Convolutional Neural Network Based Offline Signature Verification Application

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3 authors:

Adem Tekerek
Gazi University

Nurettin Topaloglu
Gazi University

Mutlu Yapıcı
Gazi University

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Muhammed Mutlu Yapıcı
Computer Technologies Department
Ankara University
Ankara, Turkey
mutluyapici@ankara.edu.tr

Adem Tekerek
Information Technology Department
Gazi University
Ankara, Turkey
atekerek@gazi.edu.tr

Nurettin Topaloglu
Computer Engineering Department
Gazi University
Ankara, Turkey
nurettin@gazi.edu.tr

***Abstract*— One of the most important biometric authentication technique is signature. Nowadays, there are two types of signatures, offline (static) and online (dynamic). Online signatures have higher distinctive features but offline signatures have fewer distinctive features. So offline signatures are more difficult to verify. In addition, the most important drawback of offline signatures is that they cannot be signed with the same way even by the most talented signer. This is called intra-personal variability. All these make the offline signature verification a challenging problem for researchers. In this study, we proposed a Deep Learning (DL) based offline signature verification method to prevent signature fraud by malicious people. The DL method used in the study is the Convolutional Neural Network (CNN). CNN was designed and trained separately for two different models such one Writer Dependent (WD) and the other Writer Independent (WI). The experimental results showed that WI has 62.5% of success and WD has 75% of success. It is predicted that the success of the obtained results will increase if the CNN method is supported by adding extra feature extraction methods.**

Keywords—Deep Learning, Convolution Neural Network, Signature Verification, Offline Signature

I. Introduction

Signatures are the most commonly used biometric authentication technique for hundreds of years and they have been still signed on paper with pen since of that years. Nowadays, with the development of technology, electronic devices such as tablets and computers can be signed too. Therefore, today there are two types of signatures, offline (static) and online (dynamic). Online signatures are much easier to verify because they have higher distinctive features. On the other hand, while offline signatures are more widely used, they are more difficult to verify because they have fewer distinctive features than online signatures[1]–[3]. Offline signatures only include the signature's shape. This makes them a challenging problem for researchers.

Offline signatures, which legally impose financial and moral liabilities, are an authentication technique that is still widely used today especially in legal documents, banking and commercial transactions. Hence, offline signatures are frequently misused by malicious people and used for fraud. To prevent fraud and malicious intentions signature verification is used. With the development of machine learning, new algorithms present promising solutions that can be used for signature verification. For these reasons, signature verification is one of the most important problems remains to be solved in machine learning methods nowadays[1]–[5]. The most important drawback of offline signatures is that they cannot be reproduced in the same way. The signatures may vary depending on the writing instruments used (pencil, paper, etc.), the current mood of the writer, the physical condition of the writer and the position of the hand. Even the most talented ones can never sign the same signature in the same way. This is called intra-personal variability[2], [3]. Thus, one of the main challenges for the offline signature verification is the high intra-personal variability that exists between the various specimens belonging to the same writer. All these make the offline signature verification an NP-hard (non-deterministic polynomial-time hard) problem. The importance of this problem has been understood from various studies for signature verification since 2004. To tackle this problem, signature competitions which is named as SigComp2011[6], 4NSigComp2012[7] and SigWiComp2013 [8] were organized. Researchers have tried to solve this problem by using algorithms such as Support Vector Machines (SVM)[9]–[12], Dynamic Time Wrap (DTW)[13], [14], Principle Component Analysis (PCA), Fuzzy Systems Methods[4], Probabilistic Neural Network (PNN)[5], Deep Multitask Metric Learning (DMML)[15].

Deep learning has achieved significant developments in many areas such as autonomous vehicles, object recognition, motion recognition, voice recognition. Companies like Google, NVidia, Facebook and Microsoft are investing billions of dollars each year in deep learning that make significant contributions to this area. With academic and corporate contributions, the deep learning approach have seen to provide effective solutions to many areas[16]–[19]. Though it seems that a convincing solution could not yet be found for offline signature verification problem by applying the deep learning approach.

