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Recognizing Signatures Using Normalized Generalization Neural Network

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Abstract

One of the most prevalent behavioral biometrics is the signature. In this paper, signatures are utilized in the case of recognition. Multiple contributions are provided here. Firstly, statistical analysis of efficiency is taken into consideration for the feature extraction. Secondly, a novel classifier is suggested. It is employed to recognize the signatures and it is called the Normalized Generalization Neural Network (NGNN). In terms of error rates, comparisons are established between different neural networks in the literature and the novel NGNN. The proposed NGNN consists of the input layer, normalization layer, Radial Basis Function (RBF) layer, and output layer. It can be considered as an enhanced or developed version of the Generalized Regression Neural Network (GRNN). A large number of signatures' attributes from the Biometric Ideal Test (BIT) database is utilized. That is, 1750 patterns of attributes are exploited. A significant improvement in the error rates over previous networks is achieved when using the novel NGNN. The Mean Absolute Error (MAE) has reached 0.028 and the Mean Square Error (MSE) has obtained 0.014. In addition, further experimental results on the BIT database showed better Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) of 0.002 and 0.119, respectively.

Keywords: Behavioural Biometric, Feature Extraction, Neural Network, Signature Recognition

1. Introduction

Generally, there are two categories of biometrics, namely physiological and behavioral characteristics. Physiological characteristics are traits that are present in human anatomy, while behavioral characteristics refer to traits of mannerisms [1]. Expectedly, behavioral biometrics face bigger challenges than physiological biometrics. This is due to the fact that their attributes are affected by the facial expressions, illumination changes, and pose changes of individuals. Fingerprint, Retina, Iris, Ear, DNA, Face, Hand Geometry, and Palm are only a few examples of physiological biometrics [1]-[10]. A signature, keystroke, gait, and speech are all instances of behavioral biometrics [11]-[17]. The term "signature trait" is quite well known. It is a challenging biometric since it is a behavioral characteristic. Coordination points, pen downs and ups synthetic timestamps, and pen pressures are a few possible attributes to be considered [18]. Every individual has a signature form of drawing manner. Therefore, various signatures can be seen for different persons. Fig. 1 shows samples of signature sketching styles.

This paper aims to recognize various signatures of different persons after exploiting a feature extraction and a classifier approach. The main contributions here can be highlighted as follows:

- Employing the statistical analysis of efficiency as a feature extraction.
- Proposing a new classifier named the Normalized Generalization Neural Network (NGNN). The NGNN is inspired and motivated by the Generalization Regression Neural Network (GRNN). It has advantages over the GRNN and other neural networks. That is, it is enhanced for multiple classes, instead of regression, and it can efficiently overcome the overfitting problem, the NGNN does not suffer from this problem as other neural networks.
- Different neural networks are evaluated and compared with the proposed NGNN.

Following this introduction, the following sections will be presented: related work is reviewed in Section 2, the research method is discussed in Section 3, findings are provided and discussed in Section 4 and a conclusion is illustrated in Section 5.

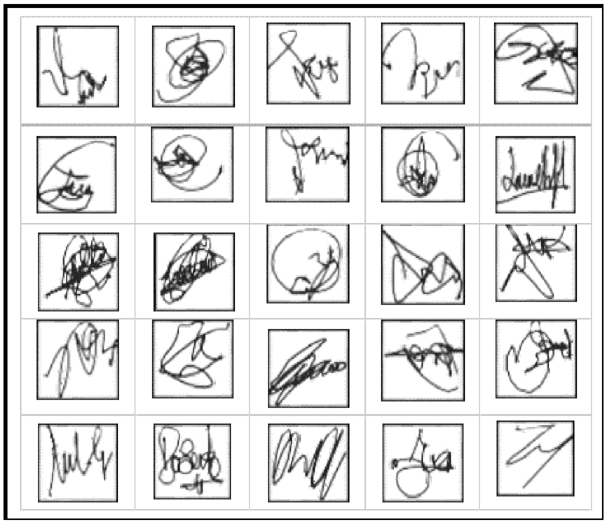

Figure 1: Samples of signature sketching styles [19]

