success. The UBIRIS V1 dataset has been employed in this study, providing a consistent benchmark for evaluating different approaches.

Our system architecture is as follows:

- Preprocessing
- Segmantation
- Normalization
- Data Augmentation
- Feature Extraction
- Performance Evaluation

We propose and compare three different methods for iris recognition, focusing on preprocessing techniques and their impact on model performance. Additionally, the effects of different preprocessing techniques, CLAHE, blurring, sharpening, gamma correction, and adaptive thresholding, on segmentation accuracy were also investigated as part of this study.

The first method applies CLAHE, followed by iris and pupil detection using Canny Edge Detection and Circular Hough Transform. The iris region is then normalized using Daugman's Rubber Sheet Model, and features are extracted using the ResNet50 architecture. The second method centers the iris to extract the region of interest (ROI), applies CLAHE, and trains a DenseNet201 model on the preprocessed data. Since there were problems in training both methods, the third method, which we will explain in this report, was created. The third method, which achieved the best performance, involves CLAHE, Gaussian Blur, and Morphological Operations to remove bright spots, followed by iris detection using Canny Edge Detection and Circular Hough Transform. The detected iris is cropped and processed with a custom-designed Convolutional Neural Network (CNN).

In the dataset used, the participant's ID, who took the photo, is included as metadata in the image filename. Labels were extracted from the file names. This process was carried out while creating the train, test, and validation sets.

The project also focuses on developing highly accurate algorithms capable of detecting and matching individual iris patterns while minimizing the false acceptance rate (FAR) and false rejection rate (FRR). These metrics are critical for ensuring the system's reliability and trustworthiness.

2. Literature Review

Zhou and his colleagues analyzed the methods and performance of image preprocessing, segmentation, and deep learning techniques in iris recognition systems [3]. For the segmentation process, the proposed algorithm combines dynamic thresholding and contour extraction to identify the pupil boundary, followed by gray-level calculations and edge detection to detect the iris region. This method proves to be faster and more accurate than four other algorithms, achieving an accuracy of 98.61% with a processing time of 0.16 seconds on the CASIA V3.0 (Interval) dataset and 98.04% accuracy with 0.32 seconds on the UBIRIS V1 dataset.

For feature extraction and classification, the study employs the AlexNet model, a Convolutional Neural Network (CNN) consisting of 5 convolutional layers and 3 fully connected layers. The CASIA V4.0 dataset was used for training and testing, with an 80/20 split. Data augmentation techniques, such as slight rotation and mirroring, were applied to enhance the diversity of the training set. During the training process, which lasted 40,000 iterations, the model stabilized at an accuracy of 98.6% after 15,000 iterations. The study shows a significant improvement in accuracy on the UBIRIS.v1 dataset when transitioning from Daugman’s method to the proposed approach. While Daugman’s method achieved 58.92% accuracy, the proposed method increased it to 98.04%, demonstrating a 39.12% improvement and highlighting its effectiveness in accurately segmenting iris images.

Overall, the proposed segmentation algorithm demonstrates significant improvements in both speed and accuracy, while the deep learning-based approach utilizing the AlexNet model achieves high recognition accuracy. This highlights the effectiveness of combining traditional segmentation methods with deep learning techniques to enhance the performance of iris recognition systems [3].

Alwawi and his colleges studied a deep learning-based Convolutional Neural Network (CNN) for iris recognition, using the Multimedia University (MMU) dataset, which consists of 460 iris images from 46 individuals [4]. Each image, representing the left and right eyes, has a resolution of 320x240 pixels. To enhance the quality of the input data, preprocessing techniques such as Histogram Equalization (HE) and CLAHE (Contrast Limited Adaptive Histogram Equalization) were applied to improve contrast. Data augmentation methods, including rotation, translation, scaling, and brightness adjustments, were utilized to increase the dataset size to 4600 images.

The proposed CNN model is composed of 10 layers, including an input layer, two convolutional layers, two ReLU activation layers, two pooling layers, one fully connected layer, a softmax classification layer, and an output layer. During the training phase, the model uses Adam optimization for weight updates, employing the backpropagation algorithm to minimize the error. The dataset was split into 80% for training and 20% for testing, ensuring a robust evaluation of the model's performance.

The results indicate exceptional performance, with a training accuracy of 95.33% achieved over 400 epochs, requiring a total training time of 17.59 minutes. The test accuracy reached 100%, demonstrating the model's ability to perfectly classify the iris images, with a processing time of just 12 seconds. These results highlight the effectiveness and efficiency of the proposed CNN-based model, proving that deep learning techniques can deliver highly accurate and reliable iris recognition systems [4].

In another article, researchers are focused on developing an iris recognition system for non-ideal iris images using a combination of segmentation, preprocessing, and feature extraction techniques [5]. For segmentation, a hybrid method combining Chan-Vese Active Contour and GrabCut algorithms was employed to accurately detect the outer iris boundary and localize the iris region.

