

Multi-Modal Biometric Recognition for Face and Iris using Gradient Neural Network (Gen-NN)

S. Sai Satyanarayana Reddy^{1*}, Harikrishna Bommala¹, Sakthidharan G R², Nikolai Ivanovich Vatin³

¹Department of CSE, KG Reddy College of Engineering & Technology, Moinabad, Hyderabad, Telangana, India

²Department of CSE, GRIET, Hyderabad, Telangana, India

³Lovely Professional University, Phagwara, Punjab, India.

Abstract. In recent years, Biometric system are the one, which is widely used method for the recognition and identification of an individual that are highly demanded approach for its absolute security and accuracy which plays a vital roles in banking, commercials, business and other fields. Moreover this research is based on the multimodal biometrics which is recommended for its high recognition performances and it overcome the demerits of unimodal biometric approach. This research concentrate two multi-modal biometric traits such as face and iris, and propose Gradient Neural Network (Gen-NN) method to improve the biometric authentication by using the VISA face and iris multi-modal biometric database also used ResNet-101 and WaveNet for the feature extraction where the input of face and iris can be extracted.

1 Introduction

The main aim of biometric security is to secure the information from an unauthorized person based on pattern recognition, which requires biometric data from every individuals, based upon physical and behavioral characteristics [11-13] [1]. Early days the traditional authentication methods such as creating passwords, account number are very much used and these such methods cannot provide security compared to biometric security [2]. In recent times, biometric security plays a vital role in all over the world. Biometric means the involving of automated recognition of individuals based on the unique physical characteristics such as iris, finger prints and behavioral characteristics such as voice , signature and they typically used for the purpose of security[14][4]. Compared to the traditional approach, biometric recognition has various merits as, the information of authorized person cannot be stolen by the unauthorized person [2]. The biometric features can be classified into two groups such as extrinsic traits and intrinsic traits. The extrinsic biometric traits are iris and finger prints, and the intrinsic biometric traits are palm vein and finger vein. The intrinsic traits cannot affect the external factors because they are not visible

* Corresponding author: saisn90@gmail.com

meanwhile the extrinsic traits can affect the external factors because they are visible [15] [4]. Recently, biometric security is the one, used in many domains such as healthcare, social network applications, cloud computing, bigdata and homeland security [16] [1].

Due to high demand in various fields, multi-modal biometric technologies are used and that helps for providing better accuracy, universality and security [20, 17] [1]. The multi-model biometric recognition system increases the reliability of decisions and the robustness to the fraudulent technologies [25] and achieved at sensor-level [30], feature level [21, 24, 27, 28, 29], score-level [11, 22], rank level [19, 23] and decision-level [18, 26], respectively corresponding to image acquisition, feature extraction, score matching and decision stage [3]. The multi-modal biometric are highly equipped by combining various single biometric verification techniques, and amassing the merits that accomplish the efficiency of the system and attain further strong techniques [31] [7]. In biometric technology, the mainly used and acceptable technology is the one, extracted from the finger due to its flexibility, imaging simplicity and other feature reliabilities [16, 17] [1]. There are four patterns can be used for biometric from the finger are finger vein (FV), finger prints (FP), finger knuckle print (FKP) and finger shape. For penetration, FP and FKP patterns are imaged by the reflecting visible light source and the FV images are visible by the near infrared (NIR) light [31] [5].

Machine Learning algorithms are used for some extraction techniques that helps to take out the raw biometric transformation into somesuitable formats. Sometimes these approaches cannot cope with the biometric image transformation. The non-deep learning methods include sub-learning based methods [23,24], code based techniques [25-29] and other local feature based methods [10-12] are incapable to achieve satisfactory results [5]. Optimization threshold techniques are used for the decision levels and did not achieved several biometric features like single fusion part, the universality properties. The system of traditional biometric has four segments they are pre-processing, feature extraction, matching and decision making components, here, the feature extraction method crucially affect the system. Recently deep learning approaches made a huge impact on biometric technologies and gives appropriate results [23-31] [4]. The multi-model based biometric finger vein, face, iris and palm recognition were implemented using deep learning. Here the deep learning algorithm improved the recognition performance using convolutional neural network (CNN) and transfer learning in the biometric system [13, 21]. The CNN is used for the lively detection and utilizes the datasets for the effective classifier performance. CNN and support vector machine (SVM), classifiers are used in the uni-model and multi-model face and iris detections [1].

