LETTER RECOGNITION USING DEEP LEARNING

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Abstract — In this paper we present inventive techniques for offline handwritten character discovery utilizing deep neural networks. In this day and age it has gotten simpler to prepare deep neural networks on account of accessibility of tremendous measure of information and different Algorithmic advancements which are occurring. Now-a- days the measure of computational force expected to prepare a neural network has expanded because of the accessibility of GPU's and other cloud based services like Google Cloud stage and Amazon Web Services which give assets to prepare a Neural network on the cloud. We have created a system that recognizes and predicts handwritten digits from 28x28px images created in paint. In our system we have also made use of OpenCV for performing Image processing and have used Tensorflow for training a the neural Network. Our front end is in the form of a web app and a mobile app.s We have developed this system using python programming language.

I. INTRODUCTION

As we are aware, in this day and age AI(Artificial Intelligence) is the new Electricity. New breakthroughs are occurring in the field of computerized reasoning and deep-learning each day. There are several fields in which deep-learning is being utilized. Handwriting Recognition is an important area where deep neural networks are being used. Perceiving handwriting is a simple undertaking for people yet an overwhelming task for computers.

Recognition of handwriting has been explored over numerous years. Handwriting recognizable proof framework can be utilized to fix many confounded issues and work with the work of creatures.

To perceive handwriting, deep learning has been often used. Text is inspected after it is composed in offline handwriting recognition. The binary output of a character against a backdrop is the sole information that can be examined. The handwriting of client is accessible as a picture. Handwriting recognition is difficult in view of many reasons. The reason being that various individuals have various styles of writing. The best reason is that, there are numerous characters like Capital letters , Small letters , Digits and Special images. As a result, a huge dataset is needed to prepare a close exact neural network model. To foster a decent framework an exactness of atleast 90% is required. However even the most modern and commercially available systems have not been able to achieve such a high accuracy.

II. LITERATURE REVIEW

In [1] a preprocessing strategy is introduced for improvingTesseract Optical Character Recognition (OCR) execution onimages with vivid foundation. The proposed strategy consists of two stages. Right away, a content division strategy is performedwhich endeavors to remove the content from the vivid background.This step depends on input picture grouping into k pictures. In thesecond step, a classifier is utilized to distinguish the picture containingtext among k pictures coming about because of theprevious step. OCR is then performed on the distinguished image.The proposed preprocessing strategy further develops Tesseract OCRperformance by around 20%.
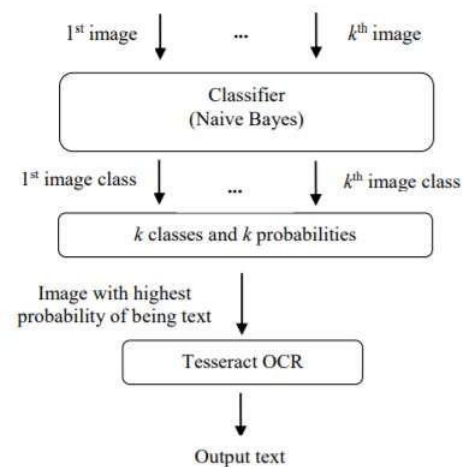

Fig 1

In [2] there are quite a few Optical Character Recognition (OCR) versatile applications available running on cell phones, both android and iOS (iPhone, iPad, iPod) stages. The impediments of cell phone processor ruin the conceivable execution of computationally serious applications that need less season of cycle. This paper proposes a structure of Optical Character Recognition (OCR) on cell phone utilizing worker based preparing. Correlation techniques proposed by this paper by directing a progression of tests utilizing independent and worker put together OCR with respect to cell phones, and look at the consequences of the exactness and time needed for the

whole OCR preparing. Worker based versatile OCR gets 5% higher person acknowledgment precision than the independent OCR and its arrangement acknowledgment exactness is 99.8%. The system attempts to defeat the limit of cell phone ability measure, so the gadgets can do the computationally serious application all the more rapidly.
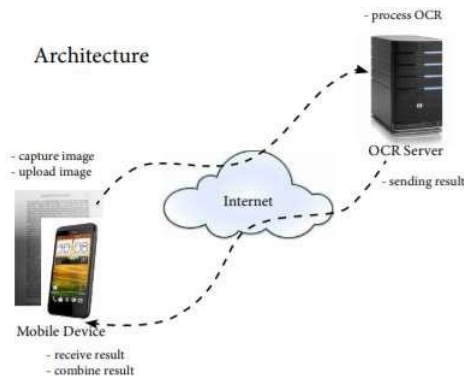

Fig 2

In [3] introduced OCR droid, a nonexclusive structure for creating OCR-put together application with respect to cell phones. Notwithstanding, this conversation zeroed in on utilizing direction sensor, inserted very good quality camera and advanced picture preparing procedure to tackle OCR issues identified with camera-caught pictures.

