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Patch Based Sclera and Periocular Biometrics Using Deep Learning

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Abstract: Biometric authentication has become an essential security aspect in today's digitized world. As limitations of the Unimodal biometric system increased, the need for multimodal biometric has become more popular. More research has been done on multimodal biometric systems for the past decade. sclera and periocular biometrics have gained more attention. The segmentation of sclera is a complex task as there is a chance of losing some of the features of sclera vessel patterns. In this paper we proposed a patch-based sclera and periocular segmentation. Experiments was conducted on sclera patches, periocular patches and sclera-periocular patches. These sclera and periocular patches are trained using deep learning neural networks. The deep learning network CNN is applied individually for sclera and periocular patches, on a combination of three Data set. The data set has images with occlusions and spectacles. The accuracy of the proposed sclera-periocular patches is 97.3%. The performance of the proposed patch-based system is better than the traditional segmentation methods.

Index Terms: CNN, Sclera, Periocular, Patch.

1. Introduction

Multi-modal biometric system takes as input more than one feature from a user. In the proposed system we considered sclera and periocular as a multimodal system. sclera is the white part of the eye that has blood vessels. These blood vessels pattern varies from person to person. The extraction of blood vessels from sclera is a complex task. The input image is divided into a group of pixels known as a patch. The different shapes of patches can be applied, depending on the application. In the proposed system the shape of the patch chosen is square. Periocular is the surrounding part of the eye that can be used for biometric authentication. The occluded sclera and periocular images are as shown in the Figure 1 and Figure 2. The periocular part of the image can change due to plastic surgery, aging and make up. In some cases, sclera veins may not be visible due to spectacles or occlusion due to hair. In these cases, sclera-periocular fusion can identify better when compared with other methods.

Most biometric features require a separate device for capturing the subject information such as a Fingerprint scanner, IR light sources for Iris etc. Even though there is rapid development in technology, capturing of biometrics features still needs to meet certain requirements. As such it is not possible to capture using smartphones with embedded cameras. Overuse of fingers can lead to erasing of patterns in the fingerprint, user cooperation is needed and cannot be captured from a distance, but accuracy is high. The limitation of Face recognition is, the features of the face can be changed due to plastic surgery and as such can be captured from a certain distance. Iris features can be captured from a certain distance, but the user cooperation is important. Another limitation if Iris recognition is the gaze direction.

The stability and accuracy of Iris and fingerprint is high but the limitation is in terms of imposter for fingerprint and user willingness for Iris is an important aspect in authentication system. Due to these limitations researchers are looking forward to the new biometric features sclera and periocular. To overcome eye occlusions, periocular components can be used. The limitation of periocular features can be overcome using sclera. As a result, a new multimodal biometric system that is a fusion of sclera and periocular is proposed.

Fig.1. Periocular.

Fig.2. Occluded Sclera.

In this research study, the proposed CNN model has been implemented using:

- Only Sclera patches as Biometric authentication system
- Only periocular patches as Biometric authentication system
- Sclera-Periocular Patches as Biometric authentication System.

Section 2 presents the literature survey on segmentation methods, patches and deep CNN models. Section 3 describes patch-based segmentation. In Section 4 the procedure of patch-based sclera-periocular segmentation is discussed. Next in Section 5 CNN based on Keras API is presented. The proposed datasets are presented in Section 6. Section 7 presents proposed CNN model. Experimental analysis and results are discussed in Section 8. Conclusion of the proposed research work is presented in Section 9.

2. Related Works

In [1] the author introduced a method, patch based neural network for brain tumor segmentation. Applied data pre-processing technique such as clipping of nonzero voxels to remove outliers. A modified Deep Medic architecture was applied. In medical image analysis segmentation plays an important role. The author [2] carried out various segmentation techniques such as fully convolutional pixel labeling networks, recurrent networks, encoder-decoder, pyramid based approaches and generative models. In [3] proposed CNN model to extract features of retinal fundus images to classify using SVM, AdaBoost, Naive Bayes and Random Forest. The performance of the CNN is 99.59% for multi-class classification. Deep learning models are used to train large number of samples. The given image is trained in forward pass [4] with a small number of samples and Image patches using a light weighted network [5] to a densely connected networks. In [6] the author explained the tradeoff between face and iris biometric which requires user cooperation. Application of periocular biometrics and a detailed study of and future research. The author [7] explains about various deep learning methods for medical image segmentation such as CNN,2D CNN,3D CNN and FCN. The author reviewed a study of periocular biometrics [8] based on existing databases, algorithms, segmentation methods, features for recognition, the discriminative regions of the periocular area, impact of plastic surgery etc. Due to the traditional hand-crafted segmentation limits in sclera extraction, [9] proposed CNN for image segmentation with noise removal using Conditional random fields. A fully automatic minutiae extractor Known as Minutianet [10] using deep neural networks to estimate minutiae score map and minutiae orientation based on CNN generates Minutiae sets that have better precision and recall values. The discriminative features of the face are extracted using Local Binary Pattern (LBP) in [11] and city block distance is used as a classifier. The many challenges in sclera segmentation are iris gaze directions [12], image capturing distance and differences in lighting conditions and proposed blood vessel enhancement and feature extraction methods to increase the adaptability to noisy sclera vessel deformations. To increase the accuracy of a biometric system multimodal biometrics is used. In [13] the author proposes a face and Iris multimodal biometric system using matching score level and feature level for feature extraction. The multimodal system is implemented using LBP [14] feature extraction method. SVM are used to improve the recognition performance of the proposed system. A patch based

