Neural Network Based Signature Authentication System with Regional Properties, Fractal Dimensions and QR code

Ashok Kumar. D
Department of Computer Science and Applications
Government Arts College
Tiruchirapalli - 620 022
drashoktrichy22@gmail.com

Dhandapani. S
Department of Computer Science and Applications
Government Arts College
Tiruchirapalli - 620 022
sdpudt@rediffmail.com

***Abstract*- Every transactions authorized by handwritten signatures are accepted worldwide. Utmost care is to be taken for the verification of genuineness of the signature. A novel method for offline signature verification in bank cheque is proposed. The system uses connected Components Labeling, Fractal Dimensions, Quick Response (QR) code and Neural Networks. The signature is scanned and preprocessed. Using connected components labeling, the regional property features are extracted and normalised. Extracted feature values and fractal dimensions are compared with the sample signature's feature values for its genuineness. A Neural Network is used to classify the signature into genuine or forged. Some complex signatures may require human intervention. An optimum signature verification model consumes less time and memory space in the database server. Conventionally the features extracted are stored in the database. Instead, the proposed model prints features in the QR code format on the cheque. Whenever the cheque comes for transaction, the QR code and the signature is scanned and verified. The proposed verification system shows very good results with good sensitivity and specificity with the CEDAR signature database. The system attains an accuracy of maximum 95% with very low false acceptance rate and false rejection rate. It is observed that, using fractal dimensions for verification purpose, improves the accuracy rate. Also the proposed model reduces the time, memory and cost for the signature verification process and may aid the banking community.**

Keywords- Signature Verification, Connected Components, Fractal Dimension, QR Code, Neural Network

I. INTRODUCTION

Signature is one of the oldest and also the simplest method of authorization. One may forget his password or may have missed his smart card used for verification purposes. Signature takes the advantage of them all [13]. It is accepted by people for many legal transactions. Signature verification has gained momentum [10] and it is considered with renewed awareness in the recent years due to the increasing bank cheque fraud cases [18]. The signature verification can be broadly classified into online or offline on the basis of image acquisition type. Online signing requires special electronic equipments like the stylus and the tablet. The signer has to be present at the place where the electronic gadgets are installed [14]. Offline signatures require only a pen. The signer can sign from anywhere and the verification is done at offices, in our case, the bank. Signature verification is easy in case of online signatures. All the necessary signature features like the signing speed, number of lifts of the electronic pen, pressure applied at various positions and also the angle of inclination can be extracted. But in offline signature verification, the researcher will have only the scanned digital copy of the signature and not the behavioural information like pressure, velocity and sequence of the strokes [22]. Figure 1. shows a sample cheque.

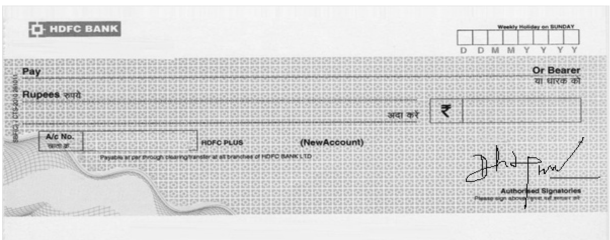

Figure 1. A Sample Cheque

Man is the most powerful machine created naturally. They get trained and their neuron's learning process is a continuous one. One can identify a signature and in a fraction of a second, he can judge its genuineness. The problem is that he may get fatigue after long time of verification process. The classification may get sluggish in the evening hours. Even professional forensic department document examiners do a correct classification rate of only about 70% [2]. A genuine signature may be questioned and a forged signature may be accepted due to human error. Either of the case may irritate bank's valuable customers. To assist in the classification, this new system is proposed. As a result of verification, signature is categorized into genuine, forged or complex. Complex signature is the one which the verification system finds that human intervention is also needed. This may be due to noise created due to cheque mutilation or scanned signature not legible. No one can put his signature so exactly the very next time. Since signature is a behavioural biometric [9], so intra-class variations are higher. The signature depends on the psychophysical state of the user. This makes the system complex by carefully managing intra-class differences and also identifying the inter-class variations. As age increases, the style of the signature gets changed but the length remains the same.