In [4] Variation in penmanship among various scholars happens since every author has own speed of composing, various styles, sizes or positions for characters or text. Variety in penmanship styles additionally exists inside unique individual's penmanship. This variety might take pl ace because of: writing in different circumstances that could possibly be agreeable to essayist; various states of mind of author; way of composing same characters with various shapes in various circumstances or as a piece of various words; utilizing various types of hard product for penmanship. This paper gives a study, and characterization of different person acknowledgment procedures.

In [5] Digital cameras are helpful picture procurement gadgets: they are quick, adaptable, portable, don't contact the article, and are somewhat modest. In OCR applications, be that as it may, computerized cameras experience the ill effects of various limits, as mathematical mutilations. In this paper, we manage the preprocessing venture before text acknowledgment, explicitly with pictures from an advanced camera. Tests, performed with the FineReader 7.0 programming as the back-end acknowledgment apparatus, affirm significance of picture preprocessing in OCR applications.

In [6] The undertaking for written by hand digit acknowledgment has been problematic because of different varieties recorded as a hard copy styles. Accordingly, we have attempted to make a base for future explores in the space with the goal that the specialists can defeat the current issues. The current strategies and

procedures for transcribed digit acknowledgment were investigated and perceived to break down the most appropriate and best technique for digit acknowledgment. Various 60,000 pictures were utilized as preparing sets of pictures with pixel size of 28x28. The pictures/preparing sets were coordinated with unique picture. It was discovered get-togethers examination and audit that classifier gathering framework has the least mistake pace of simply 0.32%. In this paper, audit of various strategies written by hand digit acknowledgment were noticed and investigated.

Numerous calculations have been produced for written by hand digit acknowledgment. However, because of limitless variety recorded as a hard copy styles they are as yet not up to stamp. Helpless difference, picture text unclearness, upset content stroke, undesirable articles, disfigurement, muddled examples and furthermore interclass and intraclass closeness additionally cause misclassification in written by hand numeral acknowledgment framework [7]

[8] sums up the top best in class commitments gave an account of the MNIST dataset for transcribed digit acknowledgment. This dataset has been widely used to approve novel strategies in PC vision, and as of late, many creators have investigated the exhibition of convolutional neural organizations (CNNs) and other profound learning methods over this dataset. Apparently, this paper is the principal comprehensive and refreshed audit of this dataset; there are some online rankings, yet they are obsolete, and most distributed papers overview just firmly related works, discarding the vast majority of the writing. This paper makes a qualification between those works utilizing some sort of information increase and works utilizing the first dataset out-of-the-case. Additionally, works utilizing CNNs are accounted for independently; as they are turning into the best in class approach for taking care of this issue. These days, a lot of works have achieved a test mistake rate more modest than 1% on this dataset; which is becoming non-testing. By mid-2017, another dataset was presented: EMNIST, which includes the two digits and letters, with a bigger measure of information gained from a data set not the same as Mnist's. In this paper, EMNIST is clarified and a few outcomes are reviewed.

[9] offers another answer for customary penmanship acknowledgment methods utilizing ideas of Deep learning and PC vision. An augmentation of MNIST digits dataset called the Emnist dataset has been utilized. It contains 62 classes with 0-9 digits and A-Z characters in both capitalized and lowercase. An application for Android, to identify manually written content and convert it into advanced structure utilizing Convolutional Neural Networks, condensed as CNN, for text characterization and discovery, has been made. Before that we pre-handled the dataset and applied different channels over it. We planned an android application utilizing Android Studio and connected our penmanship text acknowledgment program utilizing tensorflow libraries. The format of the application

has been saved basic for show reason. It utilizes a protobuf record and tensorflow interface to utilize the prepared keras chart to foresee alphanumeric characters drawn utilizing a finger.

In [10] Digitization of machine printed or manually written content archives have gotten extremely mainstream with the headways in figuring and innovation. People have attempted to automatized their work by supplanting themselves with machines. The change from manual to automatization led to a few examination regions and text acknowledgment is one among them.

