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Enhanced Offline Signature Recognition Using Neural Network and MDA

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ABSTRACT: This research identifying an individual based on person behavioural that have the capability to reliably distinguish between an authorized people therefore signature verification systems can be categorized as offline and online. Neural network based recognition of offline signatures system that is trained with low-resolution scanned signature images where signature of a person is an important biometric attribute of a human being which can be used to authenticate human identity however human signatures can be handled as an image and recognized using computer vision and neural network techniques and MDA modern computers there is need to develop fast algorithms for signature recognition where there are various approaches to signature recognition with a lot of scope of research. In this paper off-line signature recognition & verification using neural network and MDA is proposed where the signature is captured and presented to the user in an image format therefore the signatures are verified based on parameters extracted from the signature using various image processing techniques.

KEYWORDS: Offline signature recognition, Neural Network, OCR and MDA.

I. INTRODUCTION

It is an information processing paradigm that is inspired by the way biological nervous systems as the brain process information where key element of this paradigm is the novel structure of the information processing system therefore it is composed of a large number of highly interconnected processing elements working in unison to solve specific problems where artificial neural network like people learn by example. An ANN is configured for a specific application such as pattern recognition or data classification through a learning process therefore learning in biological systems involves adjustments to the synaptic connections that exist between the neurones.

Neural networks with their remarkable ability to derive meaning from complicated or imprecise data can be used to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques. A trained neural network can be thought of as an expert category of information it has been given to analyze where this expert can then be used to provide projections given new situations of interest and answer what if questions.

Adaptive learning where having the ability to learn how to do tasks based on the data given for training or initial experience.

Self-Organization is introducing the artificial neural network that can create its own organization or representation of the information it receives during learning time.

Real Time Operation where the artificial neural network computations may be carried out in parallel and special hardware devices are being designed and manufactured which take advantage of this capability.

Fault Tolerance via Redundant Information Coding where partial destruction of a network leads to the corresponding degradation of performance however some network capabilities may be retained even with major network damage.



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II. NEURAL NETWORKS IN MEDICINE

Artificial Neural Networks (ANN) is currently a popular research area in medicine where it is believed that they will receive extensive application to biomedical systems in the next few years. The research is mostly on modeling parts of the human body and recognizing diseases from various. In recognizing diseases using scans since there is no need to provide a specific algorithm on how to identify the disease it is example so the details of how to recognize the disease are not needed. The quantity of examples is not as important as the quantity where the examples need to be selected very carefully if the system is to perform reliably and efficiently. Modeling and Diagnosing the Cardiovascular System

Neural Networks are used experimentally to model the human cardiovascular system. Diagnosis can be achieved by building a model of the cardiovascular system of an individual and comparing it with the real time physiological measurements taken from the patient if this routine is carried out regularly potential harmful medical conditions can be detected at an early stage and thus make the process of combating the disease much easier.

A model of cardiovascular system must mimic the relationship among physiological variables at different physical activity levels if a model is adapted to an individual then it becomes a model of the physical condition of that individual. The simulator will have to be able to adapt to the features of any individual without the supervision of an expert this calls for a neural network.

III. LITERATURE SURVEY

ShashiKumar, R. K Chhotaray, D R K B Raja and SabyasachiPattanaik "et al." [1] introduced Off-line Signature Verification which was Based on Fusion of Grid and Global Features UsingNeural Networks. The Fusion of global and grid features were used to generate dominant feature set and neural networks are used as classifier. FAR achieved was 4.16% whereasFRR was 7.51%.

L.Basavaraj and R.D Sudhaker Samuel "et al." [2] introduced offline signature verification technique which was based on four speed stroke angle. It extractsed the dynamic features of static signature image. It is based on the idea that intensity is directly comparative to the speed of the stroke. This method achieved FAR of 13.78% and FRR of 14.25%.

Prashanth C. R. and K. B. Raja "et al." [3] proposed Off-line Signature Verification based on Angular Features (OSVAF). The scanned signature image was skeletonized and accurate signature area was obtained by preprocessing. In the first phase, the signature was divided into 128 blocks using the centre of signature by counting the number of black pixels and the angular feature in each block was determined to generate 128 angular features. In the second phase the signature was divided into 40 blocks and from each of the four corners of the signature it generated 40 angular features. Totally 168 angular features was considered from phase one and two to verify the signature. A threshold value was set to evaluate the difference of the original and forged signature. FAR was found to be 4.995 and FRR 8.5.

