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GENERALIZING CONVOLUTIONAL NEURAL NETWORKS FOR PATTERN RECOGNITION TASKS

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ABSTRACT

Convolutional Neural Network (CNN) promises automatic learning and less effort for hand-design heuristics in building an efficient pattern recognition system. It requires simple and minimal preprocessing stages for data preparation. These features enable CNN architecture to be applied to various pattern recognition applications. This paper proposes a four-layered CNN architecture that caters to face recognition and finger-vein biometric identification case studies. The methodology applied in designing the network is discussed in detail. For face recognition, the design is evaluated on three facial image databases with different levels of complexities. These databases are AT&T, AR Purdue, and FERET. The same four-layered CNN architecture is also tuned for finger-vein biometric identification problems. The design performance is evaluated on finger-vein biometric database developed in-house, consisting of 81 subjects. The results obtained from these case studies are promising. For face recognition applications, 100%, 99.5%, and 85.16% accuracies were obtained for AT&T, AR Purdue, and FERET, respectively. On the other hand, the result obtained from the finger-vein biometric identification case study has 99.38% accuracy. The results have shown that the proposed design is feasible for any pattern recognition problem.

Keywords: convolutional neural network, face recognition, finger-vein biometric identification, biometric.

INTRODUCTION

Pattern recognition continues to be an active area of research since half a century ago. The basic approach in pattern recognition is to transform raw images through a series of image processing algorithms before applying the final stage of classification. Examples of applications for pattern recognition include speech recognition, handwriting recognition, object recognition, etc. Figure 1 shows a common pattern recognition flow. The choice of sensors, preprocessing techniques, and decision-making techniques depends on the characteristics of the problem domain.

In the conventional pattern recognition approach, the pattern recognition algorithms that are used to design a specific problem domain require tedious re-designing processes whenever the problem domain changes [1]. This problem can be a barrier in designing multimodal biometric systems since the pattern recognition flow for each biometric identifier requires specific algorithm determinations. For example, the work in [2] has shown that different preprocessing methods are required for different types of face databases, although the feature extraction and classification methods remain the same.

One approach that could overcome the above problem is Convolutional Neural Network (CNN). CNN was proposed by LeCun et al. [3] in 1989. The superiority of CNN has been proved in a wide range of applications such as face detection [4, 5], face recognition [6, 7], gender recognition [8, 9], object recognition [10, 11], character recognition [12, 13], texture recognition [14], and more. CNN has several advantages. Firstly, it takes into account the two-dimensional (2-D) image topology of input changes. This makes CNN robust against changes of input patterns, including translation, scaling, and rotation. This robustness is due to the built-in invariance feature of CNN which makes it resistant to distortion. Secondly, it combines segmentation, feature extraction, and classification in one trainable module in which the network's feature extractors are formed automatically as they learn the samples adaptively. Thirdly, it accepts raw data with minimal preprocessing compared to the conventional pattern recognition approach. Finally, it applies the concept of sharedweights, which has reduced significantly the number of parameters compared to the fully-connected multilayer perceptron (MLP). Figure-2 shows an example of CNN being used for handwriting recognition application.

CNN can be used for various pattern recognition applications using network architecture. This has been proved in [15], which applied five-layered CNN for character and face recognition problems. Another example as reported in [16] applied six-layered CNN to solve face and license plate recognition problems. These works led to the motivation of this paper. In this paper, four-layered CNN architecture is designed for two case studies, namely face recognition and finger-vein biometric identification. The only difference is the number of feature maps at each layer that need to be adjusted according to the problem domain at hand.

The remainder of the paper is organized as follows. In section 2, the methodology of the proposed work is discussed. This is followed by a discussion of the

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recognition of human faces and results in Section 3.1. In Section 3.2, the finger-vein biometric identification results are discussed in detail. The final section concludes this paper.

