

Achieving Information Security by multi-Modal Iris-Retina Biometric Approach Using Improved Mask R-CNN

Original Scientific Paper

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Abstract – The need for reliable user recognition (identification/authentication) techniques has grown in response to heightened security concerns and accelerated advances in networking, communication, and mobility. Biometrics, defined as the science of recognizing an individual based on his or her physical or behavioral characteristics, is gaining recognition as a method for determining an individual's identity. Various commercial, civilian, and forensic applications now use biometric systems to establish identity. The purpose of this paper is to design an efficient multimodal biometric system based on iris and retinal features to assure accurate human recognition and improve the accuracy of recognition using deep learning techniques. Deep learning models were tested using retinographies and iris images acquired from the MESSIDOR and CASIA-IrisV1 databases for the same person. The Iris region was segmented from the image using the custom Mask R-CNN method, and the unique blood vessels were segmented from retinal images of the same person using principal curvature. Then, in order to aid precise recognition, they optimally extract significant information from the segmented images of the iris and retina. The suggested model attained 98% accuracy, 98.1% recall, and 98.1% precision. It has been discovered that using a custom Mask R-CNN approach on Iris-Retina images improves efficiency and accuracy in person recognition.

Keywords: Biometrics, iris recognition; retina recognition; mask R-CNN

1. INTRODUCTION

The emergence of biometric-based authentication is a consequence of the development of autonomous technologies and the growing threat to individual security. Variation in biometric behavioral and physical features facilitates the accurate recognition of individuals. The most common biometric features [1] are fingerprint [2], face [3], voice [4], iris [5], and retina [6], among others, but only medium-level security has been provided by features such as voice, face, and fingerprint due to limitations such as environmental changes and readily recordable nature. Using biometric features such as the iris and retina, a person can be identified with high certainty [7]. The iris is responsible for the amount of light that passes through the retina, which is the latter layer of the eye. Uniqueness and inaccessibility contribute to the increased robustness of these features.

To extract the features necessary for human recognition based on the iris, the inner and peripheral boundaries must be precisely localized. Various limitations, such as the reflection of light, the low resolution of image quality, and the presence of occlusions, can compromise the accuracy of recognition. These constraints must be considered for accurate iris segmentation. Two methods, namely light-based and near-infrared (NIR) based imaging, were used to acquire images of the iris; the NIR-based images were found to be of higher quality and have fewer light reflections [7]. For recognition purposes, the texture-based characteristics of the iris were extracted and used to create a template for each individual. Similarly, the segmentation of retinal blood vessels and extraction of both vascular and non-vascular features assists in the recognition of individuals.

Machine learning techniques were found to provide fast and accurate extraction of features to facilitate the

effective identification of individuals [8]. These techniques are used for segmentation in a variety of applications, including medical imaging detection for tumor locating [9], predicting tissue volumes [10], epilepsy and surgery planning, and so on [11], and interpretation of various important objects in satellite images, such as buildings, roads, forests, crops, and cloud detection [12].

The segmentation of the iris is the process of precisely recognizing and defining the boundary of the iris inside an image in biometric systems. Custom Mask R-CNN is an excellent deep-learning solution for this problem because it extends the well-known Mask R-CNN architecture by integrating a special segmentation head to segment the iris.

The iris is a distinct and dependable biometric feature that can be used to accurately identify individuals. Iris segmentation is an important stage in biometric systems because it provides an accurate representation of the iris pattern that may be used for recognition. This task can be handled with excellent accuracy and effectiveness by modern deep learning architecture Custom Mask R-CNN. [13]

Mask R-CNN is an important deep learning-based scheme that has been used for a variety of applications in the past. This included automated nucleus segmentation [14], detection of disease in lung nodules segmentation [15], segmentation of liver disease based on multimodal [16], automated counting of blood cells [17], segmentation and detection of the human face [18], detection of oral disease based on X-ray images [19], and detection and classification of breast tumors [20]. To the best of our knowledge, the Mask R-CNN method for the identification and authentication of humans from Iris and Retina images has not been investigated.

