Pertanika J. Sci. & Technol. 30 (1): 161 - 183 (2022)

SCIENCE & TECHNOLOGY

Journal homepage: http://www.pertanika.upm.edu.my/

Person Verification Based on Multimodal Biometric Recognition

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ABSTRACT

Nowadays, person recognition has received significant attention due to broad applications in the security system. However, most person recognition systems are implemented based on unimodal biometrics such as face recognition or voice recognition. Biometric systems that adopted unimodal have limitations, mainly when the data contains outliers and corrupted datasets. Multimodal biometric systems grab researchers' consideration due to their superiority, such as better security than the unimodal biometric system and outstanding recognition efficiency. Therefore, the multimodal biometric system based on face and fingerprint recognition is developed in this paper. First, the multimodal biometric person recognition system is developed based on Convolutional Neural Network (CNN) and ORB (Oriented FAST and Rotated BRIEF) algorithm. Next, two features are fused by using match score level fusion based on Weighted Sum-Rule. The verification process is matched if the fusion score is greater than the pre-set threshold *t*. The algorithm is extensively evaluated on UCI Machine Learning Repository Database datasets, including one real dataset with state-of-the-art approaches. The proposed method achieves a promising result in the person recognition system.

Keywords: Biometric, convolutional neural network, Oriented FAST and Rotated BRIEF (ORB), person recognition

ARTICLE INFO

Article history:
Received: 22 July 2021
Accepted: 15 September 2021
Published: 24 November 2021

DOI: https://doi.org/10.47836/pjst.30.1.09

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ISSN: 0128-7680
e-ISSN: 2231-8526

INTRODUCTION

Nowadays, the security system has becomes crucial to protect someone or an organization from burglars and intruders. However, traditional security systems have several limitations. In the past few years, it has been confirmed that conventional security systems will lead to a rising crime rate of cyber-attacks. It also has many flaws, such as passwords that may be lost, hacked, or passed, plastic IDs may be duplicated, and RFID cards can be copied. All these flaws occur because it does not provide strong security in data protection. Therefore, it is easy for unauthorized people to access or invade the system.

In recent years, human behavioral and physiological parameters are getting popular in the security system because these parameters are exclusive and human-specific than conventional ones. Physiological characteristics refer to human traits, such as fingerprint, face, hand, and iris recognition, while behavioral refers to keystrokes, signatures, and sounds. This way of security system is called biometric authentication. Biometric authentication is introduced to make cybersecurity more effective and respond to growing threats and improve an organization's cybersecurity posture to solve the problems in traditional security systems (Yang et al., 2018). It provides high accuracy and confident automatic recognition to identify the person based on biometric traits such as hand, finger-vein, iris, face, voice, fingerprint, and signature. Moreover, it provides a high accessibility system for the user without memorizing the passwords. Therefore, it is difficult for cybercriminals because they cannot access the entry points and devices of the network efficiently (Devi & Sujatha, 2017).

However, most biometric security systems are based on unimodal systems (Zhao et al., 2020; Zhu et al., 2020). Single trait recognition leading to various issues, such as noisy data, non-universality, mutations within the class, uniqueness, and deceptive attacks. For example, a facial structure such as hairstyle, facial expression, facial angles, and age changes will be a problem in facial recognition. In recognition of fingerprints, the valleys and ridges of the fingerprint will change due to human age. It is also a serious problem if there is a biometric trait disfigured. These problems can be tackled by using a multimodal biometrics security system.

A multimodal biometric system is a system that can use multiple physiological or behavioral characteristics for registration, identification, and verification. Multimodal biometric recognition has become the latest technology in human attention (Guo et al., 2019; Huang et al., 2018). One of the most important reasons for combining different biometrics is to improve recognition accuracy. However, there are other reasons for combining two or more biometrics. For example, different biometrics are more suitable for various deployment scenarios, and it became essential to protect sensitive data (Parkavi et al., 2017).

On the other hand, the traditional learning methods always face challenges such as posture changes, facial camouflage, scene lighting, image background complexity, and facial expression changes. Methods based on shallow learning only adopt some image features and rely on artificial experience to extract the characteristics of the sample. Deep learning methods can excerpt more complex face attributes. Deep learning has made a significant breakthrough in figuring out the problems plaguing the AI industry's best attempts for many years. The practice has proved that it is very good at revealing the intricate structure in the high-dimensional dataset. Thus, it is applicable for many fields such as government, business, and science. Deep learning involves some methods, such as deep belief networks (DBN) (Song & Kim, 2017), stacked autoencoders (Liu et al., 2018), and convolutional neural networks (CNN) (Ismail et al., 2020).

Therefore, in this paper, multimodal person recognition by integrating face and fingerprint biometrics is developed. Classic CNN is carried out for face images after pre-processing, considering that CNN can extract more complex face attributes. However, the same learning algorithm may not produce the optimum results for the different biometric traits. Therefore, Oriented FAST and Rotated BRIEF (ORB) is adopted for fingerprint images because they are resistant to noise and rotation invariant. ORB extracts and describes feature points very quickly. The score level fusion is performed to match the recognition of both biometric traits after both recognition is performed. For multimodal biometrics systems, fusion is essential to improve learning accuracies. Here, face and fingerprint biometrics traits are fused using match score level fusion based on weighted Sum-Rule. There are four main categories of fusion techniques: sensor level fusion, feature level fusion, match score level fusion, and decision level fusion (Peng et al., 2020). First, match score level fusion is adopted to fuse both biometrics traits. The match scores contain the richest information for all input data, less noise, and are relatively easy to implement. It also includes the wealthiest information about the input pattern.

On the other hand, sensor level and feature level fusion are hard to execute when the size of the features is not the same. The relationship between all features is not known in advance, and in most cases, it is noisy and redundant (Somashekhar & Nijagunarya, 2018). The performance of decision level fusion is low because not much information is available at this level (Mwaura et al., 2017). Based on the combination models explained above, the proposed person identification achieved satisfactory results.

The rest of the paper is organized as follows. The related works are exposed in section II. Section III present the materials used and the methodology conducted to accomplish the objectives. The results, analysis, and discussion data are discussed in section IV. Finally, section V is devoted to the conclusion and future work.

RELATED WORKS

In this section, some past researches related to biometrics systems and any relevant topics are further discussed. For example, recently, there have been numerous researches on person identification based on biometrics characteristics.

