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Machine Learning based Automated Multimodal Biometric Recognition for Person Identification

Venkata Ramana N[1], Dr.S.Anu H Nair[2], Dr.K.P. Sanal Kumar[3*]

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Abstract: Multi-modal biometric system combines feature knowledge indifferent traits to conquer the deficienciesof unimodal systems. But, over the last few years, the conventional biometric system focuses on the usage of handcrafted feature for human recognition. Feature extraction is certainly a crucial phase for the performance of this approach, because of the complexityofmounting consistent features to handle variations in the provided image. This article introduces an Optimal Machine Learning-based Automated Multimodal Biometrics Recognition for Person Identification (OML-AMBRPI) technique. The presented OML-AMBRPI technique makes use of three different biometrics namely iris, fingerprint, and microarray images for person recognition. For feature extraction, the OML-AMBRPI technique uses eXtendedCenter-Symmetric Local Binary Pattern (XCS-LBP) and Gabor feature extraction. Next, feature fusion process is carried out by the decision level fusion technique. At last, the multi-objective grey wolf optimizer (MOGWO) with feed forward neural network (FFNN) for the recognition process. The experimental outcome analysis of the OML-AMBRPI system demonstrates the significant performance of the OML-AMBRPI technique over other models.

Keywords: Biometric verification; Person identification; Deep learning; Machine learning; Multimodal biometrics

1. Introduction

The biometric-based system is used for authentication of a user and to counter the potential threat used for the purposes of security [1]. A wide-ranging system requires consistent biometric detection. It depends on two major aspects regarding human body traits: permanence and distinctiveness. The identification accuracy and applicability of a biometric trait depend mainly on this factor holds true for the population at hand [2]. Iris, Fingerprint, and face are amongst the better known physiological properties utilized in commercial biometric systems. The selection of biometric modality depends primarily on the requirements and nature of the recognition application [3]. The term multi-modal biometric system refers to any technology that combines distinct kinds of biometrics and leverages voice, physical behavioural, and face biometrics [4]. But multi-modal biometric processing sensing and the system uses processing and detection of more than two physiological or behavioural characteristics, which have demonstrated to increase the success rate of verification and identification considerably [5]. Over the last few years, there has been considerable progress in biometrics, still there are serious problems in attaining reliable identification through unimodal-biometric-based approach [6]. The detection performance of individual biometric traits hasn't been sufficient for meeting the requirement of higher security applications.

Classification in multi-biometric systems can be performed by merging data from dissimilar biometric traits [7]. The data fusion is performed at dissimilar levels that are largely separated into rank/decision level, feature level, and score level fusion [8]. This is due to the difference in features extracted from the sensor with respect to type and dimension. The feature often hasa larger dimension, and fusion becomes challenging at the feature level [9]. The predominant technique is feature concatenation utilized for dissimilar multi-biometric settings. However, for higher dimension feature vectors, feature concatenation might become non-robust and inefficient [10].

This article introduces an Optimal Machine Learning based Automated Multimodal Biometrics Recognition for Person Identification (OML-AMBRPI) technique. For feature extraction, the OML-AMBRPI technique uses eXtendedCenter-Symmetric Local Binary Pattern (XCS-LBP) and Gabor feature extraction. Next, feature fusion process is carried out by the decision level fusion technique. At last, the multi-objective grey wolf optimizer (MOGWO) with feed forward neural network (FFNN) for recognition process. The experimental outcome analysis of the OML-AMBRPI technique demonstrates the significant performance of the OML-AMBRPI technique over other models.

