Development of Palmvein Recognition System Using Fire Fly Algorithm and Linear Discriminant Analysis

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ABSTRACT

Palmvein technology is one of the most popular fields in pattern recognition. The method has received increasing attention in recent years. It is a new method of personal identification and biometric technology that identifies individuals using unique palmvein patterns, which is the first reliable and suitable area to be recognized. The most distinguishing advantage of vein features are high level of accuracy, difficult to forge and more table features. In this study, palmvein images of individuals were acquired; a Linear Discriminant Analysis and Firefly Algorithm (LDA-FA) model for feature extraction was formulated and implemented and the performance of the developed system was benchmarked with the LDA model.

Keywords: Biometrics, Palm vein recognition, Security, Firefly, LDA, Algorithms.

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1. INTRODUCTION

Biometrics refers to the identification (or verification) of an individual (or a claimed identity) by using certain traits associated with the person. Biometric traits can generally be classified into two main categories: Physiological techniques include fingerprint recognition, palmvein recognition, retinal and iris scanning, facial recognition, hand and finger geometry and DNA analysis. Behavioral techniques include handwriting recognition, voice authentication, gait, and keystroke dynamics just to name a few (Jain, Flynn & Ross, 2008). Biometric-based system should meet the specified recognition accuracy, speed and resource requirement, be harmless to users, be accepted by intended population and be sufficiently robust to various fraudulent methods and attacks to the system (Anil, et al.2008). The chemical property of blood in vein makes it absorbs more infer-red lights than the tissues around it, and thus vein structures can be clearly captured under infer-red illuminations in either reflective way or transmit way by an infer-red sensed image sensor.

The most distinguishing advantage of vein features is that they are difficult to fake, because veins lie under human skin, and can hardly be seen in visual light, so it is difficult to fake a person's vein features in biometric systems (Lu, Li, & Zhang, 2016). The research work proposed palmvein recognition system based on Linear Discriminant Analysis and Firefly Algorithm (LDA-FA). Personal identifying technology has the shape of security schemes and its importance has grown in recent years, especially authentication manners, where passwords and magnetic cards are no longer secure enough, they can be stolen easily or be forgotten by the owner. Therefore, to reach a highly secure interaction, biometric technologies have been invented to apply to wide systems categories like smart devices logins and house securing systems, and other control systems (Al-Khafaji & Al-Tamimi, 2022).

2.. LITERATURE REVIEW

Biometrics is a field of science and technology whose goal is to identify or verify a person's identity using physiological or behavioral characteristics (Jain & Demirkus, 2008). It is more reliable, convenient and secure than the traditional identification technology such as passwords and keys. Biometric based systems have found their use widely in different areas such as banking, criminal identification, education, access control and security system. There are several physiological and behavioral body traits that can be used for biometric recognition (Nandakumar, 2008) as shown in Figure 2.1. Physiological traits include palm vein, palmprint, fingerprint, hand geometry, ear shape and iris while behavioral traits include gait, signature and keystroke. Voice can be classified as a physiological or a behavioral trait because some characteristics of a person's voice such as pitch, bass/tenor and nasality are due to physical factors like vocal tract shape, and other characteristics such as word or phoneme pronunciation (e.g., dialect), use of characteristic words or phrases and conversational styles are mostly learned. Ancillary characteristics such as gender, ethnicity, age, eye color, skin color, scars and tattoos also provide some information about the identity of a person. However, since these ancillary attributes do not provide sufficient evidence to precisely determine the identity, they are usually referred to as soft biometric traits (Jain, Ross & Prabhakar, 2004).

