Deep Learning Technique for Improving the Recognition of Handwritten Signature

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***Abstract*—Handwritten signature recognition is a biometric task used extensively in our daily life. The efficacy of such system is important and challenging in that the recognition accuracy still has room for improvement. In this paper, we propose the use of Deep Convolutional Neural Networks (DCNN), which is a deep learning technique, to improve accuracy of handwritten signature recognition. We apply DCNN in two difference strategies for signature recognition: 1) transfer learning using leveraged features from a pre-trained model on a larger dataset, and 2) create CNN model from scratch. Our studied dataset consists of 600 pictures of handwritten signatures collected from 30 people. In order to evaluate the effectiveness of the proposed method, the accuracy is compared with the results obtained from various machine learning methods. The comparison reveals very satisfied recognition results in the sense that the two proposed strategies achieve 100% of the recognition rate. To compare the two strategies in terms of training time, the strategy of creating DCNN model from scratch shows much lower training time than the transfer learning strategy.**

***Index Terms*—Deep learning, deep convolutional neural networks, handwritten signature recognition, transfer learning.**

I. Introduction

Handwritten signature is a task of machine learning with the main aim to verify or identify individuals by recognizing the pattern in their signature. The recognition task is thus recognizing the specific behavior when a person signs his/her signature. Such recognition system is therefore categorized as behavioral biometric system.

Biometric is different from other identification systems such as key/object possession system which requires a keycard or smartcard, or information-based system that asks for secret information like password or pin code. The strong point of biometric is that it is easy to use and convenient in practice. The convenience comes from the free of worry to remember password/pin code or to carry any keycard, identification card (ID) or badge. People are absolutely saved from hassle of having to frequently change passwords, key cards, or badges. The problems of forgetting passwords and the losing of ID cards are very annoying in traditional verification system. Moreover, each personal signature is distinct and the security is high because of the difficultly to be forged or counterfeited. When compared to other high reliable biometric system like iris recognition or retinal recognition, handwritten signature recognition can be compromised with the advantages of economical technology, quick verification time, low intrusive level, and high social acceptability.

However, the drawback of handwritten signature recognition system is its recognition rate that still be in a middle range when compared to other biometric systems. Many researchers are thus pay attention to improve the accuracy by applying many image processing techniques or a hybrid of machine learning methods. In this work, we propose a deep learning technique based on two strategies: transfer learning and learning from scratch.

The literature review on the advance of handwritten signature recognition and preliminaries of biometrics, pattern recognition and deep learning techniques are presented in Section II. Our proposed recognition method based on deep convolutional neural networks (DCNN) is explained in Section III. The results of performance evaluation are shown in Section IV. We finally conclude our work in Section.

II. Literature Review and Theory

A. Related Work

Recently, researchers had investigated a wide range of techniques to improve the accuracy of handwritten signature recognition. The data-intensive technique proposed by Hirunyawanakul *et al.* [1] converted signature data from image file into numeric table in accordance with color intensity of gray scale with 256 level from 0 (black color) – 255 (white color). Then, numeric table was transformed to be array data and fed the array data into the pre-modeling step. At the pre-modeling step, image quality has been enhanced by applying Sobel edge detection technique. Data in high intensity area were then assigned more weight than those in less important area such as the white background. At the modeling step, support vector machine (SVM) with several types of kernel functions, multi-layer perceptron, and k-nearest neighbors (kNN) with different number of neighbors were applied to build models for signature recognition. SVM with linear kernel and k-NN with k=1 are the two most accurate modeling methods.

The work of Vagas *et al.* [2] improved signature recognition rate by focusing on the grey-scale and co-occurrence matrix technique with local binary pattern based on the MCYT-75 and GPDS-100 databases. The result of the equal error rate (EER) in such work is 16.27%. Guerbai *et al.* [3] proposed one-class SVM for handwritten signature verification. The result from the experiment was

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5-7% average error rate (AER) in recognizing signatures available in the CEDAR dataset.

