2020 International Conference on Computation, Automation and Knowledge Management (ICCAKM)
Amity University

# A Comparative Study of Handwriting Recognition Techniques

Prem Chand Vashist
*Department of Information Technology*
*G. L. Bajaj Institute of Technology and Management*
Greater Noida, India
pcvashist@gmail.com

Anmol Pandey
*Department of Information Technology*
*G. L. Bajaj Institute of Technology and Management*
Greater Noida, India
anmolpandey71297@gmail.com

Ashish Tripathi
*Department of Information Technology*
*G. L. Bajaj Institute of Technology and Management*
Greater Noida, India
ashish.mnnit44@gmail.com

***Abstract*— A computer's capacity is to obtain and understand the intelligible, handwritten information from sources, such as paper files, images, touch screens and other appliances is a handwritten word recognition (HWR) also recognized as handwritten text recognition (HTR). This initiative seeks to rank a single written term, to allow a digital translation of handwritten text. Handwriting recognition has been an active field of studies for over four centuries, but some of the key issues have not yet been resolved. This survey paper focuses on discussing the issues related to handwriting recognition and offers alternatives to the significant issues of handwriting recognition by means of machine learning methods. Also, this helps to list and explain the different approaches in the field of handwriting recognition, such as off-line and on-line handwriting. The paper is intended to explain various ways to resolve the issue of handwriting recognition.**

**Keywords—*handwritten recognition, handwritten text recognition,***

## I. Introduction

Handwriting is a way to help and develop finite biological memory by creating surface graphic artificial marks representing symbols in each language [1]. Handwriting is aimed at communicating with others through a prevalent knowledge of signs, called characters and letters, in languages [2]. Handwriting is intended to interact with others in the prevalent knowledge of language signs, recognized as characters and letters. Although, there are plenty of instruments available to write technologies, many individuals choose to traditionally take notes: with pen and paper. But the Handwriting text is inconvenient. Physical papers can hardly be stored, accessed, searched and shared effectively with others. A great deal of important knowledge gets lost or doesn't get examined because documents are never digitally transferred. Therefore this issue has been chosen to address its significance, since we think that managing digital text considerably more easily than handling written texts helps individuals access, search and exchange documents more efficiently and allows users to still use their preferred technique of writing. However, the primitive technique of communication, handwriting, and significant and easy data recording will continue to play a leading position until the start of a paper free society.

The representatives in contemporary communication methodologies are examples of Personal Digital Assistants (PDA), Electronic Pen (E-Pen), Electronic E-Mail (Email), Handy, Computers etc [3]. Over the past couple of decades, efforts have succeeded greatly in digitizing machine printed, the OCR (Optical Character Conversion). Handwriting recognition techniques differ in two ways: online or vibrant and offline or static according to the methods used by handwritten information entering identification schemes [4]. Dynamic or mobile types are frequently used to digitize the movement paths of a pen by using a unique pen on an electronic fluid crystal screen floor with a sensor. The paths of movements, texts, are collected in a timely way by two dimensional co-ordinates. However, an over-line and static scanner is used to scan and digitize a paper containing handwritten data and only saves two-dimensional data [5].

The objective of this initiative is to further investigate the assignment of handwritten text classification and the digital transmission of handwritten texts. We have been challenged in this initiative to classify a picture of any manuscripts that could be in cursive or block writing. This paper can be coupled with algorithms that edit term pictures into a specified line photograph, which in turn can be coupled with algorithms to form the line pictures in a specified manuscript picture.

The paper is organised further into four sections. Section II, provides the detail view of different types of handwriting recognition techniques such as Off-Line and On-Line handwriting recognition. Section III, discusses about the different methods for handwriting recognition. A comparative study of the handwriting recognition techniques is shown in section IV, which includes pros and cons of each technique in form of comparison table. Finally the paper is concluded in section V.