To remove reflections and noise, bicubic interpolation was applied during the preprocessing stage. Normalization was performed using Daugman's rubber sheet model, which converts the iris images from polar to Cartesian coordinates, ensuring consistency in feature extraction. For feature extraction, the Gabor Wavelet method was utilized, effectively capturing both local and global details of the iris patterns. Matching was conducted using the Euclidean Distance metric to measure the similarity between extracted iris templates.

In the initial experiment, the system was tested on a dataset of 100 individuals, using 3 images for training and 2 images for testing. The results showed a recognition rate of 97.5%, with a False Acceptance Rate (FAR) of 39% and a False Rejection Rate (FRR) of 0.025%. When the number of training images was increased to 5 per individual and 1 image was used for testing, the system achieved a 100% recognition accuracy. These results highlight the effectiveness of the proposed hybrid segmentation approach and the Gabor Wavelet-based feature extraction method, demonstrating reliable performance even on low-quality and challenging iris images [5].

In another study, researchers presents an iris recognition system that combines deep learning and image processing techniques to achieve high accuracy rates [6]. The methodology involves eye and iris detection using the Haar Cascade Classifier, followed by the Hough Transform to localize the iris region. A novel segmentation method is introduced, integrating thresholding, morphological operations such as opening and closing, and contour detection to adapt effectively to varying environmental conditions. Once the segmentation is completed, classification is performed using a DenseNet-201 based Convolutional Neural Network (CNN). The Softmax activation function in the output layer ensures precise classification of the iris images, while the Adam optimizer updates the model's weights during training to improve performance.

The system was evaluated on four well-known iris datasets, including CASIA Iris-Thousand, CASIA Iris-Interval, UBIRIS V1, and UBIRIS V2. The results demonstrated remarkable accuracy, with values ranging from 98.29% to 100%, depending on the dataset. For example, the system achieved 100% accuracy on the CASIA Iris-Interval dataset and 99.32% accuracy on UBIRIS V1, showcasing its robustness across different data conditions. The combination of the DenseNet-201 architecture and the proposed segmentation technique ensures reliable performance, even when applied to challenging iris images. These findings highlight the system's flexibility, adaptability, and effectiveness, positioning it as a highly accurate and efficient solution for iris recognition tasks [6].

In another study proposes an iris recognition system based on a Deep Convolutional Neural Network (DCNN) called IRISNet [7]. The system consists of several key steps, starting with preprocessing, where techniques such as histogram equalization and median filtering are applied to enhance image quality. Gamma correction and disk filtering are used to refine the iris and pupil boundaries, followed by Otsu's global thresholding to convert images into binary format. For segmentation, Canny Edge Detection and the Hough Transform are employed to accurately detect the iris and pupil regions. The normalized iris images are generated using Daugman's rubber sheet model, which converts the polar coordinates of the iris into a Cartesian format for analysis.

Feature extraction and classification are carried out using the proposed IRISNet model, which comprises 4 convolutional layers, 6 ReLU activation layers, 3 pooling layers, and 2 fully connected layers. The Softmax activation function is used in the output layer for classification, while Dropout layers are integrated to mitigate overfitting during training. The system was evaluated using the IITD V1 dataset under two conditions. When segmentation was skipped, the system achieved an accuracy of 97.32%, while normalized iris images yielded an accuracy of 95.98%.

In comparison with other classifiers, such as SVM, KNN, Naive Bayes, and Decision Tree, IRISNet demonstrated superior performance. The accuracy achieved by IRISNet (97.32%) significantly outperformed SVM (91.07%), KNN (93.53%), Naive Bayes (91.96%), and Decision Tree (43.56%). These results highlight the effectiveness of the IRISNet model in delivering high accuracy and reliability in iris recognition tasks, particularly when compared to traditional classification approaches [7].

In another project, a biometric authentication system has been developed using the iris recognition method [8]. The system utilizes the CASIA-Thousand-IRIS dataset and employs a Deep Convolutional Neural Network (DCNN) architecture with minimal image preprocessing steps. These preprocessing steps include resizing the images while maintaining the aspect ratio and applying normalization. Unlike traditional approaches, this method does not involve segmenting the iris region, making it an end-to-end solution. Despite not incorporating data augmentation during training, the model achieved promising results, with a testing accuracy of 93.15%. To demonstrate the feasibility of the biometric authentication system, a basic mobile application named IrisRecognizer was designed. The trained model was deployed on the application in its lightweight form, where default quantization was applied for optimized performance [8].

3. System Architecture

3.1 Data Collection

The data collection process in this project utilized the UBIRIS V1 dataset, which was specifically designed to test biometric recognition systems under challenging non-ideal conditions such as low light. The images were captured using a Nikon E5700 camera with a resolution of 2560 x 1704 pixels in RGB format. The camera was set to an ISO-200 speed, a focal length of 71 mm, and a shutter speed of 1/30 seconds, and the images were saved in JPEG format.

The dataset contains a total of 1,877 images, captured across two distinct sessions (Figure 1). It was collected in two sessions. In the first session, 1,219 high-quality images were captured under controlled indoor lighting conditions, involving 241 individuals, with each participant providing 5 or 6 iris images. This session ensured optimal conditions for capturing clear and precise images. The second session, on the other hand, involved 663 images captured under natural lighting, which introduced challenges such as reflections, glare, focus issues, and low-light conditions. In this session, 132 individuals participated, each contributing 5 or 6 iris images (Figure 2). Dataset includes both color and grayscale images with 200*150 resolution.