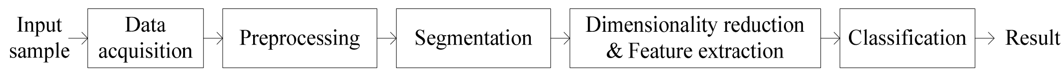

Figure-1. Typical pattern recognition flow.

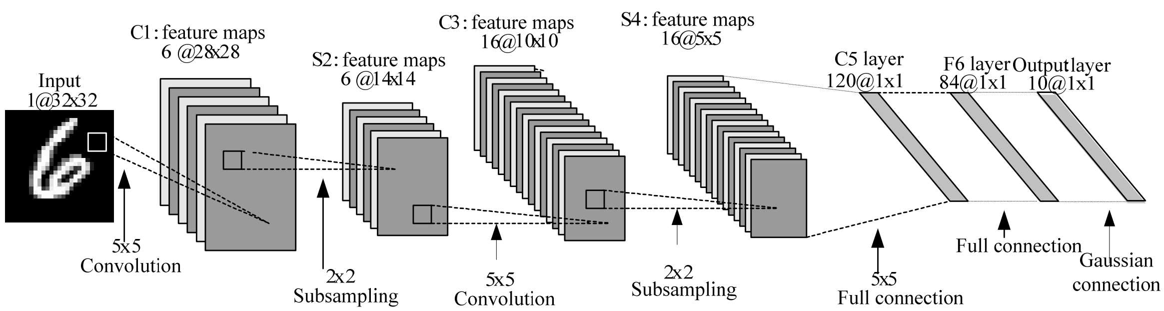

Figure-2. Example of CNN architecture used for handwriting recognition application [1].

2. METHODOLOGY

The CNN architecture proposed for both case studies is a four-layered CNN. The number of layers in these case studies is much reduced from the basic CNN architecture in [1]. The idea of reducing the number of layers, known as fusion convolution or subsampling concept, was inspired by Simard *et al*. in 2002 [17], and the mathematical model was proposed by Mamalet and Garcia in 2012 [18]. Mamalet and Garcia applied the concept to recognize characters from the MNIST database. However, examples in this paper adapt the concept to recognize faces and finger-vein samples. Details of the process can be referred to in [19].

The numbers of feature maps at each layer are different for each problem domain. The number of maps also depends on the level of complexity of the database applied. The number of feature maps at each layer is optimally determined using a 10-fold cross-validation technique. Cross-validation technique is a popular statistical approach that is appealing for designing large neural network with good generalization as a goal [20]. This technique guides the designer in the selection of the best model (best number of hidden neurons or feature maps at each layer), best parameter, and when to stop training [20]. Through cross-validation, we can evaluate a classifier experimentally to estimate the performance of the selected classifier on unseen data (the test set) [21]. Generally, the total samples will be divided into 20% and 80% portions. The 20% portion will form the test dataset while the remaining 80% samples are used for the 10-fold cross validation technique. The 80%samples are then divided into 10 folds equally in which 9 of the folds are used to train the network while 1 fold is used to validate the training process. This method is repeated using different folds as the validation set. Figure-3 shows the best model for the AT&T database.

The neurons at the output layer represent the number of subjects in the AT&T database. *Winner-takes-all* rule is applied in determining the identity of the query subject. Winner-takes-all rule is a concept that assigns the maximum value obtained at the output layer as a firing neuron, or “winner,” while the other neurons remain inactive. Total error is calculated between the target value and the output value. Next, the total error is backpropagated to adjust the current weight values. Throughout the training process, the total error in which the current weight values identifies query samples better than before will become smaller. Connection between layer C3 and the output layer is full-connection without any similarity measure applied compared to other existing works reported in [15, 22-24]. The absence of similarity measure and the implementation of winner-takes-all rule has sped up the training process. Mean square error is applied as the error function. The learning algorithm applied in this work is an enhanced version of Stochastic Diagonal Levenberg Marquardt, which is out of the scope of this paper.

