

Online Signature for Attendance Verification System using Levenberg-Marquardt Neural Network

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Abstract— This work focuses on the application of Levenberg-Marquardt based Back-propagation Neural Network for training features extracted from online signature images. In implementing this, the description of Levenberg-Marquardt back-propagation Neural Network is given. This is followed by signature image processing stages needed to produce input data for the training algorithm. Signature attendance system based on the trained network was developed and tested with data collected from fifty (50) classes. The False Acceptance Rate (FAR) and False Rejection Rate (FRR) were also calculated to give 8% and 12% respectively.

Index Terms— Verification, Online Signature, Levenberg-Marquardt, Neural Network, Attendance.

I. INTRODUCTION

SIGNATURE application is rapidly increasing even as technology is advancing towards e-banking, e-financing, e-commerce amongst many others. The verification of signatures collected is important in order to determine its authenticity and thus preventing impersonation. This also defines the level of integrity of the systems that are being deployed.[1][2]

Signature samples may be collected offline or online depending on the available technology in place. Offline signature collection means that signature is acquired using a hardcopy paper, on the other hand, the online signature collection means dynamic properties of the signature being collected is obtained in addition to high quality static signature image, it is usually implemented using a digital signature pad [3][4]

After the online signature samples have been collected, it is important to have a system in place that can virtually interface with the digital signatures and then process the signature for acceptability purpose or rejection purpose. This process is known as signature verification. [5]

Before signature verification can be achieved, there are several salient engineering procedures that have been

implemented. One of these is the training procedure. Training process is the heart of any Artificial Neural Network (ANN) based system. The output of the training process is as good as the training method that is being deployed. In this paper, Levenberg-Marquardt back-propagation training algorithm is considered because it is the fastest in training moderate dimensional matrix.

II. LEVENBERG-MARQUARDT BACK-PROPAGATION

A. Review

Training performance of an ANN is evaluated by computing the means square error of the system and this is computed as the mean of the square of the difference between the target matrix and the input matrix. The target matrix is a matrix of low input and high input data. The equation is given in (1) [6].

$$F = mse = \frac{1}{N} \sum_{i=1}^N (e_i)^2 = \frac{1}{N} \sum_{i=1}^N (t_i - a_i)^2. \quad (1)$$

Where N = number of iterations; t_i = target outputs, which is the target/reference feature vector; a_i = input a, which is the feature vector to be verified. In carrying out ANN training, the system uses Levenberg-Marquardt Back-propagation with mathematical model given in (2).

$$x_{k+1} = x_k - [J^T J + \mu I]^{-1} J^T. \quad (2)$$

Where x_{k+1} = output matrix, x_k = input matrix, T = target matrix, e = errors, μ = scalar and J = Jacobian Matrix. Jacobian matrix is a matrix of first order derivative that is given in (3).

$$J = \frac{df}{dx} = \begin{bmatrix} \frac{\partial f}{\partial x_1} & \dots & \frac{\partial f}{\partial x_n} \\ \vdots & \ddots & \vdots \\ \frac{\partial f_m}{\partial x_1} & \dots & \frac{\partial f_m}{\partial x_n} \end{bmatrix}. \quad (3)$$

If $m=n$, the Jacobian matrix turns to a square vector; if $m=1$ the matrix turns to a column vector. On the other hand, when μ in (2) equals 0, the mathematical model assumes Newton's method and when μ is large, the model assumes a gradient descent with a small size [7]. This dynamic characteristic of the model makes it the fastest method for training moderate size ANN. The Levenberg-Marquardt

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back-propagation method is also easy to implement with the feed forward training function.

In addition, the data ratio that is obtained from the input matrix is distributed into training, validation and testing so as to improve the outcome of the process. The usual division percentage is training: 70%, validation: 15% and testing: 15% but these values can be adjusted depending on the ratio that best fit the system performance output.

III. METHODOLOGY

The features extracted from signature images acquired by the signature tablet are obtained via image preprocessing and analysis algorithms. The same steps are involved either during enrolment or verification but personal user information is added during enrolment via the digitizer as illustrated in Fig 1. The feature vector is formed and used to train the ANN. In the same way, the verification process follows similar sequence in the formation of feature vector to be tested for validation. The flow chart of the proposed signature attendance system is as shown in Fig. 2.