2. Related Works

In [11], proposed a multi-modal biometrics system by using profile face and ear that improve the overall detection rate and alleviate the shortcoming of ear biometrics. Then, the histogram-based local descriptor is fused to higher dimension feature vectors that preserve complementary data in spatial and frequency domains. The kernel discriminatory common vector (KDCV) model is ultimately employed for deriving nonlinear and more discriminatory features for the recognition of individuals through KNN classifiers. Alkeem et al. [12] introduce a reliable and robust recognition method based on multimodal biometrics that uses DL approach for combining facial image, ECG, and fingerprint information, especially advantageous for the purposes of gender classification and identification. In [13] the author adopts a DL-CNN technique to execute the strong MBS. The presented method is well tested and trained through four distinct datasets, involving biometric

[1]*Department of Computer Science and Engineering, Annamalai University, Chidambaram, India*
Orcid id :0000-0002-4246-3009. E-Mail: ramana.9n@gmail.com
[2]*Department of CSE, Annamalai University, Chidambaram, India (Deputed to WPT, Chennai)*
Orcid id :0000-0001-5588-4155. E-Mail: anu_jul@yahoo.co.in
[3] *PG Department of Computer Science, R. V. Government Arts College, Chengalpattu, India*
Orcid id :0000-0002-4047-197X.
E-Mail: sanalprabha@yahoo.co.in
Corresponding author

images of the finger, face, ear, and palm. Firstly, noise from the dataset is removed by means of Gabor filtering. Furthermore, DLCNN-based classification is applied for the detection of each biometric modality which enhances the accuracy and robustness. In [14] the authors present the multimodal biometric detection by using score level fusion technique. The presented technique includes recognition score based on Multi-SVNN, pre-processed, extraction feature for every trait, recognition, and score level fusion through DBN. In [15] the authors developed a multimodal biometric technique which leverages the power of CNN for feature extraction. Then, feature was extracted from network layer: the average pooling layer and convolution layer in SqueezeNet in ResNet18 and InceptionV3.

3. The Proposed Model

In this study, a new OML-AMBRPI system was developed for Automated Multimodal Biometrics Recognition for Person Identification. For feature extraction, the OML-AMBRPI technique uses XCS-LBP and Gabor feature extraction. Next, feature fusion process is carried out by the decision level fusion technique. At last, the MOGWO with FFNN for recognition process. Fig. 1 represents the overall process of OML-AMBRPI system.

3.1. Feature Extraction

The OML-AMBRPI technique applied the XCS-LBP and Gabor feature extraction of three different biometrics namely iris, fingerprint, and microarray images for person recognition. The presented method is utilized for extracting features from the microarray and fingerprint images [16].

$$XCSLBP_{P,R}(c) = \sum_{i=0}^{\left(\frac{P}{2}\right)-1} s\left(g_1(i,c) + g_2(i,c)\right)2^i, \quad (1)$$

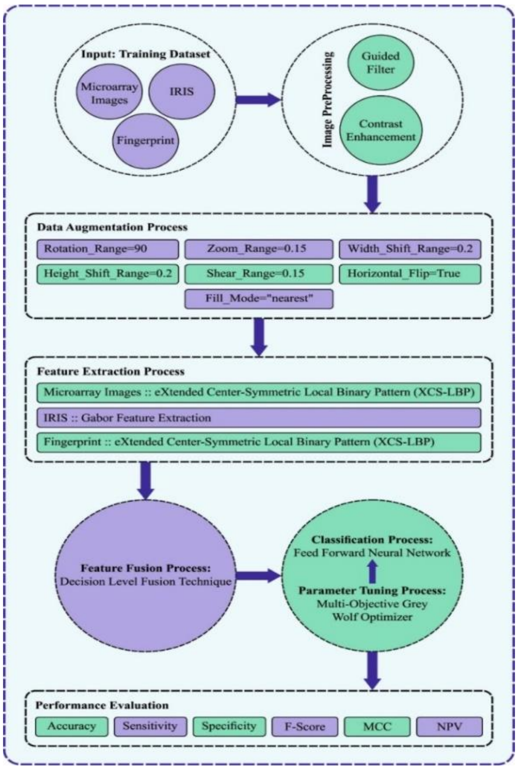

Figure. 1. Overall process of OML-AMBRPI system

Whereas $s$characterizes the thresholding function:

$$s(x_1 + x_2) = \begin{cases} 1 & \text{if } (x_1 + x_2) \geq 0 \\ 0 & \text{otherwise} \end{cases}, \quad (2)$$

and $g_1(i,c)$ and $g_2(i,c)$ are defined by:

$$\begin{cases} g_1(i,c) = (g_i - g_{i+(P/2)}) + g_c \\ g_2(i,c) = (g_i - g_c)(g_{i+(P/2)} - g_c) \end{cases}. \quad (3)$$

Additionally, XCS-LBP is prevailing to illumination variationon the other hand it is established to be powerful against noise.

