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Multimodal Biometric Recognition Using Rationalized Adaboost and Geometric Curvelet with Human Biometric Traits

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Abstract: Multimodal biometrics combines a diversity of biological traits in an attempt to produce a notable influence on identification performance. In recent years, multimodal biometric recognition using machine learning algorithms has received considerable attention. This study proposes a novel multi modal biometrics recognition method based on Multi-scale Geometric Curvelet (MGC) and Minkowski distance factor models. The new method is termed, Geometric Curvelet and Minkowski Multimodal Biometric Recognition (GC-MMBR), and works as follows. First, an intrinsic representation of multimodal features namely fingerprint, face and iris traits) using Rationalized AdaBoost is learnt. Second, a MGC Feature Extraction model is applied to the resultant preprocessed features, to extract intrinsic curve features. Finally, the reconstructed, extracted intrinsic features are used as input to a Minkowski distance-based biometric recognition approach. When compared with existing methodologies, the proposed multimodal biometric recognition algorithm is proven to perform well in terms of recognition rate. Specifically, comparative evaluation using the benchmark, CASIA Biometric Ideal Test Dataset, shows our proposed GC-MMBR achieves 35% overall recognition rate, out-performing existing methods. Comparative findings further proved the ability of proposed GC-MMBR to considerably reduce computational complexity and false acceptance rate. Thus, we conclude our proposed method can provide benchmarking performance for conventional biometric recognition methods.

Keywords: : Multimodal biometrics, machine learning algorithms, Multi-scale Geometric Curvelet, Minkowski distance, Rationalized AdaBoost

1. INTRODUCTION

Biometrics performs human identification from their personal features. As a quickly developing field, it is originally thrust forward by a requirement for strong security and surveillance applications. But, it's prospective as a real and uncomplicated means of identification also surfaced the way for a host of applications that identifies the user in an automatic manner through customized services. Several methods are introduced in multimodal biometric for biometric recognition. However, these methods are lack in terms of recognition rate, absence of intrinsic curve features extraction, higher computation complexity and false positive. The suggested Geometric Curvelet and Minkowski Multimodal Biometric Recognition (GC-MMBR) approach is intended to obtain a greater recognition rate with less computing complexity in multimodal biometric recognition, thereby addressing the shortcomings of the current method.

Biometric features are analyzed through a variety of machine learning techniques. The implementation's key component is a convolutional neural network (CNN), which recognizes images using the Softmax classifier and feature extraction [1]. This method combined three CNN models: one for the iris, one for the face, and one for the fingerprint to construct the system. The two layers of the fusion strategy—feature level fusion and score level fusion—were applied. The efficacy of the proposed model is evaluated using the two most popular multimodal datasets: CASIA and the BiosecureID biometric dataset.

An attention-based learning technique for determining the liveness of fingerprint images is proposed [2] as a solution to the problem of fingerprint liveness detection where experiments were conducted with two different datasets and the outcomes demonstrated the beneficial effects of the attention-based learning strategy. The extracted deep

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features are tested following the application of several preprocessing steps, such as merging features from various layers and dimensionality reduction using principal component analysis (PCA). The test was carried out with Delhi Finger Knuckle Print dataset [3].

To prevent overfitting problems, image augmentation and dropout techniques were applied. The CNN methods were fused using a variety of fusion techniques, including feature as well as score level techniques, to examine the effects of fusion approaches on recognition performance. To empirically assess the performance of the constructed system, a number of experiments were carried out on the CASIA dataset [4].

Algorithms for machine learning are techniques that assist in selecting appropriate feature representations, which facilitates decision-making and the fusion of multimodal data. The deep learning representations for the left and right iris were used in the creation of IrisConvNet [5]. The goal of this approach was to combine the outcomes of ranking level fusion techniques.

IrisConvNet's architecture was built using a convolutional neural network and the Softmax classifier. Combining these two methods allowed discriminative characteristics to be derived without domain expertise. Here, the input data which means image represented the localized iris region. With this localized iris region, the overall image was classified into different classes. Additionally, a discriminative CNN training scheme based on back-propagation and mini-batch AdaGrad optimization was put forth for the purposes of updating weights and learning rate adaptation, respectively. In biometric recognition, the intrinsic curve properties of the iris were not retrieved, even if overall accuracy increased and processing time was minimized. In order to solve this problem, a feature extraction model capable of obtaining the intrinsic curve features (i.e., Edge of curve, Region of interest, Pixel dimensionality) of the face, fingerprint, and iris is described in this study after pre-processing. Intrinsic curve features are used to extract relevant features of the image and provides clear recognize image of iris, fingerprint and face. This is designed using Multi-scale Geometric features and therefore referred to as the Multi-scale Geometric Curvelet Feature Extraction.

The Variational Bayesian Extreme Learning Machine (VBELM) is a multimodal fusion system for face and fingerprint pictures that was created in [6] with the use of a block-based feature image matrix. In this case, local features—also referred to as local fusion visual features—were used to extract middle layer semantic features. This offered the benefit of improved characterization with reduced dimensionality for multi-modal biometrics.

Random input weights allowed for the efficient recognition process with a clear speed advantage. Additionally, by using a non-informative full Gaussian prior, VBELM demonstrated greater stability and generalization. As a result, VBELM made it possible for multimodal biometric recognition to have a high recognition rate and concentrated fusion feature description. Despite fast learning speed, recognition rate was said to be compromised with high dimension samples. In this work, to address this issue, an unsupervised learning technique to strengthen the recognition rate, using the Minkowski distance between the testing and training samples is investigated. A dimensionality reduction Multi-scale Geometric Curvelet Feature Extraction model based on centrifugal and asymmetric windows is proposed to achieve this purpose.

The remaining sections of the document are arranged as follows: In Section 2, the rationale for the suggested approach is given along with a quick overview of a few similar papers. An overview of the suggested machine learning methods is given in Section 3. The experimental results of the suggested method are shown in Section 4 along with a discussion and graph that are covered in Section 5. Lastly, the last Section 6 reports the conclusions.

2. RELATED WORK

Biometric Recognition using fingerprint has found an application in the recent years. One of the biometric traits that are useful and an important source of forensic evidence are latent fingerprints. In [7], latent fingerprint matching was performed using top 'k' exemplar candidates. This in turn improved the latent matching accuracy by baseline matcher and hence resort the candidate list. However, it decreases the recognition rate.

Therefore, A comparative study of biometric fusion was discussed in [8] for higher recognition rate. But, it failed in terms of performance of efficiency. In order to overcome this issues, A survey on local matching using fingerprint minutiae with the objective of verification and identification along with a brief taxonomy and An excellent trade-off between efficacy and efficiency was found in [9] when examining experimental evaluation, which produced good results. However, false acceptance level is higher. To address this issue, a comparative study of different fusion techniques using various multimodal biometrics including face, fingerprint and finger vein was designed in [10]. However, recognition rate is not sufficient. With the ability to identify the individuals in an automatic manner, in the last few years, the need of biometric systems has grown, based on their behavioural and biological characteristics. In [11], a multimodal biometric recognition system to exploit the discriminative capacity with the objective of recognizing the individuals was investigated, resulting in good recognition performance. But, the computation cost is higher.