2. Related Work

Different existing methods have been widely suggested in terms of automatically recognizing signatures based on neural networks. Some of these methods have been focused on dealing with the handwritten signature in the offline state, while others have been focused on dealing with the handwritten signature in the online state. The recognition process of the signature in the offline state is more difficult than the process of recognition in the online state because only the scanned signature image can be recognized in the offline state without any dynamic information such as the spatial coordinate or the axial angle information that might be recognized with the signature in the online state. Oz et al. [20] proposed an offline signature detection and verification method based on the moment invariant technique and the Artificial Neural Network (ANN). The first neural network was built for recognizing signatures, while the other network was suggested for verifying the forgery signature. A four-step procedure was employed by both networks. The initial step is to detach the signature from the surrounding area. Next step, the original signature is normalized and digitized. Then, the moment-invariant vectors are produced. Signature identification and verification are implemented in the last step. The drawback of this method appeared in the verification of the signatures that were not previously trained. In addition, in terms of comparison, this method does not make any comparison with the state-of-the-art. Saffar et al. [21] performed an approach for authenticating online signatures. The study proposes a method for building discriminative characteristics into a one-class classifier for each user. First, a large number of unlabeled signatures have been utilized to pre-train a sparse auto-encoder, and then the auto-discriminative encoder's features are employed to define the testing and training signatures as a self-thought learning technique. Finally, a single-class classifier is utilized to model and categorize user signatures. As the suggested technique utilized self-taught learning, it is unaffected by signature datasets. Experimental results on SVC2004 and SUSIG datasets showed significant improvement in terms of accuracy. In addition, the error rate was also considered and compared with the state-of-the-art techniques. However, it is reported that there will be some variations in the accuracy results due to the small number of samples that have been utilized in the training phase when applying this approach to verify signatures in the offline state. In terms of signature verification, two machine learning methods were sequentially presented in [22], and [23], genuine and forgery sets were involved in the general set, and the other involved only the genuine set. In the first method, counter-examples with near misses have been utilized in the learning process. Both methods applied the similarity metric to measure the distance between two signature traits. Two learning methods were adopted, special and general learning. It is noted that the general learning method obtained with good accuracy when the selected number of genuine samples is less than four. In addition, the performance of the special learning method increased the accuracy by 5% over the general learning method when utilizing a sufficient number of genuine samples. However, the recognition accuracy of both methods was slightly increased compared to the state-of-the-art. To improve the performance of the method, the combination of both methods of learning was suggested.

Despite several improvements in the signature recognition accuracy that have been obtained using different suggested methods in the offline and online states, no more methods have been focused on computing accuracy utilizing a small sample size in the training phase. Çalik et al. [24] addressed this problem and suggested a method to deal with the large-scale training problem using a Convolutional Neural Network (CNN) named Large-Scale Signature Network (LS2Net). In addition, a Class Center-based (C3) algorithm has been presented with the 1-Nearest Neighbor (1-NN) classifier. 96,000 signatures in the GPDS-4000 dataset have been collected from 4,000 signers. Two splitting ratios are used to analyze the networks for each signer: 50% test and 50% train, as well as 25% train and 75% test. The obtained results are averaged to provide performance metrics. The LS2Net obtained an accuracy of 96.41% and 98.30%, respectively, for the 25%-75% ratio in MCYT and CEDAR databases. Furthermore, the method produced 96.91% accuracy for the 25%-75% ratio with the GPDS-4000 database. In terms of recognition accuracy, even though the obtained results outperform several methods in the state-of-the-art, the evaluation process does not utilize the cross-validation method to measure the average recognition accuracy. The work in [25] presented a method of verifying signatures and detecting forgery signatures utilizing the Convolution Neural Network (CNN), SURF, Crest-Trough, and Harris corner detection algorithms. A new pre-processing signature method has been proposed to improve the verification process has been adopted. This method attained 90%-94% accuracy for recognizing signatures and 85%-89% for detecting the forgery signatures. However, in terms of comparison with the state-of-the-art, there was no comparison has been established. In [26], A Deep Convolutional Neural Networks (DCNN) technique has been adopted to improve the precision of the handwritten signature recognition. Two different techniques were suggested: 1) a transfer learning technique was utilized to extract features based on the previously trained model on a large database, and 2) a CNN model from scratch was suggested. For both techniques, the evaluation of the recognition rate reached 100% when applying to the 600 handwritten signature photographs. The performance of this method cannot be fairly compared with the state-of-the-art, as the number of input samples that have been utilized in the experiment was limited.

With the intention of increasing the signature recognition accuracy and extracting features, Kiran et al. [27] proposed to use of image processing techniques and the Backpropagation Neuron Network System (BPNNS) approaches for offline signature identification. Image processing techniques included filtering, RGB2Gray conversion, modifying, picture scaling, thresholding, and cunning edge detection. Then the feature is extracted using a BPNNS with a predetermined number for both neurons and hidden layers. The experimental results showed a significant improvement in the overall recognition rate compared to other work in the literature.

