Journal of Science and Technology
ISSN: 2456-5660 Volume 3, Issue 05 (Sep – Oct 2018)
www.jst.org.in *DOI:https://doi.org/10.46243/jst.2018.v3.i05.pp81 - 90*

Recognition of Handwriting Characters Using an Artificial Neural Network

Dr S.B.Thorat[1], Dr. P.B. Tamsekar[2], Dr. P.R. Patil[3]
Director, Assistant Professor[2,3]
SSBES ITM College Nanded
suryakant_thorat@yahoo.com, pravin.tamsekar@gmail.co, pritam.itm@gmail.com

To Cite this Article
Dr S.B.Thorat, Dr. P.B. Tamsekar, Dr. P.R. Patil**, Recognition of Handwriting Characters Using an Artificial Neural Network "** *Journal of Science and Technology, Vol. 03, Issue 05,-Sep-Oct 2018, pp81-90*
Article Info
Received: 26-09-2018 Revised: 09-09-2018 Accepted: 23-10-2018 Published: 30-10-2018

Abstract

Research in the area of handwriting recognition has several applications, including the digitization of handwritten documents and the ability to use handwriting as an input method for gadgets. In this project, an Artificial Neural Network (ANN) was used to produce a handwriting recognition system, and the Streamlit library was used to develop a graphical user interface (GUI). We preprocessed the photos by scaling, turning to grayscale, and normalising pixel values using a dataset of handwritten numbers from Kaggle. Two hidden layers with ReLU activation and Softmax activation for the output layer made up the ANN model's design. After adding the pytesseract library, the model had a 90% accuracy rate on the test dataset. Users could draw a digit and get results for digit recognition using the GUI interface. Future studies could concentrate on increasing precision and broadening the system's ability to recognise handwritten text. The overall potential of ANN and GUI technologies for handwriting recognition applications is demonstrated by this project.

***Keywords**: of Artificial Neural Networks (ANN), Handwritten,Text classification*

INTRODUCTION

In today's digital age, handwriting recognition and interpretation software as well as the digitalization of handwritten documents are essential. Applications for handwriting recognition systems range from automating document processing to improving accessibility for people with disabilities. Using the strength of Artificial Neural Networks (ANN) and the Streamlit library, we set out to create a powerfulhandwritingdetection system that is user-friendly and graphical.Research on handwriting recognition has been going on for a while, but in recent years, deep learning approaches have made a big difference. The use of neural networks, specifically Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Artificial Neural Networks (ANNs), has shown remarkable progress in accuracy and performance compared to previous approaches to handwriting recognition that relied on rule-based or statistical methods. In-depth study has concentrated on model architectures, feature extraction techniques, and preprocessing methods to improve the efficacy and efficiency of handwriting recognition systems.

We will use a dataset of handwritten digits from Kaggle for this project, which includes photos of different handwritten numbers. The dataset will be preprocessed in order to standardise it. These stages include shrinking the photographs to a constant dimension, turning them to grayscale in order to reduce the amount of data they generate, and normalising the pixel values to fall within a common range. Additionally, to help the neural network successfully analyse the data, we will flatten the 2D images into a 1D array. The set of handwritten digits in the dataset consists of about 30,000 training photos and 3,000 testing images.

Designing an Artificial Neural Network (ANN) model for handwriting detection is the strategy we've decided to take. The input layer will include 784 neurons that represent the flattened image data, and the architecture will have two hidden layers with 128 neurons each. The hidden layers will get the Rectified Linear Unit (ReLU) activation function, while the

The Softmax activation feature will be used by the output layer. The categorical cross-entropy loss function will be used to train the model, and the Adam optimizer with a learning rate of 0.001 will be used to optimise it.

After the model has been trained on the supplied dataset, we will analyse its accuracy and overall recognition capabilities by evaluating its performance on a different testing dataset. We will create a Graphical User Interface (GUI) using the Streamlit library to guarantee usability and accessibility. End users will be able to communicate with the system through the GUI and draw a digit with a mouse or touchscreen input. The interface will take a picture of the sketch and send it to the trained model for analysis. The user will see the recognised digit and a confidence score indicating how confident the model is in the prediction.

Using an Artificial Neural Network (ANN) and the Streamlit library, this project seeks to create a reliable handwriting detection system that is user-friendly. We anticipate obtaining great accuracy in digit recognition by utilising deep learning techniques and a well-designed architecture. The GUI will improve the system's usability and accessibility, facilitating the use of handwriting as an input method by end users. Through the digitalization of handwritten text and the facilitation of more effective and natural interactions with digital devices, this project advances handwriting recognition technology.