Evaluation of Image Segmentation (PEIS) to [15] assess the quality of segmentation based on patch identification and patch displacement. In [16] the author proposed a novel deep learning framework for SIP-SegNet semantic segmentation of Sclera, Iris and Pupil traits in an unconstrained scenario by suppressing the periocular region. Three robust deep convolutional neural networks [17] like Plain-CNN, two MultiScale Fusion CNN for better feature extraction and improved metrics. A minimal recognizable patch to recognize an Image using a special deep network [18] is proposed. In [19-21] proposed RGB-OCLBCP dual stream CNN that accepts an RGB image to identify periocular regions in the wild using OCLBCP that achieves better performance. The deep CNN is used mainly for image processing that needs a large number of samples. In [20] proposed a capsule network that has high recognition accuracy in classification tasks, increases the robustness of the model and a modified routing algorithm.

3. Patch Based Segmentation

The input image is divided into sub images known as patches of size 50 X 50. Let image I of size h X w, is divided into patches of size p X q. The number of patches is determined as

$$N = \frac{h}{p} \ x \ \frac{w}{q}$$

The given eye image is divided into patches as shown in Figure 3 The division of the image is chosen to be a square patch as shown in Figure 4 Eye image is divided into 12 patches.

Fig.3. Eye.

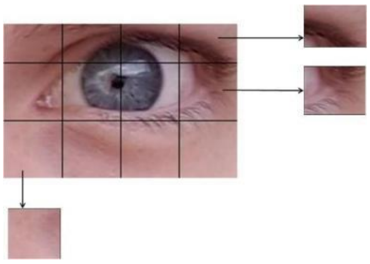

Fig.4. Eye Image Patches.

4. Patch based Sclera and Periocular Segmentation

The eye Image is from SBVPI data set. We considered images from three data sets with different variations in terms of occlusions with hairs, spectacle etc. The other two data sets are VSIOB and UBRIS data set. The eye image is divided into patches with the starting size as 100 X 100. From the segmented image, select only the Sclera and Periocular based on intensity values. The eye brows and Iris is the part that has to be discarded, which are of black color. The patches with mean pixel intensity equal to zero are discarded. Figure 5 shows the segmented periocular patches and Figure 6 shows the segmented Sclera patches.

Fig.5. Periocular Patches.

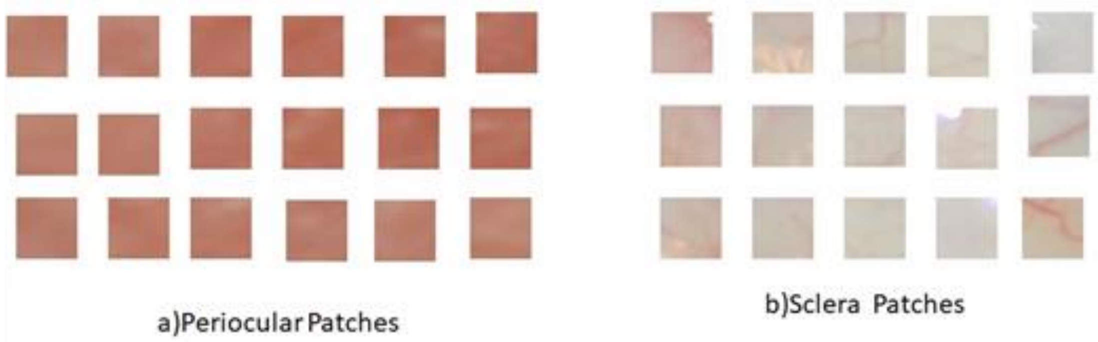

Fig.6. Sclera Patches.

5. Convolution Neural Networks

CNN is a deep learning model used mostly in image recognition, classification tasks. This deep network can learn the features of the image automatically by using the basic building blocks such as convolution layers, pooling layers and fully connected layers. Deep learning has an input, output and hidden layers. To extract features from image convolution, pooling layers are used to classify the images into 10 classes a fully connected layer is used.

5.1. Keras

Keras is an open source framework for deep learning models that runs on machine libraries like tensorflow,Theano and cognitive tool Kit(CNTK). Keras models can be executed on both a CPU and a GPU. Keras models are written using python that supports CNN and recurrent neural Networks. Keras API has three types:

- Model
- Layer
- Core Modules

5.2. Model

Keras models can be sequential and Functional APIs. Sequential model is made of a set of layers. Functional APIs are used for complex models.

5.3. Layers

Any type of ANN can be built using a set of pre-built layers such as Convolution, pooling and Dense layers.

5.4. Core Modules

Keras has a set of built in functions in order to create a neural network model.

- Activation functions - Activation function is used in all types of ANN. Some of the important activation functions are sigmoid, softmax, Relu etc.
- Loss functions- To find out the errors in predictions some of the built in modules are mean squared error, binary an entropy and categorical cross entropy
- Optimizer functions- To minimize or adjust the weights in neural network models optimizers such as SGD, Adams are used.
- Regulizers- To adjust the model parameters sometimes L1 and L2 regularizers are applied.

Fig.7. Proposed Data Set.

6. Proposed Data Set

The data set for the proposed system is a combination of images from SBVPI, UBRIS and VISOB 2.0. The data set has normal and occluded images. Images that have eye makeup, eye occluded by spectacles, hair etc. All the three datasets have a number of eye images for a particular subject. Each subject has left and right eye images. Images with gaze direction, images with different brightness and resolution. The proposed data set has 10 images to classify into 10 classes using a deep learning model. As shown in Figure 7 total 20 images where each subject has a left and right image.