The goal of the recognition process may be to associate an identity with the input data (biometric identification) or determine if two instances of input data belong to the same identity biometric verification). A simple biometric system has four (4) major components as shown in Figure. These components are discussed as follows:

- Sensor module: This is used for biometric data acquisition. It is used for capturing the biometric trait from the subject and converting it to a digital form that can be used by the subsequent module. The quality of the acquired biometric data greatly affects the overall performance of the biometric system. Factors such as noise, technology of the reader and the degree of interoperability of the user with the system affect the quality of the acquired biometric data;
- Feature extraction module: The data obtained from the sensor is preprocessed for quality enhancement. Then, some important discriminatory features are extracted to generate a representation known as template. The template is then stored in the system;
- Matching module: The feature vectors generated by the feature extraction module are compared with the template. When the system is requested to identify an individual, it does this by extracting the discriminatory features called query. Then the query is compared to the stored template. The comparison is to establish that the query and the stored template belong to the same subject.

- Decision making module: This component is used to establish an individual's identity based on the comparison done by the matching module. It also accepts or rejects a claimed identity.

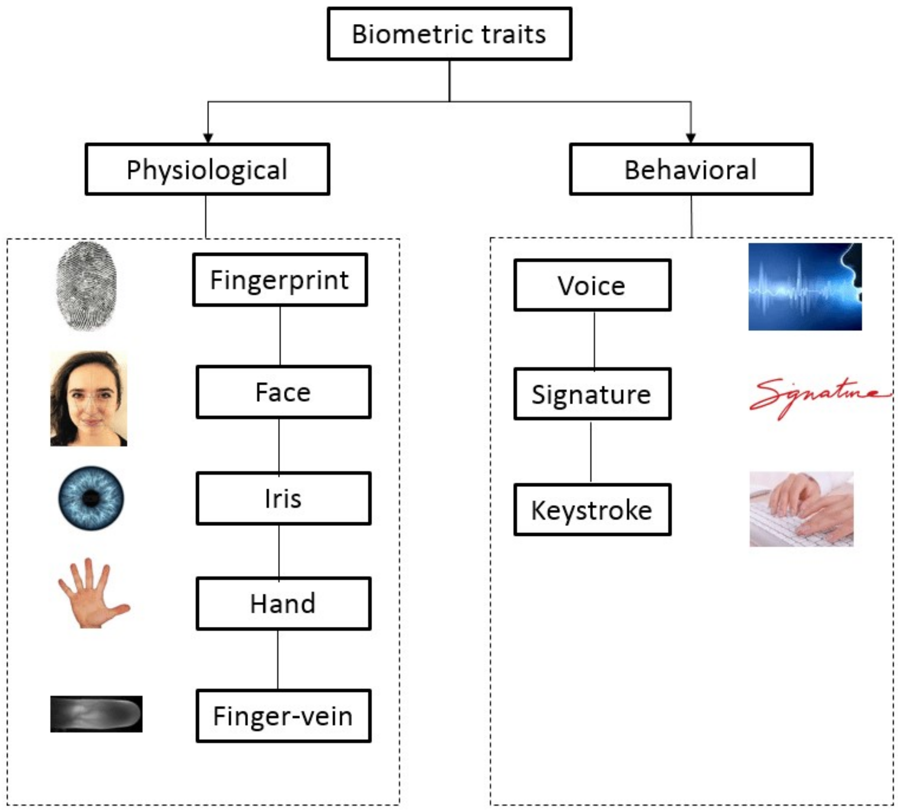

Figure 1: Examples of body traits that can be used for biometric recognition
Source: Nandakumar, 2008)

However, Biometric systems typically operate in two modes. These are the enrolment and authorization modes. In the enrolment mode, the biometric features of the users are captured and stored as templates in the system's database. In authorization mode, the templates gotten from the user's biometrics characteristics (live-template) are compared to the templates already stored in the system's database. Biometrics systems can be classified into identification and verification systems. The goal of identification is to determine who is the unknown individual from all the individuals enrolled in the database. In other words, identification answers the question "Who am I?" while verification answers the question "Am I who I claim to be?" Identification is further classified into open-set and closed-set. In closed-set, the individual to be identified must be enrolled in the database. In the open-set, this is not necessary, and the system should be able to verify if the individual is enrolled in the database or not. A number of physiological and behavioural body traits can be used for biometric recognition Examples of physiological traits include palm, fingerprint, iris, palmprint, hand geometry and ear shape. Gait, signature and keystroke dynamics are some of the behavioural characteristics that can be used for person authentication.