This comprehensive data collection process aimed to evaluate the performance of iris recognition systems under non-ideal conditions, with a particular focus on testing the system's resilience to the challenges presented by natural lighting. This dataset provides valuable diversity by simulating real-world scenarios, where images are subject to varying lighting environments

Parameter	**Good**	**Average**	**Bad**
Focus	73.83%	17.53%	8.63%
Reflections	58.87%	36.78%	4.34%
Visible Iris	36.73%	47.83%	15.44%

Figure 1. Dataset Parameters

Figure 2. Sample Raw Images from The UBIRIS V1 Dataset.

3.2 Preprocessing

Preprocessing plays a critical role in improving the quality of iris images and enhancing the performance of the recognition models. Various preprocessing methods were employed in this study to address issues such as uneven illumination, noise, and poor contrast. Histogram Equalization and CLAHE (Contrast Limited Adaptive Histogram Equalization) were used to enhance contrast in the images, making features more distinguishable. Blurring techniques, such as Gaussian Blur, helped in reducing noise while preserving essential edges. Sharpening was applied to emphasize fine details in the iris structure. Gamma Correction adjusted the brightness of the images to normalize illumination variations. Adaptive Thresholding segmented regions of interest by dynamically adjusting thresholds based on local image properties.

Additionally, Morphological Operations were used to remove bright spots and refine the image further. Specifically, a morphological closing operation with an elliptical kernel was employed to smooth out irregularities and clean up the images. These preprocessing steps ensured that the input data was of consistent quality, which is crucial for accurate iris recognition.

The segmentation effects of different preprocessing techniques are given in section 3.3 Segmentation

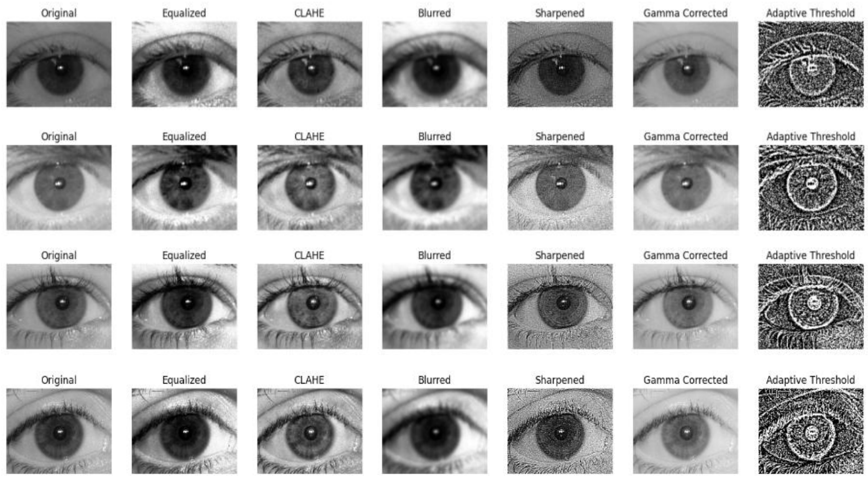

Figure 3. Illustration of Preprocessing Techniques and Their Impact on Image Quality

As a result, the preprocessing step included CLAHE, Gaussian Blur, and Morphological Operations.

3.3 Segmentation

The segmentation process in the iris recognition project is a crucial step that focuses on accurately identifying and isolating the iris and pupil regions within the eye image [5]. This step ensures that only the relevant portions of the image are processed during subsequent stages, such as feature extraction and pattern recognition. A combination of advanced algorithms and techniques is employed to address challenges such as varying lighting conditions, reflections, and occlusions.

The first stage of segmentation involves detecting the boundaries of the iris and pupil. Canny Edge Detection is applied to identify significant edges in the contrast-enhanced images, enabling the isolation of potential iris and pupil regions. To refine this process, the Circular Hough Transform is used to detect circular shapes corresponding to the iris and pupil boundaries. Through experimentation, it was found that the most accurate results were achieved by simultaneously searching for one large and one small circle, which represent the iris and pupil, respectively.

Segmentation errors are systematically analyzed to optimize the process (Figure 4.). Adjustments to parameters, such as edge detection thresholds and Hough Transform settings, are made to minimize errors and improve the accuracy of boundary detection. This iterative refinement allows the segmentation process to adapt to diverse lighting conditions and varying levels of noise in the images.

