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A Novel Approach for Cursive Handwriting Detection Using Artificial Neural Network

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Abstract— ***Abstract – Human can understand the problem of recognition well by visualising but machine of today are not par with this skill of the machine or computer. But as research is going on day by day there is need of the efficient machine recognition system like cursive handwriting detection. In this paper we are dealing with the unique method to identify cursive handwriting detection using artificial neural network (ANN). We use deterministic approach for this problem using artificial neural network. Principle component analysis (PCA) is used for feature extraction of the input cursive handwritten words by 5 people of which 10 samples for each individual tested. Artificial neural network the popular artificial intelligence technique is used for recognising the wavelet component cursive handwritten words. There is also a special error function for increasing the efficiency of the system which enhances accuracy from 76% to 82% .Matlab 7.10 is used for the simulation of the object. In this paper we are dealing with the words directly instead of characters like in optical character recognition (OCR).***

Keywords— ***Artificial neural network(ANN) , MATLAB 7.10, Detection, principle component analysis (PCA), artificial neural network, optical character recognition (OCR).***

I. INTRODUCTION

Cursive handwriting detection is useful for conversion of Cursive handwriting to the plain text format. This should be very much useful for office purpose to increase the efficiency. The neural network was inspired from working of the human brain which computes Problems differently than that of a conventional digital computer. The brain acts as a highly complex, nonlinear, and parallel computer. An artificial neural network is a massively parallel-distributed processor made up of simple processing units, known as neurons which are interconnected with the weights. It resembles the human brain in two respects:

1. Knowledge is acquired by the network from its environment through learning processes.
2. Inter-neuron connection strengths, known as synaptic weights, are used to store the acquired knowledge.

The procedure used to set the target and achieve it is called learning, the function of which is to modify the weights of the network in an orderly fashion to attain a desired design objective. An artificial neural network derives its computing power through its massively parallel distributed structure and its ability to learn and therefore generalize the problem. Generalization refers to the neural network producing reasonable outputs for inputs not encountered during training (learning). These two information-processing capabilities make it possible for neural networks to solve complex problems. In practice, neural networks often cannot provide adequate solutions by working individually. Rather, they need to be integrated into consistent system engineering approach. Specifically, a complex problem of interest is decomposed into a number of relatively simple tasks which is known as feature extraction, and neural networks are assigned to a subset of the tasks that match their inherent capabilities. In this work, the neural networks method is integrated into a system approach which uses principle component analysis as feature extraction tool.

Properties of Neural Networks:-

The use of neural networks offers the following useful properties and capabilities:

1. **Nonlinearity** >> A neural network, made up of an interconnection of nonlinear neurons, is itself nonlinear. Moreover, the nonlinearity is of a special kind in the sense that it is distributed throughout the network. Our problem of cursive handwriting detection is basically of nonlinear in nature.
2. **Input-Output Mapping** >> A popular paradigm of learning called learning with a teacher or supervised learning involves modification of the weights of a neural network by applying a set of labeled training samples or task examples. Each example consists of a unique input signal and a corresponding desired response. The network learns from the examples by constructing an input-output mapping for the problem. In this lm training algorithm is used.
3. **Adaptability** >> Neural networks have a built-in capability to adapt their weights to changes in the surrounding environment. In particular, a neural network trained to operate in a specific environment can be easily retrained to

deal with minor changes in the operating environmental conditions. Moreover, when it is operating in a non-stationary environment, a neural network can be designed to change its weights in real time.

4. **Fault tolerance** >> A neural network has the potential to be inherently fault tolerant in the Sense that its performance degrades gracefully under missing or erroneous data. The reason is that the information is distributed in the network; the errors must be extensive before catastrophic failure occurs. These are the properties that are most desirable for solving the problems at hand.

Principal component analysis: - It is the widely used feature extraction technique in digital image processing. PCA determines the highest Eigen value known as the principal eigen values which are obtain from the covariance matrix of the input image matrix.

II. SOFTWARE FRAMEWORK DEVELOPMENT

For the implementation of the software framework we use Multilayer feed forward network. In this type of artificial neural network error between calculated output and target output is back propagated and it is repeated until that error is minimized.

