English Handwritten Character Recognition using Convolutional Neural Network (CNN)

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Abstract— Character recognition is one of the most important research fields of image processing and pattern recognition. Character recognition is generally known as Optical Character Recognition (OCR).OCR is the process of electronic translation of handwritten images or typewritten text into machine editable text. It becomes very difficult if there are lots of paper based information on companies and offices. Because they want to manage a huge volume of documents and records. Computers can work much faster and more efficiently than human. It is used to perform many of the tasks required for efficient document and content management. But computer knows only alphanumeric characters as ASCII code. So computer cannot distinguish character or a word from a scanned image. In order to use the computer for document management, it is required to retrieve alphanumeric information from a scanned image. There are so many methods which are currently used for OCR and are based on different languages. The existing method like Artificial Neural Network (ANN) based on English Handwritten character recognition needs the features to be extracted and also the performance level is low. So a Convolutional Neural Network (CNN) based English handwritten character recognition method is used. It's a deep machine learning method for which it doesn't want to extract the features and also a fast method for character recognition.
Key words: ANN, Feature Extraction, CNN, English, Machine Recognition

I. INTRODUCTION

OCR means Optical Character Recognition and it is the process of converting any scanned images of machine printed or handwritten text into a computer format text. The optical character recognition is actually performed by OCR software after scanning. The scanner only produces an image of the document. The OCR software then examines the image of the scanned document, identifies each letter, number and punctuation mark and produces equivalent text in a machine-readable digital form that can be used by a computer system. So that the OCR algorithms take as input a scanned image of paper document and produce as output a symbolic text document. OCR makes it possible to edit the text, search for a word or phrase and store it more compactly.

A. *Background*

OCR or Optical Character Recognition is done to reduce much of the overheads in working places. That means in many institutions and offices there is a large volume of paper based data, which challenges their ability to manage documents and records. So as a result many of the fields are now replaced with computer because it can work much faster and efficiently than human beings. Doing this task by manually is time consuming and there is a chance for lots of human errors.

One of the main advantage of OCR is that it can edit and search for a word or phrase. Scanning a document only creates an image of it and also no further modifications is allowed and it also takes a large space because it is stored as image. The OCR is actually performed by the OCR software after scanning. The OCR software examines the image of the scanned document and produces equivalent text in a machine readable digital form.

The advantages of OCR are numerous, but namely it increases the efficiency and effectiveness of office work. The ability to instantly search through content is very useful, especially in an office setting that has to deal with high volume of scanning works. OCR is quick and accurate, ensuring the document's content remains intact while saving time as well. When combined with other technologies such as scanning and file compression, the advantages of OCR truly shine. Workflow is increased since employees no longer have to waste time on manual labor and can work quicker and more efficiently.

The model supports only English alphabets (A to Z, a to z) and digits (0 to 9). Accuracy of model is directly dependent on the quality of input document. The model can identify only individual character. OCR have many different applications such as

- Data entry for business documents e.g. passport, invoice, bank statement and receipt.
- Automatic number plate recognition.
- Automatic insurance documents key information extraction.
- Extracting business card information into a contact list.
- More quickly make textual versions of printed documents, e.g. book scanning.
- Make electronic images of printed documents searchable, e.g. Google Books.
- Converting handwriting in real time to control a computer.
- Assistive technology for blind and visually impaired users.

B. *Motivation*

OCR is a software tool that allows to convert scanned documents into text searchable files. It is now increasingly common for documents to be scanned so that they can be conveniently viewed and shared via electronic means. However a scan is merely an image capture of the original document, so it cannot be edited or searched through in any way. This results in a decrease in efficiency since employees now have to manually correct or search through multiple pages. OCR solves this problem by making the document text searchable.

C. Objectives

The purpose of this paper is to take handwritten English character as input, process the character, train the neural network algorithm, to recognize the pattern and modify the character to a beautified version of the input.

This paper is aimed at developing software which will be helpful in recognizing characters of English language. This project is restricted to English characters, digits and also to some 26 special symbols such as : = > . < - ? ” / * _ ! # $ % &) (; , [@] { } + only.