This paper presents the multi-modal biometric recognition for face and iris by using Gen-NN algorithm and feature mapping. In order to develop the recognition using multi-modal biometrics, the pre-trained modal ResNet-101 and the WaveNet are used in this research that helps to extract and classify the face and iris image from the pre-processed method, here Gabor and the Discrete Wavelet Transform (DWT) method are the combination of wavelets used in this proposed modal. The pre-processing methods include filtering, geometric normalization, and illumination normalization for face image that apply smoothness and reduce unwanted noise from the image and for the iris image, pre-processing methods include background removal, normalization and enhancement contrast are used to adjust the images pixel qualities. The visa face multi-modal biometric database [15] is the database used in this proposed modal. The contribution of this research can be summarized as follows

- A face image recognition method extracts or identify the facial features from the input image and for iris image recognition, the image quality is segmented and determined a unique patterns by using deep neural networks

- Gen-NN method for deep learning classification system is employed for both iris and face biometrics.
- Feature mapping for face and iris biometrics are also classified and the ResNet-101 extraction used for face biometric and the wavenet extraction is used for Iris biometric which is done by using the combination of Gabor and DWT wavelets.

The article is organized as, section 2 contains the related works, section 3 contains challenges of former methods, section 4 give the objectives of the proposed method, section 5 describes all methods involved in the recognition of the face iris biometric, section 6 elaborates the results obtained through the proposed research, and section 7 states the conclusion and the future works.

2 Literature review

Daas S, Yahi A, et al [1] developed multi-modal biometric recognition using deep learning based on finger vein and finger knuckle print fusion using AlexNet, VGG16 and ResNet50 datasets. This modal improved the recognition pattern in various fields such as medical, computer vision and gave better performances, but the user privacy for the facial recognition is limited. Wang Y, Shi D, et al [2] utilized Convolutional Neural Network(CNN) method for biometric recognition using AlexNet and VGG-19 datasets and build ROC and P-R curve for better performances. This method cannot be applied in mobile embedded terminals. Zhou C, Huang J, et al [3] used hybrid fusion method for biometric recognition using CASIA, PolyU and SDU datasets and achieved the average accuracy in multimodal biometric system, about this method needed improvement for higher and more stable performances. Alay N, Al-Baity HH [4] developed multi-model recognition using deep learning with SDUMLA-HMT datasets outperformed and achieved maximum accuracy using biometric traits, but during multiprocessing, the image detection required more time. Li S, Zhang B, et al [5] used local coding based convolutional neural network with our-tri and SD-tri datasets which reduced the high parameters and improved the computational efficiency, but it required large training data and computational power. Babalola FO, Bitirim Y, et al [6] developed binarized Statistical Image Features(BSIF) descriptor and CNN with CASIA, FYO, PUT, VERA and Tongji datasets, here the score level fusion method is used for palm vein recognition and achieved high accuracy, but the method cannot be implemented in hand dorsal vein and wrist vein biometric authentications.

2.1 Challenges

The challenges of former methods for multi-model biometric are as follows,

- In CNN, the feature level fusion is not implemented that is used for authentication and identification in the biometric materials [9].
- The hybrid fusion method needed some improvements to achieve higher and more stable performance [3].
- In deep learning approach, there are several multiprocessing steps required for image detection which cause more time [4].
- BSIF method cannot be implemented in hand dorsal vein and wrist vein biometric authentication [6].
- LC-CNN method requires large training data and computational power to train the data which requires more memory storage space [5].

3 Proposed Methodology

For personal identification system, several biometric indicators are used for the identification of an individual using multi-modal biometrics. In unimodal biometrics, it has only one biometric data (ie., finger print or face or palm prints or iris), but in multi-modal biometrics, it contains the combination of two or more biometric data that helps to improve the performance results and prevent from unauthorized users and reduce the False Acceptance Rate (FAR).

