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HAND WRITING RECOGNITION SYSTEM FOR FRAUD DETECTION USING DEEP NEURAL NETWORK

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ABSTRACT

Financial institutions are faced with the menace of fraud committed by criminals who forge the signatures of their customers on bank documents. This work is on the development of a handwritten text recognition system using deep neural network. Offline handwritten text recognition technique was used in this work. The code for the model was written in Keras, a backend for TensorFlow used typically as an application programmable interface (API) for building deep learning model. The system was trained using the handwritten text of one of the authors. The performance of the training model was improved by changing the learning rate, the dropout threshold, the batch size, and the number of iterations (hyper parameter tuning). The accuracy of the system in predicting handwritten text was found to be 0.9806 i.e. 98.06%. An application was developed for the fraud detection. The system was evaluated using a written text it was not trained with and it was able to detect it as a fraud.

KEYWORDS: Handwritten text, Recognition, Deep neural network, Fraud detection, Training model.

1.1 INTRODUCTION

Fraud is a menace that deserves serious attention and immediate action. Effective fraud prevention, detection and response mechanism, therefore, play a key role in safeguarding organizations' interests against negative impacts. In developing countries like Nigeria, bank cheques are authenticated manually by physically cross matching the signature of the account owner on the cheque presented with what the already have in the bank's database. This has led to a lot of fraud due to human errors in recognizing the correct signature of the account owner. Recognition of handwritten characters is significant in fraud detection especially where some form of written authentication is required like financial transactions. To aid character recognition, machine learning mechanisms like neural networks is important.

According to (Alpaydin, 2014), machine learning is programming computers to optimize a performance criterion using example data or past experience. (Expert Systems Team, 2020) defines it as an application of artificial intelligence that provides systems the ability to automatically learn and improve from experience without being explicitly programmed. Neural networks are machine learning models used to simulate the learning process that occurs in human neural system. Being one of the most powerful learning models, they are useful in automation of tasks where the decision of a human being takes too long, or is imprecise. A neural network can be very fast at delivering results and may detect connections between seen instances of data that human cannot see. The main aim of this work is to design a system for handwriting recognition using neural network that can effectively recognize a particular handwritten text. This will serve as a better security measure and fraud detection mechanism during the processing of bank cheques. It will also help to authenticate students' examination script when impersonation is suspected.

2.0 Literature Review

The authors in (Banerjee & Bhandarkar, 2015) used feed forward back propagation algorithm to classify characters. Their system was able to identify numerical digits and alphabets. The handwritten sentence recognition system developed by (Parwej, 2013) recognizes continuous English sentence through mouse-based gestures in real time using the traditional back propagation algorithm for self supervised neural network. The work, (Zheru, & Hong, 1995) applied fuzzy logic in handwritten numeral recognition. The work (Pradeep et al, 2011), was on the development of an offline handwritten alphabetical character recognition system using multi-layer feed forward neural network. The authors introduced the use of diagonal based feature extraction for the extraction of the features of the handwritten alphabet which gave higher accuracy than the conventional horizontal and vertical methods. Alavipour & Broumandnia (2014) proposed a Persian character recognition system using independent orthogonal moment as the feature extraction technique. Pseudo-zernike-mellin moment was used to extract feature vector from Persian characters. A multi-resolution technique using discrete wavelet transforms (DWT) and Euclidean distance metric (EDM) was used in (Dileep et al, 2012) for handwritten character recognition. They classified characters were into 26 pattern classes based on appropriate properties. The proposed method provides good recognition, accuracy of 90% for handwritten characters even with fewer samples. Gunjansingh & Sushmalehri (2012) proposed an offline handwritten Hindi character recognition system using neural network with an accuracy of 93%.

Most of the existing systems focused on the digitization of handwritten documents for efficient processing and storage. Most of the reviewed works were not application based.

2.1 Handwritten Character Recognition

Handwritten character recognition takes handwritten input from sources such as touch screens and paper documents to be interpreted by a computer. It can be online or offline. This work implemented the offline handwritten character recognition system which works with scanned documents or images. The written text image may be sensed as offline from a piece of paper by intelligent word recognition. For a pen-based computer screen surface, the movements of the pen tip may be sensed online and the recognition task is easier (Syahfinash, 2016). Over the years, machine learning techniques like neural networks have been used in character recognition. Neural networks can also be applied in natural language processing, image to learn things all by itself, recognize patterns, and make decisions just the way the man does. One of the benefits of using neural network is the network learning. Network learning provides efficient ability in recognition. Other advantages of neural network include adaptive learning, self organization, real time operation and fault tolerance.