The signature forgery can also be classified into skilled, simple and random. Skilled forgery is one, the forger keeps a copy of the genuine signature handy and after a couple of practices, he quickly places the signature on the required document. In simple forgery, the forger remembers the signature shape from any other document and tries to imitate the same from his memory. Random forgery is the one where the forger signs knowing only the name of the signer. Since the proposed model deals with bank cheque signature verification, only skilled forgery is focused.

The number of individual regions found using connected components labeling may be different for different signatures due to noises present. An isolated individual pixel may also be recognized as a separate region. So preprocessing along with normalization is done. Number of regions may vary in random and simple forgeries. But in skilled forgery, we assume that the number of regions may be the same as in the genuine signature.

All the extracted features are conventionally stored in the database. The system has to access the database for every transaction. A cheque should be processed in a minimum time so that the customer is satisfied, which is likely to be one of the good banking services offered to its customers. The proposed system does not use a database. With the development of Internet of Things, QR code images are widely used [23]. Figure 2. shows a sample QR code. It is a special kind of barcode. It consists of a square grid with some black squares on white background. QR codes can contain both text and numerical values. The feature name and its value are encoded in the QR code and printed on the cheque. It is difficult to reproduce the genuine signature by decoding the values in the QR code alone.

Figure 2. Sample QR code

The feature values of the signature is encoded into the QR code and printed on the cheque. Whenever the cheque comes for transaction, the QR code is decoded and the signature features are extracted for verification against the signature features on the cheque.

This paper is organized into four sections. Section II discusses the literature review and proposed system. Section III discusses about the training and signature verification process. Section IV discusses about the performance and quality measures. Section V summarizes our conclusion of the research article with future work to be carried out.

II. LITERATURE REVIEW AND PROPOSED SYSTEM

Any Signature verification system developed should be accepted universally and it should help administrative and financial offices. The verification system modeled will be better if it is of low cost, high speed and with a maximum accuracy. Handwritten Signature verification is a technique which is reliable, economical and non-intrusive to the signer [8]. Signatures can be viewed as an image and recognized using image processing and neural networks [16]. Connected components labeling was used in [4] and the similarity between the features was calculated by the Manhattan distance method. The handwriting of male writers is more consistent than that of female writers [21]. Shekar and Bharathi [20] used eigen signature construction to extract features from the signature shape and compares it with the texture based features extracted. Authors in [16] uses the preprocessed signature to extract features and detect forged signatures using artificial neural network. In [11], the authors proposed a method to extract signatures from a complex background by capturing the structural saliency.

The proposed signature verification system uses Center of Excellence for Document Analysis and Recognition (CEDAR) signature dataset. The database consists of 1320 genuine signatures and 1320 forged signatures. Each set consists of 24 genuine and 24 forged signatures from each of 55 persons. The system uses connected components labeling concept. Connected component labeling is a fundamental step in automatic image analysis. Different labels are assigned to various disjoint connected components of the image. Properties like shape, area and boundary of the labeled regions can be calculated easily. Values of these properties form the feature set. The calculated features are encoded into the QR code and printed on the cheque. The signature to be verified is scanned and preprocessed. The features are extracted and compared with the sample features decoded from the QR code using a neural network. This proposed method reduces time, space and cost. There are various steps in the entire verification process.

A. Image Acquisition

The process of digitizing the image is done in image acquisition phase. To extract handwritten information, authors in [6] used a topological criterion called filiformity. The signature can be photographed using a camera or scanned using the scanner. Since scanner gives high resolution in DPI format, signature is scanned from the bank cheque using a scanner. Cheque may contain logo and designs with different background and colour. Separating the signature from the background and design of a cheque is a tedious process [19]. Since the signature is scanned using a scanner, sampling and quantization noise may creep in [18].

B. Image Preprocessing

Preprocessing is done to reduce the noise in the scanned signatures. In connected components labeling, the regions are identified using the pixel connectivity. If a noise appears in the scanned image it has to be cleaned. The individual pixel or noise which is not a part of the signature may also be considered as a separate region. If the irrelevant pixels are labeled and used for training they may lead to error. Preparing the signature image for verification process should not consume more time. Cheque transaction time in banks is limited nowadays to offer a quick service to the account holder. Also fixing the rubber stamp seal on the cheque over the signature or part of it, may need some preprocessing to extract the signature.

