

EMiCoAReNet: An Effective Iris Recognition Using Emerging Mixed Convolutional and Adaptive Residual Network Approach

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Abstract:

Iris Recognition (IR) research has been proliferated vastly with applications in authentications and security in border controls and airports to name a few. These applications have gained significance in the use of DNNs (Deep Neural Networks). These techniques have produced excellent results in IRs surpassing humans in their benchmarked performances. However, practical applications often have to process eye images with low quality caused by various disturbances like noise resulting in low resolutions. This research work attempts to overcome this deficiency by proposing EMiCoAReNet (Emerging Mixed Convolutional and Adaptive Residual Network) scheme, which can jointly learn the feature representation and perform recognition with even low quality iris images. In the first phase of work rotation, cropping, rotation after cropping, flipping, Color space transformations and Translation data augmentation techniques are performed to produce more possible execution likely images and further IFE (Iris Feature Extraction) is performed using modified GF (Gabor Filter) called EFGF (Enhanced Fourier GF) filters. The proposed scheme's accuracy is determined by an occlusion measure while training on known IR datasets namely CASIA-Iris-IntervalV4 and UBIRIS.v2 datasets. This schema can be adapted to biometric IR tasks which need robustness, scalability and accuracy.

Keywords: Eye recognition, iris recognition, deep learning, Convolutional Neural Network, deep residual network, Mixed Convolutional and Residual Network (MiCoReNet), Emerging Mixed Convolutional and Adaptive Residual Network (EMiCoAReNet)

1. Introduction

Pattern recognitions have been applied to various areas of computer vision for solving problems. Advances in IT (Information Technology) have contributed vastly to in the area of security using biometrics traits [1]. Popular examples of this can be airport screenings, mobiles, access controls, crime investigations, border security and healthcare to name a few [2]. Unique characteristics of human eye and its invariant features have been exploited for identifying humans in computer vision [3]. Salient factors that have drawn attention towards IR biometrics are [4] unique patterns and structure permanence of the eyes which can be acquired with user-friendly image acquiring devices.

IRs refers to automatic recognition of individuals based on their eye patterns. IRAs (IR Algorithms) have implied to reduce false matches when applied on large IR databases mainly due to (a) stroma variations in textural patterns of the iris in individuals, (b) perceived permanent nature of eye attributes, and (c) narrow genetic protrusions [5, 6]. NIST (National Institute of Science and Technology) evaluations highlighted IRAs recognition accuracy in real time scenarios [7]. Their report of 2014 [8] stated that over one billion people had their eye images enrolled digitally in databases across the globe including the Indian identification scheme UIDAI (Unique Identification Authority of India), 160 million from Indonesian national ID and 10 million of American Defence Department . Thus, human eye can play a significant role in voluminous automated identification systems.

IR scheme's success can also be attributed to efficient FDs (Feature Descriptors) based on the organ's physical characteristics. Gabor phase-quadrant FDs was introduced by Daugman [5, 6] and is often referred to as iris code has been used predominantly in IRs and have exhibited low false matches and higher matching efficiencies. A wide range of classification methods have also been proposed such as hierarchical visual codebook [9], SVM (Support Vector

Machine) [10], CNN (Convolution Neural Network) [11] MNN (Modular Neural Network) [12], RBFNN (Radial Basis Function Neural Network) [13]etc., for iris recognition. Methods have their own unique advantages like RBFNN. The method does not need mathematical descriptions of input-output feature connections, but has very high training times and hence it is combined with other MLTs (Machine Learning Techniques). SVMs use kernel functions: To evade explicit feature vector mappings in higher dimensional spaces and find a linear separating boundary amongst classes. However, this separation may be difficult. DNNs are the latest innovations in MLTs and have the ability to overcome afore said problems.

This is the main motivation for this work which uses multi-level feature learning of DNNs in its schema where a complete Iris image is considered instead of segmented or normalized images. Such systems reduce burdens of segmentation processing. This work's contributions are detailed below:

- In the first step, image pre-processing of iris data is done through augmentation. Rotation, cropping, rotation after cropping, Color space transformations, Translation and flipping data augmentation techniques are performed to produce more possible execution likely images
- After augmentation iris feature extraction is performed in this work by using Enhanced Fourier Gabor filter method and generated the feature vector. Also to enhance the accuracy, in this work the entire eye image quality is measured by using occlusion measure.
- Finally proposed is EMiCoAReNet based recognition system, which utilizes the features extracted by the Enhanced Fourier Gabor Filters. The new architecture takes advantages from both CNNs (ConvNet) and AResNet (Adaptive deep Residual Network) for satisfactory outputs.

This introductory section is followed by related review of literature. Section three details on the proposed MiCoAReNet frame work while its following section displays results of the work. The paper is concluded in section five with future scope.

