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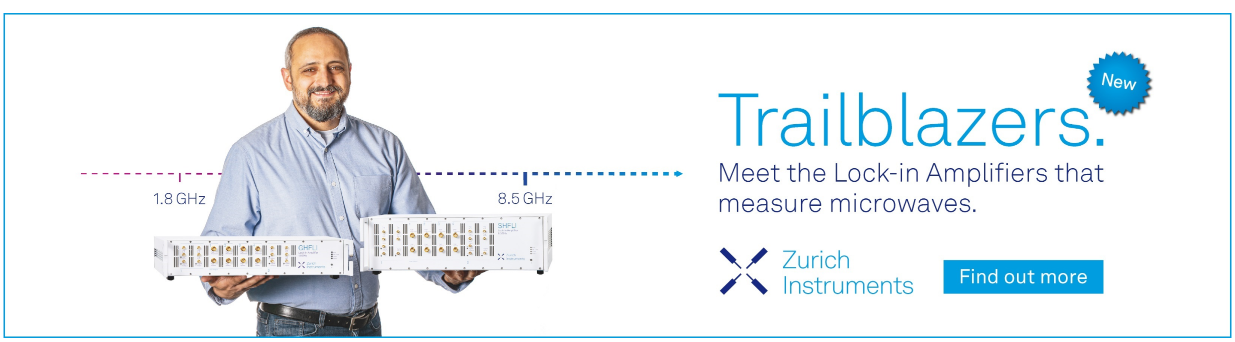

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Finger Vein and Hand-Dorsal Vein Multi-Modal Biometric System Based on Convolution Neural Network

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Abstract. Recently, the increase in the criminal in cyberspace due to unauthorized actions by cyber-attacks on identification systems. People are searching for more accurate methods of personal identification with growing numbers. However, Multi-modal biometric systems are currently being studied extensively for personal identification and verification. When the diversity of features is increasing merging with deep convolutional neural networks, then the security of biometrics systems is improved. Beside that CNN is heavily reliant on a huge data set to avoid overfitting problem. Unfortunately, many application domains do not have access to big data. This paper used two combination technique methods of the fusion of finger veins and hand-dorsal vein biometric traits and was implemented. These methods were the inspirations for the expansion technique. The expansion process used to increase the number of training images and thus trains the network of the largest number of features to overcome overfitting. Thus, the CNN model was proposed for training and classify the resulted fusion images. The proposed system tested on two public data sets (Yilong Yin and Badawi) and the experimental results proved that the system was reliable .The first fusion technique which combines the two images separately (without merging the pixels) gave an accuracy 96%. The second method fused all two opposite pixels into one pixel and gave accuracy 97% .Finally, when the second method with expansion gave an accuracy 100%.

Keywords: Multi-modal biometric, Fusion Technique, Finger vein, Hand-dorsal vein, CNN.

INTRODUCTION

Identifying people and verifying the authenticity of their identity is one of the critical processes, due to the existence of fraud and impersonation operations on a large scale, especially in security applications, bank accounts, and other operations that require verifying the identity of persons such as entering the military institutions and security departments.

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Authentication can be defined as a set of steps to ensure the identity of a person, and to ensure that the owner of this identity is authorized to use the system or access sensitive places[1]. There are three main methods in which people can be verified [2]: the first method is the things that he knows (such as using a password); the second method is the things that he owns that indicate the identity of this individual (such as using a passport or other official papers issued by a trusted authority) ;the last method is the Identification by biometrics.

Biometrics is one of the sciences that defines a person's identity and recognizes him through his chemical, physical or behavioral properties [3]. Several things of the human body that fall within the realm of biometrics, such as face, iris, palmprint, fingerprint, DNA, and odor, in addition to behavioral things such as gait, and signature [2].