This paper describes an efficient multimodal biometric system based on iris and retinal features. This biometric recognition system integrates iris and retina features for human identification and authentication utilizing multiple segmentation approaches. Prior to enhancement, the input images are segmented. The features are extracted and then fused to create a multimodal feature vector that represents the individual's distinct characteristics. Finally, the feature vector is compared to a pre-registered database of individuals using various matching methods during the matching step. The system calculates a match score which represents the degree of similarity between the input feature vector and the registered database. This method takes advantage of the iris's and retina's unique and distinguishing traits, which are highly accurate and difficult to forge or manipulate. The proposed model achieved high recognition accuracy.

2. RELATED WORKS

Several studies used these approaches to segment the iris and retinal blood vessels for effective feature extraction [21-25]. These approaches address the constraints of classic feature extraction methods to per-

form authentication without reproducing the images. A unimodal biometric system is defined as the utilization of any one of the biometric features for human identification [26, 27]. This type of biometric technology appears to be compatible with the identification of a limited number of users, but it has some disadvantages when applied to a real-time scalable set of populations.

In [28], the authors proposed a multimodal biometric system based on the iris and retina for comparing spatial features. The spatial features are initially extracted from the iris and retina individually. The features are collected and stored in the database. Then Levenshtein distance (LD) algorithm is proposed to calculate the distance between the minutiae for comparison. The comparison score is evaluated for the iris and retina individually. Finally, two biometric comparison scores are fused and provide a result for authentication. They tested numerous combinations of publicly available biometric databases and found that the optimal False Acceptance Rate and False Rejection Rate indices were 0 and 3.33%, respectively.

In [29], the author used a Deep learning-based unified framework to accurate detection, recognition, and segment the iris from raw eye images. Iris-specific Mask R-CNN, a normalization layer, and feature extraction are all part of the proposed system design. Mask R-CNN is used to segment the iris. The training samples are displayed with ground truth images. Before learning the features of the iris, the normalization layer performs iris and mask normalization. After detecting the iris, a contrast enhancement process is presented to improve the image quality. FeatNet's fully connected layer is used to extract the features. The Extended Triplet Loss (ETL) function is used to learn the features. The experiments are carried out using publically available datasets.

In [30], this paper proposed an iris segmentation method for noisy images. The proposed system includes four processes: pupillary boundary marking, marking noisy regions, marking the limbic boundary, and iris boundary regularization. Shape features are extracted in the first procedure to help localize the pupillary boundary. The second procedure marks noisy spots in photos to improve performance. The third procedure uses the Gaussian smoothing filter and rank filters to mark the limbic boundary. Finally, the circular iris boundary is converted to a non-circular iris boundary by a regularization technique. Three public datasets are used to test the results.

In [31], this paper proposed retina diagnosis utilizing biometric methods with SVM and clustering methods. The main aim of this research is to extract the features from retina images. Preprocessing is the initial step in increasing image quality. It comprises denoising, contrast enhancement, and normalization. The following step is vessel segmentation, binarization, and thinning, which is accomplished using a Gaussian-matched filter with binarization and local entropy thresholding. The final step is minutiae extraction, which is accomplished

using a crossing number technique. The proposed method automatically counts the number of minutiae after extracting them, which aids in disease diagnosis. SVM is used to determine whether or not the identified eyeballs are healthy or unhealthy.

The typical datasets show good performance using the established methodologies; nonetheless, many issues have been identified, as outlined below.

In [28], features for the iris and retina are retrieved independently. The authors used the derived features directly from the images without reducing noise, which degrades the image quality and hence the process's accuracy. They do not pay attention to iris and retina localization or image quality evaluation, which increases detection time and decreases detection accuracy. The calculation of feature scores takes a lengthy time. Furthermore, it is unstable when a trained massive number of features is necessary to calculate a score for a massive number of images.