<u>Algorithm for Back Propagation Neural Network (BPNN) Technique</u>:-

1. Select No. of Input, Hidden and Output Nodes for the desired problem.
2. Scan & Normalize the Inputs (Ii), by feature extraction and Outputs (Ti) for all Samples.
3. Initialize the weight matrices [V],[W] to randomly selected values.
4. By using linear activation function the output of the input layer may be evaluated as

Compute the inputs to hidden layer by multiplying corresponding weights of synapses as

$$[\mathrm{O}_i]_{(N\times 1)} = [\mathrm{I}_i]_{(N\times 1)}$$

5. Let the hidden layer units evaluate the output using the sigmoid function as

$$[\mathrm{I}_H]_{(NH\times 1)} = [\mathrm{V}]^{\mathrm{T}}_{(NH\times N)} \times [\mathrm{O}_i]_{(N\times 1)}$$

7. Compute the inputs to the output layer by multiplying corresponding weights of synapses as

$$[\mathrm{I}_O]_{(NO\times 1)} = [\mathrm{W}]^{\mathrm{T}}_{(NO\times NH)} \times [\mathrm{O}_H]_{(NH\times 1)}$$

$$[\mathrm{O}_O]_{(NO\times 1)} = \begin{bmatrix} \cdots\cdots\cdots \\ \cdots\cdots\cdots \\ \dfrac{1}{\left(1+e^{(-I_{oj})}\right)} \\ \cdots\cdots\cdots \\ \cdots\cdots\cdots \end{bmatrix}_{(NO\times 1)}$$

8. Let the output layer units evaluate the output using sigmoidal function as

$$[\mathrm{O}_O]_{(NO\times 1)} = \begin{bmatrix} \cdots\cdots\cdots \\ \cdots\cdots\cdots \\ \dfrac{1}{\left(1+e^{(-I_{oj})}\right)} \\ \cdots\cdots\cdots \\ \cdots\cdots\cdots \end{bmatrix}_{(NO\times 1)}$$

The above is the network output.

9. Calculate the error and the difference between the network output and the desired output as for the i^{th} training set as

$$E^P = \frac{\sqrt{\left(\sum (T_j - O_{oj})^2\right)}}{NO}$$

10. Find [d] as

$$[d]_{(NO\times 1)} = \begin{bmatrix} \cdots\cdots\cdots \\ \cdots\cdots\cdots \\ (T_k - O_{Ok}) \times O_{Ok} \times (1 - O_{Ok}) \\ \cdots\cdots\cdots \\ \cdots\cdots\cdots \end{bmatrix}_{(NO\times 1)}$$

11. Find [Y] matrix as

$$[Y]_{(NH\times NO)} = [O_H]_{(NH\times 1)} \times [d]_{(1\times NO)} .$$

12. Find

$$[\Delta W]^{t+1}_{(NH\times NO)} = \alpha_z \cdot [\Delta W]^{t}_{(NH\times NO)} + \lambda_z \cdot [Y]_{(NH\times NO)}$$

Where λ_z = Learning rate, α_z = Momentum rate.

13. Find

$$[e]_{(NH\times 1)} = [W]_{(NH\times NO)} \times [d]_{(NO\times 1)}$$

$$[d^*]_{(NH\times 1)} = \begin{bmatrix} \cdots\cdots\cdots \\ \cdots\cdots\cdots \\ (e_i) \times (O_{Hk}) \times (1 - O_{Hk}) \\ \cdots\cdots\cdots \\ \cdots\cdots\cdots \end{bmatrix}_{(NH\times 1)}$$

14. Find [X] matrix as

$$[X]_{(N\times NH)} = [O_i]_{(N\times 1)} \times [d^*]_{(1\times NH)}$$

15. Find

$$[\Delta V]^{t+1}_{(N\times NH)} = \alpha_z \cdot [\Delta V]^{t}_{(N\times NH)} + \lambda_z \cdot [X]_{(N\times NH)}$$

16. Find

$$[V]^{t+1}_{(N\times NH)} = [V]^{t}_{(N\times NH)} + [\Delta V]^{t+1}_{(N\times NH)}$$

$$[W]^{t+1}_{(NH\times NO)} = [W]^{t}_{(NH\times NO)} + [\Delta W]^{t+1}_{(NH\times NO)}$$