C. Feature Extraction

Feature extraction is the most important task in a signature verification system. The goal of feature extraction is to improve the efficiency and effectiveness of classification [7]. The effectiveness can be increased by minimizing the number of features and maximizing pattern discrimination. Since signature is a behavioural biometric system, the feature plays the major role in recognition and identification.

Any feature set for a signature verification system should provide lesser intra-class variation and large inter-class variation [5]. Also more features does not necessarily improve performance [8]. To extract the features, the signature image is scanned pixel by pixel. The pixels are scanned and labeled from left to right and then downwards. Labeling is needed to recognize connected components in a binary image [5]. If a pixel to be scanned is four connected to previously labeled pixel, it is given the same label. Some pixel will be connected to two different label names. Such equivalent pairs are found and relabeled. Now all the individual components are labeled uniquely in groups or regions. The features of the entire individual labeled regions are extracted.

The possibilities are by its shape, intensity, area and boundary. Any of the features can be taken into account. The process is repeated for sample and testing signature images. Area calculates the number of pixels in the region. Major and MinorAxis Length are the lengths of the major and minor axis of the signature that has the same normalized second central moments. Eccentricity is the ratio of the distance between the foci of the ellipse and its major axis length. Possible value will be between 0 and 1.

Orientation is the angle between the x-axis and the major axis of the ellipse that has the same second-moments as the region. ConvexArea gives the number of pixels in Convex Image. FilledArea specifies the number of on pixels in FilledImage. EulerNumber specifies the number of objects in the region minus the number of holes in those objects. EquivDiameter gives the diameter of a circle with the same area as the region. Solidity gives the proportion of the pixels in the convex hull that are also in the region. Extent gives the number of the pixels in the bounding box that are also in the region. It is calculated by dividing the Area by the area of the bounding box. Perimeter is the c-element vector containing the distance around the boundary of each contiguous region in the image, where c is the number of regions. Regionprops computes the perimeter by calculating the distance between each adjoining pair of pixels around the border of the region.

A fractal is a geometrical figure or a curve. Each part of a fractal will have the same statistical character as the whole. They are useful in modeling structures in which similar patterns recur at progressively smaller scales. Fractals are most complex in their geometry. Any fractal object will have three properties. They are self-similarity, iterative formation and fractal dimension.

Wavelets and fractals are texture feature types. In this paper fractal dimension is taken into account and show how textural information can be utilized for classification of signature images. Signature is verified online or offline depending upon the application where it is used. Transforming the fractals, Kai Huang and Hong Yan [12], has proposed a work for online signature verification. They have worked for random forgery by comparing the fractal codes and the varying distances. The authors have attempted to explore the self similarity information. A fractal dimension is a ratio providing a statistical index of complexity comparing how detail in a pattern changes with the scale at which it is measured. It is also a measure of the patterns space filling capacity. Fractal dimension tells how a fractal scales differently from the space. A fractal dimension of an irregular set does not have to be an integer. Fractal dimension can be calculated by many methods like radial mass method, correlation method, Box counting method and Hausdorff's dimension.

Figure 3. shows the signature verification model. The entire system is divided into training and testing phases. The decision making stage is where the human intervention is needed if the neural network shows abnormal results. The update stage has the facility to change or update the signature of a person with proper authorization.