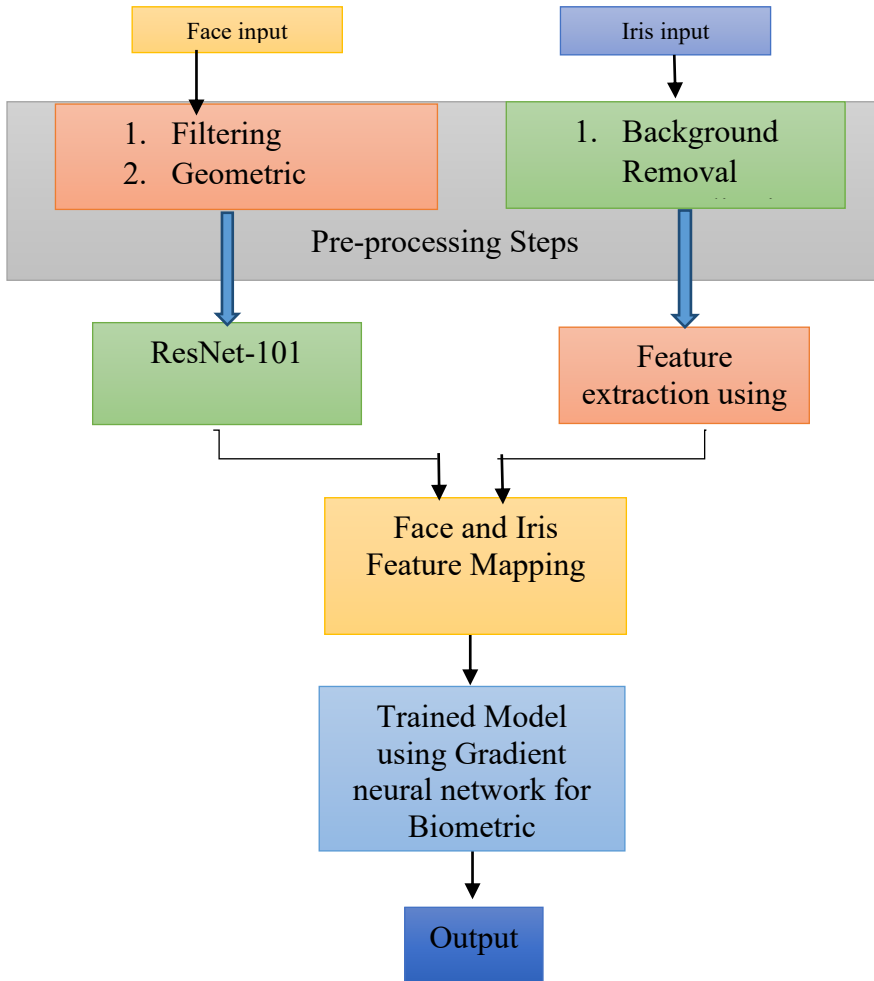


Fig. 1. The framework of the proposed model

These systems are capable of utilizing multiple physiological or behavioral characteristic features of a person for enrollment, identification or verification process. Multi-modal authentication has more number of levels of authentication compared to unimodal authentications. The multi-modal system overcome the limitations such as noisy data, intra class variations, non-universality, unacceptable error rates and spoof attacks in

unimodal approach. Here, the development of a multi-modal biometric system is based on the combination of face and iris biometrics.

The main aim of this research is the recognition of a person with the multi-model biometrics using face and iris. This proposed model is highly recommended for the approach to secure the information from the unauthorized person. For the face input dataset, it undergoes several preprocessing steps such as filtering process, geometric normalization and illumination normalization and for the iris input dataset, it undergoes background removal, normalization and enhancement contrast. After the completion of preprocessing steps, then the pre-processed images undergoes feature extraction processes using wavenet and RESNET-101 descriptors in which the raw image is transformed into features that preserve the information in the original datasets without any alternations. Then the feature apping process is done that will form the input to the gradient neural network that recognizes the person based on their multimodal biometrics. The classifier classifies the images and capture better underlying patterns in the data. Here the Gradient Neural Network is used to measure the changes in the biometric patterns with regard to change in error of the multi-modal biometric. The dataset considered is VISA dataset [25].

3.1 Input Dataset

The visa face and iris multimodal biometrics database [15] is used in the proposed system, which contains 12 subsets that corresponds to the 12 different objects and holds 10,821 images with 9,621 normal and 1,200 anomalous samples. Let us take input from the dataset

as $D = [F, I]$, where F represented as face image and I represent as iris image. The face and iris image can be written as,

$$F = \{F_1, F_2, \dots, F_i, \dots, F_n\} \quad (1)$$

$$I = \{I_1, I_2, \dots, I_i, \dots, I_n\} \quad (2)$$

From the above equation, F_i denote the i^{th} value of face image from the dataset and I_i denote the i^{th} value of iris image from the dataset and where, F_n and I_n denotes the total number of face images and iris images from the dataset.

3.2 Pre-Processing

In preprocessing, the filtering method, geometric normalization and illumination normalization are used for the face input in which, the filters are used to smoothing or changes the pixel values of an image and gives enhanced images. The geometric normalization performs the contrast adjustments to the images and the illumination normalization will reduce the variations in the facial images. For iris, background removal, normalization and enhancement contrast process is done where, the background removal process is also called semantic segmentation, in which it removes the unnecessary noise from the background and the normalization method divides the image into each pixels and the enhancement contrast process adjust the image into relative grey-scale levels to improve the visibility. The above equation (1) & (2) undergo pre-processing method and give,

$$F = \{F_1^p, F_2^p, \dots, F_i^p, \dots, F_n^p\} \quad (3)$$

$$I = \{I_1^p, I_2^p, \dots, I_j^p, \dots, I_n^p\} \quad (4)$$

Where F_i^p and I_j^p denotes the pre-processed face image and iris image. Here we take i^{th} value as an input image for both iris as $F_i = F_i^p$ and face as $I_j = I_j^p$ from the dataset.

3.2.1 Feature Extraction

The feature extraction method extract the key features from the pre-processed face and iris image, where the raw images of face and iris are modified into number of features by using ResNet-101 and WaveNet features. This extraction helps to provide an accurate recognition or identification of an authorized person.

3.2.2 ResNet-101 for face features

The resNet-101 is a CNN based network which contains 101 deep convolutional layers in the neural network that is made up of 33 and 29 layer blocks that are directly employed in previous blocks. It is a pre-trained neural network that extracts from the face image and classifies it into 1000 number of object categories and requires 224 x 224 size of input model also 155 MB allocated memory space. This method produce significant results and beat up VGG-16 several experiments. The pre-processed face image then undergo the ResNet feature extraction and give the value as $F_i^p = R_i$ here, R_i denote the face image in which the key features are extracted by ResNet method.