In [29], In this paper, the Iris detection is still poor due to the use of noisy images, which diminish image quality and consequently affect detection accuracy. Because Iris detection accuracy is dependent on image quality, noise in the images must be removed to obtain an accurate result. The author employed the Mask R-CNN network for iris segmentation, but it does not provide reliable localization because spatial information was neglected in favor of semantic information. Furthermore, it disregards the link between the pixels on the object's edge, resulting in poor localization.

In [30], this paper is not suitable for intensity-varying iris images due to the lack of normalization. The limbic boundary is marked using a Gaussian smoothing filter; however, it takes a long time to identify, increasing the processing cost. Also, noise factors are removed for effective segmentation, but it still has salt and pepper noise, which reduces image quality, contrast, and resolution, resulting in blurred images and lower segmentation accuracy.

In [31], The authors used SVM to determine whether the eyes are healthy or unhealthy, which is only appropriate for smaller datasets because larger datasets require more time for training and validation, increasing latency and kernel selection is required to optimize otherwise classification accuracy is reduced. The Gaussian matched filter is used for iris segmentation, which takes a long time. Because of a lack of important features such as color, statistical, texture, and form features, retina classification accuracy is still low.

In [32] A biometric method based on finger vein and face bimodal feature layer fusion is proposed, with the fusion occurring in the feature layer and using a convolutional neural network (CNN). The self-attention mechanism is employed to get the weights of the two biometrics, and the self-attention weight feature is cascaded using the bimodal fusion feature channel Concat when combined with the RESNET residual structure.

AlexNet and VGG-19 network models were chosen for extracting finger vein and facial image features as inputs to the feature fusion module in the experimental phase to demonstrate the high efficiency of bimodal feature layer fusion. The experiments demonstrate that both models' recognition accuracy exceeds 98.4%.

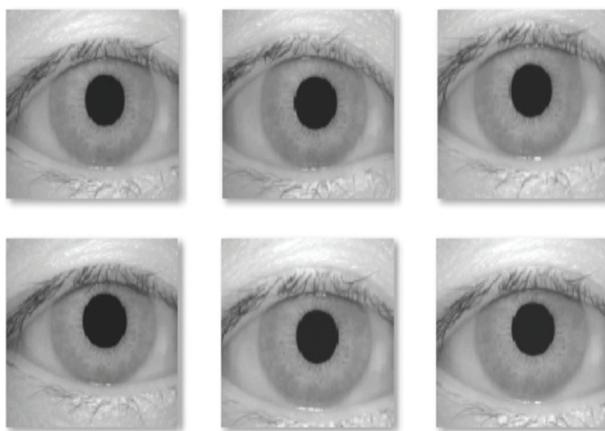
In this paper, we introduced a multimodal for identifying the same individual using two images. The first image uses customized Mask RCNN to segment the Iris region and extract informative features, while the second image uses deep neural networks based on pre-trained neural network models such as VGG16, VGG19, ResNet101, and MobileNet [33]. The fusion of the above features of a specific person is worthy of understanding the person's identity. A new technique for human recognition can be proposed using a pre-trained model and a tailored Mask-RCNN.

3. MATERIALS AND METHODS

3.1. DATASET

The two main databases used in this paper comprise colored retina and iris images. Retina images are obtained by a retinograph with or without pupil dilation during repeated clinical examinations. The MESSIDOR dataset [34] is well-known from the image database. The MESSIDOR database was a financed research study introduced by the French Ministry of Research and Defense as part of the 2004 TECHNO-VISION program [34]. In the databases, we used five images for each individual. The images will be saved in uncompressed TIFF format with a resolution of 1440 960 pixels (about 4 MB for each image).

Dataset CASIA-IrisV1 database [35] contains 765 iris images from 108 images. All images are collected in BMP format with a pixels resolution of 320 × 280. The images are collected by the research group, the National Laboratory of Pattern Recognition (NLPR), Institute of Automation (IA), Chinese Academy of Sciences (CAS), which was released to provide an iris database freely for recognition researchers by captures in homemade. Fig. 1 shows simple samples of iris and retina images.



