HandWritten Text Recognition Using Machine Learning

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Abstract: The study of handwritten character recognition has gained popularity. The handwritten characters that were scanned as input in the proposed technique were identified using a variety of machine learning algorithms.. It segments each character in the image and recognises the letters after receiving the handwritten document as input in the form of a high resolution image. Additionally, it recognises the letters before going on to find the words in the image. Based on the training it received from the training data, this is accomplished with the help of machine learning algorithms. The specified input image will be provided in word document format as the intended output. Large data sets of images that display the various writing styles and shapes can be used to train the system. When training the system with vast amounts of data, machine learning is crucial. This can also be used to businesses and organisations that only keep critical records in writing form. Keywords: OCR algorithm, simple OCR, digit recognition, digit OCR.

I.Introduction

The process of turning a handwritten text image into a text file that a computer can read and utilize for a variety of applications is known as handwritten recognition. The goal of this method is to create software that can comprehend handwritten documents. The technique extracts contour-based information to identify the character or word. One flaw in handwritten papers is that they are challenging to read through. In recent years, one of the difficult study areas in the realm of image processing and pattern recognition has been handwriting recognition. The task of handwriting recognition is difficult for a variety of reasons. The main explanation is that different writers have distinctive writing styles. The abundance of characters, including capital letters, small letters, digits, and special symbols, is a secondary factor. As a result, to train the system, a sizable dataset is needed. Since the system scans and detects static images of the characters, optical character recognition (OCR) is frequently referred to as an off-line character recognition method. We use the term "handwriting" to describe manuscript and cursive written writings. Because the characters are separated and written in block letters, manuscript-style texts are simpler to recognise. Cursive handwriting, on the other hand, joins the characters as they are written. To correctly perceive and recognise each individual character, handwriting recognition software is required. To create various text recognition algorithms that can be converted from paper format to electronics. The writing style is not constrained in a handwritten manuscript. The various human writing styles, variations in letter size and shape, and angles make it difficult to read handwritten alphabets. A branch of OCR technology called handwriting recognition, often known as handwriting OCR or cursive OCR, converts handwritten characters into corresponding digital text or commands in real-time. These systems use pattern matching to recognise diverse handwriting styles to accomplish this goal. According to Wikipedia, handwriting recognition is: a computer's capacity to read and comprehend legible handwritten input from sources like paper documents, photos, touch-screens, and other devices.

II.Related Work:

The task of handwritten text recognition has been figured out during the past few decades with emphasis work. Various techniques have been intended to be used in that effort. There have been difficult tasks that have required creative solutions for increased precision and efficiency. Below is a brief summary of the various forms of recognition for work well done. Because of the numerous areas of application, including the interpretation of ID numbers, processing of bank checks, recognition of ZIP codes, vehicle registration numbers, and handwritten text, the topic of handwritten text recognition has received increased attention in pattern recognition. As a result, handwritten text recognition is more widely used. around the globe. The feature extraction strategy that produced the greatest results with the highest degree of precision after taking into account more traditional horizontal and vertical approaches was concluded[1]. With this Neural network on better tested levels, an added feature with more noise tolerance and more precise results are produced. The neural network used in this model is referred to as feed forward, and it was predominantly trained using the back-propagation technique, which also provided training to a higher extent for character classification and recognition.

Aside from that character recognition results are improved and are more precise when normalisation is used in conjunction with feature extraction. A design must be created for the most exact outcome. We must create a larger training data set for the optimal neural network [1]. Because of the use of feature vectors, handwritten text recognition systems use artificial neural networks in supervised learning methods. Bit map representations of input samples are used as feature vectors, which are first pre-processed and then more effectively used by neural networks. This model provides better accuracy with unseen images that are inputs of the neural networks for single images that consist of rotated images. Systems for optical text recognition are created using text that has been scanned from documents and photos [3]. This includes text detection and recognition, where text is recognised and then classified . Steps are categorised, and features are described in text using the template. A determined classifier is then applied to the described characters.