To address this issue, face annotation model using collaborative framework was designed in [12]. This model not only increased the accuracy but also reduced the computation cost. However, authentication was not investigated. To address this issue, in [13], score level fusion algorithm covering cost and client specific was presented. It happens more frequently when doing multimodal biometric fusion when modalities are absent. Hence, matching is not said to be performed. Due to this, the scores are said to be missing at the match score level. To address this issue, Neutral Point Substitution (NPS) method was presented in [14] that not only achieve good generalization performance but also missing modalities. However, differentiation between fake and real images was not said to be performed.

In [15], a biometric recognition performance was designed to differentiate between the legitimate and impostor samples. However, user inconvenience and system inefficiency in parallel biometrics was found to be addressed. This was resolved in [16] by utilizing the coupling relationship between the stronger and weaker features to create semi-supervised learning algorithms. In [17], a text-based multimodal biometric technique was examined through behavioral profiling, keystroke dynamics, and linguistic analysis.

Recognizing a sample given a set of training biometric samples is a pivotal pattern recognition problem. A novel statistical method for multi biometric systems using geometric and multinomial distributions was presented in [18]. In [19], the issues related to bimodal biometric authentication in the field of mobile phones using Gaussian mixture model was discussed. Based on face and iris, a multimodal system to provide measures against attack was provided in [20].

A novel Gaze Analysis technique [21] using graph based representation was designed to provide fast and reliable identity recognition. Yet another Fisher's discriminant analysis was applied in [22] to provide suffice discriminatory information between ECG signals, confirming a very good performance. A fingerprint identification data encryption technique based on an enhanced Advanced Encryption Standard (AES) was created in [23]. A human recognition model using Grey wolf was investigated in [24], resulting in the improvement of recognition.

Support Vector Machine classifiers were used in the development of a unique 3D Local Energy based Histogram (3D-LESH) feature extraction approach [25]. Similar to prior cases, a semi-supervised learning model was created in [26] using a vector space model and random projection scaling. Support vector machines were also used to conduct reasoning on knowledge bases. Deep learning as well as reinforcement learning techniques in mining of biological data was undergone in [27]; where role of deep learning was analyzed rigorously by which rationalized AdaBoost algorithm was studied deeply. A Unimodal biometric recognition system was introduced in [28]. However, performance of recognition accuracy was not sufficient. DCD-WR (Deep multimodal biometric recognition using contourlet derivative weighted rank) designed in [29] for improving recognition accuracy. However, it failed in terms of parameter like recognition time and false acceptance rate. In [30], a multimodal biometric system was introduced for achieving higher recognition accuracy. The proposed technique utilizes three complementary characteristics—the fingerprint, finger vein, and iris—and allows for the simultaneous capture of both with a single device. By both boosting and inhibiting rival classifiers and resolving disputes between them, the best score level fusion is achieved. This method failed to consider pre-processing model. Therefore, enhanced image quality was significant problem.

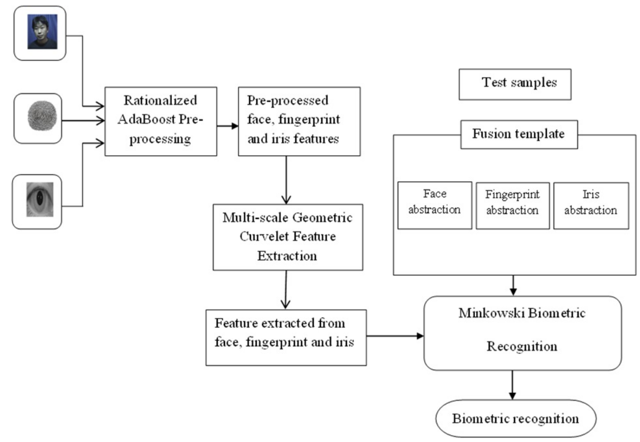

Figure 1. Geometric Curvelet and Minkowski Multimodal Biometric Recognition (GC-MMBR) Block diagram

From this related work two important facts are concluded. First, intrinsic and curve features are highly significant for biometric recognition when involving multi-modalities. Second, the removal of irrelevant or insignificant features requires the use of discriminative features. Our research demonstrates that extracting discriminative features and combining them with intrinsic and curve features leads to a higher recognition rate with less complexity.

As illustrated in the above block diagram, the GC-MMBR is divided into three stages. They are Rationalized AdaBoost Pre-processing model, Multi-scale Geometric Curvelet Feature Extraction model and Minkowski Biometric Recognition model. Here, given with the multimodal face, fingerprint and iris features, intrinsic features are first obtained. With the obtained intrinsic features, intrinsic curve features are extracted to reduce the overall dimensionality. Finally, the biometric recognition is performed using the Minkowski distance, therefore reducing the false acceptance rate. The elaborate description of the GC-MMBR method is given in the forthcoming sections.

A. *Rationalized AdaBoost Pre-processing model*

Pre-processing refers to the elimination of unwanted features with the aim of supressing the noise present in feature vectors (i.e., face, fingerprint and iris) with enhanced image quality. Entire face, fingerprint and iris region is not inevitable for biometric recognition. Only the unique region that incorporates the maximum possible length of feature vectors is adequate. Hence, feature vector positioning is also indispensable to reduce the system errors. So elimination of unwanted features and reduction of noise in the principal

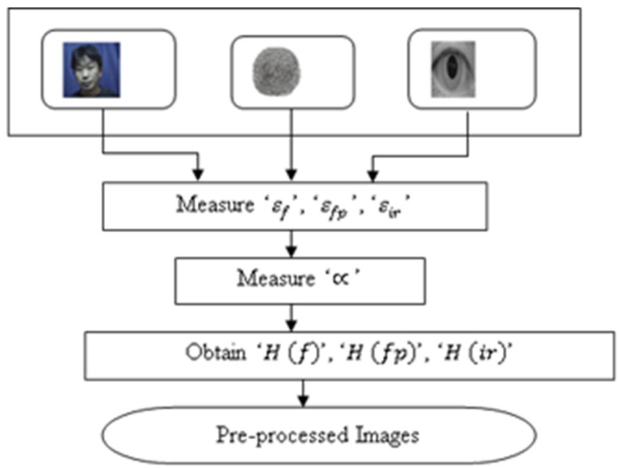

Figure 2. Flow diagram of Rationalized AdaBoost Pre-processing model

feature vectors with the objective of obtaining intrinsic features are carried out in the pre-processing stage.

There have been many techniques implemented in the past to retrieve the features of face, fingerprint and iris [5], [6] using normalization. For biometric recognition, one needs to identify the intrinsic features present in fingerprint Iris and face. By adopting Rationalized AdaBoost Pre-processing model this is accomplished. Figure 2 depicts the flow process of Rationalized AdaBoost Pre-processing model.