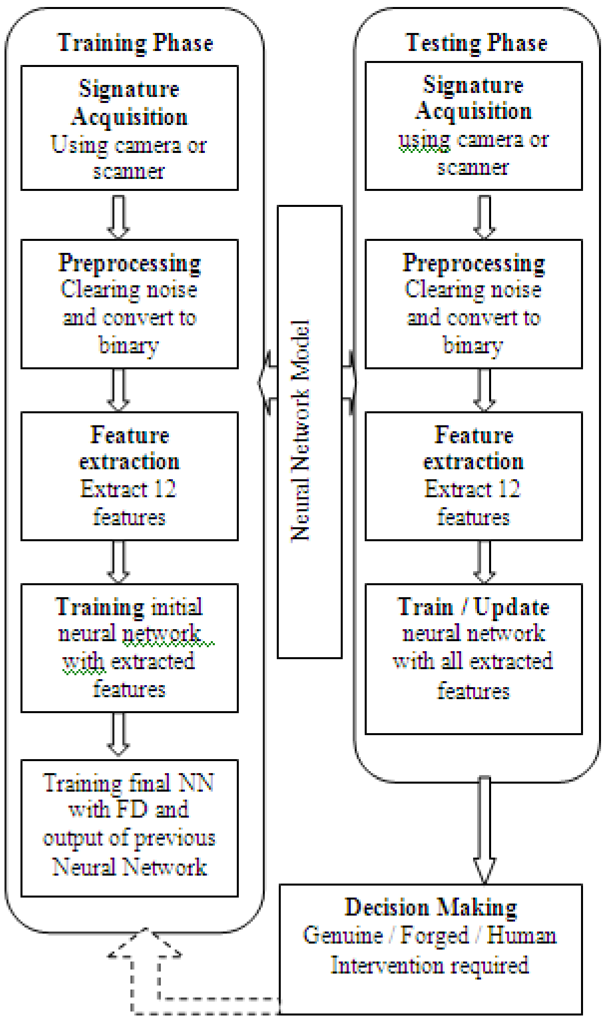

Figure 3. Signature Verification Model

In this paper we used Hausdorff's dimension to calculate the fractal dimension of the signature using the algorithm I proposed by [1].

Algorithm I: Fractional Dimension calculating algorithm

Step 1: Pad the image for a dimension of 2

Step 2: Adjust the box size so that atleast a single pixel of the signature is inside the box.

Step 3: Compute the points with log(N(e)) x log(1/e)

Step 4: Draw line by the last square method using the points.

Step 4: The slope of the line is the dimension of the signature

TABLE I. SAMPLE FEATURE VALUES OF THE REGIONAL PROPERTIES OF THE SIGNATURE

Feature	**Region1**	**Region2**	**Region3**
Area	2435	151	63
MajorAxisLength	217.3152	33.58855	15.47299
MinorAxisLength	100.2363	11.9054	6.22238
Eccentricity	0.88727	0.935076	0.902862
Orientation	10.91051	12.34612	-32.6674
ConvexArea	17962	290	76
FilledArea	3404	154	63
EulerNumber	-9	-1	1
EquivDiameter	55.68068	13.86576	8.956232
Solidity	0.135564	0.52069	0.828947
Extent	0.086357	0.347926	0.484615

Perimeter	1193.183	90.76955	37.79899

Using algorithm I, the dimension of irregular shapes like signatures can be found. They do not have uniform characteristics sizes. A conventional cheque contains at least eleven special marks of identification but the vital mark of identification is the authorized person's signature. Forgers forge the signature carefully in terms of size and shape. They may even trace the signature or draw with the genuine signature nearby. A skilled forgery takes more time [5]. When a signature is forged to the extent that, it is hectic to identify, the time taken will be more so the signature will be wrinkled. The features extracted using connected components labeling and the fractal dimensional values are encoded to a QR code and printed on the cheque. The QR code uses standard encoding modes to store features inside. QR codes are read rapidly and its strength lies in its storage capacity. The advantage of using QR code is that no preprocessing is necessary because it is on a white background.

A Neural network is trained to classify the signatures into genuine or forged with the target values 1 for genuine and 0 for forged signatures. Genuine signatures will have a neural network output values closer to 1 and forged signature to 0. Using a threshold value, we can classify the signature to genuine or forged one. Table I shows the sample list of features extracted from each region. Signature of a person changes slowly over time. After certain years, the error rate may shoot up due to the changes in the signature of the signer. It may be of his age, inconvenience in signing the existing signature, unable to remember his signature, personal preference and change of one's name. The system should be able to update the sample signatures as the signature gets changed with proper approval.

In Table II, we have presented some of the output values from the neural network and sample fractal dimensions. The genuine signatures result will be close to 1 and forged signatures results will be close to 0. Value in the 8th row, 0.6547, is a false prediction and also value in the 9th row, which is, 0.4515 is a false prediction. They are complex type and needs human intervention.