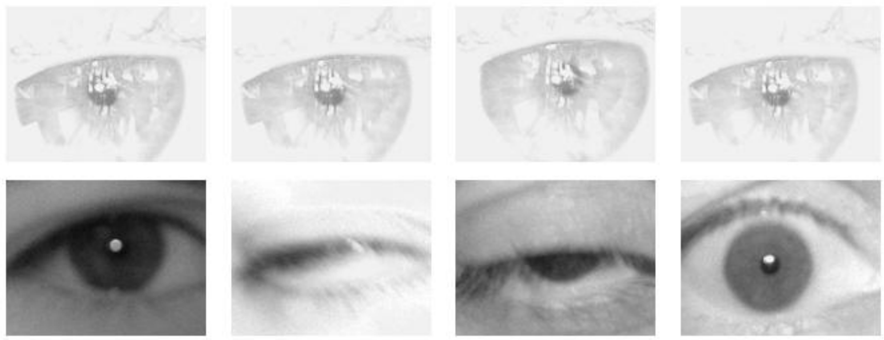

Figure 4. Segmentation Errors

Table 1. highlights the effectiveness of different preprocessing techniques in reducing segmentation errors. It demonstrates a significant improvement in the detectability of iris and pupil boundaries after specific methods such as CLAHE and sharpening, whereas gamma correction increases the error count, likely due to over-enhancement effects.

Table 1. Number of Images Where Circles Could Not Be Found After Preprocessing Steps

Category	**Number of Images Where Circles Could Not Be Found**
Original Images	1316
After CLAHE	12
After Histogram Equalization	540
After Sharpening	7
After Gamma Correction	1486

The data in Table 1. underscores the importance of carefully selecting preprocessing techniques to enhance segmentation performance while minimizing unintended effects. For example, CLAHE and sharpening significantly reduced errors, whereas gamma correction had an adverse impact, emphasizing the need for precise tuning of preprocessing parameters.

In our experiments, it was observed that the methods we used (Canny edge and Circular Hough Transformation) did not perform accurately under non-ideal conditions. Therefore, only iris detection was performed. Images where the segmentation step failed to detect the iris, even after preprocessing, were excluded from the dataset.

Overall, the segmentation process integrates robust algorithms and advanced techniques to ensure high reliability and accuracy. By addressing potential errors and adapting to diverse challenges, this stage establishes a solid foundation for subsequent steps such as feature extraction and pattern matching, significantly contributing to the performance and reliability of the iris recognition system.

3.4 Normalization

Normalization in the iris recognition process is a crucial step that transforms the segmented iris region into a standardized format, enabling consistent feature extraction and pattern matching. The primary method employed for normalization is Daugman's Rubber Sheet Model, which maps the circular iris structure into a flat rectangular format. This transformation ensures that variations in size, rotation, and positioning of the iris are accounted for, providing uniform data for subsequent analysis.

The process begins after segmentation, where the iris and pupil boundaries have been accurately identified. These boundaries serve as reference points for the rubber sheet model. The transformation is performed by unwrapping the iris region along its circular structure, creating a rectangular representation where each pixel corresponds to a specific angular and radial location within the iris. This normalized representation is essential for reducing geometric distortions and aligning all iris images to a common framework (Figure 5).

Additionally, Figure 6 provides a detailed visualization of the transformation process, showcasing how the original segmented iris is converted into a normalized rectangular format. This visual representation highlights the preservation of critical iris patterns during normalization, ensuring that they remain intact for reliable feature extraction and pattern matching.

Normalization is expected to play a crucial role in enhancing consistency while addressing variability caused by environmental factors such as lighting and camera angle. Additionally, aligning iris features to a common format aims to minimize mismatches that could negatively impact the recognition system's performance and to ensure that features extracted from the iris remain independent of external influences. However, due to errors during the segmentation step, the normalization process did not work as intended, which adversely affected the overall performance of our model.

To address this issue, an approach was adopted where only images with successful iris detection (without pupil detection) were selected. In these images, the iris region was cropped, and a simpler normalization method was applied. (Figure 7) This approach aimed to reduce errors caused by segmentation, improve the model's performance, and enable more accurate extraction of iris features.

Normalization also supports the integration of advanced machine learning models, as it provides a standardized input format for training and testing. This step significantly enhances the robustness and accuracy of the entire iris recognition system, making it a cornerstone of the biometric pipeline.

Figure 5. Segmented Iris and Its Corresponding Normalized Representation Using Daugman's Rubber Sheet Model

Figure 6. Detailed Visualization of The Transformation Process, Showcasing The Unwrapping of The Iris Into A Rectangular Format.

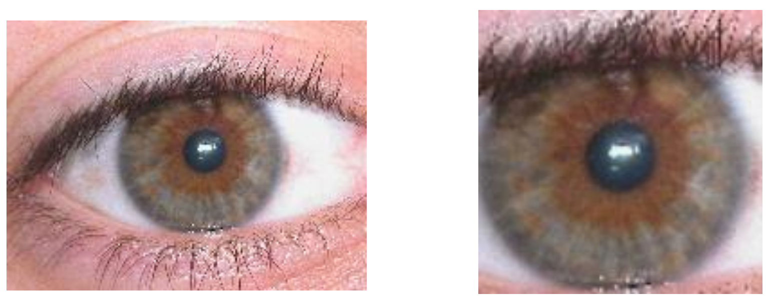

Figure 7. An Example Image and the Cropped Iris Detection Result

3.5 Data Augmentation

Data augmentation plays a pivotal role in the development of iris recognition systems by expanding the diversity of the training dataset. In biometric systems, the availability of large, high-quality datasets is often limited, which can lead to challenges such as overfitting and reduced generalization capability. Augmentation addresses these issues by creating modified versions of existing images, thereby simulating a wide range of real-world conditions. This process enables the model to better handle variations in lighting, occlusions, and other environmental factors, ultimately improving its ability to generalize to unseen data.