17. Find error rate as

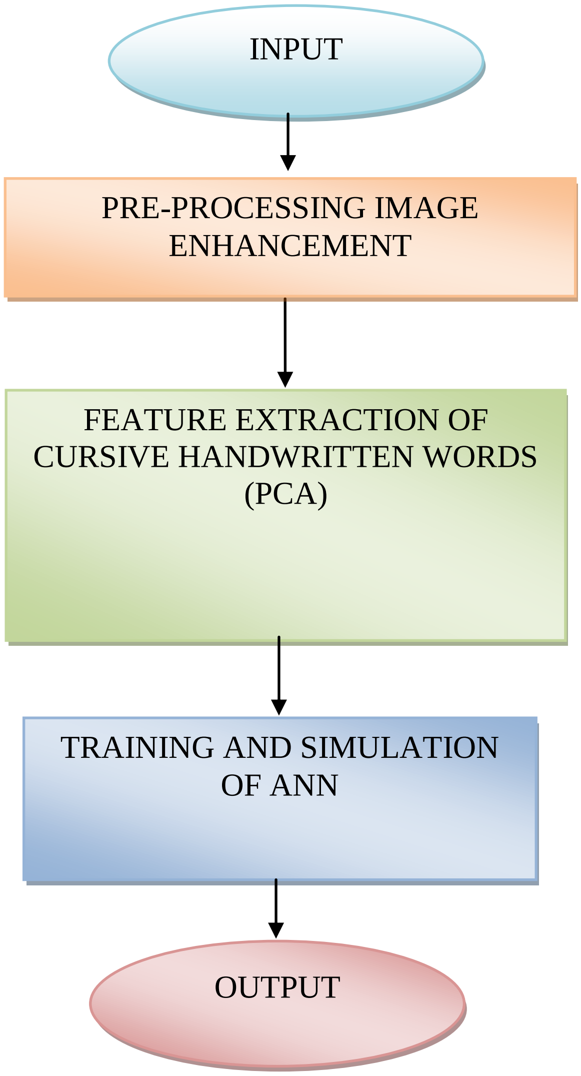
$$\text{Error rate} = \frac{\sum E^P}{NS}$$

18. Repeat steps 4-16 until the convergence in the error rate is less than the tolerance value.

III METHODOLOGY

Optical character recognition (OCR) is earlier is widely accepted technique but it has very big limitation in extracting cursive handwritten characters as there are lot of cursive styles available. So, to overcome this drawback instead of using the characters we in this paper deal in the word formats itself which makes this problem of cursive handwriting detection possible. Due to this novel approach we get very good efficiency in the results.

The flowchart for discussed algorithm is as below:



The algorithm for implementation of the work is as follows:

1. Image acquisition from digital camera or web camera of high resolution.
2. Pre-processing of the acquired image by image enhancement algorithms.
3. Image resize into 100x100 common resolutions for uniformity.
4. Feature extraction of the input image using Principal component analysis (PCA).
5. Principal Eigen values detection and get parameters.
6. Extracted features are given input to the artificial neural network for training.
7. Trained artificial neural network is then simulating to obtain the results.

IV RESULT & DISCUSSION

In this section first we discuss about the optimal neural network design parameters for minimal weight adjustments iteration. Then we discuss about implementation and results obtain.