As illustrated in the above figure, the Rationalized AdaBoost Pre-processing model selects the best features during the pre-processing stage to train classifiers that use them. To conduct pre-processing, sequence of ‘n’ samples (i.e. collected from face, fingerprint and iris) is used. At every iteration, the Rationalized AdaBoost Pre-processing, evaluates the weights to obtain a hypothesis ‘$H : P \rightarrow [0, 1]$’, with ‘n’ samples given below.

$$f \rightarrow < \{(p_{11}, y_{11}), (p_{12}, y_{12}), ..., (p_{1n}, y_{1n})\} \tag{1}$$

$$fp \rightarrow < \{(p_{21}, y_{21}), (p_{22}, y_{22}), ..., (p_{2n}, y_{2n})\} > \tag{2}$$

$$ir \rightarrow < \{(p_{31}, y_{31}), (p_{32}, y_{32}), ..., (p_{3n}, y_{3n})\} > \tag{3}$$

From above equation 1,2 and 3, ‘$p_{11}, p_{12}, ..., p_{1n}$’ represents the face vector features, ‘$p_{21}, p_{22}, ..., p_{2n}$’ represents the fingerprint vector features and ‘$p_{31}, p_{32}, ..., p_{3n}$’ represents the iris vector features respectively. The error of this hypothesis for three features (i.e. face, fingerprint and iris) is mathematically formulated as given below.

$$\varepsilon_f = \sum\nolimits_{i=1}^{n} |H(p_{1i}) - y_{1i}| \tag{4}$$

$$\varepsilon_{fp} = \sum\nolimits_{i=1}^{n} |H(p_{2i}) - y_{2i}| \tag{5}$$

$$\varepsilon_{ir} = \sum\nolimits_{i=1}^{n} |H(p_{3i}) - y_{3i}| \tag{6}$$

From the above equation (4), (5) and (6), ‘ε_f’, ‘ε_{fp}’ and ‘ε_{ir}’ symbolizes the error of three hypothesis, face, fingerprint and iris respectively along with the samples ‘p_{11}’, ‘p_{21}’ and ‘p_{31}’ with their corresponding binary labels ‘[0,1]’ denoted in ‘y_{11}’, ‘y_{21}’ and ‘y_{31}’. Followed by which, the rationalized weight boundary ‘α’ is mathematically formulated as given below.

$$\alpha = \frac{\varepsilon}{(1-\varepsilon)}, \varepsilon \in \varepsilon_f, \varepsilon_{fp}, \varepsilon_{ir} \tag{7}$$

At each iteration, the output of the above rationalized weight boundary ‘α’ is mathematically formulated as given below.

$$H(pf) = \{^{0 if(\frac{\log 1}{\alpha}) < \varepsilon_f}_{1, otherwise} \tag{8}$$

$$H(pfp) = \{^{0 if(\frac{\log 1}{\alpha}) < \varepsilon_{fp}}_{1, otherwise} \tag{9}$$

$$H(pir) = \{^{0 if(\frac{\log 1}{\alpha}) < \varepsilon_{ir}}_{1, otherwise} \tag{10}$$

From the above equations (8), (9) and (10), the pre-processed features for face ‘$H(pf)$’, fingerprint ‘$H(pfp)$’ and iris ‘$H(pir)$’, are evolved. In this manner, the positive samples contain images of iris, face, and fingerprint. But the negative samples do not. The pseudo code representation of Rationalized AdaBoost Pre-processing is given below.

As given in the above Rationalized AdaBoost Pre-processing algorithm, for each ‘m’ samples, the objective of the algorithm is to identify the intrinsic face, fingerprint and iris features. To achieve this, error of hypothesis is evaluated first with which the rationalized weight boundary is evaluated. Next, rationalized weight boundary is evaluated to obtain the final pre-processed face, fingerprint and iris images.

B. Multi-scale Geometric Curvelet Feature Extraction model

With the pre-processed features, feature extraction is the second step for modeling multimodal biometric recognition. In this work, with the objective of extracting intrinsic curve features of multimodal, Multi-scale Geometric Curvelet Feature Extraction model is designed. Here, the statistical

Input: samples face ’ m ’, feature vector ’ $p_1^{(i)}$ ’ fingerprint feature vector ’ $p_2^{(i)}$, , iris feature vector ’ $p_3^{(i)}$,
Output: Noise reduced samples face ’ pf ’, fingerprint ’ pfp ’ and iris features ’pir’
Begin
For each ’ m ’ samples
For each $p_1^{(i)}, p_2^{(i)}, p_3^{(i)}$
Measure error of hypothesis for three features using (4), (5) and (6)
5: Measure rationalized weight boundary using (7)
6: Measure output of rationalized weight boundary using (8), (9) and (10) to obtain pre-processed face, fingerprint and iris features
7: End for
8: End for
9: End

Algorithm 1: Rationalized AdaBoost Pre-processing

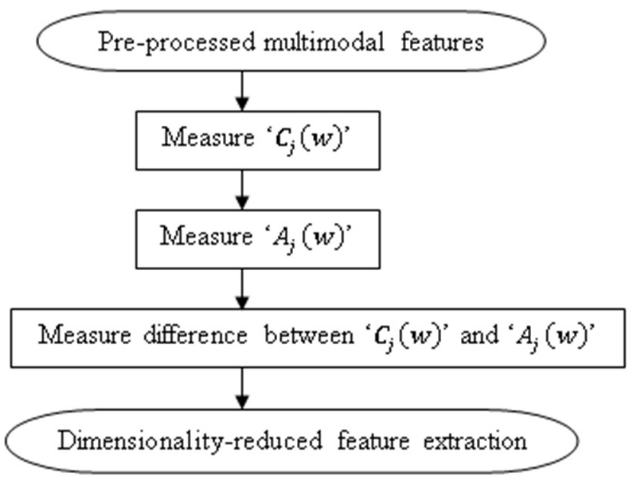

Figure 3. Flow diagram of Multi-scale Geometric Curvelet Feature Extraction

measure such as centrifugal and asymmetric windows are used, hence called as the Geometric Curvelet Feature Extraction model. The purpose of using Multi-scale Geometric Curvelet Feature Extraction model is to represent curve features of multimodal features.

