International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 10 Issue: 1s
DOI: https://doi.org/10.17762/ijritcc.v10i1s.5798
***Article Received**: 15 August 2022 **Revised**: 20 October 2022 **Accepted**: 14 November 2022*

Modified Firefly Optimization with Deep Learning based Multimodal Biometric Verification Model

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Abstract
Biometric security has become a main concern in the data security field. Over the years, initiatives in the biometrics field had an increasing growth rate. The multimodal biometric method with greater recognition and precision rate for smart cities remains to be a challenge. By comparison, made with the single biometric recognition, we considered the multimodal biometric recognition related to finger vein and fingerprint since it has high security, accurate recognition, and convenient sample collection. This article presents a Modified Firefly Optimization with Deep Learning based Multimodal Biometric Verification (MFFODL-MBV) model. The presented MFFODL-MBV technique performs biometric verification using multiple biometrics such as fingerprint, DNA, and microarray. In the presented MFFODL-MBV technique, EfficientNet model is employed for feature extraction. For biometric recognition, MFFO algorithm with long short-term memory (LSTM) model is applied with MFFO algorithm as hyperparameter optimizer. To ensure the improved outcomes of the MFFODL-MBV approach, a widespread experimental analysis was performed. The wide-ranging experimental analysis reported improvements in the MFFODL-MBV technique over other models.

Keywords: Biometric verification; Multimodality; Security; Deep learning; Parameter tuning

1. Introduction

Currently, the use of biometric recognition systems has increased which is a key form of user authentication employed in various applications and domains like airports, smartphones, websites, and banks, since a unique substitute to traditional authentication methods (i.e., personal identification numbers (PINs) and keys, relies upon the security level which is required [1, 2]. The commonly used biometric traits like voice, fingerprints, iris, face recognition, and palmprint necessitates the enrolment of such traits in databases for feature detection [3-5]. The biometric system acts as a auspicious and continuously developing technology utilized in the automatic systems for finding an individual effectively without remembering or carrying anything, such as passwords and Ids [6-9]. Numerous research works that the iris trait has higher advantages compared to other biometric systems relevant to the features such as fingerprint and face, this makes the iris to be generally adopted in several applications for high-reliability and precise biometric systems [9-12]. The biometric system can be generally classified into 2 types, namely unimodal, and multimodal biometric systems [13].

The unimodal biometric structure will establish the person's identity related to a single information source, like face, left iris, and right iris [14]. While in multimodal biometric technique it functions under identification mode, result of the technique can be observed by a ranks list gained from candidate, which indicates likely matches. Applying and modelling the multimodal biometric needs many components that have a great influence on the system's overall performance [15, 16]. The deep learning (DL) method obtained incredible achievement in computer vision (CV) and establishes prevailing performance in image classification. In short, DL was a natural and suitable method for multimodal biometric techniques, as deep neural networks (DNN) allow authentication, extracting feature, and fusion that can be executed "under one roof". But this method does not concern template protection problem [17-20]. Multimodal biometrics including template protection was not a new subject, several studies were published related to this subject. But DL related multimodal biometric techniques that add template protection persist very scarcely [21-23].

2. Related Works

This section reviews the existing biometric recognition techniques. In [24], an Improved RNN with Bi directional LSTM (I-RNN-BiLSTM) was presented where efficacy of the networks can be enhanced by the use of sigmoid-tanh

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activation function. The intrusion detection can be carried out by the I-RNN-BiLSTM for classification. It utilizes three biometrics such as face, iris, and fingerprint which are then integrated by the Shuffling method. The attributes undergo extraction via Gabor, Canny Edge, and Minutiae. In [25], a new multimodal biometric identification mechanism was modelled through a CNNs, where the author makes an early sensor level fusion of face, iris, and palmprint by stacking the 3 biometrics namely images RGB channels, after that employed as input to CNNs. This method leverages 4 well-known pretrained deep CNN methods they are SqueezeNet, Inceptionv3, ResNet18, and GoogleNet, to make a fast and robust categorization. Similarly, it evades training a novel technique from scratch which requires more calculations and data.

