Handwritten Text Recognition

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***Abstract*—Despite the plentiful technological writing tools, many of us still choose to take notes traditionally with pen and paper. We might require these notes in later times and hence it has to be stored digitally for accessing it later. Handwriting recognition is categorized into 2 types namely the offline and online mode. The main focus of this project is offline analysis where complete text is fed into the model and recognized.**

This paper will discuss the comparison of the implementation of handwritten text recognition systems using CRNN and AlexNet.The model developed in the project is coded in python. CRNN involves usage of Recurrent Neural Networks, Convolutional Neural Networks, Connectionist Temporal Classifier function and much more. The IAM dataset will be used to train the model since it has the most number of training examples and also has a variety of handwriting which gives better model for inference

***Index Terms*—Handwritten text recognition, CTC(Connectionist Temporal Classifier), CRNN (Convolutional Recurrent Neural Network), CNN, RNN, Softmax, ReLU(Rectified Linear Unit), Adam, AlexNet**

I. INTRODUCTION

This is the era of digitalization, everything is digital now. With the advancements in the area of Natural Language Processing, text processing, machine learning, Computer Vision, etc., digitalization of handwritten data occupies its own unparalleled position. Not just in technical aspects, but digitalization can also be a biggest asset in sectors like banks, post offices, tax offices, hospitals, etc. Also plays an important role in institutes that involve business and finance such as tax statements, annual inspection industries, postal address translations, population census,etc. and also in data statistics that are carried out in large scales. For all these handwritten text recognition is the means by which one can achieve digitalization and thus acts as the heart.

Handwriting recognition is basically of two kinds(two approaches), offline and online recognition. Online recognition is based on stylus trajectory i.e., recognition is done in real-time. This type of recognition starts once when the user starts writing the text on a text pad using a stylus. The other type of recognition is offline recognition. In this case, the entire handwritten text is scanned and given to the system as input, typically as a jpg/png file and then the text is recognized. This paper focuses on the offline recognition approach.

There are several methods to achieve the offline recognition approach. This project discusses the comparison of offline handwriting recognition using two models namely CRNN and AlexNet. Our system can recognize all the English alphabets, both uppercase and lowercase.

To develop a Machine Learning model for offline handwriting recognition of the English language. Though the goal of this project is to create a system for offline handwriting recognition, its primary focus is on comparing the two models by implementing CRNN and AlexNet.

The models are trained on the IAM dataset that contains 13353 images of handwritten text (with a total of 115320 words) with capital letters and small letters. The IAM database contains images of handwritten lines of text created by 657 writers, which covers a wide range of handwriting, which helps in building better models for inference. The model takes the handwritten words as the input and gives the recognized digital text as output.

The CRNN model consists of layers like Convolutional Neural Networks(CNN), Recurrent Neural Networks(RNN), Connectionist Temporal Classifier(CTC) loss function. AlexNet contains convolutional, max pooling and batch normalization layers. To sum up the main objective, it focuses on comparing the working of two methodologies of offline recognition.

II. LITERATURE SURVEY

- **[1] Hao Zeng, An Off-line Handwriting Recognition Employing TensorFlow**
  - **Introduction :** This paper discusses how to recognise offline handwriting using TensorFlow, with a main focus on digit recognition. It has aided in greater understanding of TensorFlow and its capabilities.
  - **Characteristics and implementation :**
    - Tensorflow is a programming interface for expressing Machine Learning Algorithms, as well

as a tool for implementing them. Unlike other programming languages, TensorFlow's programming concept is to train the algorithm to reach the accurate value.
  * The MNIST dataset was used to train the model because of its integrity, popularity, and diverse data collection.
  * The SoftMax algorithm was used to define the expression properties, whose job is to calculate the likelihood of each classification and to use that information to identify the input class with the highest probability.
  * The loss function is used to define the calculation accuracy. The smaller the damage, the more accurate the formula.
  * The loss is computed using cross entropy. When dealing with a huge data set, the algorithm's computational complexity becomes the critical limiting factor.
- **Results :** The model's accuracy is determined by the degree to which the real classification matches the expected value. The result obtained was 0.9195.
  * Assists in a greater understanding of TensorFlow.
  * MNSIT dataset should be used for handwritten recognition for better accuracy.
  * SoftMax algorithm is recommended for recognition of digits.
- **Limitations :**
  * Accuracy of 0.09195 can be optimized.
  * The computational complexity limits this project to only smaller datasets.