7. Proposed Model

In the existing sclera and Iris combination the accuracy of the model was 97.99%. Another combination of multimodal biometrics proposed in literature was periocular and Iris with accuracy of 92.24%. In these two fusions of biometrics, the Sclera and Iris image has to captured in the IR light and user willingness to capture is also important. In Periocular and Iris, the periocular image may change due to aging, make up and also due to plastic surgery. The limitation of the above two system has been overcome in the proposed system by considering sclera when periocular images get occluded or changed. Similarly periocular image will be considered of there any occlusions in the sclera part.

The proposed model is as shown in the Figure 8. Input is an eye image that is divided into patches in the next step. From the set of image patches, select only the sclera and periocular patches using mean pixel intensity values. The set of image patches are fed to the proposed CNN model. The model classifies the images into classes based on the labels. The classified model is then tested using test data set. A random sclera and periocular patches from the test are selected and verified with the trained model. The model predicts patch as belonging to a particular class label that is identification of the eye image.

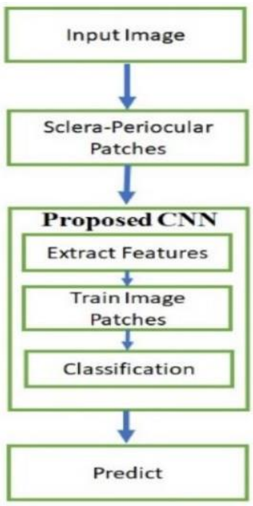

Fig.8. Proposed CNN biometric authentication Model.

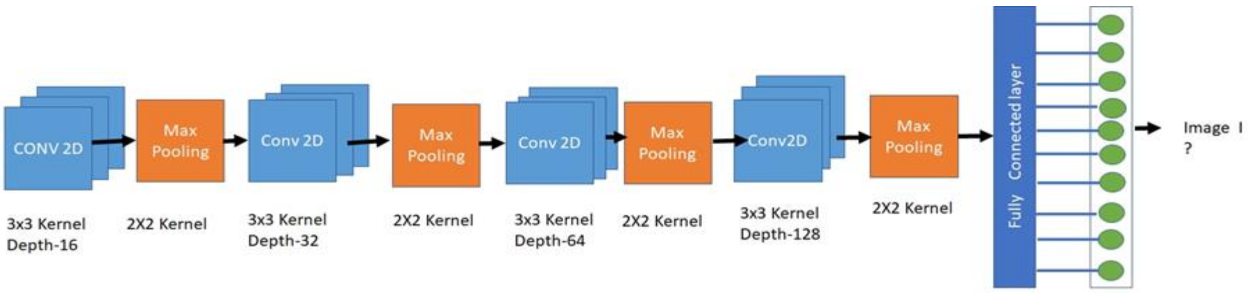

Fig.9. Proposed CNN model.

The proposed CNN model has twelve convolution layers, four Max pooling layers followed by batch normalization at each layer. To convert the Max pooling layer output into a one-dimensional vector we applied a flatten layer. In order to connect neurons of each layer to the previous layer, dense layers are added. The architecture of the proposed CNN is as shown in the figure 9.

Step 1-The first three convolution layers have sixteen kernels of size 3X3. The kernels are used to perform convolution operations. The kernel is moved across the image from left to right and top to bottom, which results in the dot product of the Sub image and kernel. At each layer the activation function Relu is used.

Step 2 -The max pooling layer is used to down sample the image with a filter of size 2X2.

Step 3-The second three convolution layers have thirty-two kernels of size 3X3 each and followed by a Max pooling layer. of size 2X2.

Step 4-The third three convolution layers have sixtyfour kernels of size 3X3 each and Followed by Max pooling layer of size 2X2.

Step 5-The final three convolution layers have 128 kernels of size 3X3 each and followed by a Max pooling layer of size 2X2.

Step 6- A fully connected layer is used to convert the max pooling layer into a one dimensional vector.

Step 7- In the last layer the softMax activation function is used to classify input patch image as one among the ten classes.

8. Experiment Results and Analysis

The proposed CNN model is applied on sclera data set and periocular data set. In this section we discuss the experimental results of the proposed model in terms of training accuracy, validation accuracy, confusion matrix and Classification Metrics.

8.1. Sclera Data Set

The images in this data set are from three different data sets. Images are resized to a shape of 3000 X 1700. Patch size is chosen as 50 X 50. Each subject has a left eye and a right eye image.

The number of patches is

$$\frac{3000}{50} X \frac{1700}{50} = 2{,}040$$

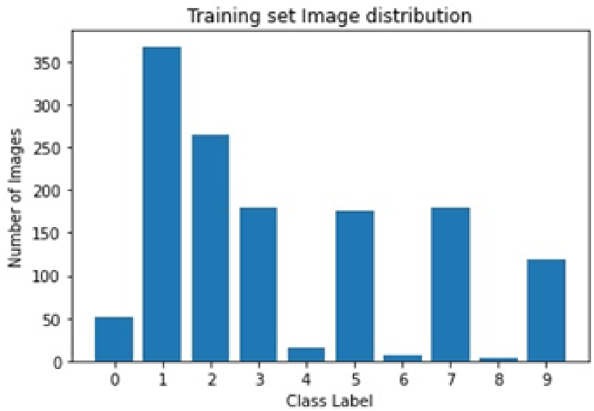

Fig.10. Training sclera set.