II. RELATED WORK

A few state of the art approaches that use hand written character recognition for text identification have been summarized here:

Indhu T. R., Bhadran V. K proposes a Malayalam Online Handwriting Recognition System: A Simplified Fuzzy ARTMAP Approach. On-line handwriting recognition is the automatic conversion of handwritten text into letter codes as it is written on a special digitizer or PDA which is usable within computer and text-processing applications. Some of the commonly used techniques for online handwritten characters include Hidden Markov Model (HMM), elastic matching, structural analysis, Time delay neural networks, and combination of multiple classifiers. This paper describes Malayalam online handwriting recognition system using SFAM artificial neural network technique. The structural and directional information is extracted/collected from each character/stroke. The extracted features, which form the feature vector, are passed as input to a Simplified Fuzzy ARTMAP (SFAM) artificial neural network (ANN) classifier. The SFAM classifier compares the input data with the trained data and finds the nearest prototype from the database that ‘resonates’ with the input pattern. The labels or recognized characters are assigned their corresponding Unicode code points and displayed using appropriate fonts.

Jomy John, Pramod K. V, Kannan Balakrishnan proposes an Offline Handwritten Malayalam Character Recognition Based on Chain Code Histogram Optical Character Recognition plays an important role in Digital Image Processing and Pattern Recognition. Even though ambient study had been performed on foreign languages like Chinese and Japanese, effort on Indian script is still immature. OCR in Malayalam language is more complex as it is enriched with largest number of characters among all Indian languages. The challenge of recognition of characters is even high in handwritten domain, due to the varying writing style of each individual. In this paper it propose a system for recognition of offline handwritten Malayalam vowels. The proposed method uses Chain code and Image Centroid for the purpose of extracting features and a two layer feed forward network with scaled conjugate gradient for classification.

Dewi Nasien, Habibollah Haron, Siti Sophiayati Yuhaniz. Proposes a Support Vector Machine (SVM) For English Handwritten Character Recognition. This paper proposes a recognition model for English handwritten (lowercase, uppercase and letter) character recognition that uses Freeman chain code (FCC) as the representation technique of an image character. Chain code representation gives the boundary of a character image in which the codes represent the direction of where is the location of the next pixel. An FCC method that uses 8-neighbourhood that starts from direction labelled as 1 to 8 is used. Randomized algorithm is used to generate the FCC. After that, features vector is built. The criteria of features to input the classification is the chain code that converted to 64 features. Support vector machine (SVM) is chosen for the classification step. NIST Databases are used as the data in the experiment.

D. K. Patel, T. Sam, Manaj Kumar Singh proposes a Multi-resolution Technique to Handwritten English Character Recognition Using Learning Rule and Euclidean Distance Metric. This paper presents a novel method of handwriting character recognition which exploits a compression capability of discrete wavelet transform to enhance the accuracy of recognition at the pixel level, the learning capability of artificial neural network and computational capability of Euclidean distance metric. The problem of handwritten character recognition has been tackled with multiresolution technique using discrete wavelet transform and learning rule through the artificial neural network. Recognition accuracy is improved by Euclidean distance metric along with recognition score in case of misclassification. Features of the handwritten character images are extracted by discrete wavelet transform used with appropriate level of multi-resolution. Handwritten characters are classified into 26 pattern classes based on appropriate properties i.e. shape. During pre-processing each character is captured within a rectangular box and then resized to a threshold size. Weight matrix of each class is computed using the learning rule of artificial neural network, and then the unknown input pattern vector is fused with the weight matrices of all the classes to generate the recognition scores. Maximum score corresponds to the recognized input character.

Manju Manuel, Saidas S. R proposes a Handwritten Malayalam Character Recognition using Curvelet Transform and ANN. Malayalam, the official language of Kerala, a southern state of India has been accorded the honor of language of eminence. Hence the researches in recognition and related works in Malayalam language is gaining more prominence in the current scenario. This paper proposes the use of Curvelet transform and neural network for the recognition of handwritten Malayalam character. Curvelet transform is to be used in the feature extraction stage and neural network for classification. Curvelet transform provides a compact representation for curved singularities and is well suited for Malayalam language. Two different back propagation algorithms had been employed and the performance is compared on varying architecture. The promising feature of the work is successful classification of 53 characters which is an improvement over the existing works. Application of character recognition include sorting of bank cheques and postal letters, reading aid for blind, data compression etc. Besides, an automated tool with graphical user interface in MATLAB has been developed for Malayalam character recognition.