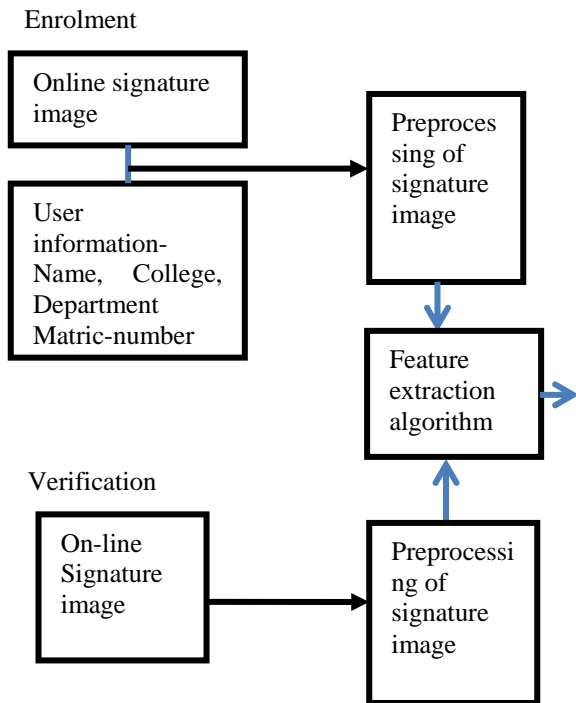


Fig. 1: System Input stages

IV. IMPLEMENTATION AND TESTING

A. Signature image Pre-processing

Colour to gray and gray to binary transformation

Firstly acquired colour signature images are converted to gray-scale images. This is achieved in MATLAB using MATLAB syntax `g=rgb2gray` [8]. Example of colour signature image and resulted gray-scale image are shown in Fig.3 and fig.4 respectively.