## II. Types of Handwriting Recognition

### *A. Off-Line handwriting Recognition*

Offline handwriting recognition (OHR) means that the text of a picture is automatically converted to the letters that can be used in computers and texting apps [6]. The information acquired by the type is considered to be a static handwriting depiction. The identification of offline handwriting is relatively hard, because there are different styles for distinct individuals [7]. And Optical Character Recognition (OCR) engines have been mainly focused on printed and Intelligent Character Recognition (ICR) machines for hand printed (written in capital letters) texts. There are broadly two types of techniques come under this, which are as follows:



978-1-7281-0666-3/20/$31.00©2020IEEE

### a. Traditional Techniques

This contains two techniques such as character extraction and character recognition which are discussed below:

(a) Character Extraction: Extract the individual characters contained in the scanned picture. In this move, though, there are a few prevalent flaws. The most frequent is when linked characters are transferred to both characters as one sub-image. In the identification phase, this creates a significant issue [8].

(b) Character Recognition: After removal of individual characters, recognition engine is used to identify the corresponding computer character [9]. Several distinct methods are now accessible. Two of them mentioned below [10]:

- Neural Networks

Each neural network uniquely learns the properties that differentiate training images, from an initial image training set. However, they can be inaccurate if they learn properties that are not important in the target data.

- Feature Extraction

This strategy provides the recognizer a more controlled understanding of the characteristics as programmers determine manually how significant they feel. Some example properties might be: aspect ratio, invariant moments, percent of pixels above horizontal half point, holes and concave arcs, percent of pixels to right of vertical half point, number of strokes, extrema, average distance from image centre, end points and junction points, is reflected y-axis, and is reflected x-axis [10].

However, every scheme that uses this strategy needs much more design time than a neural networks because characteristics are not automatically taught.

### b. Modern Techniques

Where traditional methods are concerned with segmenting individual characters for recognition, contemporary methods are concerned with acknowledging all the characters in a segmented row. They concentrate especially on machine learning methods that can learn visual characteristics [11-12].

### B. On-line Handwriting Recognition

In the on-line handwriting recognition, the automatic conversion of text is required as it is written on a special digitizer where a sensor collects pen tip motion and pen-up / pen-down commute times [6]. This type of data is called digital ink and can be seen as a dynamic handwriting representation. Generally, the elements of an online handwriting identification interface include:

- Style for the user to write with.
- A flexible touch surface that can be built into the output screens or adjacent to them.
- A software application, that interprets stylus motions across the written surface.

## III. Methods Used for Handwriting Recognition

There are different methods have been available in the literature for handwriting recognition, which are as follows:

### A. Handwritten Recognition using SVM, KNN and Neural Networks

Python, openCV and sklearn are used to identify and read the data set for this method. For training and classification assessment, MNIST results [13] are used. MNIST problem has a data set on handwritten electronic classification problem for evaluation of machine learning models. In this dataset, each image has a square size of 28 by 28 (748 pixels total). For handwritten recognition, three classification algorithms such as support vector machine (SVM) [14], k-nearest neighbor (KNN) [15] and Multi-layer Perceptron Neural Network (MLP) [16] are used. The details of these algorithms are as follows:

### a. Support Vector Machine (SVM)

For SVM, the data element is plotted as a dot for N-size space (n = number of characteristics); the characteristic value is a co-ordinate value. A hyper-plane is found to differentiate the two groups. Dense and sparse sample vectors as input are provided by SVM in scikit-learn [17]. For scikit-learn there are three categories able to distinguish multiple classes using the SVC, NuSVC and LinearSVC datasets. LinearSVC is used to classify MNIST data sets, since it has greater flexibility in selecting penalties and loss functions, and large numbers of samples should be measured.

The MNIST data set is downloaded, and the MNIST data set [13] is extracted from the Histogram for Oriented Gradients (HOG). Then, the HOG functions are measured for each image and stored in a separate numpy array. We set the number of cells to be 14 x 14 to determine the HOG characteristics. We have four blocks / cells in 14 x 14 each as we said before MNIST dataset size is 28 x 28 pixels. The vector of orientation is 9. This implies HOG vector is 4 x 9 = 36 size. Fig 1 shows the technique of SVM in classification.