Researchers have published a large number of researches in this field, the use of biometrics varied. There are those who used one type for the purpose of identification, as did Sang et al. [4], where a method was proposed to identify people using a fingerprint. After extracting the minutiae, they will be considered areas of interest. The characteristics are extracted from the areas surrounding these points using the invariant moments. Bader et al .[5], their research into the process of identifying people relied on the use of a species considered modern in biometrics. Where they used a finger vein to identify people through two algorithms (FAST and Harris) to extract the characteristics of the images used. In this way, the error rate is reduced by using two verification algorithms. A method has been presented by Jummar et al. [6], To extract characteristics for identifying people by fingerprint. After processing the images and converting them to the binary mode and then determining the area of interest, the researchers adopted two algorithms, the first is Gray level Cooccurrence Matrix (GLCM), and extracts the properties of the binary images, the other algorithm is the Invariant moments and it is used to extract the features from the double-thinning images. The hills and valleys were thinned together in one picture. During the verification process, the hybrid characteristics extracted from the two algorithms are relied upon, as the system has proven its worth with very good results. Ahmadi et al. [7], designed a system that identifies people by iris. The system is based on hybrid characteristics that are collected by means of three technologies: two-dimensional Gabor kernel (2-DGK), polynomial filtering (PF), and step filtering (SF). And in the matching phase, it was used genetic algorithm (GA) together with a radial basis function neural network (RBFNN). The system showed excellent verification results, as the recognition rate was more than 99%.

Another type of person identification, where researchers use methods of fusing features obtained from two or more types of biometrics, in order to increase the level of verification. Like fusing the features extracted from a fingerprint with features extracted from the iris. This technology is divided into two main categories: fusion of the features before matching; and fusion after matching [8]. One of the recent researches in this field, what Hammad et al. [9], presented, where the researchers used an electrocardiogram (ECG) and fused the extracted results with fingerprint features, to form a binary recognition system, in order to rise to a higher level of verification rather than using each system separately. The features were extracted using a convolution neural network (CNN). Q-Gaussian multi-support vector machine (QG-MSVM) is proposed for classification and decision-making purposes. The results released by the system were wonderful and indicate the success of the method used to integrate the features.

In another work, Cherrat et al. [10], presents a method for identifying persons based on the characteristics of a finger-vein in addition to the identification of the biometric characteristics of the face. This method extracts the features from the finger-vein using CNN and then classifies them according to the extracted characteristics. On the other hand, features are extracted from face images using CNN, and then these images are classified. The final step in the system is the process of fusing the two decisions and making the final decision to accept or reject the person. The system provided great results for up to 99.98%.

In the research paper of Alsubari et al. [11] ,the palmprint is also one of the parts that can be relied upon in the identity verification process. Employed this measurement with a dual verification system that combines the features extracted from the iris with the features obtained from the palmprint. Texture properties of palmprint are extracted by a histogram of oriented gradient (HOG) and discrete cosine transform (DCT). While the researchers used the Gabor filter with a Zernike Moment (ZM) to extract features from the iris. On the classification stage, a Gaussian fuzzy membership function was used to verify the identity of individuals. The system provided impressive results in terms of accuracy and time required.

The study that follows raises the level of people verification techniques. Boucetta et al. [12], presented a new method of recognition, by using the iris, palmprint, and face. Then comes the melting stage at the level of results from these three types. The research used particle swarm optimization (PSO) to fuse the results obtained from these three techniques. The experimental results obtained of this experiment were impressive, with an accuracy level of 100%.

One of the most recent works in the field of multiple biometric systems, presented by Kant et al. [13], in which they proposed a multi-biometric system to identify people and to detect fraud and impersonation. The proposed system is working on the level of matching, where the matching results received from three types of biometrics are fused. The

palm print, finger knuckle print, and the fingerprint are used in this work. The system has proven its worth with an accuracy level of (98.87%).
During this research, a fusion technique was used, in which the images from the finger vein and dorsal hand vein were combined. During the proposed method of fusion, we will obtain a large amount of data, compared to the number of images in the dataset for both types of biometrics. This large amount of data enables better and accurate verification of people. Many types of biometrics have been used in identifying people by many researchers. Using one type of measurement of the verification process has been often risky because the system will be vulnerable to deception through fraud and impersonation. , consequently, the system which was used the three types of biometrics resulted in a robust identity verification system. Thus, this strength was at the expense of time, such as the processing processes take longer. So, obtaining more than one measurement for individuals is a troublesome process and is not user-friendly. This work guarantees the strengths and the speed of processing and issuing the resolution by using two types of measurements (finger vein image and hand-dorsal image).That it increases accuracy and detect instances of fraud. The remaining of this work arranged as follow: section 2 illustrates fusion techniques, section 3 shows the proposed multi-modal system, and section 4 discusses the result of paper. Finally, section 5 concludes this research.