As illustrated in the above figure, in Multi-scale Geometric Curvelet Feature Extraction model, the pre-processed multimodal features are taken as input. Then, this image is split into parabolic wedges ‘w’. The wedges are then obtained from dividing the entire pre-processed images in centrifugal ‘C’ and Asymmetric ‘A’ windows for each scale ‘j’ and is mathematically formulated as given below.

$$C_j(w)[f] = \sqrt{[pf][\varphi_{j+1}^2(w) - \varphi_j^2(w)]} \tag{11}$$

$$C_j(w)[fp] = \sqrt{[pfp][\varphi_{j+1}^2(w) - \varphi_j^2(w)]} \tag{12}$$

$$C_j(w)[ir] = \sqrt{[pir][\varphi_{j+1}^2(w) - \varphi_j^2(w)]} \tag{13}$$

From above equation (11), (12) and (13), ‘φ’, corresponds to the low pass one dimensional windows for face, fingerprint and iris features respectively. Followed by which, angular window ‘A’ is measured.

$$A_j(w)[f] = [pf][A(\frac{w_1}{w_2})] \tag{14}$$

$$A_j(w)[fp] = [pfp][A(\frac{w_1}{w_2})] \tag{15}$$

$$A_j(w)[ir] = [pir][A(\frac{w_1}{w_2})] \tag{16}$$

Finally, from the above equation (14), (15) and (16), the features near the wedges ‘w_1’ and ‘w_2’ are isolated and the mathematical formulation of the final multimodal feature is given below.

$$Cf = [C_j(w)[f] - A_j(w)[f]] \tag{17}$$

$$Cfp = [C_j(w)[fp] - A_j(w)[fp]] \tag{18}$$

$$Cir = [C_j(w)[ir] - A_j(w)[ir]] \tag{19}$$

By obtaining the mean differences as given above, the curvelet features obtained for iris, face and fingerprint not only decreases the pre-processed multimodal features dimensionality but also avoid the redundancy of curvelet coefficients. The pseudo code representation of Multi-scale Geometric Curvelet Feature Extraction is given below.

As given in the above Multi-scale Geometric Curvelet Feature Extraction algorithm, for each pre-processed multimodal features, intrinsic curve features are obtained using two different geometries namely, centrifugal and angular windows respectively. By applying the two different geometries for different scales (also called as multi-scale), dimensionality reduced multimodal features are extracted. The curvelet multimodal coefficients that obtained act as the feature extracted set for biometric identification.

C. *Minkowski Multimodal Biometric Recognition model*

A matrix is created by extracting multimodal biometric features from images. Each row represents feature vectors and each column represents different samples of the cor-

Input: Pre-processed face 'pf', fingerprint 'pfp' and iris features 'pir', wedge 'w'
Output: Features extracted 'Cf', 'Cfp', 'Cir'
1: Begin
2: For each pre-processed face 'pf', fingerprint 'pfp', and iris features 'pir'
3: Measure centrifugal window '$C_j(w)$' using (11), (12), and (13)
4: Measure angular window '$A_j(w)$' using (14), (15), and (16)
5: Measure extracted face, fingerprint, and iris features using (17), (18), and (19)
6: End for
7: End

Algorithm 2: Multi-scale Geometric Curvelet Feature Extraction

responding feature vector. The matrix representation for training samples is given below.

$$\begin{bmatrix} TrCf_1 & TrCf_2 & ..... & TrCf_n \\ TrCfp_1 & TrCfp_2 & ..... & TrCfp_n \\ TrCir_1 & TrCir_2 & ..... & TrCir_n \end{bmatrix} \quad (20)$$

In a similar manner, the matrix representation for test samples is given below.

$$\begin{bmatrix} TCf_1 & TCf_2 & ..... & TCf_n \\ TCfp_1 & TCfp_2 & ..... & TCfp_n \\ TCir_1 & TCir_2 & ..... & TCir_n \end{bmatrix} \quad (21)$$

Based on training samples, the Minkowski distance predicts whether the test samples are similar to the train sample or not. The similarity is identified by Minkowski distance, which calculates the separation between training and test samples. Using multimodal features as the test sample, an extensive search technique is used to improve the biometric recognition rate in order to obtain the Minkowski distance.

$$Distance = (Tr, T) = \sum_{i=1}^{n} (Tr_i - T_i) \quad (22)$$

The above distance measure is obtained for all the three features, with which the distance between the training and test samples are evaluated. Lower the distance more efficient the recognition rate is said to be. Conversely, a higher distance is thought to result in a lower recognition rate. Below is the Minkowski Multimodal Biometric Recognition pseudo code representation.

As given in the above Minkowski Multimodal Biometric Recognition algorithm, for each extracted features, matrix

Input: Features extracted 'Cf', 'Cfp', 'Cir', Test samples 'TCf', 'TCfp', 'TCir'
Output: Optimal recognition
1: Begin
2: For each extracted features 'Cf', 'Cfp', 'Cir'
3: Obtain matrix representation for training samples
4: Obtain matrix representation for test samples
5: Measure the distance between training samples and test samples using (22)
6: End for
7: End

Algorithm 3: Minkowski Multimodal Biometric Recognition

representation for training and testing samples are acquired separately and stored in two different matrices. Using the two different matrices,Minkowski distance is applied to identify the distance between training and test samples for face, fingerprint and iris features. With this, lower identified distance is used for recognition. As a result, the biometric recognition rate is said to be improved.

3. EXPERIMENTAL EVALUATION

Biosecure Dataset and CASIA Biometric Ideal Test Dataset is chosen in our evaluation method which includes several biometric traits namely face, iris, palm print, fingerprint, and handwriting image whose goal is to integrate interdisciplinary research projects in the field of biometric identity identification. For the purpose of conducting experiments, we used face, fingerprint and iris images for biometric recognition and implemented in MATLAB simulator with several training and test samples. Experiments are conducted using 50-500 human biometric samples.

In this study, three current methods—IrisConvNet [5], Variational Bayesian Extreme Learning Machine (VBELM) [6], and Deep Multimodal Biometric Recognition using Contourlet Derived WeightedRank Fusion with Human Face, Fingerprint, and Iris Images (DCD – WR)—are compared with the proposed Geometric Curvelet and Minkowski Multimodal Biometric Recognition (GC-MMBR) method. Various features of the suggested method are assessed, including the quantity of human biometric samples, computational time, computational complexity, and recognition rate.

The term "computational time" (CT) describes how long it takes to extract the features from a face (Cf), fingerprint (Cfp), and iris (Cir) in relation to the input of human biometric samples (n). The measurement is done in milliseconds and the mathematical formulation is given below.

$$CT = n * Time(Cf + Cfp + Cir) \quad (23)$$

The computational complexity 'CC' refers to the complexity involved during the execution of algorithm or the memory required to perform Minkowski Multimodal Biometric Recognition algorithm. The measurement is done in KiloBytes and the mathematical formulation is given below

$$CC = n * MEM[Distance(Tr, T)] \tag{24}$$

The term "recognition rate" describes how well the fusion template matches the input human biometric samples. It is expressed mathematically as follows, and its measurement is expressed in percentages.

$$RR = \frac{samplescorrectlyrecognized}{n} * 100 \tag{25}$$

The amount of time needed for the fusion template to accurately identify human biometric samples among the input samples is referred to as recognition time which is given in milliseconds (ms).

$$RT = Time[\frac{samplescorrectlyrecognized}{n}] \tag{26}$$

The likelihood that the system may mistakenly approve a user who is not permitted because the biometric test samples were not properly matched to the training sample is known as the False Acceptance rate, or FAR. Stated differently, the false acceptance rate (FAR) is a measure that assesses the typical amount of false positives during biometric authentication. The FAR measures the speed at which illegal samples or users are identified in order to assess the efficacy and precision of GC-MMBR. It is expressed mathematically as follows, and its measurement is expressed in percentages (%).

$$FAR = [\frac{likelihoodofincorrectrecognitionofbiometric}{n}]*100 \tag{27}$$

4. DISCUSSION

The performance of the geometric curvelet and Minkowski Multimodal Biometric Recognition (GC-MMBR) method with the most advanced biometric recognition techniques for text categorization and biometric recognition for multimodal features is presented. The CASIA Biometric Ideal Test Dataset and Biosecure dataset are used to evaluate the computational time, computational complexity, recognition accuracy, recognition time, and face acceptance rate with varying numbers of features, ranging from 50 to 500, in order to compare the performance of biometric recognition methods.