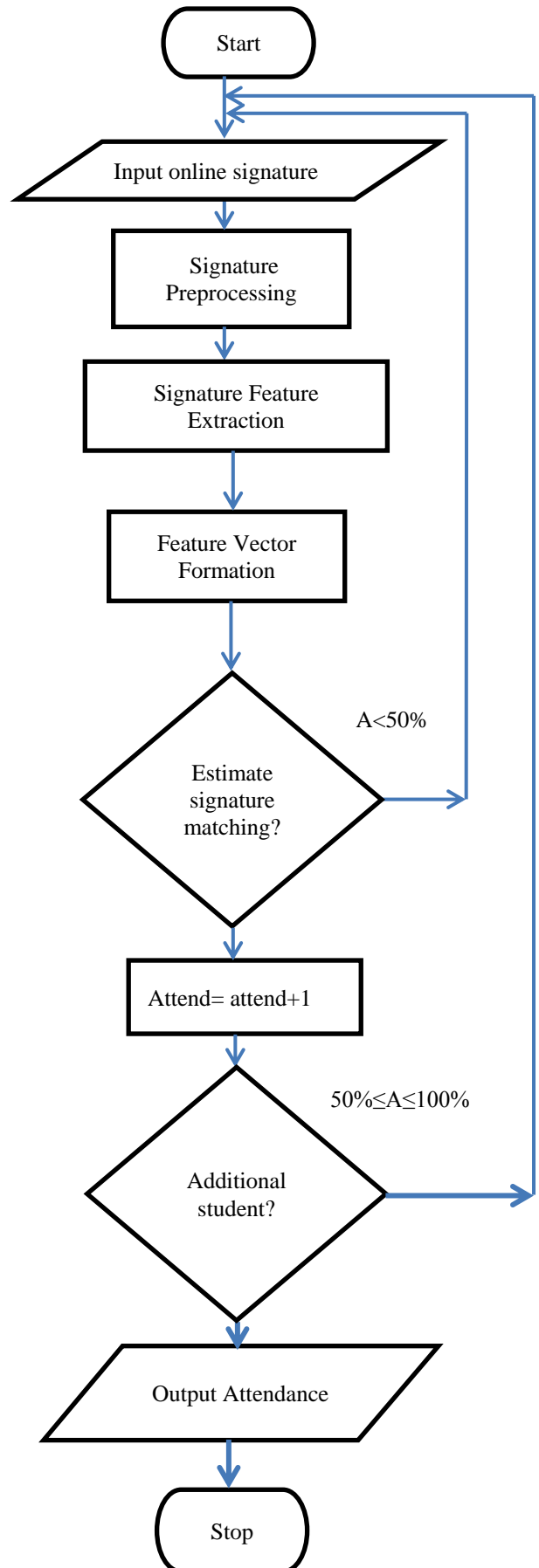


Fig. 2: Flow Chart of the System

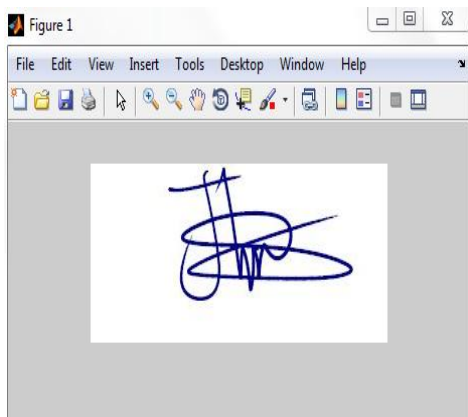


Fig. 3: Color signature image

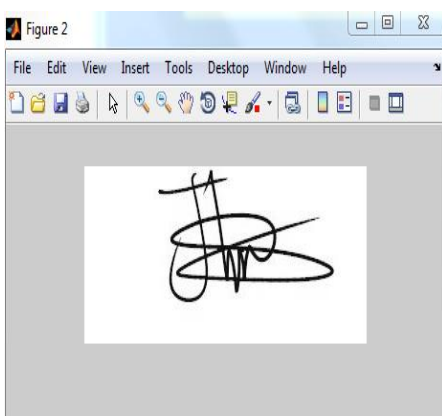


Fig. 4: Grayscale signature image

Resizing the image

The image is resized into square matrix image for speed and more accurate result. The resultant image is shown in Fig. 5. Thereafter the grayscale image is converted into binary image via thresholding operation. Example of binary image is as shown in Fig. 6.

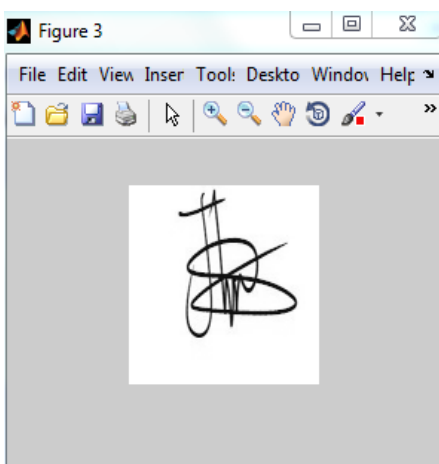


Fig. 5: Resized grayscale signature image

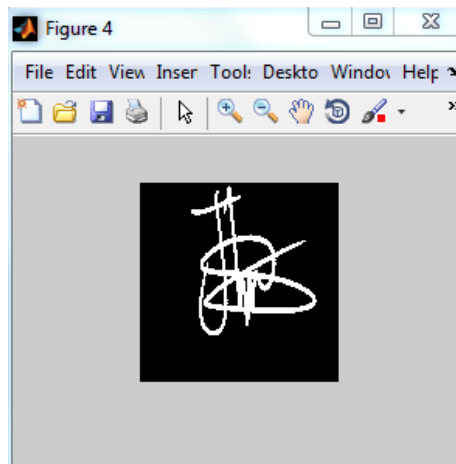


Fig.6: Binary signature image

Thinning the binary image

Binary signatures are further processed to reduce the number of pixels in the images so as to reveal the actual shape of the images. Example of a thinned binary signature image is shown in Fig. 7 [8][9].

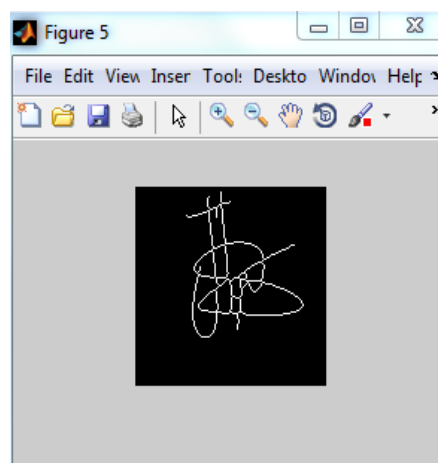


Fig. 7: Thinned signature image

B. The Signature Feature Extraction

Horizontal and vertical histogram feature

These features provide shape properties of input binary signature image. These values are obtained by summing all pixels along rows and columns in the image and thereafter find the maximum value, mean value and standard deviation

Euler Number

The Euler number is obtained based on the number of connected pixels in binary image and the number of holes formation.