FUSION TECHNIQUES

Image fusion (IF) is the mechanism by which two or more images combine their features into an image file to produce more details of an image [14]. In image processing and computer vision, IF techniques have broad applications. The activity level measurement and fusion rules design are the main problems of IF, which can be found out in one shot. The registration and fusion of features from the registered image are the main processes in any traditional IF process [16]. Figure (1) show the fusion technique uses the following steps to merge the images.

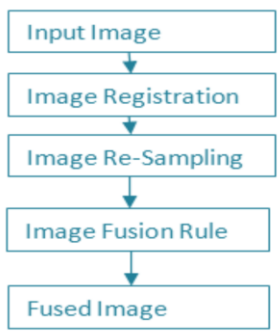

FIGURE 1: Pre-Processing Steps of Image Fusion [17].

Proper selection of fusion schemes for selecting a fusion scheme typically depends upon the data structure and the application. [18]. Conceptually, the supervised learning-based approach consists of three steps: feature extraction, classification and decision making. As below, the three schemes for fusing information from various image modalities [16]: Fusing at feature level, to find out a single image feature set, multi-modality images are combined, fusing at the classifier level, in order to figure out a separate function set of its own, images of each modality are used and fusing at the decision level, to figure out a single-modality classifier, images of each modality are used completely independently (and the corresponding feature set). Moreover, there are three levels of image fusion: the pixel level, feature level and decision level[19].

- Pixel level fusion: It is the simplest form of image fusion that directly operates on the image pixels and does not need to remove features, but involves strict registration of images.
- Feature level fusion: It involves the extraction of image characteristics, such as scale, edge, shape, texture data and other information.
- Decision-level fusion: In the fusion image, it is able to extract, recognize and classify valuable objects and perform fusion at a higher level. Due to the particularity of liver imaging, it is necessary to combine several methods to achieve IF.
- IF methods

THE PROPOSED FUSION IDENTIFICATION SYSTEM

This section presents the design and implementation of the proposed fusion identification system. It includes the layout description of the designed system, and the details about each implemented stage related to the applied system, whereas the biometric systems with deep learning consists of two main stages: enrollment and training and testing. Figure (2) shows the proposed fusion identification system.

Datasets

In this paper, the proposed multimodal applied on two different datasets. The first dataset that is known in other related works as "Dr. Badawi" hand-dorsal vein dataset. Dr. Badawi's hand vein dataset contains 500 images [20][21]. This dataset includes persons of different ages, genders, healthy conditions with different affiliations. Near-infrared lighting with a charge-coupled device (CCD) camera is used to capture hand-dorsal vein pattern images. Yilong Yin is a public database including images collected from 106 persons. 6 samples for right and left hand of each person per finger contain different position such as index, middle, and ring [5].

Image Pre-Processing

Image processing is the first stage, which uses to enhance finger vein and dorsal vein images. In this paper many filters and techniques were used in image processing stages for each type of image. These processing operations are performed in parallel for both the finger vein images and hand dorsal vein image.

Image Processing for hand-dorsal vein images

Many image processing steps used to extract hand-dorsal vein pattern from original images. Since these steps aim to obtain a batter hand dorsal vein pattern, then obtain a batter features and a high accuracy.

- Region of Interest (ROI): extract the ROI leads to reduce the number of features which extracted from images. In our system, the ROI was extracted by applying three steps: the first step applies a local threshold of the original image, this convert the image to white and black mode. The next step is replacing the white pixels with corresponding pixels in the original image. Finally, removing the black part from the image.
- Mean filter: is a smoothing filter uses to reduce the amount of intensity variation between pixels and remove noise from images. Mean filter replaces each pixel value in an image with the average value of its neighbors, including itself.
- Normalization: normalization process in image processing changes the intensity range of pixel in the images.
- Histogram Equalization (HE): HE is an image processing technique, uses of enhancing images with poor brightness. HE is a probability distribution of the gray level in the image.

Image Processing for Finger vein images

The finger vein pattern was extracted from images based on Repeat Line Tracking (RLT), after extract the ROI from finger vein images.

ROI: the Lee technique [22] was used to extract the ROI from finger vein images.

RLT: The repeated line tracking method tracks vein repeatedly, and the tracking starts at various positions. A line is tracked by moving pixel by pixel along the veins, checking the cross-sectional profiles of the image. When a dark line is not detected, a new tracking operation starts at another position. This operation is executed repeatedly.