For all the aforementioned studies, it can be noticed that there is no available study to extract the statistical analysis features of efficiency has been suggested. This paper proposes a novel method for recognizing signatures by utilizing efficiency as a feature vector. In addition, the new NGNN classifier approach based upon the Generalized Regression Neural Network (GRNN) classifier is suggested.

3. Research Methodology

3.1. Signature Attributes

The attributes of signatures are so important to be considered as they can be considered as the work basis. As far as such attributes are precise and well-acquired, this would definitely affect the overall recognition. So, here in this paper, reliable attributes of signatures from [18], and [19] are exploited and used. Primary attributes of signatures are investigated. For each signature, there are three basic factors in the analysis. These include the pressure function as a trajectory signal, Discrete Fourier Transform (DFT) to create coordination in frequency domains, and displaying all acquired signals in the time domain [19]. The major procedure for producing a signature's attributes is shown in Fig. 2. It is crucial to make clear that the pressure function is made up of two variables or parameters. For the first parameter, the binary representations of the pen up and pen down are "0" and "1", respectively. The pressure applied to a writing surface is the second parameter. Additionally, several enhancement techniques are used to extract more exact information from a signature. Translation, rotation, scaling, flourishing, and smoothing are a few examples of these [18].

Hence, each signature has 5 attributes: x coordinates, y coordinates, synthetic timestamps, pen ups, and pen downs, and pressure functions [18], [19].

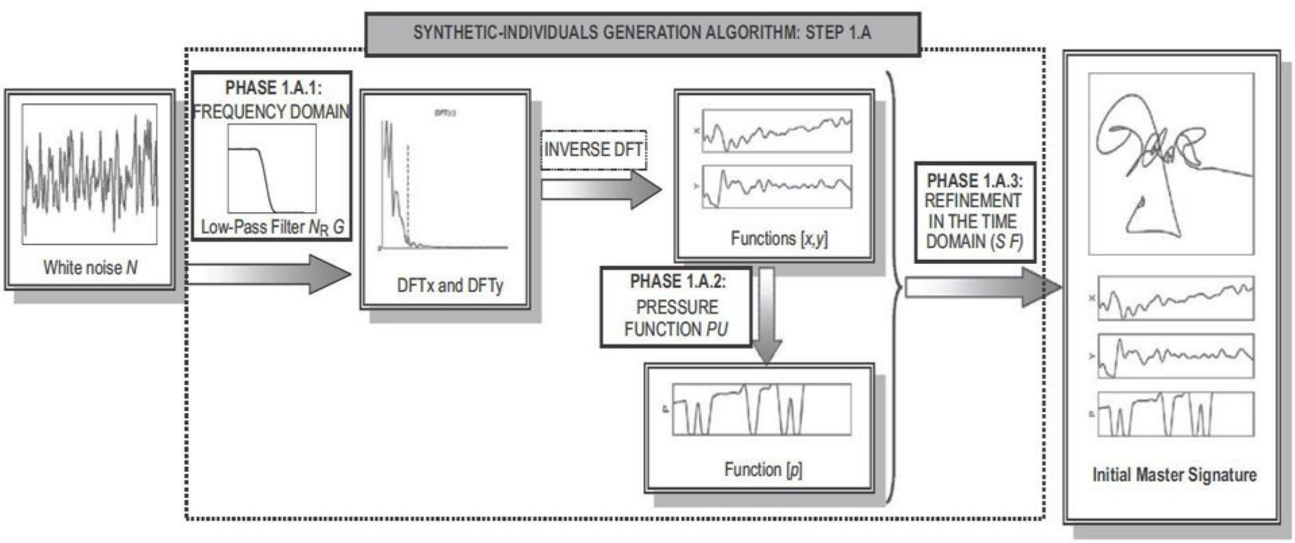

Figure 2: The major procedure for producing a signature's attributes [18].

3.2. Feature Extraction

A statistical calculation of the efficiency is considered for every 5 described values for the feature extraction. The efficiency can be demonstrated as follows:

$$\mathrm{E} = \sigma^2/Av^2 \quad (1)$$

where E is the efficiency for each set of 5 values, σ is the computed standard deviation and Av is the computed average. The standard deviation calculation can be expressed as follows [28]:

$$\sigma = \sqrt{\frac{1}{q-1}\sum_{k=1}^{q}(y_k - \bar{y})^2} \quad (2)$$

where q is the number of pixels in each block, k is the count of the pixel values for each block, y_k is the pixel's intensity, and $\bar{y}$ is the average of the block pixel values.