3.2.3 WaveNet for iris features

The WaveNet is a deep convolutional neural network (DCNN), in which, it takes the average frequency of a raw image data from the pre-processed iris input and extracts the specific values, which is encoded and quantized using two methods, such as Gabor wavelet and Discrete Wavelet Transform (DWT). The combination of Gabor and the DWT wavelets are known as WaveNet.

a) Gabor wavelet: The Gabor wavelet filter, decomposing the signal using quadrature pair with real part and imaginary part also known as even and odd symmetric components whereas, the even symmetric is represented as cosine and the odd symmetric is represented as sine and the frequency center is represented as sine/cosine. A Gabor wavelet filter for two dimension over the image domain (a, b) is represented as

$$G_w(a, b) = e^{-\pi[(a-a_0)^2/\gamma^2 + (b-b_0)^2/\eta^2]} e^{-2\pi i[x_0(a-a_0) + y_0(b-b_0)]} \quad (5)$$

Here, (a_0, b_0) denotes the position of an image, where γ, η denotes the effective length and width of the image and (x_0, y_0) denotes the specific modulation in which the spatial

frequency of this modulation can be written as $z_0 = \sqrt{x_0^2 + y_0^2}$.

To demodulating the output from the Gabor filter for compressing the data, Daugman [60], [61], [62] [59] method is used, which is done using quantizing the phase details into four different levels of each complex phase. For normalization, Daugman method uses polar coordinates which is given as,

$$D(q, \rho) = e^{-j\omega(\rho-\rho_0)} e^{-(q-q_0)^2/\gamma^2} e^{-(\rho-\rho)^2/\eta^2} \quad (6)$$

The demodulation and the quantizing of phase process can be written as,

$$d_{\{Re,Im\}} = \text{sgn Re, Im} \int u \int \phi I u, \phi e - j \omega \rho 0 - \phi e - q 0 - u 2 e - p 0 - \phi 2 u v u v \phi \quad (7)$$

Here (γ, η) represents same as that of in (5) which is the effective length and width of the image and (q, ρ) denotes the frequency center of the filter. Where, $d_{\{Re,Im\}}$ is denoted as a complex valued bit where the imaginary and real components are dependent on the sign of 2D integral and $I(u, \phi)$ denote the raw iris image in dimensionless polar coordinate system. The feature extraction with log Gabor wavelet can wrap a large amount of frequency space that maintain a Zero DC component in an even filter that will not affect the extraction and the log Gabor wavelet function can be written in the form as,

$$g(t) = e^{\frac{-(\log(t/t_0))^2}{2(\log(\theta/t_0))^2}} \quad (8)$$

Whereas the given t_0 is denoted as the frequency center of the filter and θ denoted as the bandwidth of a filter. Let the $I(a, b)$ denotes the iris image where V_m^r and V_m^s indicates the cosine ie., even symmetric and sine ie., odd symmetric wavelets of a scale m , then the quadrature pair of filters form a response vector that is,

$$[k_m(a, b), Q_m(a, b)] = [I(a, b) * V_m^r, I(a, b) * V_m^s] \quad (9)$$

The transformation of amplitude of a wavelet is given by,

$$A_m(a, b) = \sqrt{k_m(a, b)^2 + Q_m(a, b)^2} \quad (10)$$

Then the phase is given as,

$$\phi_m = T \tan^2(k_m(a, b), Q_m(a, b)) \quad (11)$$

Here the given $A_m(a, b)$ is an amplitude and ϕ_m is an angle phase. When the phase extraction happens, the iris image divides it into n by m of blocks in which the data from each block is encoded into 2-bit codes, and therefore the 2-bit codes describes each of codes and $2nm$ bits describes the whole iris.

b) Discrete Wavelet Transform: DWT is one of the WaveNet extraction in which, introduces the low redundancy and improve the directionalities in the iris dataset. The authentication using DWT is faster than any other approach and improves the iris based identification. As the name indicate, this technique is used to transform the image pixels into

multiple wavelets, that is defined as, $I_j^p = W_j$ here, W_j denote the iris image in which the key features are extracted by the WaveNet method.

3.2.4 Face and Iris Feature Mapping

In feature mapping method, the iris and face features extracted from the previous steps are then analyzed for the band identifications using the filter in order to match the feature classes. This mapping involves effective spotting of specific features from the input images in order to verify the uniqueness of a human iris and face. While undergo feature mapping, the face and iris images are defined as,

$$M = \{R_i \oplus W_j\} \quad (12)$$

Here, M denotes the mapped features of iris and face images.