TABLE II. SAMPLE NEURAL NETWORK OUTPUT VALUES AND SAMPLE FRACTAL DIMENSIONAL VALUES

S.NO	GENUINE	FORGED	FRACTAL DIMENSION
1	0.8723	0.2103	0.460897
2	0.8610	0.21031	0.47297
3	0.8229	0.0167	0.28683
4	1.0271	0.24905	0.13568
5	0.6258	0.1972	0.373129
6	0.9418	0.1841	0.255157
7	0.6670	0.2412	0.081818
8	1.1157	0.6547	0.36085
9	0.4515	0.0254	0.300408
10	0.6317	0.4417	0.434795

Algorithm II: Region labeling algorithm

Step 1: Scan the binary signature from left to right and downwards and initialize label (li) to 0.

Step 2: if (top & left pixel) = 0, assign label li +1

Step 3: if (top or left pixel) = 1, label = label (top or left pixel)

Step 4: if (top and left pixel) =1, label = label(top or left pixel) note that top and left are equivalence classes

Step 5: repeat till the last pixel.

Step 6: equivalent classes are analyzed and labeled commonly

III. TRAINING AND SIGNATURE VERIFICATION

Signature verification is a binary type of classification since it predicts whether the signature is genuine or forged. Neural network is one of the methods used to learn and train binary classifiers. The sample signatures are collected for training the neural network. The feature values are computed using the connected components labeling and regionprops as shown in Algorithm II. The computed feature values for each signature is fed to the neural network for classification. Fractal dimensions of each signature is calculated and the result of the neural network and the calculated fractal dimensions are fed to another network. The results were found encouraging when fractal dimensions are included for classification purpose. The feature values extracted from the signature are coded into QR code and printed on the cheque. It is hard to reproduce a signature with the feature values alone. Whenever a cheque comes for collection, the QR code and the signature is scanned. The feature values of the signature and the feature values in the QR code are compared using the designed neural network. The input to the neural network is the preprocessed and normalized feature values decoded from the QR code.

A feed forward fitness neural network is developed with 10 neurons in the hidden layer and trainlm function is used for the network. Levenberg-Marquardt algorithm is used for training since it has the fastest convergence. It is also able to obtain lower mean square errors. 70 % of the data is used for training, 15 % is used for validation and remaining 15% is used for testing purposes. Verification is done using the trained neural network. The trained network predicts the output for the given sample input. The proposed system shows a good performance and the results are better than the network designed using the GLCM features [3]. In [3], gray level co-occurrence matrix was used along with feed forward back propagation neural network. The accuracy claimed was 92.08%. The result of the neural network with regional features and the fractal dimensions of the signature is fed to another neural network of same design and the results are more convincing than without the fractal dimension.

IV. PERFORMANCE AND QUALITY MEASURES

The quality of a signature verification system is usually measured by terms like FAR, FRR, TP, TN, FP, FN. FAR is the false acceptance ratio and FRR the false rejection ratio. TP is the number of correct positives, TN is the number of correct negatives, FP is the number of incorrect positives and FN is the number of incorrect negatives. False Rejection is also called Type I errors and False Acceptance is also called Type 2 errors. Also statistical measures like sensitivity, which measures the proportion of actual positives and specificity, which measures the proportion of actual negatives are measured. In signatures there are inter-class and intra-class variations. Intra-class variations are variations that arise in signatures by the same person the next time [17]. No one can put the exact signature next time and so exact pixel matching for verification is not feasible. Table III shows the performance measures.

TABLE III. PERFORMANCE MEASURES

FAR	FN / (TN + FN)
FRR	FP / (TP + FP)
Sensitivity	TP / (TP + FN)
Specificity	TN / (TN + FP)
Accuracy	(TP + TN) / (TP +TN + FP +FN)

Figure 4. shows the designed network. It has 6 inputs with 10 hidden layers. Output will be a value 0 or 1 or closer to it. The network uses 70% of the data for training, 15% of the data for validation and 15% of the data for testing. Trainlm function is used for training the network. Levenberg-Marquardt algorithm is used for training since it has the fastest convergence.