A. Computational time and its impact

We first test the biometric recognition method when Multi-scale Geometric Curvelet Feature Extraction algorithm is used. Figure 4 given below shows the computational time performances of the proposed GC-MMBR method with comparison made to the existing IrisConvNet [5], VBELM [6], DCD-WR and Multimodal biometric system for biometric recognition text categorization on Biosecure dataset and CASIA Biometric Ideal Test Dataset.

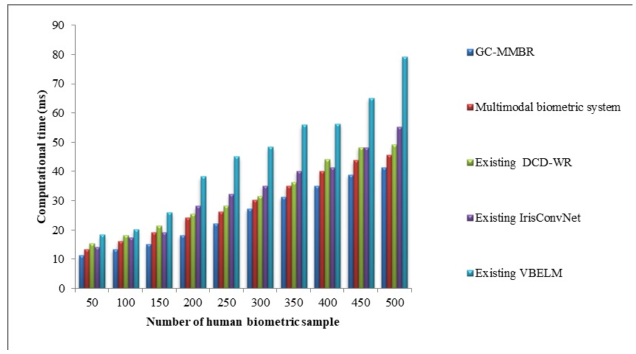

Figure 4. Comparison performances of computational time using CASIA Biometric Ideal Test Dataset

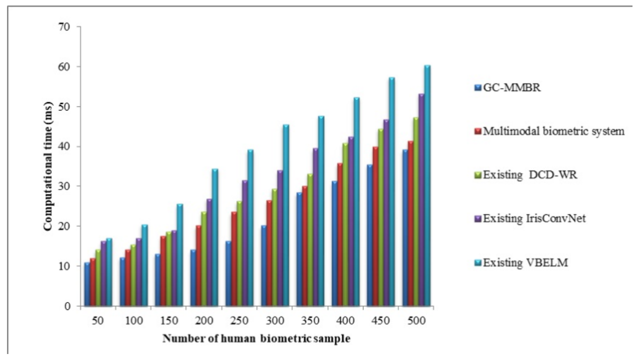

Figure 5. Comparison performances of computational time using Biosecure Dataset

The computational time performances of biometric recognition on the Biosecure dataset and the CASIA Biometric Ideal Test Dataset are displayed in Figures 4 and 5 above. The chart shows that, when the number of human biometric samples gets increased then higher feature set is said to be exist and therefore the time taken to extract is also said to be increased using all the three methods. However, comparison shows betterment achieved using GC-MMBR method than two other existing methods. It shows that the GC-MMBR method perform at least as well as traditional biometric recognition methods at a very small sample size, and are continuously better when the sample size increases. This is because by applying two different geometries namely, centrifugal and angular windows in Multi-scale Geometric Curvelet Feature Extraction algorithm, dimensionality reduced multimodal features are extracted. With dimensionality reduced multimodal features extracted, optimal samples or features are said to be selected with higher discriminative capacity and intrinsic features. This in turn minimizes the computational time using GC-MMBR method when compared to IrisConvNet [5] by 24%.

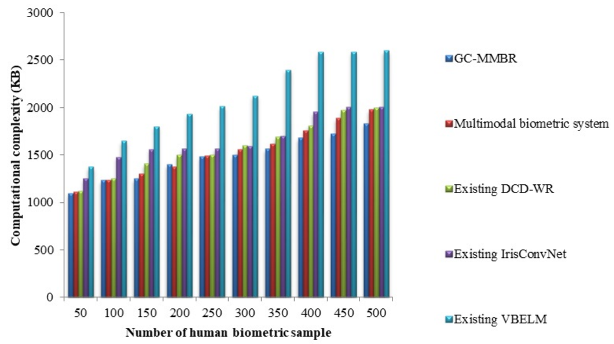

Figure 6. Comparison performances of computational complexity using CASIA Biometric Ideal Test Dataset

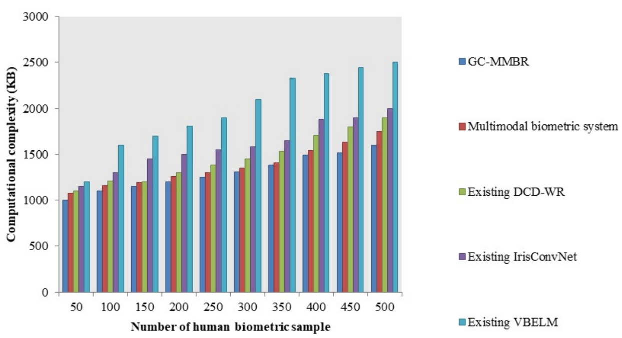

Figure 7. Comparison performances of computational complexity using Biosecure Dataset

Moreover, based on mean differences, the resultant curvelet features avoid redundancy in curvelet coefficients. This in turn helps in minimizing the computational time using GC-MMBR method by 43% when compared to VBELM [6] and 21% when compared to DCD-WR and 14% when compared to Multimodal biometric system. Similarly, the computation time using proposed GC-MMBR method is found to be increased by 33% compared to IrisConvNet [5], 45% compared to VBELM [6], 25% compared to DCD-WR and 16% compared to Multimodal biometric system.

B. *Computational complexity and its impact*

In order to further investigate, another experiment was conducted by varying the biometric samples in the range of 50 to 500 and measured their corresponding computational complexity for GC-MMBR method and that methods is compared with IrisConvNet [5], VBELM [6], DCD-WR and Multimodal biometric system.

The performances of computational time were measured according to the Minkowski distance with respect to 500 samples considered for experimentation. It is clear that when there were less human biometric samples, the computational complexity was found to be better; but, when the number of human biometric samples increased, it was discovered that the computational complexity associated with employing all three approaches was rising. Also, comparatively, better performance was observed using GC-MMBR method and highest complexity was found to be involved using VBELM method. It is observed from the figure that all the variants of the proposed GC-MMBR method significantly outperform the traditional biometric recognition, IrisConvNet [5], VBELM [6] , DCD-WR and Multimodal biometric system. This is because by applying the Minkowski, the Minkowski metric is optimized, to optimize recognition time and biometric samples respectively. Since a lower distance means more efficient recognition rate and therefore biometric recognition is said to be improved, we can conclude that optimization based on Minkowski distance is quite effective with 12% found to be improved than IrisCovNet [5] and 29% than VBELM [6] , 6% than DCD-WR and 3% than Multimodal biometric system correspondingly when applied in CASIA Biometric Ideal Test Dataset. In the similar manner, it is reduced by 18%, 33%, 10% and 5% when compared to existing IrisCovNet [4], VBELM [6], DCD-WR and Multimodal biometric system respectively when applied in Biosecure Dataset. It is shown in figures 5(a) and 5(b).