3.2.5 Gradient Neural Network

The Gen-NN is an unsupervised learning approach that helps to train the modals using the face-iris mapped features, where the parameters are adjusted to achieve equal to or close enough to zero error. In order to minimize the error, Backpropagation is one of the dynamic method, which is used for training the model that captures the training parameters adaptively. The input vector undergoes several processes that depend on the weight and bias that can be $I = f(l, B)$ in which the dynamics of the interconnected networks of a neurons are connected dynamically of each neurons and synapse from the input vector,

$$\vec{B} = R\vec{h} + X\vec{i} + \vec{Y} \quad (13)$$

Here R denotes the recurrent connectivity weight matrix, X is the input weight matrix, $\vec{i}(t)$ denotes the input feature vector and \vec{Y} indicates the bias of the input vector.

3.2.6 Gradient calculation

The backpropagation utilizes the following dynamic modified ad-joint state of variables such as (k_l, k_h) can be written as,

$$-\dot{k}_l = \partial_l f k_l - g k_h \quad (14)$$

$$-\tau \dot{k}_h = -k_h + \xi \quad (15)$$

Here (k_l, k_h) are the modified ad-joints of l and h , where $\partial_l f \equiv \partial f / \partial l$ and ξ is the bias, in which the recurrently connected network of the bias has a following expression that merge with the backpropagation dynamics of each neurons,

$$\dot{\xi} = R^t (\partial_B \vec{f} k_l) + \partial_h d \quad (16)$$

From the equation (7) (8) and (9) of ad-joint state vectors, the sum of cost of a gradient neural network with regard to the neural network parameters are calculated as follows,

$$\nabla_R C = \int (\partial_B \vec{f} k_l) \vec{h}^T dt$$

$$\nabla_X C = \int (\partial_B \vec{f} k_l) \vec{i}^T dt$$

$$\nabla_Y C = \int (\partial_B \vec{f} k_l) dt$$

$$\nabla_Z C = \int (\partial_z d) \vec{h}^T dt$$

Where d denotes the cost function of a parameter, here the multiplication is included in the calculation of gradient in between the presynaptic input source and the postsynaptic ad-

joint state of k_l , that is extracted from the $g k_h$ has a similar coupling terms for the forward-propagating dynamic functions.

4 Performance Analysis

The performance analysis for recognition using multi-modal biometrics of face and iris image based on Gen-NN is analyzed with metrics such as accuracy, sensitivity, and specificity and carried out by the VISA dataset. The discussion below shows the analysis with varying epochs and constant training of 90%.

4.1 Performance analysis of accuracy using Gen-NN method

The performance analysis of Gen-NN is measured with accuracy and the values of the parameters vary with the epochs such as 100, 200, 300, 400, and 500 with the constant training percentage of 90%. The accuracy of a proposed method is 75.34%, 80.861%, 82.01%, 88.29% and 93.77% for the epochs 100, 200, 300, 400, and 500 respectively shown in Figure 2.

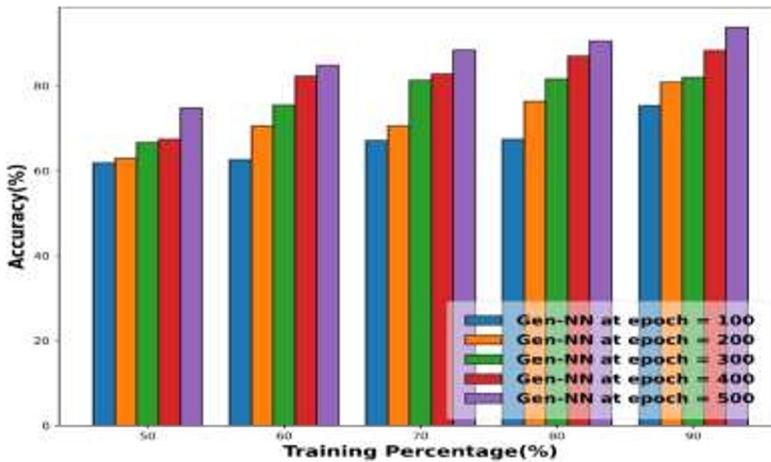


Fig. 2. Performance analysis of accuracy using Gen-NN method

4.1.1 Performance analysis of sensitivity using Gen-NN method

In Figure 3, the performance analysis of Gen-NN is measured with sensitivity and the values of the parameters vary with the epochs such as 100, 200, 300, 400, and 500 with 90% of constant training percentage. The accuracy of a proposed method is 71.93%, 79.81%, 82.85%, 89.03% and 91.82% for the epochs 100, 200, 300, 400, and 500 respectively.