The aforementioned works were based recognition performance on current machine learning techniques such as SVM. In the age of big data [4], state-of-the-art technique called deep learning is gaining dramatic interest from researchers in various fields. Deep convolutional neural network (DCNN) is a kind of deep learning developed from artificial neural network. DCNN has been claimed [5] a powerful technique for general image recognition. We are thus interested in applying DCNN for a specific task of handwritten signature recognition.

Our DCNN-based signature recognition method is structured to be composed of two learning strategies, which are transfer learning using parameters available from existing deep learning network architecture (also called a pre-trained strategy), and learning from scratch in which we create new deep learning network architecture from our own design. For the pre-trained strategy, we employ the two existing models: AlexNet and VGG16. AlexNet was invented by Alex Krizhevsky and teammates and has big impact in machine learning and image recognition communities [6]-[10]. VGGNet is a new architecture of deep learning developed by Simonyan and Zisserman and widely adopted by many researchers [11]-[14]. VGGNet consists of 16 layers in its deep network with 138 million parameters and can classify objects as much as 1,000 categories. We are thus interested in comparing performance of VGGNet and AlexNet in recognition the biometric.

B. Biometrics

Biometrics is a part of pattern recognition [15]-[17]. It is a technical term for individual identification or verification using features extracted from either human's physical or behavior. Biometric systems have one of the two modes of operation: verification and identification. For the verification mode, after the user sends a signature or information of biometrics to the biometric system, the system checks the identity of the user via PIN, Login name, or others. The system will recognize and verify the requested user as 1:1 (one-to-one) data. The applications of this kind of biometrics always found in E-Commerce, access control, or mobile devices access control.

For the identification mode, the biometric system tries to recognize the sender or the requested biometric information through the comparison against the registered dataset. The operation of this mode is 1:N (one-to-N). The recognition of this system will be automatically compared without the identification request (like login name, login id).

Biometric system is more complex than traditional identification system such as object possession system or information-based system. However, it is traded off with simplicity, efficiency, and social acceptability. Password or information-based system is the simplest system but it is vulnerable to attack from electronic theft.

The object possession system such as smartcard, key card or identification documents is very useful and easy to use. However, it can be easily lost, stolen or forgotten at somewhere. Even though the system is integrated with cryptography methods, it makes the system more expensive to implement. On the contrary, the biometric system is very difficult to falsify, since it is encrypted by the complicated mathematic operations. It is considerably less falsifiable than the manual recognition. Another benefit of biometrics is that the information is unique for each individual and tolerate to the time variations.

C. Pattern Recognition, Intelligence, and Deep Learning

The pattern recognition [16] is the field of study closely relate to artificial intelligence (AI) and machine learning. It involves object classification with respect to “feature” of each “class”. Pattern recognition can be applied to various fields. For example, the individual identification using physical biometrics such as face, fingerprint, iris, DNA, and behavioral biometrics such as signature. The classification technique in pattern recognition requires knowledge of various branches, e.g. data mining, neural network, machine learning, and data improvement processes such as image enhancement.

Pattern recognition can be considered a sub-field of AI that has been defined by John McCarthy as “the science and engineering of making intelligent machines that have the ability to achieve goals like humans do” [17]-[19]. Broadly speaking, AI is human intelligence exhibited by machines. Currently, we can group AI into two separated tasks, which are Artificial General Intelligence (AGI) and Artificial Narrow Intelligence (ANI). AGI is the intelligence of a machine that could successfully perform any intelligent task that a human being can. It is a primary goal of AI research. For ANI, it focused on one narrow task. Almost all existing systems that claim to use AI are likely operating as a narrow AI because they focused on a specific problem. The examples are spamming e-mail classification system, face recognition, and a well-known board game AI “AlphaGo”.

Machine learning is defined as another large sub-field of AI [16], [20]. It is a field concerning how to make computers being able to learn without being explicitly programmed. Therefore, machine learning is an approach to achieve AI. This is exactly how humans learn as well. When kids learn to identify objects/person, we do not tell them an algorithm/procedure to identify the features. We just simply show them multiple examples of that object and then our human brain automatically identifies the features and learns to identify that object. This is indeed what a machine-learning model does.