In the literature, the best results for offline signature verification was obtained by DL methods and hybrid methods. Ribeiro et al[20] proposed a two-step hybrid classifier system composed of identification phase of the signatures owners and determining the authenticity of signatures. Zhang et al[21] proposed a new Deep Convolutional Generative Adversarial Network (DCGANs) model for offline signature verification and reported that the method is promising, even though doesn't achieve performance close to the state-of-the-art for GPDS. Hafemann et al [22] used CNN model with two methods as WI for feature extraction and WD for classification stage. In another study, they [2] compared two different CNN architecture that consist of AlexNet and VGG for increasing the success of signature verification. In 2017 Hafemann et al[23] reported EER 1.72% success in the GPDS-160 dataset with using the CNN model. Tayeb et al[24] published CNN based signature verification application which was tested on the SIGCOMP 2011 dataset and reported that they achieved about 83 percent success.

In the literature, it has been seen that, although there are some studies using DL method for offline signature verification, it has not yet achieved enough success [20] -

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[23]. We aim to contribute to the field of signature verification with this study. With the study, we highlight that the CNN model, which has been proven successful in many areas, can achieve high performance in the offline signature verification if it is supported by extra feature extraction methods.

İn this study, we emphasize the success of CNN over the signature verification. We believe that CNN has proved its success over signature verification, even though the results we obtained do not reach the state of art in the field of signature verification. We note that high success will be achieved if CNN is supported by extra feature-extraction methods.

This manuscript consists of 5 sections. In second section methodologies used in this study are summarized. In third section proposed application is described. In forth section experimental results is given and fifth section conclusion of this study is presented.

II. Methodologies

In this study, deep learning method is used for offline signature verification. A Convolutional Neural Network (CNN) ad hoc models were used as deep learning method. The Convolutional Neural Networks used have been trained separately from each other by using two formats: Writer Dependent (WD) and Writer Independent (WI).

CNNs were firstly proposed by LeCun et al[25] for image processing and they consisted of two basic features such spatially shared weights and spatial pooling. In 1998, they[26] improved the CNNs as LeNet-5 which is a pioneering 7-level convolutional network for digit classification. Nowadays, CNNs are the most widely used DL architecture in feature learning and they have successful applications in many areas such as autonomous vehicles[27]–[34], character recognition[25], [35]–[45], video processing [17], [46]–[52], medical image processing and object recognition [17], [46], [53]–[59].

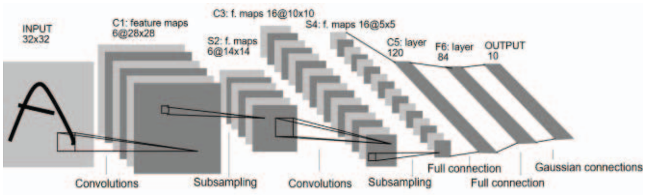

Fig. 1. Fig. 1 Basic structure of CNN

A CNN consists of three main layers such as, convolutional layer, subsampling layer (pooling layer), fully-connected layer, as presented in Fig. 1 that was taken from study of LeCun et al[25]. CNN aims to learn the abstract features of images using convolutional operations and pooling operations. The features obtained in the first layers define edges or color data, while in the last layers they describe parts of shapes and objects[26]. In the convolution layer, the convolution process is performed by shifting the filter data matrix on the input data matrix and adding a bias to the multiplication of these matrixes. Basic convolution process represents in Fig. 2, Basic formulation of the convolution process has been given in equation (1). In the equation, pixels of the output image, pixels of the input image, pixels of the filter (kernel) and bias term were represented by *y, x, w* and *b* respectively.

