Published by :
http://www.ijert.org
International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 11 Issue 12, December 2022

Analysis of Epoch Length on the Classification of a Noisy Iris Biometric System

*Preeti Gupta[1], Naveen Aggarwal[2], Renu Vig[3]
[1,3] ECE department,
[2] CSE department,
UIET, Panjab University,
Chandigarh,India

Abstract— **Iris recognition is one of the many Biometric systems used for persons personal identity supported on their particular iris attribute, which are incomparable characteristic for each individual. It is lucid that the development in deep learning exhibit that convolutional neural networks (CNNs) extracted attributes are efficient enough to depict the complex structure of images. Due to poor focus, lateral view, movement blur, s and other artifacts and under undesirable conditions, quality of image can be severely affected . Noisy iris images add on intra-individual fluctuation, which evidently decreases recognition accuracy. To surmount these difficulties, we suggest a newfound iris recognition algorithm supported on deep learning for the iris images degraded by noisy factor and examine the final result of epoch length on it.**

Keywords—Ubiris, Epochs, CNN, Alexnet, Accuracy, Stochastic Gradient Descent (SGD)

I. INTRODUCTION

For effective biometric recognition, there has been an endless challenge to check the continuous changes in human traits, reason may be external or internal. There is a number of biometrics, such as face, fingerprints, etc which gets affected by the internal factors, such as aging, expression, etc. while the iris biometrics is able to handle these factors. So, the use of iris biometrics has drastically increased as it offers uniqueness, stability and non-evasiveness [1]. On the other hand, the performance of iris biometrics is limited by the external factors, such as the quality of images, illumination, resolution, noise, etc [2], [3]. Quality images and impressive accuracy in terms of low error rates is possible to obtain under several constraints like rigid image capturing [4]. When the images do not have enough quality, the reason may be focus, brightness or contrast these error rates increase substantially [5]. Many authors commonly identified this problem, which has been addressed in this paper.

II. NETWORK ARCHITECTURE

AAs per literature, according to the need of the user, the number of approaches exist that use the major information present in the image by feature extraction and/or feature selection to perform information processing [1], [6], [7], [8]. In comparison with the traditional methods of feature extraction, better accuracy and application results can be achieved using deep-learning models [9]. In the present paper, a deep learning technique utilised to take out the information from noisy dataset (iris) and an effective iris recognition system is designed. Figure 1 represents the basic model architecture [10] of the CNN (convolutional neural network) .

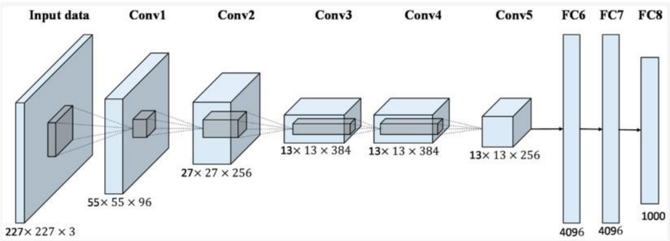


Figure 1: Architecture for proposed model [10]

The feature extraction of the iris image is carried out by deep learning model. The pre-processing step for the model is to resize the images to 227x227x3 so that they can be fed as an input to the network. It consists of 25 layers with 5 convolutional and 3 max-pooling layers. The simulation is carried out in the MATLAB 2019a environment.

III. DATASET USED

UBIRIS v1 is a database of noisy iris images, that is used for the proposed model to develop the robust iris recognition system [11]. In September 2004, in 2 well-defined sessions, around 1877 images are acquired from two hundred forty one persons. There are 241 classes in the first session of image capture. Noise factors are minimized, particularly reflections, contrast and luminosity during the enrollment by installing the framework of image capture inside a dark room.

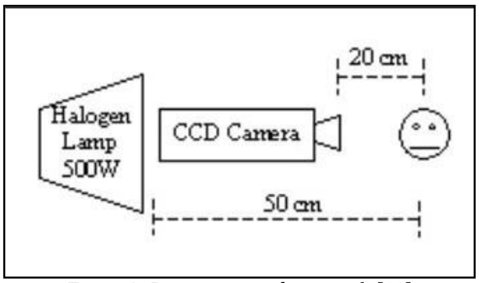


Figure 2: Image capture framework [11]

For the second session, there are 132 classes and natural luminosity factor is introduced in the images by changing the place of capture framework. This will result in the creation of diverse images in context to the reflections, focus, luminosity and contrast problems. Thus, several noise components are present in these images which will be used for recognition.