In terms of learning method and technique, machine learning can be divided into two groups: supervised and unsupervised learning. For supervised learning, the computer or machine is presented with example inputs and their real outputs, which can be seen as guiding solutions. The goal of learning is to create a general rule that can correctly relate inputs to outputs [21]. Examples of supervised learning are perceptron, SVM, naïve Bayes. In case of unsupervised learning, there is no need for guiding solutions. The learning objective is it find common structures or patterns in the training data. Examples of unsupervised learning are association mining and clustering.

Deep learning is a new kind of machine learning method that makes its learning via data representations. It is opposed to task-specific algorithms in that its learning can be both supervised or unsupervised [22]-[24]. One of the most prominent deep learning architecture is deep neural networks. It has been successfully applied to many fields including speech recognition, natural language processing, biometrics, board game programs, and image recognition. For image recognition applications, they can produce results comparably to human experts [25]-[27]. The use of deep learning for handwritten recognition are investigated and researched in textual form of different languages [28]-[32].

Deep neural network can recognize raw images through a numerous of connected network layers. Each layer processes and computes the information sent from the previous stacked layer. This layer-by-layer processing runs until the output layer has been reached. The result from a network is a class label. The most applicable deep neural network is convolutional neural network.

D. Convolutional Neural Network (CNN)

Convolutional Neural Network (CNN) is a learning method inspired by biological processes. It is believed that the main computation element of living creatures is neuron. The connected network of neurons forms the basis of all the decisions made based on the information gathered. CNN is a feed-forward network with three key mechanisms: local receptive fields, weight sharing, and sub-sampling [33]. The network is trained like a normal neural network using back-propagation algorithm. The common architecture of a CNN is structured by four main layers [34].

1) Convolutional layer: This layer has main function for applying a filter mask. The filter is applied on a specified area of the image. The area that has been filtered is called the receptive field. The operation of this layer involves computing the weighted summation of the values covered by the receptive field using the weights of the filter mask. Then, the weighted summation is added with a bias and passes through an activation function. Once this value is computed, receptive field moves on the feature map by a number of strides to cover new area for computation of next value using the same filter mask. The purpose of filter mask is to learn basic pattern of object in the image. The weights of filter mask are shared across a feature map in the model [7]-[9].

2) ReLU layer (rectified linear units layer): This layer is placed immediately after the convolutional layer. It aims at applying the nonlinearity to the system because during convolutional layers, just linear operation is used. The transfer functions like sigmoid and tanh that are preferred in the past do not used in CNN. It instead uses ReLU or Rectified Linear Unit transfer function. ReLU is claimed to improve the network in both accuracy and training times [35]. It also mitigates the gradient problem issue. The ReLU applies function in equation 1 to all input values.

$$f(x) = max(0, x) \tag{1}$$

According to equation 1, the ReLU layer changes all negative values into zero value. This layer increases the nonlinear properties of the model.

3) Pooling layers: The pooling layer is preferred to say as a down-sampling layer. There are many layer options. However, the most popular one is max-pooling. The algorithm of max-pooling applies on input volume and outputs the maximum value in every sub region that filter mask move around. Example is demonstrated in Fig. 1.

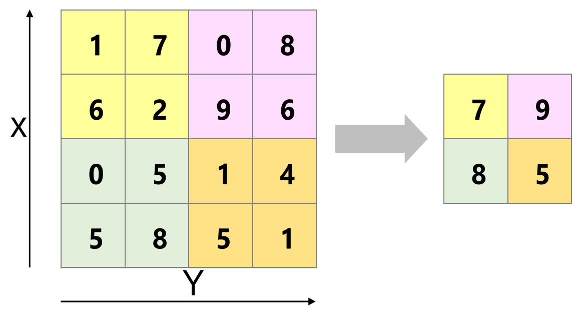

Fig. 1. Example of Max-pooling with filter mask = 2x2 and Stride = 2.

