Deep fingerprint classification network

Abdulsattar M. Ibrahim, Abdulrahman K. Eesee, Raid Rafi Omar Al-Nima
Department of Medical Instrumentation Technology Engineering, Northern Technical University, Iraq

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ABSTRACT

Fingerprint is one of the most well-known biometrics that has been used for personal recognition. However, faked fingerprints have become the major enemy where they threat the security of this biometric. This paper proposes an efficient deep fingerprint classification network (DFCN) model to achieve accurate performances of classifying between real and fake fingerprints. This model has extensively evaluated or examined parameters. Total of 512 images from the ATVS-FFp_DB dataset are employed. The proposed DFCN achieved high classification performance of 99.22%, where fingerprint images are successfully classified into their two categories. Moreover, comparisons with state-of-art approaches are provided.

Corresponding Author:

Abdulrahman K. Eesee
Department of Medical Instrumentation Technology Engineering,
Technical Engineering College/Mosul,
Northern Technical University
Iraq
Email: abdulrahman.kh@ntu.edu.iq

1. INTRODUCTION

Biometric recognition is the approach that comprises most of the identification features [1]. Biometrics can be either a physiological trait such as iris [2, 3], face [4-6], palm [7, 8], ear [9], finger texture [10-12], footprint [13] and fingerprint [14-16], or a behavioural trait as signature [17], handwriting [18], gait [19, 20] and voice [21, 22]. On the other hand, traditional methods for individuals' recognition and authentication are based on what a person have or know such as cards, keys, PIN codes, passwords. However, these traditional methods can be lost, forgotten or stolen which may affect their reliability [1, 23]. The recent development in computer processing has led to increase the dependency on biometrics comparing with the traditional methods [1, 23].

In the biometric recognition system, there is no need to carry a key or card and no need to remember a PIN code or password. These facilitate the validation processes of users [1, 24]. However, several drawbacks have been presented in biometric systems which include but not limited to their lower secrecy and security that make them vulnerable to external threats [1, 25, 26]. Fake biometrics are the most popular threats against biometric security systems. For instance, fake fingerprints can easily be constructed by using gummy fingers made from specific materials like silicone, wood glue and gelatine [27]. Figure 1 shows samples of real and fake fingerprints from ATVS-FakeFingerprint DataBase (ATVS-FFp_DB) [1] which are used in this study.

These challenges have increased the demand of developing robust biometric recognition systems [28, 29]. Basically, fingerprint classification techniques of spoofing detection can be categorized into two classes based on additional sensors that are used or not:

(a) Hardware based techniques: These are the fingerprints readers and classifiers which are able to scan the fingers with high resolution images for detecting the spoof and real fingerprints [30, 31]. The aim of using the hardware classification techniques is to detect the main liveness features such as the skin distortion [32] and blood flow [33].
(b) Software based techniques: These methods can classify the fingerprints into fake and real fingerprints based on their scanned images by the used sensors without the need to utilize more hardware. This classification can also be divided into two categories:
  - Feature extraction and recognition methods: they depend on liveness detection of fingerprints. However, due to their low accuracies for several spoofing materials and also the required long processing time for extracting features, many researchers have become less interest in this type [23, 31].
  - Deep learning methods: these on the other hand have made great success in the field of recognition and classification such as fingerprints [34], emotions [35, 36], bone fissures [37] and disorder classifications [38]. Deep learning technique is based on using adequate number of training data which lead to automatically learn their structures and features [34, 39]. The classification processes in this field are most likely concentrate on either classifying the fingerprints into their features (right loop, left loop, arch and whorl) or classifying the fingerprints into real and fake.

(a) (b)

Figure 1. Samples of fingerprints from ATVS-FFp_DB [1]: (a) the first row demonstrates real fingerprints, and (b) the second row shows fake fingerprints

There are various approaches that were suggested for fingerprint detections. Examples of these are: an approach of using statistical weight calculation with non-reference fingerprint was presented in [24], an alternative approach for generating cancellable fingerprint was described by considering operations in matrices [15] and fingerprints can be used for advanced encryption to generate fuzzy vault crypto biometric key [16]. This paper proposes an efficient model of deep learning termed the DFCN to achieve an accurate classification of fingerprints into real and fake. The remaining sections in this paper are organized as follows: section 2 presents the prior work of fingerprint classifications, section 3 displays the methodology of the proposed model, section 4 clarifies the employed dataset specifications, section 5 demonstrates the results and discussions and section 6 yields the conclusion.