2. Related work

DLTs (Deep Learning Techniques) have demonstrated their utility in many domains including computer vision, NLP (Natural Language Processing), IRs and speech recognition application achieving remarkable success in their supervised learning tasks. The study in [14] proposed a pair wise filter bank learning to connect heterogeneous eye images. The scheme called DeepIris, however, had a disadvantage in manually designing encoding filters for complex heterogeneous eye images. CNNs were used in [15] to define ROIs (Regions-Of-Interest) implicitly in inputs implying learning/test samples will not have any masked area.

The work based on periocular biometrics disruptiveness in visible parts, optimized recognitions by discarding components inside iris and the sclera and focussed on information around the Iris. DLT was used in a framework that could recognize Iris in [16].The scheme reduced data collection procedures, enhanced anti-fakes in its biometric identifications. The study used MiCoReNet for recognizing Iris. The study had difficulties with high resolution iris images and its segmentations of ROIs made it complex to be deployed in practical large scale applications.

Periocular regions were exploited using DFFN (Deep Feature Fusion Network) in [17]. The proposed scheme applied maxout units in CNNs to obtain condensed representations of modalities and fused discriminative features of modalities using a weighted concatenation procedure. The study failed in its accuracy due to low resolution images. DLT based capsule network architecture was used in [18] to recognize eyes from images. The proposed network structure adjusted values between two capsule layers by using a modified dynamic routing algorithm adapted IR. Learning migrations allow computations even with limited samples. However, the scheme showed poor performances in the presence of noise in eye images.

DLTs usage in IR was investigated by the study [19]. The study attempted to enhance IR accuracy using more simplified frameworks to recover most representative features. The proposal clubbed RN (Residual Network) based learning with dilated convolution kernels for optimizing training and aggregations of Iris contextual information. The study could not

procure required amount of samples due to personal privacy issues. cGANs (conditional Generative Adversarial Networks) were proposed in [20] for IR augmentations. The study stressed on error reductions in imposter matches which can occur when IR patterns are not clear and dependency on periocular regions increase. Three models of ensembles were proposed in [21] with the aim of enriching heterogeneous (cross-sensor) IRs. The study had difficulties in reducing noises from input images thus affecting IR performances.

Fuzziness was used by [22] to improve Iris images which were then trained by DLTs for quick convergences and increased IR accuracies. The study's use of fuzzy operations on images followed by DLT image processing did not produce the desired results as eyelashes, noises and skin were deterrent factors and also the models needed more iterations to extract IR pattern information. DLT based IrisParseNet was introduced by the study [23]. The scheme was a comprehensive solution for IR segmentations where iris information was retrieved with its inner and outer boundaries parameterized. This study also like many other studies suffered due to noisy images.

Entropy was the main focus of [24] which proposed a scheme for heterogeneous IRs. The study used LNN's (Lightweight Neural Network) entropy feature values in a multi-source feature fusion. The study split its image processing into processing and recognition modules. Processing module converted eye images recognizable labels using CNNs while their recognitions were based on statistical learning and designed multi-source feature fusion mechanism. This literature work has enlightened various existing methods of iris recognition proposed by diverse researchers occasionally with deep learning method. Also training with occluded data slows this decline but still yields poor performance with high occlusion. This research work attempts to overcome afore described challenges found in previous studies by proposing a hybrid schema involving CNNs and AResNet for IRs and augmentations for enhancing IRs without occlusion.

3. Proposed Methodology

The proposed framework consists of three main parts: data augmentation, feature extraction and EMiCoAReNet based classification as shown in Fig.1. Data augmentation including rotation, cropping, rotation after cropping, flipping, Color space transformations and Translation and the combination of them, can greatly enrich the feature of each sample or class of the training set using EFGF, which provides the deep neural network with more information. In this study, EMiCoAReNet is implemented followed by flatten and two fully connected layers. The EMiCoAReNet clubs ConvNet and Adaptive ResNet operations by beginning with a CNN layer and then adding a CNN layer between two Adaptive Residual layers. This interleaving of layers is a part of the proposed architecture to gains advantages of used MLTs. This clubbing is advantageous in terms of quick CNN convergences and non-saturation feature of RNs.