Gabor feature extractor is used to derive features from the iris image and it extracted features at dissimilaramplitudes and orientations.

$$\psi(x,y) = \frac{f^2}{\pi\gamma\eta} e^{-}\left(\frac{f^2}{\gamma^2}x'^2\right)' + \left(\frac{f^2}{\eta^2}y'^2\right)e^{J^{2\pi}fx'} \quad (4)$$

$$x' = x\cos\theta + y\sin\theta$$

$$y' = x\sin\theta + y\cos\theta$$

The Gabor filter is the product of $2D$origin-centred Gaussian and Fourier basis function, whereby $f$specifies the central frequency of a filter, γ, and ηcorrespondingly signifies the bandwidth or sharpness measured alongside the major and minor axis of Gaussian, θspecifies the angle of rotation, and (η/γ)represents the aspect ratio and it is expressed as follows:

$$\psi(u,v) = e^{-\frac{\pi^2}{f^2}(\gamma^2(u'-f)^2+\eta^2 v'^2)} \quad (5)$$

$$u' = u\cos\theta + v\sin\theta$$

$$v' = u\sin\theta + v\cos\theta$$

The function is a single real-valued Gaussian center at f. The simplest form of $2D$ Gabor filter function that implements a collection of self-similar filters, i.e., Gabor wavelet (scaled and rotated form of one another, neverthelessfrequency f and orientation θ.

Gabor feature or Gabor bank are created from the response of the Gabor filter based on various filters on fewfrequencies f_m and orientations $\theta_n$in the following:

$$f_m = k^{-m} f_m ax, m = \{0, \ldots, M-1\} \quad (6)$$

Now, fmindicates the $m\text{-}th$ frequency, $f\theta = f_m ax$denotes the maximal frequency desired, and $k > 1$represents the frequency scaling factors

3.2. Feature Fusion

In this phase, the data fusion takes placeafterward every unimodal biometric system makesaseparate individual decision regarding the user identityand it is called the simple form of fusion because the concluding output of individual modality is merged to form the multi-modal biometric. Various approaches are introduced for the decision level fusion, e.g., AND' and 'OR' rules and Majority voting. Afterward unimodal has produced the output label that is, reject or accept in anauthentication system, a single final class label couldbe obtained by utilizing approaches like majority voting.

3.3. Biometric Recognition

For biometric recognition, the FFNN model is applied in this work. FFNN is a variant of NN with uni-directional neuronal connection. This NN stack neuron in various layers namely input and output. Hidden layers are between input and output. Single hidden-layer FFNN or MLP [17]. MLPs output inputs, biases, and weights. Fig. 2 showcases the architecture of FFNN. Firstly, we calculate the input weight as follows:

$$S_j = \sum_{i=1}^{n} (W_{ij} \times X_i) - \theta_j, j = 1,2,\dots,h \tag{7}$$

Whereas n indicates the overall amount of input nodes, W_{ij} characterizes the connection weight from the i-th input to j-th hidden nodes, j shows the bias (threshold) of j-th hidden nodes, and X_i represent the I-th input. n denotes the overall amount of input nodes. The subsequent computation is utilized for determining the output of the hidden node:

$$S_j = sigmoid\ S = \frac{1}{(1+\ \exp\ -(-S_j))}, j = 1,2,\dots h \tag{8}$$

Then, the computed outcomes from the hidden node are utilized for defining the concluding outcomes in the subsequent means:

$$O_k = h\sum_{j=1}^{h} (W_{jk}.S_j) - \theta_k, k = 1,2,\dots m \tag{9}$$

$$O_k = sigmoid(O_k) = \frac{1}{(1+\exp(-O_k))}, k = 1,2,\dots,m \tag{10}$$

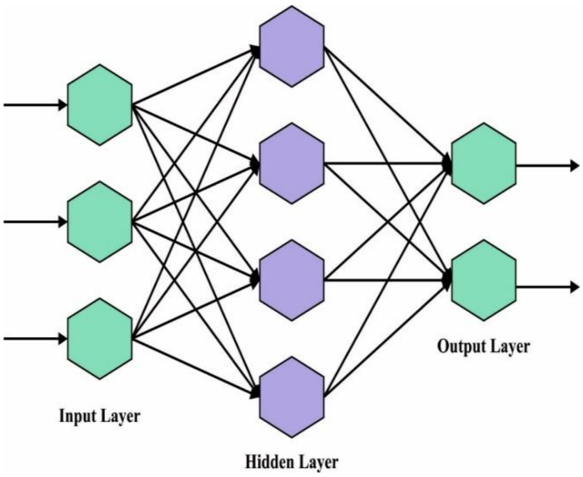

Figure. 2. Structure of FFNN

3.3. Parameter Tuning

Finally, the FFNN parameters are adjusted by the MOGWO approach. The MOGWO similar to the NSGA II is a population based approach inspired by the performance of GW [18]. In the presented technique, every wolf is presented as a primary solution (define the accurate quantity of investment) that aim is to accomplish the primary solution that contains maximum predictable profit and lowest investment risk. But, it can be dominate ω. The remaining candidate solution is considered Omega (X). For hunting, GW should find and surround their prey and it can be given in the following equation.

$$\vec{D} = \left|\vec{C}.\overrightarrow{X_p}(t) - \vec{X}(t)\right|, \tag{11}$$

$$\vec{X}(t+1) = \vec{X}(t) - \vec{A}.\vec{D}. \tag{12}$$

In the abovementioned relationship $\vec{C}$ and $\vec{A}$ are coefficient vectors. $\overrightarrow{X_p}$ denotes the vector of hunting location and $\vec{X}$ represent the GW location vector. Thus, the search radius should be enhanced. For these purposes, the equation is associated with the two coefficients utilized in the abovementioned relationship.

$$\vec{A} = 2\vec{a}.r_1 - \vec{a}, \tag{13}$$

$$\vec{C} = 2\overrightarrow{r_2}. \tag{14}$$

The abovementioned equation enables the GW to upgrade the location around the prey. Consequently, the following equation is utilized for hunting.

$$\vec{D} = \left|\vec{C}_1.\vec{X}_\alpha - \vec{X}\right|, \vec{D}_\beta = \left|\vec{C}_2.\vec{X}_\beta - \vec{X}\right|, \vec{D}_\delta = \left|\vec{C}_1.\vec{X}_\delta - \vec{X}\right|, \tag{15}$$

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1.\vec{D}_\alpha, \vec{X}_2 = \vec{X}_\beta - \vec{A}_2.\vec{D}_\beta, \vec{X}_3 = \vec{X}_\delta - \vec{A}_3.\vec{D}_\delta, \tag{16}$$

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3}.$$

4. Results and Discussion

To validate the biometric recognition performance, a series of simulations were performed on diverse images. Here, data augmentation take place to increase the size of the dataset using following ways: rotation_range=90, zoom_range=0.15, width_shift_range=0.2, height_shift_range=0.2, shear_range=0.15, horizontal_flip=True, and fill_mode="nearest". The dataset after augmentation process is given in Table 1. Fig. 3 illustrates some sample images.

Table 1 Dataset details

Label	Class	No. of Samples (After Augmentation)
P1	Person - 1	26
P2	Person - 2	26
P3	Person - 3	26
P4	Person - 4	26
P5	Person - 5	26
P6	Person - 6	26
P7	Person - 7	26
P8	Person - 8	26
P9	Person - 9	26
P10	Person - 10	26
Total Number of Samples		**260**