They propose to use the unified character descriptor (UCD) to illustrate characters who fit that description. Then, categorization is used to ensure that the matching. In consistently scanned text files, that recognition approach operates with excellent precision [4]. That does not indicate characters with more font variation or deformation. A neural network with a classifier is used to improve recognition. Convolutional neural networks are very popular today because they perform better. Comparability between this paper's work and the multilayer perceptron (MLP) plus CNN. In CNN, a convolutional network (Lenet-5) that supports 62 classes is used for handwritten and machine-printed character recognition. Adding letters and the number [5] as well. We would have a database specifically for the recognition task. Because this data base serves as the foundation for several handwriting recognition projects [6]. Amazing work has been done on the recognition in several languages, including Arabic [7] and Malayalam [6]. English, Bangla [8, etc. Convolutional Neural Networks (CNN), a type of deep neural network, in particular, have provided promising results in a variety of fields in recent decades. greatest accuracy With 96% accuracy, the CNN models used in this work produce superior outcomes for recognising quantitative data, and 96% accuracy can continue to produce better results even when noisy conditions make it more challenging.

III.THE PROPOSED ARCHITECTURE FOR HANDWRITTEN TEXT RECOGNITION USING MACHINE LEARNING

In this machine learning project, we will use tensor flow to build a convolutional neural network (CNN) model that will recognise handwritten characters, or the English alphabets from A to Z. A significant portion of the dataset on which we will train our model includes pictures of the English alphabet.

An active topic of study in pattern recognition, artificial intelligence, and computer vision is handwriting recognition (HR). The offline handwritten text recognition (HTR) process converts the scanned image into digital text as seen in Fig. 1. The neural network is created using an IAM dataset that has been trained and handwritten text recognition (HTR) process converts the scanned image into digital text as seen in Fig. 1. The neural network is created using an IAM dataset that has been trained and comprises word images. Although neural networks can be best executed on the GPU and CPU, all layers are only slightly combined with word pictures. Handwritten Tensor flow text recognition requires straightforward execution.

Fig. 1. Scanned text image to digital text conversion.

IV.MACHINE LEARING FOR DIGITAL TEXT CONVERSION

A contemporary area of study that includes pattern recognition, artificial neural networks, and computer vision is handwritten text recognition. This use of artificial neural networks, which provides the ability to autonomously learn and improve from experience without being explicitly designed, uses machine learning techniques. The creation of computer programmes that acquire information and utilise it to learn for themselves is primarily what machine learning refers to. By using algorithms from touch screen devices and pictures, handwritten text is recognised and its features are obtained. It is then translated into machine-readable form. Similar to this, a variety of sectors and industries, including image processing, classification, regression, medical diagnosis, prediction, and learning association, are adopting machine learning.

A. *Training the model in machine learning*

The IAM data source, which includes a comprehensive English sentence database for off-line handwriting recognition, was utilised in the paper by Marti and H. Bunke [11]. the database of sentences written in different handwriting styles in English. This database contains complete sentences in English. We would have a database specifically for the recognition task because this data base is used as a base for several handwriting recognition projects [12, 13]. This database was developed using a substantial amount of word images. To prepare the batch elements' average loss values are input into an optimizer like RMSProp using a neural network. All of the words in this IAM data neural network are aligned to the left. So the system never learns how to handle the graphics in the white areas, but it is certainly possible to learn to overlook white space.

B. *Framework used in machine learning*

Different frameworks are used in machine learning to recognise handwritten text in a very accurate manner. Some of these topics were covered, including Tensor flow, NumPy, and others.

1) Tensor Flow: Tensor flow is an open source library for large-scale machine learning and numerical computation. In deep learning, tensors are the de facto standard for data representation. Although machine learning is a complicated field of study, using tensor flow makes it much easier to put the models into practise. Since data acquisition, model training, shopping prediction, and feature preservation are processes, machine learning frameworks like Tensor Flow have made this possible.

The health care sector of GE Healthcare is training a neural network to identify and specific anatomy during the MRI brain exam in order to help speed and reliability [14]. Tensor flow is used by many companies, including Airbnb company, which is applying machine learning using tensor flow to classify the emergence and detect objects at a scale helping to improve test experience. Tensor flow is being used by PayPal to stay on the cutting edge of fraud detection. Adopting Keras for high-level APIs that make machine learning relatively simple and for additional flexibility, as well as Eager execution that allows for fast iteration and debugging, are features of Tensor Flow that set it apart from the competition. Tensor flow kernels run instantly when eager execution is enabled rather than building graphs that will execute later.