3.3. NGNN Approach

The NGNN is a supervised network developed from the GRNN. It is adapted here to recognize a large number of signatures. It consists of four layers: input, normalized, Radial Basis Function (RBF), and output. Fig. 3 depicts the fundamental architecture of the proposed NGNN.

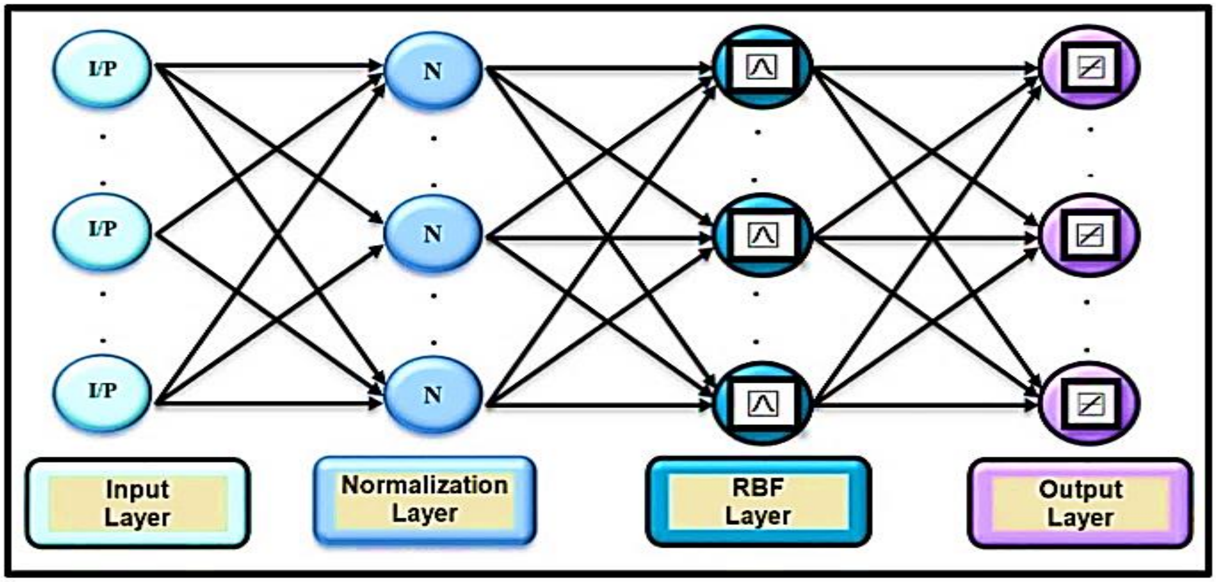

Figure 3: Fundamental architecture of the proposed NGNN approach

The first hidden layer is termed the normalization layer. The key ideas of this layer are: reducing the input values, preserving their variances, and preventing overload in the network. It considers the following calculation:

$$\hat{x}_{ij} = \frac{x_{ij}}{\sum_{i=1}^{n} x_{ij}} \quad (3)$$

where $\hat{x}_{ij}$ is the calculated normalized value, x_{ij} is the original input value, j is an index for the number of input patterns and n is the number of nodes in the normalized layer, which equals to the number of input nodes in the input layer.

The second hidden layer of the NGNN has a transfer function known as the RBF [29].

In such an RBF layer, the following equation formulae are applied [30]:

$$z\_in_j = \hat{\mathbf{x}}^T \mathbf{w}_j\ , \quad j = 1,2, \dots, p \quad (4)$$

$$z_j = \exp\left[\frac{z\_in_j - 1}{s^2}\right] \quad (5)$$

where z_in_j is the previously computed hidden value, $\hat{\mathbf{x}}$ is the vector of normalized values, T is the transpose parameter, $\mathbf{w}$ is the weights vector between the hidden and input layers, p is the neuron number in the hidden layer, z_j is the calculated output hidden value, and s is the transfer function smoothing parameter. A linear function is utilized in the output layer. As a result, it is possible to directly use the following equation [31], [32]:

$$y_j = \sum_{j=1}^{p} z_j w_j \quad (6)$$

where y_j is an output value of the output layer.