IV. RESULTS AND DISCUSSION

In the section 2 we discussed the network against UBIRIS database [11]. In this section, simulated results achieved by the proposed model have been discussed.

a. HYPER-PARAMETERS USED

The model has a learning algorithm and a number of hyper-parameters. To update the model an iterative learning algorithm called Stochastic Gradient Descent (SGD) uses a training dataset [12]. The batch size controls the number of training samples is a hyper-parameter of gradient descent and works before the model's internal parameters are updated. Its value is taken as 10. A training dataset have numerous rows of a feature vector. The learning rate is taken as 1e-4. The number of epochs is a hyper-parameter. It defines how many times the learning algorithm will work through with the whole training dataset.

In actual, how many times training algorithm will run that depends upon factors like no. of classes, no. of epochs. The total number of iterations value is a range of hundreds or thousands and it runs till the incorrectness from the model is decreased to adequate value, as given in Table 1.

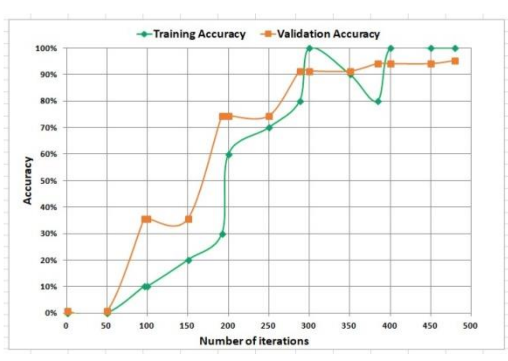
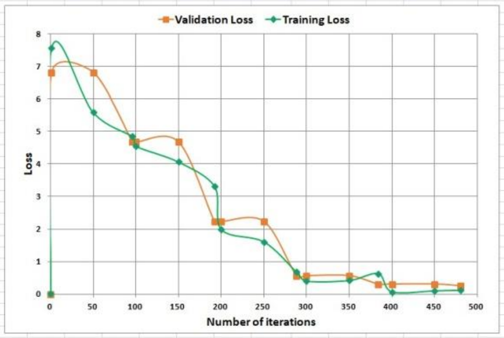
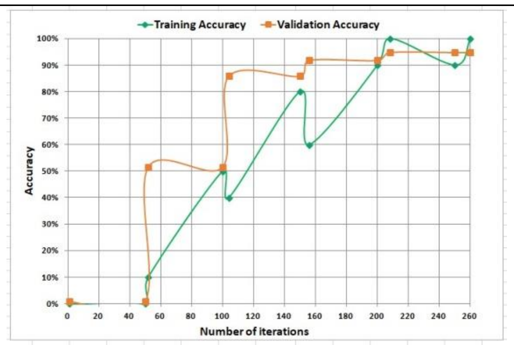
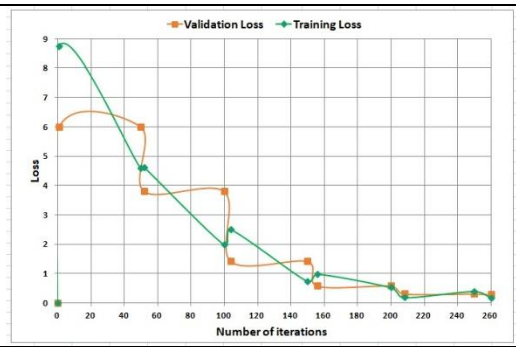
Table 1: Details of different sessions for UBIRIS v1 database