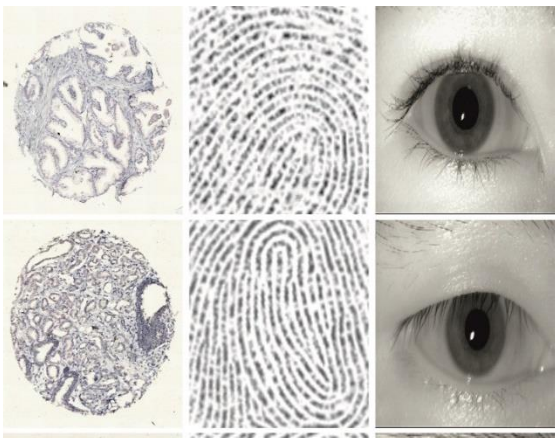

Figure. 3. Sample images

The confusion matrices of the OML-AMBRPI model on biometric verification process areshown in Fig. 4. The outcomes inferred that the OML-AMBRPI model has proficiently recognized all the ten classes.

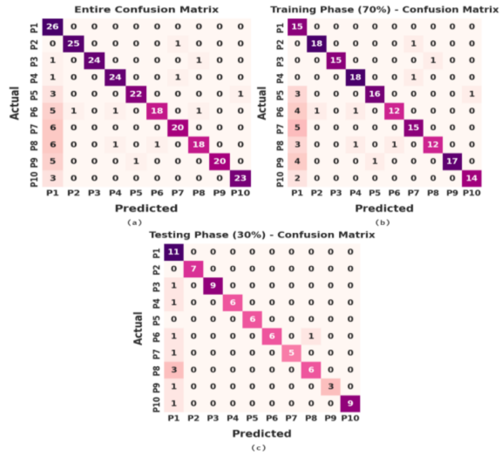

Figure. 4. Confusion matrices of OML-AMBRPI system (a) Entire database, (b) 70% of TR database, and (c) 30% of TS database

Table 2 and Fig. 5 indicate the experimental outcomes of the OML-AMBRPI model on entire dataset. The result demonstrates that the OML-AMBRPI approach has maximum results under each class. For instance, in P1 class, the OML-AMBRPI model has gained $accu_y$, $sens_y$, $spec_y$, F_{score}, MCC, and NPV of 88.46%, 100%, 87.18%, 63.41%, 63.62%, and 100% respectively. Along with that, in P3 class, the OML-AMBRPIapproach has attained $accu_y$, $sens_y$, $spec_y$, F_{score}, MCC, and NPV of 99.23%, 92.31%, 100.00%, 96.00%, 95.67% and 99.15% correspondingly. In line with, on P7 class, the OML-AMBRPImethodology has reached$accu_y$, $sens_y$, $spec_y$, F_{score}, MCC, and NPV of 96.92%, 76.92%, 99.15%, 83.33%, 82.00% and 97.48% correspondingly. Also, in P10 class, the OML-AMBRPIsystem has reached $accu_y$, $sens_y$, $spec_y$, F_{score}, MCC, and NPV of 98.46%, 88.46%, 99.57%, 92.00%, 91.24% and 98.73% correspondingly.

Table 2 Result analysis of OML-AMBRPI algorithm with distinct classes under entire database

Entire Dataset						
Labels	**Accuracy**	**Sensitivity**	**Specificity**	**F-Score**	**MCC**	**NPV**
P1	88.46	100.00	87.18	63.41	63.62	100.00
P2	99.23	96.15	99.57	96.15	95.73	99.57
P3	99.23	92.31	100.00	96.00	95.67	99.15
P4	98.46	92.31	99.15	92.31	91.45	99.15
P5	98.08	84.62	99.57	89.80	88.94	98.31
P6	96.54	69.23	99.57	80.00	79.31	96.68
P7	96.92	76.92	99.15	83.33	82.00	97.48
P8	96.15	69.23	99.15	78.26	76.98	96.67
P9	97.69	76.92	100.00	86.96	86.60	97.50
P10	98.46	88.46	99.57	92.00	91.24	98.73
Average	**96.92**	**84.62**	**98.29**	**85.82**	**85.15**	**98.32**