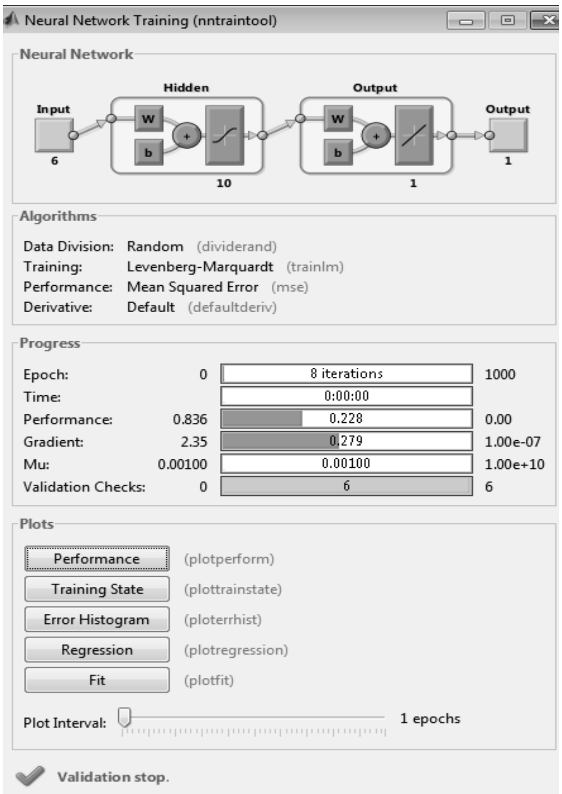

Figure 4. Neural Network Training Simulation

TABLE 1V. VALIDATION PERFORMANCE

Signature	Best Validation Performance
Sign.set-1	0.23061
Sign.set-2	0.11964
Sign.set-3	0.27153
Sign.set-4	0.04874
Sign.set-5	0.19410
Average	**0.17292**

Table IV shows the validation performance of the neural network deigned. Inter-class is the variations found in forged signatures. Pixel to pixel matching is not possible because of the behavioral nature of the signature. So an amount of threshold is used for verification. The value of threshold depends on the application the system is used. If FAR is lowered too much then FRR will increase [15]. Since this work deals with bank cheque signatures, the threshold is kept at a minimum.

TABLE V. EXPERIMENT AND RESULT ANALYSIS OF THE PROPOSED SYSTEM WITHOUT FRACTAL DIMENSION

	TP	TN	FP	FN	FAR	FRR
Sign.set-1	10	11	2	1	8.33	16.66
Sign.set-2	10	11	2	1	8.33	16.66
Sign.set-3	11	12	1	0	0	8.33
Sign.set-4	11	12	1	0	0	8.33
Sign.set-5	12	11	0	1	8.33	0
Average	**10.8**	**11.4**	**1.2**	**0.6**	**8.33**	**11.11**

TABLE VI. EXPERIMENT AND RESULT ANALYSIS OF THE PROPOSED SYSTEM WITHOUT FRACTAL DIMENSION

Run	Sensitivity	Specificity	Accuracy
Sign.set-1	90.90	84.62	87.5
Sign.set-2	90.90	84.62	91.67
Sign.set-3	100	92.31	95.83
Sign.set-4	100	92.31	95.83
Sign.set-5	92.31	100	95.83
Average	**94.82**	**90.78**	**93.33**

Table V and VI shows the experimental results of the system using the regional properties of the signature sets. The result lies in proper execution of the entire process like scanning, preprocessing and training the neural network. Any signature system should have some facility to update the specimen signature. As the years pass on, the signer may change his sign due to many reasons.

TABLE VII. EXPERIMENT AND RESULT ANALYSIS OF THE PROPOSED SYSTEM WITH FRACTAL DIMENSION

	TP	**TN**	**FP**	**FN**	**FAR**	**FRR**
Sign.set-1	12	12	0	0	0	0
Sign.set-2	11	12	1	0	0	8.33
Sign.set-3	10	12	2	0	0	16.66
Sign.set-4	10	12	2	0	0	16.66
Sign.set-5	11	12	1	0	0	8.33
Average	**10.8**	**12**	**1.2**	**0**	**0**	**9.99**

TABLE VIII. EXPERIMENT AND RESULT ANALYSIS OF THE PROPOSED SYSTEM WITH FRACTAL DIMENSION

Run	**Sensitivity**	**Specificity**	**Accuracy**
Sign.set-1	100	100	100
Sign.set-2	100	92.30769	95.83333
Sign.set-3	100	85.71529	91.66667
Sign.set-4	100	85.71529	91.66667
Sign.set-5	100	92.30769	95.83333
Average	**100**	**91.21**	**95.00**

Table VII and VIII show the result analysis when the fractional dimension of the signature image is included to the neural network. It is seen that the accuracy of the system increases by 1.37% when the fractal dimensional feature is included. Performance of proposed signature verification model is found to be encouraging.

