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Interpreting Doctor notes using Handwriting Recognition and Deep Learning Techniques: A Survey

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Abstract—Handwritten recognition is becoming one of the most researched areas in the field of computer science. As the technologies are growing, everyone wants advanced life, which makes life easier. Even in the recognition of handwriting, mainly doctors notes, they are very difficult for everyone to understand and it takes time for a person to analyse it. So, this paper mainly focused on interpreting doctor's notes using handwritten recognition and deep learning techniques. The handwritten or printed document pictures are transformed into their electronic counterparts using an optical character recognition (OCR) system. Due to individuals' inconsistent writing styles, dealing with handwritten texts is significantly more difficult than dealing with printed ones. Handwritten text recognition could be done by Image processing, Machine Learning or Deep Learning Techniques. Out of these Deep Learning remains to be the most popular and prominent. Some of the Deep Learning techniques includes Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs). This paper gives a review of the various handwritten recognition methodologies used for interpreting handwritten texts. This paper includes the most important algorithms that could be used for detecting the handwritten word/text/character by using various approaches for the recognition process. In the end we are thus comparing the accuracies provided by these systems.

Keywords – ***Image processing, Deep learning, Handwritten text, Classification.***

I. INTRODUCTION

Doctor notes are really hard to interpret so Handwriting recognition models and Deep learning techniques help in transforming the written text into the computer understandable and programmable format. The following model and technique contains large image data sets. The objective behind these applications which recognize the handwritten messages or notes system is to create a convenient application for symbol recognition that allows positive dataset mining of text message into computer understandable text. Recognition of written documents corresponding to additional smart applications delivers some services in cellular phones, robotics applications and other devices for documentation and corroboration purposes.

Handwriting recognition is a technology that can be used to interpret and extract information from handwritten documents, such as doctors' notes [3]. This can be a challenging task, as handwriting can vary widely in terms of style, legibility, and formatting. However, advances in machine learning and OCR technology have made it possible to develop handwriting recognition systems that can accurately interpret a wide range of handwriting styles.

There are several approaches that can be used to develop a handwriting recognition system. One approach is to use machine learning algorithms to train a model on a large dataset of handwritten documents. The model can then be used to recognize and interpret handwriting in new documents. Another approach is to use OCR technology to convert handwritten text into digital text, which can then be processed using NLP techniques to extract meaning from the text [12].

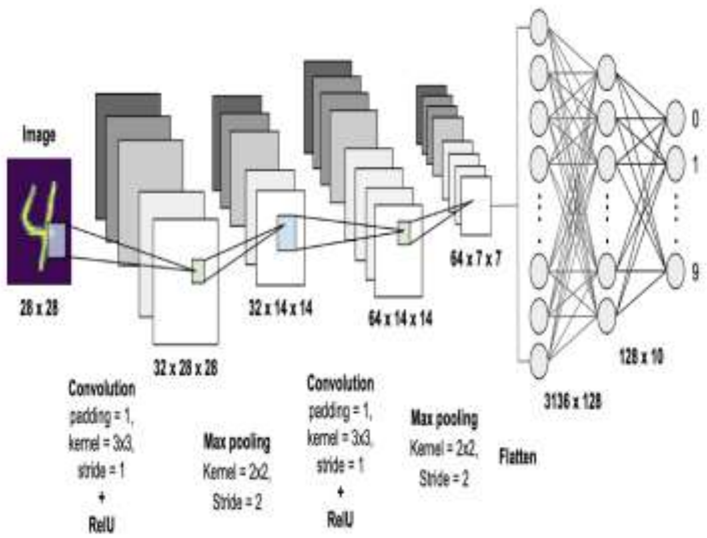

Fig-1: Deep Learning Based Handwritten character recognition

As shown in Fig-1, There are several types of classification models used for handwritten character recognition, including:

A. *Image Processing:* Converting an image using digital technologies and functions to output a magnifying image this way it leads to Image Processing [11]. By this technique we can produce and retrieve necessary information for the future uses. There are input and output data where we can input images, videos or frame and the excepted output can be an image or its characteristics which belong to that image.