The proposal of this layer is to reduce the spatial dimension of the input volumes, which are not as important as other features. Another proposal of this layer is to prevent a problem of over fitting [12].

4) Dropout layers: To avoid the over fitting problem, the dropout layer is applied to contain the switching function that randomly selects neurons during each iteration of the model training stage. It can prevent the neurons to learn features of which relevant only when a different neuron is present [12], [36].

5) Fully connected layers: This is the traditional layer of neural network model in which each neuron is connected to every output from previous layer. This layer integrates all features learned from previous layers across the image to identify the larger patterns. The last layer of fully connected layer is to classify the images [37].

There are numerous architectures using the concept of CNN. The prominent ones include AlexNet [38], GoogleNet [39], VGGNet [7], and ResNet [40]. These architectures are the inspiration for many research works to use them to solve variety of problems. The applications of these CNN architectures are in two main strategies: transfer learning [41], and create new CNN from scratch [42]. We adopt both strategies in our research work. The details of these strategies are in the nest section.

III. Material and Method

This section presents material and method used in our work. It consists of research framework, research workflow, and strategies of network creation. Details of our dataset and computation resource are also presented in this section.

A. Research Framework

The main idea of our research is graphically shown in Fig. 2. Based on the objective of improving the accuracy rate of handwritten signature recognition using state-of-the-art learning method, we design our research to contain deep learning-based technique as a core function. As a result, two strategies of DCNN "Transfer Learning" and "Training from scratch" are used in this work to build up the network model. For performance evaluation, we compare the recognition accuracy and training time of DCNN and machine learning techniques.

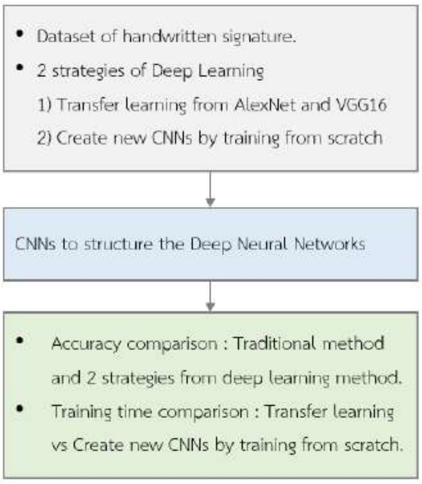

Fig. 2. Research framework.

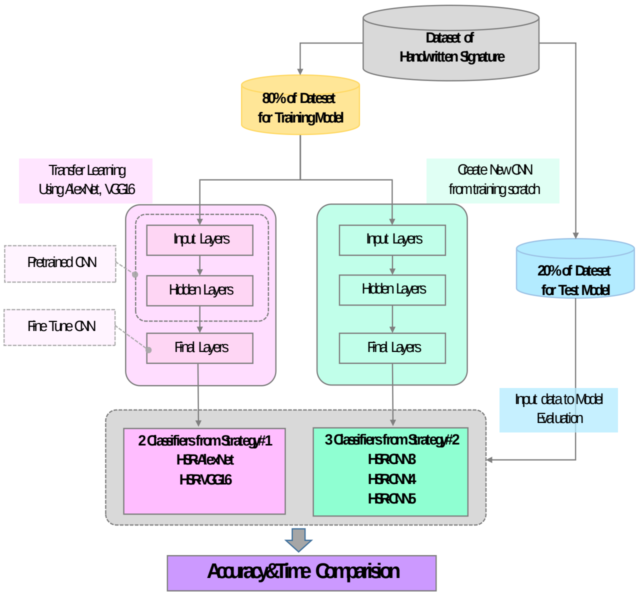

Fig. 3. Research workflow diagram.

B. Research Workflow

The flow chart shown in Fig. 3 demonstrates our research steps. Starting by using the dataset of handwritten signatures [1], which is publicly available at https://sites.google.com/site/nhinganusaracpesut/signature/datasets. Firstly, we separate dataset into two parts. The first part, 80% of data, is for training model and the rest 20% is for testing model performance. The training set is fed into both strategies. The strategy 1 is called "Transfer Learning" that applied the pre-train DCNN based on the AlexNet and VGG16 architectures. The strategy 2 is named "Training from scratch" in which all weights of the DCNN are learned solely from our dataset.