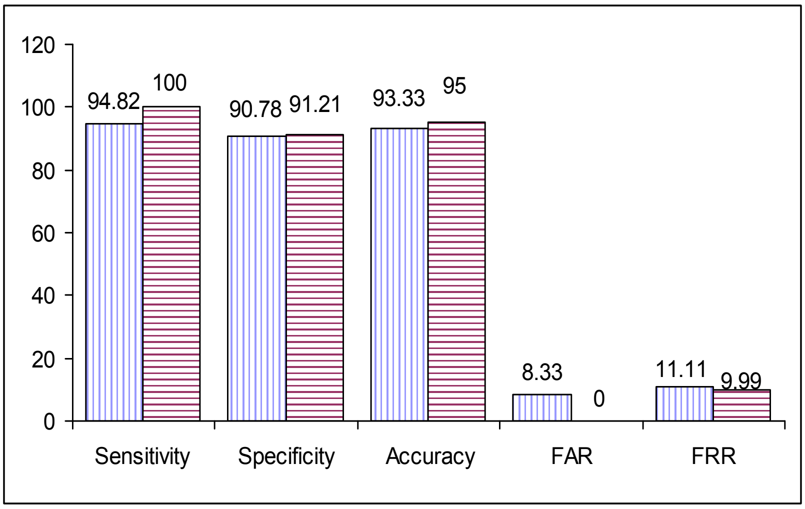

Figure 5. Experimental Results without and with FD

Figure 5. shows the chart analysis of the system. It projects sensitivity, specificity, accuracy, FAR and FRR values without adding Fractal Dimension and after adding fractal dimension. It shows that the results have improved when the fractal dimension of the signature image is included as a feature for classification. Further the false acceptance rate has been reduced to an excellent level which is the vital thing of a signature verification system. Even a genuine signature can be refused and later with clarification it can be accepted. But a forged signature should not be accepted on any grounds. Also it shows that the false rejection rate has also been reduced from 11.11% to 10% and the proposed system tends to act as a good signature verification system.

V. CONCLUSION AND FUTURE WORK

In this research, the authors have modeled a signature verification system for verifying signatures on bank cheques. The modeled system uses Connected Components Labeling, Fractal Dimensions and Neural Networks for verification. Signature is scanned and divided into components based on pixel connectivity. The features of individual components of the sample signatures are extracted and used to train an initial neural network. The result of the initial network along with the fractal dimension is fed to another neural network, which classifies the signature. The system modeled works very fine with signatures tested from CEDAR database. The system shows excellent results with the accuracy of 95%. Excellent performance is seen with good sensitivity and specificity when the fractal dimension of the signature is added for classification with the neural network. Also the system modeled reduces time, space and cost by using the QR code. The feature values are encoded in QR code and printed on the cheque and used for the verification.

ACKNOWLEDGMENT

The authors are very thankful to the researchers who have given their valuable inputs to bring out this model. The authors thank everyone who has extended their help and support.

REFERENCES

[1] Alceu Ferraz Costa, Joe Tekli, Agma Juci Machado Traina, “Fast Fractal Stack: Fractal Analysis of Computed Tomography Scans of the Lung”, International ACM Workshop on Medical Multimedia Analysis and Retrieval (MMAR), pp. 13-18, 2011.

[2] Alonso-Fernandez, M.C. Fairhurst, J. Fierrez and J. Ortega-Garcia, “Impact of Signature Legibility and Signature Type in Off-Line Signature Verification”, Biometrics Symposium, pp. 1,6, 11-13, Sept. 2007.

[3] Ashok Kumar and S. Dhandapani, “A Bank Cheque Signature Verification System using FFBP Neural Network Architecture and Feature Extraction based on GLCM”, IJETTCS, vol. 3, no. 3, May – June 2015.

[4] Chalechale, G. Naghdy, P. Pramaratne & Mertins, “Document image analysis and verification using cursive signature”, Proc. IEEE International Conference on Multimedia and Expo(ICME '04), pp. 27-30, June 2004.