According to (Al-Khafaji & Al-Tamimi, 2022), One of the most important advantages of biometric security devices is that they may help you improve your security. Cloning or stealing a fingerprint, for example, is significantly more difficult than cloning or stealing an access card. Biometrics can also be utilized for multifactor verification in instances where security is a concern. Personal verification has become an important and high demand technique for security access systems over the last decade. Shape of the subcutaneous vascular tree of the dorsal hand contains information that is capable of authenticating the individual to a reasonable accuracy for automatic personal authentication purpose. Wang et al. (2007) suggested the vein pattern biometric with infrared imaging as a potential biometric. Vein pattern proves to be advantageous compared with the other biometric techniques because it cannot be forged easily as it lies in the subcutaneous layer. Sarkar et al. (2010) have mentioned other advantages of palm veins like accuracy and reliability, contact-less, cost-effective and usability.

2.1 Benefits of biometrics

Biometric has enormous benefits. The following are some of the important benefits of biometrics.

a) Increased security: Security provided by classical systems has some limitations in that passwords is readily guessed, forgotten or copied. Also, tokens can be stolen or hacked. (Harrell & Langton, 2015) reported that over 17.6 million people in USA were victims of one or more incidents of identity theft in 2014. Among the victims, existing bank (38%) or credit card (42%) accounts were the most common types of misused information. Whereas, incidents of identity theft in biometric systems are very few. Biometrics, as intrinsic characteristics, cannot be guessed, copied, forgotten or stolen. These traits cannot be separated from the subject; therefore, subject's presence is needed at the time of authentication.
b) Increased convenience: In classical systems, users have to remember, or write down their passwords on paper or take their tokens with them. Access to services will not be granted if credentials are forgotten or lost. On the other hand, biometrics are always with you and you do not need to be remembered. The available services can be accessed at any time.
c) Increased accountability: In cases where transferability is of concern, biometrics are excellent technologies. In a token-based attendance system, users can be easily replaced by others by transferring their identifiers. Biometrics can proffer solution to this issue in accountability applications, for example, recording the biometric identities of people boarding an aircraft, signing for a piece of equipment.
d) Negative recognition: In classical recognition systems, an individual can enroll as many times as possible with different identities. For example, an individual can submit several visa or social welfare applications. Users can readily deny one enrolled identity after having benefited from the service. Classical systems cannot detect this fraudulent act.
e) Non-repudiation service: This is the ability of the system to associate an action to a user who carried it out in such a manner that this individual cannot deny his responsibility for that act. Tokens and passwords-based systems do not have such ability because they cannot confirm that one user is responsible for an act audited by the system as being performed by him. The user can deny the act and claims that another person did it using his credentials. For instance, an individual can access a particular computer resources and later denies the act. To consolidate the system reports, managers would use the usual alternatives of video surveillance which don not make employees feel comfortable. Since biometric characteristics are difficult to be tricked, there is a higher chance that any action associated to that biometric is likely to have been performed by

the legitimate possessor of the biometric in question. This makes it difficult to believe excuses in which a misdeed was allegedly committed by another who fraudulently obtained one's biometric.

3. METHODOLOGY

This research work developed an efficient method to extract features from the sub-images of palmvein which can be used for personal identification and verification. Histogram equalization was used at preprocessing, Firefly algorithm and Linear Discriminant Analysis (LDA) were used at feature extraction.

3.1 Stages of Palmvein Recognition System Development

The required stages involved in developing palmvein recognition are highlighted as follows:
STAGE1: Palmvein Acquisition
STAGE2: Palmvein Pre-processing
STAGE3: Feature extraction
STAGE4: Training and Classification
STAGE5: Recognition/Testing

3.1.1 Palmvein Image Acquisition

Data acquisition is the first stage of any pattern recognition process. It is the process that involves the sampling of biometric feature and the conversion of these features into the form that can be manipulated by the computer. Palmvein images of 100 individuals were captured. This acquisition was achieved using an infrared CCD sensitive camera. For each individual, 5 images of both left and right hand were captured. Users are required to stretch their palm straight on the platform of the scanner. Five palmvein images were captured (100*5 images). Figure 2 shows the captured palmvein samples stored in a database. 270 images (were used for training the system while 230 images were used to test the system and finally saved in jpeg format.