In order to improve the robustness and generalization of the iris recognition model and expand our small training set by introducing transformations that mimic real-life scenarios, data augmentation techniques were applied to artificially expand and diversify the training dataset. Various transformation methods were utilized to simulate real-world variations and address potential challenges in iris recognition.

The first technique is rotation, where images are randomly rotated by up to 15 degrees. This ensures that the model becomes invariant to slight orientation changes of the iris. The second method is width shift, which introduces random horizontal shifts of up to 10% of the image's width. Similarly, height shift allows for random vertical shifts of up to 10%, simulating slight positioning variations.

Another important augmentation technique is shearing, where a shear transformation is applied with a range of up to 10%, helping the model handle geometric distortions. Zoom augmentation is also employed, where the image is zoomed in or out by up to 10%, enabling the system to adapt to different distances between the camera and the subject.

Horizontal flipping is another method that randomly flips images horizontally. While this technique enhances diversity by simulating mirror variations, it must be carefully considered in iris recognition applications, where flipping might not always be appropriate. Finally, the fill mode is applied to fill any empty pixels resulting from the aforementioned transformations by using the nearest available pixel values.

In summary, data augmentation serves as a critical component in the iris recognition pipeline, addressing the limitations of small datasets and enhancing the model’s resilience to diverse conditions. Through transformations such as rotation, reflection, and noise addition, the process enables the system to achieve higher accuracy, reliability, and adaptability, making it an indispensable technique in the development of advanced biometric solutions.

3.6 Feature Extraction & Model Training

In the iris recognition project, feature extraction and classification are fundamental processes that will be implemented using Convolutional Neural Networks (CNNs) [1, 9, 10]. CNNs are a powerful class of deep learning models particularly suited for analyzing visual data, making them ideal for extracting intricate patterns in iris images. The architecture of CNNs used in this project is informed by a review of various studies, each employing specific variations in the composition of layers to optimize performance.

In our project, three different models were used for feature extraction. The first model is the pre-trained ResNet50. The architecture of the ResNet model is shown in Figure 7. In Method 1, this model was trained for 1 hour and 38 minutes, resulting in an training accuracy of only 1.57%. The low performance can be attributed to several factors, including the small size of our training dataset, which made it difficult for the pre-trained model to adapt. Additionally, the lack of proper data shuffling, insufficiently effective segmentation and normalization steps, and the potential loss of discriminative information contributed to the poor results.

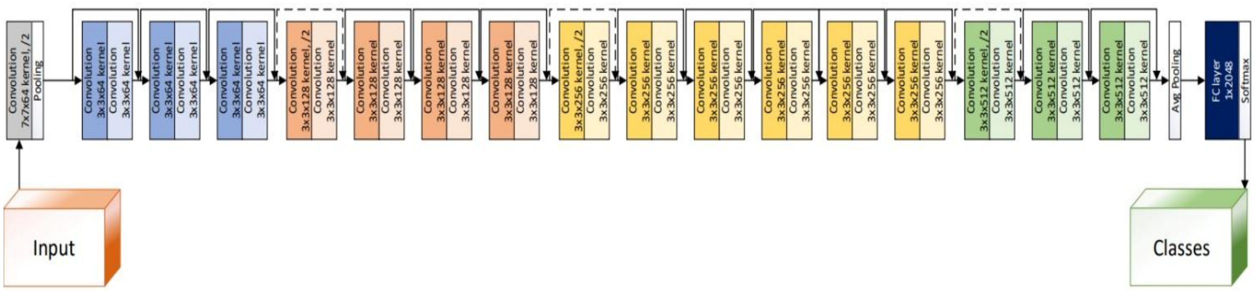

Figure 8. The architecture of ResNet50 neural network.

In Method 2, the DenseNet201 model was employed, achieving a train accuracy of 2.5%. During the training process, this model was trained using preprocessed and cropped iris images. The poor results can be attributed to multiple factors. Firstly, the limited size of the dataset hindered the model's ability to generalize and capture meaningful patterns. Secondly, the complexity of the DenseNet201 architecture may have led to underfitting, where the model failed to learn essential features from the data. Additionally, working with preprocessed but non-segmented images made it difficult for the model to focus on the critical iris patterns, further reducing the effectiveness of feature extraction.

In Method 3, a Convolutional Neural Network (CNN) architecture has been implemented to effectively extract and analyze features from iris images [8]. The model is composed of multiple layers and operations designed to capture relevant patterns while ensuring robust performance and minimizing overfitting. The architecture integrates essential components, including convolutional layers, batch normalization, pooling, dropout, and fully connected layers.