[5] Dinesh Kumar and Premith Unikrishnan, “Class Specific Feature Selection for Identity Validation using Dynamic Signatures”, Journal of Biometrics and Biostatistics, 2013.

[6] Djeziri, F. Nouboud,R. Plamondon, "Extraction of signatures from check background based on a filiformity criterion", IEEE Transactions on Image Processing, doi: 10.1109/83.718483, vol.7, no.10, pp. 1525, 1538, Oct. 1998.

[7] Donato Impedovo and Giuseppe Pirlo, “Automatic Signature Verification:The State of the Art”, IEEE transactions on systems, man, and cybernetics—part c: applications and reviews, vol. 38, no. 5, Sept. 2008.

[8] Dullink, B.Van Daalen, J. Nijhuis, L. Spaanenburg, H. Zuidhof, “Implementing a DSP Kernel for Online Dynamic Handwritten Signature Verification Using the TMS320 DSP Family”, EFRIE, France, Dec. 1995.

[9] Fairhurst, “Signature verification revisited: promoting practical exploitation of biometric technology”, Electronics & Communication Engineering Journal, Dec. 1997.

[10] George Nagy, “Twenty Years of Document Image Analysis”, IEEE Transactions on Pattern Recognition and Machine Intelligence, vol 22, no. 1, Jan. 2000.

[11] Guangyu Zhu, Yefeng Zheng, David Doermann, and Stefan Jaeger, “Multi-scale Structural Saliency for Signature Detection”, 1-4244-1180-7/07/2007.

[12] Kai Huang, Hong Yan, “Signature verification using fractal transformation”, International Conference on Pattern Recognition 2000 Proceedings, vol.2, pp. 851-854, 2000.

[13] Meenu Bhatia, “Off-Line Hand Written Signa

[14] ture Verification using Neural Network”, International Journal of Application or Innovation in Engineering & Management (IJAIEM), vol. 2, no. 5, May 2013.

[15] Mohamad Hoseyn Sigari, Mohamad Reza Pourshahabi, Hamid Reza Pourreza, “Offline Handwritten Signature Identification using Grid Gabor Features and Support Vector Machine”, ICEE, pp. 281-286, 2008.

[16] Mukta Rao, Nipur, Vijaypal Singh Dhaka, “Enhancing the Authentication of Bank Cheque Signatures by Implementing Automated System Using Recurrent Neural Network”, Journal Of Advanced Networking and Applications, vol. 1, no.1, pp. 15 -24, 2009.

[17] Oladele, K.S.Adewole and A.O.Oyelami, “Forged Signature Detection using Artificial Neural Network”, African journal of Computing and ICT, vol. 7, no.3, 2014.

[18] Perez-Hernandez, A. Sanchez and J.F. Velez, “Simplified Stroke-based Approach for Off-line Signature Recognition”, Second COST 275 Workshop, 2004.

[19] Pushpalatha, Aravind Kumar Gautham, D. R.Shashikumar, K. B. ShivaKumar and Rupam Das, “Offline Signature Verification with Random and Skilled Forgery Detection Using Polar Domain Features and Multi Stage Classification-Regression Model”, International Journal of Advanced Science and Technology, vol. 59, pp. 27-40, 2013.

[20] Ranju Mandal, Partha Pratim Roy, Umapada Pal, “Signature Segmentation from Machine Printed Documents using Conditional Random Field”, ICDAR, 2011.

[21] Shekar, R.K. Bharathi, "Eigen-signature: A robust and an efficient offline signature verification algorithm", International Conference on Recent Trends in Information Technology (ICRTIT), pp.134-138, June 2011.

[22] Swati Srivastava, “Analysis of Male and Female Handwriting”, International Journal of Computer and Communication System Engineering (IJCCSE), ISSN: 2312-7694, vol. 1, no. 2, Aug. 2015.

[23] Vu Nguyen, Michael Blumenstein, Graham Leedham, “Global Features for the Off-Line Signature Verification Problem”, 10th International Conference on Document Analysis and Recognition, 2009.

[24] Wu, BangZheng, Zhong, Shangping, "A Distortion Rectification Method for Distorted QR Code Images Based on Self-Adapting Structural Element", 8th International Conference on Wireless Communications, Networking and Mobile Computing (WiCOM), IEEE, pp. 1-6, Sept. 2012.