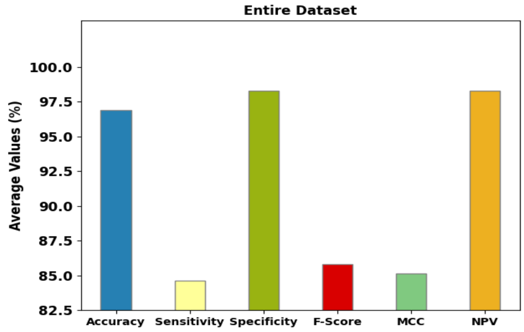

Figure. 5. Average analysis of OML-AMBRPI algorithm under entire database

Table 3 and Fig. 6 demonstrates the experimental outcomes of the OML-AMBRPI algorithm on 70% of TR data. The outcomesexhibited that the OML-AMBRPI system has depicted maximal results under each class. For instance, on P1 class, the OML-AMBRPI method has obtianed$accu_y$, $sens_y$, $spec_y$, F_{score}, MCC, and NPV of 88.46%, 100.00%, 87.43%, 58.82%, 60.35 and 100.00% correspondingly. Followed by, on P3 class, the OML-AMBRPI model has gained$accu_y$, $sens_y$, $spec_y$, F_{score}, MCC, and NPV of 99.45%, 93.75%, 100.00%, 96.77%, 96.53% and 99.40% correspondingly. Similarly, in P7 class, the OML-AMBRPIalgorithm has achieved$accu_y$, $sens_y$, $spec_y$, F_{score}, MCC, and NPV of 96.15%, 75.00%, 98.77%, 81.08%, 79.28% and 96.97% correspondingly. Besides, in P10 class, the OML-AMBRPIsystem has reached$accu_y$, $sens_y$, $spec_y$, F_{score}, MCC, and NPV of 98.35%, 87.50%, 99.40%, 90.32%, 89.48% and 98.80% correspondingly.

Table 3 Result analysis of OML-AMBRPI algorithm with distinct classes under 70% of TR database

Training Phase (70%)						
Labels	**Accuracy**	**Sensitivity**	**Specificity**	**F-Score**	**MCC**	**NPV**
P1	88.46	100.00	87.43	58.82	60.35	100.00
P2	98.90	94.74	99.39	94.74	94.12	99.39
P3	99.45	93.75	100.00	96.77	96.53	99.40
P4	98.35	94.74	98.77	92.31	91.42	99.38
P5	97.25	80.00	99.38	86.49	85.32	97.58
P6	96.15	66.67	99.39	77.42	76.57	96.45
P7	96.15	75.00	98.77	81.08	79.28	96.97
P8	96.70	70.59	99.39	80.00	79.07	97.04
P9	97.25	77.27	100.00	87.18	86.56	96.97
P10	98.35	87.50	99.40	90.32	89.48	98.80
Average	**96.70**	**84.03**	**98.19**	**84.51**	**83.87**	**98.20**

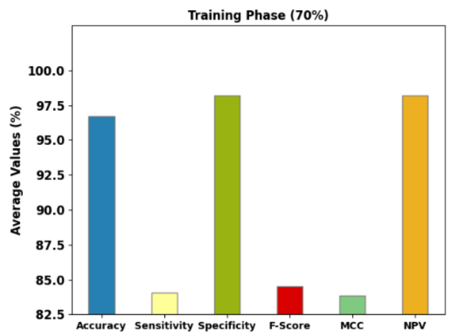

Figure. 6. Average analysis of OML-AMBRPI algorithm under 70% of TR database

Table 4 and Fig. 7 showcase the experimental outcome of the OML-AMBRPI approach on 30% of TS data. The outcomes stated that the OML-AMBRPI algorithm has outperformed higher outcomes under each class. For sample, in P1 class, the OML-AMBRPImethodology has reached$accu_y$, $sens_y$, $spec_y$, F_{score}, MCC, and NPV of 88.46%, 100.00%, 86.57%, 70.97%, 69.00% and 100.00% correspondingly. Likewise, in P3 class, the OML-AMBRPIalgorithm has attained$accu_y$, $sens_y$, $spec_y$, F_{score}, MCC, and NPV of 98.72%, 90.00%, 100.00%, 94.74%, 94.18% and 98.55% correspondingly. Furthermore, in P7 class, the OML-AMBRPI model has achieved$accu_y$, $sens_y$, $spec_y$, F_{score}, MCC, and NPV of 98.72%, 83.33%, 100.00%, 90.91%, 90.66% and 98.63% respectively. At last, in P10 class, the OML-AMBRPI system has reached$accu_y$, $sens_y$, $spec_y$, F_{score}, MCC, and NPV of 98.72%, 90.00%, 100.00%, 94.74%, 94.18% and 98.55% correspondingly.