Numpy: NumPy is a software that can carry out a number of operations and is utilised in scientific computing. Due to the operation of multidimensional array tools and objects and the usage of the same datatype for storage, it provides exceptional performance in arrays. This array's indexing follows numbers starting at zero. NumPy is a powerful N-dimensional object of array that is a general-purpose array handing out package.

Edit distance: This is defined as a change between two strings that involves a minimum amount of insertions, deletions, and replacements. Sys and argparse are two other frameworks that are utilised. There are system-specific parameters and functions in sys, and this access is used for some variables. According to the needs of scripting, argparse offers a recommended command line parsing module in the Python standard library.

IV. Study of handwritten text recognition

It uses Optical character recognition algorithm to recognize the handwritten Text. By 2025, the market for optical character recognition (OCR) is anticipated to be worth USD 13.38 billion, growing 13.7% annually. Rapid business process digitalization employing OCR to cut labour expenses and conserve valuable man hours is what is driving this growth. Although handwriting recognition (Handwriting OCR) or handwritten text recognition (HTR) is a crucial part of optical character recognition, it is still regarded as a difficult problem statement. Converting handwritten text into machine readable text is extremely difficult due to the wide variation in handwriting styles across individuals and the inferior quality of handwritten text compared to printed text. However, it's an issue that several sectors, including banking, insurance, and healthcare, need to solve.

Today, typed characters in high-quality photographs can be read with greater than 99% accuracy thanks to OCR technology. However, as you can see in the accompanying image, the variety of human writing styles, spacing variations, and inconsistencies of handwriting lead to less precise character recognition. As a result, technologies that read handwriting cannot be as accurate as OCR systems on typed text.

However, because of ongoing study in this area, handwriting recognition now employs extremely complex algorithms to address this issue, increasing its accuracy.

A dynamic research field like pattern recognition, artificial intelligence, and others is called handwritten recognition (HR). Because handwritten text contains so many varied styles of handwriting, it became challenging. Although word and character recognition rates have increased, rates for offline handwritten text recognition have not increased as much. The field of text recognition has experienced great success in a variety of real-world applications, including security applications, e-government systems, and other areas [15]. The several methods of handwritten text recognition and how the process works are covered here. Here, each step for handwritten text techniques and procedures is described in brief. Information that has been recognised primarily depends on the recognition strategy systems that recognise text

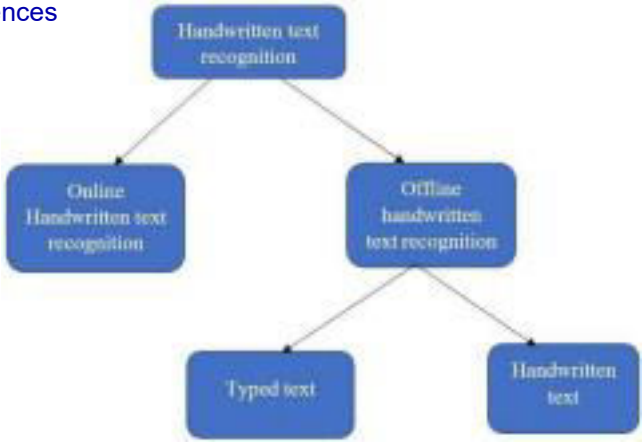


Fig. 2. Scanned text image to digital text conversion

VI. Flow of the process

This section covered the fundamental workflow of a handwritten text recognition system. The system will take a handwritten text image as input and produce the desired handwritten text as the output. The conventional text recognition system goes through a number of steps, including image collecting, pre-processing, segmentation, and feature extraction, with classification as the last stage. Some of these processes are occasionally combined by researchers. The basic process flow of the HTR system is shown in Fig. 3.

Online handwritten text recognition allows for real-time composition and recognition of handwritten text [16]. To create such type, special digitizer tablets and pens are utilised. A digitizer has an electromagnetic tablet that continuously sends the coordinates of the pen position to the computer. The primary examples that generate the text for online text recognition are tablets and Personal Digital Assistants (PDAs). Due to the dynamic information that is typically present in online handwritten text, online handwritten text recognition is easier than offline handwritten text recognition.

Text recognitions such as the number of strokes, the speed at which each stroke is written, and the direction of each stroke. When compared to offline systems, this document recognition process typically results in systems that perform well.