The NGNN operates in two stages: train and test, like other neural networks. Each stage deals with certain signatures. In the training stage, the necessary weights are generated. Consequently, these weights are used to produce intelligent outputs in the testing stage.

3.4. NGNN Advantages

The following advantages can be highlighted for the proposed NGNN approach:

- It is so fast in the training stage as it does not consume time to iterate until establishing the necessary weights as other neural networks.
- It does not suffer from the overload problem because it exploits normalization.
- It is not deceived by the local minima problem as other neural networks that require iterations in their training algorithms.

The NGNN architecture has further improvements over the traditional GRNN. It has been adapted for multiple classes, whereas, the GRNN uses only a single class of regression. In addition, the NGNN architecture has also developed to overcome the overfitting issue. This is accomplished by providing the normalization layer directly after the input layer. Therefore, it can address any overfitting issue from the beginning.

3.5. Performance Measurements

To accurately assess the effectiveness of the proposed NGNN approach, different metrics are used. These are the: Mean Absolute Error (MAE), Mean Square Error (MSE), Mean Absolute Percentage Error (MAPE), and Root Mean Square Error (RMSE). Moreover, in terms of comparison, the training and testing time were sequentially computed, and then compared with different neural networks.

For the MAE, the absolute difference between each actual value and its matching anticipated value is taken into account during the calculation. The MAE formula is represented as follows [33]:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|r_i - \hat{r}_i| \tag{7}$$

where n is the number of data points, r_i is the actual (observed) value for the i^{th} data point and $\hat{r}_i$ is the predicted value for the i^{th} data point.

For the MSE, the square difference between each actual value and its matching anticipated value is used, which is then derived by averaging these squared values. The MSE formula is expressed as follows [33]:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(r_i - \hat{r}_i)^2 \tag{8}$$

For the MAPE, the average percentage difference between the actual values and the anticipated values is utilized. Following is the MAPE formula [34]:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{r_i - \hat{r}_i}{r_i}\right| \times 100 \tag{9}$$

For the RMSE, the average squared between actual and anticipated values is exploited. The RMSE formula can be expressed as [34]:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(r_i - \hat{r}_i)^2} \tag{10}$$

4. Results and Comparisons

4.1. Exploited database

As a foundation, a database from the Biometric Ideal Test (BIT) [35] is employed. It has been attributed to 8750 signatures, acquired from 350 individuals (each one participates by 25 patterns of signatures). Within-session variability is provided in the first five patterns. The remaining patterns, however, exhibit inter-fluctuation. Session's duplicate samples are produced by developing the lognormal parameters of the main signatures, as demonstrated in [18]. According to [18], and [19], each signature pattern contains five attributes: x coordinates, y coordinates, synthetic timestamps, pen ups and downs, and pressure function. Each one of these attributes has a variety of values.

4.2. Prepared parameters

Since the shortest length of signature attributes has fewer values, all values of signatures have been downsized to only 65 values. The efficiency statistical calculation is thus done for each of the five stated attributes. Correspondingly, there are 65 NGNN inputs of efficiency values for each signature pattern or sample. The NGNN output is enhanced for multiple classes, each is assigned to recognize a signature. A number of classes equal to 70 is utilized here for 70 people. There are 875 hidden nodes or units in the RBF layer of the NGNN. A total of 1750 patterns of signatures are exploited and partitioned into two halves, 50% for the training stage and 50% for the testing stage.

4.3. Error Evaluations

The proposed NGNN has been evaluated using the MAE, MSE, MAPE, and RMSE. In terms of comparison, the evaluated results of the proposed NGNN approach have been compared with other neural networks. These are the: Cascade-Forward Neural Network (CFNN), Backpropagation Neural Network (BNN), Backpropagation Neural Network with Momentum (BNNM), Backpropagation Neural Network with Adaptive learning rate (BNNAL), and Backpropagation Neural Network with Adaptive Learning-rate and Momentum (BNNALM), which have been utilized in [34]. To accomplish a fair comparison, it is important to mention that the evaluation processes of the NGNN, CFNN, BNN, BNNM, BNNAL, and BNNALM are carried out under the same conditions. Table 1 shows the comparison performances between our proposed NGNN approach and other compared networks.