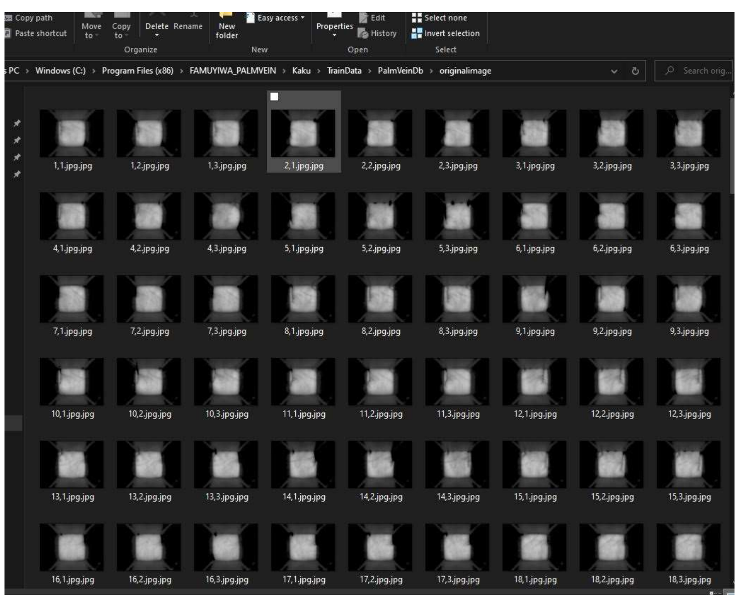

Figure 2: Palmvein captured images for training

3.1.2 Palmvein preprocessing stage

Preprocessing activities involves the following:

1) Scaling of Pictures: Palmvein images were cropped from its original captured sizes and were later resized from the original dimension of 480*640 to 180*200 pixels.
2) Organizing the captured images into palmvein folder: The resized images of each individual were grouped into two major folders. One folder contained training images while the other was used for testing the system. The folder containing the training images were sub-divided into five (5) folders with each containing different resolutions of training images.
3) Cropping: The images were cropped to sizes of 50*50 pixels from the center of the image by the program in order to extract features. The different pixel sizes indicate varying number of important palm feature.
4) Gray Scale Conversion: The cropped images in the database were converted into gray scale to make it suitable for the palmvein recognition system. This was done because most of the present palmvein recognition algorithms require two-dimension arrays in their analysis.

3.1.3 Feature Extraction

This is the process of using the most important information of the cropped palmvein images for classification purpose. Enhanced Linear discriminant Analysis with Firefly Algorithm was used to extract sufficient (set of) features that will enhance the recognition rate.

3.1.4 Training and Classification Stage

Computed Eigen palms (eigenvectors) were ordered at this stage to form Eigen space. The centered training image vectors were then projected onto the Eigen palm space. Back Propagation Neural Network (BPNN) was used to determine the class the training and the testing image belong.

3.1.5 Palmvein Recognition/Testing Stage

Testing and recognition were performed on different training images per individual to determine performances under different threshold.

3.2 Experiments

3.2.1 Un-scaling the Input to the BPNN

The raw input to BPNN were unscaled between 0 and 255, all other projection values were then made to fall between the ranges.

3.2.2 Scaling of Input to the BPNN

Inputs to the BPNN were scaled to between 0 and 0.9 against the wide range interval of between 0 and 255.

New_value=((0.9-0.1) *Old_value/(Amax-Amin))+(0.9-(0.9-0.1)*Amax-Amin)),

where Amax and Amin are the maximum and minimum values within the projection of all images. These greatly improve the output of the BPNN when compared to that of the unscaled inputs.

3.3 Performance Metrics of the developed system

The performance on trained and recognized subjects was measured against recognition rate, total training time, Sensitivity, Specificity and false positive rate.