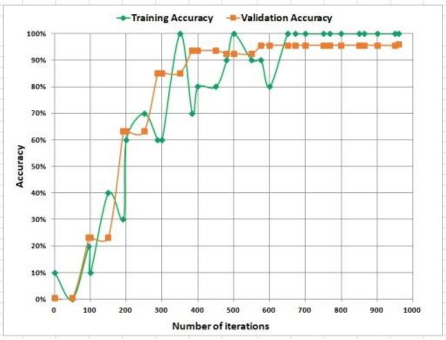
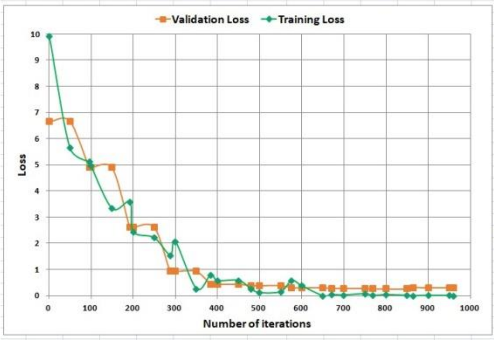
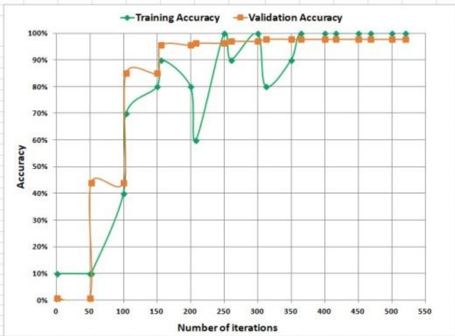
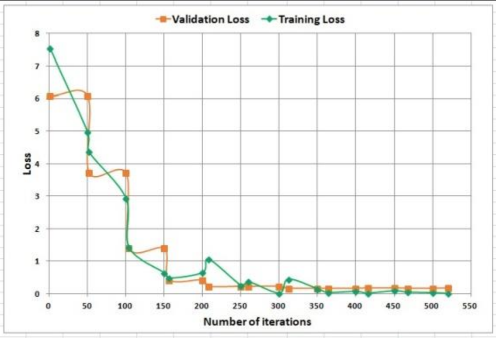
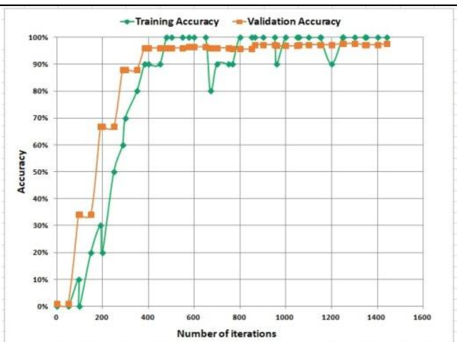
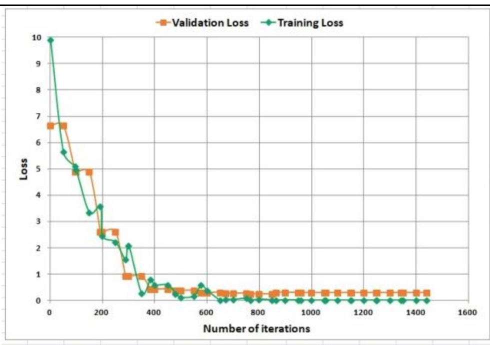
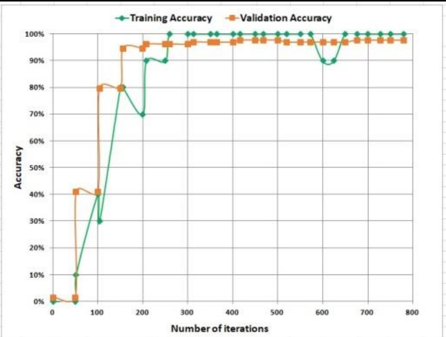
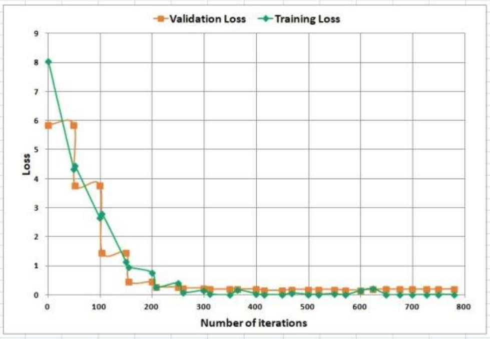
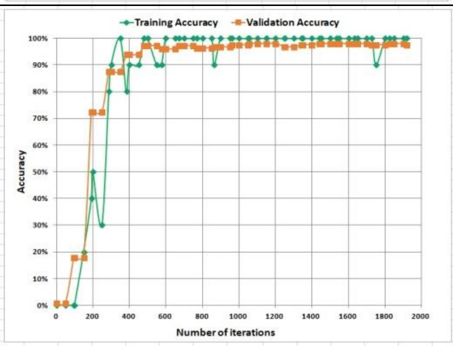
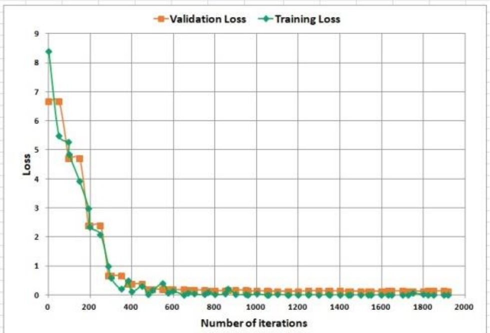
Session-1 (with minimized noise) 241 classes		Session-2 (with significant noise) 132 classes	
No. of epochs	**No. of iterations**	**No. of epochs**	**No. of iterations**
5	480	5	260
10	960	10	520
15	1440	15	780
20	1920	20	1040