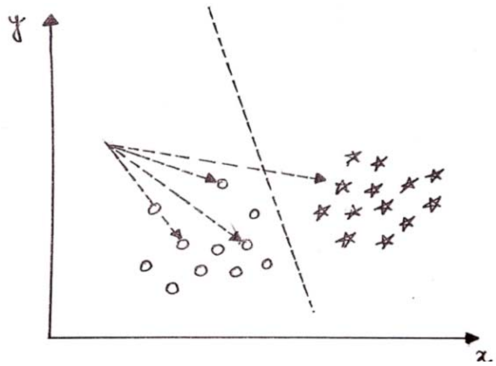

Fig. 1. SVM Classification

### b. K-Nearest Neighbour (KNN)

In reality, the KNN classification learns nothing. The distance between functional vectors is the basis of this algorithm. KNN algorithm classifies unidentified data points by identifying among the closest examples the most common class. Every data item in the nearest k casts a vote and winner is the highest category. The working of KNN is shown in fig 2.

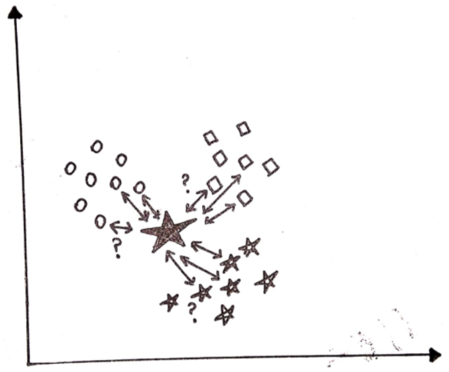

Fig. 2. KNN Classification

The MNIST data set is loaded into the device first. Instead we divide the data into training and testing details. We split the information into 70% for training and 30% for testing. Then the classification system is trained and the value of k is optimum. The reliability of the classifier will also be determined. We loop k between 1 and 20 in this classifier. Then, the classifier will be validated. We then use the test data classifier. We are going to use k equal to 15. We will then perform the final assessment.

*c. Multi-Layer Perceptron Neural Network*

A supervised algorithm, Multilayer Perceptron, is a function:

$$f(\cdot) : R^m \rightarrow R^o \quad (1)$$

Through learning on a dataset, the function must learn where m is the number of input dimensions, and o is the number of output dimensions. With the X = $x_1, x_2, \ldots, x_m$ and target y set of characteristics, it can know the non-linear classification or regression function approximate. It differs from logistic regression because there may be one or more nonlinear layers between the input and output layer, which can be called hidden layer.

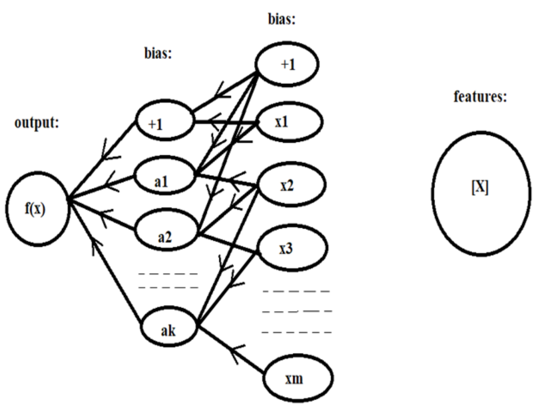


Fig. 3. MLP Neural Network

We must access the MNIST dataset. Afterwards the MNIST dataset function is replaced with Histogram of oriented gradients (HOG). In a numpy array and corresponding labels, the data sets images of the digits are saved. The HOG features for individual pictures will be measured next and stored in another numpy range. KNN and SVM correctly predict the dataset, but it is a mistake to predict number 9 for the MLP Neural network. It predicts directly from the feature extraction for KNN and SVM. For MLP, however, the function is non-linear. It is therefore better suited for studying non-linear models. Yet MLPs are nonconvex, with hidden layers where over a local minimum occurs. Yet MLPs with hidden layers are non-convex, with more than a minimum locality. It's a nonlinear function for MLP, though. It is therefore better suited for studying non-linear models. And MLPs have a nonconvex loss feature with hidden layers where there is more than a minimum local level. The working model of Multi-Layer Perceptron Neural Network has been shown in fig 3.

