Mini Project 2B Report
On

Handwriting Recognition Using AI

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CERTIFICATE

This is to certify that the Mini Project entitled **“HandWriting Recognition Using AI”** is a bonafide work of **Shubham Soni Nath (9143), Leroy Machado (9138), Alisha Rawat (9154)** submitted to the University of Mumbai in partial fulfillment of the requirements for Mini Project 2B (ECM601), Semester 6, Third Year **Electronics and Computer Science.**

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Mini Project Approval

This Mini Project entitled "Handwriting Recognition Using AI" by **Shubham Soni Nath (9143), Leroy Machado (9138), Alisha Rawat (9154)** is approved for the requirements for Mini Project 2B (ELM601), Semester 6, Third Year **Electronics and Computer Science.**

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Contents

Abstract

Handwriting has been a conventional means of communication and recording in daily life since early times. Given its ubiquity in human transactions, machine recognition Of handwriting has practical significance, such as, in reading handwritten notes in a PDA, in postal addresses on envelopes, in amounts in bank checks, or in handwritten fields in forms. Handwriting recognition is a vital application in daily activities and the research of handwritten digits recognition is vital.[8] Despite decades of research and development, modern handwriting recognition systems still exhibit suboptimal performance in the real world applications. Recent studies show great potential of Recurrent Neural Networks (RNN) with Long Short-Term Memory (LSTM) for unsegmented handwritten word recognition.[10] This paper focuses on using deep neural networks by comparing using past research papers. To do the research, a deep learning model to recognize handwriting in IAM dataset using the LSTM algorithm is built.

List Of Figures

Acknowledgments

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Chapter 1
Introduction

This chapter gives us a brief understanding and introduction to our topic and the motivation and reason behind why we chose this topic. This chapter also specifies the various problems that may have arisen without a system for handwriting recognition and how this system has made the users life much more easy and comfortable.

1.1 Introduction

Writing has been one of the most natural forms of collecting, storing and transmitting the information through the centuries, and now serves for the communication of humans and machines. The intensive research in the field of Handwriting Recognition (HR) provides efficient applications such as the automatic processing of bulk amounts of papers, ease of transferring data into machines[1]. This technique helps the computer systems to recognize digits and other symbols which are written by a human hand in its natural handwriting[2]. The human brain allows individuals to recognize different Handwriting objects such as digits, letters, and characters. However, this isn't the case for computerized systems. There is a need for such systems to understand human-read underwriting[3].

Handwriting Recognition(HR) System is capable of recognizing handwritten text from scanned images and converting it into machine-readable text. The system uses advanced deep learning algorithms to accurately identify patterns and structure in the handwriting, making it a highly efficient tool for a variety of applications, such as document scanning and digitization, signature verification, and more. Our project begins firstly with comparing the different machine learning algorithms available for handwriting recognition and choosing the best algorithm with the highest accuracy rate. Which will then be followed by the creation, training and testing of the model to give a highly functional system for handwriting recognition.

1.2 Motivation

Handwriting recognition using AI is a fascinating and rapidly growing field that has a wide range of applications in various industries, such as finance, healthcare, education, and more. The ability to automatically recognize and convert handwritten text into digital form can greatly enhance efficiency, productivity, and accuracy in many areas. For instance, it can help healthcare professionals to digitize patient records, assist educators in grading exams, and enable banking institutions to process checks more quickly.

In addition to its practical applications, handwriting recognition using AI is also an interesting research topic with many challenges and opportunities for innovation. Researchers in this field are constantly developing new algorithms and models that can improve the accuracy and robustness of handwriting recognition systems, as well as handle various writing styles and noisy images. Handwriting recognition using AI is a challenging problem due to the high variability and complexity of handwriting styles.

By working on a project related to handwriting recognition using AI, we had the opportunity to explore and learn about various aspects of this field, including deep learning, computer vision, natural language processing, and more. We also developed practical skills in programming, data analysis, and machine learning, which are highly in demand in today's job market. Overall, handwriting recognition using AI is a fascinating and rapidly growing field with many research opportunities and practical applications. With the advancements in deep learning and computer vision, there is great potential for developing accurate and efficient handwriting recognition systems that can be used in various industries and fields.

1.3 Problem Statement & Objectives

Develop an AI system to recognize handwritten characters and convert them to digital text with high accuracy and efficiency, capable of handling various writing styles, adaptable to changing styles, and able to identify characters in noisy images.