(a)

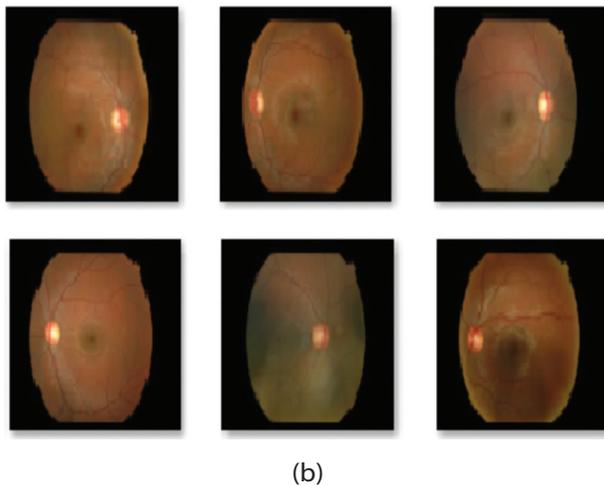


Fig. 1. Examples of images for iris CASIA-IrisV1 database (a) and retina MESSIDOR database (b).

3.2 METHODOLOGY

Fig. 2 depicts the general layout for human identification based on a biometric approach. We tested the approach on 100 individuals, each with five iris and retina images.

3.2.1. Preprocessing

Denosing. The iris and retina images contain noise and other artifacts that degrade image quality since they must be removed. Denoising is used to improve image quality, while illumination is used to remove noisy pixels from images. The noise in the iris and retina images was eliminated independently. Speckle noise in iris pictures and Gaussian noise in retina images are reduced using the Fast Guided Filter (FGF) [36], which is computationally efficient and considerably superior to a wiener filter, local means filter, and Bilateral filter.

FGF is marked by preserving the edges of the objects in the Image by using the content of the guidance image [37].

Boundary Localization and Segmentation Using Custom Mask R-CNN. Accurate iris and retina detection and localization is a critical step in achieving high detection accuracy in iris and retina-based recognition. In this article, boundary detection is a tough procedure since it varies from person to person and helps in precisely recognizing the iris. Initially, the center point and radius are retrieved from denoised or preprocessed iris images. Based on such information, the inner and outer boundaries of the iris are located and done using a customized Mask R-CNN. Traditional custom Mask R-CNN emphasized on pixel edge information and ignored object borders and shapes, resulting in poor localization. To that end, we present a custom Mask R-CNN that localizes the inner and outer boundaries by extracting local features (boundary information) and masking the boundary. Mask R-CNN enhances the mask head with local features in the Mask R-CNN. FPN (Feature Pyramid Network) is utilized here to extract and build the pyramidal features for RPN (Region Proposal Network) and proceed to the second step. The mask head learns the boundaries of the mask and the object and updates the information in the Mask R-CNN. For better segmentation results, the learning information is optimized using the Adam optimizer, which takes less memory and is more computationally efficient than gradient descent and stochastic gradient descent algorithms.

It extracts the blood vessels from the retina for segmentation. Vessel Extraction of Retinal Fundus Image Using Principal Curvature [38], which results in a segmented binary image. MATLAB 2020a can be used to obtain the proposed blood vessel segmentation methods based on adaptive principal curvature and derivative operators [39].