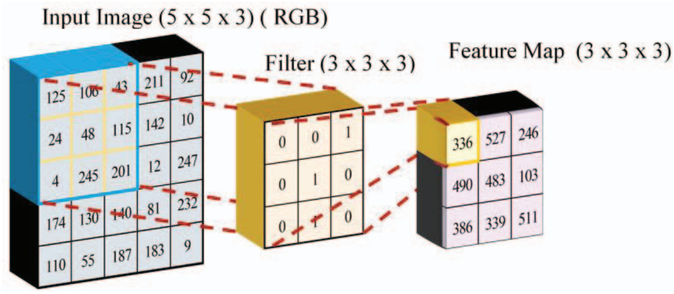

Fig. 2. Fig. 2 Basic convolution process

$$y_n = \sum_{n=1}^{9} (x_n . w_n + b_n) \quad (1)$$

Another power tool that CNNs use is called pooling. The pooling[58] is used to spatially down-sample the activation of the previous layer by propagating the maximum activation of the previous neuron groups. The main goal of the pooling layers is reducing the computational complexity of the model by gradually decreasing the dimensionality of the representation [26].

If it is preferred an activation function called rectified linear unit (ReLU) can be used on end of every layer for normalization. Basic process of ReLU has been given in equation (2).

$$\mathrm{ReLU(x)} = \begin{cases} 0 & if\ x < 0 \\ x & if\ x \geq 0 \end{cases} \quad (2)$$

The last layer in CNN is Fully Connected layers (FC), which are the basic building blocks of traditional neural networks. FC is formed by the connection of neurons to every neuron in the next layer. It is then normalized to a probability distribution using a Soft Max layer. FC aims to take the high-level filtered images and translate them into votes. These votes are expressed as weights, or connection strengths, between each value and each category [26], [35], [60], [61].

Another method that we use in this study is to separate the training data into two data sets according to the authors such Writer Dependent (WD) and Writer Independent (WI) and then to train the CNN model separately for these two data sets. In the literature, it is seen that there are two approaches, such as WD and WI [9], which are used in offline signature verification systems. In WD the classifier is trained for each individual separately by using only their own signatures. However, in WI, it is trained by using signature of all individuals. WI aims tackle to the problem of limited number of training samples is alleviated, but it is possible that many signature authors' features will be lost. WI aims to tackle the problem of small training sample, but it is possible that many features may be lost[1], [2], [23].

III. Proposed Application

In this study we proposed a CNN based signature verification method to prevent signature fraud by malicious people. We aim to contribute to this area by emphasizing the success of the proposed method in the field of signature verification. Our method consists of separately trained CNN architects for WI and WD. In the model, we used GPDSsyntheticSignature[62] data set which has been widely used in the signature verification field. The signature dataset was obtained from “Instituto Universitario para el Desarrollo Tecnológico y la Innovación en Comunicaciones (IDeTIC)”. GPDSsyntheticSignature dataset consists of signatures of 4000 different individuals. Every individual has 24 genuine signatures together with 30 sample of forged signatures. All the signatures were generated with different modeled pens. The signatures are in "jpg" format and equivalent resolution of 600 dpi. The genuine and forged signatures examples from this database is shown in Fig. 3.

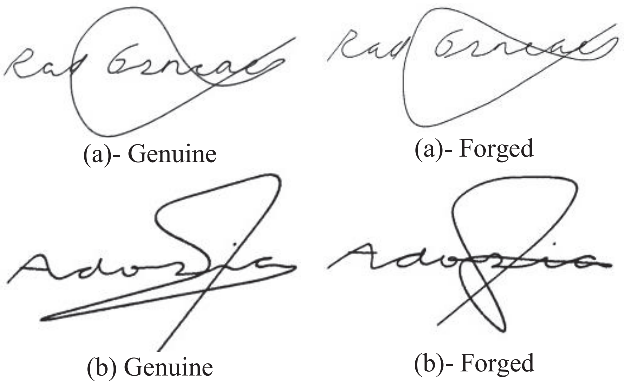

Fig. 3. Fig. 3 Forger and Genuine signature examples from GPDSsyntheticSignature

The application was developed on Python language by using Keras Framework. Keras Framework has two backend as Theano and Tensorflow. In this study, Tensorflow backend was used. Although the models were not supported by any extra feature extraction methods, the obtained results have been promising.