The objectives of our project are :

- To theoretically compare between different recognition algorithms on the basis of accuracy and reliability. Every algorithm has its pros and cons and choosing the right one depends on the project requirements and constraints.
- Conversion of recognized handwritten characters into digital text, making it usable for a variety of applications.
- To make a neural network that can adapt to different writing styles and different writing surfaces making it more versatile. By improving its versatility, the network can become a more powerful tool for recognizing and processing handwritten characters.

Chapter 2
Literature Review

Narumol Chumuang, Mahasak Ketcham, "Model for Handwritten Recognition Based on Artificial Intelligence", 2018 IEEE.[4]

The paper proposes a model for more efficient handwritten recognition based on artificial intelligence (AI) techniques and genetic algorithms. Handwritten recognition is a challenging issue as it involves the translation of various forms of correspondence such as letters, postcards, history, inscriptions, Bai Lan books, newspaper texts, and other documents. The proposed algorithm was designed and developed to accurately recognize Bangla, Latin, and MNIST handwritten alphabet series. The algorithm showed 94.05% accuracy for Bangla, 98.58% accuracy for Latin, and 100% accuracy for MNIST.

The paper outlines the related works in the field including the data set used for the experiment and the support vector machine (SVM) algorithm for multiple group classification problems. The proposed methodology includes chromosome encoding, fitness function, selection, uniform crossover, and mutation. The experiment and results section provide details on the evaluation of the proposed algorithm, and the results highlighted that the proposed algorithm was more accurate than the normal SVM algorithm.

Overall, the proposed model has implications for reducing the workload in converting documents into letters and increasing accuracy in handwritten recognition. The paper provides a detailed methodology for the development of the proposed algorithm and discusses the different steps involved including fitness function, selection, uniform crossover, and mutation. The paper also reports the results of the experiment which show that the proposed algorithm is more accurate than the normal SVM algorithm. The paper highlights the importance of developing more efficient algorithms for handwriting recognition in order to reduce the workload and increase accuracy.

Darapaneni, Subramaniyan, Mariam, Venkateshwaran, Ravi, Paduri, Gunasekaran, Asha, "Handwritten Form Recognition Using Artificial Neural Network," 2020 IEEE 15th International Conference on Industrial and Information Systems (ICIIS), RUPNAGAR, India, 2020.[5]

The paper presents a method for recognizing handwritten forms using artificial neural networks (ANNs). The authors propose an end-to-end system that can recognize different types of handwritten forms such as application forms, survey forms, and feedback forms. The form they have taken into consideration is the PAN application form.

The authors begin by discussing the importance of form recognition in various domains such as finance, healthcare, and education. They then describe the limitations of traditional methods for form recognition and highlight the potential advantages of using ANNs. The proposed system uses a convolutional neural network (CNN) to extract features from input images of handwritten forms. The extracted features are then fed into a fully connected neural network for classification. The authors explain the architecture of the CNN and the various hyperparameters used in the model. The authors also describe the dataset used for training and testing the model, which consists of handwritten forms from different sources. They report high accuracy rates on the test set, indicating that the proposed method can be used for practical applications.

In conclusion, the paper presents a promising approach for recognizing handwritten forms using ANNs and highlights the potential benefits of using CNNs for this task. The proposed system could be useful in various applications that require accurate and efficient recognition of handwritten forms.

P. Thangamariappan, Dr. J.C.Miraclin Joyace Pamila, "Handwritten Recognition by using Machine Learning Approach",International Journal of Engineering Applied Sciences and Technology,2020.[6]

The document discusses the use of deep learning techniques and convolutional neural networks (CNN) for the recognition of handwritten digits. The study aims to recognize 70,000 handwritten digits using the MNIST dataset. The authors experimented with CNN algorithms and a multi-layer perceptron (MLP) neural network model. The CNN model achieved an accuracy rate of 93%, while the MLP neural network model achieved a maximum accuracy rate of 98.5%. The accuracy of handwritten recognition is crucial in real-time applications such as digit conversion, signature verification, and number plate recognition. The document discusses in detail the implementation of the recognition system, covering topics such as dataset analysis, preparation, and model creation. Tools such as TensorFlow, Anaconda3 5.3.1, and Python 3.7 are used for the implementation. The author provides tables and figures to present the experimental results and compare the accuracy rates of different algorithms. The study highlights the importance of improving pre-processing of data fed into deep convolutional neural networks to further enhance accuracy in handwritten recognition. Overall, the paper aims to present the use of deep learning techniques and neural networks for achieving accurate and efficient recognition of handwritten digits.