The authors in [26] presented complete detection accuracy without executing any preprocessing over the obtained images of fingerprint and face. To gain this, the features will be derived by utilizing HoG and Speeded up Robust Features (SURF) techniques. Such attributes were merged for offering as input to train deep networks. To authenticate and secure multimodal biometric data an innovative structure was modelled in [27]. The modelled structure offers the best solution to secure and authenticate images at the time of communication. In this work, 3 kinds of biometric inputs are resolute and considered as input: Iris images, Fingerprint, and Face.

Leghari et al. [28] establish a CNN-based method for feature level fusion of online signs and fingerprints. 2 kinds of feature-level fusion approaches for online signatures and fingerprints are executed. A primary method termed as early fusion integrates the features of online signature and fingerprints earlier the fully connected (FC) layer, but the secondary fusion approach termed as late fusion integrates the features afterward FC layer. Xiong et al. [29] examine a new multi-modal biometric detection approach for face-iris detection. It can be dependent upon binary PSO. The face feature is extracted with 2D Log-Gabor and Curvelet transform, but iris feature is mined with Curvelet transform. For reducing the difficulty of feature-level fusion, the authors present a modified chaotic binary PSO (MCBPSO) approach for selective features. It utilizes KELM as a fitness function (FF) and chaotic binary series for initializing particle swarm. The authors in [30] project a DL approach for human authentication dependent upon hand dorsal features. The presented system utilizes fingernail (FN) and finger knuckle print (FKP) extracting in index, ring, and mid fingers. A multi-modal biometric approach was utilized for improving the authentication efficiency of the presented method and creating it further resistant to spoofing attacks. A DL-oriented method utilizing a CNN with AlexNet as a pre-training approach was utilized. The authors in [31] establish a novel approach for performing fusion at feature level with an optimum feature level fusion; at this point, the significant features were selectively utilizing an optimized system. In order to detect, the authors utilize the multi-kernel SVM approach. The authors in [32] establish the method for multi-modal biometric detection dependent upon score level fusion approach. The entire process of the presented system contains 5 stages namely pre-processed, extracting feature, detection score utilizing multi-support vector NN (Multi-SVNN) for every trait, score level fusion, and detection utilizing DBN method. The detection score was computed dependent upon Multi-SVNN classification for offering score separately for every 3 traits, and the 3 scores were offered to DBN. The DBN was skilled to utilize chicken earthworm optimization algorithm (CEWA).

This article presents a Modified Firefly Optimization with Deep Learning based Multimodal Biometric Verification (MFFODL-MBV) model. The presented MFFODL-MBV technique performs biometric verification using multiple biometrics such as fingerprint, DNA, and microarray. In the presented MFFODL-MBV technique, EfficientNet model is employed for feature extraction. For biometric recognition, MFFO algorithm with long short-term memory (LSTM) model is applied with MFFO algorithm as hyperparameter optimizer. To ensure the improved outcomes of the MFFODL-MBV approach, a widespread experimental analysis is performed.

3. The Proposed Model

In this article, we have proposed a new MFFODL-MBV technique for automated biometric verification process, which make use of multiple biometrics such as fingerprint, DNA, and microarray. In the presented MFFODL-MBV technique, a series of processes were involved they are pre-processing, EfficientNet based feature extraction, and recognition. Fig. 1 illustrates the working process of MFFODL-MBV system.