The convolutional layers (Conv2D) serve as the core feature extraction component of the network. In this method, multiple convolutional layers with 32, 64, 128, 256, and 512 filters are utilized. Each convolutional layer employs a filter size of 3x3 or 5x5 with 'same' padding, ensuring that the spatial dimensions of the input remain intact. The Leaky ReLU activation function is applied after each convolutional operation, addressing the vanishing gradient problem by maintaining a small gradient for negative values. These layers effectively detect complex patterns such as edges, textures, and shapes within the iris images.

Following each convolutional operation, batch normalization is applied to improve training stability and efficiency. This normalization technique reduces internal covariate shift, allowing the model to converge more quickly and effectively. Additionally, max pooling layers (MaxPooling2D) are incorporated to reduce the spatial dimensions of the feature maps. This operation decreases computational complexity while preserving the critical spatial information necessary for accurate pattern recognition.

To prevent overfitting, dropout layers are integrated after each convolutional and pooling layer. Different dropout rates, such as 0.1, 0.25, 0.45, and 0.5, are applied to randomly deactivate neurons during training. This strategy ensures that the model does not over-rely on specific features, thereby promoting better generalization and model robustness. Furthermore, Gaussian noise is introduced in some layers to simulate real-world imperfections in iris images, such as variations in lighting conditions and image quality.

The fully connected layers follow the feature extraction layers, where the Flatten layer reshapes the feature maps into a one-dimensional vector. This vector is then processed by the dense layers, with the first dense layer containing 128 units and a Leaky ReLU activation function. The final output layer consists of 246 units, employing the Softmax activation function. This output layer corresponds to a probability distribution across 246 classes, each representing an individual participant in the dataset.

The model is compiled using the Adam optimizer, with an initial learning rate of 0.001, an adaptive optimization algorithm well-suited for this application. The loss function is set to "sparse_categorical_crossentropy", which is appropriate for multi-class classification tasks. Additionally, accuracy is used as a performance metric throughout the training and validation phases.

For training Model 3, Clahe, Gaussian Blur and Morphological Operations were applied, and 150*150 resolution images with cropped iris area were used. Due to the inability to detect the iris in some images, certain pictures were removed, resulting in a dataset size of 1483 images for 244 participants. These images were split into 908 for training and 331 for validation, ensuring that each session contains at least one image. Additionally, 244 images were allocated for testing, with each participant represented by one photo in the dataset. The training process was conducted for 130 epochs, and the epoch with the lowest validation loss was saved.

3.7 Matching Performance

The third method, which was selected as the main approach for this project, was trained with the assistance of a GPU and completed in approximately 25 minutes. The training accuracy reached 92%, the validation accuracy was 76%, and the test accuracy achieved 70.08%. The accuracy and loss graphs are presented in Figure 10 and Figure 11.