In conclusion, the document details an analysis of various machine learning techniques and algorithms for recognizing handwritten digits. The study was conducted using the MNIST dataset, and the results showed that deep learning techniques such as CNN and MLP neural networks can be used to achieve high accuracy rates in recognizing handwritten digits. The paper highlights the importance of accurate recognition in real-time applications and suggests future work in improving pre-processing of data to further enhance recognition.

Sara Aqab,Muhammad Usman Tariq,"Handwriting Recognition using Artificial Intelligence Neural Network and Image Processing ",International Journal of Advanced Computer Science and Applications(IJCSA),2020.[7]

This document discusses the development of a handwriting recognition system using artificial neural networks and image processing. The objective of the research is to design an expert system for handwriting character recognition using a neural network approach to address the issue of accuracy in handwriting character recognition while demonstrating the usefulness of neural network technology. The paper highlights the different techniques and methods used in handwriting character recognition, including machine learning, Hidden Markov Model (HMM), and Support Vector Machine. However, the paper focuses on the effectiveness of artificial neural networks in character recognition, which are considered more efficient and robust than other computing techniques used in handwriting character recognition. The paper discusses the system's methodology, design, architecture, testing, and results. The system consists of five phases, including image acquisition and digitization, preprocessing, segmentation, feature extraction, and recognition. The paper explains how each phase works in detail, including the methods used for each phase. The paper discusses the testing and results of the OCR system, which was implemented using a neural network. The testing focused on several units of the system, including image acquisition and digitization, preprocessing, segmentation, feature extraction, and recognition modules. The testing helped to identify bugs in the code and made it easy to fix the code. The OCR system was used to recognize handwriting characters and digits. The system showed single and sentence recognition with a recognition accuracy of at least 99.9%. The system also recognized special characters and digits.

In conclusion, the paper highlights the importance of developing a computer system that can identify handwriting to solve tasks that may otherwise be time-consuming and costly. The paper demonstrates how neural network technology is useful in developing an efficient handwriting recognition system.

Hao Zeng, "An Off-line Handwriting Recognition Employing TensorFlow", 2020 International Conference on Big Data, Artificial Intelligence and Internet of Things Engineering (ICBAIE).[8]

One of the topics discussed in the paper was the development of handwriting recognition technology, using Tensorflow and Softmax Regression for optimal results. The conference papers highlighted the practical implementation of big data and the importance of AI models in pattern recognition. The need for intelligent and robust solutions to optimize the impact of these technologies on future capabilities was also discussed. The document underlines the importance of improving recognition accuracy and designing better pattern recognition models using new architectures. Additionally, it suggests bringing about newer innovations in the field of the Internet of Things and connecting multiple devices to make them more intelligent, which calls for newer methods of managing and manipulating data. The conference papers and discussions focused on the integration of these cutting-edge technologies to enhance future capabilities. Overall, the 2020 International Conference on Big Data, Artificial Intelligence, and Internet of Things Engineering (ICBAIE) highlighted the importance of the integration of these cutting-edge technologies. The papers and discussions showcased the potential of big data and AI models in pattern recognition for enhancing data-based solutions. The conference emphasized the need for innovative technologies to handle IoT devices and data, and the development of newer architectures to optimize the impact of these technologies on future capabilities. And to do this research, a neural network to recognize handwriting in MNIST dataset using Softmax Regression algorithm with high accuracy is built.

Jinze Li, Gongbo Sun, Leiye Yi, Qian Cao, Fusen Liang, Yu Sun, "Handwritten Digit Recognition System Based on Convolutional Neural Network", 2020 IEEE International Conference on Advances in Electrical Engineering and Computer Applications (AEECA).[9]

The system proposed in this paper is designed for offline recognition and utilizes the MNIST dataset as its training data. The paper describes how the system pre-processes images using the OpenCV toolkit, extracts features using the convolutional neural network, and uses a Softmax regression model to determine the result with the highest probability. The system has the potential to greatly reduce labor costs and improve work efficiency in various fields. The system in the article is designed for offline recognition, which is the recognition of characters written on paper by the computer. The two modules of the system are the data source module, which includes the provision of original handwritten digits, and the feature extraction of handwritten digit pictures. The digit recognition module comprises convolutional neural networks (CNN) and recognition. The paper concludes by emphasizing the significance of the system in the field of handwriting recognition and machine learning. Handwriting recognition is a bridge between handwriting and machines, which can greatly reduce labor costs in finance, accounting, education, and other fields. However, the accuracy and recognition delay need to be improved. Improving the recognition accuracy and reducing the recognition delay is considered as an important issue today. In summary, the paper highlights a handwritten digit recognition system based on convolutional neural networks that utilizes the MNIST dataset for training. The system is designed for offline recognition and can significantly reduce labor costs and increase work efficiency in various fields. The paper also provides a detailed description of the system's design, including the use of the Opencv toolkit for image preprocessing and feature extraction, and the principles and structure of convolutional neural networks