The following parameters were used to measure and evaluate the overall performance of the developed system:

False Positive Rate = FP/(FP+TP) (3.12)
False Negative Rate = FN/(FN+TP) (3.13)
Overall Accuracy = (TP+TN)/(TP+TN+FP+FN) (3.14)

Where,

- True Positive (TP): If a neutral template is verified present in a dataset and the system test also confirms the presence of the template, the result of the system is true positive. Therefore, classified images are in the created database
- True Negative (TN): If a neutral template is verified absent in a dataset and the system test also confirms the absence of the template, the result of the system is true negative. Therefore, classified images are not in the created database
- False Positive (FP): If the system confirms the presence of template in a dataset who actually does not have such, the test result is false positive. Therefore, misclassified images are in the created database.

Table 4.1: Parameters Considered for the Palmvein Recognition System using LDA and LDA-FA

Threshold	Total Number of Images used in Testing		False Positive Rate FRR (%)		False Negative Rate FRR (%)		Recognition Accuracy (%)		Average Recognition Time (Secs)	
	LDA	LDA-FA	LDA	LDA-FA	LDA	LDA-FA	LDA	LDA-FA	LDA	LDA-FA
0.25	500	500	22	18	4.44	1.11	91.74	95.22	219.76	200.32
0.46	500	500	14	10	5	2.22	93.04	96.09	219.93	199.87
0.6	500	500	10	6	5.56	2.78	93.48	96.52	220.38	201.94
0.85	500	500	4	2	6.67	3.33	93.91	96.96	220.71	202.91

4. RESULTS

The code implementing the palmvein recognition system was tested on a core i3 system board with 2.4GHz processor speed. The experimental results got were basically limited by the medium level state of the computer system, palmvein scanner, different environmental conditions, and the quality of palmvein images. The palmvein database under consideration was developed entirely from the scratch and the facilities for proper palmvein alignment used were the ones at our disposal. The palmvein recognition system was experimented with a total of 500 images, out of which 270 images were used in training the database and 230 images were used for testing the created database. This represents five images (three training and two testing) for 100 individuals representing a class each. The model was experimented using threshold value 0.25, 0.46, 0.60 and 0.85. the choice of the selected threshold was gotten from the graph of Threshold against Accuracy. The comparative results of the developed LDA-FA system and only LDA systems were generated and reported.

4.1 Comparison Results Between LDA and LDA-FA

The comparison of the developed system (LDA-FA) and LDA system as presented in Table 4.1, based on false positive rate, false negative rate, recognition accuracy, average recognition time. The results generated based on True Positive (TP), False Negative (FN), False Positive (FP), True Negative (TN), that is, the recognition accuracy was determined by the threshold value set as deduced in figure 3, figure 4, figure 5 and figure 6. It was discovered that, high threshold value generates high recognition accuracy and low threshold value generates low recognition accuracy.