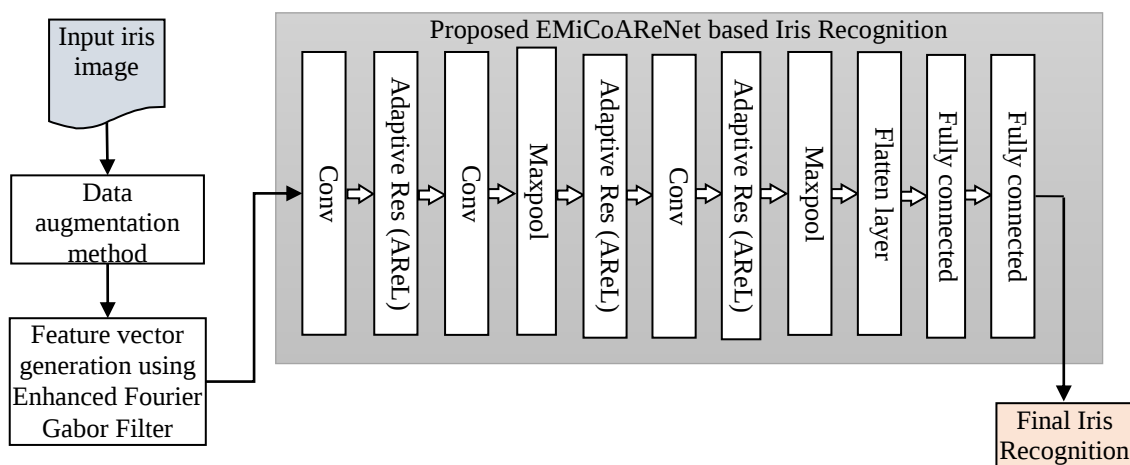


Fig.1.Iris Recognition with EMiCoAReNet

This research work uses a total of eleven layers including one flat layer, three CNN and three Adaptive residual layers,

two max-pooling and two fully connected layers. The residual layer includes a building block where training samples are down-sized to 70×70 pixels after data augmentation. The EFGF method was used to extract the features of the iris image. Then the image batches are fed to the CNN layer followed by the residual layer where both layers have eight feature maps with 5×5 sized kernel. Blocks with 1 CNN and 1 residual layer is an EMiCoARe layer. RN layer's outputs are fed into a second same sized kernel CNN, but with an increased count of

feature maps (16). The size of the max-pooling layer is 2×2 and implemented as 2 pixel strides resulting in 16 feature maps of size 35×35 before it comes to the 2nd RN. The output of the 2nd RN is sent to the next EMiCoARe block without changing parameters like previous layers, but kernel size is increased to 3×3 . This configuration similar to the first is used for implementing another max-pooling layer which is then fed to flat layer. Two fully connected layers each with 512 neurons follow the flat layer. Softmax is used in the 2nd fully connected layer and PReLU activation function is implemented in all layers as shown in Figure 2.

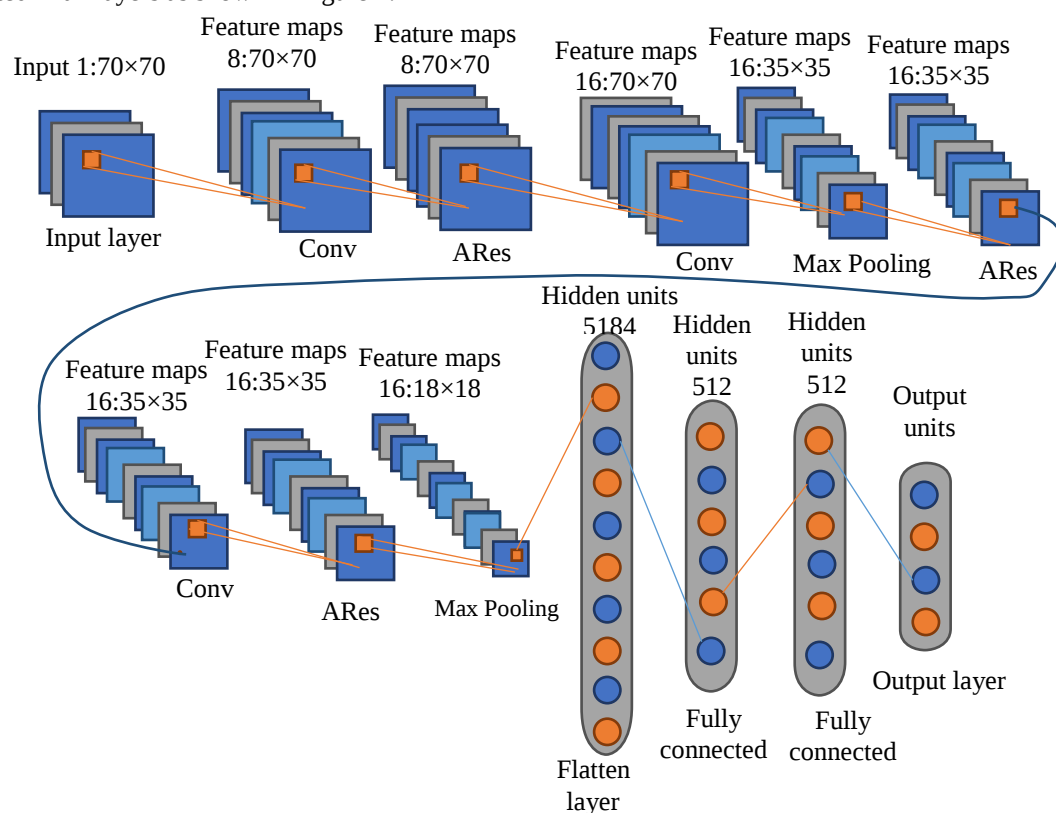


Fig.2.The EMiCoAReNet framework

3.1. Data Augmentation

DNNs rely more on feature diversity unlike FGFs (Fourier Gabor Filter). Data improvements is a significant part of DNNs in IR as eye digital images are framed under various environments like and varying conditions like lights, angles, distances, etc. Hence, this work improves the quality of eye images using various augmentation methods including image cropping, image rotations and flipping of images followed by color space transformations/translations. Parameters are chosen based on the strategy and their results are compared. Figure 3 depicts training images.