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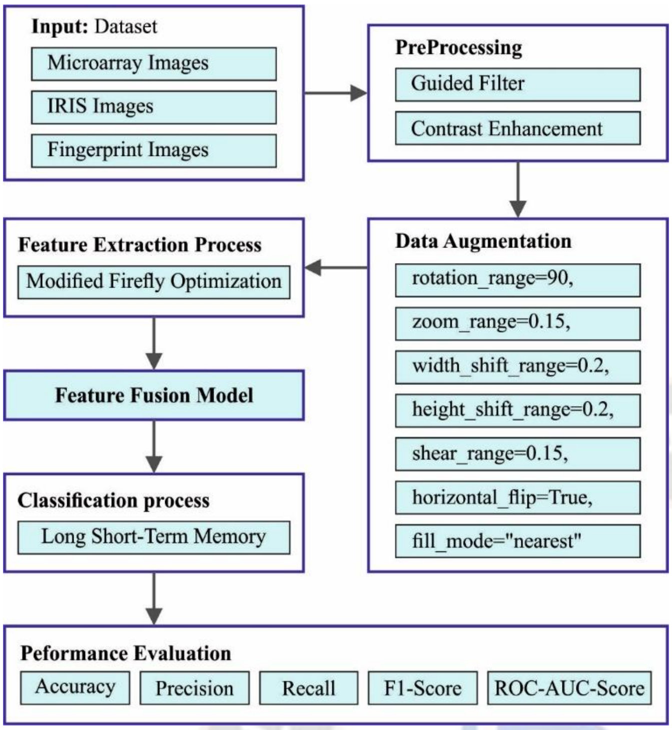

Fig. 1. Working process of MFFODL-MBV system

3.1. Data Pre-processing

Initially, the proposed MFFODL-MBV methodology will pre-process the biometric images to enhance visual quality. At first, it eradicates the noise presented in the biometric images by using the Guided filtering method. Then, the image contrast level will be significantly increased.

3.2. Feature Extraction using EfficientNet Model

Here, the EfficientNet model is employed for feature extraction. EfficientNet is a family of CNN frameworks from EfficientNet-B0 to EfficientNetB7. EfficientNet-B0 is the baseline network of EfficientNet family [33]. EfficientNet-B0 critical components are mobile inverted bottlenecks (MBConv). This baseline network uses compound scaling model to scale resolution, depth, and width to obtain EfficientNet-B1 to EfficientNet-B7. EfficientNet employs a method named compound coefficient to scale up model in a simple and efficient way. EfficientNet-B0 is framework of EfficientNet family. The image size of this framework input layer requires 224*224. This framework has 237 layers. EfficientNet-B3 is the fourth framework of EfficientNet family. The size of image that this framework input layer requires is 300*300. This framework has 384 layers.

3.3. Biometric Recognition

For biometric recognition, the LSTM model is applied in this study. Hochreiter and Schmidhuber introduced an LSTM model and popularized and refined it by large number of individuals in the subsequent work [34]. LSTM was clearly devised to prevent long-run dependency problems.

Initially, LSTM decides what data must be detached from cell state and it can be formed by sigmoid layer named "forget gate layer." Input is h_{t-1} and x, and outcome was a number among 0 and 1 for all the numbers in a cell state C_{t-1}. Where "1" implies "keep this completely," and "0" implies "forget this completely":

$$f_t = \sigma\left(W_f \cdot \left[h_{t-1)} x_t\right] + b_f\right) \tag{1}$$

Next, determines what data to save in a cell state, involving 2 parts. Firstly, "input gate layer" defines that value would be upgraded, and later tanh layer generates a vector of novel candidate value, $\overline{C}_t$. Then, the two layers are integrated for creating an update to the state [35, 36]:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{2}$$

$$C \sim t = \tanh\,(W_C \cdot [h_{t-1}, x_t] + b_C) \tag{3}$$

Then, multiply older state by f_t, forgetting things we decided to do prior. After that, add $i_t^* \tilde{C}_t$:

$$C_t = ft^* C_t + i_t^* C \sim t \tag{4}$$

The last step was to run sigmoid layers that determines which part of cell states to outcome. Next, put a cell states via tanh (to force the value to be amongst -l and 1) and multiplies them by the outcome of sigmoid gate:

$$O_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \tag{5}$$

$$h_t = o_t^* \tanh\,(C_t) \tag{6}$$

3.4. Hyperparameter Tuning

To adjust the LSTM hyperparameters automatically, the MFFO algorithm is derived. FFO is considered most effective algorithm stimulated by the light intensity and behavior of FFs and found with dissimilar intensity of flashes produced by bioluminescence of their body [37]. The flashes contain several objectives, namely attracting suitable mates, and reaching the prey, and have been utilized as safety warning systems. Female and Male FFs have allured a dissimilar frequency of flashes, depends upon the period and speed of flash. The relationships amongst light intensity (I) discharged from body of FF and distance(r) can be represented as $I \propto \frac{1}{r^2}$. Furthermore, it becomes more attractive to another FF as the light intensity of FF rises. The fundamental principles of FFO are given as follows [38, 39]. The brightness I of FF at a given point x is represented as $(x) \propto f(x)$. But attractiveness β is not absolute and depends on another FF as follows:

$$I(r) = \frac{I_s}{r^2} \tag{7}$$

The light intensity I relies upon distance r in a medium have constant light absorption coefficient γ:

$$I = I_0 e^{-\gamma r} \tag{8}$$

Consequently, absorption and distance are given in the following:

$$I(r) = I_0 e^{-\gamma r^2} \tag{9}$$

Since flashing and attractiveness are related directly:

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$$\beta = \beta_0 e^{-\gamma r^2} \quad (10)$$

For making the attractiveness function smoother and accelerate the calculation, the abovementioned function can be expressed by:

$$e^{-\gamma r^2} \approx 1 - \gamma r^2 + \frac{1}{2}\gamma^2 r^4 + \cdots$$

$$\frac{1}{1+\gamma r^2} \approx 1 - \gamma r^2 + \gamma^2 r^4 + \cdots \quad (11)$$

$$\beta = \frac{\beta_0}{1+\gamma r^2}$$

The typical distance of abovementioned equation is $= \frac{1}{\sqrt{\gamma}}$, whereby the exponential function differs between β_0 and $\beta_0 e^{-1}$ in the initial function and between β_0 and $\frac{\beta_0}{2}$ in next function. The real format of attractiveness function is denoted as a descending function and matches the types of problem:

$$\beta(r) = \beta_0 e^{-\gamma r^m}, (m \geq 1) \quad (12)$$

For these cases, the typical distance would be:

$$\Gamma = \gamma^{-\frac{1}{m}} \to 1, (m \to \infty) \quad (13)$$

In Eq. (13), m in algorithm is two, and values of β_0 in FFO optimizer was selected 2 for every part.

The attractiveness coefficient would be directly determined. Finally, length between any of the 2 populations in FA, i and j at x_i and x_j is shown below:

$$r_{i_j} = \|x_i - x_j\| = \sqrt{\sum_{k=1}^{d}(x_{i,k} - x_{j,k})^2} \quad (14)$$

The movement of $i\text{-}th$ FF attracted towards a brighter FF ($j\text{-}th$) is shown below:

$$x_j = x_i + \beta_0 e^{-\gamma r_{ij}^2}(x_j - x_i) + \alpha \in_j \quad (15)$$

The other rule address the attraction, mete third rule was randomness, whereby α indicates a random variable $\alpha_{t+1} = \alpha_{damp} \times \alpha_t \in [0,1]$, and $\alpha_{damp} = 0.98$, and

$$\in_j = round(rand - O.5) \times rand(1, D) \times (O.05(X\min{}_{\max}))$$

The third term represents a FF step to the shinier FF; therefore, if its value was zero, FF takes a random step.

The MFFO algorithm will be derived through the concept named opposition-based learning (OBL). The OBL was a new term in metaheuristic approaches [40]. The correct solution is obtained achieved when initial population which was randomly generated contains a solution near the best point. The OBL system was formulated below:

$$X_i' = X_{mox} + X_{\min} - X_i \quad (16)$$

whereas, X_i' designates the opposite location of X_i, X_{max} and X_{min} define the upper and lower bounds of the variables in the problem. The novel location enables us to obtain the optimal solution. X_i' is evaluated by cost function. Likewise, if X_i' is in a superior location than X_i, it is substituted.