- **[2] Handwriting Recognition- Offline Approach P. Shankar Rao, J. Aditya**
  - **Introduction :**
    * In the offline approach, this paper discusses the pre-processing procedures and different approaches that contribute to character recognition, word recognition, and difficulties encountered during this process of recognition.
    * Here, the handwriting data is digitalized by scanning and writing with a special pen on an electronic board.
    * Two ways of recognizing handwriting are offline and online.
  - **Methodology :** Handwritten acknowledgement is broken into various stages :
    * Pre-processing is further separated into four phases :
      · **Thresholding :** which is used to separate the foreground from the context i.e., ink from the paper.
      · **Noise removal :** Noise may be injected into the digital capturing via Scanning equipment and transmitting media. Noise reduction will improve precision.
      · **Line Segmentation :** It is based on the assumption that people write on an imaginary line that serves as the core for each word on the line.
      · **Character and Word Segmentation :** The writing styles are captured in terms of spacing by characterising the disparity in spacing between the neighbouring characters as a function of the corresponding character.
    * Character Recognition : As a result, each sample is identified by a collection of micro feature vectors that correspond to the characters in the sample. Handwritten characters use 'micro feature vectors' to analyse the handwriting individuality effectively.
    * Word Recognition : HMM is used here. It is a form of word recognition that uses a state transformation diagram to decide pre-segmentation points and then it determines the best direction.
  - **Limitations :**
    * Noise caused due to scanning the handwritten characters has resulted in decreased accuracy.
    * Issues with segmentation due to different writing patterns.

- **[3] A survey by May Mowaffaq**
  - **Introduction :** In 2017,S. S. Kharkar, H. J. Mali, and their colleagues suggested an offline handwriting recognition based on Neural Network (NN) to identify numbers (0-9) and English letters small and capital letters (a-z, A-Z), as well as special symbols (ampersand, dollar, hash, percent and *).
  - **Methodology :**
    * It involves many operations such as -
      · grey image conversion,
      · noise reduction,
      · thresholding,
      · binarization,
      · segmentation,
      · normalization of the extracted character matrix into 12*8 matrix,

      and then conversion of this matrix to a column one was used in the proposed model to perform the pre-processing stage.
    * After that, this function vector was sent to the classifier.
  - **Results :** It was proven that the proposed Neural Network (NN) based approach is more accurate and effective than many other current approaches, as it yields higher precision.

- **[4] Handwritten Text Recognition using Faster R-CNN by junquin yang**
  - **Methodology :** The four main steps involved in the recognition are :
    * Preliminary processing
    * Meticulous processing
    * Character recognition
    * Data consolidation

        * Convolutional neural networks are used to derive important features from an input image. It learns with tiny squares of input data and maintains the spatial relationship between pixels, Spatial pooling (also known as down-sampling) technique is used to reduce every function map's dimensionality. The two key stages in CNNs ate the attribute and description extraction.
        * R-CNN- can be categorized into four methods : "function extraction", "idea extraction", "bounding box regression ", and "grouping into a network".
            · Extraction of features
            · Proposal Networks for regions
            · "Region of interest pooling" (RoI pooling)
            · Regression classification

          To retrieve the function diagram, scale the input image to a desired size and enter it into the convolution and pooling layers. Second the function map is fed into the RPNs, which create a list of potential target candidate boxes. In the final step the original feature map as well as all the candidate boxes are included.
    - **Results and Conclusions :** The algorithm used in this paper has greater robustness and precision, according to the results of the experiments. Character segmentation rates for letters will exceed 95 percentage on average. Character segmentation can be completed with high precision using an algorithm based on Faster R-CNN.
        * Loss of preliminary processing
        * Loss of meticulous processing