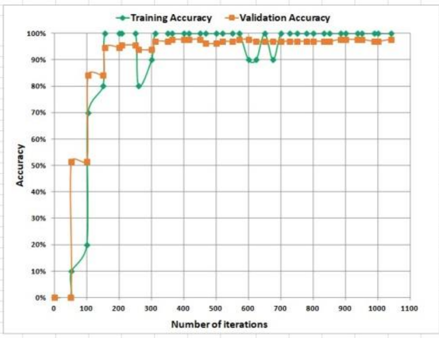
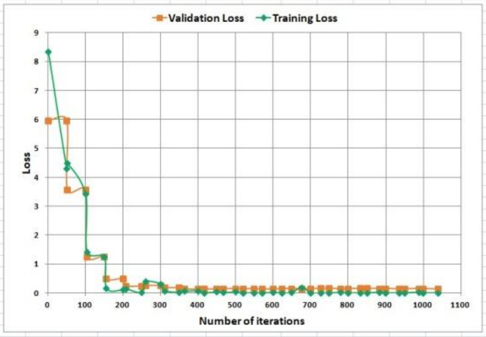
b. LEARNING CURVES

The learning curves are shown in Table 2, for different values of epochs and two sessions of UBIRIS dataset. Different values of epoch lengths are taken for both the sessions and accordingly the performance of the network is obtained by using the accuracy of training and validation phase. Similarly, considering training and validation loss as the evaluation metrics as shown in Table 2.

Table 2: Learning curves for different sessions of UBIRIS v1 database

Number of epochs	Training and Validation Accuracy	Training and Validation Loss
Epochs=5 Session-1		
Epochs=5 Session-2		
Number of epochs	**Training and Validation Accuracy**	**Training and Validation Loss**

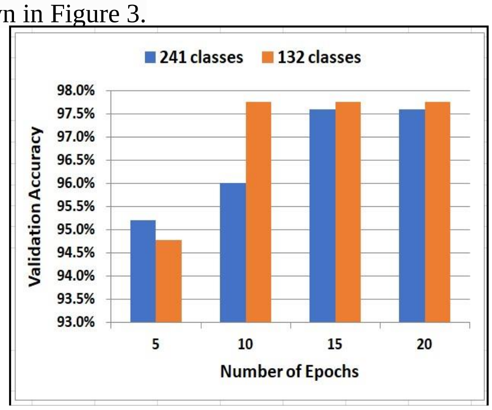
<table>
<tr><td>Epochs=10
Session-1</td><td></td><td></td></tr>
<tr><td>Epochs=10
Session-2</td><td></td><td></td></tr>
<tr><td>Epochs=15
Session-1</td><td></td><td></td></tr>
<tr><td>Epochs=15
Session-2</td><td></td><td></td></tr>
<tr><td>Epochs=20
Session-1</td><td></td><td></td></tr>
<tr><td>Number of epochs</td><td>Training and Validation Accuracy</td><td>Training and Validation Loss</td></tr>
</table>

Epochs=20 Session-2		

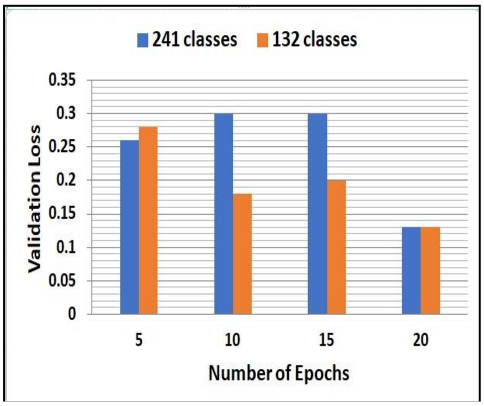
This indicates that the proposed method is adequate for less constrained image capture environments, such as non-cooperative environments, and extends the range of areas where iris recognition can be applied.

c. EFFECT OF EPOCH LENGTH

This section gives a comparative analysis of the validation accuracy as well as validation loss to the number of epochs, as shown in Figure 3.