The MFFO algorithm would derive a fitness function to have enhanced classification outcome. And it will determine a positive value to exhibit the superior outcome of the candidate solutions. The reduction of the classifier error rate can be signified as the fitness function in this work, which is given in Eq. (17).

$$fitness(x_i) = ClassifierErrorRate(x_i) = \frac{number\ of\ misclassified\ samples}{Total\ number\ of\ samples} * 100 \quad (17)$$

4. Results and Discussion

This section validates the multimodal biometric recognition results of the MFFODL-MBV model on a dataset containing record of 10 persons. The dataset holds 260 samples with 26 samples under each class. Fig. 2 illustrates some sample images.

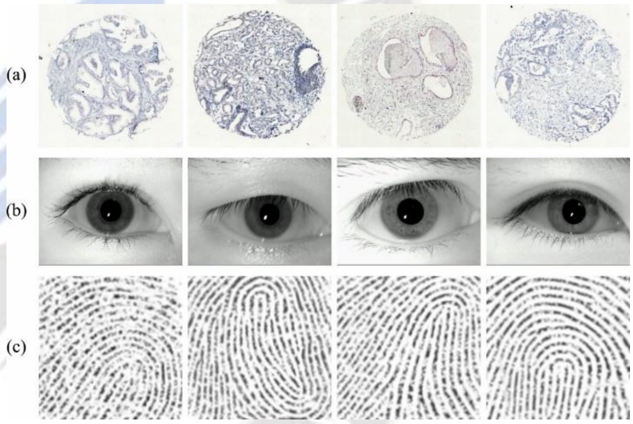

Fig. 2. a) Microarray Images b) Iris images c) Fingerprint Images

Fig. 3 reports the confusion matrices of the MFFODL-MBV model on applied dataset. The outcomes show that the MFFODL-MBV model has properly identified all the class labels.

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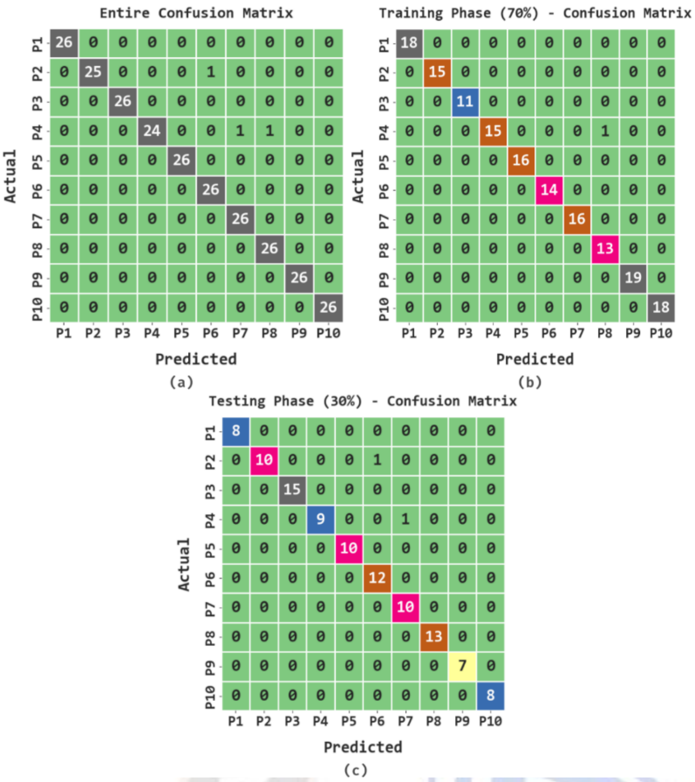

Fig. 3. Confusion matrices of MFFODL-MBV system (a) Entire database, (b) 70% of TR database, and (c) 30% of TS database

In Table 1 and Fig. 4, a brief biometric recognition result of the MFFODL-MBV model on entire dataset is provided. The simulation values demonstrated the MFFODL-MBV method has attained effectual classification under all classes. It is noticed that the MFFODL-MBV model has gained average $accu_y$ of 99.77%, $prec_n$ of 98.89%, $reca_l$ of 98.85%, F_{score} of 98.84%, and ROC_{score} of 99.36%.