2. PREVIOUS WORK

In the literature, deep learning techniques that were used to classify fingerprints into real and fake can recently be found. Previous studies can be reviewed as follows: In 2016, Nogueira *et al.* used fine-tuned VGG-S and VGG-F convolutional neural networks (CNNs) to classify fingerprints into four classes (right loop, left loop, arch and whorl) using the NIST special database 4 (NIST SD4). The achieved classifying accuracies for both networks (the VGG-S and VGG-F) were 95.05% and 94.4%, respectively [27]. In 2018, El Hamdi *et al.* also used the NIST SD4 database to test their proposed model. The model was constructed based on the combination of conic radon transform (CRT) and CNN. The results showed high classification accuracy of 96.5% [40]. A patch-based model using a fully CNN with optimal threshold to detect spoof fingerprint was utilized by Park *et al.* in 2018. They employed the liveness detection (LivDet) datasets (LivDet-2011, 2013, 2015) in the experiments. Their proposed method revealed high performance with 1.35% average classification error [41]. In 2019, Uliyan *et al.* proposed a deep learning model to classify fingerprints from LivDet datasets (LivDet-2013, 2015) into real and fake by using both discriminative restricted boltzmann machines (DRBM) network and deep boltzmann machine (DBM) network. Linear discriminant analysis (LDA) followed by the K-Nearest Neighbour was used for the classification purposes. The achieved accuracy by the proposed model was about 96% [31]. In 2019, another deep learning method for forged fingerprints detection was proposed by De Souza and his colleagues. The suggested method depended on deep boltzmann machine

(DBM) network and used the LivDet-2013 dataset. The proposed model was mainly consisted of three steps: starting with image normalization followed by training process and ended with the classifying process of support vector machine (SVM). The accuracy of the suggested system was 85.82% [42]. Also in 2019, Yuan *et al.* achieved satisfactory classifying results by using a deep model of deep residual network (DRN) followed by an enhanced and classified method named the local gradient pattern (LGP) [43]. Last but not least, Zhang and his researching team proposed a simple deep system depending on residual CNN called the Slim-ResCNN to classify the fingerprints into real and fake. Datasets from LivDet-2013, LivDet-2015 and LivDet-2017 were used to check the reliability of their proposed system. They managed to get the highest classification accuracy equal to 95.25% for LivDet-2017 dataset [44].

It can be seen that classifying fingerprints has almost been implemented by applying combinations of multiple processes, which may affect on their performances through spending long processing time. It can also be investigated from the literature that the accuracies of of detecting spoof fingerprints are not sufficient. We are aiming to contribute to this important area by presenting one intelligent model called the DFCN, which has the ability to detect the real and fake fingerprints with high performance and accuracy.

3. METHODOLOGY

This paper approahced an efficient deep learning model named the DFCN. This network model is based on the convolutional neural network (CNN). It aims to classify fingerprints into real (original) and fake fingerprints. Figure 2 shows the DFCN architecture. The proposed model consists of multiple layers. The following points summarize the layers of the DFCN model starting from a fingerprint input to the last classification layer:

– Reading fingerprint image. The DFCN is adapted to accept an image of real or fake fingerprint in its input. Any grayscale fingerprint image of size 300×300 pixels can be used as an input to our DFCN model. Each pixel value in a fingerprint image could be within the range [0-255].
– The convolutional process is the first layer in the DFCN. Two-Dimensional (2D) convolutions are here implemented for each input fingerprint image. We used 8 filters in this layer with the size 5×5 pixels. Each of the eight filters was specified to extract useful features from a fingerprint input. Let *l* is the current hidden layer, *l-1* is the previous hidden layer and *n* is the number of nodes in the current layer. The following mathematical expression shows the general formula of the convolutional layer:

$$y_n^l = \sum_m^{M^{l-1}} w_{n,m}^l * x_m^l + b_n^l \tag{1}$$

where: y_n^l is the *n-th* output of *l* layer, x_m^l is the *m-th* input to *l* layer, $w_{n,m}^l$ is the convolution kernel between the input and output (*m-th* and *n-th,* respectively), (*) is the operation of the convolution, M^{l-1} is the number of input channels, and b_n^l represents the bias of the *n-th* output [45].
– Activation function is used after the convolution layer. The Rectified Linear Unite (ReLU) is employed as the activation function. The following formula represents the ReLU operation:

$$z_n^l = \mathrm{ReLU}(y_n^{l-1}) = \begin{cases} y_n^{l-1}, & y_n^{l-1} \geq 0 \\ 0, & y_n^{l-1} < 0 \end{cases} \tag{2}$$

where: z_n^l is an output of the ReLU activation function [46].
– Max-pooling layer is applied to shrink the size of resulted data from the previous layer. The size of used filter in this layer was 5×5 pixels with the stride of 5 pixels. The max-pooling layer took the highest value of each 5×5 block of pixels. This value was considered as the most activated pixel on behalf of other pixels. This layer lead to decrease the computational load and the required processing time. It also plays a role in decreasing the overfitting process. The following formula represents the function of this layer:

$$p_n^l = \max\,(\mathbf{Z}^{l-1}) \tag{3}$$

where: p_n^l is an output of the max-pooling layer and $\mathbf{Z}$ is a block of 5×5 pixels.
– Fully connected layer is provided to perform matching between the previous layer (the max-pooling layer in our case) and the next layer. Based on the function of this layer, the number of output classes can be specified here. In this study, 2 outputs are required for the real and fake classes. Then as mentioned, the fully connected layer will match between the number of required classes and the nodes of the max-pooling layer.
– Softmax layer is subsequently given to prepare the data for the classification purposes. The output of this layer is represented by values in the range of 0 to 1. Each value gives the probability of the relationship

between the current fingerprint input and an output class. The mathematical formula of the softmax function is represented as follows:

$$o_n^l = \frac{e^{q_n^{l-1}}}{\sum_{n=1}^{C} e^{q_n^{l-1}}} \quad (4)$$

where: o_n^l is an output of the softmax layer and q_n^{l-1} is an input to this layer and C is the number of classes. The denominator is the summation of the exponentials of all the values in the vector [45].
– The final layer in the proposed DFCN model is the classification layer. It takes its inputs from the softmax layer as numbers between 0 and 1, two values for each input fingerprint image. The function of this classification layer is to decide whether the fingerprint is real or fake depending on the provided values from the softmax layer. The closer the input to 1 lead to select its corresponding output class and vice versa.

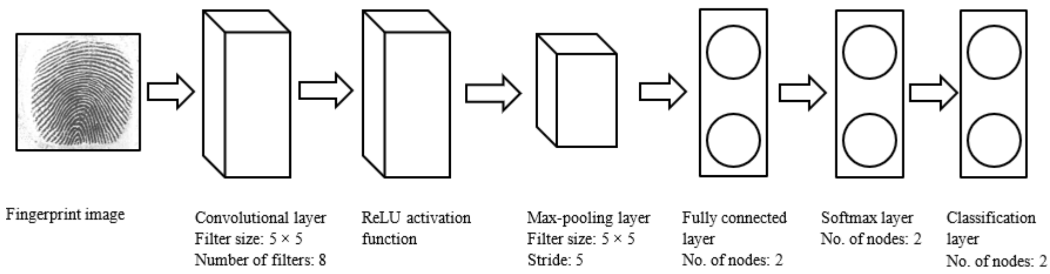

Figure 2. The architecture of the proposed DFCN model

4. EMPLOYED DATASET

To assess our model, we have used two groups of real and fake fingerprint images from the ATVS-FakeFingerprint DataBase (ATVS-FFp DB), specifically, the without cooperation dataset. The middle and index fingers of both hands were used to capture their fingerprints by a capacitive sensor. Four fingerprint images for each finger were acquired [1, 47]. The total numbers of fingerprints that are utilized in this study is 512 images. They are equally divided into two groups of real and fake fingerprints. We have exploited half of the dataset (50% of real fingerprints plus 50% of fake fingerprints) for the learning purposes. Whilst, the second half has been exploited for the DFCN efficiency testing.