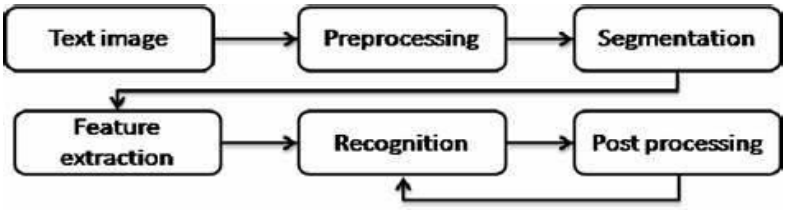


Fig. 3. Basic process flow of HTR.

In the HTR system, the handwritten text data is first converted into a digital format with the fewest possible deteriorations. Using a camera and scanner with a purchase, a grayscale or colour image is captured in offline handwritten word recognition mode.

Pre-processing, which comes after the image capture stage, is the main step that must be completed in a recognition method. Pre-processing generally does not stop with handwritten text recognition. Pre-processing is used in picture processing. By eliminating noise reduction, edge identification, picture normalisation, and thresholding, the pre-processing converts the image path to the following stage of analysis. The acquisition circumstance in this case, such as poor document or file formatting, introduces noise. Therefore, it is necessary to maintain relevant information while reducing noise as much as possible, which makes this a crucial pre-processing step. When scanning a writing instrument or an image, noise can also be present. This can result in line segments that are not connected and gaps between the lines, so it is first priority to remove this noise. Various techniques, including high pass filters, low pass filters, median filters, and bandpass filters, can be used to accomplish this. In pre-processing, these filters are employed to reduce noise.

PREPROCESSING OF THE DATA

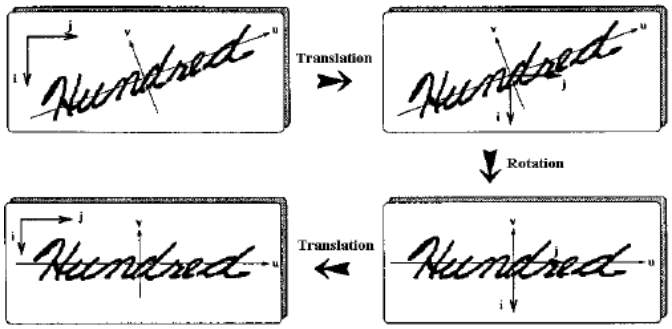
- Before starting text recognition an image with text needs to be analyzed. For that purpose we need to provide preliminary image preprocessing.
- The preprocessing algorithm includes following steps:
  1. Skew Correction
  2. Binarization

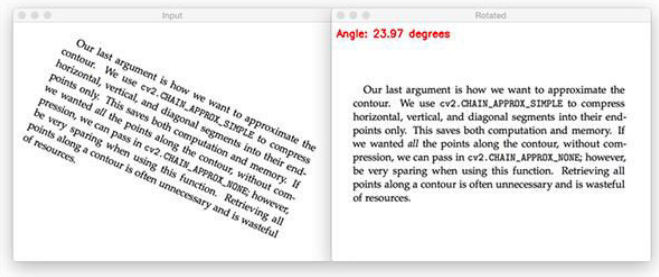
3.Noise Removal
4.Thinning and Skeletonization

1.Skew Correction : We need to fix the text skew in an image with a block of text rotated at an unknown angle by:

1. Detecting the text in the image.
2. Finding the angle of rotated text.
3. Rotating the image to correct for the skew.

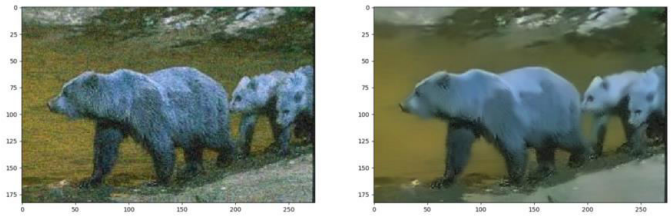
We typically apply text skew correction algorithms in the field of automatic document analysis, but the process itself can be applied to other domains as well.





2.Binarization : It is the process of turning a coloured image into one with only black and white pixels (black pixels have a value of 0 and white pixels have a value of 255). As a general rule, this can be accomplished by setting a threshold, which is often 127 because it corresponds to exactly half of the pixel range 0-255. The pixel value is regarded as a white pixel if it above the threshold; else, it is seen as a black pixel.