Area and center of gravity

Area of a binary signature image is derived from the total number of pixels contain in the image and center of gravity of binary image is calculated to determine the midpoint within the image. .

C. The Feature Vector Implementation

This is a vector of all the extracted features in section B above. This gives feature matrix of 5X150 dimensions, i.e., five (5) signature features were used per signature, and there are three (3) different signature samples that were used to train the ANN for fifty classes. In general, fifty (50) different students' signatures were collected with each of them giving out five signature samples each (three (3) for training feature vectors and two (2) for genuine signature testing purpose). This result in 5X150 matrix of feature vectors which forms the input matrix of the ANN. One sample each from pool of signature folder of five each is shown in Fig. 8.

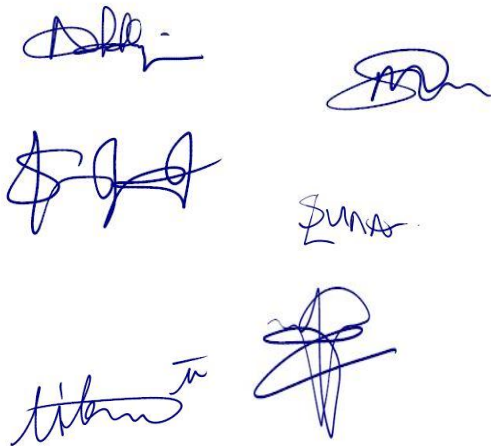


Fig. 8: Online signature images

The formation of the target vectors of signatures in comparing with output vectors takes a similar procedure. This gives the 50X150 matrix that is made of ones and zeros. Also, genuine signatures and forged signatures were also used to test the system

D. Implementation and Testing on Artificial Neural Network (MATLAB)

The next implementation stage is on the Artificial Neural Network using MATLAB. The ANN is trained using the feature vectors. There are two methods of running an ANN. It could either be by using GUI in ANN tool box or by writing the script in m.file format. For this work, the scripting method is used but the knowledge of using the GUI is also gained.

To launch the ANN, a MATLAB syntax 'nstart' is used but the syntax command is used to implement this research to enable easy modification of MATLAB code and flexibility of operation of the system. The resulting ANN structure for training is as shown below in Fig. 9.

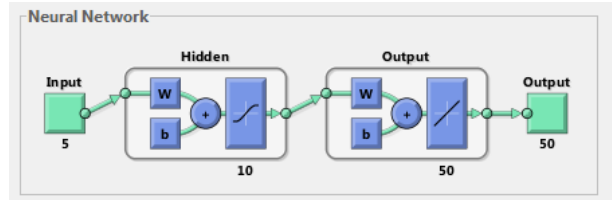


Fig. 9: ANN structure for training

The whole design phase of this work was implemented on MATLAB GUIDE which is the Graphics User Interface (GUI) design platform in MATLAB. These are shown in Fig.10 to fig.14.