Mohammed A. Abdala& Noor AyadYousif "et al." [4] proposed a system based on two neural networks classifier and three powerful features sets(grid feature, universal,texture and global).It consisted of three stages: the first was preprocessing stage, second feature extraction stage and the last was neural network (classifiers) stage which consisted of two classifiers, the first classifier consisted of three Back Propagation Neural Network and the second classifier consisted of two Radial Basis Function Neural Network. The system recognized the signature of two BP neural network of the first classifier recognized it and the identification rate was 95.955%.

Jesus F. Vargas and MioguelA.Ferrer "et al." [5] proposedOfline Signature Verification which was Based on Pseudo-Cepstral Coefficients. This technique included from gray-scale images, its histogram was calculated and used as "spectrum" which further calculated the pseudo-cepstral coefficients. Finally, the unique minimum-phase sequence was estimated and was used as feature vector for signature verification. Here the optimal number of pseudo-coefficients was expected for best system performance and FAR and FRR awere 7.35 and 5.05 respectively.

J. B. Fasquel and M. Bruynooghe "et al." [6] proposed one offline signature verification system which combined some statistical classifiers, here the signature verification system was found to be of three steps in which the first step consisted of transforming the original signatures using the identity and using Gabor transforms, the second step was to intercorrelate the computed signature with the alike transformed signatures of the learning database and then in the third step verification of the genuineness of signatures by merging the decisions related to each transform. The proposed system also allowed the refusal of 62.4% of thefabrication used for the experiments when 99% of genuine signatures were correctly recognized. FAR and FRR were 2.56 and 1.43 respectively.

IV. RESULTS & DISCUSSION

The results are discussed over here where proposed work result for offline signature system is explained where it is used for security of identification purposes.Systems are explained with algorithms used in the process.

System includes the input where image taken as a input, as shown in figure and using the Matlab software then stored for further operations.

Load the original signature that is the first input image after that load the test signature which is the second image of the signature.

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Spanture verification Image: Signature verification Signature Verification Image: Signature Signature Verification Image: Signature Signature Verification Image: Signature Signature Image: Signature Si

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Then process these by clicking on pre-processing button where it pre-process these input images.

The common method detection where technique uses the difference of the current image to detect the region its calculation is simple and easy to implement.





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Then applying the MDA and match the signature.

Hidden	Output	
9 10		Output 3
Algorithms	10.75	
Data Division: Random (divide	rand)	
Training: Scaled Conjugate	Gradient (trainscg)	
Performance: Mean Squared Err	or (mse)	
Derivative: Default (defaulto	deriv)	
Progress		
Epoch: 0	28 iterations	1000
Time:	0:00:00	
Performance: 0.206	2.28e-07	0.00
Gradient: 0.267	7.62e-07	1.00e-06
Validation Checks: 0	0	6
Plots		
Performance	(plotperform)	
Training State	(plottrainstate)	
Error Histogram	(ploterrhist)	
Confusion	(plotconfusion)	
Receiver Operating Characteri	stic (plotroc)	
	4	
Plot Interval:	1 еро	chs

After this previous step finally display the result on clicking button which show on below image.





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In the below figure this show that the points are matched of the signature image which is taken.



If the points are matched that means the signature is matched successfilly.



Then conclude the result in FAR versus FRR against the threshold value that shows the error rate in decreasing form in the following graph shows the improvement. Here the error rate is decrease which shows the better results that error is decreased against threshold decision value.



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96.9024	Offline Signature Ver	fication Using Surf, MDA Approach.	and NN
06 0084 70	Ofensification	1	0/
30.3004	Ratio:-	96.9084	70
	Classification Ratio:-	96.9084	
	_		
		Display	

Then it shows the values of graph in bar graph also where using the parameters in that form results are obtained. Here the classification ratio in bar graph taken the number of samples where compare the values with previous work nd our algorithm which applied.



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Here calculating the classification ratio value that shows if the value is increased which means the error is decreases and noise is reduces where taking less number of sample show the less error and noise ratio decreased. In comparison with previous base paper work our algorithm value is better with less error.

Here increasing the accuracy that shows that this system having good efficiency and better performance.





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File	Edit	View	Insert	Tools	Desktop V	Vindow	Help	
		Com	pariso	n of A	ccuracy b	etwee	n Previ	ious and our algorithm
					Previous Work	Propose	d Work	

V. CONCLUSION

This research concluded that the proposed algorithm enhances the performance, better classification ratio and accuracy. Offline signature using neural network algorithm doesn't degrade the quality of signature this defines that it is also less costly and more accurate in comparison to previous results. The MDA and neural network is a very important technique and there is a real interest in this kind of applications therefore there are many methods for realizing this and providing better performances.

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