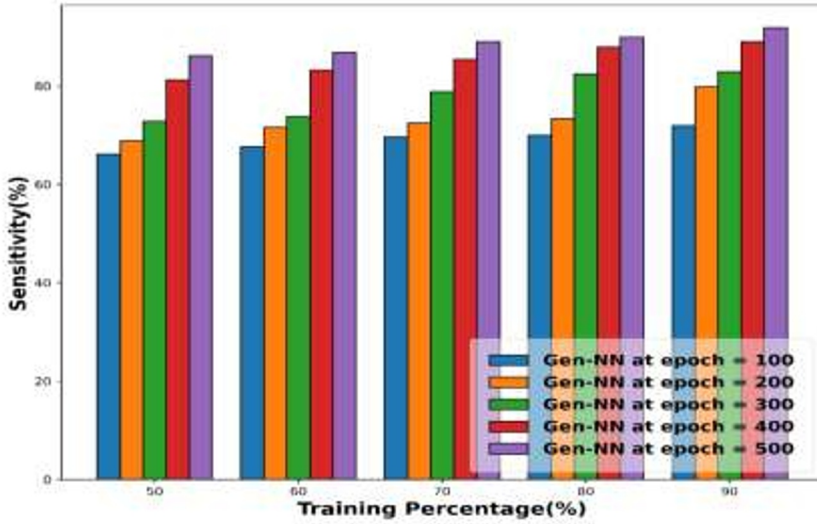


Fig. 3. Performance analysis of sensitivity using Gen-NN method

4.1.2 Performance analysis of specificity using Gen-NN method

The performance analysis of Gen-NN is measured with specificity and the values of the parameters vary with the epochs such as 100, 200, 300, 400, and 500 with 90% of constant training percentage. The specificity of the modal with epoch 100 is 76.06%, with epoch 200 is 81.21%, with epoch 300 is 84.74%, with epoch 400 is 88.11% and with epoch 500 is 91.99% which is shown in Figure 4.

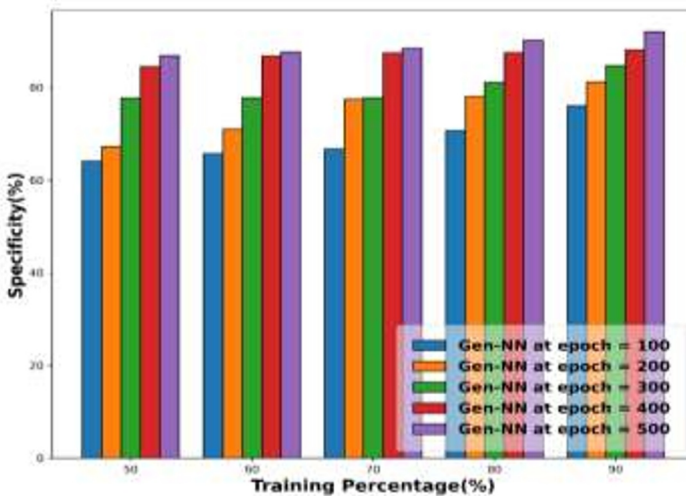


Fig. 4. Performance analysis of specificity using Gen-NN method

4.1.3 Comparative analysis

The comparative analysis of the proposed method of Gen-NN is evaluated with other certain methods such as Random Forest (RF) classifier, Decision Tree (DT) classifier, Deep Convolutional Neural Network (DCNN), long short-term memory networks (LSTM), Neural Network (NN) classifier, and Gen-NN

4.1.4 Comparative analysis of accuracy

The comparative analysis results with accuracy measure of proposed method with existing classifiers such as RF classifier is 62.18%, DT classifier is 63.57%, Deep CNN is 64.05%, LSTM classifier is 70.28%, NN is 71.478% and Gen-NN 75.11% with least training percentage of 50 and the accuracy with 90% high training percentage is 81.91%, 86.78%, 88.05%, 88.36%, 88.98%, and 93.83% for RF classifier, DT classifier, DCNN classifier, LSTM, and NN, which shows comparatively high accuracy for proposed method is shown in Figure 5.

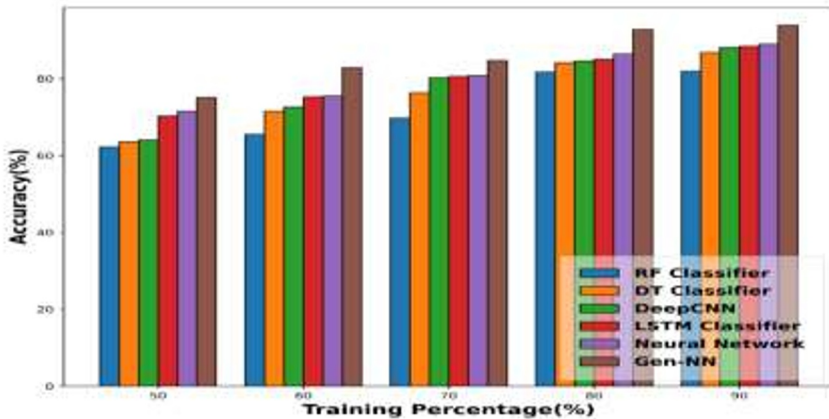


Fig. 5. Comparative analysis of accuracy

4.1.5 Comparative analysis of sensitivity

The comparative analysis results with sensitivity measure of proposed method with existing classifiers such as RF is 65.67%, DT classifier is 66.38%, Deep CNN is 68.395%, LSTM classifier is 73.19, NN is 73.39% and Gen-NN 75.11% with least training percentage of 50 and the sensitivity with the high training percentage of 90% is 88.65%, 89.55%, 92.57%, 93.01%, 93.15%, and 93.90% for RF classifier, DT classifier, DCNN classifier, LSTM, and NN, which shows comparatively high sensitivity for proposed method is shown in Figure 6.