3.Noise Removal : The noise removal stage's primary goal is to smooth the image by removing tiny dots or patches that are more intense than the rest of the image. Both coloured and binary images can have their noise removed. Using the fastNlMeansDenoisingColored function in OpenCV is one method of accomplishing noise removal.



4.Thinning and Skeletonization :

Depending on the setting in which OCR is being utilised, this preprocessing step is optional.

→ There is no need to complete this operation if we are using an OCR system for printed text because the printed text always has a consistent stroke width. This operation must be completed since various writers have varied writing styles and, consequently, different

stroke widths when utilizing the OCR system for handwritten text. Therefore, we must execute Thinning and Skeletonization in order to uniformly reduce the width of the strokes.

SEGMENTATION :

Any recognition system must include segmentation as a vital and essential phase. This step breaks apart the operation of the image for the handwritten text. This results in the concealment of any image, including handwritten words, characters, or subwords. However, this is not always achievable. Generally speaking, this procedure detracts from the system's credibility by In handwriting recognition, there are two categories of segmentation methods: • Explicit segmentation: using this technique, characters and sub-words are converted into characters or sub-characters. • Implicit Segmentation: This technique separates the lower, or so-called "grapheme," portions of the handwritten text, which are typically the words and characters. The words and characters are made up of these grapheme-based elements.

Segmentation of the image done in three levels :

1. Line Segmentation
2. Word Segmentation
3. Character Segmentation

Line Segmentation : At this level of segmentation, a skew-corrected image with text that is written in lines is presented to us. To segment the image into lines is the goal of line level segmentation.

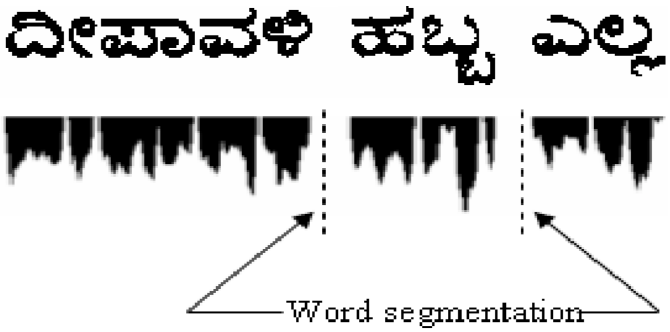
If we horizontally project the binary image ,

- High numbers of foreground pixels in rows that indicate text in a line translate into higher peaks in the histogram.
- High numbers of background pixels are found in the rows that depict the spaces between the lines, which correspond to lower histogram peaks.
- Rows that correspond to lower peaks in the histogram can be selected as the segmenting lines to separate the lines.

Word Segmentation : At this stage of segmentation, we are given an image with a single line that was previously segmented and contains a list of words. Word level segmentation aims to separate the image into individual words. The idea is similar to the previous step, but the only change is, here we have to project the image vertically (Sum is taken along columns) because we have to segment words vertically.

If we vertically project the binary image,

- High numbers of foreground pixels in columns that indicate text translate into higher peaks in the histogram.
- High foreground pixel counts in text-indicating columns correspond to greater histogram peaks.

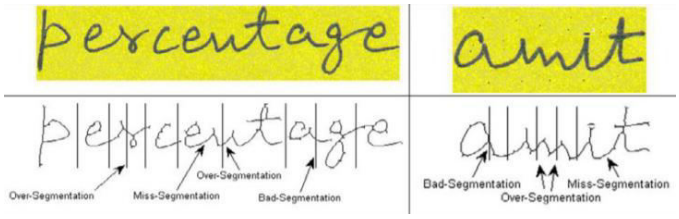


For segmenting words, lower peaks should be selected in such a way that they should span through a certain width (threshold). This is because we'll find lower peaks which correspond to the gaps between disconnected characters within a word, which we are not

interested in. As we know, the gaps between the words are greater than the gaps between the characters within a word, the threshold should be chosen in such a way that neglects the thin gaps between the characters within the words.

Character Level Segmentation : At this stage of segmentation, we are given an image containing a single word that was previously segmented and is composed of a string of characters. Character level segmentation aims to divide the image into distinct characters. This level of segmentation is optional, which depends upon the context where the OCR is being used.