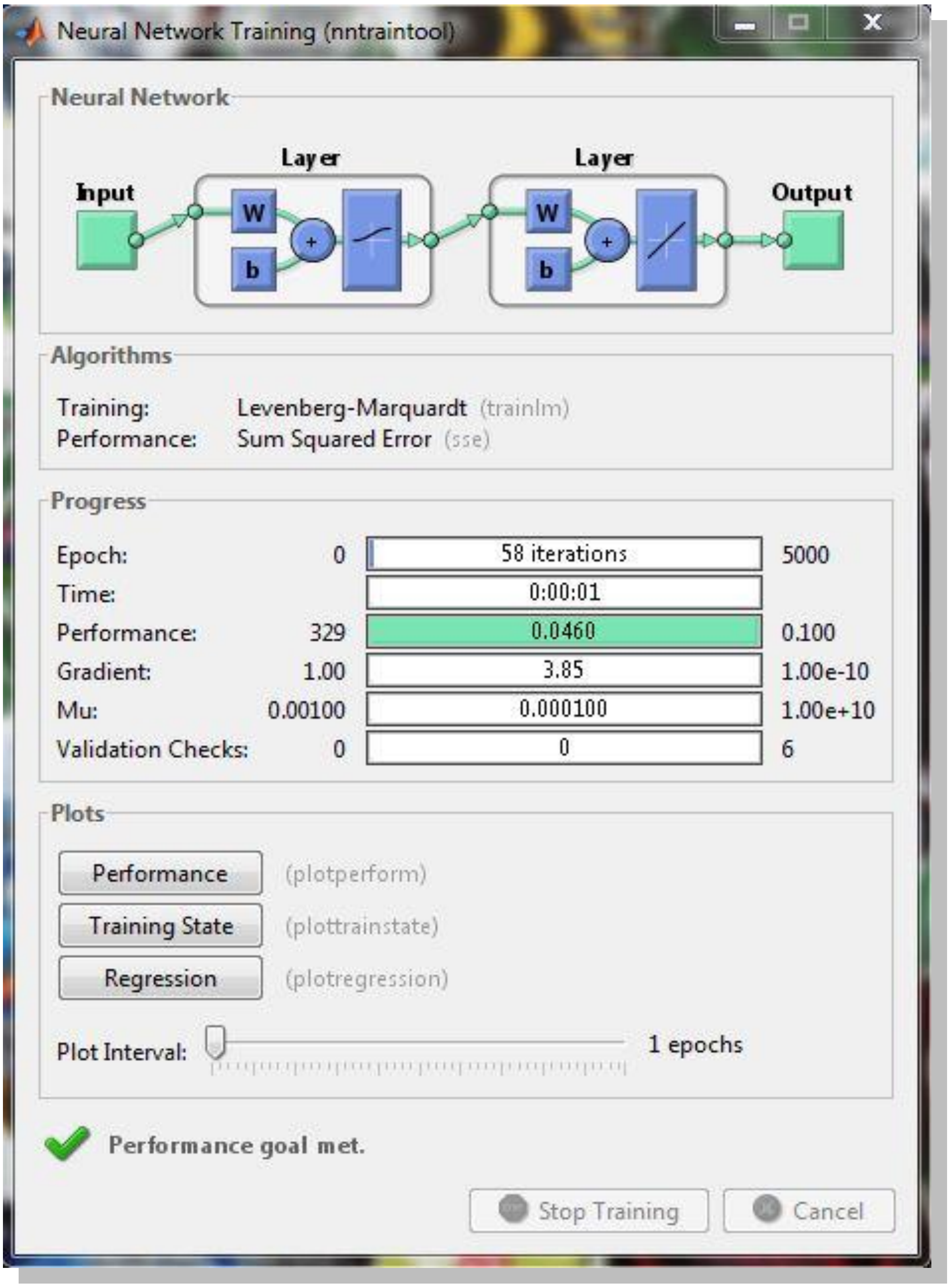


Fig.1 Artificial neural network training parameters

Fig. 1 shows the optimal parameters setting we have used to minimise the training iterations .The performance goal is achieves and with error reducing new add-on function we achieved this optimised result.

The parameters in setting in MATLAB code are written as below:

```
S1 = 5;
S2 = 1;
Net = newff (minmax (annINPUTpattern),[S1 S2],{'tansig' 'purelin'},'trainlm');

% net = newff (minmax (annINPUTpattern), [S1 S2], {'logsig' 'logsig'},'trainlm');


%    TRAINING THE NETWORK

net.performFcn = 'sse';        % Mean-Squared Error performance function
net.trainParam.goal = 0.01;     % Sum-squared error goal.
net.trainParam.show = 20;       % Frequency of progress displays (in epochs).
net.trainParam.epochs = 5000;   % Maximum number of epochs to train.
net.trainParam.mc = 0.95;       % Momentum constant.
```