*B. Handwritten Test Image Authentication using Back propagation*

In back propagation the image is transformed into a matrix (or text) because this cannot be used directly into the neural network as output. The image is converted to the red, green and blue (RGB) values and these values are normalized by using some normalization function, which is shown in fig 4. The color of each pixel of the image is represented by this method.

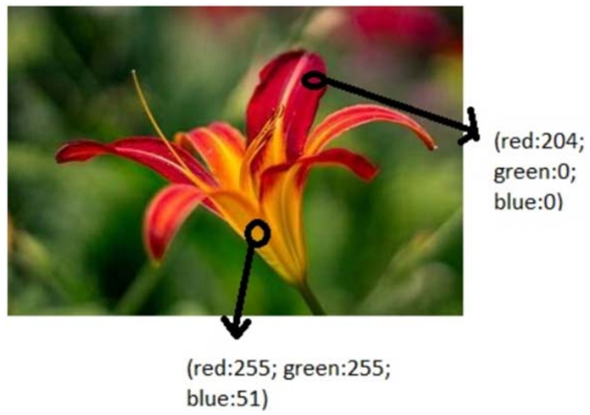


Fig. 4. Reading pixel values

Upon transforming the image into a matrix consisting of numbers, we can give it to the neural network as an input, and the image matrix can be trained as a training sample. This can be represented by eqn. 2

$$C_n = C_t/255 \quad (2)$$

Where Ct is the value of Red or Green or Blue components of the graphical password, 255 is the maximum value for any color and Cn represents the output obtained from solving this equation.

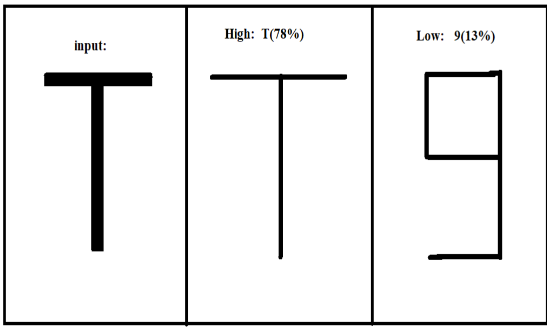


Fig. 5. Screen showing how to recognize image

Two patterns suit the data, one with low error i.e. T (78%) and another one with a high error i.e. 9 (13%). Because T has more similarity than 9, the application recognizes the pattern given as T, which is shown in fig 5.

### *C. Distilling GRU (Gated Recurrent Unit) With Data Augmentation for Unconstrained Handwritten Text Recognition*

The network needs to project a sequential pen-tip trajectory into feature charts through the path-signature and eight-directional feature extraction methods in optimized convolutional neural network (CNN) and Long Short-Term Memory (LSTM) processes. They can of course capture sequential pen-tip path dynamics and have been used without preprocessing, such as feature extraction and over segmentation, for character and text recognition. Nevertheless, this approach was employed only in solving the usual manuscript horizontal text problem with no consideration of actual text types, such as overlapping, vertical, right-down, and multi-line handwritten text recognition as depicted in fig 6.

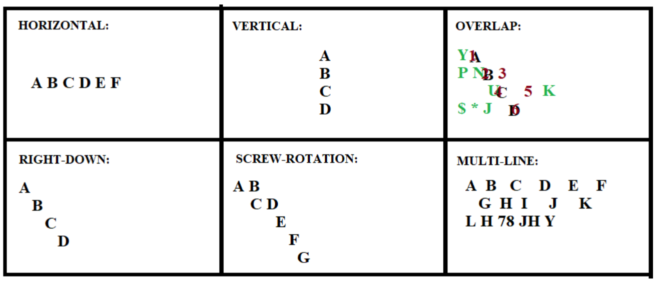


Fig. 6. Unconstrained handwritten text recognition, including horizontal, vertical, overlap, right-down, screw-rotation and multi-line

We have a multilayer distillation GRU network with data augmentation for the difficulty of the unconstrained handwritten text that has the following distinct benefits:

- The only way to reduce the disparity between texts of different types is by concentrating on the difference between adjacent points.
- We suggest multi layer distilling GRU to better model the unconstrained pen-tip route to process input data sequentially, thus speeding up the convergence phase without sacrificing recognition precision.