      The Faster R-CNN findings reveal that it outperforms standard OCR. Character segmentation is the most challenging aspect of handwriting text recognition; but, by translating the problem of "character segmentation" into an "object detection problem", accurate character segmentation with high precision can be achieved.
- **[5] HDR using CNN. Chao Zhang**
    - **Introduction :** In the training phase, the failure feature serves as a predictor. The loss function between the goal and expected categories in this scheme is cross entropy, and preparation often tries to reduce the loss function.
    - **Methodology :** "TensorFlow" can distinguish the loss function for each vector and then find the gradient descent route to change the weight. TensorFlow comes with a vast range of optimization algorithms pre-installed. The "RMSProp algorithm optimizer" tf.train is included in this article. RMSPropOptimizer with a learning rate of 0.001 and attenuation value of 0.9 is used to maximise cross entropy. This article uses 64 testing samples in each loop and then performs a training session. After every 100 cycles of service, the system outputs a log, for 20,000 cycles in total. The training results cannot be significantly changed because this article assumes that the preparation is over at a point. The system's bottleneck is not inadequate preparation, but the structure of the algorithm.
    - **Results :** The results obtained from the training samples show that as the number of training steps is directly related to the recognition accuracy gradually, and the average recognition accuracy of the final result is 97.6 percentage
- **[6] A Review Paper on Handwritten Character Recognition By Bhagyashree D. Upadhyay, Dr.Sachin Chaudhary**
    - **Introduction :**
        * Automatic interpretation of handwritten text is no longer the primary bottleneck of record analysis and retrieval development systems. "Extraction" and "Line detection" in complex texts, as well as language recognition in multilingual streams, have a greater impact on their results.
        * It is expected that the learned features that are good for text recognition may provide ways to solve these problems, and that 'deep learning' opens up new ways to solve these problems.
        * To take advantage of the large amount of data and improve model accuracy, we need a way to "train the networks" in days rather than weeks to take advantage of the vast amount of data and increase model accuracy. Production systems, on the other hand, rely heavily on tempo. Convolutions can be parallelized more quickly than MDL-STMs.
    - **Implementation :**
        * A NN architecture has been proposed based on these results, which include a "Convolutional encoder for the input image" and a "BLSTM decoder" for character prediction. Such architectures have been investigated in the past, but none have yet outperformed the "MDLSTM", which is the current state of the threat.
        * "MDLSTMs" are dynamic neurons with a sophisticated gating mechanism for controlling flow of information and repeated "network vanishing" and "bursting gradient problems". It is assumed that the "gates" are a critical component in the performance of such an architecture, since they do more than just allow effective recurrence.
        * This paper discusses and applies a character recognition approach that is useful. Since typed text recognition did not require a large number of datasets to train the system, handwritten recognition was the primary goal. For such 36 alpha numerals, a dataset of 200 samples are used, with another 100 samples for special characters. ML and gated CRNN are useful for obtaining classification labels from features. This information is then saved in an excel sheet for further review.
- **[7] Handwritten Recognition to get Editable Text by Prof. Vaibhav. V. Mainkar**

– **Methodology :**
  * Image Acquisition - The Android Smartphone is used by the machine, i.e., OCR. The camera aids in the image capture of handwritten papers. This is simply the screening procedure. The original image can be converted to a digital image using the scanning technique. The initial photographs are shown in black text against a white backdrop. As a result of this process, the digital image becomes a grayscale image.
  * Preprocessing - One of the most critical steps of character identification is pre-processing. It makes grayscale images easier to interpret for software. It removes the impurities from photographs and cleans it. It is an import phase for handwritten images that are more vulnerable to noise.
  * Segmentation - It is the most critical method. The aim here is to separate the individual characters. Handwritten text is first segmented into lines, then the lines are segmented into words and finally words are segmented into characters.
  * Feature Extraction

  OCR recognises alphabets based on various groups during the feature extraction process. The transformation of input to features is known as feature extraction. The features are extracted from the text image. Their qualities are their features. Slant angle, height, curves and other factors are used to classify the alphabets. The selected text is compared to the system's normal database and the dataset, with the highest similarity being chosen and proclaimed as a character. The primary focus of feature extraction is representation of the symbols. The character is translated into text after it has been recognised based on classification.