Finally, the loci the lines overlap, and the finger-vein pattern is obtained statistically. This method must avoid repeating local U-turns [23][24]. Using the Repeat Line tracking algorithm during the image processing phase, has helped to produce a good finger vein pattern, that benefits to extract features from this pattern accurately.

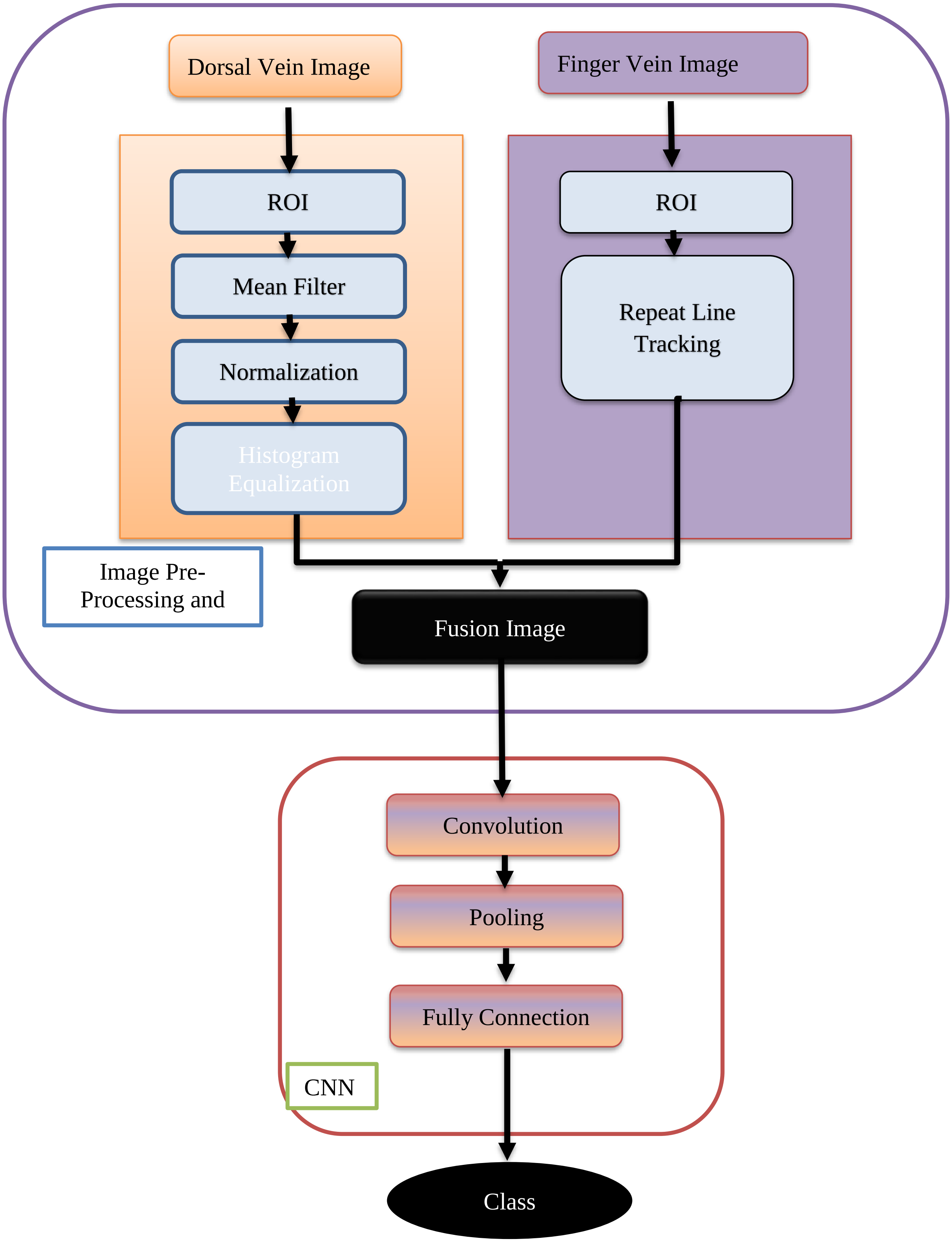

FIGURE 2: The Proposed System.

The Proposed Fusion Techniques

Fusion is a process of combining two or more images in one image. The main aim of use fusion in biometric identification systems, is to make the fusion image more informative, in addition to increase the security of the system, by making the process of bypassing the system and stealing the biometric image more difficult. This paper uses two techniques to combine the images of finger vein with the images of hand-dorsal vein.