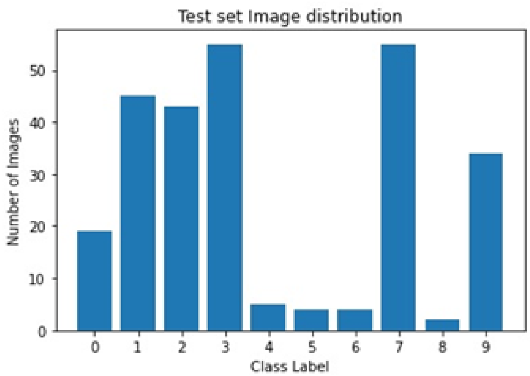

Fig.11. Test Sclera set.

Out of these 2,040 patches after discarding other features such as Iris, Periocular and eye brows, we get the number patches as 1279.This data set has 1113 Training Image patches and 266 test image patches. In the training set we include 20% of image patches as validation data set. Figure 10 shows the training set distribution of sclera image patches and Figure 11 shows the distribution of sclera test set image patches. Table 7.1 lists the number of patches in the training set, validation set and test set for the ten classes.

Table 1. Sclera Patches class wise.

Class Label	0	1	2	3	4	5	6	7	8	9
Training Patches	52	368	265	180	15	175	7	180	3	118
Test Patches	19	45	43	55	5	4	4	55	2	34

A. *Training using CNN on Sclera Data*

In this training model the patc sizes 100X100. To Train the model NVIDIA-SMI 495.44 CUDA version 11. 2 Persistence-M is used. The training was completed with 100 epochs for 6s at the rate of 70ms/Step. In order to classify into 10 classes categorical cross entropy loss function is applied in combination with Adam optimizer. The learning rate is 0.001. To improve the performance of the model and to expand the training data set, data augmentation using keras API Image Data Generator class is used. The batch size is 16, with a total of 85 batches.

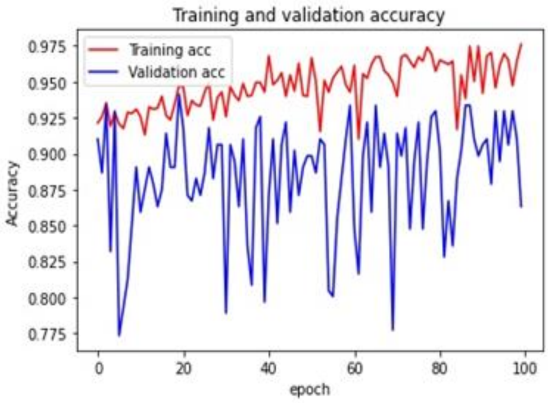

Fig.12. Accuracy.

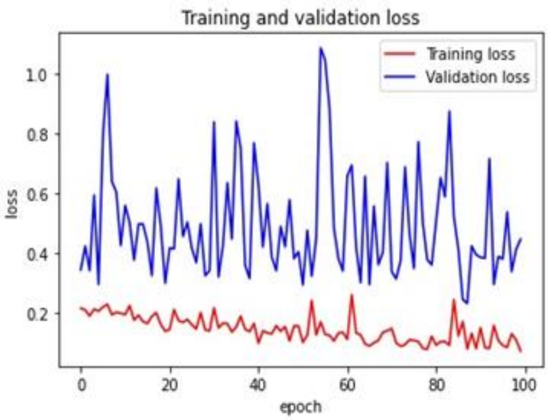

Fig.13. Loss.

The Training, validation accuracy and loss of the sclera classification is shown in Figure 12 and 13. The training accuracy is 97.62 % and the validation accuracy is 86.33%. The training Loss is 0.0716 and Validation loss is 0.4459. The validation curve is more fluctuating as there are few sclera patches in the test data set.

B. *Confusion Matrix*

Confusion matrix is used to identify the mis-classifications in a multi-class classification problem. The following Figure 14 shows the mis classifications of sclera patches for the ten classes. The sclera part corresponding to image class 10 is classified correctly for 44 patches and in correctly classified as patch belonging to class 9 one time.

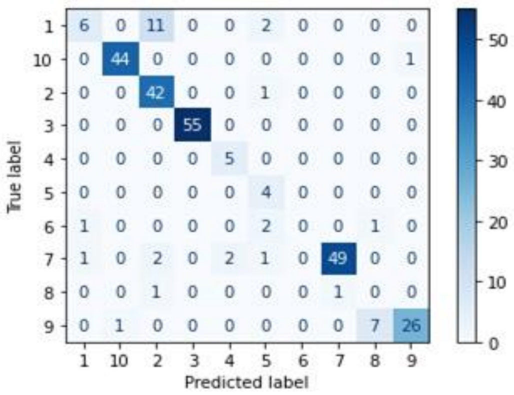

Fig.14. Sclera Confusion Matrix.

C. *Classification Metrics*

To evaluate the performance of a deep learning model the metrics are accuracy, precision, recall and F1 score. This metrics for classification is as shown in the Table 7.2. The Image label 1 has a precision value of 75% which indicates the true positive predictions, 32% Recall value indicates the true positive predictions, F1 score 44% indicates the accuracy of the mode for sample of 19 patches in the test set.

Table 2. Classification Metrics.