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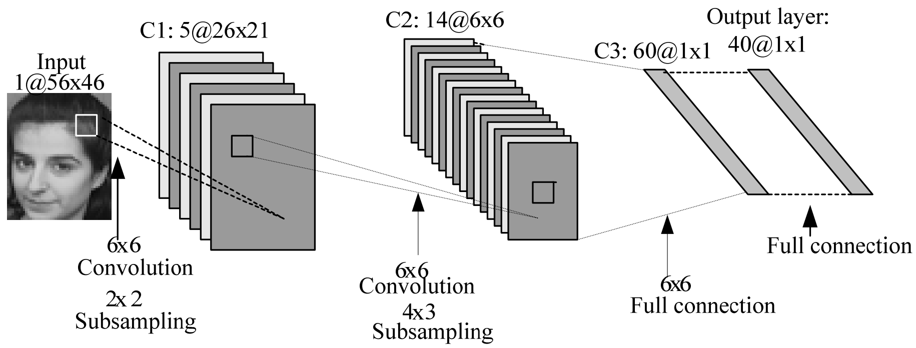

Figure-3. The best model for the AT&T face database.

After determining the best model of CNN, the partial connection is determined between the first two layers. The purpose of partial connection is to avoid the same features being selected for classification and also to reduce network parameters (number of neurons, trainable parameters, and connections). This method was first proposed in [1] with random types of connections. In this paper, we propose a way to determine optimum partial connection scheme using a 10-fold cross validation technique. Figure-4 explains the flow of determining an optimum partial connection scheme. Table-1 shows variant types of connections between the C1 and C2 layers. After implementing the flow presented in Figure-4, the optimum partial connection scheme is obtained for the AT&T face database as shown in Table-2. Figure-5 depicts an example of connections for feature map C2 [0].

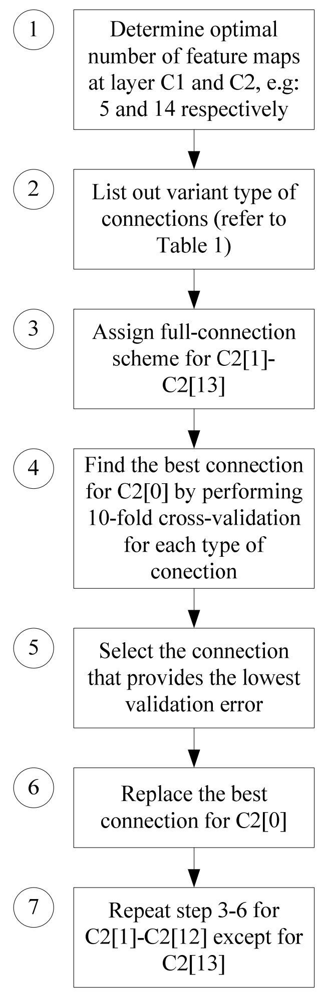

Figure-4. Methodology of determining the optimum partial connection scheme.

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Table-1. Variant types of connections between C1 and C2 layer.

Conn (0)	Conn (1)	Conn (2)	Conn (3)	Conn (4)	Conn (5)
×	0	0	×	×	0
×	×	0	0	×	×
×	×	×	×	×	×
0	×	×	0	×	×
0	0	×	×	0	×

Table-2. The optimum partial connection scheme for AT&T face database.

C1 \ C2	0	1	2	3	4	5	6	7	8	9	10	11	12	13
0		X												X
1		X	X	X		X	X	X			X	X		X
2	X	X	X	X	X	X	X	X	X	X	X	X	X	X
3	X		X	X	X	X	X	X	X	X	X	X	X	X
4	X				X				X	X			X	X

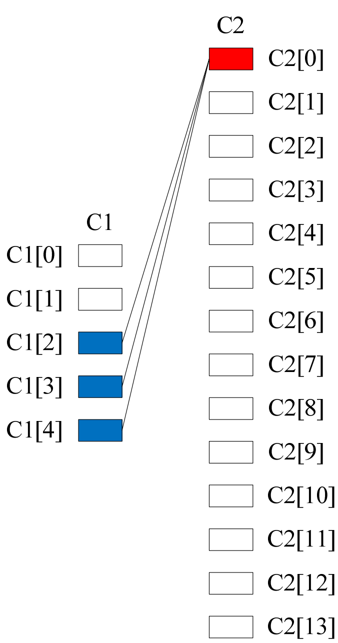

Figure-5. Example of connections for C2 [0].