Sabatelli, Matthia & Shkarupa, Yaroslav & Mencis, Roberts, "Offline Handwriting Recognition Using LSTM Recurrent Neural Networks", BNAIC 2016 Proceedings.[10]

The document discusses the challenges in handwriting recognition and evaluates two approaches – CTC and Sequence-to-Sequence Learning – RNN with LSTM for recognizing word-level labels in handwritten medieval Latin texts. The authors use a dataset consisting of scanned pages of handwritten medieval Latin texts, which they make available through the Monk System. The training dataset consists of 118 scanned pages of handwritten medieval Latin texts from two sources. The authors applied preprocessing steps to each word image to make it easier and faster for the recognizer to learn from them, such as dataset augmentation, conversion to grayscale, and resizing. Both approaches show promising results with 78.10% and 72.79% word-level accuracy on the test dataset for respective methods. The Connectionist Temporal Classification approach consistently outperforms the Sequence-to-Sequence Learning approach in terms of generalization and prediction of long words. Even though the models showed good results on provided datasets, it is hard to infer the performance of examined methods on different handwritten text sources.

In conclusion, the document provides a full pipeline of the recognition system alongside the achieved results. The authors conclude that the use of RNNs with LSTM shows great potential for offline handwriting recognition. Further research could consider more advanced methods like Multidimensional Long-Short Term Memory (MDLSTM) and attention mechanisms.

Victor Carbune, Pedro Gonnet, Thomas Deselaers, Henry A. Rowley, Alexander Daryin, Marcos Calvo, Li-Lun Wang, Daniel Keysers, Sandro Feuz, Philippe Gervais, "Fast multi-language LSTM-based online handwriting recognition", International Journal on Document Analysis and Recognition (IJDAR) (2020).[11]

This paper supports 102 languages and achieves faster recognition times and higher accuracy rates. The system is based on a deep neural network architecture and uses Bézier curves for input encoding, which led to up to 10x faster recognition times compared to the previous system. The models in this system are more accurate, smaller, and faster than previous models and do not require a large number of engineered features and heuristics. The system also achieved new state-of-the-art results on the IAM-OnDB dataset for both the open and closed dataset settings. This system replaces the previous segment-and-decode system by removing the numerous preprocessing, segmentation, and feature extraction heuristics, and consists of a simple stack of bidirectional LSTMs, a single Logits layer, and the CTC loss. The main contributions of the paper are the use of a novel input representation based on Bézier curve interpolation and the detailed experimental comparison with the previous segment-and-decode-based stack. The article further provides detailed information on the end-to-end model architecture of the system, the input representation, feature functions, and experimental evaluation on various datasets, including IBM-UB-1 and VNDB-Word. The new system has completely replaced the previous segment-and-decode-based system and reduced the error rate by 20–40% relative to most languages. Additionally, a separate model has been trained for each script to support potentially many languages per script. The new system introduces prior knowledge about the underlying language into the system through language-specific language models and feature functions.

In conclusion, the new online handwriting recognition system is a significant improvement over the previous system, achieving faster recognition times, higher accuracy rates, and new state-of-the-art results on various datasets.

Chapter 3
Proposed System

This chapter gives more details of our project by specifying the structure and implementation details of our project. It also gives detailed information about the various technologies and tools that we used for developing the handwriting recognition system.

3.1 Introduction

The Handwriting Recognition System is a model developed so as to recognise the handwriting characters given as input. The system is based on the Long Short Term Memory (LSTM) algorithm using the IAM dataset.

Handwriting recognition has been an active research area for many years due to its wide range of applications in various domains such as document analysis, bank check processing, and postal automation. One of the challenges in handwriting recognition is dealing with the variability of handwriting styles and the difficulty of accurately recognizing different characters. In recent years, deep learning models, particularly Long Short-Term Memory (LSTM) networks, have shown remarkable results in handwriting recognition tasks. The IAM dataset, which contains handwritten text samples from different writers, is a popular benchmark dataset for evaluating handwriting recognition systems. In this chapter, we aim to provide a comprehensive review of the proposed systems, their strengths, and limitations, and to identify potential areas for future research in this domain.