2.2 Phases of Handwriting Recognition System

According to Zheng & Zhu (2006), there are five major steps in offline handwriting recognition system as shown in figure 1.

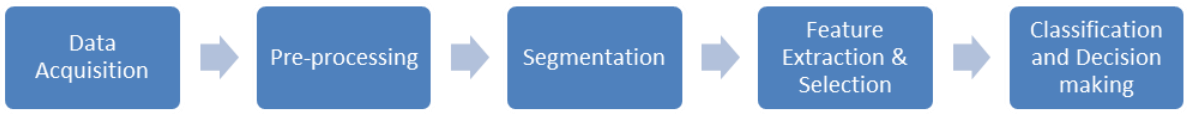

Figure 1: Steps in Offline Handwriting Recognition.

i. **Image Acquisition:** The offline recognition system requires an optically scanned image, as an input image. This step involves the capturing of the handwritten document using a digital camera or scanner. The image is then converted to image file formats like bitmap or jpeg through a process called digitization. To acquire the handwriting of a person, a paragraph of text is printed on top of a form. Then the writer is asked to write down the sentences on the empty area of the form in his or her everyday handwriting.

ii. **Preprocessing:** Noise Removal, Binarization, Morphological Operations and Size Normalization are carried out on the image to normalize input and remove variations like noise etc., or in another word discard irrelevant information in the put data that can negatively affect the recognition.

iii. **Segmentation:** Segmentation is the process that isolates character from handwritten character image. Segmentation is divided into explicit and implicit segmentation. In implicit segmentation, words are predicted directly without segmenting it as individual letters where as in explicit segmentation, the word is segmented into individual character. Segmentation is carried out using threshold based, edge based, region based, clustering techniques etc.

iv. **Feature Extraction:** this highlights important information for the recognition model. Data needed for this stage may include pen pressure, velocity or the changes of writing direction. It removes the misperception regarding characters that are near identically shaped.

v. **Classification:** in classification, labels are assigned to instances of data. The label is a simple number that identifies the class for a particular instance. The most commonly seen classifiers are neural networks, support vectors machine, and nearest neighbor classifier. In this work convolution neural network was used.

2.3 Post- Processing

In post-processing words returned from a recognizer are corrected. A dictionary consisting of frequent words is used to generate the closest string to the one returned by the recognizer. Post-processing increase the recognition accuracy considerably.

2.4 Training

During training, rules of recognition, templates, or statistical and network model training are generated. The learning can be generic in which case the system learns to recognize writing of a wide sample of the society and users are made to adapt to the machine rather than the machine adapting to their writing. On the other hand, the machine is trained to have the capability to perform well on a certain word or character in terms of recognition. This training could usually be in batch mode or online.

3.0 METHODOLOGY

To classify each handwritten paper by its writer is a challenging problem due to variations in individual writing styles. The traditional approach to solving this problem is to extract language dependent features like curvature of different letters, spacing between letters etc. and then use any of the classifiers e.g. support vector machine (SVM) to distinguish between writers.

In this work, deep learning based approach was used to identify these features by passing small patches of handwritten images through a convolution neural network (CNN) for training. This work implemented offline handwriting recognition technique. The block diagram of the proposed system is shown in figure 2.