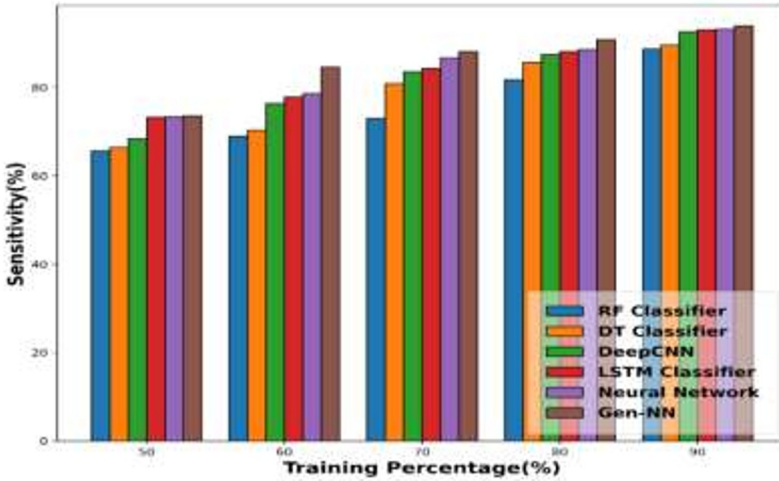


Fig. 6. Comparative analysis of sensitivity

4.1.6 Comparative analysis of specificity

The figure 7 shows the comparative analysis results of specificity measure of a proposed method with the existing classifiers such as RF is 63.14%, DT classifier is 63.62%, Deep CNN is 66.20%, LSTM classifier is 66.48, and NN is 66.87% with least training percentage of 50 and the specificity with the high training percentage of 90% is 78.61%, 85.55%, 87.47%, 90.96%, 91.16%, and 92.07% for RF classifier, DT classifier, DCNN classifier, LSTM, and NN which shows the proposed method performance is higher than the existing methods.

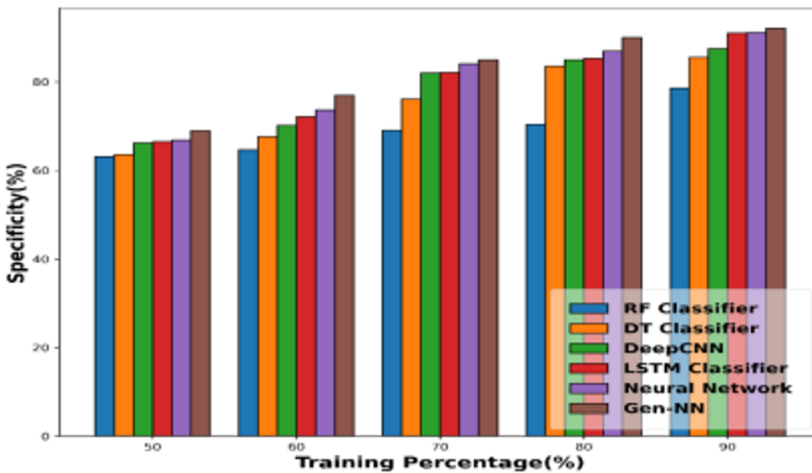


Fig.7. Comparative analysis of specificity

5 Conclusion

The proposed method of multi-modal biometrics using Gen-NN model for recognition using face and iris images are the effective and efficient method used for identifying the authorized person. The ResNet-101 and WaveNet are the feature extraction methods used for face and iris images that are very much useful for extracting the key features and reduces the over-fitting issues also gives less computational time. The proposed method gives the better accuracy, sensitivity and specificity as 93.77%, 91.82%, and 91.99% with the epoch 500 compared to the existing methods.