Saidas S. R, Rohithram T, Sanoj K. P, Manju Manuel proposes an Malayalam Character Recognition using

Discrete Cosine Transform. This paper describes a feature extraction method for optical character recognition system for handwritten documents in Malayalam, a South Indian language. The scanned image is first passed through various pre-processing stages of operations like noise removal, binarization, thinning and cropping. After pre-processing projection profiles of each character is found. 1- D Discrete Cosine Transform (DCT) of projection profiles used as a feature. A multilayer artificial neural network (ANN) with logsig activation function is used for classification. The promising feature of the work is that successful classification of 44 handwritten characters.

Shyla Afroge, Boshir Ahmed, Firoz Mahmud propose an Optical Character Recognition using Back Propagation Neural Network. This paper represents an Artificial Neural Network based approach for the recognition of English characters using feed forward neural network. Noise has been considered as one of the major issue that degrades the performance of character recognition system. Our feed forward network has one input, one hidden and one output layer. The entire recognition system is divided into two sections such as training and recognition section. Both sections include image acquisition, pre-processing and feature extraction. Training and recognition section also include training of the classifier and simulation of the classifier respectively. Pre-processing involves digitization, noise removal, binarization, line segmentation and character extraction. After character extraction, the extracted character matrix is normalized into 12x8 matrix. Then features are extracted from the normalized image matrix which is fed to the network. The network consists of 96 input neurons and 62 output neurons.

Implemented an ANN based character recognition method by considering the above existing method for comparing it with the proposing method named Convolutional Neural Network (CNN). This is done to show in the result that both the method is compared and CNN has better Accuracy than ANN. Because ANN needs features to be extracted manually. This comparison is also done by implementing different methods separately using the same number of datasets for training and testing. According to ANN it mainly consists of several neurons and are arranged in relation to each other. It mainly divides into three parts: input layer, hidden layer and output layer. Input layer is responsible for receiving information from external environment. Hidden layer is composed of neurons and is responsible for extracting patterns associated with the process or system being analyzed. Output layer is responsible for producing and presenting the final network output. It uses the supervised learning method. It has two subsets: training (60-90%) and testing subset (10-40%). This method also uses feed forward back propagation mechanism. For each layer a particular scale, moment, number of iterations and number of neurons hidden is given. Based on these parameters adjustment the result is obtained. So it is very essential to train the system by adjusting weight and bias for getting a good result. There is an error value and if it doesn't meet that value the steps are repeated again. That's why it is called as feed forward back propagation mechanism. Also the output will also depends on the dataset. If the number of datasets is more the outcome will also more accurate and high. The stages of existing ANN OCR system is shown in fig.1. Modules in ANN are:

1) Database building and image acquisition. Database of 62 characters are created (i.e. a-z, A-z, 0-9). There are 62 folders and each contains 45 images. So there are 45*62 = 2790 images in the database for training. For testing 10 images are taken.
2) Pre-processing
   Improves the quality of image for better recognition. Avoids unwanted noise from scanned images. Some of the Pre-processing methods are:
   a) Smoothing
      Removing unwanted noise from the image.
   b) De-skew
      The process of straightening an image.
   c) Thinning Iteration
      Reducing an object in a digital image to the minimum size for machine recognition.
3) Feature Extraction
   All the character image is given a unique dimension. Each character image have a size of 35*35. Histogram of Gradient (HOG) method is used for feature extraction.
4) ANN Training and XML file Creation
   This mainly consists of parameter adjust and design. Page segmenter is used for reading the lines and characters. Result will be an XML file.
5) Load XML file and Testing
   XML file is loaded for Testing.