5. RESULTS AND DISCUSSION

The proposed approach has been thoroughly evaluated by changing different deep learning parameters. Many experiments were implemented to examine the accuracies of tuning various deep learning parameters. It is worth mentioning that the starting parameters were initialized according to the novel approach in [48]. Table 1 shows the 8 cases that are considered in this paper, where each case represents tuning values for a certain parameter.

To reach the most efficient performance of the suggested DFCN model, the tuning processes of the deep learning parameters are divided into eight cases. Each of these eight cases includes adjusting one parameter while leaving the others without alteration. The number of epochs was assigned to 50 for all experiments as this would provide fair comparisons between all experiments and address the problem of implementing variations.

Starting with the initialization case, the proposed parameters of the novel approach in [48] were used without adjustment. These variables yielded the first accuracy of 87.89% in Table 1. The filter size in this case was modified in descending steps from 15×15 pixels to 3×3 pixels while the other parameters were left unchanged. The highest accuracy in this case was 96.88% when using the filter size of 5×5 pixels. The filter size (5×5 pixels) that gave the highest accuracy in the first case was fixed in the second case whereas the number of filters was considered as the changeable variable from 16 to 4 filters. The best number of filters was 8 filters, where it achieved the highest accuracy of 99.22% and this is the rationale behind using this number of filters. Increasing or decreasing this number leads to reduce the performance of the applied application as it can clearly be seen in the same table. The rest cases of 3, 4, 5, 6, 7 and 8 in the same table included changing only one parameter in each case. However, the experiments showed that the alteration of the other parameters in these steps did not enhance the accuracy of the proposed model. Case 3 involved changing the stride of filters in the convolution layer between [1 1] pixels and [4 4] pixels. Case 4 focused on changing the padding process from the 0 padding, which gave the best results, to the 1, 2, 3 and (same) padding values. Case 5 examined the changing of pooling filter size, followed by case 6 which comprised of changing the pooling stride. The final two cases 7 and 8 included the adjusting of padding value and type of pooling, respectively. At the end of the tuning experiments, the parameters that have resulted with the highest accuracy are benchmarked for the DFCN model.

Table 1. Implemented experiments to examine the accuracies of detecting real and fake fingerprints by tuning various deep learning parameters (50 epochs each)