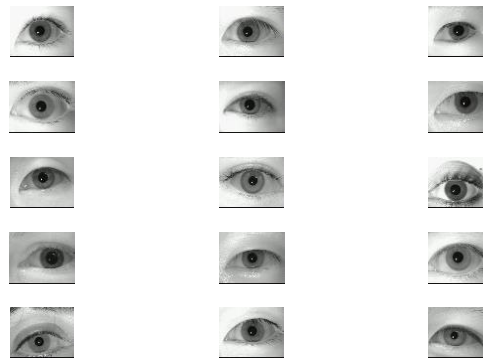


Fig.3.- Training images

Cropping: When images of different dimensions are contained in samples, cropping images is a realistic processing step in image processing. The central patch of specified size is extracted from images. In some cases, randomized cropping is used to obtain results similar to translations. These techniques basically differ in their outputs where in cropping an image size reduces like $(256,256) \rightarrow (172, 172)$ while translations reduce images with preserved spatial dimensions. The reduction threshold value plays a significant role in preservation in transformed images. Figure 4 depicts this study's cropping outputs.



Fig.4.The result of crop for the training image

Rotation: Rotation is an augmenting step in image processing where images are rotated in a range of 1 to 359 degrees in a clockwise or anti-clockwise direction. The result of this improvement is based on the degree of rotation. Marginal rotational degree between 1 and 20 or -1 to -20 can be used in the cases of IR applications, but the rotation angle increases data labels are lost post transformations. Figure 5 depicts the output of Image rotations.

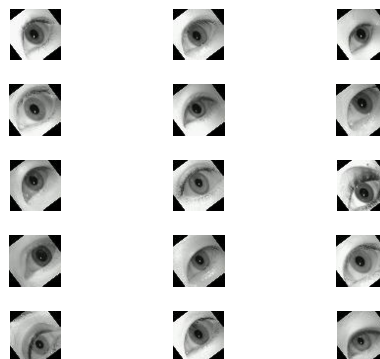


Fig.5.The result of rotation for the training image

Translation: Images are shifted in any direction like left/right or up/down in translation for avoiding positional bias. For example, when all dataset images are centered in face recognition datasets, the model has be tested with perfectly centered images. If images are translated in a particular direction, remaining spaces are assigned fixed values like 0 or

255 in a random or Gaussian distribution manner. The padding of this constant value in images helps in preserving its spatial dimensions, post-augmentation.

Transformations: Image data is encoded in three stacked matrices where the matrices represent images RGB (Red Blue Green) color space values. Differences in illuminations are a major challenge for IR applications while processing images. Hence, this study uses color space transformations (photometric transformations) for enhancements. The result of transformation is shown in Fig.6.

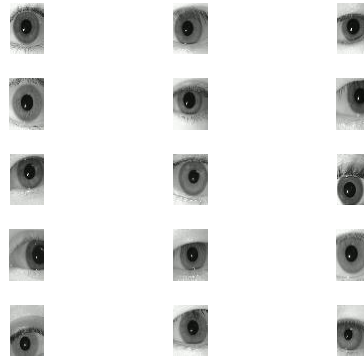


Fig.6.The result of transformation for the training image

Flipping: Horizontal flipping of the coefficients matrix around the horizontal axis for each iris image is performed and then the coefficients are reversed horizontally. The result of flipping is shown in Fig.7.

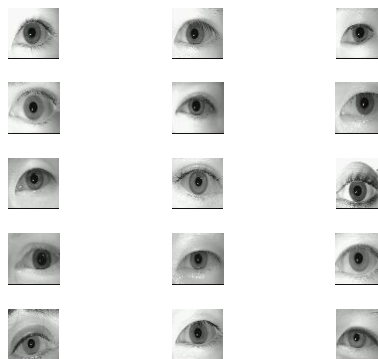


Fig.7.The result of flipping for the training image

Occlusion Measure: After executing augmentations on the samples, Iris occlusions are measured in eyelids and eyelashes. As a result, the occluded region in the iris is effectively decreased. This work uses multiple level masks for iris occlusions. In another method, the affected area of iris and noise free iris mask is compared to evaluate the percentage of occlusion in iris images. The occlusion measure (Om) signifies percentage of invalid iris area due to eyelids, eyelashes, and other noise. The total amount of available iris pattern scan decides the recognition accuracy. The occlusion measure is given as follows:

$$Om = \text{mean}(tot_{gray})$$

Where tot_{gray} described as gray value of the image after augmentation.

3.2. Feature Extraction EFGF

This work uses EFGF to extract features of the eyes. EFGF works in two phases where features are extracted in the first phase. Weights are assigned to features in the second phase using FTs (Fourier Transforms). FTs play significant role in reducing dimensions of in many image processing application result vectors. Dimensionality reductions also minimize computations in convolutions. The weighting of features are executed using discrete degrees of proximity. This also adds to enhanced effectiveness and robustness of feature selections.