Implementation result shows that it has 80.8064% accuracy in character recognition of 62 characters (such as capital letters, small letters and digits).
The result is as follows:
Number of classification: 620
Correct: 501 (80.8064%)
Wrong: 119 (19.1936%)

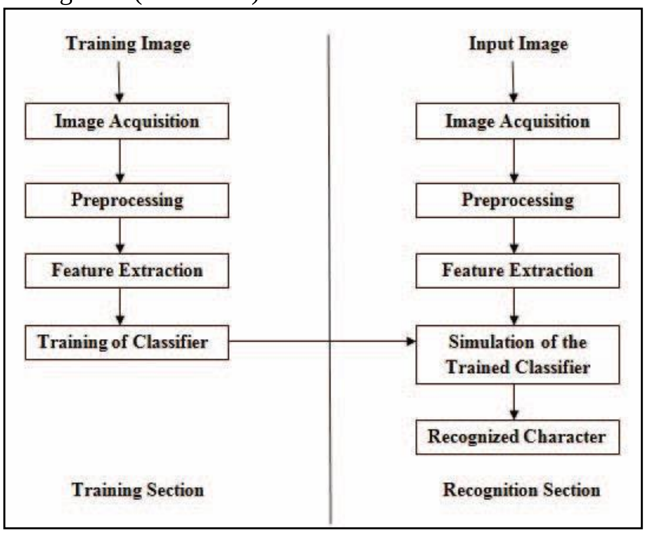

Fig. 1: Stages of existing ANN OCR system

The main drawback of the existing system is that it can recognize only English characters and digits. And also the recognition accuracy is not that much better. In ANN based handwritten character recognition the feature extraction is done manually and here it uses HOG method for extracting it.

III. Methodology

A. *Problem Definition*

OCR Stands for "Optical Character Recognition." OCR program can convert the characters on the page into a text document that can be read by a word processing program. More advanced OCR programs can even keep the formatting of the document in the conversion. Here hand written character recognition based on English characters is used. For identification it mainly uses English capital letters, small letters, digits and some special symbols. Here we are using Convolutional Neural Networks (CNN) based character recognition method. In order to show better accuracy in character recognition and also the features need not to be extracted because the method itself extract features from the character during training phase. And the final result will be in an editable format. This is done to reduce burden on large volume of paper work on various fields and also reduce much of human efforts.

B. *Overview*

Convolutional neural networks (CNNs) are widely used in pattern and image recognition problems as they have a number of advantages compared to other techniques. A neural network is a system of interconnected artificial "neurons" that exchange messages between each other. The connections have numeric weights that are tuned during the training process, so that a properly trained network will respond correctly when presented with an image or pattern to recognize. The network consists of multiple layers of feature-detecting "neurons". Each layer has many neurons that respond to different combinations of inputs from the previous layers. As shown in Fig. 2, the layers are built up so that the first layer detects a set of primitive patterns in the input, the second layer detects patterns of patterns, and the third layer detects patterns of those patterns, and so on. Typical CNNs use 5 to 25 distinct layers of pattern recognition.

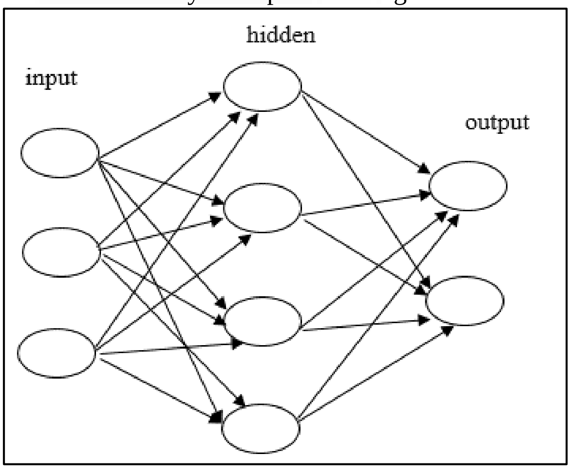

Fig. 2: A Neural Network

Training is performed using a "labelled" dataset of inputs and that input patterns are tagged with their intended output response. Training uses general-purpose methods to iteratively determine the weights for intermediate and final feature neurons. Fig. 3 demonstrates the training process at a block level.