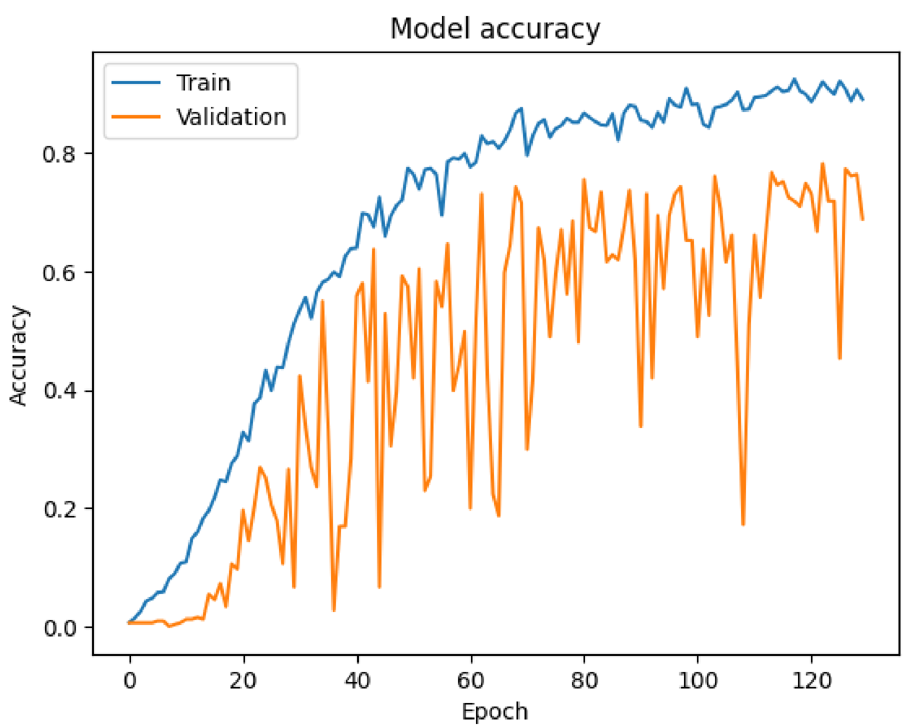

Figure 10. Model Accuracy Curve for Train and Validation

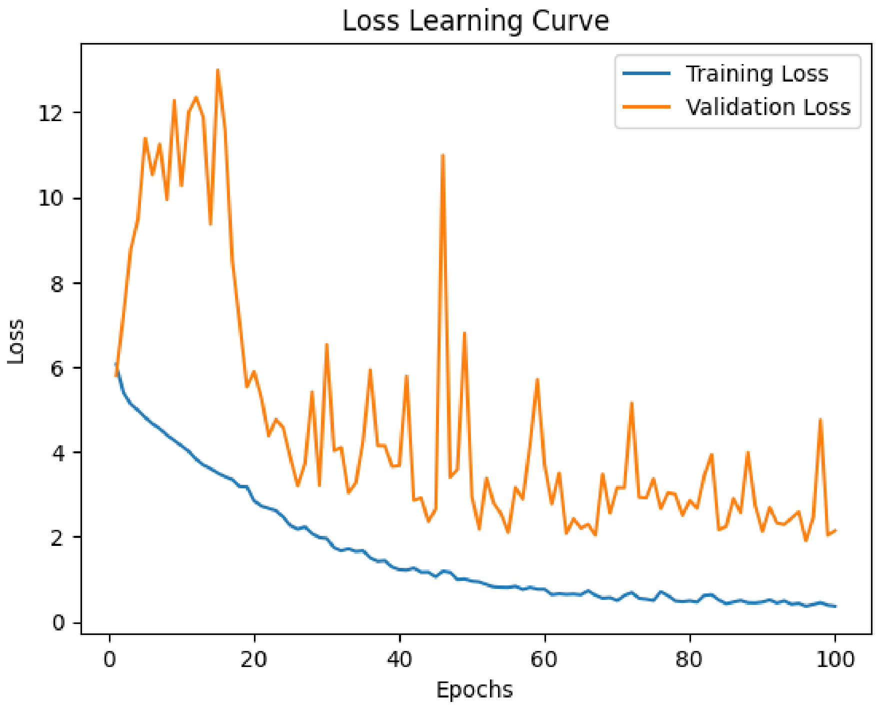

Figure 11: Model Loss Learning Curve for Train and Validation

3.8 Model Performance & Performance Comparison

The key performance metrics for our iris recognition project are presented in the Table 2 below.

Table 2: Performance Metrics

Metrics	Values
Correctly identified participant	171
Incorrectly identified participant	73
False Accept Rate (FAR)	0.5
False Reject Rate (FRR)	0
Accuracy	70.08 %
Precision	70.08 %
Recall	100%
F1	%82.4
Equal Error Rate (EER) Threshold	0.0313

The performance metrics of your iris recognition system reveal a mixed but promising outcome. The system correctly identified 171 participants while incorrectly identifying 73 participants, showing a significant number of errors. The False Accept Rate (FAR) of 0.5 is particularly concerning, indicating a high likelihood of incorrect matches, which is a serious issue in biometric security. While the False Reject Rate (FRR) is 0, meaning no valid participants were mistakenly rejected, this trade-off suggests that the system prioritizes minimizing false negatives but at the cost of higher false positives.

The accuracy of 70.08%, along with precision also at 70.08%, is a decent starting point but not ideal. These numbers imply that almost 30% of predictions are still incorrect, highlighting the system's vulnerability to errors in feature extraction and segmentation. On a positive note, the F1 score of 82.4% shows a good balance between precision and recall. Additionally, the system’s 100% recall suggests that all actual samples were identified, which is a strong point. The Equal Error Rate (EER) threshold of 0.0313, while informative, indicates that your system’s trade-offs between false positives and negatives are not yet well-optimized.

Overall, while the system demonstrates good recall and balanced F1 performance, the high FAR and relatively moderate accuracy show that improvements are necessary. The ROC curve created for each class is included in Figure 12.