Cases	Conv. (No. of required parameters 4)				Pooling (No. of required parameters 4)				Accuracy (%)
	Filter size	No. of filters	Stride	Padding	Type	Size	Stride	Padding	
1	15×15	10	[1 1]	0	Max	5×5	[5 5]	0	87.89
	13×13	10	[1 1]	0	Max	5×5	[5 5]	0	84.38
	11×11	10	[1 1]	0	Max	5×5	[5 5]	0	91.80
	9×9	10	[1 1]	0	Max	5×5	[5 5]	0	78.13
	7×7	10	[1 1]	0	Max	5×5	[5 5]	0	92.97
	5×5	**10**	**[1 1]**	**0**	**Max**	**5×5**	**[5 5]**	**0**	**96.88**
	3×3	10	[1 1]	0	Max	5×5	[5 5]	0	93.36
2	5×5	16	[1 1]	0	Max	5×5	[5 5]	0	91.41
	5×5	14	[1 1]	0	Max	5×5	[5 5]	0	95.31
	5×5	12	[1 1]	0	Max	5×5	[5 5]	0	92.97
	5×5	10	[1 1]	0	Max	5×5	[5 5]	0	96.88
	5×5	**8**	[1 1]	**0**	**Max**	**5×5**	**[5 5]**	**0**	**99.22**
	5×5	6	[1 1]	0	Max	5×5	[5 5]	0	93.36
	5×5	4	[1 1]	0	Max	5×5	[5 5]	0	92.97
3	**5×5**	**8**	**[1 1]**	**0**	**Max**	**5×5**	**[5 5]**	**0**	**99.22**
	5×5	8	[2 2]	0	Max	5×5	[5 5]	0	92.97
	5×5	8	[3 3]	0	Max	5×5	[5 5]	0	92.19
	5×5	8	[4 4]	0	Max	5×5	[5 5]	0	91.80
4	**5×5**	**8**	**[1 1]**	**0**	**Max**	**5×5**	**[5 5]**	**0**	**99.22**
	5×5	8	[1 1]	1	Max	5×5	[5 5]	0	91.41
	5×5	8	[1 1]	2	Max	5×5	[5 5]	0	94.92
	5×5	8	[1 1]	3	Max	5×5	[5 5]	0	97.66
	5×5	8	[1 1]	same	Max	5×5	[5 5]	0	94.92
5	5×5	8	[1 1]	0	Max	15×15	[5 5]	0	96.09
	5×5	8	[1 1]	0	Max	13×13	[5 5]	0	92.58
	5×5	8	[1 1]	0	Max	11×11	[5 5]	0	98.44
	5×5	8	[1 1]	0	Max	9×9	[5 5]	0	94.14
	5×5	8	[1 1]	0	Max	7×7	[5 5]	0	94.14
	5×5	**8**	**[1 1]**	**0**	**Max**	**5×5**	**[5 5]**	**0**	**99.22**
	5×5	8	[1 1]	0	Max	3×3	[5 5]	0	91.80
6	5×5	8	[1 1]	0	Max	5×5	[2 2]	0	86.33
	5×5	8	[1 1]	0	Max	5×5	[3 3]	0	92.97
	5×5	8	[1 1]	0	Max	5×5	[4 4]	0	96.09
	5×5	**8**	**[1 1]**	**0**	**Max**	**5×5**	**[5 5]**	**0**	**99.22**
7	**5×5**	**8**	**[1 1]**	**0**	**Max**	**5×5**	**[5 5]**	**0**	**99.22**
	5×5	8	[1 1]	0	Max	5×5	[5 5]	1	96.88
	5×5	8	[1 1]	0	Max	5×5	[5 5]	2	98.83
	5×5	8	[1 1]	0	Max	5×5	[5 5]	3	98.83
	5×5	8	[1 1]	0	Max	5×5	[5 5]	same	98.83
8	**5×5**	**8**	**[1 1]**	**0**	**Max**	**5×5**	**[5 5]**	**0**	**99.22**
	5×5	8	[1 1]	0	Average	5×5	[5 5]	0	91.80

Figure 3 shows the accuracy of each case with respect to its changeable parameter. Additional executed experiments for assessing different deep learning optimizers. The three training optimizers: stochastic gradient descent with momentum (SGDM), adaptive moment estimation (Adam) and root mean square propagation (RMSProp) were evaluated according to the classification accuracy. Table 2 summarizes the effects of examining these optimizers on the DFCN accuracy.

Table 2. Additional executed experiments for assessing different deep learning optimizers (50 epochs each)