First fusion technique, combine two images in one image orthogonally, one perpendicular to the other without combining the pixels of the two images. Conversely, the second method resizes the image of finger and hand-dorsal vein to make these images the same size and spin on all pixels in two images. The combining process depending on the following equation:

$$fusion(i,j) = \frac{finger(i,j)+dorsal(i,j)}{2} \tag{1}$$

Where fusion is a fusion image, *finger* is a finger vein image, *dorsal* is a hand dorsal image and (i,j) are the index of pixel in each image. Moreover, this research suggested a new technique, as far as we know. This method expands the number of pictures in the database when there are a few pictures taken of individuals. To overcome this hurdle, the proposed expansion method fuses each image from the first dataset with all images in the second dataset in the same class and continues in this order. These changes increase the size of the training dataset in addition to teaching the deep learning network all possible features by combining two biometric features (images) in the identification system. Figure 3 illustrates the image processing stages and the fusion techniques of the proposed fusion identification system.

The Proposed CNN Network

Convolution Neural Network (CNN) is a type of Artificial Neural Network uses to recognition and classification. CNN consists of two main parts: feature extraction and classification. The main process in feature extraction part is a convolutional layer, Rectified Linear Unit (ReLU) and pooling, whereas the connection layer plays the role of the classifier.

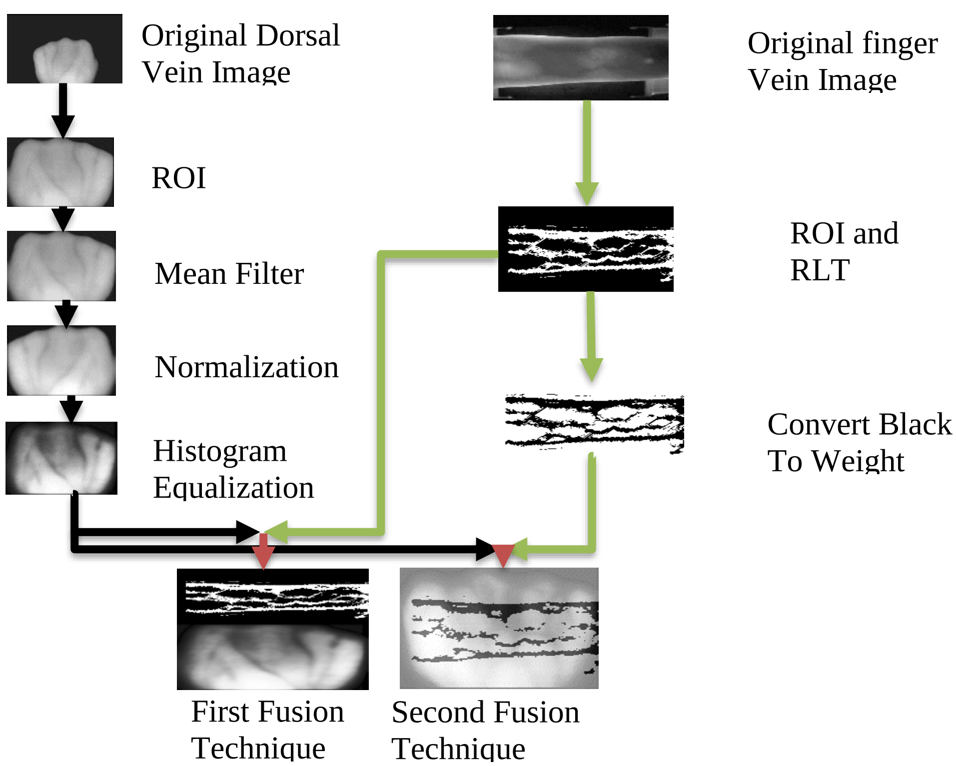

FIGURE 3: Image Processing and Fusion Techniques for the Proposed System.

The proposed CNN topology consists of 16 layers in addition to fully connected layer and softmax layer. We used input images of size 150x10. Four grouped of layers was used. First part contain three filters in convolution layer that apply on original image with size (150x150x3), Batch normalization used to speed up the training process, ReLU and max pooling to make the image with size (75x75x3). In the second part, convolution layer applies with nine filters, Batch normalization, ReLU and pooling with size (37x37x9). Third part consists of convolution with 27 filters, Batch normalization, ReLU and pooling with size (18x18x27). Finally, 81 filters in convolution layer, Batch normalization and ReLU followed by fully connection neural network layer with 100 classes in addition to softmax layer. The proposed Convolutional Neural Network Topology shown in Figure 4.