3. RESULTS AND PERFORMANCE

The performance of the proposed CNN is evaluated for recognition of human faces and also identification of finger-vein biometric samples. Two case studies are conducted in the experiment to prove that the proposed design is viable for various case studies. For the best model in each case study, optimum partial connection and accuracy is presented. The total samples for each database or case study are separated into 80% and 20% portions representing training and test samples respectively. The details of selecting the best model are beyond the scope of this paper. The methodology of selecting the best model can be referred to in[19].

3.1 Recognition of human faces

The evaluation of the face recognizer is carried out using standard face databases, which include AT&T, AR Purdue, and FERET. In the following section, information and results for each database are discussed separately.

3.1.1 AT&T database

AT&T contains images of “moderate challenge,” which indicates a moderate degree of variation in poses (up to 20 degrees), lighting (dark homogenous background), facial expressions, and head positions. Figure-6 illustrates the samples and Figure-7 depicts the preprocessing stages for AT&T. The best model and optimum partial connection scheme for AT&T can be seen in Figure-3 and Table-2. The experimental setup and accuracy obtained is outlined in Table-3. The accuracy achieved is 100.00%. Other existing works such as [25, 26] also report 100.00% accuracy. This is expected since the database is less challenging.

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Figure-6. Sample of images from AT&T database.

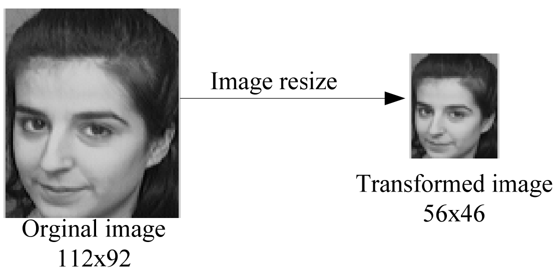

Figure-7. Preprocessing stages for AT&T database.

Table-3. Experimental setup and performance for AT&T database.

CNN model parameters	Results
Architecture (C1-C2-C3 feature maps)	5-14-60
Normalization and weight initialization method	Min-max and Gaussian weight
Optimum input image size	56×46
No. of train samples	320
No. of test samples	80
Accuracy	100.00%

3.1.2 AR Purdue

On the other hand, AR Purdue represents images of "complex challenge," which indicates a high degree of variation in facial expressions, lighting (illumination), and partial occlusions (wearing sunglasses or scarf). Figure 8 illustrates the samples and Figure 9 depicts the preprocessing stages for AR Purdue. The best model and optimum partial connection scheme for AR Purdue can be seen in Figure 10 and Table 4. The experimental setup and accuracy obtained is stated in Table 5. The accuracy achieved is 99.50%, which outperforms other existing works [27-29] using the same database and number of subjects.

Figure-8. Sample of images from AR Purdue database.

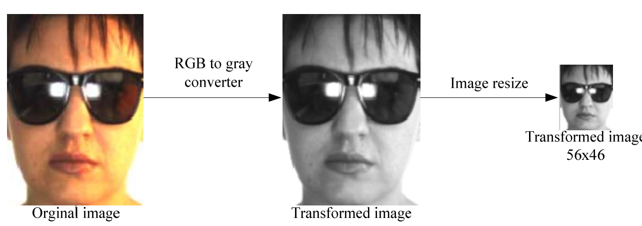

Figure-9. Preprocessing stages for AR Purdue database.