B. *Machine Learning:* Artificial intelligence is a vast sector or technological field thus it subcategory is Machine Learning.

Computers need teaching and this can be done from data input and the process with improvise the experience of computers. Technique is used to replace the programming which is explicitly being used [2]. Machine learning includes algorithms that are used to find patterns and interdependencies in huge sets of data this leads to the best outputs and predictions based on previously assumed analysis.

C. *Deep Learning:* Convolution Neural Network is the full form of CNN. Convolutions allude to complexity and enlargement [1]. Human brains are similar to neural networks. These are planned by taking inspiration from human brain. The cause of CNN is being used for Image classification. Depending on the requirements of technology CNN constitutes of many layers [3]. RNN is an abbreviated form of Recurrent Neural Network that utilises feedback connections [4][5]. It bases its output on the input received from the previous computation, which is stored in its internal memory.

Over the course of several computations, RNNs are able to retain information inside its internal memory and use those in subsequent processes. Hence, the information flows in sequence. A type of handwriting where letters of each word may be connected to each other is used here, it is a necessity to use RNN to get more accurate results of the words. Bidirectional LSTM - To improve accuracy of recognition model, this technique is implemented in addition to RNN. LSTM is a special type of RNN that can store data as it processes through a sequence for a long duration. Bidirectional LSTM is the summation of two reverse LSTM and thus, would be able to learn information from both backward and forward of the input sequence. By applying this technique in a place of a single bidirectional LSTM gives us more effective and enhanced results as the sequence of every word detected in the handwritten images is preserved throughout several complex neural network processes.

The organization of this paper is as follows. We categorise many methods for classifying insects in Section II. We outline all conceivable insect classifications using taxonomy as a criterion in Section III. We discuss the value of deep learning approaches in Section IV in order to close the insect categorization knowledge gap. The study on deep learning models for insect detection and classification is discussed in Section V. Finally, we use a table to present a summary of the various detection and classification techniques addressed throughout the survey paper and to outline the goals and inspirations for next computational entomology research.

II. CONVENITIONAL METHODS USED IN HANDWRITTEN CHARACTER RECOGNITION

There are several approaches to handwriting recognition that have been developed over the years. Here are a few of the most common techniques:

A. *Feature-based methods:* Feature-based methods for handwritten character recognition involve extracting certain features from the handwriting and using them to classify the character. Some common features that are used in these methods include:

- Stroke width: The width of the strokes used to write the character can be a useful feature for distinguishing between different characters.
- Stroke direction: The direction in which the strokes are written can also be a useful feature. For example, characters that are written with strokes that mostly go left to right will be different from characters that are written with strokes that mostly go up and down.
- Loop and curve features: Characters that contain loops or curves, such as the letter "o" or the letter "s," will have different features than characters that do not, such as the letter "t" or the letter "l."
- Aspect ratio: The aspect ratio of a character is the ratio of its width to its height. Characters with different aspect ratios will have different features.
- Stroke order: The order in which the strokes are written can also be a useful feature. For example, the character "h" is written with two strokes,

the first of which is written from left to right and the second of which is written from top to bottom.

Once these features have been extracted from the handwriting, they can be used to train a classifier to recognize the character. The classifier could be a simple rule-based system or a more complex machine learning model, such as a neural network.

B. *Template matching:* In template matching for handwritten character recognition, a template is created for each character in the handwriting set. The template is a representation of the character that is used as a reference for comparison. When an input character is presented for recognition, the system compares it to each of the templates and selects the template that best matches the input character. There are several ways to create the templates for template matching. One approach is to use a set of pre-defined shapes, such as circles, squares, and triangles, to represent the different strokes in the character. Another approach is to use a grid of pixels, with each pixel representing a small area of the character. The pixels that are part of the character are set to a value of 1, while the pixels that are not part of the character are set to a value of 0. To compare the input character to the templates, a similarity measure is used. This could be a simple measure, such as the number of matching pixels, or a more complex measure, such as the Euclidean distance between the template and the input character. The template that gives the highest similarity score is selected as the best match. Template matching can be a simple and effective approach to handwriting recognition, but it can be sensitive to variations in the handwriting, such as variations in stroke width or the spacing between strokes. To improve the robustness of the system, it is often necessary to use multiple templates for each character, each of which represents a different variation of the character.