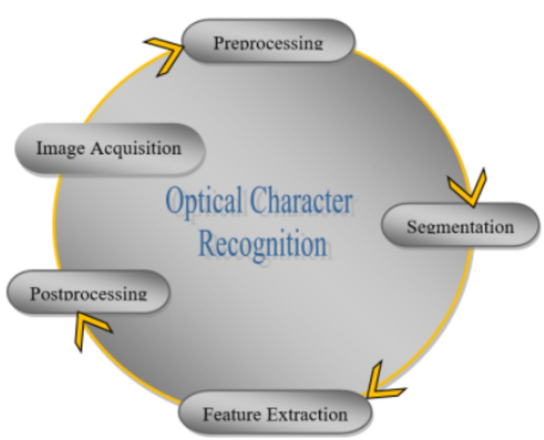


Fig. 1. OCR algorithm

- **[8] Robust HWR with Noisy and limited Data by Hai pham and Amrith Setlur**
  – **Methodology :** There are mainly three parts in the text image recognition, given below :
    * **First : text image recognition with blank background :** The recognition process mentioned here uses a specified method for identifying each character. After the extracting process of the characters from the skeletonization process, extraction of feature vectors is done. This is then compared to the database. The goal of this process is specified selection from a set of important features/aspects that will reduce the redundancy.
    * **Second : text image recognition with unspecified background(if any) :**
      · This is a process about the text at random places like a complex background, with no proper style at unspecified places, with no proper structure.
      · The solution can be Convolutional Neural Network and Convolutional Neural Networks with some language based features. However when compared to their specifications our size varying forms adds to the noise.
    * **Third : text image recognition with noisy background :** Here the model used is a two step model
      · Process 1 : Segmentation
      · Process 2 : Recognition

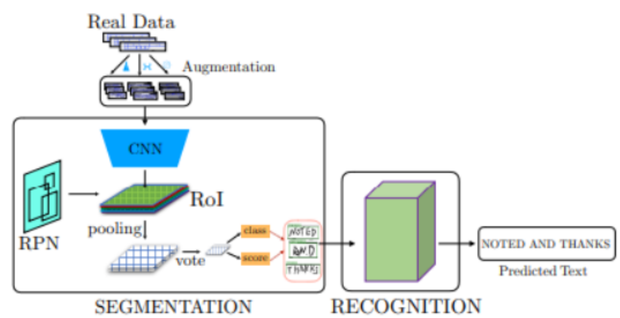


Fig. 2. Step Model

  – **Implementation :** Segmentation : Here instead of concentrating on getting the correct boundary boxes and recognition of words inside the boundary simultaneously, the proposed model focuses only on finding out the exact boxes of boundaries at phases of the model called word model. This type of model is very effective and feasible because separation of words based on spaces is very efficient. Types of Segmentation approach -
    * Similarity Detection (Region Approach)
    * Discontinuity Detection (Boundary Approach)
    * Recognition
    * Scale Invariant Feature Transform
    * Speeded up Robust Features
    * Analysis using Linear Discriminant
    * Analysis using Principal Components

    There are 2 models used here :
    * Word Model : This uses CNN. It takes the input from a predefined set of words.

  * Character Model : The architecture is quite similar to that of word model which enables the benefit of initializing weights from a pre-trained Word Model, instead it uses CTC loss.
- **Results :**
  * Experimental Results : The types of data used here are DA and real.

Dataset	Type	Train	Valid	Test
Segmentation	Real	2,358	-	1,362
	+DA	40,159	-	-
Recognition	Real	6,639	3,400	1,249
	+DA	660,000	-	-
Pipeline	Real	-	-	1,362

Fig. 3. Experimental Result for 2-step model

  * Pipeline performance of the very best model when compared with baselines.

Segmentation	Recognition	WER($\downarrow$)	CER($\downarrow$)
R-FCN [6]	Word	31.5	22.9
	CTCSeq2Seq	**30.1**	**18.5**
PixelLink [8]	MORAN [28]	80.7	47.4
Convolve-Attend-Spell [21]		38.9	24.1

Fig. 4. CER and WER values

III. Motivation and Scope

The use cases and user classes of 'Handwriting Recognition' are not limited to single domain/space. The users can range from professionals like Hospital staff, Tax Inspectors, Historians, etc., who can use this technology to digitalize handwritten texts. Below are some domain/user classes/areas where handwriting recognition systems can be used.

- **Postal Address Recognition :** Post offices can use this technology to recognize the text on the post envelopes. This helps in massive digitalization of post-office benches leading to a permanent elimination of feed-address staff. It can act as an alternative to address-lookup, staff can be added to ensure recognition is working smoothly and to correct if any errors are incurred.
- **Form Processing :** One of the highly used areas of forms are hospitals, tax offices, banks, etc.. It becomes really time consuming for the respective staff of these places to digitalize them through manual typing. Similar to post offices, digitalization of these forms using this technology leads to massive time-saving and human power elimination.
- **Ancient Transcripts translation :** Historians and Archaeologists rely massively on transcripts of ancient times for their study. Since these aren't digitalized, it becomes difficult for them to quote and source them whenever necessary. Hence digitalization in this domain ensures safety, availability and no-data-loss feature.

IV. Dataset

- The IAM dataset is used to build the model. It is the most widely used dataset for training models and handwriting recognition. It has wide variety of sub-datasets ranging from images that contain letters to complete sentences.
- The lines subset of IAM dataset is used here to build the model. It contains 13353 images of handwritten lines(with a total of 115320 words). The IAM database contains images of handwritten lines of text created by 657 writers, which covers wide range of handwriting.