In strategy 1 that we use the classifiers from transfer learning technique of AlexNet and VGG16, we call them as HSR-AlexNet and HSR-VGG16, respectively. HSR is the acronym for handwritten signature recognition. In strategy 2, we design three classifiers from different architectures of DCNN, and we call these classifiers as HSR-CNN3, HSR-CNN4, and HSR-CNN5. The differences among these three classifiers are the number of convolutional layers.

C. Strategies of DCNN in This Research

1) Transfer learning from pre-train of big dataset: Transfer learning using AlexNet and VGG16 is the strategy that we fine-tune the pre-trained models of AlexNet and VGG16 to best suit our current dataset. AlexNet is a well-known architecture that are pre-trained from numerous images (more than 1 million images), where the output classes or object categories are 1,000 classes. AlexNet is claimed its success in classification for wide range of applications. VGGNet is a popular deep learning like AlexNet, but the number of layers in VGGNet is deeper. In this work, we use VGG16, which consists of 16 layers (There are only 8 layers for AlexNet). VGGNet is attractive word wide because of its uniform architecture. In this experiment, we use the pre-trained network of AlexNet and VGG16 as a starting point to learn the new task of our dataset. On the key parameters of a fine-tuning task, we tune the model with varying number of Epoch (10, 20, and 50). Other parameters are shown in Table I. Such parameters are back propagation learning algorithm that we use SGDM (stochastic gradient descent with momentum), set mini batch size to 10, set the initial learning rate to 0.0001, the validation frequency (VF) equals 30, and the validation patience is "Inf".

TABLE I: KEY PARAMETER SET UP IN "TRANSFER LEARNING" BY USING ALEXNET AND VGG16

Parameter Name	Value
Learning Algorithm	SGDM
Mini Batch Size	10
Initial Learning Rate	0.0001
Validation Frequency	30
Validation Patience	Inf
Max Epochs	10, 20, 50

2) Create new CNN from scratch: The starting point of this strategy is different from the transfer learning scheme. To create new CNN from scratch, we need a model to learn our new training dataset. That means model from this method is purely influenced from our dataset with no overwhelming by millions of data as the scheme pre-trained by AlexNet or VGG16. On creating the suitable CNN architecture, we tune the number of convolutional layers in order to investigate the effective trend in terms of accuracy and training time. The requirements of input image size between each technique are not the same. Pre-trained AlexNet require 227x227 pixels, VGG16 require 224x224 pixels. By creating new CNN from scratch, we can use the original size of image, which is 38x144 pixels. Table II shows detail of the two strategies for comparison.

TABLE II: DETAIL COMPARISON OF "TRANSFER LEARNING" AND "CREATE NEW CNN FROM SCRATCH"

Transfer learning	Create New CNN from scratch
Start with the pre-train of AlexNet, VGG16	Start with new learn from our dataset
# Convolution Layers : 5 layers for AlexNet 13 layers for VGG16	# Convolution Layers : 3 for HSR-CNN3 4 for HSR-CNN4 5 for HSR-CNN5
Image size: 227x227 pixels (AlexNet) 224x224 pixels (VGG16)	Image size: 38x144 pixels

D. Dataset of This Research

We experiment on 600 signature images collected from 30 individuals. Original size of images in a dataset is 38x144 pixels. However, for a strategy "Transfer learning by Using AlexNet", we need to feed pictures with the exact size of 277x277 pixels. But for the strategy "Transfer learning by Using VGG16", the image size must be 224x224 pixels. As a result, we need to firstly resize each image into the acceptable size of both AlexNet and VGG16. Fig. 4 shows four examples of the resized handwritten signature pictures. Each example shows the original 38x144 size, the 224x224 size for VGG16, and the 277x277 size for AlexNet.