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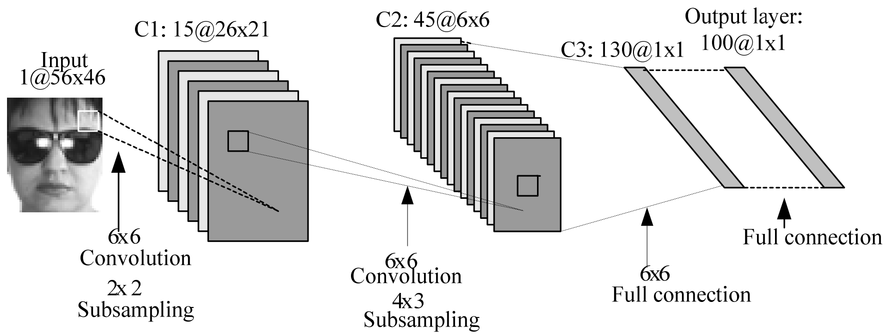

Figure-10. Best model for AR Purdue database (15-45-130).

Table-4. Optimum partial connection for AR Purdue database.

C1 \ C2	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44
0								x								x								x									x												x
1					x			x						x		x				x				x									x				x			x					x
2					x	x		x			x			x		x				x				x						x			x				x			x					x
3					x	x		x		x	x			x		x				x				x				x		x			x			x	x			x	x				x
4					x	x		x	x	x	x		x	x	x	x	x			x		x	x	x		x		x		x	x		x			x	x			x	x			x	x
5					x	x		x	x	x	x		x	x	x	x	x			x	x	x	x	x		x	x	x	x	x	x		x		x	x	x	x		x	x			x	x
6		x	x	x	x	x	x	x	x	x	x		x	x	x	x	x	x		x	x	x	x	x		x	x	x	x	x	x	x	x		x	x	x	x	x	x	x		x	x	x
7	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
8	x	x	x	x	x	x	x		x	x	x	x	x	x	x		x	x	x	x	x	x	x		x	x	x	x	x	x	x	x		x	x	x	x	x	x	x	x	x	x	x	x
9	x	x	x	x		x	x		x	x	x	x	x		x		x	x	x		x	x	x		x	x	x	x	x	x	x	x		x	x	x		x	x		x	x	x	x	x
10	x	x	x	x			x		x	x		x	x		x		x	x	x		x	x	x		x	x	x	x	x		x	x		x	x	x		x	x		x	x	x	x	x
11	x	x	x	x			x		x			x	x		x		x	x	x		x	x	x		x	x	x		x		x	x		x	x			x	x			x	x	x	x
12	x	x	x	x			x					x						x	x		x				x		x		x			x		x	x			x	x			x	x		x
13	x	x	x	x			x					x						x	x						x							x		x					x			x	x		x
14	x											x							x						x									x								x			x

Table-5. Experimental setup and performance for AR Purdue database.

CNN model parameters	Results
Architecture (C1-C2-C3 feature maps)	15-45-130
Normalization and weight initialization method	Z-score and Gaussian weight
Optimum input image size	56×46
No. of train samples	2000
No. of test samples	600
Accuracy	99.50%

3.1.3 FERET database

The “extreme challenge” database can be found in FERET, which includes a high degree of variation in facial expressions, appearances, illumination, and poses (up to 90 degrees). Figure-11 illustrates the samples and Figure-12 depicts the preprocessing stages for FERET database. The best model and optimum partial connection scheme for FERET can be seen in Figure-13 and in Table-6. The experimental setup and accuracy obtained is stated in Table-7. The accuracy achieved is 85.16%, which is still within the same range as other existing works [2, 30] with a similar database and number of subjects.

Figure-11. Sample of images from FERET database.