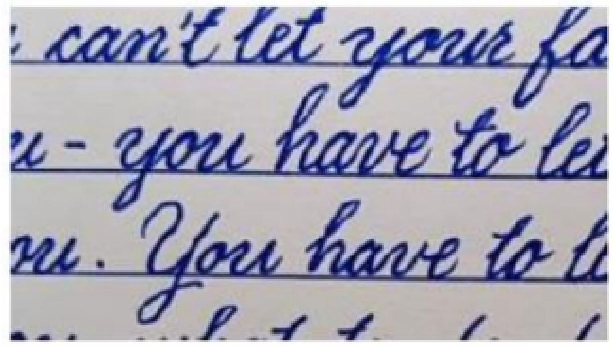


Fig. 5. Sample Input

- The database also contains a text file that has every handwritten line with its ground text and with appropriate mapping to their original handwritten images.

V. Proposed Methodology

The design of the handwritten text recognition is as shown in fig.6 The detailed implementation of the model is shown in

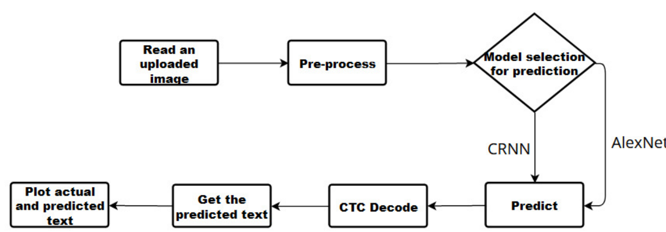


Fig. 6. Design Proposed

the high level architecture in fig.7. The model is compressed of two models namely, CRNN and AlexNext. The model is trained on a variety of text which includes uppercase alphabets and lowercase alphabets.

A. *Overview of Model workflow :*

- Words are extracted from words.txt file by neglecting the commented lines
- The dataset is split into 8:1:1 for train, test and validation respectively
- Find image paths by splitting and striping

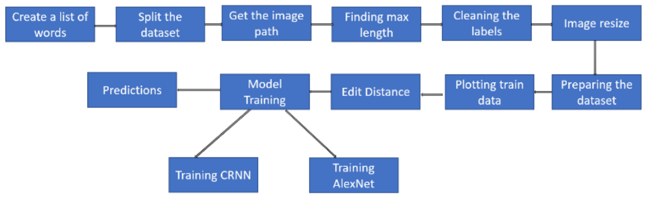


Fig. 7. High Level Architecture

- Find the maximum length of label from the list of labels present in the dataset
- Resize each image according the maximum length obtained
- Convert the image into vector format
- Plot graphs for training set along with the actual labels
- A CRNN with 4 convolutional and 2 recurrent layers, trained for 120 epochs
- Make predictions on test images using CRNN
- An AlexNet with 5 convolutional, 3 max pooling and 4 batch normalization layers
- Make predictions on test images using AlexNet.

B. Real time predictions :

The steps to be followed by real-time input image to obtain output is clearly depicted in the Real Time Prediction in fig.8.

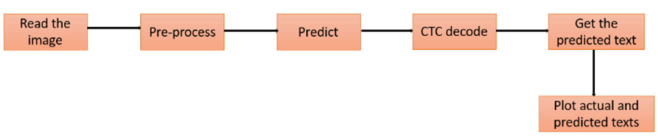


Fig. 8. Real Time Prediction

- The image uploaded onto Google Colab is read
- As a part of pre-processing the uploaded image is resized according to the maximum length
- Predictions are made using CRNN or AlexNet
- Only the handwritten text is given as the input to the CTC fuction during the testing process.
- The CTC function decodes the digital text based on its learning.
- To visulaize a graph is plotted for the uploaded image with the predicted text

C. Proposed Methodology :

Image acquisition :

- The first and foremost step of the design of handwriting recognition model.
- Collection and organization of data.
- importing the dataset.
- original image to grayscale image conversion.