Our experiments run by program MATLAB R2018a on a personal computer with CPU Intel Core i5-7300HQ (2.50 – 3.50 GHz) 4 Cores/4 Threads, GPU NVIDIA GeForce GTX 1050 (4GB GDDR5), HDD 1 TB 5400 RPM, and RAM 8 GB with DDR 4.

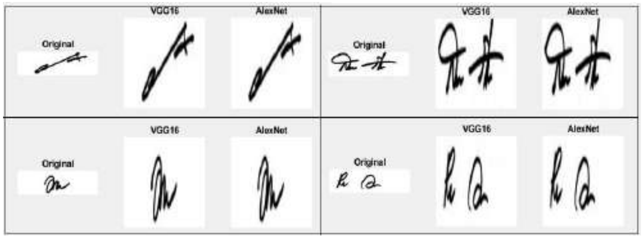

Fig. 4. Examples of the resized handwritten signature picture.

IV. Experimental Results

This section explains experiments and experimental results. The key point is the comparison of performances between 2 strategies of deep learning techniques: "Transfer learning by using AlexNet and VGG16" and "Create new CNN from scratch". Accuracy and training time comparison of "Transfer learning by using AlexNet and VGG16" are shown in Table III and the comparative results of "Create new CNN from scratch" are illustrated in Table IV. Both deep learning techniques provide higher accuracy when compared to traditional machine learning methods as shown in Table V.

From the results demonstrated in Table III, it can be seen that HSR-AlexNet is able to achieve highest accuracy at 100% when Max Epochs = 50 with 312 seconds of training time (the example of training progress result is shown is Fig. 5). On the contrary, the HSR-VGG16 can reach 100% accuracy at earlier iteration since Max Epochs = 20. However, the training time of VGG16 is quite long at 2,012 seconds, as compared to 312 seconds used by the AlexNet.

From Table IV that shows the results obtained from the "Create new CNN from scratch" strategy, the highest accuracy is reached when Max Epochs equal 50. HSR-CNN3 can reach its highest accuracy at 94.17% with training time of 90 seconds. HSR-CNN4 can reach a better accuracy at 98.33% using 104 seconds of training time, whereas HSR-CNN5 is the best model with the highest accuracy of 99.17%. The tradeoff is that HSR-CNN5 uses the longest training time at 115 seconds. It can be noticed from the results that, at the same value of Max Epochs (i.e., 50), the greater number of convolutional layers, the higher accuracy.

TABLE III: Accuracy and Training Time Comparison between HSR-AlexNet and HSR-VGG16 from Strategy "Transfer Learning by Using AlexNet and VGG16"

Deep learning technique	Max Epochs	Accuracy	Time (sec)
HSR-AlexNet (Transfer Learning from AlexNet)	10	89.17	63
	20	98.33	136
	50	**100.00**	312
HSR-VGG16 (Transfer Learning from VGG16)	10	93.33	460
	20	**100.00**	2012
	50	**100.00**	2283

TABLE IV: Accuracy and Training Time Comparison between HSR-CNN3 HSR-CNN4 and HSR-CNN5 from Strategy "Create New CNN from Scratch"

Deep learning technique	Max Epochs	Accuracy	Time (sec)
HSR-CNN3 (3 Convolutional Layers)	10	92.50	18
	20	93.33	37
	50	94.17	90
HSR-CNN4 (4 Convolutional Layers)	10	95.00	20
	20	97.50	43
	50	98.33	104
HSR-CNN5 (5 Convolutional Layers)	10	94.17	24
	20	97.50	48
	50	**99.17**	115

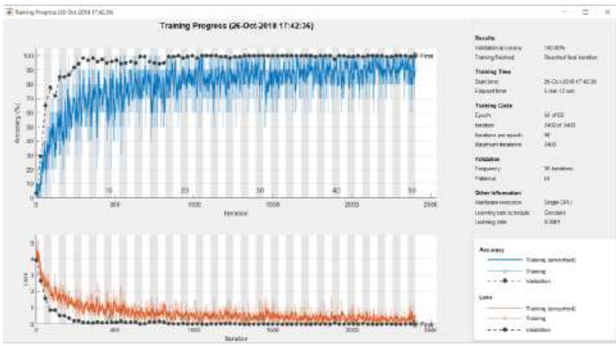

Fig. 5. Training progress from modeling of HSR-AlexNet when Max Epochs = 50.