Profound learning and AI procedures have been end up being entirely reasonable for optical person acknowledgment. In this work, a forward-thinking outline of four AI and profound learning models, viz., Support vector machine, Artificial neural organization, Naive Bayes and Convolutional neural organization have been examined exhaustively.

III.   SYSTEM DESIGN AND ARCHITECTURE

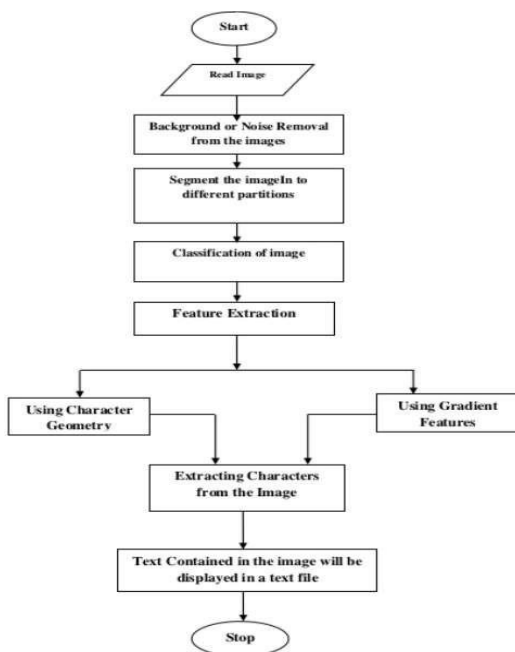The design and architecture of the proposed system has been illustrated in the following flow chart.

Fig 3

IV. IMPLEMENTATION

Objective

1. Use of Neural signs in literature domain.

2. Reducing the man-power required to transform physicalliterature into digitized form manually.

3. Creating a rich and digitized library with English language.

Purpose -

Users will be able to convert signatures and notes into electronic words in a text document format using our system. The benefit of electronic storage is that it takes up considerably less physical space than physical copies and also takes fewer personnel to sift and arrange the records.

Aside from that, another benefit of handwriting recognition is data retrieval. Physical data retrieval necessitates employees sorting through old physical copies of data. The data had to be kept and maintained properly at all times. To keep this information or data,

We do an electronic data retrieval utilising a file search that includes particular keywords, such as the file or document's titles and dates. Handwriting recognition software makes it possible to store ancient files in an electronic format. This is how handwriting recognition software aids in the preservation of vital documents or old data. Some clinics, for example, prefer to retain their patients' medical data in the computer, and handwriting recognition aids in this case by keeping these medical records safe. This information or files may be examined and updated as needed without fear of losing the information.

Another benefit of our system is that it preserves historical information. Physical copies of historical documents are the most common. Genealogical material, written manuscripts, ancient family documents, personal diaries, and even shared old past stories are examples of historical papers. However, these historical documents may be destroyed or distorted due to accidents, and this is where handwriting recognition software comes in handy. Handwriting recognition aids in the conversion of handwritten text into a text document format, often known as a readable electronic format. Historical facts may be readily kept, examined, and shared with a large number of individuals this manner.

Textual studies are a type of literary research. Literature studies entail comparing and contrasting the original manuscripts with the printed form. This indicates that the narrative was dug up and modified by various authors as it was passed along. This is why original manuscripts are treated with great care, although this still necessitates a thorough study of the document. Handwriting recognition makes it possible to retain these original manuscripts intact in an electronic version, where they may be studied without causing damage to the original copy.

Working Principle –

A server - Our system's backend consists of a server. This server is a machine with the ability to run Python scripts. It's necessary since an Android phone lacks the computing capacity needed to run neural networks and execute image processing operations. Users of older smart phones can also utilise our system since we use a server to execute computationally intensive activities. In our system, we

employed the Convolutional Neural Network Model. We utilised the NIST Dataset, which is open to the public and comprises examples of handwritten characters from thousands of authors. Convolutional Neural Network is the neural network model that we utilised. CNNs are cutting-edge neural networks that have a wide range of applications in the field of computer vision. Tensorflow, an open source framework for machine learning applications, was used to train the neural network model.

OpenCV was utilised to conduct image processing operations such as segmentation, thresholding, and morphological operations. OpenCV is a free and open source image processing library. It correctly detects handwritten text, as demonstrated below.

An application - This is our system's frontend. We have used flutter architecture to implement this in the form a

V. DETAILED SOFTWARE IMPLEMENTATION

Character recognition is performed utilising deep learning principles in this project. It can divide a picture into 36 categories (0...9 + A...Z). It was designed to recognise characters from a number plate that only has digits and uppercase alphabet letters.