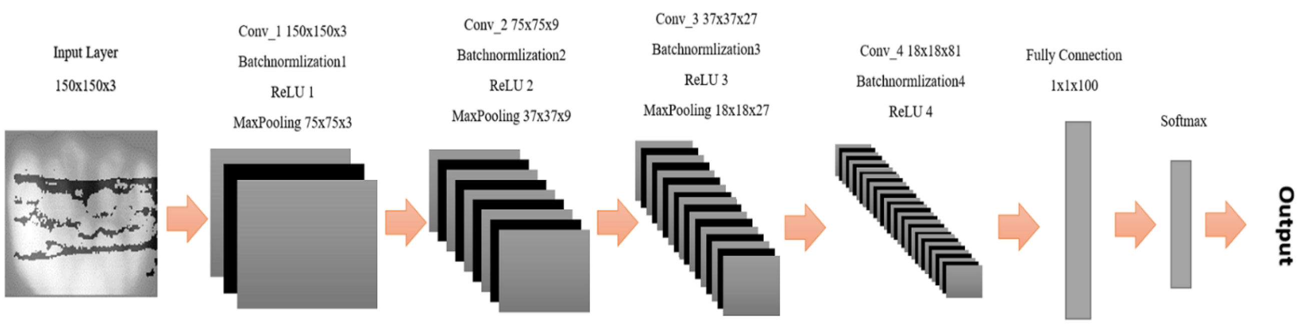

FIGURE 4: The Proposed Convolutional Neural Network Topology.

RESULTS AND DISCUSSION

The proposed systems of this paper were developed by using MATLAB 2018b software, all tests were conducted on the computer have a core I7-7500 CPU, and 16 G of RAM. Two datasets were used to experiments the proposed methods, one for finger vein images and another for the hand dorsal dataset. Yilong Yin is a public finger vein database contain images for 600 images, six images for each finger and we choose images of 100 fingers (600 samples) randomly. Badawi is a public hand-dorsal vein database that consists of 500 images for 100 hands. We used 70% of images in each training process and 30% of images in testing and validation.
Table 1, illustrates the results of six proposed methods, each row shows the results of each method. The first and second rows present the results of test every type of image separately. The result shows that the finger vein gave 94% accuracy, whilst the accuracy of hand dorsal images was 93%. The third and fourth rows present the results of using the two proposed fusion methods. The accuracy of used first method was 96% and the accuracy of using the second fusion method was 97%. Finally, the fifth and sixth rows, describe the results obtained from the use of the proposed fusion expansion method, with two image fusion methods. The proposed fusion method with expansion given 99.88% accurately, while in the second fusion the accuracy was 100%.

TABLE 1: The Results of Proposed system.

Method	Number of images	Type	Accuracy (%)
Finger vein images	600	Unimodal	94
Palm vein images	500	Unimodal	93
First fusion method	500	Multimodal	96
Second fusion method	500	Multimodal	97
First fusion method with expansion	3000	Multimodal	99.88
Second fusion method with expansion	3000	Multimodal	100

According to the obtained results, all multi-modal methods show higher performance than unimodal. Moreover, the expansion method enhanced the accuracy of the proposed identification systems. The new method helps the CNN network to train on all the features that may result from the combination process, because all the images in the first database are fused with all the images from the second dataset of the same class. In addition, the new method increases the number of images that are used for training, and thus the trained network has better accuracy, where the number of images resulting from the fusion process was 3000 instead of 500 or 600 in the traditional method. Therefore, the proposed expansion method is suitable for all classification systems based on the pixel fusion technique.

CONCLUSION

This paper proposed a multi-modal identification system .Which can be used to classify persons based on his/her finger vein image and hand-dorsal image. Two methods have been used in the proposed work, with expansion and without expansion. Then the experimental results demonstrated that the proposed fusion technique obtained better accuracy compared to using each system separately. Furthermore, the proposed fusion expansion technique improves the accuracy of the network, because it trained on all possibilities. We can also be seen that the proposed CNN topology gives promising results in all tests. Moreover, this research paper opens a new perspective on the field of data augmentation to expand the data set. Our future work is to use the proposed system with other biometric traits, thus, measuring the effectiveness of the system in other fusion images.

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