C. *Hidden Markov models:* A hidden Markov model (HMM) is a probabilistic model that can be used to recognize handwriting by modeling the sequence of strokes used to write each character. In an HMM, the character is represented as a sequence of states, each of which corresponds to a stroke or group of strokes. The transitions between the states are governed by probabilistic rules, which can be learned from a training dataset of handwriting. To use an HMM for handwriting recognition, the first step is to collect a large dataset of handwritten characters and label them with the correct character class. The dataset is then used to train the HMM. During training, the HMM is presented with a sequence of strokes and it uses the probabilistic rules to determine the most likely sequence of states that could have produced the strokes.

Once the most likely sequence of states has been determined, the HMM can use it to classify the character. HMMs are particularly well-suited for handwriting recognition because they can capture the temporal dynamics of the handwriting process. They can handle variations in the speed and direction of the strokes and can take into account the fact that some strokes may be omitted or added. However, HMMs can be sensitive to variations in the handwriting and may require a large amount of training data to achieve good performance.

D. *Dynamic time warping:* Dynamic time warping (DTW) is a technique that can be used to compare two sequences that may have different lengths or be time-shifted. It is often used in speech recognition, but it can also be applied to handwriting recognition. In DTW, the two sequences being compared are represented as a pair of time series. The goal is to find the best alignment between the two sequences, such that the difference between them is minimized. To do this, DTW computes a similarity matrix that represents the similarity between each element in the first sequence and each element in the second sequence. It then finds the optimal path through the matrix that minimizes the overall difference between the sequences. To use DTW for handwriting recognition, a reference character is first selected from a pre-defined set of characters. The input character is then compared to the reference character using DTW. The degree of similarity between the two characters is then calculated based on the distance between them, as measured by DTW. If the distance is below a certain threshold, the input character is classified as the reference character. Otherwise, it is classified as an unknown character. DTW can be a useful approach for handwriting recognition because it can handle variations in the speed and timing of the strokes and can take into account the fact that some strokes may be omitted or added. However, it can be computationally intensive, especially for long sequences, and may require the use of specialized hardware to achieve good performance.

E. *Artificial neural networks:* Artificial neural networks (ANNs) are machine learning models that are inspired by the structure and function of the human brain. They can be used to recognize patterns in handwriting and classify the characters. To use an ANN for handwriting recognition, the first step is to collect a large dataset of handwritten characters and label them with the correct character class. The dataset is then used to train the ANN. During training, the ANN is presented with a handwritten character and it tries to predict the correct character class. If the prediction is incorrect, the ANN adjusts its internal weights and biases to reduce the error. This process is repeated for many characters in the training set, and the ANN eventually learns to recognize the characters with a high degree of accuracy. There are many different types of ANNs that can be used for handwriting recognition, including feedforward networks, convolutional neural networks, and recurrent neural networks. The choice of ANN architecture will depend on the characteristics of the handwriting dataset and the performance requirements of the recognition system.

ANNs are generally considered to be powerful and effective for handwriting recognition, but they can be sensitive to variations in the handwriting and may require a large amount of training data to achieve good performance.

III. WHY DEEP LEARNING FOR HANDWRITTEN CHARACTER RECOGNITION

Deep learning has also been applied to handwriting recognition and has achieved state-of-the-art results on many benchmarks. There are several reasons why deep learning is well-suited for handwriting recognition:

A. *Ability to learn complex patterns:* Deep learning neural networks are able to learn complex patterns in the handwriting data that are difficult to capture with other methods. This makes them effective at recognizing characters that are written in a variety of styles or that have variations in stroke width, spacing, and other features.

B. *Robustness to variations:* Deep learning models are generally more robust to variations in the handwriting than other methods. This is because they can learn to recognize a wide range of variations in the training data and generalize well to new examples.