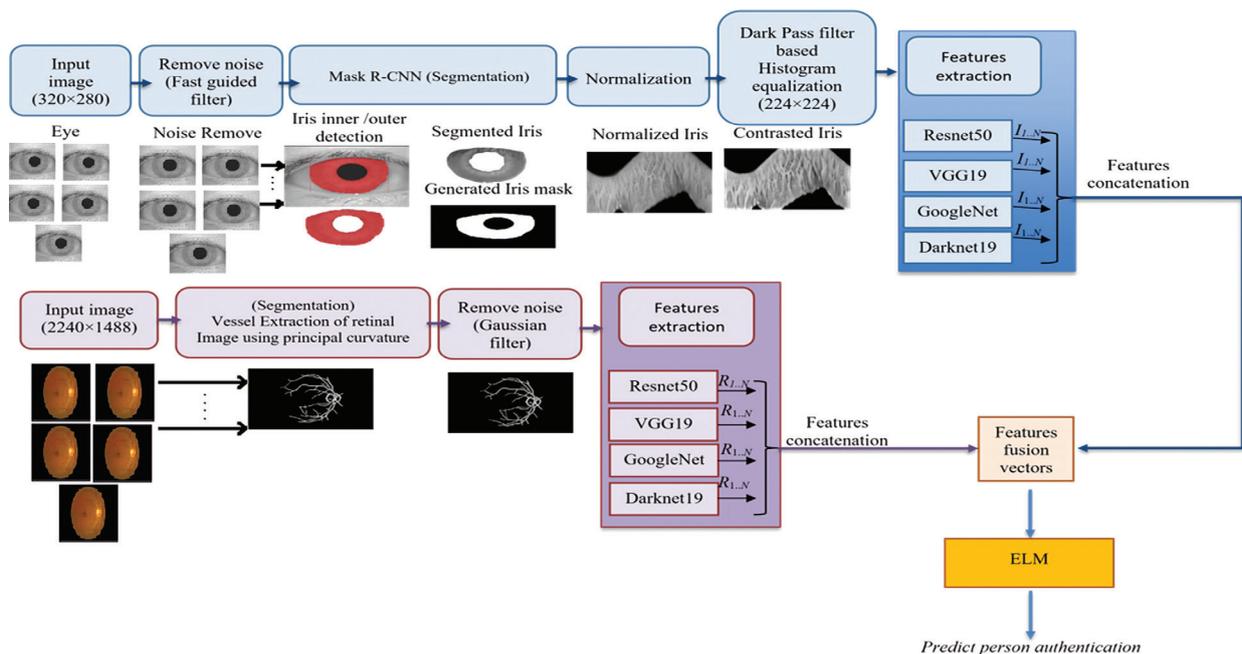


Fig. 2. The general methodology layout for human identification is based on a biometric approach.

Normalization and Contrast Enhancement. The majority of normalizing approaches, including the Daugman rubber sheet model, have been applied for iris recognition [40]. Because the size of the iris varies from person to person due to variations in intensity, the Iris image will need to be normalized. The iris is converted into a rectangular zone for this purpose, which normalizes the intensity of the Iris images.

Contrast enhancement is a method that improves the quality of normalized images by increasing brightness and increasing detection accuracy [41]. We proposed Dark Pass Filter-based Histogram Equalization for this purpose. The low-contrast image is divided into sub-histograms based on the median of each partition. The Histogram is needed for segmentation; thus, it must go across all of the pixels. Where the histogram for an image is produced and parts for the image are created based on the peak of the histogram. This method is repeated until no more pieces of an image emerge [42].

3.2.2. Feature Extraction

A lightweight deep learning model is proposed in this research to extract features from iris and retina images. We presented an Attention-based pretrained deep learning model (VGG19, ResNet 50, GoogleNet, and DarkNet 19) for feature extraction [43]. The key advantage of using a pretrained model is that it is easier to use and provides free network architecture. Furthermore, they often produce superior results for object identification and require less training. Tab 1 displays the training settings for the Custom pretrained model training in detail.

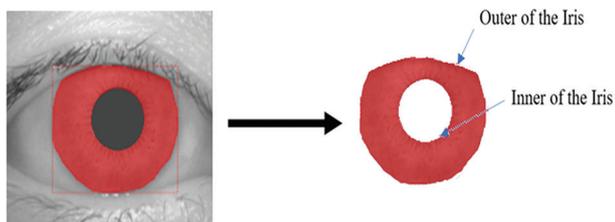


Fig. 3. Inner and Outer of Iris image detection by Custom Mask R-CNN

The computing system is configured with Windows 11 Pro, Intel Core i7, 1.6GHz, GPU Nvidia GeForce 8GB, 3295MHz DDR3 RAM memory. When the algorithm is implemented on more powerful computing platforms, the execution time will be reduced.