Kurban et al. (2017) proposed a multimodal biometric system based on face and body gestures. In their research, the VGG face model in Convolution Neural Network (CNN) is adopted for face feature extractor while body gesture feature is extracted using energy imaging method. Both modalities were fused using the score level fusion technique, and then Principal Component Analysis (PCA) was adopted to reduce the dimensionalities for both features. Finally, standard deviation Euclidean distance is utilized to produce the similarity scores. Their proposed method shows promising results.

Mwaura et al. (2017) proposed a face and fingerprint biometric-based on the match score level fusion method. Both individual biometric traits are developed using Scale Invariant Feature Transform Features (SIFT). The distance between the key points is measured by hamming distance. K-Nearest Neighbor (KNN) is adopted for the matching by comparing the images in the databases. Their method achieved the performance of 92.5% of accuracy.

Somashekhar and Nijagunarya (2018) proposed a face and fingerprint multimodal biometric system by integrating two fusion methods: feature level fusion and decision level fusion. The accuracy is studied based on Gabor and Scale Invariant Feature Transform Features (SIFT) extraction for both biometric traits. First, a fusion of face and fingerprint is carried out at the feature level using all possible combinations of feature vectors. Then the feature vectors are later fed into the fusion classifier, which is Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Radial Basis Function (RBF), and Naïve Bayes (NB). Their method achieves an accuracy of more than 90%.

In the same year, Xin et al. (2018) proposed another person identification system based on face, fingerprint, and finger vein images. The algorithm is carried out based on the Fisher vector, and the biometric traits are fused using feature-level fusion. In their works, the fake feature is also investigated to improve the learning accuracy. Their results achieved an excellent recognition rate compared to the unimodal approach.

Alazawi et al. (2019) proposed a multimodal biometrics method for face and fingerprint traits using general feature fusion vectors. Their approach involved two main processes in which fused share features of both biometric characteristics are extracted first. In contrast, Euclidean distance is adopted to recognize these features for the right person at the second step. The same algorithm is used for both biometrics traits. The method achieved an accuracy of 86%.

In Gavisiddappa et al. (2019), face, fingerprint, and iris are fused using feature-level fusion. In their approach, Bi-directional Empirical Mode Decomposition (BEMD) and Grey Level Co-occurrence Matrix (GLCM) algorithm are adopted for the feature extraction. After the feature extraction, the Hilbert-Huang transform (HHT) is carried out to obtain local features. The performance of their proposed method is based on False Acceptance Ratio (FAR), False Rejection Ratio (FRR), and accuracy. Their approach gave 96% of accuracy.

Ammour et al. (2020) developed multimodal person identification based on face and iris traits. An efficient multi-resolution 2D Log-Gabor filter carries the textural information from the iris attribute, and the Singular Spectrum Analysis (SSA) is adopted for facial features. Two biometric traits are united at a hybrid fusion level, and their results show the robustness of the proposed method.

Alay and Al-Baity (2020) discussed the multimodal biometrics system combining face, iris, and finger–vein traits, and the proposed method was implemented using deep learning techniques. VGG-16 CNN is adopted. Adam optimization method is applied where categorical cross-entropy is adopted as loss function. The biometric traits are fused based on feature-level fusion and score-level fusion. The results from the experimental works showed that their proposed method is outperformed state-of-the-art methods.

Lv et al. (2020) presented feature-level fusion based on fingerprint and finger–vein biometrics. Fingerprint and finger vein feature-layer fusion recognition algorithm is investigated based on a single ICNIR finger image. Their proposed method shows that person identification using multimodal biometrics is better than the unimodal biometric system.

Aleem et al. (2020) proposed another multimodal biometric identification system by fusing both biometric traits using score level fusion. Fingerprint matching is done using an alignment-based elastic algorithm, while extended local binary patterns (ELBP) are used for facial feature extraction. In their proposed method, local non-negative matrix factorization is carried out for dimensionality reduction. The proposed method achieved the recognition of 99.59%.

Recently, Kumar et al. (2021) proposed an improved biometrics system based on face and fingerprint. Whale optimization is adopted with minutiae feature for fingerprint recognition and Maximally Stable External Regions (MSER) for face recognition. In addition, Support Vector Machine (SVM) is carried out along with pattern net to improve the classification accuracy. As a result, the proposed method achieved averaged more than 90% accuracy.

Next, Pawar et al. (2021) have described works on biometrics systems based on face and fingerprint biometrics. Scale-invariant feature transform (SIFT) is adopted for feature extraction. The particle swarm is used to optimize features while the ridges and minutiae extractions are carried out for fingerprint biometrics. Both biometric traits are fused by using the summing rule. Their approach attains more than 99% accuracy.

Based on the comprehensive literature review explained above, recently developed biometrics systems based on face and fingerprint traits are summarized in Table 1.

Table 1

Recently developed biometrics system based multimodal biometric traits

Authors	Method Applied	Advantages	Disadvantages
Mwaura et al. (2017)	Match score level fusion	Scale Invariant Feature Transform (SIFT) is introduced for feature extraction. SIFT method has the advantages of rotation invariance; scale invariance has strong robustness for occlusion problem and noise and affine invariance	KNN is used where time and space complexity is enormous, which is a significant disadvantage of KNN.
Somashekhar and Nijagunarya (2018)	Feature level fusion and Decision level fusion	A new method has been proposed where face images and fingerprint are processed with compatible feature extraction algorithms to extract features from the dataset	This method may heavily depend on the physical nature of the input in a real application scenario
Xin et al. (2018)	Feature level fusion	Use of the Discrete Cosine Transform (DCT) algorithm for bioassay that produces better accuracy and effectively improves the anti-forgery capability in-person identification.	PCA is used for face recognition where this is an ancient technique for feature extraction
Alazawi et al. (2019)	Feature level fusion	The method has good performance in terms of precision using invariant moments to extract shape features vectors and the direct Euclidean distance for similarity measurement.	Using the same learning algorithm for face and fingerprint biometrics, which in reality may not produce the optimum results for different biometric traits.