C. *Recognition rate and its impact*

To find the recognition rate, a third series of experiments is carried out. Higher the rate of recognition then it ensures efficiency of the method. The experiment conducted the recognition rate for two different methods. The first technique is a straightforward but effective training procedure that extracts discriminative features using a convolutional neural network and a softmax classifier. The second approach uses a deep learning machine learning model for multimodal biometric recognition, which is also a fusion model. Finally the proposed method in this study is analyzed. Below are some sample computations.

CASIA Biometric Ideal Test Dataset

- Proposed GC-MMBR: Suppose the input i.e biometric trait samples given is 50 and the correctly recognized sample is 46 then the recognition rate will be $RR = \frac{46}{50} * 100 = 92\%$
- IrisConvNet method applies the same logic mentioned above for the 50 numbers of samples and 36 numbers of correctly recognized samples. The recognition rate will be $RR = \frac{36}{50} * 100 = 72\%$
- Similarly the same calculation method is used for computing recognition rate for VBELM, DCD-WR and Multilodal biometric systems.

  For VBELM, $RR = \frac{35}{50} * 100 = 70\%$

  For DCD-WR, $RR = \frac{41}{50} * 100 = 82\%$

  For Multimodal biometric system, $RR = \frac{42}{50} * 100 = 82\%$

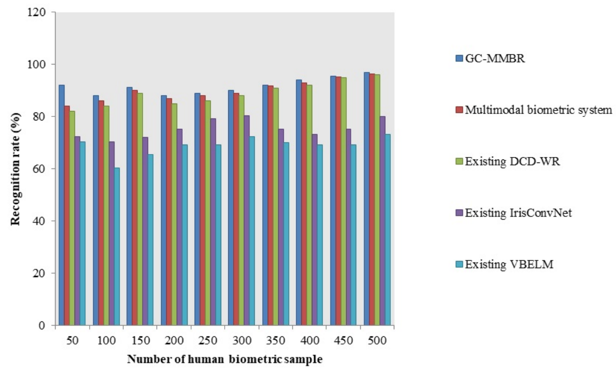

Figure 8. Comparison performances of recognition rate using CASIA Biometric Ideal Test Dataset

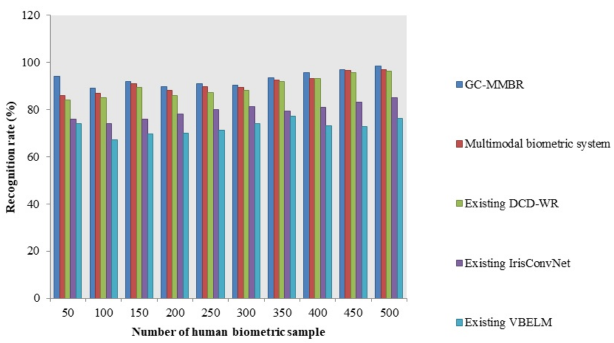

Figure 9. Comparison performances of recognition rate using Biosecure Dataset

Sample calculation (using Biosecure Dataset)

- Proposed GC-MMBR: Suppose the input i.e biometric trait samples given is 50 and the correctly recognized sample is 46 then the recognition rate will be $RR = \frac{47}{50} * 100 = 94\%$
- IrisConvNet method applies the same logic mentioned above for the 50 numbers of samples and 36 numbers of correctly recognized samples. The recognition rate will be $RR = \frac{38}{50} * 100 = 76\%$
- Similarly the same calculation method is used for computing recognition rate for VBELM, DCD-WR and Multilodal biometric systems.

  For VBELM, $RR = \frac{37}{50} * 100 = 74\%$

  For DCR-WR, $RR = \frac{42}{50} * 100 = 84\%$

  For Multimodal biometric system, $RR = \frac{43}{50} * 100 = 86\%$

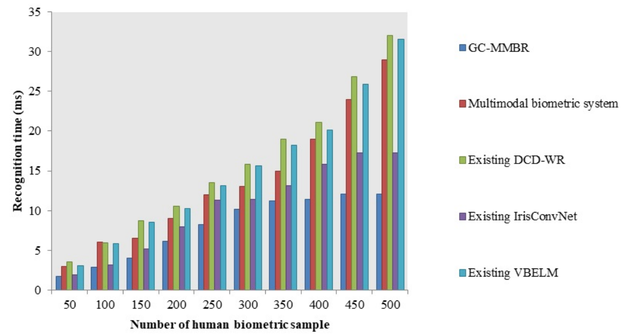

Figure 10. Comparison performances of recognition time using CASIA Biometric Ideal Test Dataset

Figures 8 and 9 demonstrate how the GC-MMBR approach performs better when the intrinsic curve features are extracted using the Geometric Curvelet feature. When compared to alternative biometric recognition techniques, the intrinsic curve feature-extracted GC-MMBR method yields a more reliable outcome. The GC-MMBR method and the VBELM [6] method both uses machine learning algorithm to extract optimal features, but our method is found to be better than the other two methods, for in the VBELM method, through Variational Bayesian technique, random input weights are applied, which is only a fusion in the form, and therefore ignores the intrinsic curve information. On the other hand, by applying two different geometrics in GC-MMBR, intrinsic curve features are extracted. The biometric recognition rate utilizing the GC-MMBR approach is therefore found to be enhanced using the CASIA Biometric Ideal Test Dataset by 11% than IrisConvNet, 24% than VBELM, 3% than DCD-WR, and 2% than Multimodal biometric system. In Biosecure Dataset, the biometric recognition rate using GC-MMBR method is discovered to be enhanced by 17% than IrisConvNet , 28% than VBELM and 4% than DCD-WR and 2% compared to Multimodal biometric system respectively.

D. Recognition time and its impact

Performance of recognition time or biometric recognition time is evaluated by fourth set of experiment. The time taken to recognize the biometrics via three features analyzed for 500 distinct samples taken from Biosecure dataset and CASIA Biometric Ideal Test Dataset.