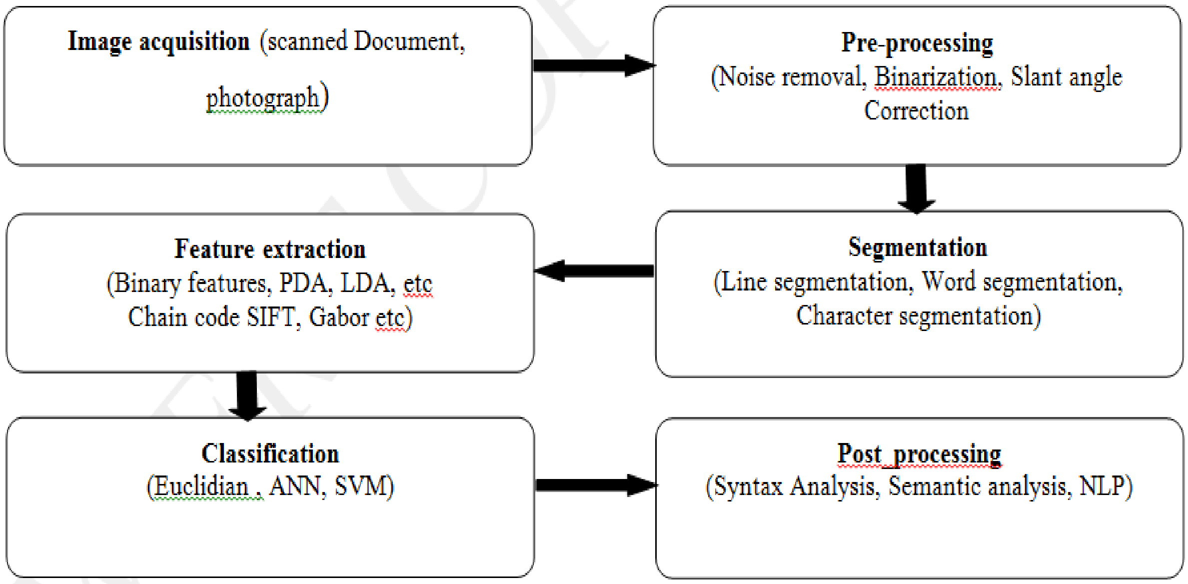

Figure 2: Block Diagram of Handwriting Recognition System.

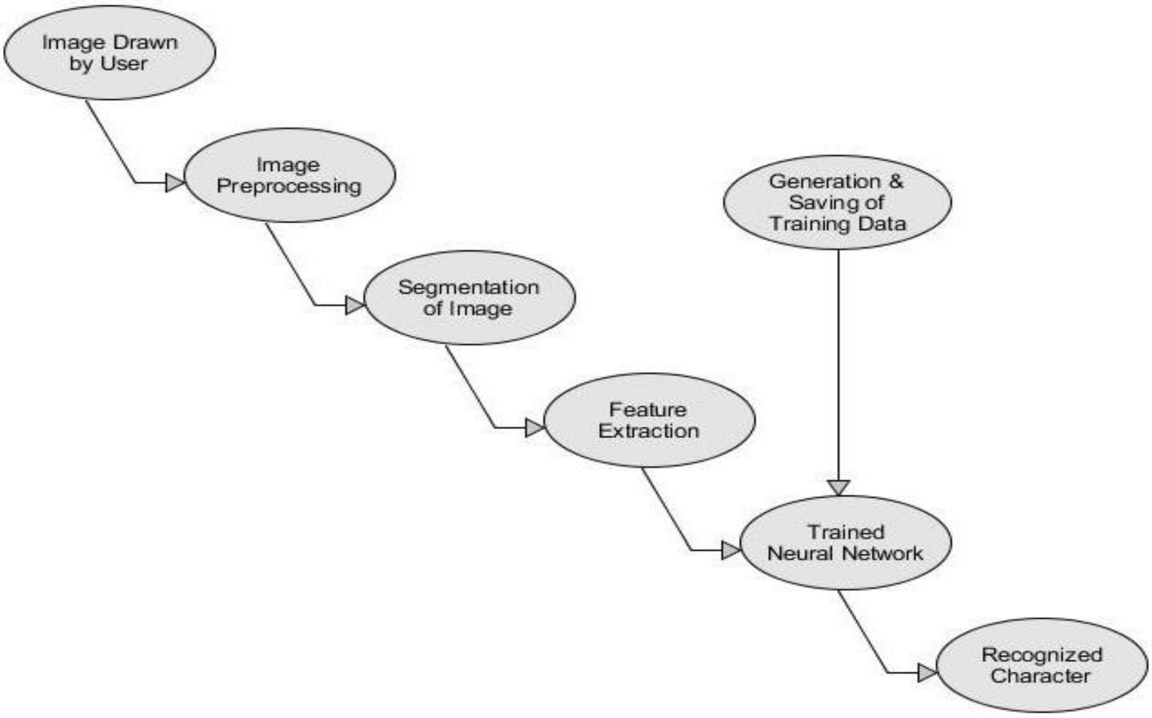

Figure 3: Control Flow diagram for Handwriting Recognition System.

The control flow diagram for the system is shown in fig.3.

3.3 Building a Neural Network

Hand writing recognition was implemented by building a convolution neural network (CNN) using tensorflow backend, an open-source Python library developed by the Google Brain labs for deep learning research. Hand written text image samples were used to train the neural network to enable it recognize the writings. The steps in the building the neural network includes the following:

i. **Configuration:** Some dependencies were installed and a work space was created for file storage. Python 3 virtual environment was used to manage the dependencies. The virtual environment was then set up after which libraries were installed.

ii. **Importing the Dataset:** This is the second stage. The datasets were collected from written sentences by the authors as shown in fig.4 and stored in Google drive.