References

1. S. Daas, A.Yahi , T.Bakir ,M. Sedhane , Boughazi .M, Bourennane .EB, Multimodal biometric recognition systems using deep learning based on the finger vein and finger knuckle print fusion, *IET Image Processing*, **14**, 15 (2020)
2. Wang Y, Shi D, Zhou W, Convolutional Neural Network Approach Based on Multimodal Biometric System with Fusion of Face and Finger Vein Features, *Sensors* **22**, 16, (2022)
3. Chenyi Zhou, Jing Huang, Feng Yang, and Yaqin Liu, A hybrid fusion model of iris, palm vein and finger vein for multi-biometric recognition system, *Multimedia Tools Appl.* **79**, 39–40 (2020)
4. N.Alay, Al-Baity .HH, Deep learning approach for multimodal biometric recognition system based on fusion of iris, face, and finger vein Traits,*Sensors* **20**, 19 (2020)
5. Li. S, Zhang. B, Zhao .S, Yang. J,Local discriminant coding based convolutional feature representation for multimodal finger recognition,*Information Sciences, Information Sciences*, **547**, 1170-1181(2021)
6. FO. Babalola, Y. Bitirim , Ö .Toygar., Palm vein recognition through fusion of texture-based and CNN-based methods,*Signal, Image and Video Processing*, **15**,459–466 (2021)
7. PS .Chanukya, TK.Thivakaran, Multimodal biometric cryptosystem for human authentication using fingerprint and ear,*Multimedia Tools and Applications*, **79**, 659–673 (2020)
8. H. Shao , D. Zhong , Du .X, A deep biometric hash learning framework for three advanced hand based biometrics,*IET Biometrics*,**10**,3 (2021)
9. P .Shende ,Y. Dandawate , Convolutional neural network-based feature extraction using multimodal for high security application.,*Evolutionary Intelligence*,**14**,1023–1033(2021)
10. RS.Kuzu ,E. Maiorana , P.Campisi , Vein-based biometric verification using densely-connected convolutional autoencoder,*IEEE Signal Processing Letters*, **27**,1869-1873 (2020)
11. Guo, G., Wechsler, H., *Mobile biometrics*, 3 *IET*, **488**,2, (2017)
12. Nait-Ali, A., *Hidden biometrics: when biometric security meets biomedical engineering*, (Springer Nature, France, 2019)
13. Vatsa, M., Singh, R., Majumdar, A., *Deep learning in biometrics*, CRC Press, USA, 328(2018)
14. Jain A.K, Ross, A.A, Nandakumar. K, *Introduction to Biometrics*, (Springer Science & Business Media: Berlin, Germany, 2011)

15. Shaheed.K, Liu. H, Yang. G, Qureshi. I, Gou. J, Yin. Y, A systematic review of finger vein recognition techniques, *Informatics*, **9**, 213, (2018)
16. Mitra, S., Gofman, M., *Biometrics in a data driven world: trends, technologies, and challenges*, (CRC Press, USA, 2016)
17. Kisku, D.R., Gupta, P., Sing, J.K. *Advances in biometrics for secure human authentication and recognition*, (CRC Press, USA, 2013)
18. A. Al-Tayyan ,K. Assaleh , T.Shanableh , Decision-level fusion for single-view gait recognition with various carrying and clothing conditions, *Image and Vision Computing*, **61**, 54-69 (2017)
19. Gopal, S.Smriti , Accurate human recognition by score-level and feature-level fusion using palm phalanges print, *Arab J SciEng* ,**43**,6 (2017)
20. R .Jeng , W.Chen ,Two feature-level fusion methods with feature scaling and hashing for multimodal biometrics, *IETE Tech Rev* ,**34**,1 (2016)
21. W.Kabir ,AM. Omair , Swamy. MNS, Normalization and weighting techniques based on genuine impostor score fusion in multi-biometric systems, *IEEE Trans Inf-Foren Sec* **13**,8 (2018)
22. A.Kumar , S.Shekhar ,Personal identification using multibiometrics rank-level fusion,*IEEE Trans Syst Man Cy Part C*, **41**, 5 (2011)
23. M .Regouid, M .Touahria, M.Benouis, Multimodal biometric system for ecg, ear and iris recognition based on local descriptors, *Multimed Tools Appl*, **78**,16 (2019)
24. Ribaric S, Fratric I, A biometric identification system based on eigenpalm and eigenfinger features, *IEEE Trans Pattern Anal Mach Intell* ,**27**,11, (2005)
25. Tao Qian, Veldhuis Raymond, Threshold-optimized decision-level fusion and its application to biometrics, *Pattern Recogn*, **42**,5 (2009)
26. Yan . X, Kang .W, Deng .F, Qiuxia .W, Palm vein recognition based on multi-sampling and feature-level fusion, *Neuro computing* ,**151**,798-807(2015)
27. Yang J, Sun Q, A novel generalized fuzzy canonical correlation analysis framework for feature fusion and recognition, *Neural Process Lett*, **46**, 2 (2017)
28. You. X, Wang .R, Tao. D,Diverse expected gradient active learning for relative attributes, *IEEE Trans Image Process*, **23**,7 (2014)
29. Yue .Z, You .X, Yu. S, Chang X, Tao D,Multi-view manifold learning with locality alignment, *Pattern Recognition*,**78** (2018)
30. Yang JC, *Biometrics verification techniques combing with digital signature for multimodal biometrics payment system*, In Proceedings of the IEEE international conference on management of e-commerce and e-government, 23-24 October 2010, Chengdu, China (2010)
31. Liu, W.; Li, W.; Sun, L.; Zhang, L.; Chen, P, *Finger vein recognition based on deep learning*, In Proceedings of the 12th IEEE Conference on Industrial Electronics and Applications, 18–20 June 2017, Siem Reap, Cambodia (2017)