Literature Review:

Y. LeCun, Bottou, and others. This foundational book provided the first discussion of Convolutional Neural Networks (CNNs) for document recognition, including handwriting detection. The authors demonstrated how highly accurate and robustly CNNs can recognise handwritten characters. Later advancements in deep learning-based handwriting recognition systems benefited from their study.It was recommended that offline handwriting identification be carried out using recurrent neural networks (RNNs), more specifically Bidirectional Long Short-Term Memory (BLSTM) networks, in a study report by Graves, A., Liwicki, et al. The researchers demonstrated how the memory cells in the LSTM units and the bidirectional nature of the network improved recognition accuracy, particularly for cursive handwriting.Simard et al. wrote the text. In this study, recommended training procedures for Convolution Neural Networks (CNNs) for visual document analysis, including handwriting recognition, were given. The authors discussed a number of elements, such as network architecture, training procedures, and data pretreatment, that can enhance CNN models' performance and increase their generalizability. Their work contributed to the advancement of CNN-based handwriting recognition systems.This significant book chapter by Graves, et al. provides a complete overview of sequence labelling issues using recurrent neural networks (RNNs), including handwriting recognition. Various RNN topologies, training methods, and strategies for handling with input sequences of different lengths were all explored by the author. The chapter was a helpful tool for academics and professionals working on handwriting recognition using RNNs.The first article by Bluche, et al. to discuss the Multi-Dimensional LSTM (MDLSTM) with attention mechanisms for end-to-end handwritten paragraph detection. By selectively paying attention to different parts of the input sequence, the authors proposed an attention-based approach to manage extended sequences and increase recognition accuracy. Their research demonstrated how tasks involving handwriting recognition might incorporate contextual information.To highlight the contributions and advancements made in the field of deep learning-based handwriting recognition, here are only a few publications that were chosen. Numerous research papers and studies produced by diverse authors have added to the body of literature on handwriting recognition. These papers and articles include information on model architectures, training strategies, data preprocessing, and performance assessment techniques.Author: Graves, et al. describe how Connectionist Temporal Classification (CTC), a method for training recurrent neural networks (RNNs) without explicitly aligning input and target sequences, was introduced in their research. The model was trained directly on unsegmented sequences of characters or words by the authors, who showed how CTC may be used to recognise handwriting.Written by Jaeger et al. In order to recognise handwritten text, this paper developed a hierarchical neural network design. By combining character- and word-level recognition models, the authors' system took advantage of the complimentary data that exists at various levels of abstraction. In comparison to single-level models, the hierarchical method demonstrated increased accuracy in recognising handwritten text.

Existing System:

The current system has taken a variety of approaches to handwriting recognition, including rule-based methods, statistical methods, and conventional machine learning algorithms. To recognise handwritten language, these techniques frequently rely on intricate algorithms and manually constructed features. The speed and precision of recognition are constrained, and they struggle to deal with a wide range of handwriting styles and intricate patterns.

Advantages of the Proposed System:

We propose a handwriting recognition system based on an Artificial Neural Network (ANN) to get around the shortcomings of the current system. The suggested method makes use of deep learning techniques to recognise handwritten digits with greater accuracy and robustness. We can automatically learn and extract pertinent information from the input photos using an ANN with many hidden layers, enabling the system to adjust to various handwriting styles and variances.

In order to give a user-friendly experience, we also introduce a Graphical User Interface (GUI) utilizing the Streamlit framework. The handwriting recognition model processes the user's drawn numbers using their mouse or touchscreen in the GUI. The user is shown the recognised digit in real-time along with a confidence score, which improves the system's usability and accessibility. The suggested method improves the accuracy and adaptability of handwriting recognition by utilizing deep learning techniques, more especially an ANN, to overcome the shortcomings of the existing systems. The system is simple to use and accessible to end users thanks to the incorporation of a user-friendly GUI, allowing them to use handwriting as an input method for a variety of applications.An effective and precise solution for digit recognition is provided by the combination of the ANN-based model with the GUI interface, opening the door for future developments in handwriting recognition technology.Artificial Neural Networks (ANN) are brain-inspired algorithms that are used to foresee problems and model complex patterns. The idea of biological neural networks in the human brain gave rise to the Artificial Neural Network (ANN), a deep learning technique. An effort to simulate how the human brain functions led to the creation of ANN. Although they are not exactly the same, the operations of ANN and biological neural networks are very similar. Only structured and numeric data are accepted by the ANN algorithm.