3.2 Algorithm and Process Design

LSTM Algorithm

Long Short-Term Memory (LSTM) is a type of Recurrent Neural Network (RNN) architecture that was first introduced by Hochreiter and Schmidhuber in 1997[12]. Since then, it has become one of the most popular RNN architectures due to its ability to overcome the vanishing gradient problem in traditional RNNs. The basic idea behind LSTM is to use a memory cell that can store information over long periods of time and a set of gates that control the flow of information into and out of the cell[12]. The gates are implemented using sigmoid and element-wise multiplication operations that allow the network to learn which information should be kept, which information should be discarded, and which information should be updated.

The LSTM architecture consists of three gates: the input gate, the forget gate, and the output gate. The input gate controls the flow of new information into the memory cell, the forget gate controls which information should be discarded from the memory cell, and the output gate controls the flow of information from the memory cell to the output layer[13].

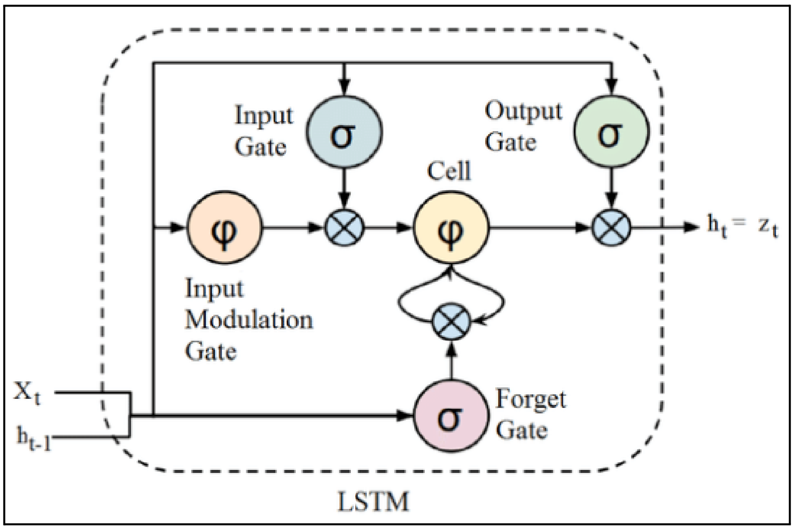

Figure 3.2.1 LSTM Architecture[14]

By learning the optimal values for the weight matrices and bias vectors, the LSTM network can effectively capture long-term dependencies in sequential data and achieve state-of-the-art performance in many applications[13].

```python
def Model1():
    inputs = Input(shape=(32,128,1))

    conv_1 = Conv2D(64, (3,3), activation = 'relu', padding='same')(inputs)
    pool_1 = MaxPool2D(pool_size=(2, 2), strides=2)(conv_1)

    conv_2 = Conv2D(128, (3,3), activation = 'relu', padding='same')(pool_1)
    pool_2 = MaxPool2D(pool_size=(2, 2), strides=2)(conv_2)

    conv_3 = Conv2D(256, (3,3), activation = 'relu', padding='same')(pool_2)

    conv_4 = Conv2D(256, (3,3), activation = 'relu', padding='same')(conv_3)
    pool_4 = MaxPool2D(pool_size=(2, 1))(conv_4)

    conv_5 = Conv2D(512, (3,3), activation = 'relu', padding='same')(pool_4)
    batch_norm_5 = BatchNormalization()(conv_5)

    conv_6 = Conv2D(512, (3,3), activation = 'relu', padding='same')(batch_norm_5)
    batch_norm_6 = BatchNormalization()(conv_6)
    pool_6 = MaxPool2D(pool_size=(2, 1))(batch_norm_6)

    conv_7 = Conv2D(512, (2,2), activation = 'relu')(pool_6)

    squeezed = Lambda(lambda x: K.squeeze(x, 1))(conv_7)

    blstm_1 = Bidirectional(LSTM(256, return_sequences=True, dropout = 0.2))(squeezed)
    blstm_2 = Bidirectional(LSTM(256, return_sequences=True, dropout = 0.2))(blstm_1)

    outputs = Dense(len(char_list)+1, activation = 'softmax')(blstm_2)

    act_model = Model(inputs, outputs)

    return act_model,outputs,inputs
```

Figure 3.2.2 Layers of LSTM Model

Model: "model_1"