Table 1 *(Continued)*

Authors	Method Applied	Advantages	Disadvantages
Gavisiddappa et al. (2019)	Feature level fusion	Combination of Bi-directional Empirical Mode Decomposition (BEMD), Hilbert-Huang transforms (HHT) and Grey Level Co-occurrence Matrix (GLCM) to form the MMB-BEMB-HHT method. MMB-BEMD-HHT method was constructed to identifying the individual biometric features of fingerprint, face, and iris to improve the security of the desired system	The proposed method is applied to a limited dataset
Aleem et al. (2020)	Score level fusion	Histogram equalization is adopted to improve the intensity level of the face images; Extended Local Binary Pattern (ELBP) and Local Non-Matrix Factorization (LNMF). is adopted for face images in which it is a pixel-based texture extraction method that has achieved remarkable performance along with low computational cost.	It does not mention the criteria or threshold to set the most significant base information for LNMF. The optimum result depends on the size of the choices of dimensionality in LNMF.
Alay and Al-Baity (2020)	Feature Level Fusion and score level fusion	The first study is to investigate deep learning algorithms for a multimodal model with three biometric traits.	Adopted CNN (VGG) for all biometric traits in which, in the actual case, different biometric characteristics may not produce the optimum results in all biometric features.

Table 1 *(Continued)*

Authors	Method Applied	Advantages	Disadvantages
Kumar et al. (2021)	Feature level fusion	Their paper proposed a novel approach to improve the accuracy and maximizes the accuracy of biometric traits for noisy data	This work is carried by using an SVM classifier where the SVM algorithm is not suitable for large datasets.
Pawar et al. (2021)	Fusion using summing rule	The features are extracted using scale-invariant feature transform (SIFT), and the feature optimization is done using particle swarm optimization.	The fusion technique is not clearly explained in the paper.

From Table 1, the most recently developed works focus on the feature level method as a fusion method and SIFT for feature extraction. Not many works have been carried out using CNN. Even though Alay and Al-Baity (2020) also use CNN for their work, they focus on the combination of feature-level and score-level fusion. In addition, their works focused on three modalities: face, iris, and finger vein. It is the first work focusing on face recognition based on CNN and fingerprint recognition based on ORB, then fused by score level fusion to the best of our knowledge. The process of the ORB algorithm is faster than SIFT. Based on the advantages of CNN, match score level fusion, ORB, and the motivation why the different algorithms should be used for the different biometric traits explained in the previous section. Hence, this paper aims to develop a multimodal biometric system using classic CNN for face recognition and ORB for fingerprint. The recognition of both biometric traits is fused using score level fusion considering the advantages of score level fusion stated in the previous section.

METHODOLOGY

In this section, the development of the system is explained and illustrated clearly with a block diagram, as shown in Figure 1.

The system consists of three main processes that involve face recognition, fingerprint recognition, and score level fusion. First, face recognition involves image pre-processing, feature extraction, and classification. The second process is fingerprint recognition, and the process includes pre-processing and feature matching. Finally, two biometric features are combined into the same domain for the last operation, executed in the decision-making process.

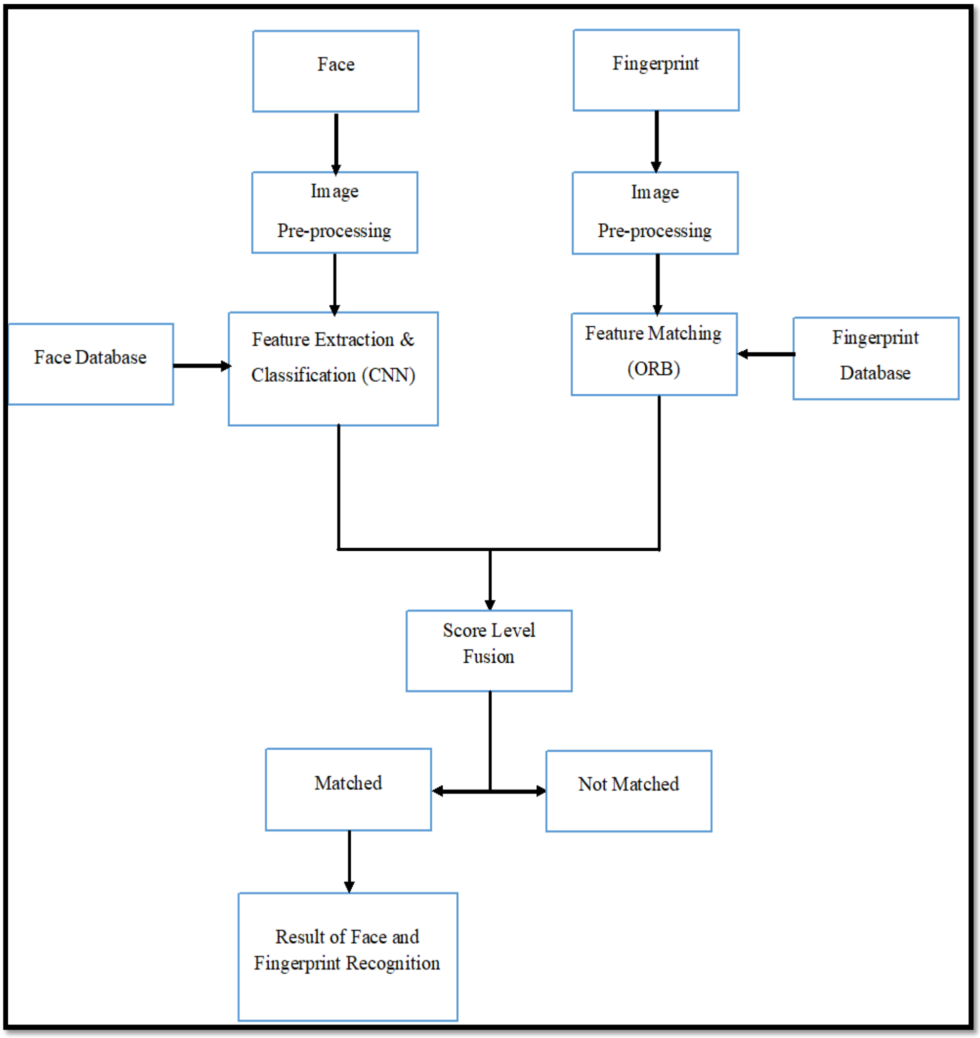

Figure 1. Multimodal biometric system diagram

Based on Figure 1, the pre-processing and feature extraction steps are first applied to face images, and classic CNN is adopted to train the face images. The pre-processing stage is also applied to fingerprint datasets and feature matching by using the ORB algorithm. Then, two biometrics are fused with score level fusion based on the weighted sum rule. The verification process is matched if the fusion score is higher than the pre-specified threshold *t*. In this case, *t* is set to 0.57. Otherwise, the verification process indicates a mismatch. Therefore, there is an opportunity for fraud in a unimodal biometric system, but this problem can be solved if we integrate multiple functions. For an instant, fingerprint data can be easily stolen if the system is only used fingerprint biometric. However, if fingerprint recognition and facial recognition are combined, identification and verification will be more promising, where the system will be challenging to crack.