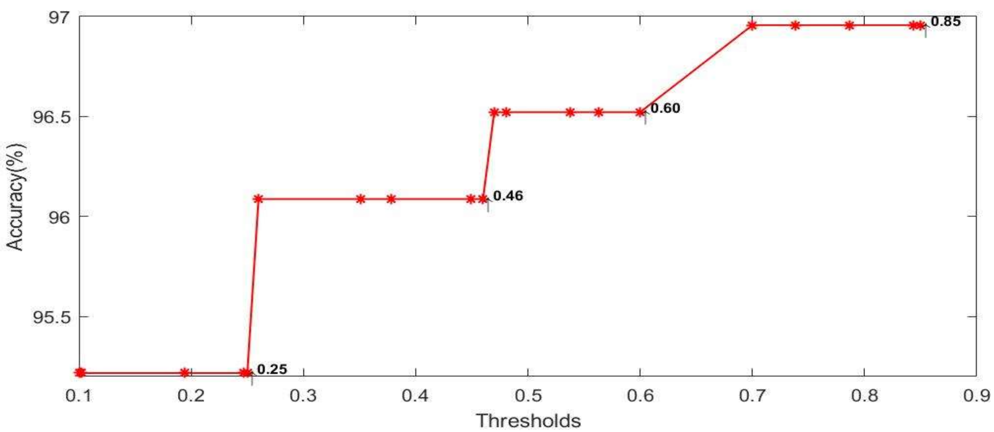

Figure 4.1: The graph of Accuracy against Threshold

The results obtained by LDA and LDA-FA techniques are presented in this chapter. The time spent increases as the threshold of the system increases, which implies that the time consumed depends on the features in the training set for LDA and LDA-FA. The average training time generated by application of LDA-FA at threshold 0.25, 0.46, 0.60 and 0.85 are 200.32s, 199.87s, 201.94 and 202.91 respectively. Similarly, The average training time generated by application of LDA at threshold 0.25, 0.46, 0.60 and 0.85 are 219.76s, 219.93s, 220.38s and 220.71 respectively as presented in Table 1. The result shows that the LDA-FA is less computationally expensive in terms of training time compared to the LDA model.

4.1.1. Experimental Results for LDA-FA

Table 4.2(a) presented the result obtained by the LDA-FA at threshold value of 0.25, 0.46, 0.60 and 0.85 with respect to the performance metrics. The table reveals that the performance of LDA-FA varies with change in the threshold value. Also, it was discovered that accuracy increases with increase in threshold value while the false positive rate and false negative rate decreases with increase in the threshold value. However, the optimum performance was achieved at threshold value of 0.85. The LDA-FA achieved a false positive rate of 18.00%, 10.00%, 6.00%, 2.00%, false negative rate of 1.11%, 2.22%, 2.78%, 3.33% and accuracy of 95.22%, 96.09%, 96.52% and 96.96% at threshold value of 0.25, 0.46, 0.60, 0.85 respectively. The table also shows that the computation time is within the range of 200.32 to 202.91 seconds with increase in the threshold values.

4.1.2 Experimental Results for LDA

Table 4.2(b) presented the result obtained by the LDA at threshold value of 0.25, 0.46, 0.60 and 0.85 with respect to the performance metrics. The table reveals that the performance of LDA varies with change in the threshold value. Also, it was discovered that accuracy increases with increase in threshold value while the false positive rate and false negative rate decreases with increase in the threshold value. However, the optimum performance was achieved at threshold value of 0.85.

Table 1(a): Parameters Considered for the Palmvein Recognition System with LDA-FA

Threshold	True Positive (TP)	False Positive (FP)	False Negative (FN)	True Negative (TN)	False Positive Rate FPR (%)	False Negative Rate (FRR%)	Accuracy (%)	Recognition Time (sec)
0.25	178	9	2	41	18.00	1.11	95.22	200.32
0.46	176	5	4	45	10.00	2.22	96.09	199.87
0.60	175	3	5	47	6.00	2.78	96.52	201.94
0.85	174	1	6	49	2.00	3.33	96.96	202.91

Table 1(b): Parameters Considered for the Palmvein Recognition System with LDA

Threshold	True Positive (TP)	False Positive (FP)	False Negative (FN)	True Negative (TN)	False Positive Rate FPR (%)	False Negative Rate (FRR%)	Accuracy (%)	Recognition Time (sec)
0.25	172	8	11	39	22	4.44	91.74	219.76
0.46	171	9	7	43	14	5.00	93.04	219.93
0.60	170	10	5	45	10	5.56	93.48	220.38
0.85	168	12	2	48	4	6.67	93.91	220.71