Table 1 Biometric recognition outcome of MFFODL-MBV approach under entire dataset

Entire Dataset					
Labels	**Accuracy**	**Precision**	**Recall**	**F-Score**	**ROC Score**
P1	100.00	100.00	100.00	100.00	100.00
P2	99.62	100.00	96.15	98.04	98.08
P3	100.00	100.00	100.00	100.00	100.00
P4	99.23	100.00	92.31	96.00	96.15
P5	100.00	100.00	100.00	100.00	100.00
P6	99.62	96.30	100.00	98.11	99.79
P7	99.62	96.30	100.00	98.11	99.79
P8	99.62	96.30	100.00	98.11	99.79
P9	100.00	100.00	100.00	100.00	100.00
P10	100.00	100.00	100.00	100.00	100.00
Average	**99.77**	**98.89**	**98.85**	**98.84**	**99.36**

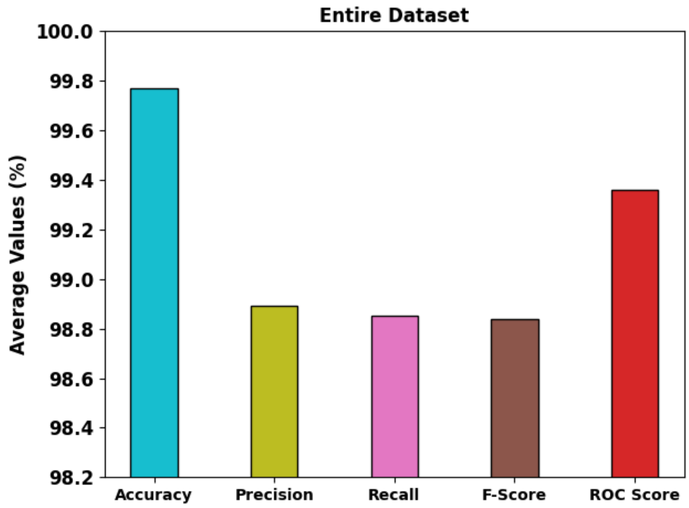

Fig. 4. Average analysis of MFFODL-MBV approach under entire dataset

In Table 2 and Fig. 5, a detailed biometric recognition outcome of the MFFODL-MBV approach on 70% of TR database is provided. The simulation values depicted the MFFODL-MBV system has attained effectual classification under all classes. It is observed that the MFFODL-MBV algorithm has reached average $accu_y$ of 99.87%, $prec_n$ of 99.29%, $reca_l$ of 99.38%, F_{score} of 99.31%, and ROC_{score} of 99.99%.

Table 2 Biometric recognition outcome of MFFODL-MBV approach under 70% of TR database

Training Phase (70%)					
Labels	**Accuracy**	**Precision**	**Recall**	**F-Score**	**ROC Score**
P1	100.00	100.00	100.00	100.00	100.00
P2	100.00	100.00	100.00	100.00	100.00
P3	100.00	100.00	100.00	100.00	100.00
P4	99.36	100.00	93.75	96.77	99.98
P5	100.00	100.00	100.00	100.00	100.00
P6	100.00	100.00	100.00	100.00	100.00
P7	100.00	100.00	100.00	100.00	100.00
P8	99.36	92.86	100.00	96.30	99.96
P9	100.00	100.00	100.00	100.00	100.00
P10	100.00	100.00	100.00	100.00	100.00
Average	**99.87**	**99.29**	**99.38**	**99.31**	**99.99**