The software used in this paper is Python 3.7.3. The Desktop-NJTDRNO PC is used to run the software and the program. The processor provides Intel(R) Core (TM) i5-4460M 3.20 GHz, and the memory of this laptop is 8GB RAM. NVIDIA GeForce GTX 1650 Graphic card is used. This laptop also contains 240GB SSD and 1TB HDD.

Image Dataset

In this paper, two biometrics image datasets are obtained from the UCI machine learning repository database. There are 400 face images and 120 fingerprint images. Three hundred sixty images are adopted as a training set for face recognition, while 40 images are used as a testing set. One hundred images are adopted as a training set for fingerprint recognition, and 20 are used as a testing set. ORB is used to define descriptors around key points with Hamming distance, and the matching is decided based on the threshold set initially. The dataset for face and fingerprint is not equal because in the actual case, faces may face various conditions such as different lighting conditions, different angles, and facial expressions. However, these condition does not affect the fingerprint ridges too much. Therefore, more dataset is needed to train the face images.

Face Recognition

Face recognition consists of three steps. First, it starts from the pre-processing step: color space conversion and image resizing. They were then followed by facial features extraction by CNN before the classification by using Softmax Classifier.

In a pre-processing step, the collected datasets are first converted from BGR to RGB before being resized to 200x200. Next, essential features from datasets are extracted by using CNN and classification by Softmax classifier. CNN is a neural network that has been established to be very valuable in feature extraction and classification. The structure of CNN consists of convolution functions, pooling functions, and ReLU functions. Simultaneously, the Python library is adopted to implement the multi-layer perceptron MLP to complete the connection and classification layers. The Fully Connected Layer (FCL) stacks the convolutional layer, pool, and ReLu layer to simplify the CNN model. Thus, the CNN model comprises a convolutional, pooling, ReLU, FCL, and Softmax classifier to train face datasets.

Fingerprint Recognition

The fingerprint recognition process consists of two stages. It starts from the pre-processing stage, which is Oriented Gabor Filter, binarization, and thinning. Next, the ORB algorithm is performed in three steps: feature point extraction, generating feature point descriptors, and computing feature point matching. Before a detail-based function is completed, it is necessary to perform image enhancement processing on the fingerprint images. It can make the image clearer and adjust the picture to an appropriate resolution. If image enhancement is not performed, noise may be generated. In addition, the process creates a sharp contrast between the ridges and valleys. Therefore, enhancement processing is vital to improve recognition accuracy. The enhancement step is adopted by using Oriented Gabor Filters. The direction of the Gabor filter is determined by the direction of the ridges in the input image, as shown in Figure 2. Thus, there are two steps of the minutiae-based feature used in fingerprint recognition: binarization and thinning.

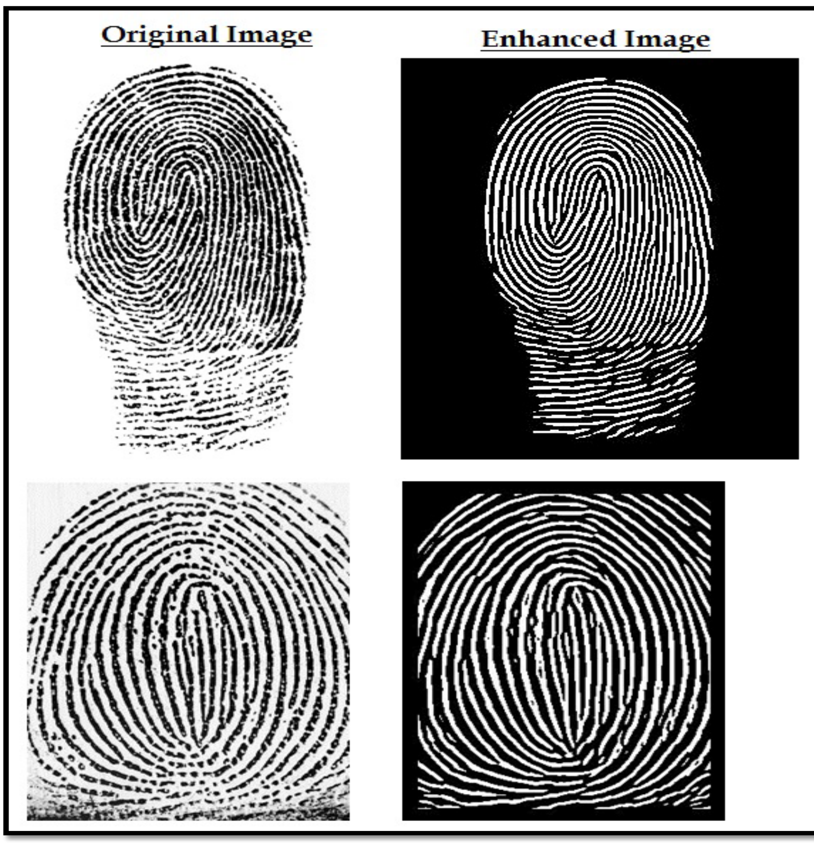

Figure 2. Left side: original image, right side: enhanced image (Chanklan et al., 2015)

Binarization

Binarization is one of the pre-processing methods based on the minutiae-based method. The binarization process converts the image from 8-bit grayscale to a 1-bit grayscale image, as shown in Figure 3.