Optimizer	Accuracy (%)
SGDM	99.22
Adam	96.48
RMSProp	97.27

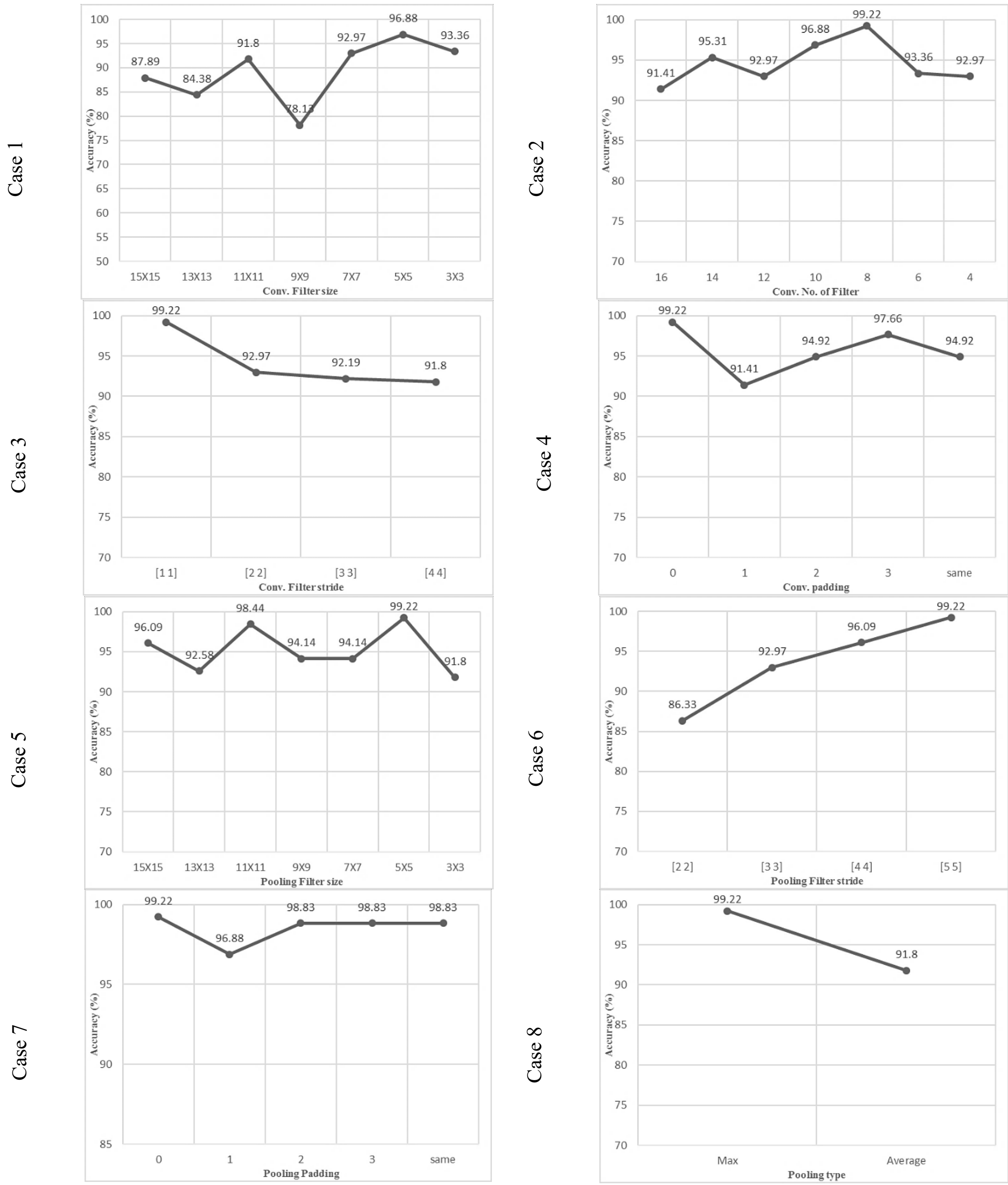

Figure 3. The accuracies of each case with respect to its changeable parameter (the number of epochs was assigned to 50)

Figure 4 shows the training curves of our suggested approach. The parameters that are utilized for training stage were set up as follows: SGDM optimizer, momentum=0.9, weight decay=0.0001, learning rate=0.03, minimum-batch size=128 and maximum epoch=50. The curves of the accuracy and the loss show that the suggested model started with high loss and low accuracy during the first iterations. However, the loss was then dramatically decreased and the accuracy was significantly increased at the same time. The curves show that the loss and accuracy reached their best performances and continued until the end of training.

For establishing fair comparisons with state-of-the-art networks, previous proposed models have been simulated and evaluated for our employed dataset and outputs. Three deep learning networks were used in these comparisons. These are the CNN [48], DFTL [49] and DFL [50]. Table 3 shows these comparisons. This table clearly demonstrates that the suggested DFCN surpassed other state-of-the-art models and it attained superior performance of 99.22%. Furthermore, the improvements in the accuracies yield 9.06%, 7.08% and 2.76% comparing to the CNN, DFTL and DFL networks, respectively.