This is a completely separate module from the identification of number plates. We may start this job by locating and segmenting number plates. I present a neural network implementation for character recognition in this paper. It uses the most famous library tensorflow to create a basic yet efficient convolution neural network.

Specification of this project

1. Tensorflow model (diagram + boundaries) which is self saved and self stored, is made by model.py, you don't have to give any outside code to save and reestablish model.

2. You can run training measure on different occasions. Whenever it starts, it begins training the model from where it was stoped last training. At the end of the day it stacks your model from last(latest) designated spot and resume training measure

3. In each training, your plot of training exactness is embedded or affixed into logdir document for tensorboardrepresentation.

4. Training in enormous model requires numerous days so you require a model that can be stoped and continued. In the event of force disappointment you would prefer not to prepare your entire model again from introduction of factors, So you needa model that begin training from last designated spot.

5. This project likewise utilize early stopping. Early halting means when your model exactness drops in numerous bordering cycles, then, at that point it quits

web app andas well as an android app.

The Android application allows the user to utilise their smartphone camera to take a photo of text that has to be identified. This image is then given to a python script running on a server, which analysesit further to extract the important information. The application we created may use the mobile camera or a previously taken photo from the gallery.

The text in the image is then detected and printed together with thecolumns. It is also aware of the difference between tiny and uppercase letters and recognises them as distinct.

The input can be given to the system either by selecting a preciously taken or downloaded text from the gallery, or by usinga the camera of the mobile phone to take a picture.

training.

A brief overview of the steps involved:

1. **Segmentation:** In the division stage, a succession of characters is sectioned into a sub-picture of an individual person. Each character is resized into 30×20 pixels.

2. **Classification and Recognition:** This stage is the dynamic phase of the acknowledgment system. The classifier contains two secret layers, utilizing a log sigmoid actuation capacity to prepare the calculation.

3. **Feature extraction:** The highlights of info information are the quantifiable properties of perceptions, which is utilized to break down or order these occurrences of information. The undertaking of highlight extraction is to distinguish important highlights that separate the examples that are autonomous of one another.

4. **Neural Network System for Continuous Handwritten Word Recognition:** A technique for consistent transcribed word acknowledgment is inferred when the word is fragmented into trios (containing 3 letters). Two resulting trios have 2 normal letters. The greatest test for acknowledgment systems is to perform procedure on a ceaseless word. In this, each word is partitioned into trios, each containing three letters. Figure 10a shows trio "aba" and figure 10b shows trio "boycott". Two neighbor trios consistently contain two normal letters which address the covering between letters. This sort of covering results is a higher acknowledgment rate.Data Sets

MNIST & EMNIST

The dataset has been specified in two file formats. Both contain identical information, and are provided entirely for the sake of convenience. The first dataset is provided in a Matlab format that is accessible through both Matlab and Python (using the scipy.io.loadmat function). There are six

different splits provided in this dataset. A short summary of the dataset is provided below:

- EMNIST ByClass: 814,255 characters. 62 unbalanced classes.

- EMNIST ByMerge: 814,255 characters. 47 unbalanced classes.

- EMNIST Balanced: 131,600 characters. 47 balanced classes.

- EMNIST Letters: 145,600 characters. 26 balanced

We have trained it to recognize digits in the form of images of size 28x28 px, which we have created in paint. Samples of such images are provided below:
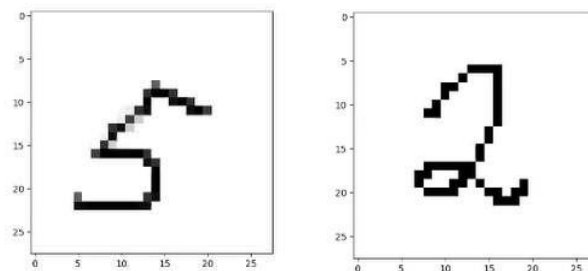
- classes.

- EMNIST Digits: 280,000 characters. 10 balanced classes.

- EMNIST MNIST: 70,000 characters. 10 balanced classes.

The EMNIST Digits and EMNIST MNIST dataset give adjusted written by hand digit datasets straightforwardly viable with the first MNIST dataset. We have used MNIST dataset and Tensorflow to create as digit recognition system.

Characterized in the portion is determined. This grid is then gone through an initiation work "ReLu" that changes each regrettable worth in the framework over to nothing.