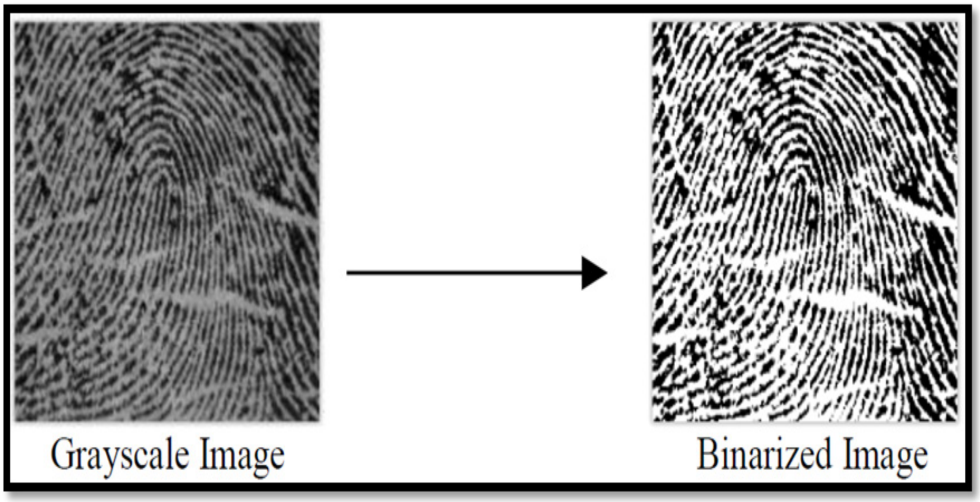

Figure 3. Result of binarization of fingerprint (Fatt et al., 2017)

Thinning

The thinning process is applied to the binarized image to reduce the thickness of the ridge pattern. This process is essential to ensure the exact location of the thorough extraction. The thinning therefore maintains the position of the minute points in comparison with the original fingerprint. Finally, the result of the thinning process is obtained, as shown in Figure 4.

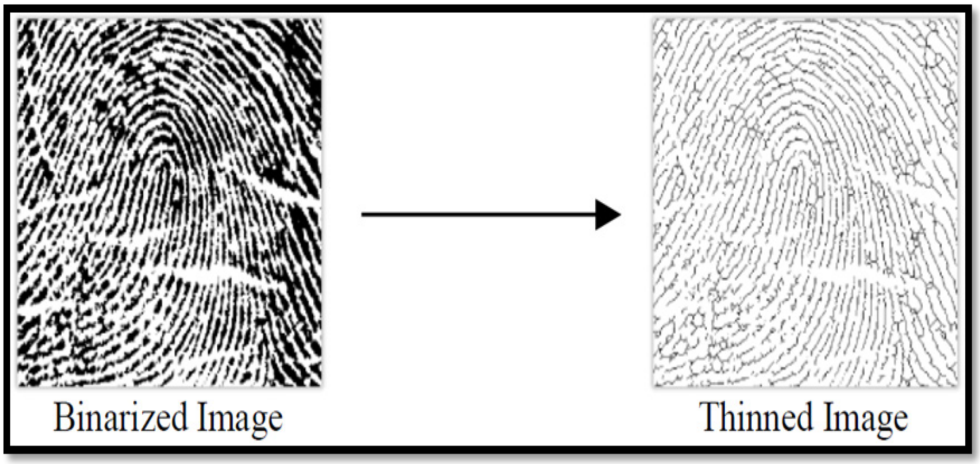

Figure 4. Result of thinning of fingerprint (Fatt et al., 2017)

Fingerprint Matching with ORB (Oriented FAST and Rotated BRIEF)

Oriented FAST and Rotated BRIEF (ORB) algorithm consists of three steps: feature point extraction, defining feature point descriptors, and calculating feature point matching. ORB uses an improved FAST (Accelerated Testing Function) algorithm to detect fingerprint image features (Rosten et al., 2010). If the pixels in the picture are different from nearby pixels, this is likely to be a corner point. The detected image feature point is screened after the feature point is extracted. Scale invariance is added to the features after FAST features are extracted. Finally, the direction point of the feature is determined. Updated Brief algorithm (Calonder et al., 2010) is adopted to generate descriptors after the directional FAST feature points are extracted. The ORB algorithm then uses the updated Brief algorithm (Calonder et al., 2010) to create descriptors after extracting the directional FAST feature points.

After the fingerprint feature point descriptor is generated, it is necessary to find similar feature points in two different fingerprint images to determine the matching, as shown in Figure 5. Suppose the image I_t is extracted from feature points $x_t^m, m = 1,2, \ldots, M$, and the image I_{t+1} is extracted from feature points $x_t^n, n = 1,2, \ldots, N$. A brute force matcher is adopted to determine the distance on every feature point x_t^m and all x_{t+1}^n descriptors. The nearest one is selected as the matching point. Hamming distance is applied for the Brief binary descriptor to estimate the number of different characters between two strings of the same length character (Luo et al., 2019).

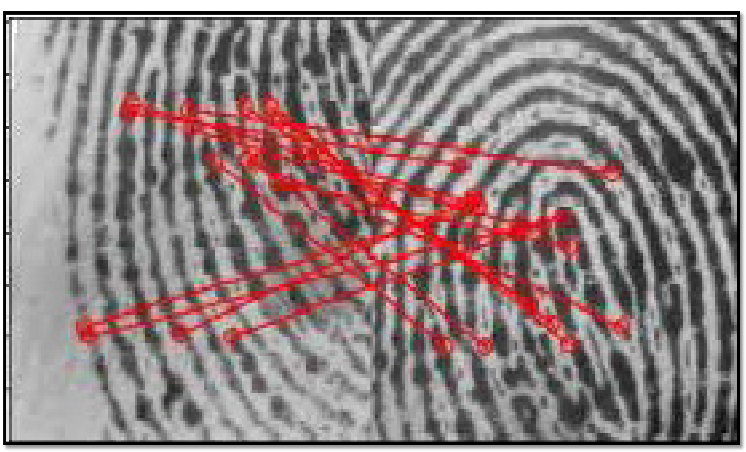

Figure 5. Result of brute force matcher (Luo et al., 2019)

After the recognition training is performed on both biometrics data set, the score level fusion is used as a final stage to match the two types of recognition—the adopted weighted sum rule for the fusion score levels. The rule sets the weighted sum of all scores generated by the matcher is given in Equation 1.

$$S_{fusion} = \sum_{i=1}^{N} w_i s_i \tag{1}$$

Here, $\boldsymbol{w_i}$ are weights assigned to the $\boldsymbol{s_i}$ score generated by the matcher and w sum of the weights assigned to the matcher that meet the conditions (Equation 2).

$$w = \sum_{i=1}^{N} w_i = 1 \tag{2}$$

Equation 1 can be written in Equation 3 since there are two biological features, "face" and "fingerprint".

$$S_{fusion} = w_1 s_1 + w_2 s_2 \tag{3}$$

where $\boldsymbol{w_1} + \boldsymbol{w_2} = 1$, $\boldsymbol{w_1}$ and $\boldsymbol{w_2}$ are weights assigned to face and fingerprint matching scores. The weights are calculated based on Equation 4,

$$w_m = \frac{1}{\frac{\sum_{m=1}^{M} \frac{1}{a_m}}{a_m}} \tag{4}$$

Here, w_m is weighted associated with matcher m and a_m is the accuracy of matcher m. The different parts of the model are illustrated in details in Figure 6.