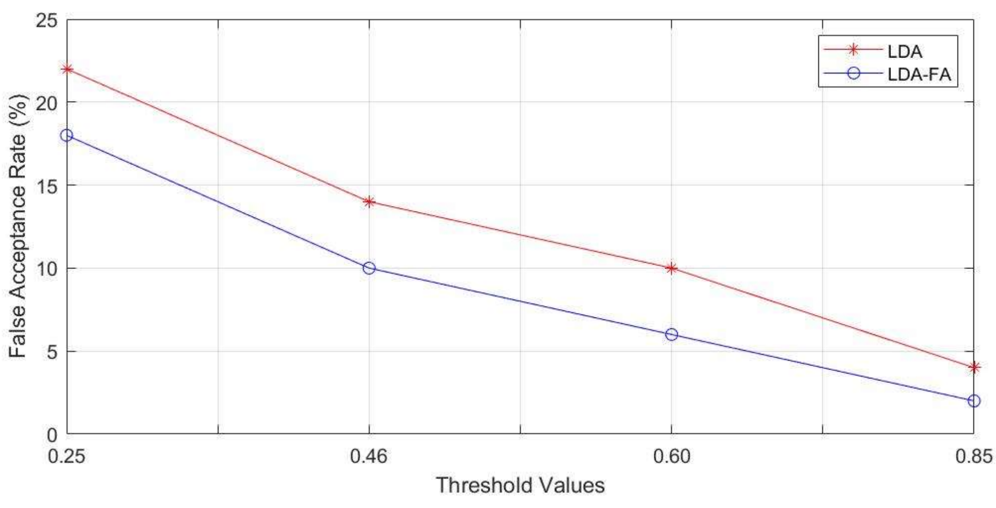

Figure 3: False Positive Rate against Threshold Value

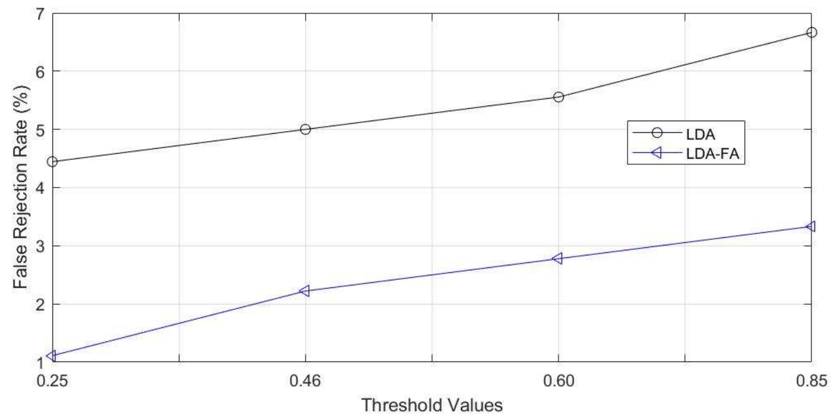

Figure 4.: False Negative Rate against Threshold Value

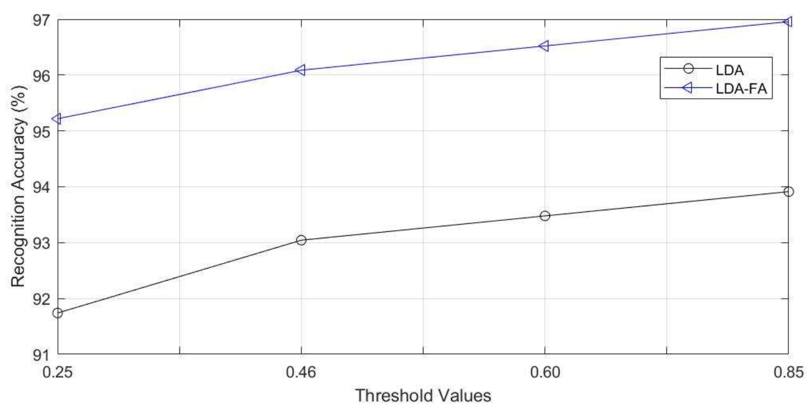

Figure 5: Recognition Accuracy against Threshold Value

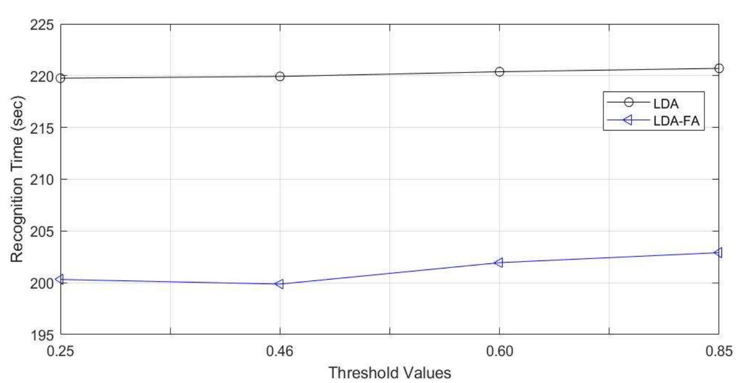

Figure 6: Recognition Time against Threshold Value

The LDA achieved a false positive rate of 22.00%, 14.00%, 10.00%, 4.00%, false negative rate of 4.44%, 5.00%, 5.56%, 6.67% and accuracy of 91.74%, 93.04%, 93.48% and 93.91% at threshold value of 0.25, 0.46, 0.60, 0.85 respectively. The table also shows that the computation time is within the range of 219.76 to 220.71 seconds with increase in the threshold values.

5. DISCUSSION OF RESULTS

The experimental results discussion in terms of training and recognition computation time analysis, evaluation of other performance metrics and statistical analysis is presented in this section. Based on Performance Metrics the results obtainable in Table 4.1 shows the performance of LDA-FA and LDA model. The results show that there is significant variation in the performance metrics with increase in threshold value and the best result is obtained at the threshold value of 0.85 across all metrics (false positive rate, false negative rate, accuracy and recognition time) for LDA-FA and LDA. Therefore, the performance of these techniques is dependent on the threshold value.

It can be inferred from the results based on the performance metrics that the LDA-FA model gave an increased 3.05% recognition accuracy and a decrease FNR of 3.34% and a decrease FPR of 2.00% over the LDA model at 0.85 threshold value. Hence, LDA-FA outperformed LDA in terms of FPR, FNR and recognition accuracy. The result achieved in this study is in line with the work of (Prince and Elder, 2007) which state that the variation in each of the variant of linear discriminant-based algorithms will have a varying performance recognition application due to improvement on the basic LDA. The results reveal that LDA-FA outperformed the basic LDA with LDA-FA having the optimum performance. Hence, the enhancement on LDA improves the performance in palmvein recognition system. In view of the results, the LDA-FA is more accurate with minimal false positive and false negative than LDA. Therefore, LDA-FA gave an improved accuracy, false positive rate and false negative rate than LDA.