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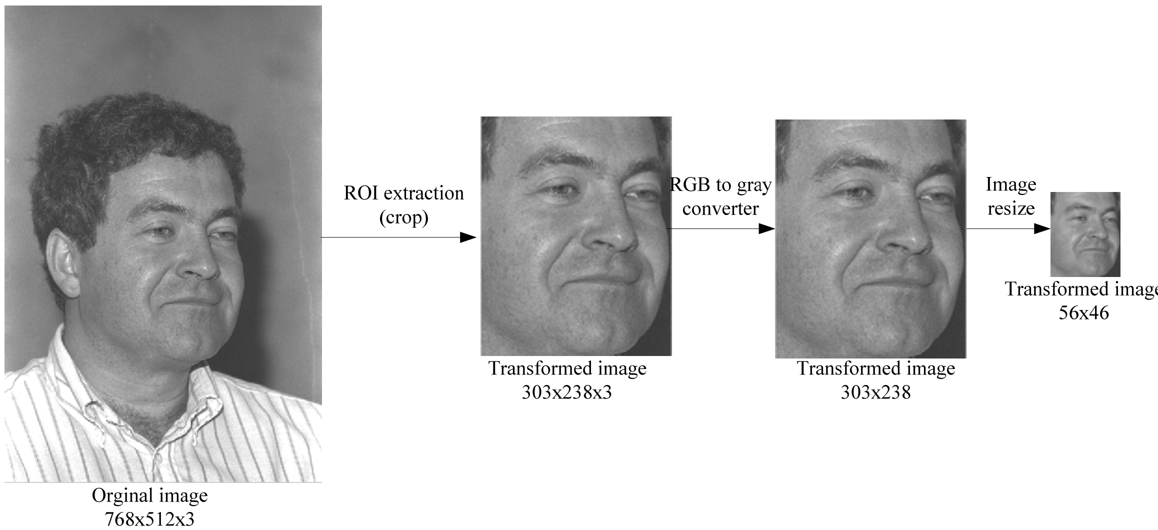

Figure-12. Preprocessing stages for FERET database.

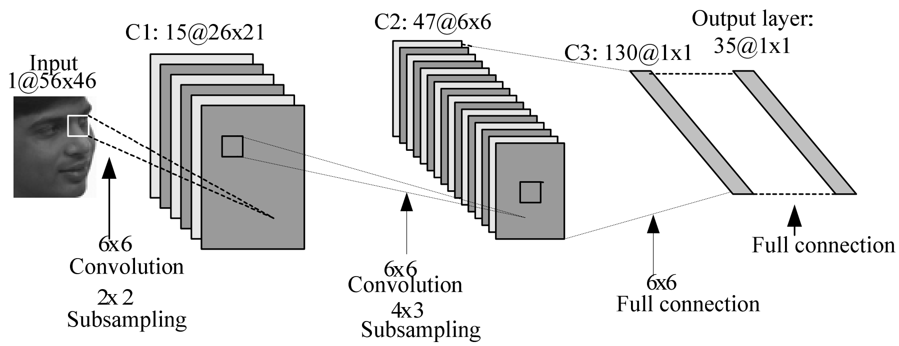

Figure-13. Best model for FERET database (15-47-130).

Table-6. Optimum partial connection for FERET database.

C1 \ C2	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46
0															x				x				x					x																		x	x
1						x	x			x					x				x	x			x					x																		x	x
2		x			x	x	x			x					x				x	x			x					x						x											x	x	x
3		x		x	x	x	x			x				x	x				x	x			x					x						x						x					x	x	x
4		x	x	x	x	x	x	x		x		x		x	x			x	x	x			x	x	x			x						x	x				x	x	x				x	x	x
5		x	x	x	x	x	x	x		x		x		x	x			x	x	x			x	x	x			x						x	x				x	x	x		x		x	x	x
6	x	x	x	x	x	x	x	x		x		x		x	x		x	x	x	x	x	x	x	x	x			x		x	x			x	x	x	x		x	x	x		x		x	x	x
7	x	x	x	x	x	x	x	x	x	x	x	x	x	x			x	x		x	x	x		x	x				x	x	x		x	x	x	x	x	x	x	x	x		x		x		x
8	x	x	x	x	x			x	x		x	x	x	x		x	x	x			x	x		x	x	x	x		x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x		x
9	x		x	x				x	x		x	x	x	x		x	x	x			x	x		x	x	x	x		x	x	x	x	x		x	x	x	x	x	x	x	x	x	x			x
10	x		x					x	x		x	x	x			x	x	x			x	x		x	x	x	x		x	x	x	x	x		x	x	x	x	x		x	x	x	x			x
11	x								x		x		x			x	x				x	x				x	x		x	x	x	x	x			x	x	x				x	x	x			x
12	x								x		x		x			x	x				x	x				x	x		x	x	x	x	x			x	x	x				x		x			x
13									x		x		x			x										x	x		x			x	x					x				x		x			x
14																x										x	x					x										x		x			x

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Table-7. Experimental setup and performance for FERET database.