Layer (type)	Output Shape	Param #
input_2 (InputLayer)	[(None, 32, 128, 1)]	0
conv2d_7 (Conv2D)	(None, 32, 128, 64)	640
max_pooling2d_4 (MaxPooling2D)	(None, 16, 64, 64)	0
conv2d_8 (Conv2D)	(None, 16, 64, 128)	73856
max_pooling2d_5 (MaxPooling2D)	(None, 8, 32, 128)	0
conv2d_9 (Conv2D)	(None, 8, 32, 256)	295168
conv2d_10 (Conv2D)	(None, 8, 32, 256)	590080
max_pooling2d_6 (MaxPooling2D)	(None, 4, 32, 256)	0
conv2d_11 (Conv2D)	(None, 4, 32, 512)	1180160
batch_normalization_2 (BatchNormalization)	(None, 4, 32, 512)	2048
conv2d_12 (Conv2D)	(None, 4, 32, 512)	2359808
batch_normalization_3 (BatchNormalization)	(None, 4, 32, 512)	2048
max_pooling2d_7 (MaxPooling2D)	(None, 2, 32, 512)	0
conv2d_13 (Conv2D)	(None, 1, 31, 512)	1049088
lambda_1 (Lambda)	(None, 31, 512)	0
bidirectional_2 (Bidirectional)	(None, 31, 512)	1574912
bidirectional_3 (Bidirectional)	(None, 31, 512)	1574912
dense_1 (Dense)	(None, 31, 79)	40527

Total params: 8,743,247
Trainable params: 8,741,199
Non-trainable params: 2,048

Figure 3.2.3 Summary Of LSTM Model

3.3 System Requirements

Operating System:	Any OS is compatible
Processor:	Intel i5 (7th gen) or later
Memory(RAM):	8 GB minimum, 16 GB recommended
GPU:	GTX1050 or later
Memory(VRAM):	4GB or more
Internet connection is not required	

3.4 Software Requirements

1. Operating System: Windows 7 or higher
2. Jupyter Notebook or Google Colab
3. Python 3.x
4. Tensorflow
5. Numpy
6. Pandas
7. Matplotlib
8. Keras
9. Scikit Learn
10. PIL

Chapter 4
Results and Description

The result of our system is shown in this chapter in the form of figureures. The different applications of the Handwriting Recognition is also mentioned in this chapter and finally concludes our project with positive outcomes and the modifications we can implement in the future.

4.1 Display Of Result

Following figureures are the end result. Here we have successfully implemented our system.