Finally, a multimodal person identification system based on face and fingerprint biometrics is developed using GUI in Python IDE, as shown in Figure 7. The accuracy of the system is displayed on the GUI.

RESULT AND DISCUSSION

In this section, the performance of the person identification based on face and fingerprint biometrics is discussed. Score level fusion generated by the Face and Fingerprint matcher is then combined using the weighted sum rule, and the performance is further discussed in the rest of this section.

Face Recognition

For face recognition, the datasets for 20 people are obtained from UCI Machine Learning Repository Database, including images for one real person. Thus, twenty photos are obtained from each person. Figure 8 shows the face recognition based on one testing image.

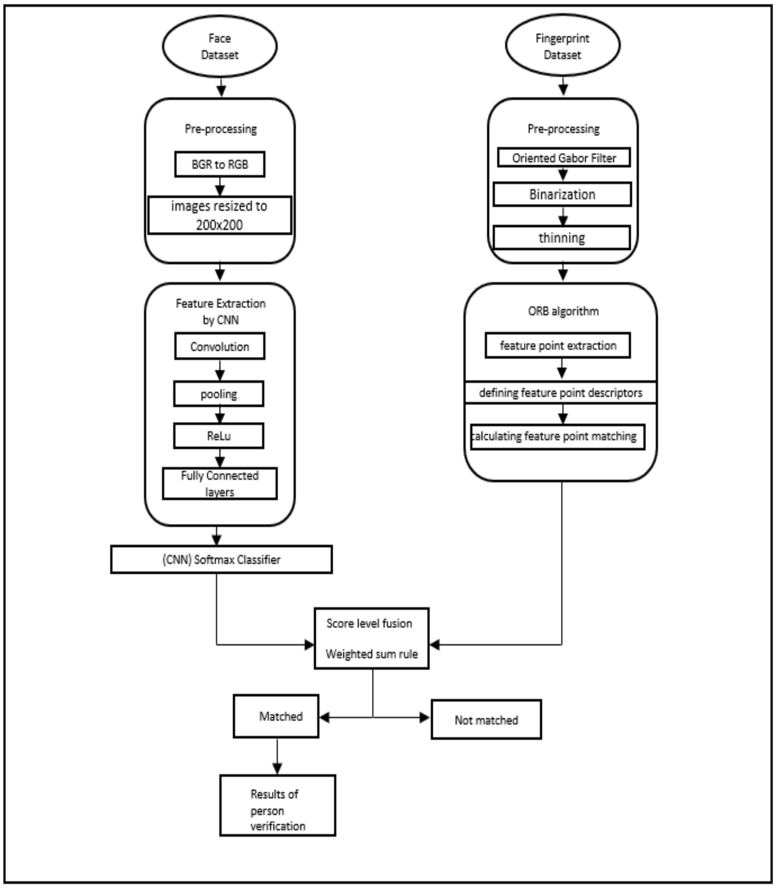

Figure 6. The details flowchart of the face and fingerprint recognition system

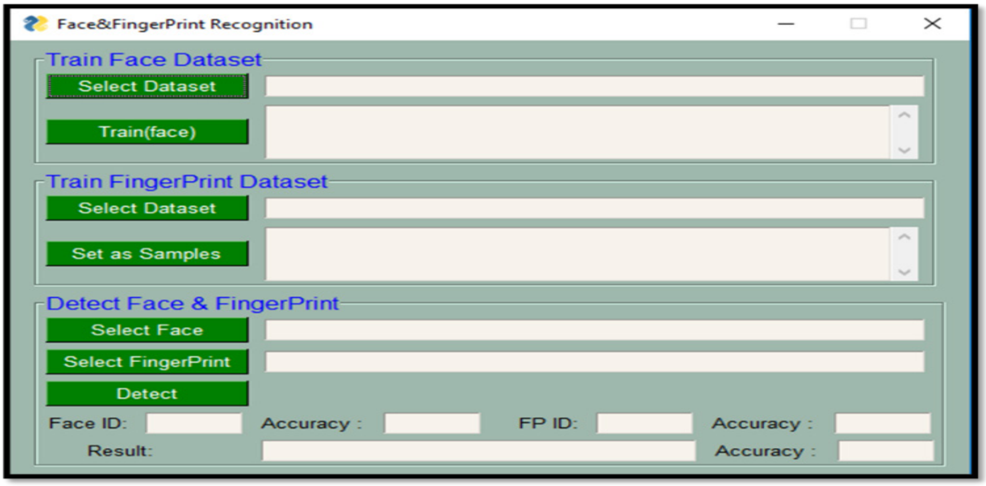

Figure 7. Python GUI for multimodal biometric recognition

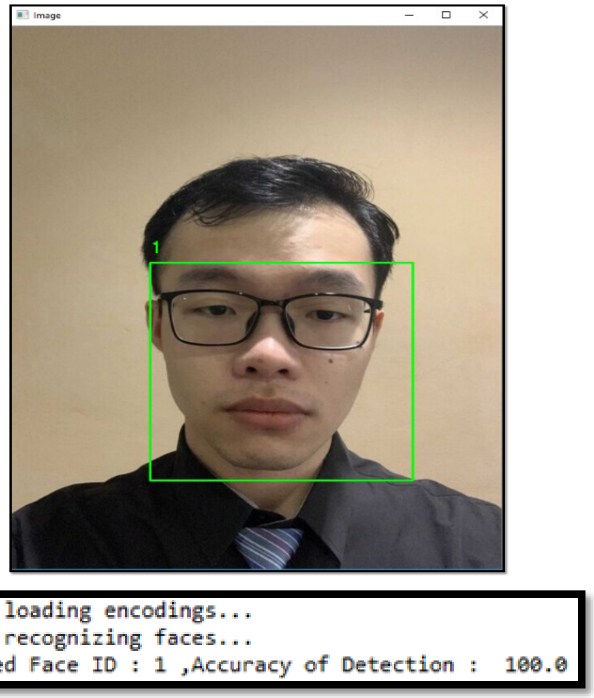

Figure 8. Recognition accuracy based on one testing sample

As mentioned in the previous section, 360 images are adopted as a training set, while 40 images are used as a testing set. The average recognition accuracy and standard deviation based on the testing datasets are illustrated in Table 2.