Gabor filters extracts information based on Gabor functions which satisfy specified mathematical requirements [24]. This study's filtering resulted in eight orientations and five resolutions. Gabor filtering function is the product of a Gaussian

and a complex exponential function that fulfils mathematical requirements. Features are extracted by modulating a complex sinusoid with a Gaussian function where filters are defined by:

$$\begin{aligned} Gabor(x, y, \theta, \sigma) &= \frac{\|\rho\|^2}{\sigma^2} \exp\left(\frac{-\|\rho\|^2(x^2 + y^2)}{2\sigma^2}\right) \alpha - \beta \\ \alpha &= \exp(i\rho * (x, y)) \\ \beta &= \exp\left(\frac{-\sigma^2}{2}\right) \\ \rho &= \frac{\pi}{2(\sqrt{2})^\delta} e^{i\frac{\pi\theta}{8}} \end{aligned}$$

Where, x, y – Two dimensional input point, θ - Gabor kernel's orientation, σ - Gabor kernel scale, $\|\cdot\|$: - Norm operator, σ - SD (standard Deviation) of the kernel window, ρ - wave vector and α, β - parameters.

x and y specify Gabor sub-matrices output locations and assume the values $[x \text{ and } y \in \{1, 2 \dots 70\}]$ while $\theta \in \{0, 1, \dots, 7\}$ and $\sigma \in \{0, 1, \dots, 4\}$, in this study .

Fourier Gabor wavelet representation of an image is a convolution ($\mathcal{C}$) of Fourier image ($\mathcal{F}r(I)$) with Fourier filter banks. The convolution operation on the Fourier image with a Fourier Gabor kernel ($\mathcal{F}r(Gabor(x, y, \theta, \sigma))$), Fourier Gabor feature can be defined as:

$$\mathcal{C}(x, y, \theta, \sigma) = \mathcal{F}r(I(x, y)) \times \mathcal{F}r(Gabor(x, y, \theta, \sigma))$$

The result of the convolution of Fourier Gabor kernel in the above equation is a complex function which has a real part R and imaginary part I . This study uses its real part to represent extracted Gabor features. The complete set of Gabor wavelet representations of the image $I(x, y)$ can be defined as :

$$Gabor(I) = \{\mathcal{C}(x, y, \theta, \sigma)\}$$

Fourier Gabor feature vectors are resulting features of orientations. Fourier-Gabor filter's iris recognition is depicted as algorithmic steps and is detailed below:

- Call GaborBlock(i, j) and prepare 5×8 Gabor sub-matrix, the size of each sub-matrix is 70×70 , where $i=1, 2 \dots 5$ and $j=1, 2, \dots, 8$
- Apply the FT (Fourier Transform) to each Gabor matrix and 70×70 sized image in the training set.
- Convolute each FT images of size 70×70 by Fourier transformed Gabor images of 8 orientations and 5 scales.
- Construct the image by EFGF ($70 \times 70 \times 40$) from the sub images obtained in the previous step)

Gabor filters consume more processing time, due to convolutions of the complete image. Hence, this study limits the images to 70×70 which is convolved with 40 Gabor filters with eight orientations and five scales. Thus the EFGF extracted the iris image information as feature vectors.

F_{ij} is the extracted feature set where i is the i^{th} FG filter and j is j^{th} feature extracting sub-window and $F_{ij} \in W$ where W is the feature weighting group. FGF's feature weighting is FW_{il} , where i is i^{th} FG filter while l is W 's first feature and defined as $FW_{il}(\mathcal{C}(x, y, \theta, \sigma)) = \frac{1}{N-1} \sum_{\mu_{il} \in FW_{il}} \{\mu_{il} \mathcal{C}(x, y, \theta, \sigma) - \overline{\mu_{il}} \mathcal{C}(x, y, \theta, \sigma)\}^2$

$$\overline{\mu_{il}} \mathcal{C}(x, y, \theta, \sigma) = \frac{1}{N} \sum_{\mu_{il} \in FW_{il}} \mu_{il} \mathcal{C}(x, y, \theta, \sigma)$$

Where N represents the number of the feature, μ is the mean value. $\overline{\mu_{il}} \mathcal{C}(x, y, \theta, \sigma)$ is the resulting feature weighting. The results of EFGF is given in Fig.8.

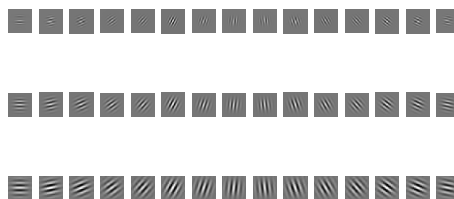


Fig.8.The result of EFGF

3.3. EMiCoARNet

The proposed novel architecture of EMiCoAReNet is detailed in this section. CNN and Adaptive residual layers are interleaved alternatively to form a mixed network as depicted Figure 2. This style of alternate stacking of the network layers results in imbibing the advantages of both architectures. The proposed interleaving learns faster than CNNs and also overcomes the issue of saturations found while using plain CNNs and an advantage found in ARNs (Adaptive Residual Networks). EMiCoAReNet implements a 3-stack layer architecture with three convolution and Adaptive residual layers, two Max-pooling and Fully Connected layers and one flat layer for its IRs.