Fig 4

The Steps involved are given as follows:

1) **Pre-preparing:** This is the initial step acted in picture handling. In this progression the clamor from the picture is

   eliminated by utilizing middle separating. Middle sifting is perhaps the most broadly utilized commotion decrease method. This is on the grounds that in middle separating the edges in picture are protected while the commotion is as yet taken out.

2) **Conversion to Gray-Scale:** After the pre-preparing step, the picture is changed over into grayscale. Transformation into grayscale is fundamental on the grounds that various authors use pens of various shadings with fluctuating powers. Additionally dealing with grayscale pictures diminishes the general intricacy of the system.

3) **Thresholding:** When a picture is changed over into grayscale, the manually written content is more obscure when contrasted with its experience. With the assistance of thresholding we can seperate the more obscure locales of the picture from the lighter areas. Along these lines due to thresholding we can seperate the manually written content from its experience.

4) **Image Segmentation:** A client can compose text as lines. In this manner the thresholded picture is first divided into singular lines. Then, at that point every individual line is divided into singular words. At long last each word is sectioned into singular characters.

Convolutional Neural Network

A Convolutional Neural Network (CNN) is a sort of neural organization generally utilized for picture acknowledgment and arrangement.

CNNs are regularized forms of multi-facet perceptrons. Multi-facet perceptrons generally mean completely associated networks, that is, every neuron in one layer is associated with all neurons in the following layer.

Convolution layer :

A "Kernel" of size for instance, 3X3 or 5X5, is disregarded the picture and a spot result of the first pixel esteems with loads
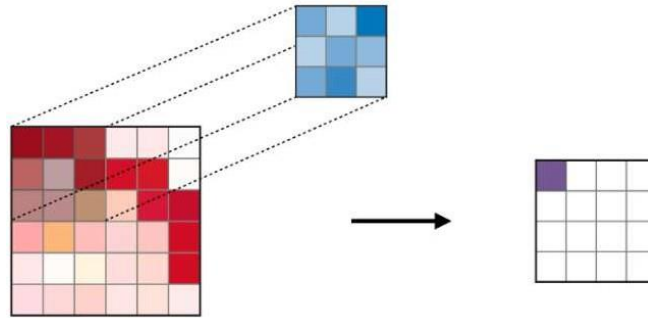

Fig 5

The Model

It uses csv python module to open given csv file into appropriatecsv module. Here we use 5 layers.

1. Convolutional layer

    Input : 4d tensor, dim:[N, w, h, Number of input channel

    = 1], where N is batch size.

    Output : 4d tensor, dim:[N, w/2, h/2, Number of filters atcnn layer-1]

2. Convolutional layer

    Input : 4d tensor, dim:[N, w/2, h/2, Number of filters atcnn layer-1]

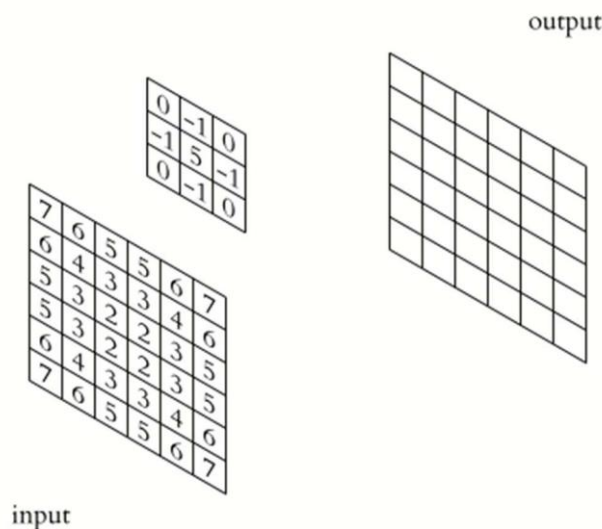   Output : 4d tensor, dim:[N, w/4, h/4, Number of filters atcnn layer-2]

Fig 6

Now this output 4d tensor is flattened in order to provide input tofully connected layer-1.

3. Fully connected layer

Input : 2d tensor, dim:[N, Flattened size]

Output : 2d tenser, dim:[N, Number of neurons at fullyconnected layer-1]

4. Fully connected layer

Input : 2d tensor, dim:[N, Number of neurons at fullyconnected layer-1]

Output : 2d tenser, dim:[N, Number of neurons at fullyconnected layer-2]
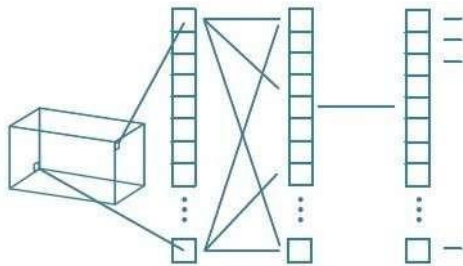
Fig 7

5. Output layer.

Input : 2d tensor, dim:[N, number of neurons at fullyconnected layer-2]

Output : 2d tenser, dim:[N, Number of classes]

OpenCV Text Detection (EAST text detector)

OpenCV's EAST text detector is a profound learning model, in light of an original design and training design. It is able to do

(1) running at close to ongoing at 13 FPS on 720p pictures and

(2) gets best in class text identification precision.