Image Labels	Precision	Recall	F1 Score	Support
1	0.75	0.32	0.44	19.00
10	0.98	0.98	0.98	45.00
2	1.00	1.00	1.00	55.00
3	0.71	1.00	0.83	5.00
4	0.71	1.00	0.57	4.00
5	0.40	1.00	0.57	4.00
6	0.00	0.00	0.00	4.00
7	0.98	0.89	0.93	55.00
8	0.00	0.00	0.00	2.00
9	0.96	0.76	0.85	34.00

8.2. *Periocular Data Set*

Images are chosen from three different data sets. All the images are resized into images of size 3000 X 1700 as shown in Figure 75.

The number of patches are is

$$\frac{3000}{100} \times \frac{1700}{100} = 510$$

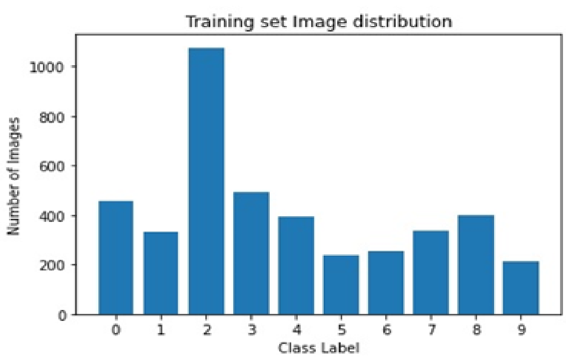

Fig.15. Periocular Training set.

Each subject has two images one as Left eye image and the second one as right eye image eye. The total number of patches is 4,720. In the proposed system we train periocular image patches only. After discarding the other patches of the other eye image features such as Iris, sclera and eye brow, we get the resultant data set for each subject. This data set has

4062 training set patches and 658 test set patches of ten classes. The training set includes validation set patches that is 20% of the training set. Figure 15 shows the distribution of training set image patches and Figure 16 shows the distribution of test set image patches. In Table 7.3 lists the number of training, validation and test set patches for the ten classes.

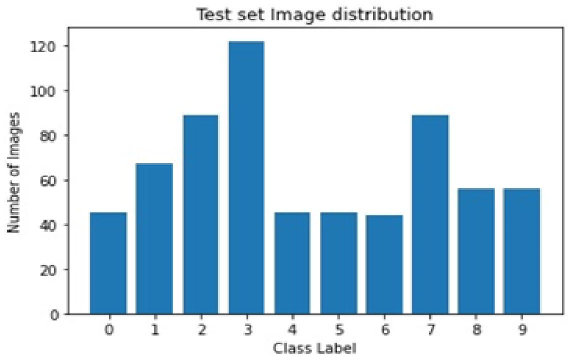

Fig.16. Periocular Test set.

Table 3. Periocular Patches Class wise

Class Label	0	1	2	3	4	5	6	7	8	9
Training Patches	457	332	1075	492	392	238	251	336	399	211
Test Patches	45	67	89	122	45	45	44	89	56	56

A. Training using CNN on Periocular Data Se

The periocular Data set is trained using the proposed CNN model. The training is performed on 4,702 patches. The model is trained using NVIDIA-SMI 495.44 CUDA version 11. 2 Persistence-M GPU is used. The training is iterated for 100 epochs with a batch size of 16, around 261 batches. The execution time for each batch is 8s at the rate of 68ms/step.

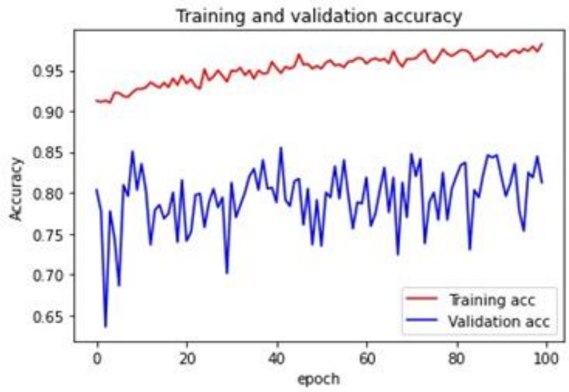

Fig.17. Accuracy.

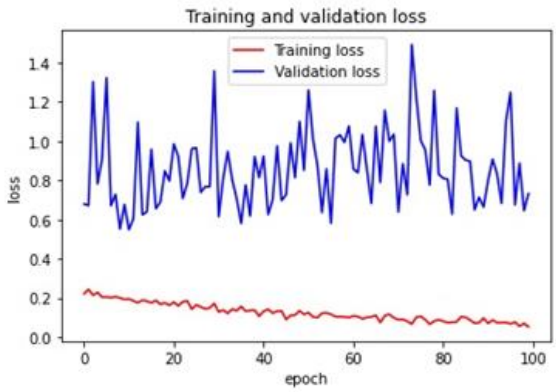

Fig.18. Loss.

The training accuracy is 98.20% and validation Accuracy is 81.25. The validation accuracy and loss curves are better when compared with sclera curves. The number of periocular patches in the data set is more when compared to sclera patch data set. The accuracy is shown in Figure 17 and loss is shown in the Figure 18.

B. Confusion Matrix

The periocular patches classification using the proposed CNN is as shown in the Figure. 19. The total number of patches of class 1 in the test data set is 45, among these 33 patches are classified correctly. The remaining 11 patches are classified as class 2 and one patch as class 5. The diagonal values in the confusion matrix indicates true positives and below diagonal are mis classifications.