CNNs: The proposed 3 layer CNN is implemented by 5×5 convolutional kernels for the first two layers followed by a 3×3 convolutional kernel for the last layer. Along with that there are two Maxpooling layers are used with 2×2 kernels with 2 pixels strides. Initially after augmentation the training samples are down-sized to a fixed 70×70 pixel size and given as input to CNN layer.

ARUs (Adaptive Residual Units): The proposed ARUs differ from ARN block in three distinct areas. The difference lies in using PReLU (Parametric Rectified Linear Unit) activation function in place of ReLU (Rectified Linear Unit) activation function [25] while training. Second major difference is in connecting inputs with stacked layers, deviating from the normal trend of linking outputs of previous layers to the current layer. This is done for preserving useful input information. The final difference is in the introduction of parameters α and β with which important information between inputs and outputs of the previous layer are balanced. This work uses the parameters α and β in its ARN weight assignments for optimality in training. It may be noted, that scaling parameters to a constant value beneficial results were obtained as also proposed theoretically.

Activation Function [PReLU]:

DNNs commonly use ReLU as the activation function. In ReLU, inputs lesser than zero is considered as zero and helps in meagre representations. Neural Networks' activation layer values represent sparse inputs which accelerate ReLU towards faster convergences and generation of better solutions. It is for this reason, ReLUs are preferred in place of sigmoid function for activation by researchers. The study [25] states that PReLU slope is adaptive to learn the parameters offsets ReLU's positive mean making it symmetric. Experimental results also show PReLU's faster convergences when compared with ReLU convergences while obtaining a better performance. Thus, this work justifies the use of PReLU in its ARUs. PReLU is defined by [25]:

$$f(y_i) = \begin{cases} y_i & y_i > 0 \\ a_i y_i & y_i \leq 0 \end{cases}$$

Above, y_i is any input on the i th channel and a_i is the negative slope which is a learnable parameter.

- if $a_i = 0$, f becomes ReLU
- if $a_i > 0$, f becomes leaky ReLU
- if a_i is a learnable parameter, f becomes PReLU

PReLU is similar to Leaky ReLU, the only difference being that the ac parameters are learned. The gradient of PReLU is:

$$\frac{\partial f(y_i)}{\partial a_i} = \begin{cases} 0 & \text{if } y_i > 0 \\ y_i & \text{if } y_i \leq 0 \end{cases}$$

Flatten Layer: In this work's training phase, two fully connected layers with 512 neurons follow the flat layer in classifications. The final layer used in classifications has 512 neurons where each neuron represents a class from the Iris training set with a softmax-loss function. The previous layer of the fully-connected layer reduces the dimensionality of features. Figure 5 depicts the result of the proposed EMiCoAReNet scheme.

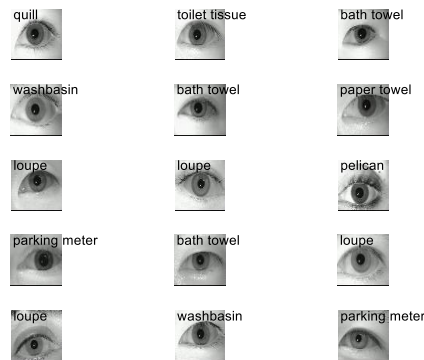


Fig.9.The results of EMiCoArNet

4. Experimental Results and Discussion

Experimental setup and input database: Iris image datasets are used for IR applications. This research work uses CASIA-Iris-IntervalV4 [28] and UBIRIS.v2 [29] for evaluating the proposed algorithm. The former dataset is a standard eye database used in most IR applications. The dataset has enough samples on regions surrounding the eyes. It encumbers 249 classes with eye samples from left and right containing between 1 to 10. This study uses a minimum of five samples of left or right eyes for ensuring scalability. Since samples are equally represented, dataset samples are chosen randomly for experimentations. One random sample from each class is the testing set while the remaining form the training set. This experiment used 218 classes, 1,346 training samples and 218 testing samples.

This study chose the UBIRIS.v2 for its noisy eye images. The dataset includes 2 sessions with 261 left and right eyes totalling to 522 with 11,102 samples. Its images collected using different distances (4 – 8 metres) and visible wavelengths in movements, encompasses frontal perspective with left and right off-angle combinations. Thus, the dataset has samples to test the robustness of IR systems. A session's Left eye samples were retrieved for experimentations in this study. Thus, 258 classes with 3,866 samples were used in this work. Images acquired at a distance of 4 metres and in a right side off-angle view were trained while the balance was a part of the testing set.