- Character Level Segmentation is not necessary if the OCR technology is being used on text when words have independent characters. We can segment the characters in the previous step since a uniform space is maintained (even though it is small) between the characters within a word (by setting a very low threshold).
- Character Level Segmentation must be used to separate the characters if the OCR system is being applied to text that contains connected characters within words (cursive handwriting).
-



A few precautions should be followed while performing character recognition. The below figure shows one such problem, the segments shown in the below figure are not accurate ,as h is extracted as l and i. Such errors are undesirable. Another precaution is of ligatures . If the text image contains cursive type font then while segmenting the ligature should be separated for better efficiency.

FEATURE EXTRACTION :

This is the very important stage of handwritten character recognition system. The main objective of feature extraction is to extract all the essential features of the scanned image.

In feature extraction stage each character is represented as a feature vector, which becomes its identity. The major goal of feature extraction is to extract a set of features, which maximizes the recognition rate with the least amount of elements. Due to the nature of handwriting with its high degree of variability and imprecision obtaining these features, is a difficult task. Feature extraction methods are based on 3 types of features:

- Statistical
- Structural
- Global transformations and moments

Statistical Features :

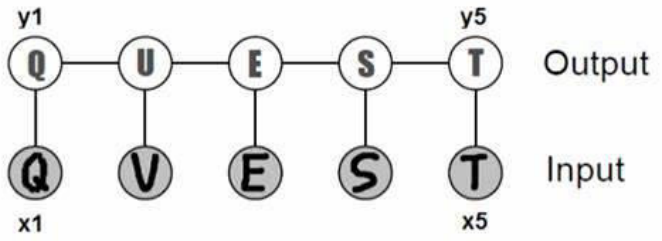
o Representation of a character image by statistical distribution of points takes care of style variations to some extent.

o The major statistical features used for character representation are:

- Zoning
- Projections and profiles
- Crossings and distance

CLASSIFICATION :

Extracted features in the feature extraction steps are used to classify the images by assigning labels to the features.



Classification, arguably the most well-liked problem in machine learning, involves categorising images based on their properties and in conjunction with a training dataset. For handwriting recognition, the essential elements of an input image are extracted and fed into classifiers like logistic regression, kernel neural networks, and ANNs. These ML classifiers then classify the image more precisely by comparing the featured image to the training dataset.

Post-processing is in charge of correcting photos that were previously misclassified and changing detection at this step. It is impossible to omit this procedure because it ensures the most accurate outcomes. Post-processing can be broken down into a number of processes depending on the desired result.

Due to the significant issue of inter-class unevenness, feature extraction is one of the crucial processes in the recognition of handwritten text. Characters have different forms depending on their positions. Useful data was needed by the handwritten text recognition system to distinguish between one thing and other things. Therefore, this feature extraction stage is applied. Fourier features, structural features, global transformations, and statistical features are a few examples of feature extraction techniques. Any recognition system must include segmentation as a vital and essential phase. This step breaks apart the operation of the image for the handwritten text. This results in the concealment of any image, including handwritten words, characters, or subwords. However, this is not always achievable. Generally speaking, this procedure detracts from the system's credibility by In handwriting recognition, there are two categories of segmentation methods: • Explicit segmentation: using this technique, characters and sub-words are converted into characters or sub-characters. • Implicit Segmentation: This technique separates the lower, or so-called "grapheme," portions of the handwritten text, which are typically the words and characters. The words and characters are made up of these grapheme-based elements.

VII. Overview of Work

As shown in Fig. 4, the model is created utilising recurrent neural networks, convolutional neural networks, and lastly, a connectionist temporal classification layer. Equation (1), which transfers a picture (i.e., a matrix) M of size WH to a character sequence of c1, c2, that has length from 0 and L, is utilised here as a neural network as a mathematical function. Due to the fact that text is recognised at the character level, messages or words that are not included in the training data can also be recognised. Characters can be accurately determined if they are defined as unique individuals.