6. CONCLUSION

The palmvein recognition system using Firefly Algorithm (FA) and Linear Discriminant Analysis (LDA) was developed. Back Propagation Neural Network (BPNN) classifier was used to classify the vein patterns for making necessary decision and the work has resulted in an overall success, being able to perform reliable recognition in a constrained environment. This work presents results of experiments using Firefly Algorithm to Enhanced LDA. LDA-FA and LDA model gives recognition accuracies of between (95.22% and 96.96%) and (91.74% and 93.91%) respectively at a threshold of between 0.25 and 0.85. Also, further experiments were performed to determine the error rate at the above-mentioned threshold values. These were to investigate the efficiency of the developed system either to legitimate users or imposers.

The palmvein images that were used for the False Positive Rate (FPR) were not part of the training set and were tagged imposers while those used for the False Negative Rate (FNR) were those included in the training set of the developed system. The FPR and FNR were between (18.00% and 2.00%) and (22.00% and 4.00%) respectively. Errors in recognition can similarly be attributed to poor normalisation. Emphasizes should be placed on the importance of strictly standardised databases. The design of the palmvein recognition system was separated into four major sections: Image acquisition and standardization, Dimensionality reduction, feature extraction, Training and testing for recognition.

The application of the algorithms for palmvein recognition requires a perfectly standardized and aligned database of palmvein; palmvein cropping and image resizing were done before the dimensionality reduction stages to account for background removal and uniformity in sizes of the images for the training and testing of the image to be able to really take place in the palmvein recognition system. Different results obtained from the algorithms considered showed that standard palmvein recognition system can be developed.

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