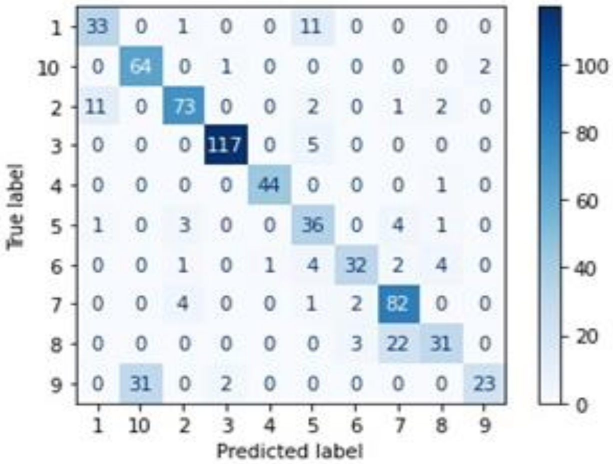

Fig.19. Confusion Matrix.

C. Classification Metrics

The performance of the periocular patches can be obtained using precision, recall and F1 score on the test data set. The Precision values indicate the true positive classifications and the recall value indicates the true baseline performance of the proposed model. F1 scores are used to evaluate an imbalanced data set.

Table 4. Classification Metrics.

Image Labels	Precision	Recall	F1 Score	Support
1	0.73	0.73	0.73	45
10	0.67	0.96	0.79	1
2	0.89	0.82	0.85	89
3	0.97	0.96	0.97	122
4	0.98	0.98	0.98	45
5	0.61	0.80	0.69	45
6	0.86	0.73	0.79	44
7	0.74	0.92	0.82	89
8	0.79	0.55	0.65	56
9	0.92	0.41	0.57	56

8.3. Training of CNN on Sclera Periocular Fusion

The sclera periocular fusion data set is trained using the proposed CNN model. The Model Is trained using NVIDIA-SMI 495.44 CUDA version 11. 2 Persistence-M GPU. This fusion data set has 7379 patches. the training set has 5958 patches and the test set has 1421 patches. The model training has been iterated for epochs with a batch size of 16 and the total of 297 batches. the time taken for executive the model on Epic basis is 33s at the rate of 110 ms/step. The learning rate is 0.0001 and the loss function is categorical cross entropy to classify the ten class patch images.

The distribution of training and test set images with class wise patch distributions areas shown in the Figure 20 and Figure 21.

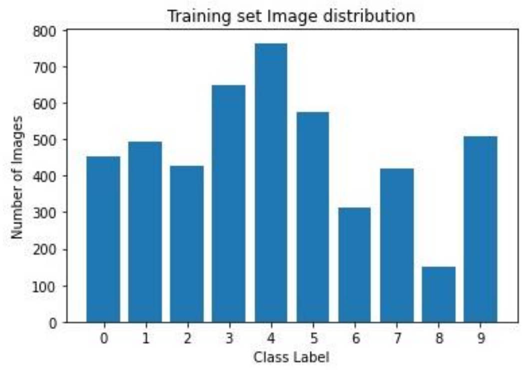

Fig.20.Training set.

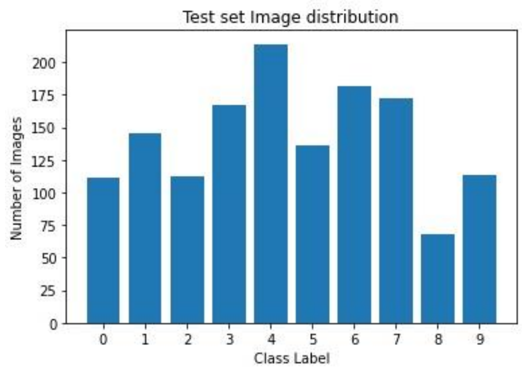

Fig.21. Test set.

The number of patches in the training, validation and test set are as shown in the Table.

Table 5. Sclera Periocular Patches.

Class Label	0	1	2	3	4	5	6	7	8	9
Training Patches	454	493	428	648	764	573	314	420	151	509
Validation patches	113	123	106	162	190	143	78	105	37	127
Test Patches	111	146	112	167	214	136	182	172	68	113

A. The Training, Validation Accuracy and Loss of the Sclera-periocular

Data set is as shown in the Figure 22 and Figure 23The training accuracy is 97.13% and the validation accuracy is 84.73 %. The training loss is 0.0751 and the validation loss is 0.6642. The crazy and loss curves indicate an improvement when compared with sclera and periocular classifications. from the curves we can observe that there is little bit of overfitting of the patch data set. This overfitting of the patch image data set can be resolved by increasing the number of patches in the data set and reducing the size of the image patch.

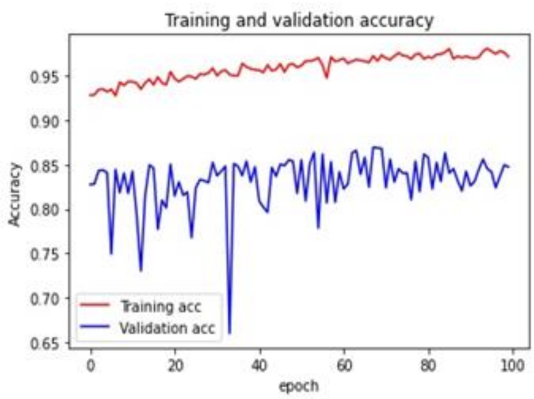

Fig.22. Accuracy.