$$NN: M \rightarrow (C_1, C_1, \ldots, C_n) \quad (1)$$

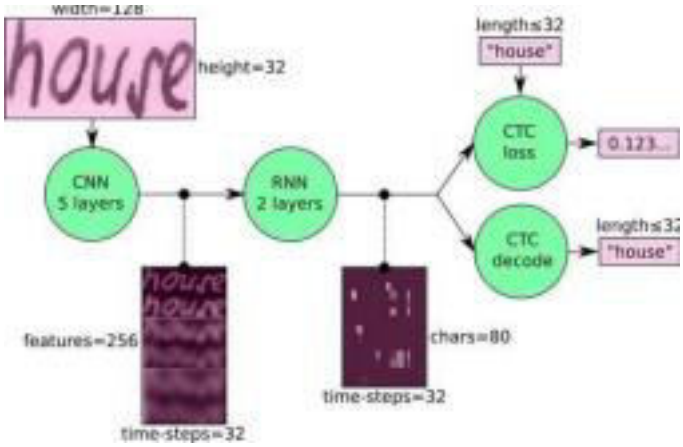


Fig. 4. Overview and data process of the neural network.

A. Function of Model

CNN: convolutional neural network used to process scanned image input (CNN). The trained layers extract the picture's crucial key characteristic. Initially, the layers apply a convolution function. The first two layers receive a kernel filter (size 55), while the final three levels (33) receive a kernel filter. A non-linear RELU operation was then applied after this. Finally, the pooling layers condense image regions. However, layers' image height is reduced by 2 and the channels are also added (maps). As a result, an output with a feature sequence (or map) of 32256 size is shown in Fig. 6.

RNN: A time step of a feature sequence of 256 features is used by the recurrent neural network to convey pertinent information. This RNN uses a broad LSTM execution and provides a considerably better training representation than a vanilla RNN. The output sequence of the RNN records a matrix with a size of 3280. For the CTC blank label or CTC function, a 79-character IAM data base is needed, thus every 32 time steps, a total of 80 accesses are made, as illustrated in Fig. 7.

CTC: Despite neural network training. The CTC output for RNN is supplied (Connectionist temporal classification). The ground truth text is also supplied by CTC. The CTC determines the value of the loss. As a last step, CTC provides a matrix, which the final text then uses to decode. Both the recognised text and the ground truth text have characters that are 32 characters long.

VIII. THE PROPOSED ARCHITECTURAL FLOW

For the handwritten text recognition from input to output of handwritten text that convert to a scanned image to a digital text, the major details of the model are briefly given below.

A. Input of the model

The image, or gray-value image, is standardised to make the duty of neural network simpler. Instead of arbitrarily scaling the image or aligning it to the left, make a copy of the image and place it in random locations. Here, the gray-value image measures 128 by 32 pixels. This size is typically not exactly the same as what is needed for the data set. So, the image gets adjusted till it is either 32 inches tall or 128 inches wide. Then, this image is copied into a target image that is white and has a size of 128 by 32. An example of this is shown in Figure 5, where the left image is a random size that has been mapped to fit a dataset target image with a size of 128 by 32, and the empty space is filled with the target level's white colour.

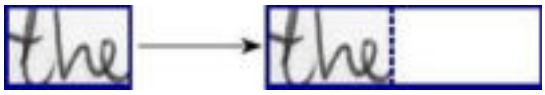


Fig. 5. Random image is converted into target image with white color

CNN Output: The output of CNN layers is a 32-word sequence, with each entry having 256 features. Additionally, these properties are governed by RNN layers.

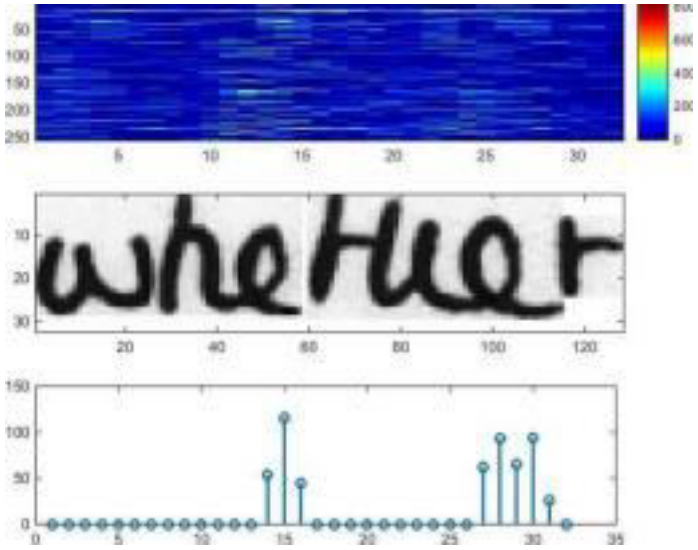


Fig. 6. Computation of 256 features per time-step by CNN layers, middle fig shows input image and below fig show 32nd feature that have character “e” image with high correlation.