Pre-processing :

- Once the dataset is fed, pre-processing of this raw data is an important phase where the motive is to clean the raw data into an understandable form before training and testing of the model.
- This is one of the critical stage in the model building. Since most of the images of IAM dataset are already at pre-processed state with minimal/no noise, very less pre-processing is used.
- However, this can be achieved by :
  - Damaged images are detected and replaced with blank images.
  - Resize the image without distortion to image contents.
  - vectorize the labels and pre-process image labels

Edge Detection :

- The important step of the model is edge detection.
- Padding is done in order to get clearly inferable images and shown in fig. 9

Fig. 9. Visualization of training examples after Pre-processing

Model Description :

- **Convolutional Recurrent Neural Network(CRNN) :** The methodology diagram of CRNN depicts clearly the construction, working and importance of CRNN as shown in fig.9.
  - CRNN involves CNN followed by RNN.
  - **Convolutional Neural Networks(CNN) :** A CNN is a type of NN which is widely used in visual and image field. It mostly deals with edge detection(feature extractions) from the input images to help in further conclusions. In each layer of CNN a fixed size of Kernel is used to detect edges in input image. The output of CNN's last layer is given as input to RNN's first layer.
  - **Recurrent Neural Networks(RNN) :** RNN used here is a bi-diectional LSTM implementation. The reason behind this LSTM model is that we need to propagate the information of handwritten lines through larger distances. Bidirectional RNN is used to get two variables i.e., forward and backward and concatenate them to achieve better learning rate. After concatenation, the ouput of RNN has input image which is converted into horizontal positions called the time-steps. The output of RNN's last layer is given as an input to the CTC function.
  - An input layer of shape (128,32,1) is used to process the input image. The Activation function used here

is *ReLU*. The CRNN consists of four convolutional layer. In the first convolutional layer the dimensionality of output space is 32, in second, third and fourth convolutional layer the dimensionality of output space is 64. A *reshape layer* is used to resize the input so that it can be fed to RNN. Additionally dense layer and dropout layer are used. *Bi-directional LSTM* layer without dropout is used to *avoid overfitting*.CTC layer is used as a loss function and *Adam* optimizer is used.

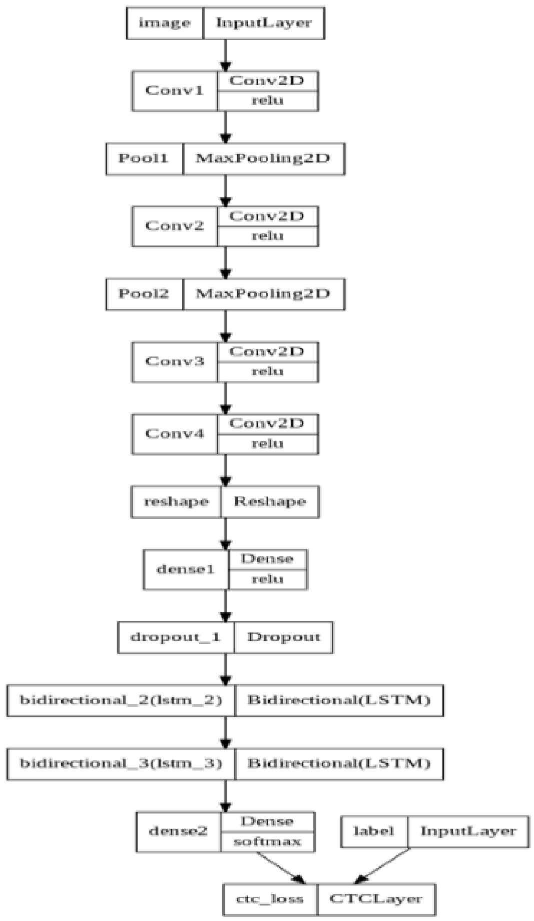


Fig. 10. CRNN

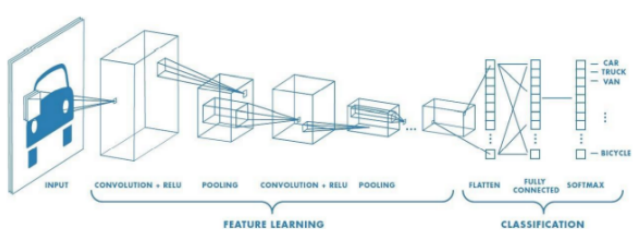


Fig. 11. Convolutional Neural Networks

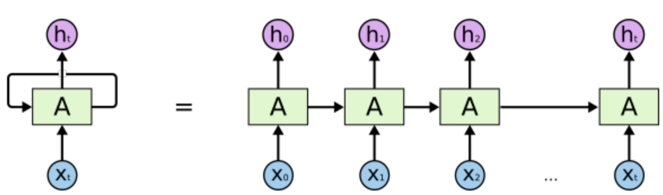


Fig. 12. Recurrent Neural Networks

- **AlexNet :** The methodology diagram of AlexNet depicts clearly the construction, working and importance of AlexNet as shown in fig.9.