Table 4 Result analysis of OML-AMBRPI algorithm with distinct classes under 30% of TS database

Testing Phase (30%)						
Labels	**Accuracy**	**Sensitivity**	**Specificity**	**F-Score**	**MCC**	**NPV**
P1	88.46	100.00	86.57	70.97	69.00	100.00
P2	100.00	100.00	100.00	100.00	100.00	100.00
P3	98.72	90.00	100.00	94.74	94.18	98.55
P4	98.72	85.71	100.00	92.31	91.94	98.61
P5	100.00	100.00	100.00	100.00	100.00	100.00
P6	97.44	75.00	100.00	85.71	85.39	97.22
P7	98.72	83.33	100.00	90.91	90.66	98.63
P8	94.87	66.67	98.55	75.00	72.90	95.77
P9	98.72	75.00	100.00	85.71	86.02	98.67
P10	98.72	90.00	100.00	94.74	94.18	98.55
Average	**97.44**	**86.57**	**98.51**	**89.01**	**88.43**	**98.60**

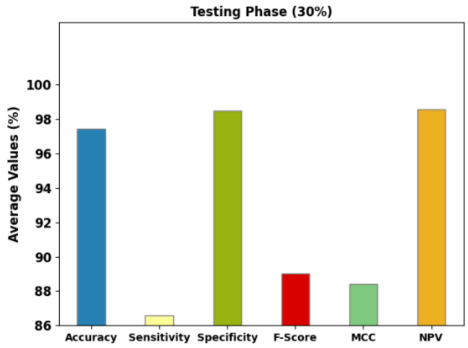

Figure. 7. Average analysis of OML-AMBRPI algorithm under 30% of TS database

A comparison study of the OML-AMBRPI model is depicted in Table 5 and Fig. 8. The experimental outcomes signified that the DTCWT-KNN model has reached least $accu_y$ of 88.46%. Followed by, the DTCWT-RF and DTCWT-XGBoost models have resulted in closer $accu_y$ of 96.92% and 96.54%. But the OML-AMBRPI model has shown supreme results with $accu_y$ of 97.44%.

Table 5 Accuracy analysis of OML-AMBRPI algorithm with existing systems

Methods	**Accuracy (%)**
dtcwt-knn	88.46
dtcwt-random_forest	96.92
dtcwt-xgboost	96.54
OML-AMBRPI	97.44

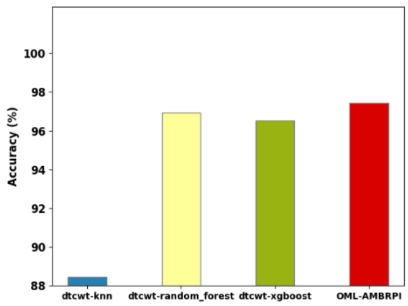

Figure. 8. Accuracy analysis of OML-AMBRPI algorithm with existing systems

5. Conclusion

In this study, a new OML-AMBRPI system was developed for Automated Multimodal Biometrics Recognition for Person Identification. The presented OML-AMBRPI system makes use of three different biometrics namely iris, fingerprint, and microarray images for person recognition. The OML-AMBRPI technique applied the XCS-LBP and Gabor feature extraction. Next, feature fusion process is carried out by the decision level fusion technique. At last, the MOGWO with FFNN for recognition process. The experimental outcome analysis of the OML-AMBRPI system demonstrates the significant performance of the OML-AMBRPI technique over other models. In future, the recognition performance of the OML-AMBRPI system was improvised using the segmentation process.

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