The figures 7(a) and 7(b) given above illustrate the comparison performances of recognition time using GC-MMBR method, IrisConvNet [5], VBELM [6], DCD-WR and Multimodal biometric system respectively. As seen in the picture, the sizes of the three distinct features—the face, fingerprint, and iris—increase as the quantity of human biometric samples grows. As a result, the recognition time is also said to be increased with the higher set of biometric samples. However, comparison revealed that the time taken for biometric recognition using GC-MMBR method to be better than the other two methods. This is because by

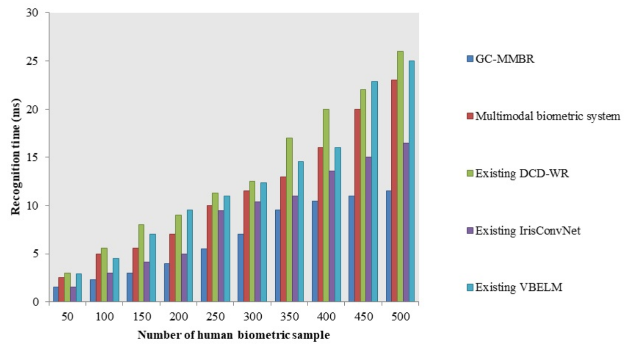

Figure 11. Comparison performances of recognition time using Biosecure Dataset

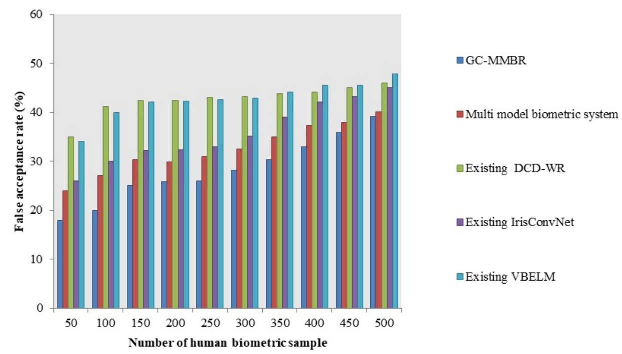

Figure 12. Comparison performances of false acceptance rate using CASIA Biometric Ideal Test Dataset

applying Rationalized AdaBoost Pre-processing algorithm, only the intrinsic face, fingerprint and iris features are obtained through rationalized weight boundary. With the intrinsic features when applied to two different geometrics, centrifugal and asymmetric windows, the intrinsic curve features are extracted. As a result, the biometric recognition time using GC-MMBR method is found to be reduced by 20% when compared to IrisConvNet [5] and 46% when compared to VBELM [6] and 47% than DCD-WR and 39% than multimodal biometric system in CASIA Biometric Dataset. Similarly, when proposed GC-MMBR method is compared with existing the recognition time ie reduced by 24% than IrisConvNet [5] and 48% than VBELM [6], 52% compared than DCD-WR, 42% compared to multi-modal biometric system respectively when using Bio Secure dataset.

E. False acceptance rate and its impact

Using the GC-MMBR approach, the effect of false acceptance rate is finally assessed and compared with the current IrisConvNet [5], VBELM [6], DCD-WR, and Multi-modal biometric system, in that order. The patterns of many human biometric samples are used to train the system during the biometric identification process. In this training step, a biometric template is computed for each human biometric sample. The identified test sample is matched against every known training template yielding a distance describing the similarity between the test samples and training samples. The sample calculation is as given below.

Sample calculation (using CASIA Biometric Ideal Test Dataset)

- Proposed GC-MMBR: Suppose the input i.e bio-metric trait samples given is 50 and the correctly recognized sample is 46 then the FAR will be,
  $FAR = \frac{9}{50} * 100 = 18\%$
- IrisConvNet method applies the same logic mentioned above for the 50 numbers of samples and 36 numbers of correctly recognized samples. The FAR will be,
  $FAR = \frac{13}{50} * 100 = 26\%$
- Similarly the same calculation method is used for computing FAR for VBELM, DCD-WR and Multi-lodal biometric systems.
  For VBELM $FAR = \frac{17}{50} * 100 = 34\%$
  For DCD-WR $FAR = \frac{18}{50} * 100 = 36\%$
  For Multimodal biometric system $FAR = \frac{12}{50} * 100 = 24\%$

Sample calculation (using Biosecure Dataset)

- Proposed GC-MMBR: Suppose the input i.e bio-metric trait samples given is 50 and the correctly recognized sample is 46 then the FAR will be,
  $FAR = \frac{8}{50} * 100 = 16\%$
- IrisConvNet method applies the same logic mentioned above for the 50 numbers of samples and 36 numbers of correctly recognized samples. The FAR will be,
  $FAR = \frac{12}{50} * 100 = 24\%$
- Similarly the same calculation method is used for computing FAR for VBELM, DCD-WR and Multilodal biometric systems.

  For VBELM, $FAR = \frac{15}{50} * 100 = 30\%$

  For DCD-WR, $FAR = \frac{16}{50} * 100 = 32\%$

  For Multimodal biometric system, $FAR = \frac{10}{50} * 100 = 20\%$

Figures 12 and 13 illustrate the execution comparison by adopting the GC-MMBR method, IrisConvNet [5], VBELM [6], DCD-WR and Multimodal biometric system respectively. As seen in the figure, as the quantity of human biometric samples increases, though pre-processing has

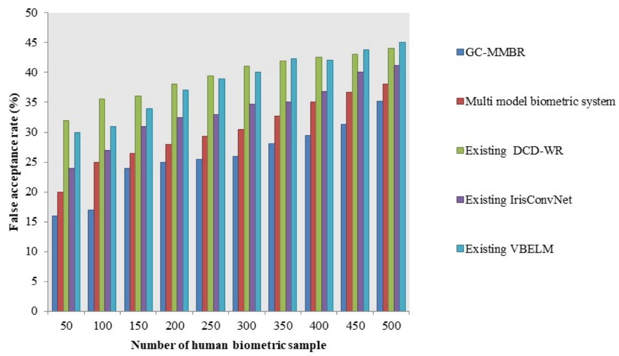

Figure 13. Comparison performances of false acceptance rate using Biosecure Dataset

been performed, some noise remains and is not discarded. This in turn results in noise and therefore false acceptance is said to occur. However, the false acceptance rate using GC-MMBR method is found to be comparatively lesser than using IrisConvNet [5], VBELM [6] and DCD-WR and Multimodal biometric system. This is because of applying using Rationalized AdaBoost model in the GC-MMBR method only the best features are selected based on the acceptable value of hypothesis. The resultant values greater than the hypothesis are discarded, therefore comparatively lesser noise is said to be observed. This in turn reduces the false acceptance rate using GC-MMBR method by 22% compared to IrisConvNet [5]. Besides based on the rationalized weight boundary, only the positive samples are considered and neglecting the negative samples reduces the false acceptance rate using GC-MMBR method by 35% compared to VBELM [6], 34% compared to DCD-WR and 14% compared to multimodal biometric system respectively using CASIA Biometric Ideal Test Dataset. In a similar manner, the proposed GC-MMBR method reduces the false acceptance rate by 24% compared to IrisConvNet [5] and 33% compared to VBELM [6], 35% compared to DCD-WR, 15% compared to multimodal biometric system respectively when applied with Bio Secure dataset.

5. CONCLUSION

Multi-scale Geometric Curvelet (MGC) and Minkowski distance factor models for face, fingerprint, and iris are constructed in order to present a reliable and quick multimodal biometric system for person recognition. The proposed method starts by applying a Rationalized AdaBoost Preprocessing model to obtain intrinsic features based on error of hypothesis and increased the recognition rate and also the computational time is reduced in further stages. In order to extract intrinsic discriminative curve features, a multi-scale geometric curvelet feature extraction model based on a mix of centrifugal and asymmetric windows is then suggested. Finally, by using extracted intrinsic discriminative curve features, Minkowski Multimodal Biometric Recognition model is designed for effective recognition. Extensive experiments have been conducted on CASIA Biometric Ideal Test Dataset and Biosecure Dataset to evaluate different number of parameters. The efficiency of the suggested GC-MMBR approach was confirmed by experimental findings, which showed a 15% increase in recognition rate and reducing the false acceptance rate by 20% using CASIA Biometric Ideal Test Dataset. Similarly, the proposed GC-MMBR method shown the results by improving the recognition rate by 13% and reducing the false acceptance rate by 27% using Biosecure dataset by which it is proved that recognition rate is considerably improved and false acceptance rate is reduced.