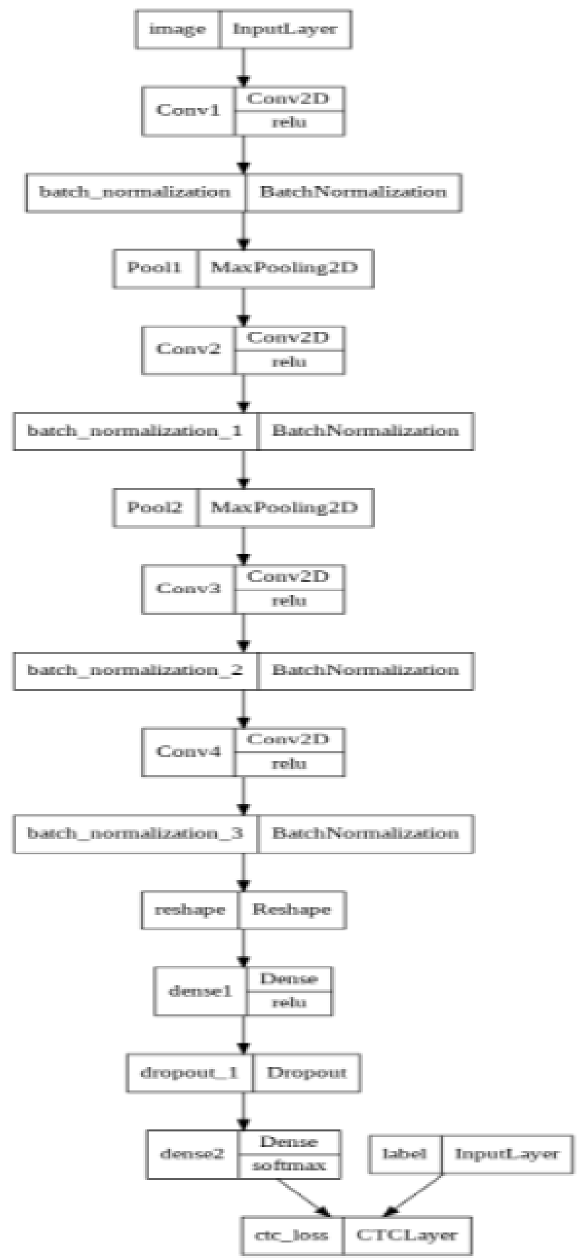


Fig. 13. AlexNet

  - AlexNet involves only the use of CNN

- An input layer of shape (128,32,1) is used to process the input image.
- Activation function used is *'ReLu'*.
- AlexNet consists of 5 Convolutional Layers. In the first convolutional layer the dimensionality of output space is 32, in second, third, fourth and fifth convolutional layer the dimensionality of output space is 64.
- After each convolutional layer, a *BatchNormalization layer* is used to normalize the inputs.
- Additionally *MaxPooling layer* is used,
- *Reshape layer* is used to resize the input
- Two dense layers with ReLu and third dense layer with softmax function and *dropout layers* are used for smooth processing of input to output
- A *CTC layer* is used as a loss function and the optimizer used *Adam*

• **Edit Distance :**
  - The similarity measure used is edit distance
  - At the end of epoch, the predictions are made for validation images
  - For every batch, labels are converted into sparse tensors
  - This computes Levenshtein distance

• **CTC(Connectionist Temporal Classifier) Loss function :** This is the heart of the built model. Entire recognition of text takes place here. It uses CTC greedy decode function to decode the actual text.The handwritten character will be mapped to the digital character on the basis of scores of character. Then, during training, both the ground text and handwritten text is given as an input to the CTC function. It recognizes characters and checks its loss function. This process continues until there is no change in loss or the minimal loss(i.e., obtained after 120 epochs).