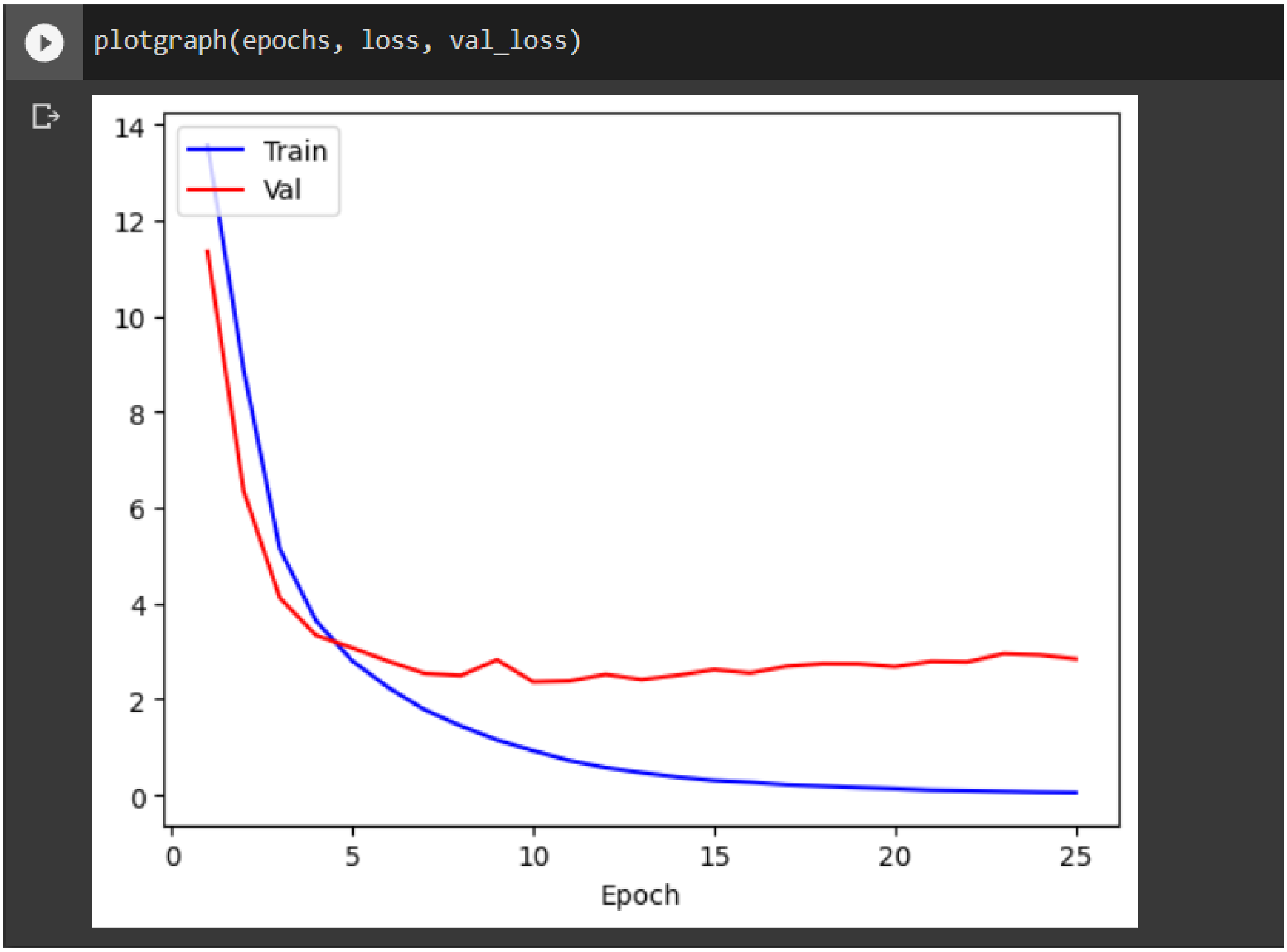

Figure 4.1.1 Value Loss Graph

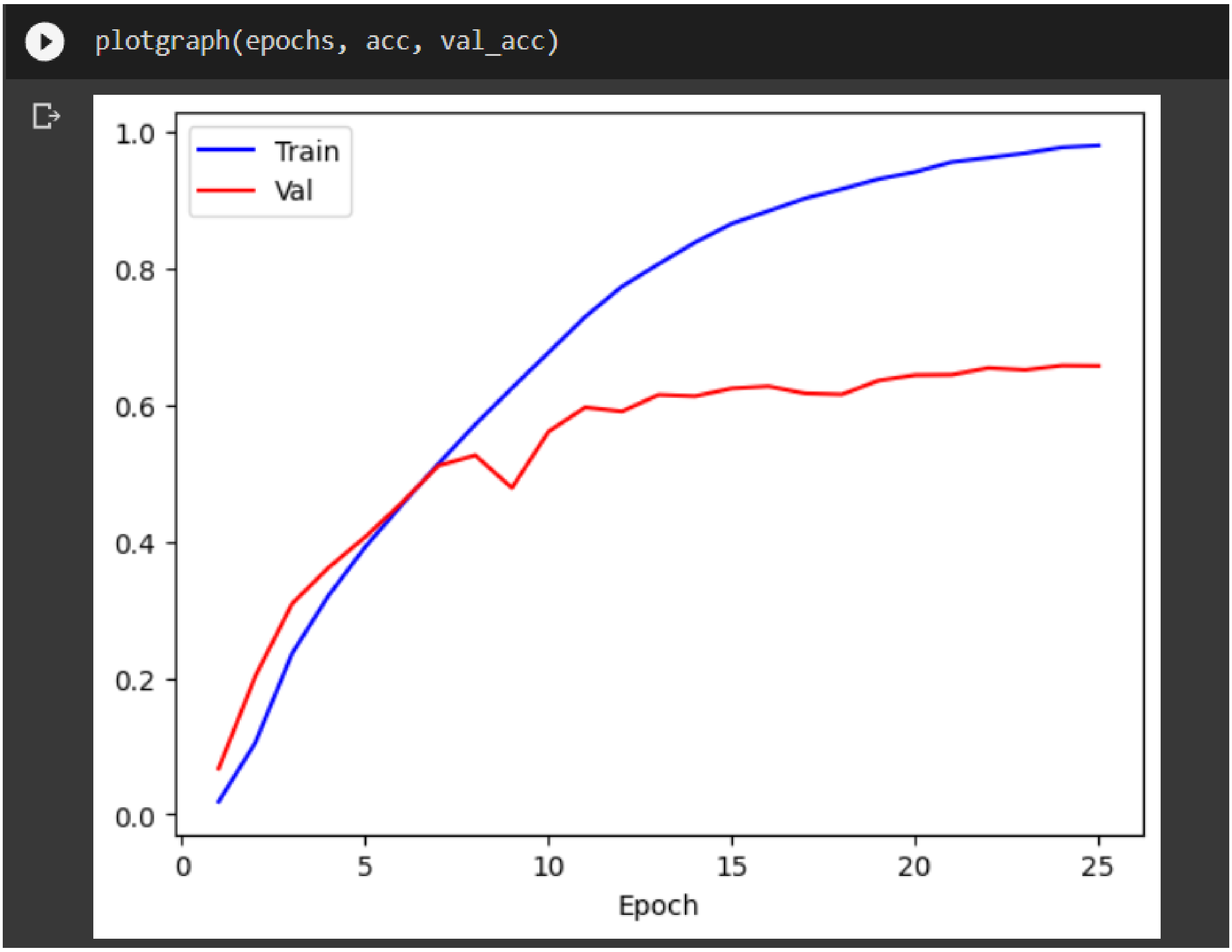

Figure 4.1.2 Value Accuracy Graph

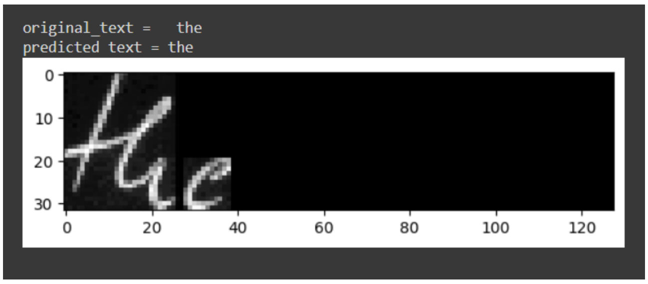

Figure 4.1.3 Verification 1

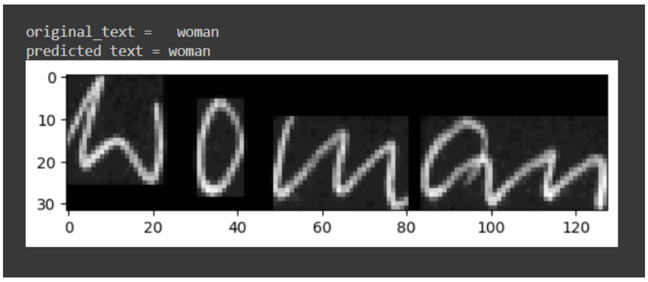

Figure 4.1.4 Verification 2

4.2 Applications

- Handwriting recognition can be used to digitize handwritten documents, such as historical manuscripts, personal letters, or legal documents.
- Handwriting recognition can be used to recognize handwritten signatures on delivery receipts or to read handwritten addresses on packages. This can help improve the efficiency and accuracy of order processing and delivery.
- It can be used as an input method for digital devices, such as tablets or smartphones, allowing users to write on the screen with a stylus or their fingers. This can be useful for tasks such as text messaging, note-taking, or drawing.
- Handwriting recognition can be used to automate the processing of handwritten checks, loan applications, and other financial documents. This can help reduce processing times, errors, and costs.
- It can be used to digitize and process handwritten forms and applications, such as passport applications, voter registration forms, and tax returns. This can help reduce processing times and improve the accuracy of data entry.

4.3 Conclusion and Future Work

In conclusion, handwriting recognition using LSTM algorithms is a promising approach for accurately recognizing and interpreting handwritten text. It is a special type of neural network that is good at understanding patterns in sequences of data. They are able to capture the long-term patterns and dependencies in sequential data, such as the strokes and curves of handwritten text, which is important for accurate handwriting recognition. By training LSTM models on large datasets of labeled handwritten text, it is possible to achieve high accuracy in recognizing different handwriting styles, languages, and variations in writing patterns. One of the key advantages of using LSTM for handwriting recognition is its ability to handle variable-length input sequences, making it suitable for recognizing text of different lengths and complexities. LSTM models can also learn to adapt to variations in writing styles and account for individual writing habits, making them robust and adaptable to different handwriting samples.

The future work of our project is to develop real time recognition of handwriting. Integration of other technologies, such as speech recognition or gesture recognition, can enable multimodal input methods, providing users with more flexible and convenient ways of interacting with digital devices.

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Appendix