In the first model, CNN was trained via WD signatures. One person's 54 signatures which includes 24 genuine and 30 forgeries were used. Randomly selected 30 signatures from the pool of signatures used for training. The signatures were consisted of 15 genuine and 15 forgeries. Other 24 signatures were used for test. The model is composed of five Conv2D layers, two MaxPooling2D layers, three Dense layers and two Dropout layers. In the model, every Conv2D layers are supported by ZeroPadding2D layer. Used signature images are gray scale images sized as 300px width and 210px height. Therefore, the shape of the model is "shape (210,300,1)", which is the same with the size of the images. Rectified Linear Units (ReLU) is used as the activation function in the Conv2D layers. Respectively, the structure of the layers used in the first model is composed as: First Conv2D layer had 32 dimensions that are 3px width and 3px height. Second Conv2D layer had 64 dimensions that are 3px width and 3px height. After the second Conv2D layer, first MaxPooling2D layer had the size of 3px width and 3px height with stride size of 2px width and 2px height. Third Conv2D layer had 128 dimensions that are 3px width and 3px height. Fourth Conv2D layer had 64 dimensions that are 3px width and 3px height. Fifth Conv2D layer is again had 128 dimensions that are 3px width and 3px height. After the fifth Conv2D layer, second MaxPooling2D layer that is composed of the same properties as the first MaxPooling2D layer was used. First and second Dense layers (Fully connected convolution layers) are composed of two hundred fifty-six dimensions and ReLU activation function. A Dropout layer with the 0.5 parameter was used after both Dense layers. Lastly, third Dense layer which has SoftMax activation function was used for classification.

In the second model, CNN was trained via WI signatures. Ten different persons' 540 signatures which includes 240 genuine and 300 forgeries was used. Signatures were selected randomly for training. 300 signatures which consisted of 150 genuine and 150 forgeries were used. Other 240 signatures were used for testing. The second model has the same structure of layer as the first model. Obtained results for both two models have been given in Table1 and comparison graphs have been given in Fig. 4.

TABLE I. TABLE 1 OBTAINED RESULTS FOR WI AND WD APPROACHES

DL Architecture	Signature Method	Test Data	Training Data	Accuracy
CNN	WI	240	300	62.5%
	WD	24	30	75%

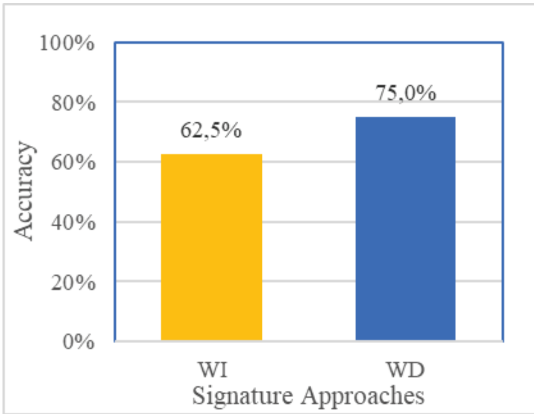

Fig. 4. Fig. 4 Accuracy comparison for WI and WD approaches

The results showed that WI has 62.5% of success and WD has 75% of success. It is predicted that the success of the obtained results will increase if the CNN method is supported by adding extra feature extraction methods.

IV. Conclusion

After the verification of handwritten signatures, which are the subject of many frauds, is one of the important research topics in recent years. In this study, DL application based on CNN architecture, which achieved successful results in many field, was applied for signature verification. In the study, CNN architecture was trained separately as WD and WI as two different models. One of the biggest problems of the CNN is the problem of inadequate training data for signature verification application. To addressing this problem, we used two different CNN models. We aimed to solve the problem of inadequate signature example with WI while increasing the classification success with WD. The obtained results showed that CNN architecture is promising for signature verification. In this study, GPDSsyntheticSignature database is used. In other studies, using this database in literature, more successful results were obtained because the DL architecture was supported by extra feature extraction methods. It will increase success of the signature verification if the CNN is supported by extra feature extraction methods. In future works, we aim to increase the obtained results by using different DL approaches which is supported by extra feature extraction methods.

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