(a) No. of epochs vs. validation accuracy



(b) No. of epochs vs. validation loss

Figure 3: Performance analysis versus number of epochs

It can be seen from the results that as the epoch length increases, the accuracy also increases. Beyond a certain point, the values remain same, thereby showing that they represent the optimum values for that system. For the figure, the optimized value of epochs is 20 for noisy iris database.

V. CONCLUSION

In this paper, we highlighted the issues connected to the presence of noise in acquired iris images and the comparable increase in error rate, with special reference to false positives, in the context of non-cooperative iris recognition. Popular feature extraction methods mainly concentrate on the low and mid-low frequency components of a signal. It shows small portion of unobserved interference can vitiate the entire biometric signature and reduce identification accuracy. On the basis of this, a new robust iris recognition system was proposed with high accuracy. The computer simulation experimentation on the iris database, UBIRIS v1 shows that the proposed methodology provides a highly efficient and robust system for real-time applications.

REFERENCES

[1] J. J. Winston and D. J. Hemanth, "A comprehensive review on iris image-based biometric system," *Soft Comput.*, vol. 23, no. 19, pp. 9361–9384, Oct. 2019, doi: 10.1007/s00500-018-3497-y.

[2] S. Bharadwaj, M. Vatsa, and R. Singh, "Biometric quality: a review of fingerprint, iris, and face," *EURASIP J. Image Video Process.*, vol. 2014, no. 1, p. 34, Dec. 2014, doi: 10.1186/1687-5281-2014-34.

[3] J. Daugman, "Recognising Persons by Their Iris Patterns," in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 3338, 2004, pp. 5–25. doi: 10.1007/978-3-540-30548-4_4.

[4] T. Tan, Z. He, and Z. Sun, "Efficient and robust segmentation of noisy iris images for non-cooperative iris recognition," *Image Vis. Comput.*, vol. 28, no. 2, pp. 223–230, Feb. 2010, doi: 10.1016/j.imavis.2009.05.008.

[5] H. Fathee and S. Sahmoud, "Iris segmentation in uncooperative and unconstrained environments: State-of-the-art, datasets and future research directions," *Digit. Signal Process.*, vol. 118, p. 103244, Nov. 2021, doi: 10.1016/j.dsp.2021.103244.

[6] F. Jan, "Segmentation and localization schemes for non-ideal iris biometric systems," *Signal Processing*, vol. 133, no. July 2016, pp. 192–212, Apr. 2017, doi: 10.1016/j.sigpro.2016.11.007.

[7] K. Nguyen, H. Proença, and F. Alonso-Fernandez, "Deep Learning for Iris Recognition: A Survey," *Comput. Vis. Pattern Recognit.*, vol. 1, no. 1, pp. 1–35, Oct. 2022, doi: https://doi.org/10.48550/arXiv.2210.05866.

[8] D. T. U. Virtusio, F. J. D. Tapaganao, and R. G. Maramba, "Enhanced Iris Recognition System Using Daugman Algorithm and Multi-Level Otsu's Thresholding," in *2022 International Conference on Electrical, Computer and Energy Technologies (ICECET)*, Jul. 2022, no. June, pp. 1–6. doi: 10.1109/ICECET55527.2022.9873032.

[9] M. De Marsico, A. Petrosino, and S. Ricciardi, "Iris recognition through machine learning techniques: A survey," *Pattern Recognit. Lett.*, vol. 82, pp. 106–115, Oct. 2016, doi: 10.1016/j.patrec.2016.02.001.

[10] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet classification with deep convolutional neural networks," *Commun. ACM*, vol. 60, no. 6, pp. 84–90, May 2017, doi: 10.1145/3065386.

[11] H. Proença and L. A. Alexandre, "UBIRIS: A Noisy Iris Image Database," in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 3617 LNCS, 2005, pp. 970–977. doi: 10.1007/11553595_119.

[12] Y. Liu, Y. Gao, and W. Yin, "An Improved Analysis of Stochastic Gradient Descent with Momentum," *Adv. Neural Inf. Process. Syst.*, vol. 2020-Decem, no. 2, pp. 1–11, Jul. 2020, [Online]. Available: http://arxiv.org/abs/2007.07989