C. *High accuracy:* Deep learning models have achieved high accuracy rates on handwriting recognition tasks. In some cases, they have outperformed other methods by a significant margin.

D. *Ease of use:* Deep learning libraries, such as TensorFlow and PyTorch, provide pre-built neural network architectures and tools for training and deploying models, making it relatively easy to apply deep learning to handwriting recognition.

Overall, deep learning has proven to be an effective approach for handwritten character recognition and is likely to continue to be an important area of research and development in this field.

IV. RELATED WORK

Handwriting Recognition for Medical Prescriptions using a CNN-Bi-LSTM Model **-** Tavush Jain et al. in 2021[1] presented CNN-Bi-LSTM model which was used in conjunction with Connectionist Temporal Classification to demonstrate its use. Three parts make up the model: convolutional layers for feature extraction, a Bi-LSTM network for context vector predictions, and a final decoding step that uses the CTC loss function to convert each character in the recognized sequence from an LSTM character to an alphabetic character. To determine the final probabilities, which are decoded, a linear layer is added after the Bi LSTM layer.

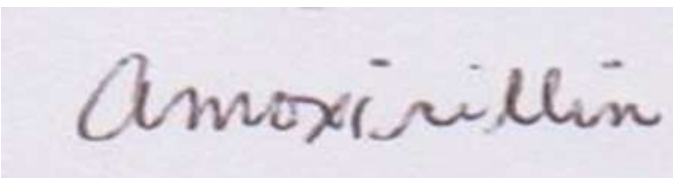

Fig 2: Prescribed Medicine Amoxicillin[1]

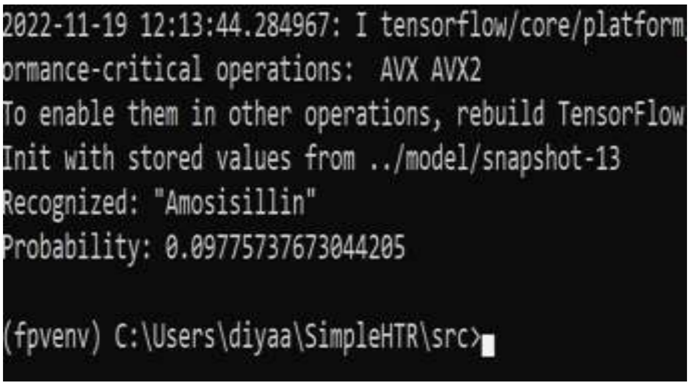

Fig 3: Result predicted by the model for the input medicine Amoxicillin[1]

Fig-2 shows an image with the name of a medicine fed to the model, and in Fig-3 we can see the recognized word "Amosisillin" with a probability of 9 percent, The right word should have been "Amoxicillin".

Comparative Study and Implementation of Supervised and Unsupervised Models for Recognizing Handwritten Kannada characters **-** Subhrajyoti Sen et al. in 2018[2] presented a paper where a classification of Kannada-language characters is proposed. The characters were segmented, processed, and extracted from written documents using NumPy and OpenCV to perform different image processing operations such as contrast normalisation, denoising, thinning, etc. The dataset utilised combines the Chars74k dataset with a specially created dataset. A comparison of the accuracy of classifiers based on K Nearest Neighbors, Support Vector Machines, Inception V3 and Convolutional Neural Networks developed using OpenCV and Keras is provided. On the Chars74k dataset, the CNN classifier was successful in achieving an accuracy of 99.84%.

Bangla Handwritten Word Recognition System Using Convolutional Neural Network **-** In their study from 2021[3], Md. Tanvir Hossain et al. developed a multi-zoned character segmentation and merging method that may create the handwritten phrase. For character-level precision, Convolutional Neural Network (CNN) reached 84%, and for word-level precision, 82%.

Framewise and CTC Training of Neural Networks for Handwriting Recognition **-** It was shown by Theodore Bluche et al. in their study from 2015[4] that CTC training is comparable to forward-backward training of NNIHMMs and may be expanded to more conventional HMM topologies. In order to examine the characteristics of CTC, specifically the modelling of character by single labels and the function of the special label, this method is applied to Multi-Layer Perceptron's (MLPs). WERs / CERs were more than 90%.