UBIRIS.v2 dataset images were converted to 8-bit gray-scale images. EMiCoArNet, CNN, SVM and MiCoReNet approaches were benchmarked using MATLAB (Version 2018a) implementations on the performance metrics Accuracy, Precision, Recall, F-measure and Error Rate.

Accuracy: It is one of the most commonly used measures for the classification performance, and it is defined as a ratio between the correctly classified samples to the total number of samples as follows:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision: It represents the proportion of positive samples that were correctly classified to the total number of positive predicted iris samples as indicated:

$$Precision = \frac{TP}{FP + TP}$$

Recall: The recall of a classifier represents the correctly predicted positive iris samples to the total number of positive samples, and it is estimated as follows:

$$Recall = \frac{TP}{TP + FN}$$

F-measure: This is also called F_1 -score, and it represents the harmonic mean of precision and recall as follows:

$$F - measure = \frac{2 * (Recall * Precision)}{(Recall + Precision)}$$

Error rate: It is calculated as the number of all incorrect predictions divided by the total number of the dataset as given below:

$$Error\ rate = \frac{FP + FN}{TP + TN + FP + FN}$$

Table.1.The numerical results of accuracy, precision, recall, f-measure and error rate

Metrics	CASIA-Iris-IntervalV4				UBIRIS.v2			
	SVM	CNN	MiCoReNet	EMiCoAReNet	SVM	CNN	MiCoReNet	EMiCoAReNet
Accuracy	77	80	88	95.2	79	81	89	95.6
Precision	71	78	85	93	70	77	89	91
Recall	75	77	84	94	76	78	83	92
F-measure	73	77	86	92.7	73	77	88	94
Error rate	23	20	12	4.8	21	19	11	4.4

4.1. Accuracy

Accuracy defines no of instances detected against total instances of the database.

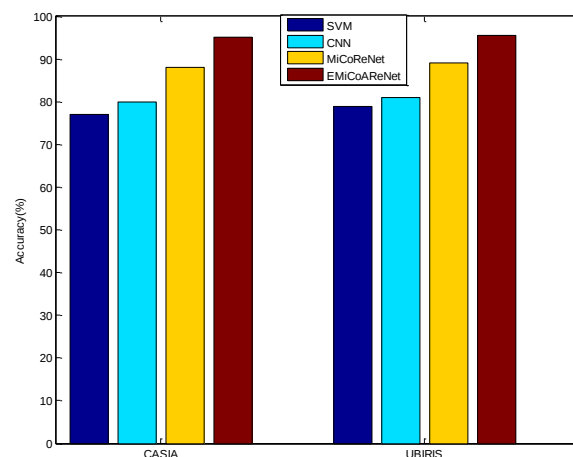


Fig.10. Accuracy Comparison Results

The proposed EMiCoAReNet's benchmark results with MiCoReNet, CNN and SVM classifiers in terms of accuracy implemented on MATLAB with previously defined datasets is depicted in the above figure 10. The samples taken for training were limited to 126,524. The detection accuracy of EMiCoAReNet is 95.2% and 95.6% acquired on the CASIA-Iris-IntervalV4 and UBIRIS.v2 datasets respectively. EMiCoAReNet's fully connected layer, learns features from features combinations using EFGF and augmentation is improved to reduce occlusion which leads to the improvement of detection accuracy in proposed scheme.

4.2. Precision Rate comparison

The proposed EMiCoAReNet's benchmark results with MiCoReNet, CNN and SVM classifiers in terms of precision implemented on MATLAB with previously defined datasets is depicted in the above figure 11. EMiCoAReNet has higher precision values in the datasets with 93% and 91% in benchmark results and increases further with data volume increases implying EMiCoAReNet has better Precision Rate due to its use of CNNs and ARNs and the best choice for IR applications.

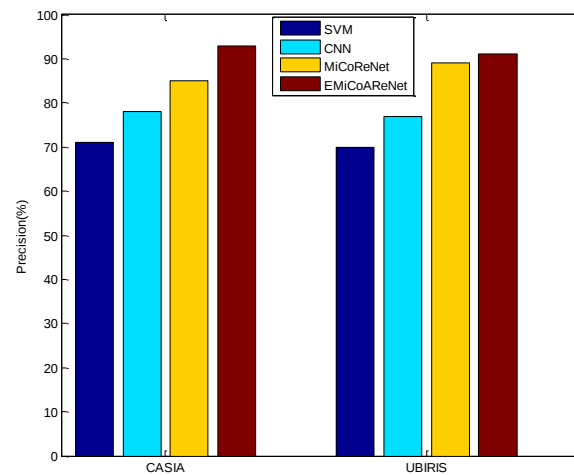


Fig.11. Result of Precision Rate

4.3. Recall Rate comparison

The proposed EMiCoAReNet's benchmark results with MiCoReNet, CNN and SVM classifiers in terms of Recall implemented on MATLAB with previously defined datasets is depicted in the above figure 12. EMiCoAReNet has higher recall values in the datasets with 94% and 92% in benchmark results and increases further with data volume increases. MiCoReNet converges faster than SVMs but accuracies get saturated in deeper network operations. EMiCoAReNet has better Recall Rate due to its use of CNNs and ARNs and the best choice for IR applications as it has an improved data augmentation strategy using EFGF feature extractions.