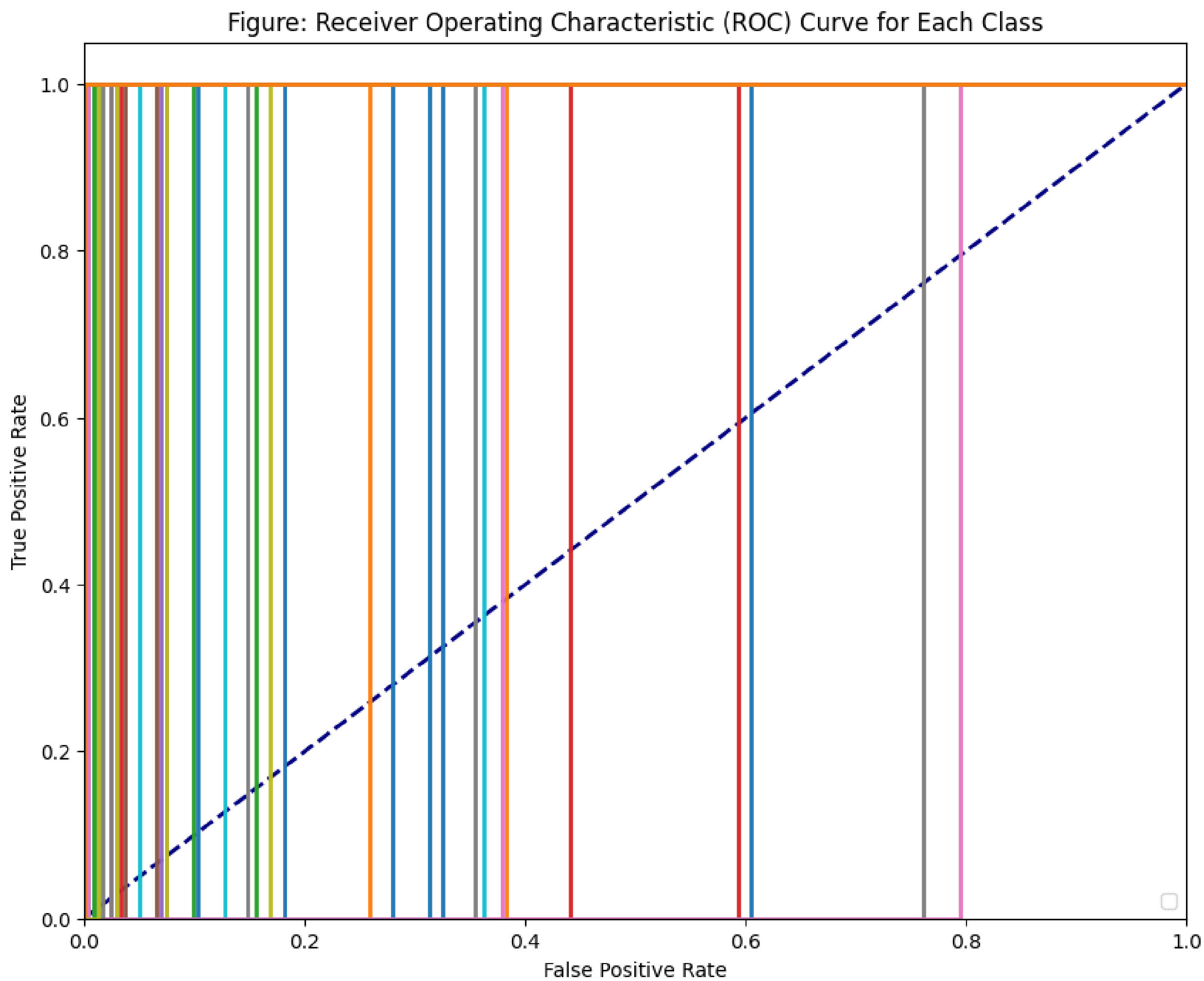

Figure 12. ROC Curve for Each Class

When examining the ROC curve, a significant disparity between class distributions becomes apparent. This issue is primarily due to the limited number of samples available for each class and the presence of examples captured under non-ideal conditions. The presence of these faulty samples has hindered the effectiveness of segmentation and feature extraction processes. Consequently, errors in these preprocessing steps prevent the system from accurately identifying distinct iris patterns, leading to reduced performance across various metrics. Addressing these issues requires more robust data collection and preprocessing methods to ensure higher-quality segmentation and feature extraction outcomes. Prediction and actual class comparison was shown in Figure13.

Figure13. Prediction and actual class comparison

When investigating the impact of using color images and cropping the iris regions on model performance, we obtained the result in Table3.

Table 3. The Effect of Image Color and Segmentation on Accuracy

	Accuracy
GreyScale and Non Segmantated	%55.28
Colored and Non Segmanted	%62.50
Colored and Segmanted	%70.08

When comparing the accuracy of our study with other research that utilized the same dataset, our performance appears to be significantly lower. Zhou and his colluege showed a significant improvement in accuracy on the UBIRIS.v1 dataset when transitioning from Daugman's method to the proposed approach in their study. While Daugman's method showed 58.92% accuracy, the proposed method increased it to 98.04%, demonstrating a 39.12% improvement [3]. In another paper, researchers studied with UBIRIS. v1 datatset and accuracy was 99.32% [6]. Another research was showed that, accuracy was 97.5% when the same dataset was used [5]. This suggests that our current approach and model architecture may not be fully optimized or robust enough to effectively capture the unique patterns present in the dataset.

4.Conclusion

As a result of the literature review conducted in this project, usable models have been identified, and through experimentation with these models, the most suitable one was selected. It was observed that the segmentation step is the most critical part of the project. Due to the inability to achieve high accuracy in the segmentation process and the small size of our dataset, using pre-trained models proved to be inefficient.

To address the challenges faced during segmentation, approaches were chosen that minimize segmentation errors, and simpler CNN architectures were employed. Despite these efforts, the comparison with research studies in the literature showed that our resulting accuracy indicates that our model is not yet fully optimized.

Furthermore, the model's prediction results demonstrate that it performs well under ideal conditions but suffers from misclassification issues under non-ideal circumstances. To improve the performance and robustness of the system, enhancing the segmentation process is a recommended next step. Future studies could explore CNN-based models that are specifically optimized for better segmentation performance.

Moreover, to increase resilience against challenging conditions, using larger datasets would be a beneficial strategy. Larger datasets would provide more diverse examples and allow the models to generalize better, ensuring more robust performance across different environments and lighting conditions.

5. References

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