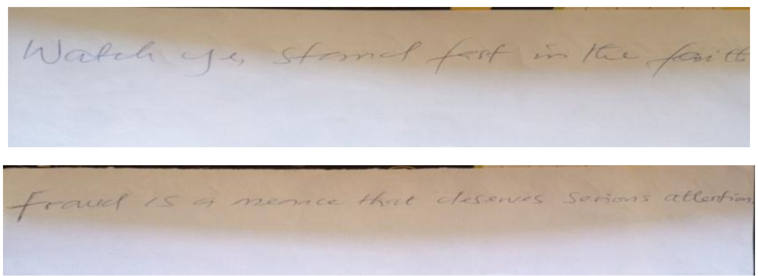

Figure 4: Sample handwritten texts.

No modifications were made on the dataset since neural networks do not require much preprocessing of raw data rather small patches of the text were used. A python program to work on the data set was then created. The data sets were divided into three groups – for training, validation and testing.

iii. The Neural Network Architecture: The architecture of the neural network refers to elements such as the number of layers in the network, the number of units in each layer, and how the units are connected between layers as shown in fig.5. The hyper parameters were defined since they were set initially and are meant to remain constant throughout the process unlike the parameters that are updated during the training. The learning rate of the network depicts how much the parameters will adjust at each step of the learning process. Larger learning rates means faster convergence rate but it also have the potential to overshoot the optimal values as they are updated.

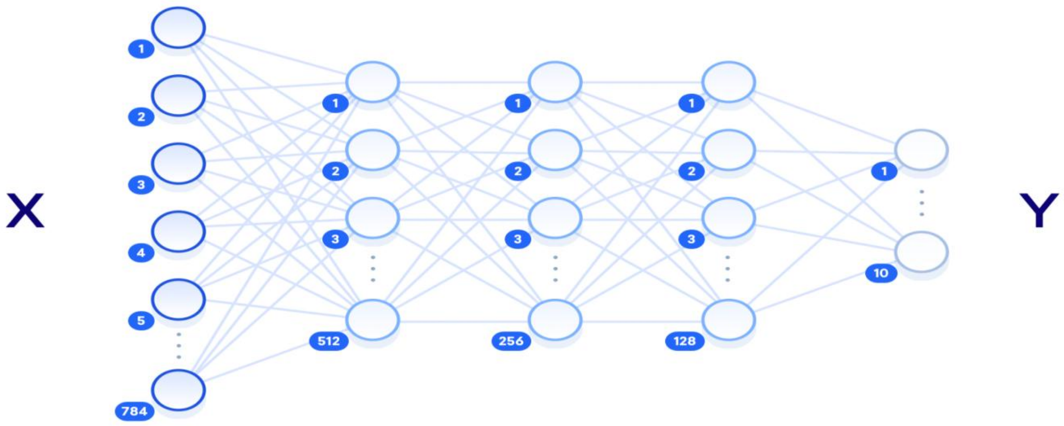

Figure 5: Visualization of the neural network architecture.

The code for the model was written in Keras, a backend for TensorFlow used as typically an API for building deep learning model. The final model comprises of a one (1) layered Convolution Network followed by three (3) sub-sampling or max_pooling layer after every convolution layer, this in turn was connected to three (3) fully connected networks (dense neural network layer). Between each of these layers is a dropout layer (except between the pooling layers) to typically avoid model over fitting. The input images are fed as a 64 * 64 matrix to the deep network. After every Convolution layer, a batch normalizer was used to ensure that the gradients do not vanish very quickly resulting in saturation.

iv. **Training and Testing**: at this stage, the training dataset is fed through the graph and the loss function is optimized. The network updates the parameters whenever it iterates through a batch of training images in order to reduce loss leading to higher accuracy in the prediction of the written text. The test dataset is then run through the trained graph while keeping track of the number of images predicted correctly. For loss calculation, both the ground truth text and the matrix are fed to the operation. In this session the network is fed with training examples, and once trained, the graph is also feed with new test examples to determine the accuracy of the model. Training is used for the optimization of loss function. The output of the training stage is a model for each writer that is an expert on the handwriting style of that particular training. The process involves four steps which are repeated for a set number of iterations:

- Forward propagation of values through the network
- Computation of loss
- Backward propagation of values through the network
- Parameter updates

After 100 iterations of each training step in which a mini-batch of images were fed through the network, the loss and accuracy of that batch is printed out. At this stage Note that we should not be expecting a decreasing loss and increasing accuracy here, as the values are per batch, not for the entire model. To speed up the training process, mini-batches of images were used. At the end of the training, the session is run on the test images. A keep_prob dropout rate of 1.0 was used o ensure all units are active in the testing process.

v. **Analysis:** At this stage, the system's accuracy in predicting handwritten text is tested. The Accuracy on test set was 0.9806 i.e. 98.06%. The accuracy of the system was improved by changing the learning rate, the dropout threshold, the batch size, and the number of iterations.

3.4 Training the Model

The next part of this process is to train the model that has been compiled with Keras to learn the needed parameters. This will use a gradient descent approach that is based on back propagation to help the model learn through optimization of the cost functions after every training step. The model will also train on 17053 samples and validate on 1064 samples.

4.0 RESULTS AND DISCUSSION

The metrics of the model training is shown in fig.6. It shows the performance of the model over time. The figure shows that the training was poor as the model's training and validation barely increased while their losses barely decreased over training time. The model is improved further through hyper parameter tuning to extract more features for learning as shown in fig.7. it can also be achieved through the addition of more convolution layers. This improvement will take a longer training time because of the increase in learning parameters.

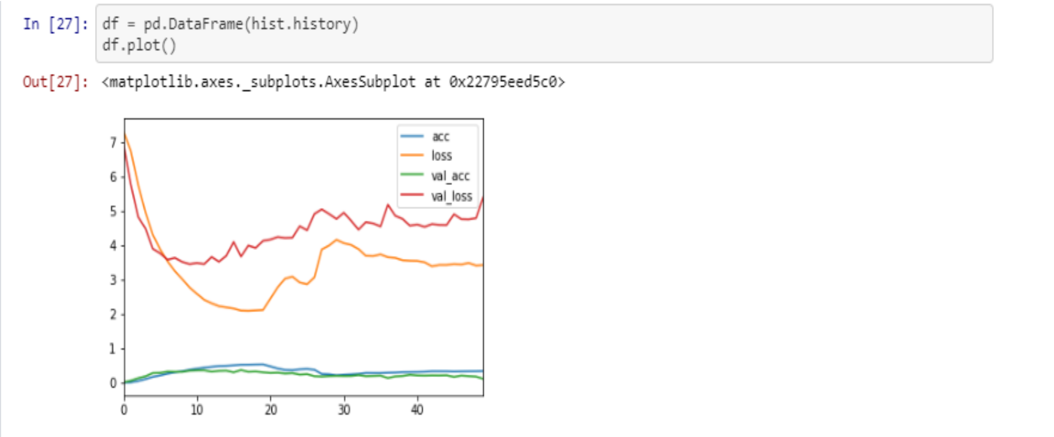

Figure 6: Performance of the Training Model.