Detection :

- It takes predictions as input and generates plot for predicted and actual text for test images as output.
- it involves the detection of input length of text.
- Here, the image is flipped, transposed and plotted
- The plot comprises of the image and the predictions made by the model

RESULTS AND CONCLUSIONS

- This implementation gives the conversion of handwritten sentence to digital text. The image with no noise and well segmented with the text is given to the model and the digital text is obtained on the screen.
- The recognition system has been successfully built and is capable of recognizing English words.
- The project mainly dealt with comparing the working of two models which is CRNN and AlexNet on handwritten English words recognition.
- The accuracy of the obtained digital text highly depends on the clarity of the individual letters in the image and also on the skew in the handwriting(higher the skew lesser the accuracy of recognition)

- The number of epochs in CRNN is 120 and in AlexNet is 25. The reason to choose 25 epochs for AlexNet model is because, if the number of epocs is increased more than 25 then it leads to overfitting, which can be clearly inferred from the model loss graph of AlexNet shown in fig.14

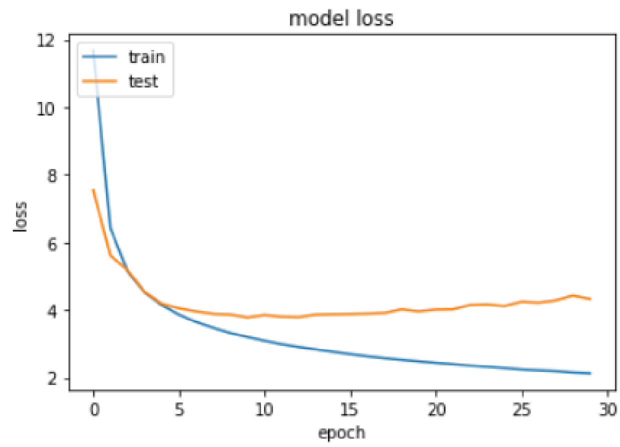
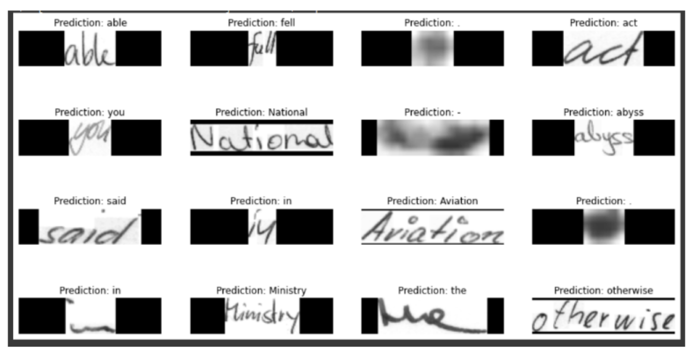


Fig. 14. Model Loss Graph of AlexNet

- The Predictions of the test set of CRNN model is shown in fig.15



8.1 CRNN predictions

Fig. 15. Test set Predictions for CRNN

- The Predictions of test set of AlexNet model is shown in fig.16

Fig. 16. Text set Predictions for AlexNet

- The accuracy obtained by CRNN model and AlexNet model is 73.4375% and 34.375% respectively.
- It can be seen that among these two models, CRNN is giving best results on both test and real time predictions. Whereas, AlexNet is capable of recognizing only a few words in both test and real time predictions.

Further Study :

This technology(Handwriting recognition) is a never ending space. With advancements in deep learning techniques, there is a lot of scope for one to explore in this. With the emergence of robust neural networks and R-CNNs, there are even studies that explain how model train time can be reduced. Also, most of the data scientists are currently exploring de-slantation technologies that help to correct the skewness of the handwritten text before feeding it into the model. Hence, this domain as said above is a never ending space and advancements can be made every time one explores and researches on it.

There are many ways to improve the model to achieve better results.Some of the techniques are :

- The system can be extended to recognize sentences and a whole page as a part of future work.
- GUI is not included in the project. So this can be released as an android app as a part of future work.
- De-slantation algorithm that can increase the accuracy of the model on cursive handwriting
- . Use of robust neural networks that can rapidly decrease the train and test time and much more of this kind.

VI. Abbreviations and Acronyms

- NN - Neural Network
- CRNN - Convolutional Recurrent Neural Network
- RNN - Recurrent Neural Network
- CNN - Convolutional Neural Network
- CTC - Connectionist Temporal Classifier
- ReLU - Rectified Linear Unit
- CER - Character Error Rate
- WER - Word Error Rate
- NLP - Natural Language Processing
- ML - Machine Learning
- MDLSTM - Multi-Dimensional Long Short-Term Memory
- HMM - Hidden Markov Model
- OCR - Optical Character Recognition
- R-CNN - Regions with Convolutional Neural Network
- Adam - Adaptive Moment Estimation
- Img - Image
- Dr - Doctor
- Prof - Professor
- etc - Etcetera
- i.e - That is

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