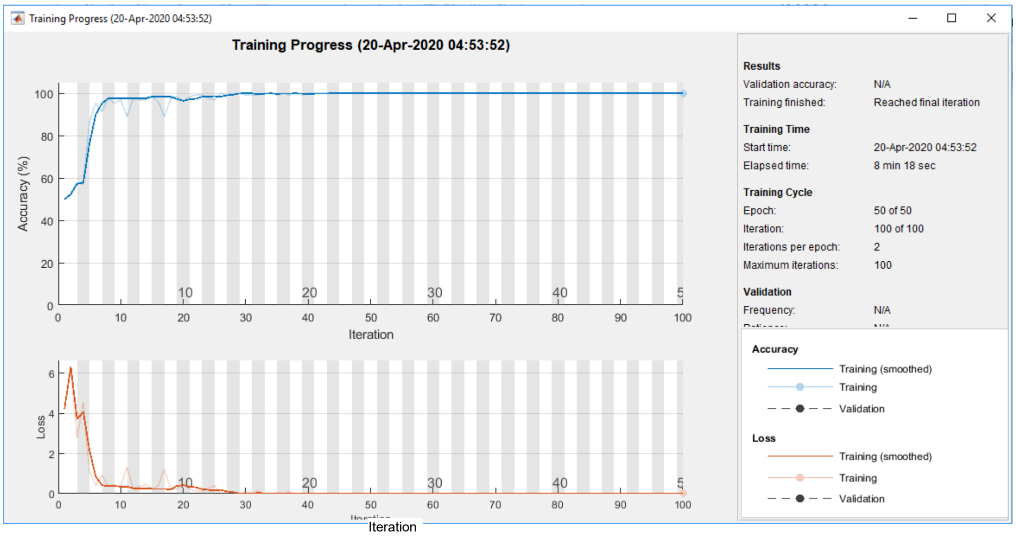

Figure 4. The training curves of our suggested DFCN model

Table 3. Comparisons with state-of-the-art approaches

Approach	Accuracy (%)
CNN [48]	90.23
DFTL [49]	92.19
DFL [50]	96.48
Our approach	**99.22**

6. CONCLUSION

Due to the importance of fingerprint as a physiological trait for individual recognition and due to the reality of its vulnerability to be breached by fake samples, we proposed an efficient deep learning model named the DFCN to classify fingerprints into two categories: real and fake. The suggested model was approached after applying many experiments that extensively evaluate various deep learning parameters. We used ATVS-FFp DB fingerprint images for our proposed model. The DFCN achieved great success with a classification accuracy reached to 99.22%. The experiments also showed that the DFCN outperformed state-of-art approaches when utilizing the employed dataset. In future work, different types of fingerprint fake samples can be considered. It appears that it is important to establish additional classification approach which can recognize the type of spoofing.

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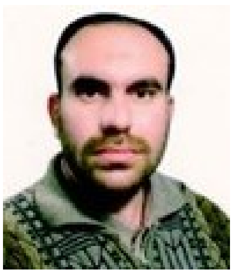
BIOGRAPHIES OF AUTHORS

Abdulsattar M. Ibrahim works as a lecturer in the Northern Technical University (NTU), Technical Engineering College, Mosul. Holding Master degree MSc in the Electrical and Electronic Engineering from University of Belgrade. The main researching fields are the signal processing and deep learning.

Abdulrahman K. Eesee is a Lecturer in the Technical Engineering College of Mosul/Northern Technical University (NTU), Iraq. He received Master degree MSc in the Biomedical Engineering from the University of Strathclyde/United Kingdom in 2015. His Bachelor B.Eng was in the Medical Instrumentation Technology Engineering from the NTU in 2011. The main researching fields are the Bio-signal processing, Deep Learning, medical sensors and image processing.



Raid Rafi Omar Al-Nima received the BSc and MSc degrees in Technical Computer Engineering in 2000 and 2006, respectively. During 2006, he worked as an Assistant Lecturer in the Technical College of Mosul, Iraq. In 2011, he obtained the Lecturer scientific title in the same college. In 2017, he accomplished his PhD in the School of Electrical and Electronic Engineering at Newcastle University, UK. His research interests are in the fields of pattern recognition, security, artificial intelligence and image processing.