Table 2
Accuracy for face recognition based on testing data

Mean accuracy, $\bar{x}$	Standard Deviation, s
95.57	5.97

Fingerprint Recognition

There are 120 fingerprint images for fingerprint recognition obtained from UCI Machine Learning Repository Database, where 100 datasets are adopted as training set while 20 as testing datasets. These images are obtained from 20 people, including one real person in which every one of them consists of six shots. The pictures for fingerprints are processed using the ORB algorithm, and the recognition accuracy for one fingerprint image is shown in Figure 9.

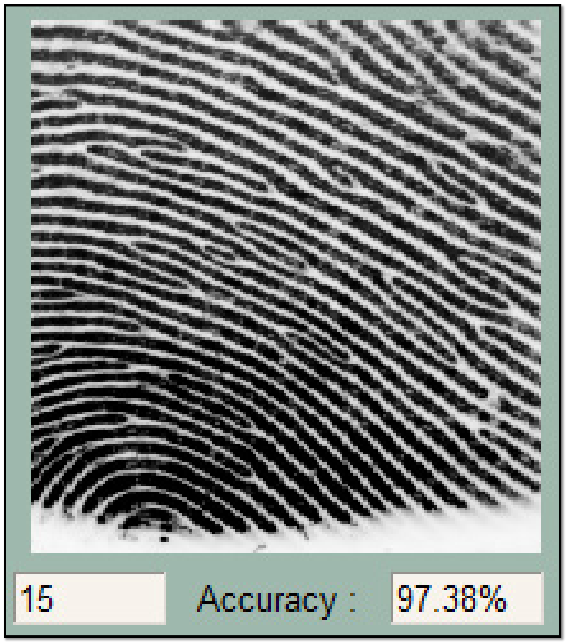

Figure 9. The result of sample 1

The average recognition accuracy and standard deviation based on the testing datasets are illustrated in Table 3.

Table 3
Accuracy for fingerprint recognition based on ORB algorithm

Mean accuracy, $\bar{x}$	Standard Deviation, s
97.28	0.61

Multimodal Biometric Recognition (Face and Fingerprint)

After both recognition results were obtained, score level fusion is adopted to combine the two biometrics based on the weighted sum rule. The development of the multimodal biometric system is shown in Figure 10. Python IDE is adopted to develop GUI for multimodal biometric recognition. Results of samples 1, 8, 11, and 18 show that face ID and fingerprint ID are matched with 98.77%, 98.56%, 99.44%, and 87.53%. Figure 11 shows that the matching for both biometrics is not successful if both biometrics are not from the same person.