Pen-tip is normally a sequence of points reported in the (xt, yt) and pen-up / pen-down status st sequences, however, this form of representation can't be used to identify text, as the input function, i.e., x and y, can't be normalized between any given bound. Thereby it creates additional stress on the network and is not appropriate for general purposes. Therefore, further suggested to only focus on the difference between neighboring points, i.e., the pen-tip movement (Δxt, Δyt) where

$$\Delta xt = xt+1-xt \quad (3)$$

$$\Delta yt = yt+1-yt \quad (4)$$

eqn. 3 and 4 is used for the input text data.

There are two benefits. Firstly, the pen-tip movement is much more stable than the pen-tip coordinate for most situations and distributes between a given bond. Furthermore, from this viewpoint a very similar pattern is typical to unconstrained texts in several types, including horizontal, vertical, overlapping, multilines, screw rotation and right-down.

The main components of the conceptual system are three. First, in the feature extraction layer, the online pentip path is followed, so the pentip movements and pen-up / pen-down states are drawn. Then the multi-layer GRU distillery then learns to capture the sequence of information within the input and distillation data, in order to speed up the convergence. In the last study, the transcription layer with the CTC extracts the alignments from the expected probability grid to estimate the post-label sequence likelihood.

## IV. Pros an Cons of Handwriting Recognition Techniques

Table I summarizes the various pros and cons related to various hand recognition techniques discussed in the paper.

Table I. Pros and Cons of different techniques

| S. No. | Technique | Pros | Cons |
|---|---|---|---|
| 1. | Character Extraction | Simple form of technique to recognize the handwriting. | Problem becomes non-trivial if the character overlaps such that there is no gap for character extraction. |
| 2. | Character Recognition:<br>i) Neural Network<br>ii) Feature Extraction | • It can learn and model non-linear complex relationships from initial inputs and their relationships.<br>• Removes redundancy from data and enhances the class patter variability. | • Fails if the property learnt from previous input is not important for the current data.<br>• Needs more time as the characteristics are needed to be minutely verified. |
| 3. | SVM (Support Vector Machine) | • Beneficial is there is no idea of the data.<br>• Risk of over-fitting is less. | • Long time on training the datasets.<br>• Difficult to understand and |

| | | | |
|---|---|---|---|
| | | • Works good for unstructured and semi-structured data.<br>• With the application of Kernel function complex problem can be solved. | interpret final model.<br>• Choosing kernel function is not easy. |
| 4. | KNN (K-Nearest Neighbour) | • It is simple technique.<br>• It requires only a small training datasets with small number of training samples.<br>• It is instance based learning approach, therefore, requires less processing time. | • It requires greater processors and physical memory.<br>• Higher time is consumed during the classification of images. |
| 5. | MLP (Multi-Layer Perceptron Neural Network) | • Sufficient hidden nodes with the two layer backpropagati-on network prove to be a universal approximation<br>• Gives the required decision based on training the datasets. | • It gets struck in local minima as the minima where it stops; it cannot guarantee that it is a global minima. |
| 6. | Back Propagation | • It is simple to compute.<br>• It descends stochastically in weight space. | • Slow and Inefficient.<br>• A large amount of inputs and outputs are there but relating it to the output is difficult. |
| 7. | GRU (Gated Recurrent Unit) | • GRU use internal memory functionality to store and filter the data using update and reset gates.<br>• The last output can easily be replicated by saturating the input gate to zero. | • At each step, the output is the same and the hidden state can cause problems to learn latent sequence feature that is not directly linked to sequence elements. |

## V. CONCLUSION

This paper shows the different strategies for recognizing handwritten documents. The emphasis of this paper is also on how very challenging but significant is the reorganization in today's world of reading. Many apps in the actual globe include postal recognition, handling of bank checks, hand-picked handling of documents, converting field notes and historical documents are of significance and need for handwriting recognition. This Paper is a comparison of all techniques for handwriting recognition.