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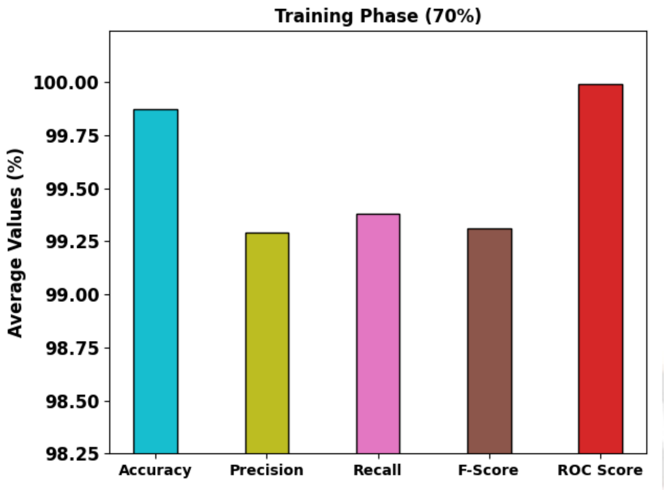

Fig. 5. Average analysis of MFFODL-MBV approach under 70% of TR database

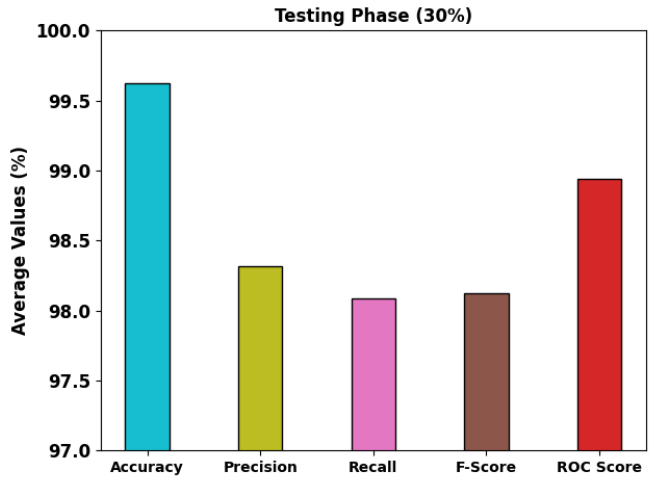

Fig. 6. Average analysis of MFFODL-MBV approach under 30% of TS database

In Table 3 and Fig. 6, a brief biometric recognition outcome of the MFFODL-MBV system on 30% of TR database is provided. The experimental values stated that the MFFODL-MBV approach has accomplished effective classification under all classes. It is experimental that the MFFODL-MBV model has reached average $accu_y$ of 99.62%, $prec_n$ of 98.32%, $reca_l$ of 98.09%, F_{score} of 98.12%, and ROC_{score} of 98.94%.

Table 3 Biometric recognition outcome of MFFODL-MBV approach under 30% of TS database

Testing Phase (30%)					
Labels	**Accuracy**	**Precision**	**Recall**	**F-Score**	**ROC Score**
P1	100.00	100.00	100.00	100.00	100.00
P2	99.04	100.00	90.91	95.24	95.45
P3	100.00	100.00	100.00	100.00	100.00
P4	99.04	100.00	90.00	94.74	95.00
P5	100.00	100.00	100.00	100.00	100.00
P6	99.04	92.31	100.00	96.00	99.46
P7	99.04	90.91	100.00	95.24	99.47
P8	100.00	100.00	100.00	100.00	100.00
P9	100.00	100.00	100.00	100.00	100.00
P10	100.00	100.00	100.00	100.00	100.00
Average	**99.62**	**98.32**	**98.09**	**98.12**	**98.94**

The TACC and VACC of the MFFODL-MBV method are examined on biometric recognition performance in Fig. 7. The figure stated that the MFFODL-MBV system has revealed enhanced performance with maximal values of TACC and VACC. It is observable that the MFFODL-MBV system has gained maximal TACC outcomes.