We have used Pytesseract to implement OpenCV EAST text detector to detect handwritten text in teal time. When it is unsure of what it is detecting it, it follows the prediction with a "?" sign.

VI. SYSTEM TESTING AND PERFORMANCE ANALYSIS

We used Tensorflow for system testing and performance analysis and we awere able to achieve an accuracy of >=99% over 7 epoch and a limited dataset.

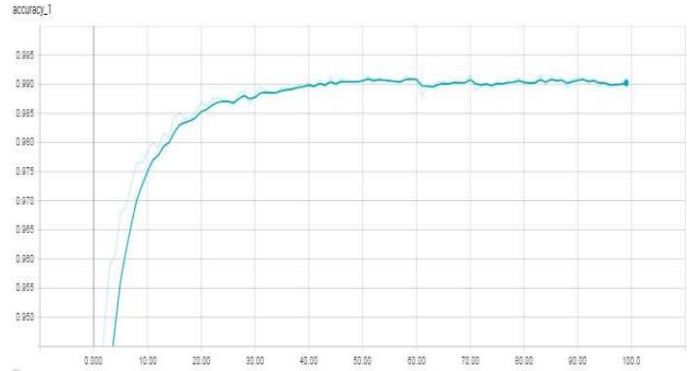The plot of accuracy versus epoch is shown below.

Fig 8

This process inevitably leads to loss of data. The amount of data lost during processing in analysed ucing loss validation curve

We lost <=0.1% pf data in our system.

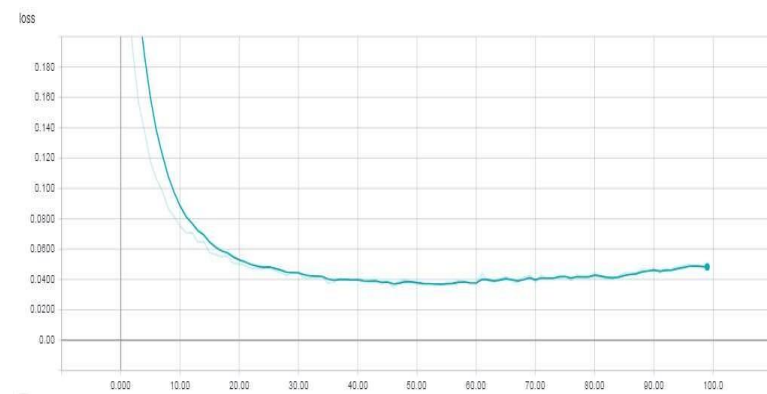The plot of loss validation versus epoch is shown below.

Fig 9

VII. CONCLUSIONS

We have examined exhaustively all advances in the space of written by hand character acknowledgment. The most exact arrangement gave in this space straightforwardly or by implication relies on the quality just as the idea of the material to be perused. Different procedures have been depicted above for character acknowledgment in penmanship acknowledgment system. Grouping of characters and learning of picture preparing methods is done in this project.

The outcome which was got was right up to over close to 100% of the cases, yet it would be improved toward the end. This work was fundamentally centered around imagining techniques that can effectively remove include vectors from every individual person. The technique I concocted gave productive and compelling outcome both for highlight extraction just as acknowledgment. There are likewise various strategies through which 'manually written person acknowledgment' is accomplished.

VIII.   FUTURE SCOPE

That there is a tremendous extension to expand this work forward. We can go further in perceiving characters in a really difficult situation. AI has been applied to various applications. A portion of the writings covering these are dialects other than English, for example, Hindi, Bangla, Tamil, Kannada and so forth Optical Character Recognition or OCR has empowered filtered reports to turn out to be something beyond picture records, transforming into completely accessible archives with text content perceived by PCs. There are numerous uses of this system conceivable.

A portion of the applications are Processing of checks in Banks , Helping hand in Desktop distributing , Recognition of text from buisness cards , Helping the visually impaired in perceiving manually written content on letters.

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