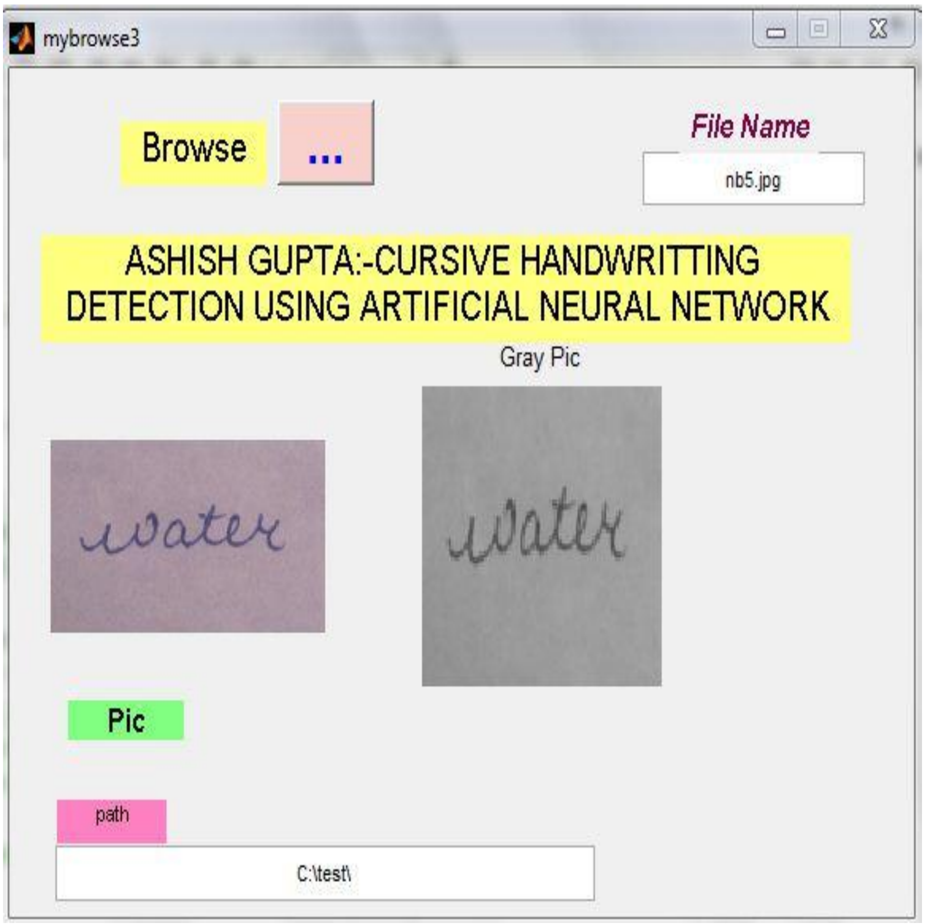


Fig.2 Input cursive handwriting image with GUI build in MATLAB.

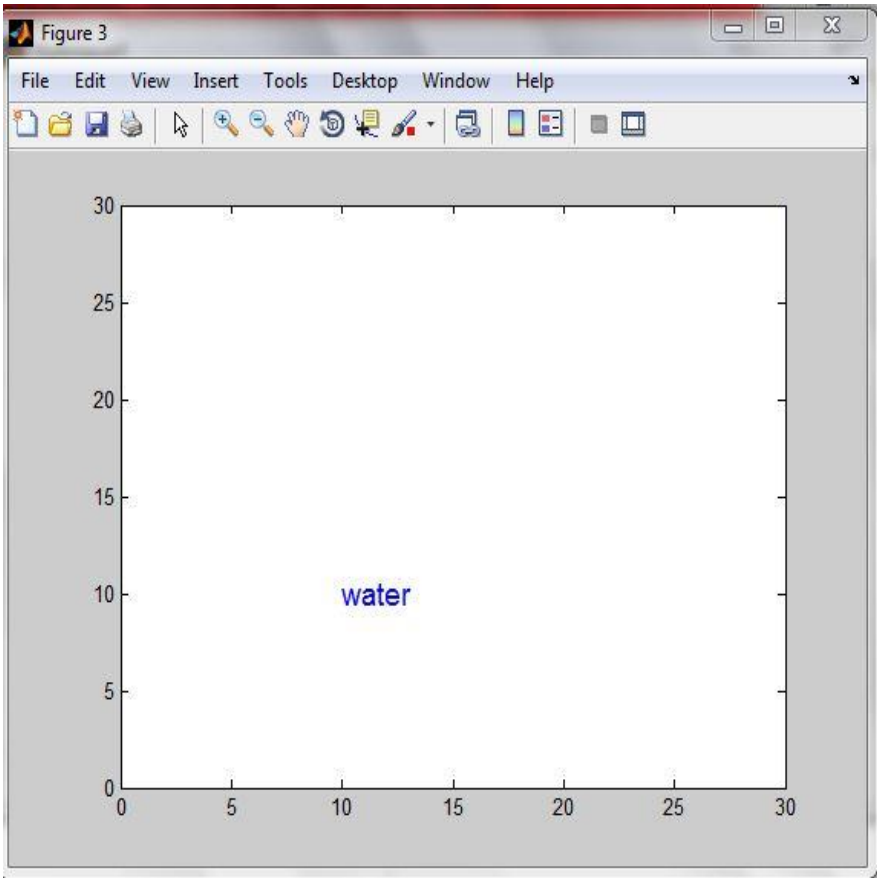


Fig.3 Output cursive handwriting image with output plain text in MATLAB

Fig.2 and 3 shows the result for one of our samples where plain text water is extracted from cursive handwriting image of water.

V. CONCLUSIONS

The performance of the given artificial neural network method is tested with 50 samples. The results were given in detailed about the network, node properties and training periods. The simulation results for each test data gives good result with less convergence time. Principal component analysis is proved to be very efficient feature extraction function. The Error rate during each iteration is plotted showing the convergence characteristics of the proposed method. The time of training, testing shows how fast the detection process is over. For further study of this problem wavelet transform can be use as feature extraction technique for comparative study with the principal component analysis.

There is also a special error function for increasing the efficiency of the system which enhances accuracy from 76% to 82%.

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