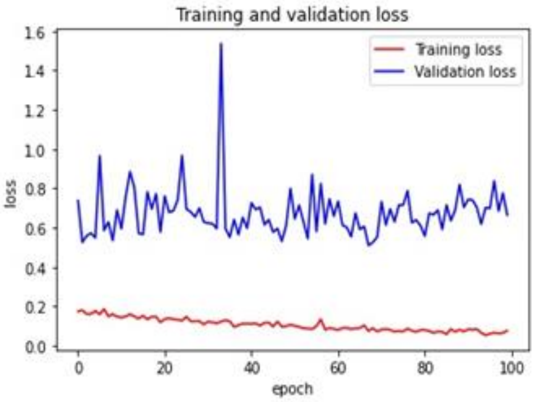

Fig.23. Loss.

B. Confusion Matrix

Figure 24 Indicates the confusion matrix of fused sclera periocular patches. The number of correct classifications for class 10 is 64, number of mis-classifications such as class 2 is 10, class 5 is 2 and class 7 is 3. The performance of classification of patches in this combine model has improved.

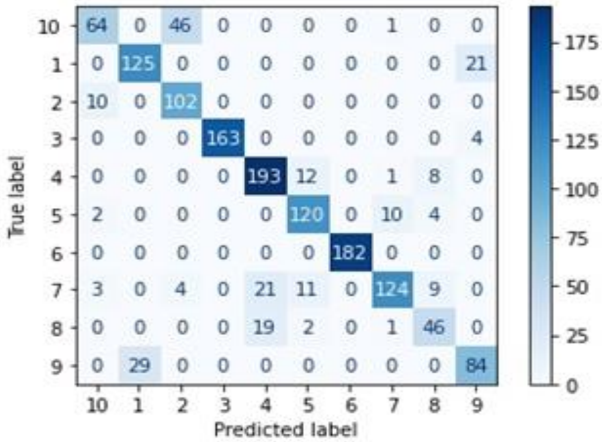

Fig.24. Sclera Periocular Confusion Matrix.

C. Classification Metrics

The performance of the proposed CNN model for sclera and periocular data set is as shown in the table with the help of precision, recall and F1 score.

Table 6. Classification Metrics.

Image Labels	Precision	Recall	F1 Score	Support
1	0.73	0.73	0.73	45
10	0.67	0.96	0.79	1
2	0.89	0.82	0.85	89
3	0.97	0.96	0.97	122
4	0.98	0.98	0.98	45
5	0.61	0.80	0.69	45
6	0.86	0.73	0.79	44
7	0.74	0.92	0.82	89
8	0.79	0.55	0.65	56
9	0.92	0.41	0.57	56

8.4. Comparison of Sclera, Periocular and Sclera Periocular

A. Accuracy

The accuracy of sclera, periocular and sclera_Periocular fusion training accuracy is as shown in the Figure 25. From the curves, the sclera-Periocular fusion performs better when compared with individual sclera and periocular Classifications. All the three models are trained for 50 epochs, with batch size 16. The implementation of the proposed model is carried out in google colab with GPU.

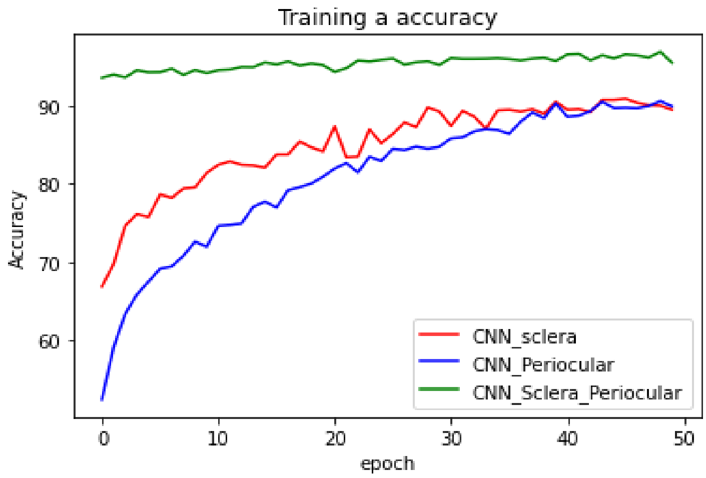

Fig.25. Accuracy of Proposed CNN sclera, Periocular and Sclera_Periocular.

B. Recall

Is the ratio of True positive to all positive classification.

$$\mathrm{Re}\,call = \frac{TP}{TP + FN} \quad (1)$$

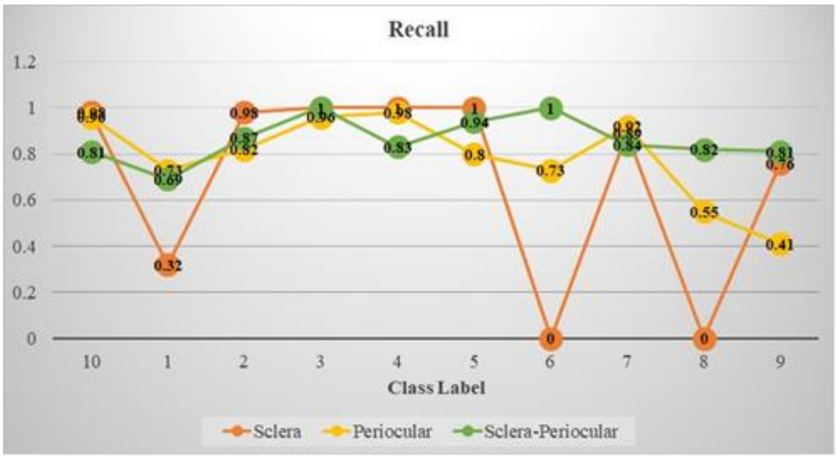

Fig.26. Recall of sclera, periocular and sclera-Periocular.