## REFERENCES

[1] Patel, M.S., Reddy, S.L. and Sandyal, K.S., 2015. An Improved Handwritten Word Recognition Rate of South Indian Kannada Words Using Better Feature Extraction Approach. In Proceedings of the 3rd International Conference on Frontiers of Intelligent Computing: Theory and Applications (FICTA) 2014 (pp. 553-561). Springer, Cham.

[2] Pal, U., Jayadevan, R. and Sharma, N., 2012. Handwriting recognition in indian regional scripts: a survey of offline techniques. ACM Transactions on Asian Language Information Processing (TALIP), 11(1), p.1.

[3] https://www.interaction-design.org/literature/book/the-encyclopedia-of-human-computer-interaction-2nd-ed/mobile-computing.

[4] Xu, L., Krzyzak, A. and Suen, C.Y., 1992. Methods of combining multiple classifiers and their applications to handwriting recognition. IEEE transactions on systems, man, and cybernetics, 22(3), pp.418-435.

[5] Loudon, G.H., Wu, Y.M. and Pittman, J.A., Institute of Systems Science National Univ of Singapore and Apple Inc, 2005. Methods and apparatuses for handwriting recognition. U.S. Patent 6,956,969.

[6] Plamondon, R. and Srihari, S.N., 2000. Online and off-line handwriting recognition: a comprehensive survey. IEEE Transactions on pattern analysis and machine intelligence, 22(1), pp.63-84.

[7] Marti, U.V. and Bunke, H., 1999, September. A full English sentence database for off-line handwriting recognition. In Proceedings of the Fifth International Conference on Document Analysis and Recognition. ICDAR'99 (Cat. No. PR00318) (pp. 705-708). IEEE.

[8] Choudhary, A., Rishi, R. and Ahlawat, S., 2013. A new approach to detect and extract characters from off-line printed images and text. Procedia Computer Science, 17, pp.434-440.

[9] Choudhary, A., Rishi, R. and Ahlawat, S., 2013. Off-line handwritten character recognition using features extracted from binarization technique. Aasri Procedia, 4, pp.306-312.

[10] Pradeep, J., Srinivasan, E. and Himavathi, S., 2011, March. Neural network based handwritten character recognition system without feature extraction. In 2011 international conference on computer, communication and electrical technology (ICCCET) (pp. 40-44). IEEE.

[11] Liu, C.L. and Fujisawa, H., 2008. Classification and learning methods for character recognition: Advances and remaining problems. In Machine learning in document analysis and recognition (pp. 139-161). Springer, Berlin, Heidelberg.

[12] Deng, L., 2012. The MNIST database of handwritten digit images for machine learning research [best of the web]. IEEE Signal Processing Magazine, 29(6), pp.141-142.

[13] http://yann.lecun.com/exdb/mnist/.

[14] Ahmad, A.R., Khalia, M., Viard-Gaudin, C. and Poisson, E., 2004, November. Online handwriting recognition using support vector machine. In 2004 IEEE Region 10 Conference TENCON 2004. (pp. 311-314). IEEE.

[15] Kumar, M., Jindal, M.K. and Sharma, R.K., 2011, November. k-nearest neighbor based offline handwritten Gurmukhi character recognition. In 2011 International Conference on Image Information Processing (pp. 1-4). IEEE.

[16] Singh, G. and Sachan, M., 2014, December. Multi-layer perceptron (MLP) neural network technique for offline handwritten Gurmukhi character recognition. In 2014 IEEE International Conference on Computational Intelligence and Computing Research (pp. 1-5). IEEE.

[17] https://machinelearningmastery.com/a-gentle-introduction-to-scikit-learn-a-python-machine-learning-lib