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References

[1] V. Rajasekar *et al.*, “Efficient multimodal biometric recognition for secure authentication based on deep learning approach,” *International Journal on Artificial Intelligence Tools*, vol. 32, no. 03, May 2023.

[2] D. Kothadiya *et al.*, “Enhancing fingerprint liveness detection accuracy using deep learning: A comprehensive study and novel approach,” *Journal of Imaging*, vol. 9, no. 158, August 2023.

[3] A. S. Tarawneh *et al.*, “Deepknuckle: Deep learning for finger knuckle print recognition,” *Journal of Electronics*, vol. 11, no. 513, February 2022.

[4] A. N and A.-B. HH, “Deep learning approach for multimodal biometric recognition system based on fusion of iris, face, and finger vein traits,” *Journal of Sensors*, vol. 20, no. 19, p. 5523, September 2020.

[5] A. S. A. Waisy, R. Qahwaji, S. Ipson, S. AlFahdawi, and T. A. M. Nagem, “A multi biometric iris recognition system based on a deep learning approach,” *Pattern Analysis and Applications*, September 2017.

[6] Y. Chen, J. Yang, C. Wang, and N. Liu, “Multimodal biometrics recognition based on local fusion visual features and variational bayesian extreme learning machine,” *Expert Systems With Applications*, July 2016.

[7] S. S. Arora, E. Liu, K. Cao, and A. K. Jain, “Latent fingerprint matching: Performance gain via feedback from exemplar prints,” *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 36, no. 12, December 2014.

[8] I. G. Damousis and S. Argyropoulos, “Four machine learning algorithms for biometrics fusion: A comparative study,” *Applied Computational Intelligence and Soft Computing*, vol. 2012, 2012.

[9] D. Peralta, M. Galar, I. Triguero, D. Paternain, S. García, E. Barrenechea, J. M. Benítez, H. Bustince, and F. Herrera, “A survey on fingerprint minutiae-based local matching for verification and identification: Taxonomy and experimental evaluation,” *Information Sciences*, May 2015.

[10] S. Sarhan, S. Alhassan, and S. Elmougy, “Multimodal biometric systems: A comparative study,” *Arabian Journal for Science and Engineering*, June 2016.

[11] S. Barra, A. Casanova, M. Fraschini, and M. Nappi, "Fusion of physiological measures for multimodal biometric systems," *Multimedia Tools and Applications*, August 2016.

[12] J. Y. Choi, W. D. Neve, K. N. Plataniotis, and Y. M. Ro, "Collaborative face recognition for improved face annotation in personal photo collections shared on online social networks," *IEEE Transactions on Multimedia*, vol. 13, no. 1, February 2011.

[13] N. Poh, T. Bourlai, and J. Kittler, "A multimodal biometric test bed for quality-dependent, cost-sensitive and client-specific score-level fusion algorithms," *Pattern Recognition*, March 2015.

[14] N. Poh, D. Windridge, V. Mott, A. Tatarchuk, and A. Eliseyev, "Addressing missing values in kernel-based multimodal biometric fusion using neutral point substitution," *IEEE Transactions on Information Forensics and Security*, vol. 5, no. 3, September 2010.

[15] J. Galbally, S. Marcel, and J. Fierrez, "Image quality assessment for fake biometric detection: Application to iris, fingerprint and face recognition," *IEEE Transactions on Image Processing*, vol. 23, no. 2, February 2014.

[16] Q. Zhang, Y. Yin, D.-C. Zhan, and J. Peng, "A novel serial multimodal biometrics framework based on semi-supervised learning techniques," *IEEE Transactions on Information Forensics and Security*, vol. 9, no. 10, October 2014.

[17] H. Saevanee, N. Clarke, S. Furnell, and V. Biscione, "Continuous user authentication using multi-modal biometrics," *Computers & Security*, June 2015.

[18] S. Kumar, R. Nair, B. Bhanu, S. Ghosh, and N. S. Thakoor, "Predictive models for multi biometric systems," *Pattern Recognition*, June 2014.

[19] E. Khoury, L. E. Shafey, C. McCoo, M. Günther, and S. Marcel, "Bi-modal biometric authentication on mobile phones in challenging conditions," *Image and Vision Computing*, October 2013.

[20] M. Gomez-Barrero, J. Galbally, and J. Fierrez, "Efficient software attack to multimodal biometric systems and its application to face and iris fusion," *Pattern Recognition Letters*, September 2014.

[21] V. Cantoni, C. Galdi, M. Nappi, M. Porta, and D. Riccio, "Gant: Gaze analysis technique for human identification," *Pattern Recognition*, March 2014.

[22] Y. N. Singh, "Human recognition using fisher's discriminant analysis of heartbeat interval features and ecg morphology," *Neurocomputing*, May 2015.

[23] P. Yang, G. Sun, J. He, P. Zhou, and J. Liu, "A student information management system based on fingerprint identification and data security transmission," *Journal of Electrical and Computer Engineering*, vol. 2017, 2017.

[24] D. Sánchez, P. Melin, and O. Castillo, "A grey wolf optimizer for modular granular neural networks for human recognition," *Computational Intelligence and Neuroscience*, vol. 2017, 2017.

[25] S. K. Wajid, A. Hussain, and K. Huang, "Three-dimensional local energy-based shape histogram (3d-lesh): A novel feature extraction technique," *Expert Systems with Applications*, vol. 112, pp. 388–400, December 2018.

[26] A. Hussain and E. Cambria, "Semi-supervised learning for big social data analysis," *NeuroComputing*, vol. 275, pp. 1662–1673, January 2018.

[27] M. Mahmud, M. S. Kaiser, A. Hussain, and S. Vassanelli, "Applications of deep learning and reinforcement learning to biological data," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 29, no. 6, pp. 2063–2079, 2018.

[28] S. Bashir, S. Sofi, S. Aggarwal, and S. Singhal, "Unimodal & multimodal biometric recognition techniques a survey," vol. 4, no. 1, pp. 1–8, February 2015.

[29] K. Gunasekaran, J. Raja, and R. Pitchai, "Deep multimodal biometric recognition using contourlet derivative weighted rank fusion with human face, fingerprint and iris images," *Automatika*, vol. 60, no. 3, pp. 253–265, 2019.

[30] G. S. Walia, T. Singh, K. Singh, and N. Verma, "Robust multimodal biometric system based on optimal score level fusion model," *Expert Systems with Applications*, vol. 116, pp. 364–376, February 2019.