RNN Output: the top-most graph showing character scores, with the last (80th) row in the matrix and the CTC label left blank. For the depiction of the RNN output, the image contains the text "small." Every entry in the matrix is also arranged from higher to lower.

IX. Results and Discussion

The IAM off-line HTR dataset was used to train the tensor flow algorithm for handwritten text recognition. This neural network model can recognise text that is contained within a word-segmented image. Complete text lines appear larger in the image than individual words do. In this case, the neural network is kept small to make CPU training practical. Around 34 of the validation-words set's are correctly predicted, and 10% of the words have character errors. The IAM dataset was used to pre-train this model, and higher word accuracy was found when converting the input image to digital text. Here, the above-described word beam search strategy is employed in this model with Python 3.6 and Tensor Flow 1.3 on Windows 10.

Figures 8 and 9 depict the output in relation to location, visible letters in the word, contrast of the image, writing style, and similar factors of scanned input images of words. Accuracy can be increased by eliminating spelling errors, using writing styles, and in relation to positions.

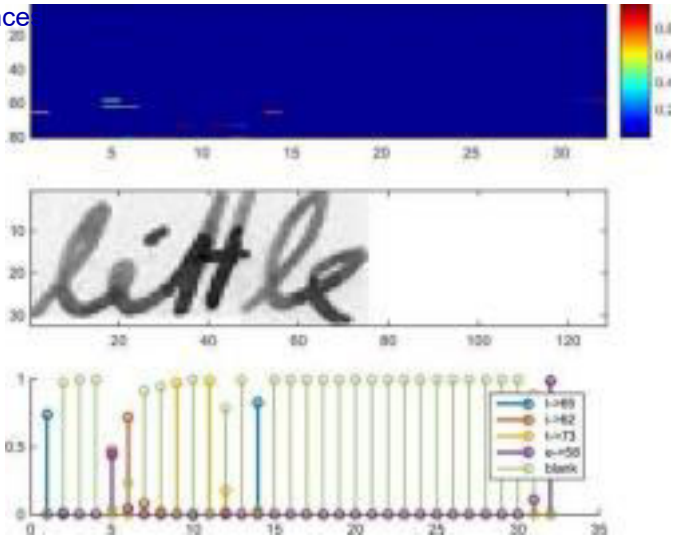


Fig. 7. Output matrix, middle fig is input picture and below fig shows CTC blank label and probabilities of character like “l”, “i”, “t”, “e” of RNN layers.

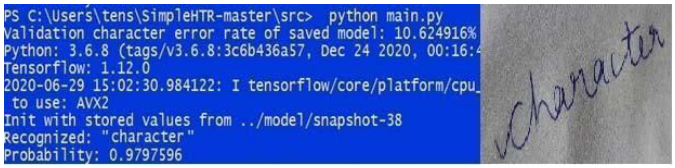


Fig. 8. Output is “character” from input of “character” with probability 97.97 percent

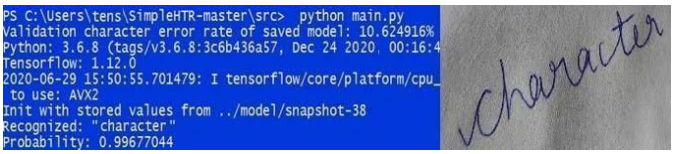


Fig. 9. Output is “character” from input of “character” with probability 99.67 percent

X.CONCLUSION AND FUTURE WORK

When compared to the prior system, the new system achieves relatively good recognition rates for both the evaluation of text line elements and the collection of horizontal, vertical, and skewed lines. This handwritten letter recognition neural network includes two recurrent neural networks, five convolutional neural networks, and character probability matrices as outputs. Finally, this detection and implementation using Tensor flow provides suggestions for improving accuracy. FASTag deployment in India and books are currently the key application areas for this. digital translation from one language to another. By minimising several types of handwriting, such as Data augmentation techniques include normalising contrast, skew, slant, and size of the handwritten text or character, as well as other ways to increase the accuracy of neural networks.

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