CNN model parameters	Results
Architecture (C1-C2-C3 feature maps)	15-47-130
Normalization and weight initialization method	Z-score and Gaussian weight
Optimum input image size	56×46
Learning	Results
No. of train samples	504
No. of test samples	108
Performance	Results
Accuracy	85.16%

The results achieved by the three databases prove that the proposed four-layered CNN architecture could be adjusted according to the complexity level of a particular database. Exploring other existing algorithms for different databases is not required in CNN as it would be in conventional methods. The only method needed involves adjusting the number of feature maps at each layer and determining an optimum partial connection scheme at the first two layers of CNN. The results presented in this paper can be used as a guide with which to recognize faces from other databases as long as the complexity level of such databases is known. For example, in order to recognize images from JAFFE database, the 5-14-60 model for the AT&T database can be used.

3.2 Finger-vein biometric identification

The second case study is finger-vein biometric identification. To the best of our knowledge, this case is the first attempt to apply CNN to classify finger-vein samples. The database is developed in-house by VeCAD Laboratory, Universiti Teknologi Malaysia, and consists of 81 subjects with 10 samples each on 6 different fingers. The age group of participants is between 18 and 50 years and their occupations range from staffs to university students. The samples of the database are depicted in Figure-14 and preprocessing methods are depicted in Figure-15. These samples are captured using fixed illumination of near-infrared (NIR) sources. Hence, inappropriate lighting occurs in some of the samples. In conventional finger-vein biometric approach, inappropriate lighting can cause deterioration of classification accuracy. However, due to the special features of CNN in learning the samples adaptively, some of the typical preprocessing methods are not required, such as noise removal, image enhancement, segmentation, and binarization techniques.

The best model and optimum partial connection scheme for the VeCAD-UTM database is portrayed in Figure-16 and Table-8. The experimental setup and accuracy obtained is stated in Table-9. The accuracy achieved is 99.38%, which stands at the same level as other existing works [31-33].

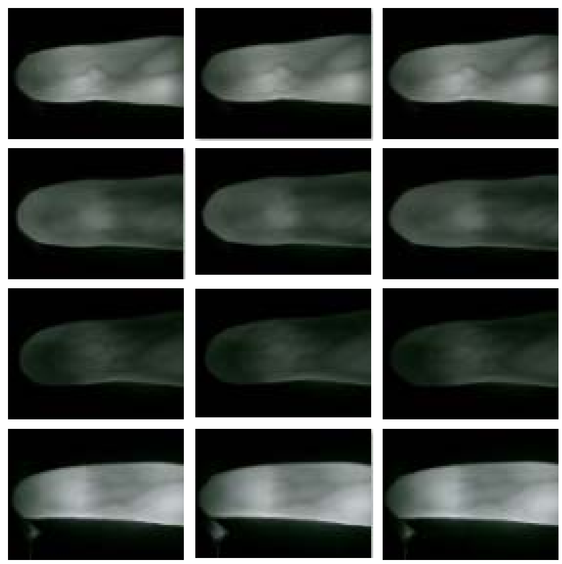

Figure-14. Sample of images from VeCAD-UTM database.