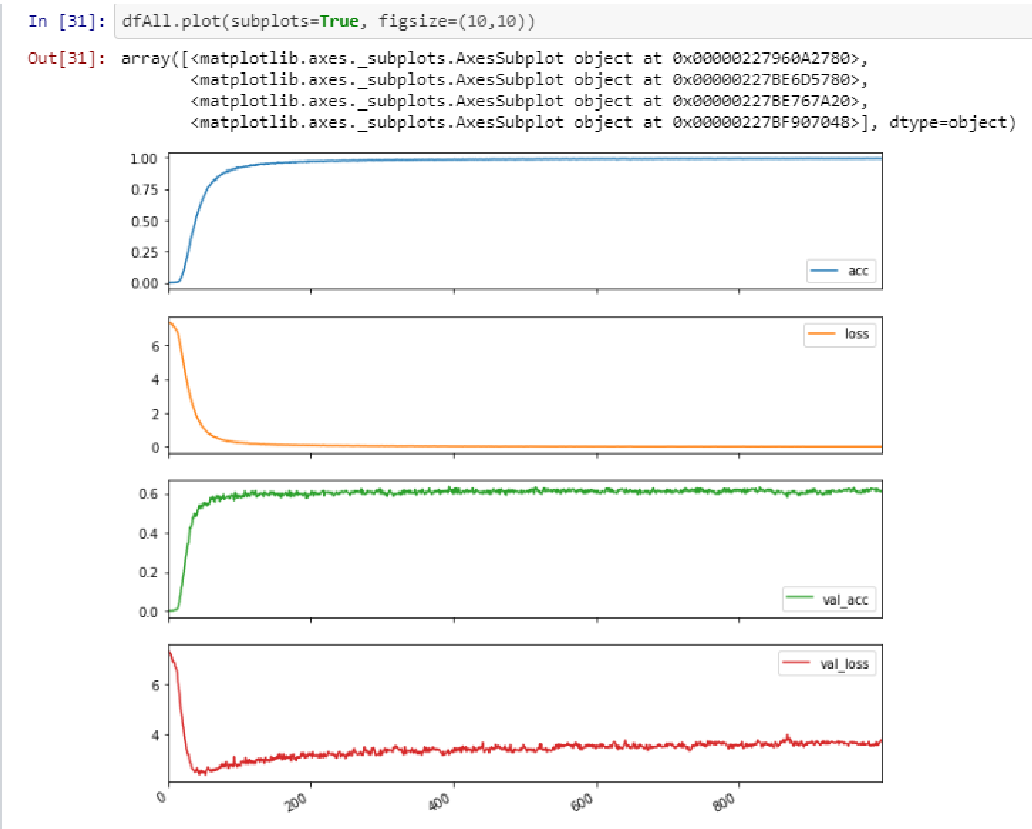

Figure 7: Improved performance of model using hyper parameter tuning.

4.1. Model Testing and Evaluation

The model predicts different classes of writers as a probabilistic score between 0 and 1. Towards 0 represents a low confidence score and towards 1 represents a high confidence score. The model was evaluated by passing a test set it was not trained with to it and the prediction value was zero (0) showing low confidence. Therefore this model is able to detect when a wrong signature was signed on a bank document.

5.0 CONCLUSION

The system developed in this work focused only on offline handwriting recognition and how it can be utilize as fraud detection mechanism to authenticate an individual writing on bank cheques and examination answer sheet of a student. This system was developed using multiple deep learning techniques. It interprets data from visual and movement oriented perspectives. The visual perspective is realized as a convolution neural network (CNN) and the movement perspective as a Long Short Term Memory (LSTM). Both perspectives were combined by a Deep Neural Network (DNN).

REFERENCES

1. Alavipour F. & Broumandnia A. Persian character recognition using new hybridization of independent orthogonal moments, *International journal of computational science and information technology (IJCSITY)*, 2014; *2(2).*
2. Alpaydin E., Introduction to Machine Learning, 3rd Edition, The MIT Press Cambridge, Massachusetts London, England, 2014.
3. Barnejee S., & Bhandarkar A. Handwritten character recognition training a simple NN for classification using MATLAB. *International journal of science and research (IJSR) ISSN (online),* 2015; *2319-7064.*
4. Dileep, K. P., Tanmoy, S., Sushu, K.Y., & Manoj K.S., Handwritten character recognition using multi-resolution technique and Euclidean Distance metric. *Journal of signal and information processing, 2012; 3: 208-214. doi: 10.4236 /jsip.202. 32028 (http//www.scirp.org/journal/jsip)*
5. Expert Systems Team, 2020) What is Machine Learning? A definition, https://expertsystems.com/machine-learning-definition/
6. Gunjansingh, P. & Sushmalehri, N. Recognition of handwritten Hindi characters using back propagation neural network. *International journal of computer science and information technology ISSN: 0975-9646,* 2012; *3(4): 4892-4895.*

7. Parwej, F. English recognition using ANN through mouse based Gestures; *International journal of computer application (0975-8887)*, 2013; *61- No.17.*
8. Pradeep, J., Srinivasan, E., & Himavathi, S. Diagonal Based feature extraction for handwritten alphabetic recognition system using neural network, *International journal of computer science and information technology (IJCSIT),* 2011; *3(1).*
9. Syahfinash B.S. Character Recognition using, *Fakulti Kejuruteraan Elektronikdan Kejuruteraan Komputer Universiti Teknikal Malaysia Melaka*, 2016.
10. Zheng, J. & Zhu, G. “On-line Handwriting Signature Recognition Based onWavelet Energy Feature Matching”, *Proceedings of the 6th World Congress onIntelligent Control and Automation*, 2006; 9885-9888,
11. Zheru, C. & Hong, Y. Handwritten numeral recognition using a small number of fuzzy rules with optimized defuzzification parameters. *Neural network,* 1995; *8(5): 821-827.*