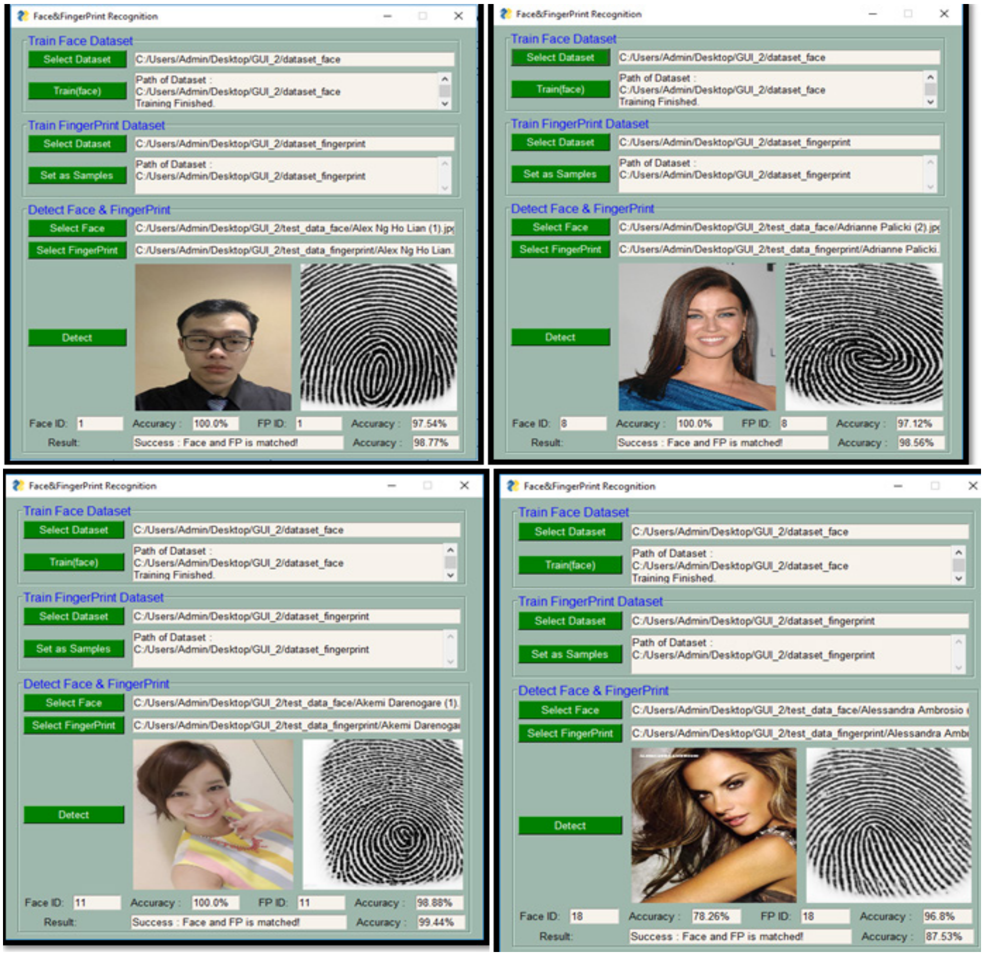

Figure 10. The result of several samples after fusion

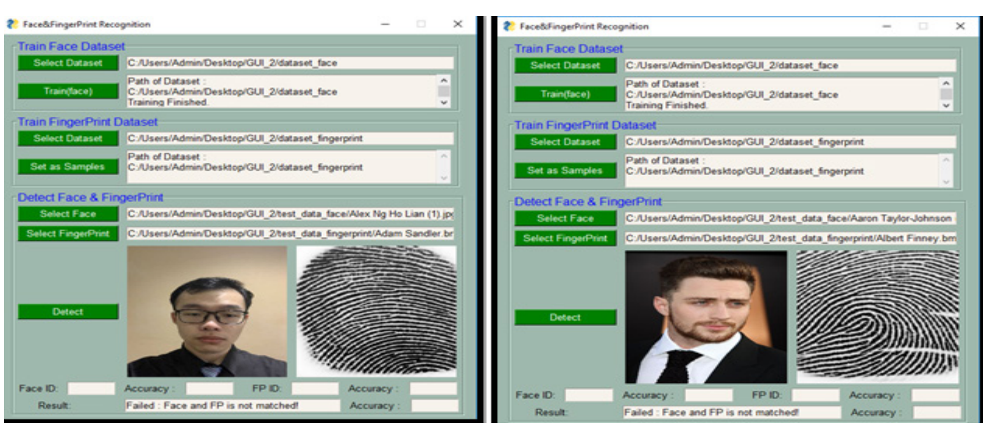

Figure 11. The results of several samples if the biometrics are not matched

Table 4
The matching results for 20 samples

No of Samples	Face Recognition (%)	Fingerprint Recognition (%)	Fusion (%)
1	100	97.41	98.7
2	94.74	97.48	96.11
3	100	96.32	98.16
4	94.44	96.92	95.68
5	94.74	97.23	95.98
6	100	97.31	98.66
7	81.82	97.59	89.7
8	100	97.08	98.54
9	100	96.66	98.33
10	90	98.63	94.32
11	100	98.77	99.38
12	100	96.56	98.28
13	94.44	96.98	95.71
14	100	97.56	98.78
15	87.5	97.28	92.39
16	100	97.48	98.74
17	100	97.25	98.62
18	78.26	96.73	87.5
19	100	96.81	98.4
20	100	97.62	98.81

The face, fingerprint, and fusion recognition based on 20 datasets are shown in Table 4. Multimodal Biometric systems achieve 87.5% to 99.38%. It shows that overall accuracy in multimodal biometric accuracy recognition is consistent and precise. Average recognition accuracy based on the proposed method and the baseline approaches with face and fingerprint biometric traits to validate the proposed method are shown in Table 5.

Table 5
Comparison of accuracy for various multimodal methods

Authors	Method Applied	Accuracy
Proposed method	Match score level+CNN+ORB	96.54%

Table 5 *(Continued)*

Authors	Method Applied	Accuracy
Mwaura et al. (2017)	Match score level fusion+SIFT	92.5%
Somashekhar and Nijagunarya (2018)	Feature level fusion and Decision level fusion	91.47%
Alazawi et al. (2019)	Feature level fusion +Euclidean distance	86%
Aleem et al. (2020)	Score level fusion+LBP	99.60%
Kumar et al. (2021)	Feature level fusion+SVM	99.60%
Pawar et al. (2021)	Fusion using summing rule+SIFT	99.2%

In Table 5, it is shown that the accuracy of the proposed method is better than Mwaura et al. (2017), Somashekhar and Nijagunarya (2018) as well as Alazawi et al. (2019). The result of the proposed method is slightly lower than Aleem et al. (2020), Kumar et al. (2021), and Pawar et al. (2021) because of the two samples: sample 7 and sample 18, as shown in Table 4. Overall, the result of the proposed method is comparable to Aleem et al. (2020), Kumar et al. (2021) and Pawar et al. (2021). As mentioned in the previous section, match score level fusion contains the richest information for all input data, less noise, and is relatively easy to implement. It also includes the wealthiest information about the input pattern compared to feature-level fusion. Both Kumar et al. (2021), and Pawar et al. (2021) are using feature-level fusion, where in most cases, feature-level fusion is hard to execute when the size of the features is not the same. In most conditions, the relationship between all features is not known in advance, noisy and redundant. Even though Aleem et al. (2020) use score level fusion to fuse face and fingerprint, the optimum results vary depending on the choices of dimensionality in LNMF. The proposed method is superior to the baseline approaches taking into account various aspects.

In summary, the result of a multimodal biometric system is successfully obtained. The score level fusion based on weighted sum-rule is used to fuse the scores of the face matcher samples and the fingerprint matcher samples, and it is observed that the weighted sum rule with optimized weight provides excellent performance. It is concluded that the multimodal biometric system achieves more than 96% accuracy.

CONCLUSION AND RECOMMENDATIONS

In conclusion, an effective and efficient face and fingerprint multimodal biometric system has been developed. Fingerprint recognition is performed using directed FAST and Rotated Brief (ORB), while face recognition is achieved using the Classic CNN model. The combination of two biometrics produces a robust multimodal biometric system. Score level fusion is adopted to perform the fusion of facial and fingerprint features. The experiment is performed on the UCI Machine Learning Repository database, including one real dataset. Experimental results show that the proposed multimodal biometric system provides better security compared to single biometric recognition. The best recognition rate is obtained through the weighted sum rule, and the higher recognition rate is 99.38%, as shown in Table 4 for sample 11. The recognition rate is based on the average of the recognition rate of face and fingerprint. The result of the proposed method is slightly lower than Aleem et al. (2020), Kumar et al. (2021), and Pawar et al. (2021) because of the two samples: sample 7 and sample 18, as shown in Table 4. Overall, the proposed method is comparable to those baseline approaches. Thus, there remain some future works that need to be done in the future. More training is set to be included for the training process with cross-validation to improve learning accuracy. In the future, a balanced dataset will be included for both multimodal face and fingerprint recognition systems. Different type of CNN models is to be included to check the performance of the system.

ACKNOWLEDGMENT

This work is supported by Universiti Malaysia Sarawak (UNIMAS) through research grant F02/SpTDG/1772/2018.

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