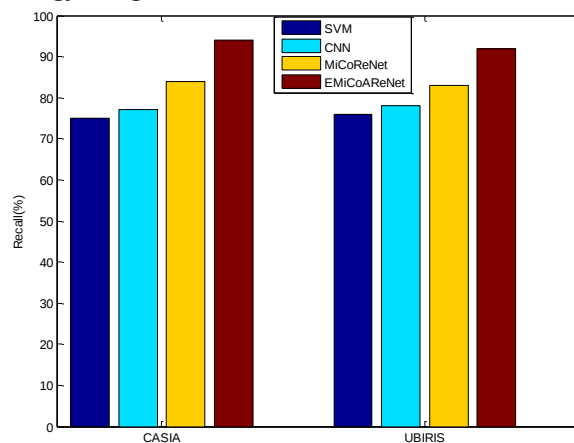


Fig.12. Result of Recall Rate

4.4. F-measure Rate comparison

The proposed EMiCoAReNet's benchmark results with MiCoReNet, CNN and SVM classifiers in terms of F-measure implemented on MATLAB with previously defined datasets is depicted in the above figure 13. EMiCoAReNet has higher F-measure values in the datasets with 92.7% and 94% benchmark results and increases further with data volume increases. MiCoReNet converges faster than SVM and CNN but accuracies get saturated in deeper network operations. EMiCoAReNet has better F1- Score due to its use of CNNs and ARNs and the best choice for IR applications as it has an improved data augmentation strategy using rotation, cropping, rotation after cropping and flipping as there are no or limited occlusions.

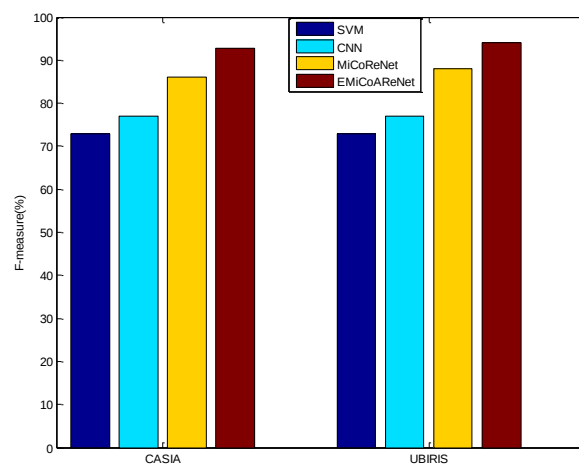


Fig.13. Result of F-measure Rate

4.5. Error rate comparison

The proposed EMIcoARENet's benchmark results with MiCoReNet, CNN and SVM classifiers in terms of Error rates implemented on MATLAB with previously defined datasets is depicted in the above figure 14. EMIcoARENet has lower error rates in the datasets with 4.8% and 4.4% benchmark results. MiCoReNet converges faster than the legacy methods but accuracies get saturated in deeper network operations. EMIcoARENet has better Error Rate due to its use of CNNs and ARNs and the best choice for IR applications as it has reduced error rates thus proving its efficiency.

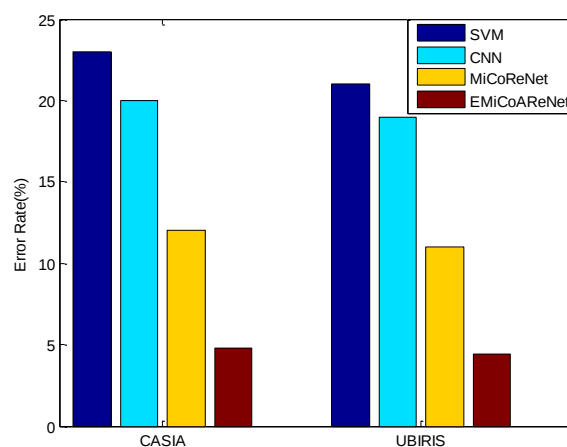


Fig.14. Result of Error Rate

Conclusion and Future Work

This study has proposed a new iris recognition method, where EMIcoARENet containing the benefits of convolutional neural network and Adaptive Residual Network. The training dataset of CASIA-Iris-IntervalV4 and the UBIRIS.v2 was input again as a testing dataset in the fully trained generator of the EMIcoARENet after the data augmentation was performed. The EFGF was used to extract features of the iris image and it was fed into the EMIcoARENet as an input. The proposed work avoids occlusions proving that frameworks using data augmentation strategies can show good results on Iris datasets. EMIcoARENet's accuracy increases with increasing epochs and outperforms SVM, CNN and MiCoReNet in all areas of performances based on the metric values. EMIcoARENet is a promising architecture for IR applications. In future, this research proposes to further improve the recognition and classification accuracy of EMIcoARENet. As an enhancement for this iris recognition model we plan to propose a new technique for the sclera feature extraction in addition to the existing iris features.

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