Figure 26 shows the comparison of recall values for the three models. From the graph it's clear that the sclera-periocular set performs well when compared with the other two data sets. The sclera has very few patches when compared with the other two data sets, for class 6 and class 8 the recall value is zero for the sclera model. The periocular model recall value is better than the sclera model. The recall value indicates the missed true positive cases

C. Precision

Is the ratio of true positives to the sum of all positive predictions. This metric denotes the exactness of the classifiers. Among all positive classifiers, what value is correctly classified as positive.

$$\mathrm{Pr}\,ecision = \frac{TP}{TP + FP} \quad (2)$$

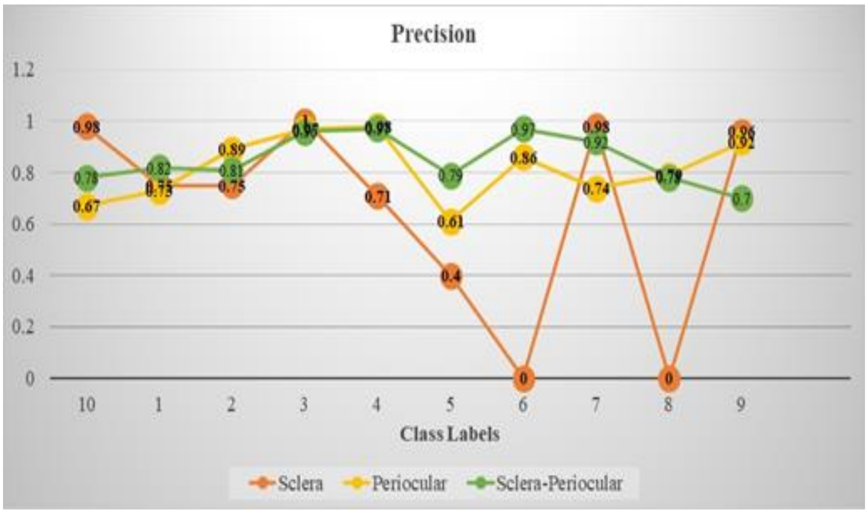

Fig.27. Precision of sclera, periocular and sclera-periocular.

The Precision value is a sign of the classification of True positive cases out of all the positive cases. As shown in the Figure 27 the Precision of sclera-periocular curve is better than sclera and periocular. The sclera-periocular model is able to identify the true classifications from the data set very efficiently when compared with the other two models.

D. F1 Score

Is the harmonic Mean of Precision and Recall. The F1 best score is 1.0 and the worst score is 0.0.

$$F1-Score = 2*\frac{\Pr ecision*\operatorname{Re} call}{\Pr ecision+\operatorname{Re} call} \quad (3)$$

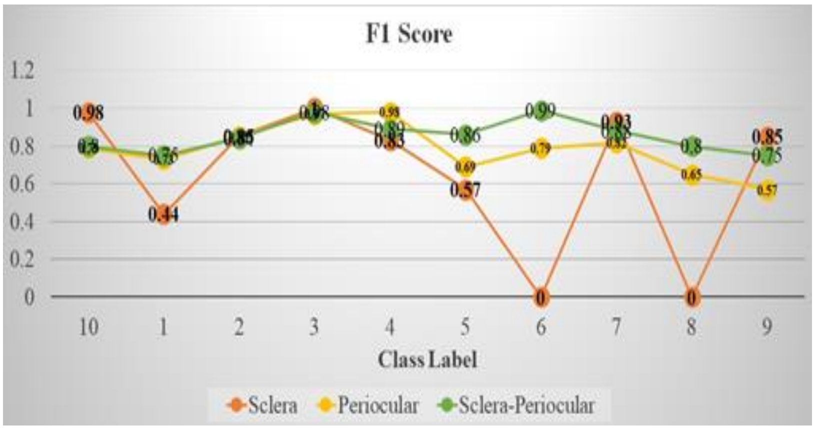

Fig.28. F1 score of Sclera, Periocular and Sclera-periocular.

F1 score is used to identify the performance of an imbalanced Data set with respect to Precision and recall values. F1 score is used to select an efficient model in deep learning. from the figure the F1 score of sclera- periocular model is better when compared with sclera and periocular models as shown in Figure 28.

9. Conclusions

In the proposed system the model has been trained individually for sclera and Periocular data sets. The performs of these data set are not accurate as the sclera vein pattern are few and if occlusions are present then very few sclera patches will be extracted. The fusion of sclera and periocular patches improves the proposed model accuracy. The model performs well for a combination of data sets with occlusions, eye makeup also. In this paper two set of images for each image class is considered. The number of samples in the data set can be increased for the proposed model. The performance of the CNN model can be improved based on the patch size chosen. For a patch size of 100x100 the accuracy is 97.32%, patch size of 50x50 the accuracy is 98.2% and for a patch size of 25x25 the accuracy is 99.3%. By decreasing the patch size, the accuracy increases but at the same time depends on the number of layers chosen in the CNN model. In this proposed system, Patch Size reduction is proportional to the number of layers in the model. A model invariant patch size can be a future scope. For a very large Sclera-Periocular Data Set which is of millions of patches, then the proposed Model has to be improved.

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