Table 1. Hyperparameters details

Parameter	value
Epochs	100
Learning rate	0.001
Bach size	8
Optimization	Adam
Gradient Threshold	1

In this research, we extract the feature from the fully connected layer prior to the classification process's final layer. The features are extracted from the iris and retina independently. Then concatenation of all the output features vectors from each pretrained model from both Iris and Retina $I_{N \times 1}$ and $R_{N \times 1}$ because it makes output features more informative for a person. For iris recognition, texture features are extracted from iris images. We extract features from both iris and retina images based on the weight values, which enhances detection accuracy.

3.2.3. Fusion Score Evaluation

The feature fusion technique is used to evaluate the feature fusion score at this step. The collected features from the segmented iris and retina are concatenated and sent into the Extreme Learning Machine (ELM) for recognition. We did feature fusion here and calculated the comparison score for that feature. We introduced the kernel aware Extreme Learning Machine (ELM) method [43] for this purpose, which randomly selects the hidden nodes and calculates the weight value of the inputs. The kernel selection procedure is critical for generating correct results, and the kernel-aware ELM method may select related kernel functions based on the inputs. As a result, based on the feature fusion score, our method achieves excellent detection accuracy, and human recognition is done.

4. RESULTS

The model was built with the Keras and TensorFlow frameworks, as well as the MATLAB toolbox for preprocessing and feature extraction. We initialized the model by preprocessing all Iris and Retina images and utilizing pretrained weights COCO with extension file *.h5. We then used transfer learning to modify the model on the segmented Iris and Retina images. For the experiment, we used a 70:30 split, done at random, and divided the images into training (70%) and test (30%) groups.

During experimentation, the performance of the proposed study is evaluated using the following metrics: Accuracy, Sensitivity/True positive rate, Specificity/True negative rate, Precision/Positive predictive value, Negative Prediction value, and F1-Score.

In this research, we use Average Precision (AP) to evaluate Mask R-CNN's performance on diverse datasets. Precision is generally defined as Eqs. (1) to (4).

$$Precision = \frac{TP}{TP+FP} = \frac{true\ positive}{total\ person\ identification} \quad (1)$$

where, True Positive (TP): A correctly identified person based on Iris and Retina traits. False positive (FP): An incorrectly identified person. True negative (TN): The correct identification of a negative person. False negative (FN): An inaccurate identification of a negative person. Average precision (AP) is frequently referred to as Average Precision for COCO datasets or COCO type datasets. To properly comprehend AP, we require Recall, Precision accuracy, and F1-score, which is defined as

$$Recall = \frac{TP}{TP+FN} = \frac{true\ positive}{total\ ground\ truth\ identification} \quad (2)$$

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \quad (3)$$

$$F1 - score = 2 \times \frac{Precision \times Recall}{Precision+Recall} \quad (4)$$

The findings of the human recognition evaluation are presented in Table 2. In the first test case, we use the extracted features from the blood vessels segmentation approach from Retina images based on the adaptive principal curvature for human recognition. In the second test case, we use the extracted features from the output of the Iris images from the applied custom Mask R-CNN for identification, and in the third example, we use the extracted features from both Iris and Retina images based on the proposed system. According to the findings, the case of Iris and Retina using the proposed method may reliably identify the person with a 98% accuracy.