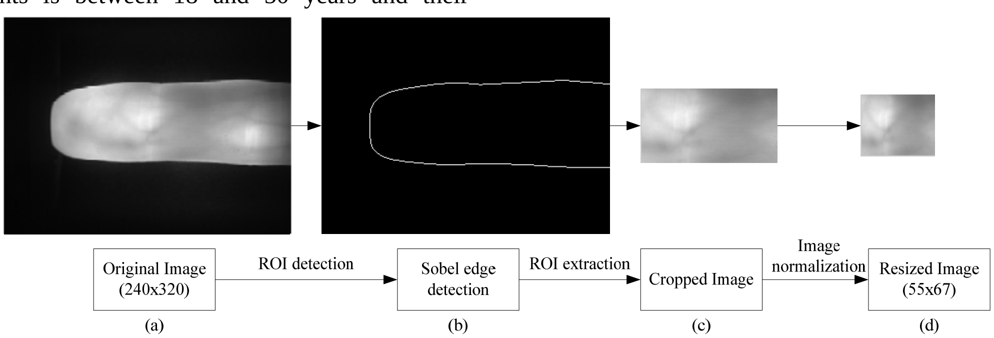

Figure-15. Preprocessing methods for finger-vein biometric identification case study.

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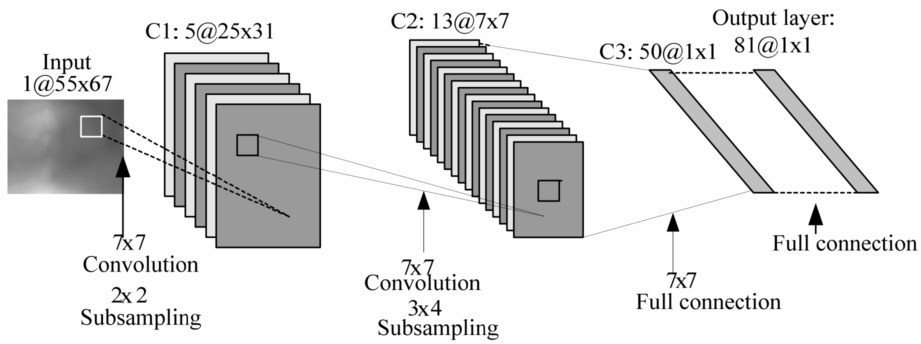

Figure-16. Best model for VeCAD-UTM finger-vein database (5-13-50).

Table-8. Optimum partial connection for VeCAD-UTM finger-vein database.

C1 \ C2	0	1	2	3	4	5	6	7	8	9	10	11	12
0		x	x	x		x		x					x
1	x	x	x		x		x	x	x			x	x
2	x	x	x	x	x	x	x	x	x	x	x	x	x
3	x	x			x		x		x	x	x	x	x
4				x		x	x			x	x	x	x

Table-9. Experimental setup and performance for VeCAD-UTM finger-vein database.

CNN model parameters	Results
Architecture (C1-C2-C3 feature maps)	5-13-50
Normalization and weight initialization method	Z-score and uniform weight
Optimum input image size	55×67
No. of train samples	648
No. of test samples	162
Accuracy	99.38%

The results obtained from this case study have proved that implementing CNN on finger-vein samples is feasible. It has also proved that the proposed CNN architecture can be generalized to other case studies, such as the finger-vein biometric identification problem, and it has the potential to be generalized to other types of pattern recognition problems too.

4. CONCLUSIONS

In this article, two types of case studies have been used to prove that the proposed CNN architecture is viable in generalizing its structure to other pattern recognition problems. The first case study on face recognition has shown that the four-layered CNN could be adjusted in terms of the number of feature maps at each layer to suit to the complexity level of such a database. The design is evaluated on three standard face databases, namely AT&T, AR Purdue, and FERET, which produce accuracies of 100.00%, 99.50% and 85.16% respectively. The results on the AT&T and AR Purdue databases have outperformed other existing works. The CNN design has also been extended for the finger-vein biometric identification case study. Even though this is the first attempt of implementing CNN on finger-vein biometrics problems, the accuracy of 99.38% for 81 subjects has proved that the attempt is viable. From the results obtained from these two case studies, it can be concluded that the proposed CNN architecture applies to any kind of pattern recognition problem and can be adapted for a multimodal biometric approach.

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