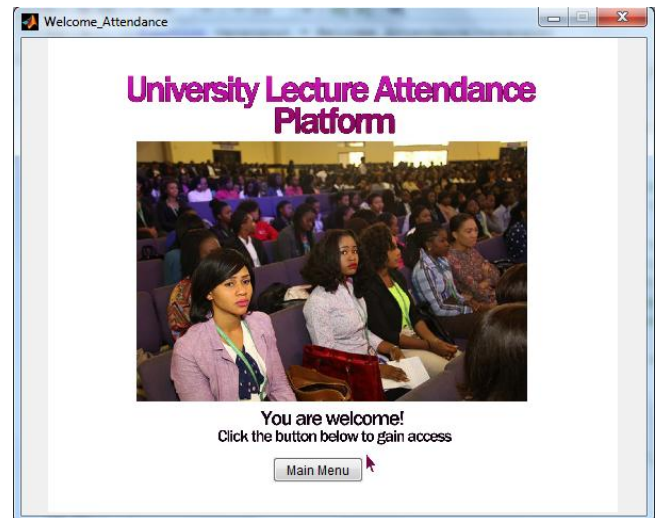


Fig.10: The Attendance system welcome page

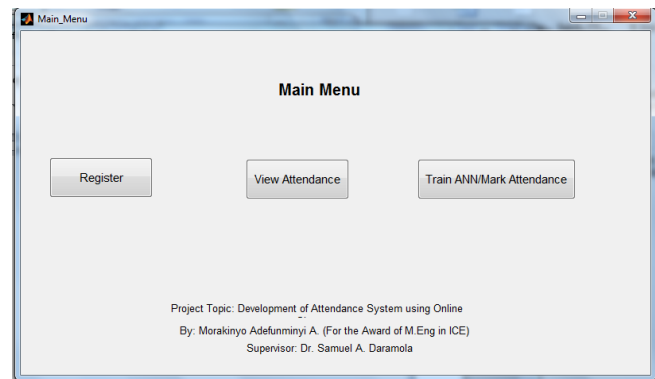


Fig.11: Main menu page

V. TESTS AND RESULTS

During signature verification process, the percentage accuracy (A) of each signature used to test the system is computed. The metrics used for FAR and FRR calculation are given as:

If $50\% \leq A \leq 100\%$ = valid signature and if $A < 50\%$ = invalid signature [6].

Fig. 12: Student registration page

The signature marking and result display platform designed using MATLAB GUIDE is shown in Fig. 15 and Fig. 16.

Fig. 15: Tested signature (41.756% accuracy- invalid signature)

Fig. 13: ANN training and attendance marking GUI

Fig. 16: Tested signature (51.756% accuracy- valid signature)

Matric Number	Surname	Othernames	Sex	College	Department	Level	Attendance
02CK06277	KOLAWOLE	ENIOLA MARY FEMALE		SOCIAL SCIE. POLITICAL S.	500		6
02CK06279	KOLAWOLE	ENIOLA MARY FEMALE		SOCIAL SCIE. POLITICAL S.	500		0
06CK06277	Ajayi	Tolu					2
07CK06265	Adefunmami						1
07CK06266							9
07CK06268	Sola						1
07ck07377	Akinyode	Olayomi	Male	CDS	Accounting	400	1
07CK34324	Aluko	Femi					1
09CK06277	Morakinyo	Ifedayo Ayo	Male	CST	Computer	400	1
09ck04848	gggggg	gggggg		gggggg	gggggg	gggggg	1
15665rrr	gggggg	gggggg		gggggg	gggggg	gggggg	1
Matric_Num	gggggg	gggggg		gggggg	gggggg	gggggg	1
mmmm	mmmm	mmmm		mmmm	mmmm	mmmm	0
uuuuu	gggggg	gggggg		gggggg	gggggg	gggggg	1

Fig. 14: Attendance report page

A. *False Rejection Rate (FRR):*
 There are six signatures that satisfy the $R < 50\%$ condition under the genuine signature test category while 44 genuine signatures were appropriately accepted as genuine. The FRR is given as follows:
 $6/50 \times 100\% = 12\%$

Therefore, the FRR of the system using ANN is 12%.

B. False Acceptance Rate (FAR):

There are four signatures that satisfy the $50\% \leq A \leq 100\%$ condition under the forgery signature test category while 46 forged signatures were appropriately reject as invalid signatures. The FAR is given as follows:

$$4/50 \times 100\% = 8\%$$

The result can be improved upon by using advance digital signature pads that can reduce the level of perfection of skilled and unskilled forged signatures. Also, more data can be collected to further improve the training ability of the ANN hereby increasing the overall system efficiency with improved FRR and FAR.

VI. CONCLUSION

In this work attendance system based on online signature images and Artificial Neural Network has been developed. Populations of fifty students have signed into the system to test its functionality. A very encouraging result was obtained. The excellent result achieved can be traced to the type of training algorithm adopted and feature vector that was engaged. Therefore this type of system can be deployed in schools and offices to replace manual signing of signatures on papers for verification, collation and reporting.

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