Development of CNN Transfer Learning for Dyslexia Handwriting Recognition **-** Mohamed Syazwan Asyraf Bin Rosli̲ et al. in 2021[5] proposed to develop a transfer learning system for dyslexic handwriting identification using convolutional neural networks (CNNs), which are based on the well-known LeNet-5 handwriting recognition architecture in their paper. A total of 138,500 handwriting picture datasets underwent data augmentation and preprocessing before being fed into the network. In classifying the three types of dyslexic handwriting, the model's hyper-parameter was tweaked and examined. The constructed CNN model was successful in classifying three different types of dyslexic handwriting with an astounding accuracy of 95.34 percent. The goal of creating the CNN model for dyslexia handwriting recognition was successfully attained, according to the outcome.

Recognition of Doctors' Cursive Handwritten Medical Words by using Bidirectional LSTM and SRP Data Augmentation **-** An online handwritten recognition system was suggested by Shaira Tabassum et al. in 2021[6] in their article as a way to forecast the handwriting of the doctors and create a digital prescription. To enhance the sample size and increase the variety of handwriting styles, the SRP (Stroke Rotation and Parallel Shift) approach is a new data augmentation methodology that is suggested. From the 1,591,100 sample enhanced image dataset, a sequence of line data is collected and fed into a bidirectional LSTM model. The recognition accuracy for the suggested technique was 89.5%, which is 16.1% better than the recognition accuracy with no data expansion.

Medical Prescription Recognition using Machine Learning - Esraa Hassan et al. offered a method in their research article from 2021[7] that uses a mobile app to read handwritten drug names and produce a readable digital text of the drug and its dosage as a solution for both the pharmacist and the patient. In the post-processing phase, low-accuracy optical character recognition on the medications will be performed on the pre-processed images. The names of the medications will then be ascertained by comparing the results with a dataset containing all the medications. The pre-processed images will be subjected to some processing, including classification, feature extraction using a convolutional neural network, and finally. When put to the test on various test cases, the suggested system's

Image Processing for improving OCR Accuracy **-** In this paper, before the demonstration of the text recognition, a preprocessing step is done, specifically with the images clicked from a digital camera[11]. Here any OCR system typically includes image preprocessing, binarization, segmentation, actual recognition, spellchecker-guided post processing, saving the output in some standard format. This experiment uses FineReader 7.0 software as the back-end recognition tool to process the original input image and with each successive algorithm layer, the accuracy improves to reach less than 1% error

Text Extraction using OCR: A Systematic Review **-** In this paper a fully functional OCR is developed which has the following six steps.

They are Image Acquisition, preprocessing, segmentation, feature extraction, classification, post processing[12]. A new methodology is introduced to extract the text from images which has 7 steps. That is initially the filtering process is utilised for pre-processing to improve the image quality.

Handwriting recognition on form document using convolutional neural network and support vector machines ***(CNN-SVM)*** - This paper proposes handwritten character recognition on form documents using an extraction feature convolutional neural network (CNN) and classifier support vector machine (SVM).

TABLE -1: COMPARATIVE STUDY ON VARIOUS METHODS APPLIED FOR HANDWRITTEN CHARACTER RECOGNITION.