Fig. 6. Accuracy and Training time comparison of deep learning models from both strategies of "Training by using AlexNet and VGG16" and "Create new CNN from Scratch".

TABLE V: Accuracy Comparison between Deep Learning and Traditional Machine Learning

Method	Model	Highest Accuracy
Deep Learning	HSR-AlexNet	100.00
	HSR-VGG16	100.00
	HSR-CNN5	99.17
Traditional Machine Learning	SVM + Sobel Edge + Additional Intensive Data	98.00
	k-NN + Sobel Edge + Additional Intensive Data	98.00

A bar chart in Fig. 6 compares the accuracy and the training time from the best model with the highest accuracy in each strategy. We can see that the accuracies of transfer learning technique (diagonal stripes bar chart) are higher than the create new CNN from scratch (solid colored bar chart). But the trade-off in terms of increasing training time can also be observed (solid line). Especially for VGG16, the training time usage is more than 10 times higher than the create new CNN from scratch strategy (2,012 seconds and 2,883 seconds compared to 115 seconds).

Table V presents a comparison in terms of accuracy to recognize handwritten signature between deep learning models and the machine learning models. The machine learning algorithms are SVM and k-NN plus the image enhancement with Sobel edge detection technique and data intensive weighting. We found that all models from deep learning with both "Transfer learning by using AlexNet and VGG16" strategy and "Create new CNN from scratch" scheme perform better than the methods based on traditional machine learning algorithms. The maximum accuracy of the traditional machine learning is 98.0%, whereas the minimum of deep learning (learning from scratch scheme) is 99.17%. At maximum performance of a pre-trained deep learning, the accuracy is as high as 100%. In detail comparison of each model, HSR-AlexNet, HSR-VGG16, and HSR-CNN5 are more accurate than traditional machine learning by 2%, 2% and 1.17%, respectively.

V. Conclusion

In this research, we study the problem of offline-handwritten signature recognition with the main focus to improve recognition performance by applying the novel technique of deep learning. We use two strategies of deep learning, that are 1) transfer learning from pre-trained model of AlexNet and VGG16, and 2) create new CNN from scratch. We demonstrate through experimentation that our proposed method using deep learning technique can improve the accuracy rate of handwritten signature recognition. We also do the comparison in terms of the training time of both strategies of deep learning. Our dataset of this research is collected from users who use their handwritten signature in daily life. This kind of data can guarantee that our method can practically be applied in the real-world scenario.

In part of the performance comparison from transfer learning technique, both HSR-AlexNet and HSR-VGG16 are able to achieve the perfect accuracy at 100% of recognition rate. Moreover, we can observe that HSR-VGG16 achieve an accuracy 100% with the lower number of Max Epochs (HSR-VGG16 achieve 100% at max epoch = 20, while HSR-AlexNet archive at max epoch = 50). Such results also relate to the training time that each model uses. HSR-VGG16 always takes longer time than HSR-AlexNet. The reason is that the architecture of VGG16 has more layers and more number of parameters than the AlexNet architecture. According to the "creating new CNN from scratch" strategy, the models can provide maximum accuracy at 99.17% (with HSR-CNN5 architecture using max epoch =50). The accuracy is a bit lower than transfer learning technique but compromising by significant shorter training time. Moreover, we observe that when increase the number of convolutional layers, we will get higher accuracy result.

Finally, when we compare both strategies of deep learning to the traditional machine methods, it is clearly to conclude that deep learning method can help improving the performance of handwritten signature recognition.

In this research, we perform handwritten signature recognition with offline version. The limitation is that the number of sample size is only 600 signatures. For more robustness of the research result, we plan to include more samples in our dataset in the future. Another research direction that we plan to perform is the extension of current task to cover online handwritten signature verification.

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