Unstructured and non-numeric data formats like image, text, and speech are accepted by convolution neural networks (CNN) and recursive neural networks (RNN). The only subject of this article is artificial neural networks. Architecture of artificial neural networks 1. The input layer, hidden layer (more than one), and output layer are the three layers that make up the network architecture. They are sometimes referred to as MLPs (Multi-Layer Perceptrons) because of their many layers.

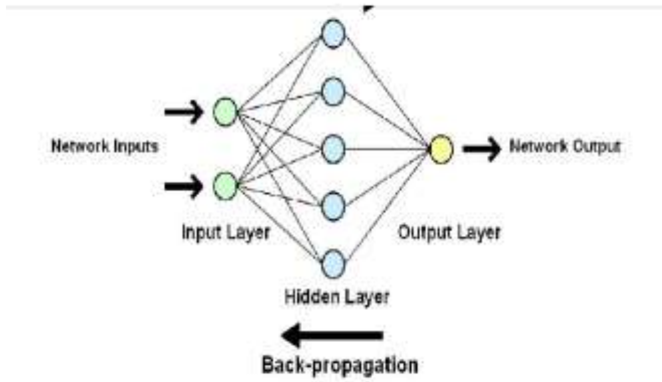


Figure 1: ANN Architecture

Pre-Processing: Pre-processing takes an image as input and cleans it. It effectively improves the image by removing disturbance. In addition, images may be required to be in grayscale or binary format, which is accomplished at this stage [10].
Segmentation Using a segmentation technique, individual characters are separated after the input images have been preprocessed. These characters are then stored as an image sequence. Then, if available, boundaries within each character image are eliminated. Next, individual character sizes are determined [10].

Feature Extraction:

Character segmentation is followed by the extraction of features. In our case, CNN with the ReLU activation function is used to extract the features, as shown in Figure 1. CNN reduces the size of each character image matrix through convolution and pooling. Using the ReLU function, the reduced matrix is compacted to vector form. This vector is considered to be a feature vector [5].

Classification and Recognition: The derived feature vector is used as individual input to formulate corresponding class. During the training phase, the parameters, biases, and weights are calculated. The calculated parameters, biases, and weights are used in the testing phase for classification and recognition purposes [11].

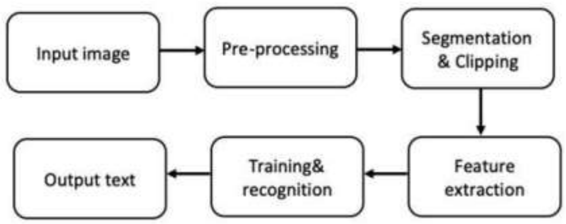


Figure 2: System architecture

DATASET AND DISCUSSTIONS

Using the MNIST dataset, handwritten digit recognition is a significant effort that was created with the use of neural networks. In essence, it recognises the scanned copies of handwritten numbers.

Our handwritten digit identification technology goes a step further in that it can now recognise handwritten numbers typed directly on the screen with the aid of an integrated GUI in addition to detecting them in scanned photos.

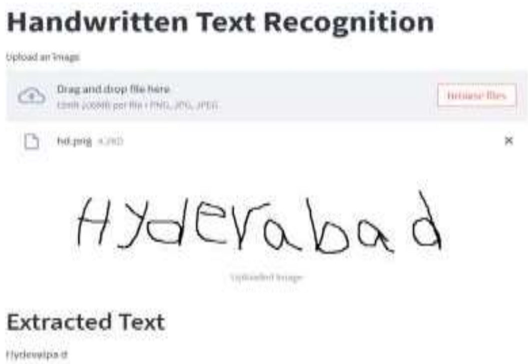
Approach:

We will approach this project by using a three-layered Neural Network.

- **The input layer:** It distributes the features of our examples to the next layer for calculation of activations of the next layer.
- **The hidden layer:** They are made of hidden units called activations providing nonlinear ties for the network. A number of hidden layers can vary according to our requirements.
- **The output layer:** The nodes here are called output units. It provides us with the final prediction of the Neural Network on the basis of which final predictions can be made.