Author &Year	Method	Accuracy	Purpose
T. Jain et al., 2021[1]	Handwriting Recognition using a CNN-Bi-LSTM Model	Character error rate of 0.08891%	Medical prescription decoding
S. Sen et al., 2018[2]	Handwriting character recognition using machine learning techniques	CNN gives an accuracy of 99.84%.Inception v3 gives an accuracy of 75%	Classification of Kannada-language characters.
M. T. Hossain et al., 2021[3]	Convolutional Neural Network (CNN) for training	84% precision is accomplished for character level, and 82% precision is achieved in word level using CNN.	Bangla handwritten word recognition System.
T. Bluche et al., 2015[4]	RNN trained with the Connectionist Temporal Classification criterion	Word Error Rate / Character error rates were above 90%	Techniques for handwriting recognition
M. S. A. B. Rosli et al.,2021[5]	CNN Transfer Learning	Accuracy of 95.34 percent	Dyslexia Handwriting Recognition
S. Tabassum et al., 2021[6]	Bidirectional LSTM	89.5% accuracy	Recognition of Doctors' Cursive Handwritten Medical Words
E. Hassan et al., 2021[7]	Convolutional Neural Network (CNN) for training	Proposed system's accuracy reached 70%	Medical Prescription Recognition
Darmatasia et al., 2017[8]	Handwriting recognition on form document using convolutional neural network and support vector machines (CNN-SVM) Design and simulation of handwritten recognition system	Proposed system's accuracy is 83.37% 98% of KNN highest accuracy	Handwritten characters on form document Easier recognition of handwritten characters
M A Abuzaraida et al., 2020[10]	Online handwriting Arabic recognition system using k-nearest neighbors classifier and DCT features	99.10% obtained accuracy	Enhanced method of arabic handwriting recognition
W. Bieniecki et al., 2007[11]	Image Preprocessing for Improving OCR Accuracy	Error rate of 0.96% obtained	Optical character recognition
R. Mittal et al., 2020[12]	Text extraction using OCR: A Systematic Review	99% accuracy was obtained	Extraction of Text using OCR Techniques

Design and simulation of handwritten recognition system - This paper demonstrates the design and simulation of a handwritten recognition system using both supervised and unsupervised machine learning for better results. Algorithms include Random forest, Logistic regression, Support Vector Machine(SVM) and K-Nearest Neighbour(KNN).By comparing various machine learning algorithms, KNN provides 98% of highest accuracy rate[9].

Online handwriting Arabic recognition system using k-nearest neighbors classifier and DCT features This paper proposes a method for the online handwritten Arabic recognition using a direction-based segmentation technique and discrete cosine transform (DCT). Total of 18 structural features were used to extract using DCT and KNN classifiers[10]. Total of 2500 words were used in the dataset. Using KNN classifier, the obtained accuracy rate is 99.10% of 6650 characters.

H. Scheidl "Handwritten text recognition in historical documents". Technische Universität Wien, 2018. - Handwriting recognition system proposed by Harald Scheidl is composed of layers of Convultional neural network(CNN) and recurrent neural network (RNN) which extracts text from an image passed through the model. Ultimately, the Connectionist Temporal Classification (CTC) decoding algorithm is applied, which converts the extracted text to the final version.

V. CHALLENGES IN HANDWRITTEN TEXT RECOGNITION

Handwritten character recognition is a challenging research problem that has been the focus of many researchers over the years. Some of the challenges are as follows: *Variability in handwriting* - Handwriting varies significantly from person to person and even within the same person. This makes it difficult to build a model that can accurately recognize characters written by different people. *Overlapping characters* - In some cases, handwritten characters may overlap, making it difficult to segment the characters correctly. *Poor quality images* - Handwritten characters may be written on poor quality paper, or the images may be distorted due to scanning or other factors. This can make it difficult for the recognition model to accurately interpret the characters. *Unconventional writing styles* - Some people may have unconventional writing styles that deviate significantly from the standard forms of characters. This can make it difficult for the recognition model to accurately recognize these characters. Despite these challenges, significant progress has been made in the field of handwritten character recognition, and there are many powerful models available today that can accurately recognize handwritten characters with a high degree of accuracy.

CONCLUSION

The common areas of failure for OCR systems are hardware limitations that hinders the system from efficiently delivering the results. The users of such systems might have to scan the image by a camera phone with high camera resolution, photos should be captured from an appropriate perspective and zoomed in angle, to get a clear image with its content evident. As for the future work, existing dataset will be augmented with more handwritten medicine names and will be used and trained to obtain higher accuracy. Pre-processing techniques from all the mentioned papers will be implemented. Bi Directional LSTM along with layers of CNN and RNN will be implemented to acquire higher accuracies.

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