From this table, it can be noticed that our proposed NGNN has recorded the lowest MAE, MSE, MAPE, and RMSE values compared to other networks. That is, the lowest (best) error values are benchmarked as MSE = 0.014, MAE = 0.028, MAPE = 0.002, and RMSE = 0.119. These results yield the highest performances which have been reported by our proposed NGNN approach. The NGNN approach outperforms other networks in multiple cases as the error values and working times. These are due to its ability compared to other neural networks. It has reasonable layers in its architecture, where these layers can outperform some essential problems in other neural networks such as the problem of overfitting. On the other hand, the NGNN has potential limitations as it requires a large number of hidden nodes and it ignores biases in its architecture, which can be useful in many applications.

Table 1: Comparison of performances between our proposed NGNN approach and other networks.

Network	MSE	MAE	MAPE	RMSE
CFNN	0.579	0.542	0.043	0.761
BNN	0.539	0.522	0.042	0.734
BNNM	0.527	0.516	0.041	0.726
BNNAL	0.071	0.178	0.014	0.266
BNNALM	0.030	0.109	0.009	0.173
Proposed NGNN	**0.014**	**0.028**	**0.002**	**0.119**

4.4. Time Evaluations

The training and testing times of the proposed NGNN have also been computed and compared with other networks. Table 2 demonstrates the training and testing time comparison. As default settings of a fair comparison, one hidden layer, tan-sigmoid activation function in the hidden layer, pure-linear activation function in the output layer, maximum number of 1000 epochs, and minimum objective error of 0 are utilized. It is worth mentioning that all compared neural networks require many epochs or iterations during their training stages. Whereas, our proposed NGNN requires only one epoch or iteration as illustrated in the previous section. So, the maximum number of iterations is fixed to 1000 epochs for all compared networks.

It is reasonable to expect that an NGNN consumes a very short training time. Table 2 shows that the BNN, BNNM, BNNAL, BNNALM, and CFNN wasted a very long time during their training stages where they recorded 42.14, 42.30, 43.89, 45.05, and 47.35 seconds, respectively. Whilst, the proposed NGNN has a big advantage in the case of consuming a very short time in the training stage as it reported here only 0.22 seconds. Consuming a very short training time is a significant confirmation of the superiority of our proposed NGNN.

Testing times in neural networks are expected to be very short and this is what can be noticed for all compared networks. BNN, BNNM, BNNAL, BNNALM, CFNN, and our proposed NGNN required during their testing stages 0.24, 0.21, 0.20, 0.20, 0.20 and 0.25 seconds, respectively. The proposed NGNN indeed reported the highest testing time, however, this time is still very short (a difference of less than 0.1 seconds compared with the testing time of any compared network). This can be considered insignificant to exploiting the big facilities and abilities of computer technology in the testing stage.

The NGNN can be applied in more general and potential applications. Examples of such applications are iris classification, palm print verification, and voice identification. In fact, its ability to work on multiple classes makes it adaptable to any biometric recognition case.

Table 2: Training and testing time comparison times between our proposed NGNN approach and other compared networks.

Network	Training Time (sec.)	Testing Time (sec.)
CFNN	47.35	0.20
BNN	42.14	0.24
BNNM	42.30	0.21
BNNAL	43.89	0.20
BNNALM	45.05	0.20
Proposed NGNN	**0.22**	**0.25**

5. Conclusion

In this paper, recognizing signatures was considered. Firstly, signature attributes were collected and employed. Then, multiple contributions were presented. These were the statistical analyses of efficiency for the feature extraction. The novel NGNN classifier was proposed and adopted.

Comparisons between different neural networks and the novel NGNN are provided.

In this investigation, 1750 patterns of attributes were employed, which took advantage of using a large number of signatures. For the training and testing stages, the total number of data was divided into two halves. In addition, the proposed network has been compared with different neural networks of BNN, BNNM, BNNAL, BNNALM, and CFNN. The results were interesting as the best and lowest error values have been benchmarked as MSE equal to 0.014, MAE equal to 0.028, MAPE equal to 0.002, and RMSE equal to 0.119. Moreover, the proposed NGNN approach approved its capability of consuming a very short training time as it reported only 0.22 seconds in this paper.

For future work, it can be suggested that the NGNN will be discovered in other topics or fields. Examples of such topics are iris recognition, face identification, and voice verification. Moreover, it is worth employing the NGNN approach in practical applications of real-world signature recognition. This requires collecting real data of signatures and extracting their useful features.

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Conflict of Interest

Regarding the publication of the manuscript, the authors declared that they have no conflicts of interest.

Author Contribution Statement

The hypothesis of this paper is proposed by the first author Saadoon ALSUMAIDAEE. In addition, the first author wrote the paper, while the supervision and revision of this paper were implemented by the second author Wai Lok Woo.

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