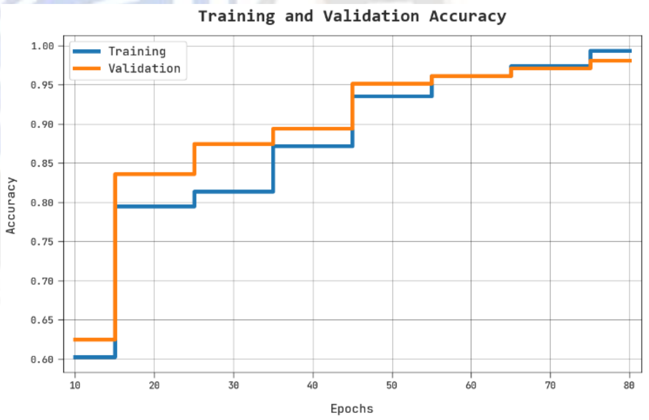

Fig. 7. TACC and VACC analysis of MFFODL-MBV approach

The TLS and VLS of the MFFODL-MBV method are tested on biometric recognition performance in Fig. 8. The figure referred that the MFFODL-MBV system has outperformed better performance with least values of TLS and VLS. It is perceptible that the MFFODL-MBV system has resulted in minimal VLS outcomes.

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Fig. 8. TLS and VLS analysis of MFFODL-MBV approach

Table 4 and Fig. 9 report the overall biometric verification results of the MFFODL-MBV model. The experimental values indicated that the MFFODL-MBV model has obtained $accu_y$ of 99.87%, $prec_n$ of 99.29%, $reca_l$ of 99.38%, $F1_{score}$ of 99.31%, and ROC_{score} of 99.99%.

Table 4 Overall biometric verification outcome of MFFODL-MBV system with distinct measures

Metrics	**MFFODL-MBV**
Accuracy	99.87
Precision	99.29
Recall	99.38
F1-Score	99.31
ROC-SCORE	99.99

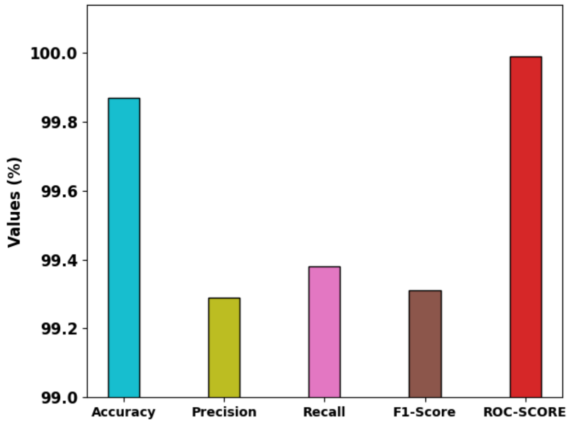

Fig. 9. Overall biometric verification outcome of MFFODL-MBV system

These results revealed that the MFFODL-MBV model has gained maximum outcomes over other models.

5. Conclusion

In this article, we have proposed a new MFFODL-MBV technique for automated biometric verification process, which make use of multiple biometrics such as fingerprint, DNA, and microarray. In the presented MFFODL-MBV technique, a sequence of processes was involved namely pre-processing, EfficientNet based feature extraction, and recognition. For biometric recognition, the LSTM model is applied in this study, and the MFFO algorithm is applied as a hyperparameter optimizer. To ensure the improved outcomes of the MFFODL-MBV approach, a widespread experimental analysis is performed. The wide-ranging experimental analysis reported improvements in the MFFODL-MBV technique over other models. Thus, the MFFODL-MBV technique can be utilized for automated biometric verification. In future, hybrid DL classifier can be included to improve the recognition efficiency of the MFFODL-MBV model.

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