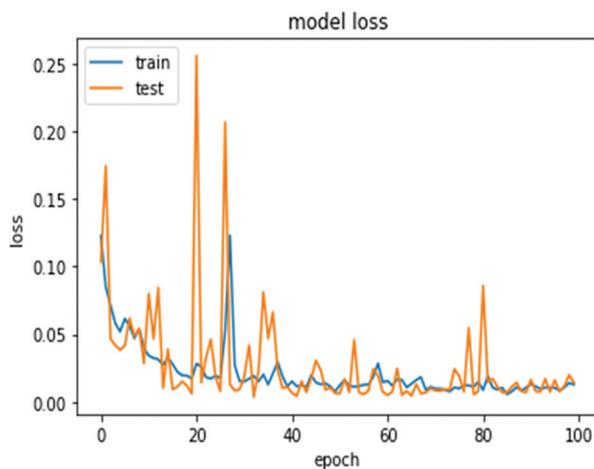


Table 2. Presents the human recognition evaluation results

Test Case	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Retina only	90	91.5	91.7	91
Iris only	93	92.5	92.5	92.7
Iris-Retina	98	98.1	98.1	97.7

The dataset has been examined with multiple models in order to determine the optimal model for this system. Both the concatenated features of retina and iris images. Each model is trained for 100 epochs, and the train\test accuracy graph alters the model. Fig. 3 depicts the performance versus training and test-validation set of the presented models. As seen in Fig. 3, the proposed system produces superior results.

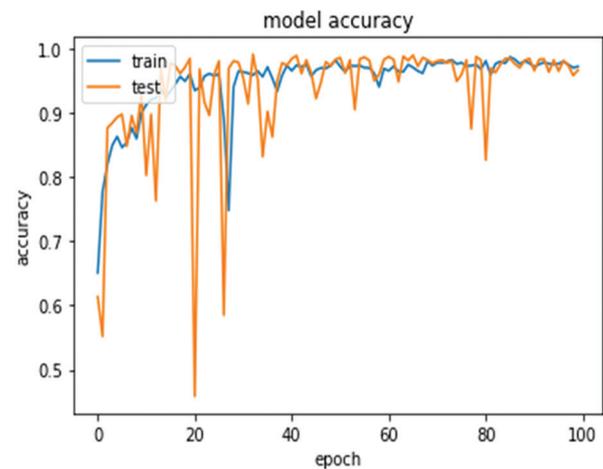


Fig. 4. Figure 3: model accuracy and loss.

5. DISCUSSION AND COMPARISONS

To achieve a high level of information security, the proposed approach employs multimodal iris-retina biometric features via an improved Mask-RCNN model. Accuracy, Precision/Positive predictive value, Negative Prediction value, and F1-Score were calculated. Human recognition attained higher accuracy in the case of iris-retina than either retina or iris alone, according to the data. The lowest recognition accuracy of the experimental results in [32], a multimodal Convolutional Neural Network Approach Based on the Fusion of Face and Finger Vein Features, was 98.84%, and the greatest recognition accuracy was 99.98%. Furthermore, in [28], The Levenshtein distance is used for spatial feature comparison in a multimodal retina-iris biometric system, and a comparison of different iris-retina multimodal techniques is shown. The systems guarantee that multimodal approaches outperform unimodal approaches in terms of accuracy. Our proposed method emphasizes the aforementioned results, where recognition accuracy exceeded 98%. In the future, we can

test the proposed approach on different datasets with varied percentages of training and testing data.

6. CONCLUSIONS

We introduced a deep learning strategy for custom Mask-RCNN for precise and automatic segmentation of Iris from images and segmenting blood vessels from Retina images using adaptive principal curvature and derivative in this study. We present several powerful pretrained models for extracting informative features from segmented iris and retina images. We tested our framework on MESSIDOR and CASIA-IrisV1 databases and performed cross-dataset validation on the databases to demonstrate the model's robustness. The results show that an improved Mask-RCNN can compute deep features with effective representation of human recognition more accurately using retina and iris images for the same individual than using simply iris images, or retina images. Fusion is calculated in our work feature using ELM, which determines the feature fusion score, thereby increasing iris and retina recognition.

ACKNOWLEDGMENT

The researchers would like to acknowledge the Dean-ship of Scientific Research, Taif University for funding this work.

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