Sample screens

Journal of Science and Technology
ISSN: 2456-5660 Volume 3, Issue 05 (Sep – Oct 2018)
www.jst.org.in *DOI:https://doi.org/10.46243/jst.2018.v3.i05.pp81 - 90*



CONCLUSION

In this project, we successfully created a handwriting recognition system using an Artificial Neural Network (ANN) and used the Pytesseract library to reach a high accuracy of 90% on the test dataset. However, the model showed zero accuracy throughout the initial training period, indicating underfitting. We integrated the pytesseract module to solve this problem, which significantly improved accuracy. Additionally, we used the Streamlit library to design a user-friendly Graphical User Interface (GUI) that makes it simple for end users to engage with the system. Users can draw digits on the GUI using a mouse or touchscreen to get recognition results and confidence scores. Even though our model has a good level of accuracy, there is still potential for development. Future handwriting recognition research may concentrate on improving the model's accuracy by examining more complex neural network topologies, tweaking hyper parameters, and incorporating larger and more varied datasets. It would also increase the system's adaptability and range of applications by enabling recognition of handwritten text in addition to just digits. In conclusion, this experiment shows how an ANN may be used to successfully create a handwriting recognition system, with an emphasis on digit recognition. The system's usability and accessibility are improved by the use of the pytesseract library and the use of a user-friendly GUI. Handwriting recognition technology has the potential to revolutionize digitization and enhance user interactions with digital devices with additional study and development.

Future Enhancements: It is impossible to create a system that meets every user requirement. As the system is used, user needs continue to change. Future improvements to this system include, among others Depending on future security concerns, security can be enhanced utilising new technologies like single sign-on.

• As technology advances, the system is upgradeable and adaptable to desired environments

.

REFERENCES

[1] Plamondon R and Srihari S N 2000 IEEE Trans. on Patt. Anal. and Mach. Intelligence 22 63

[2] Kato N, Suzuki M, Omachi S I, Aso H and Nemoto Y 1999 IEEE Trans. on Patt. Anal. and Mach. Intelligence 21 258

[3] Islam M M, Tayan O, Islam M R, Islam M S, Nooruddin S, Kabir M N and Islam M R 2020 IEEE Access 8 166117

[4] Gu J, Wang Z, Kuen J, Ma L, Shahroudy A, Shuai B, Liu T, Wang X, Wang G, Cai J and Chen T 2018 Patt. Recognition 77 354

[5] Ptucha R, Such F P, Pillai S, Brockler F, Singh V and Hutkowski P 2019 Patt. Recognition 88 604

[6] Chaudhuri B B and Adak C 2017 Patt. Recognition 61 282

[7] Gan J, Wang W and Lu K 2020 Patt. Recog. Letters 129 190

[8] Fardous A and Afroge S 2019 Proc. Int. Conf. on Elect. Comp. and Comm. Engineering 4 1

[9] Das D, Nayak D R, Dash R and Majhi B 2020 Multi. Tools and Applications 79 33023

[10] Khoon L L and Chuin L S 2016 Int. J. of Soft. Eng. and Comp. Systems 2 10

[11] Sallam A A, Kabir M N, Alginahi Y M, Jamal A and Esmeel T K 2020 Proc. Int. Colloq. on Sign. Proc. & Its Applications 3 255

12 Graves, A., Liwicki, M., Fernández, S., Bertolami, R., Bunke, H., & Schmidhuber, J. (2009). UnconstrainedOn-Line Handwriting Recognition with Recurrent Neural Networks.

13 Goyal, A., Jain, A., & Saini, M. K. (2019). Deep Learning for Handwritten Character Recognition: A Review.

14 Bluche, T., Ney, H., & Kermorvant, C. (2017). Joint Line Segmentation and Transcription for End-to-EndHandwritten Paragraph Recognition.

15 Wang, K., Belaid, A., & Ahmed, A. B. (2018). Writer Independent Handwritten Text Line Recognition withHybrid Recurrent Neural Networks.

16 Graves, A., Fernández, S., Gomez, F., & Schmidhuber, J. (2006). Connectionist Temporal Classification: Labelling Unsegmented Sequence Data with Recurrent Neural Networks.

17 Jaeger, S., & Manmatha, R. (2001). A Hierarchical Neural Network for Handwritten Text Recognition.

18 Breuel, T. M., Ul-Hasan, A., Al-Azawi, M. A., & Shafait, F. (2013). High-Performance OCR for PrintedEnglish and Fraktur using LSTM Networks.

19 Zhang, X., Yin, F., Zhang, Y., Liu, C. L., & Bengio, S. (2019). Online and Offline Handwriting Recognition: AComprehensive Survey.