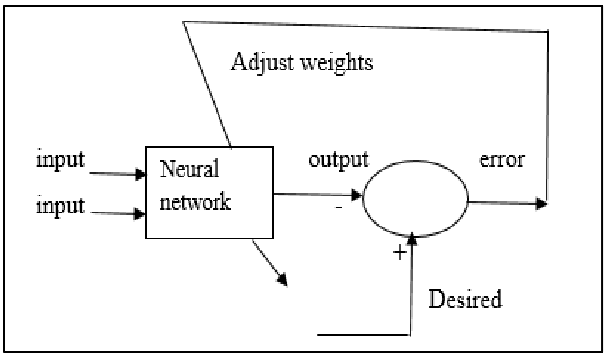

Fig. 3: Training of Neural Network

A CNN consists of one or more convolutional layers, often with a subsampling layer, which are followed by one or more fully connected layers as in a standard neural network. In a CNN, convolution layers play the role of feature extractor. But they are not hand designed. Convolution filter kernel weights are decided on as part of the training process. Convolutional layers are able to extract the local features because they restrict the receptive fields of the hidden layers to be local. CNNs are used in variety of areas, including image and pattern recognition, speech recognition, natural language processing, and video analysis. There are a number of reasons that convolutional neural networks are becoming important.

In traditional models for pattern recognition, feature extractors are hand designed. In CNNs, the weights of the convolutional layer being used for feature extraction as well as the fully connected layer being used for classification are determined during the training process. The improved network structures of CNNs lead to savings in memory requirements and computation complexity requirements and, at the same time, give better performance for applications.

1) *Layers of CNNs*

There are so many layers in CNN (such as convolution layer, ReLU layer, pooling layer, dropout layer, normalized layer and fully connected layer etc.) and each layers performs different functionality. The pictorial representation of layers of CNN is shown in fig.4. Among them four types of layers are most common: convolution layers, pooling/subsampling layers, non-linear layers, and fully connected layers.

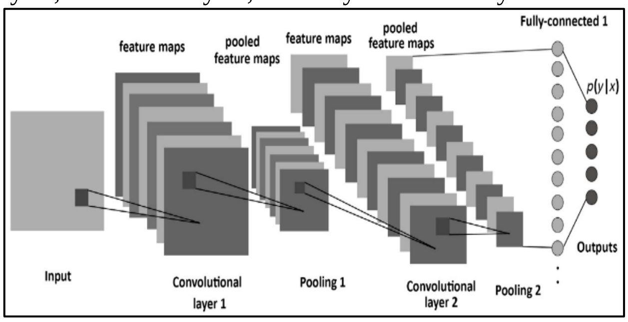

Fig. 4: Layers in CNN

– Convolution layers

The convolution operation extracts different features of the input. The first convolution layer extracts low-level features like edges, lines, and corners. Higher-level layers extract higher-level features.

– Pooling/subsampling layers

The pooling/subsampling layer reduces the resolution of the features. It makes the features robust against noise and distortion. There are two ways to do pooling: max pooling and average pooling.

– Non-linear layers

Neural networks in general and CNNs in particular rely on a non-linear "trigger" function to signal distinct identification of likely features on each hidden layer. CNNs may use a variety of specific functions such as rectified linear units (ReLUs) and continuous trigger (non-linear) functions to efficiently implement this non-linear triggering.

– Fully connected layers

Fully connected layers are often used as the final layers of a CNN. These layers mathematically sum a weighting of the previous layer of features, indicating the precise mix of "ingredients" to determine a specific target output result. In case of a fully connected layer, all the elements of all the features of the previous layer get used in the calculation of each element of each output feature.

C. System Architecture

Convolutional Neural Networks are a special kind of multi-layer neural networks. Like almost every other neural networks they are trained with a version of the back-propagation algorithm. Where they differ is in the architecture. Convolutional Neural Networks are designed to recognize visual patterns. LeNet-5 is the latest convolutional network designed for handwritten and machine-printed character recognition. The LeNet architecture was first introduced by LeCun et al. in their 1998 paper, Gradient-Based Learning Applied to Document Recognition. As the name of the paper suggests, the authors' implementation of LeNet was used primarily for OCR and character recognition in documents. The LeNet architecture is straightforward and small, making it perfect for teaching the basics of CNNs. It can even run on the CPU (if your system does not have a suitable GPU), making it a great "first CNN". However, if you do have GPU support and can access your GPU via Keras, you will enjoy extremely fast training times (in the order of 3-10 seconds per epoch, depending on your GPU).

Convolutional Neural Network (CNN) is deep machine learning method. It is based on many neurons which exchanges information between them. CNN mainly consists of so many layers and based on that layer the method is performing. CNN is an important method in image processing and pattern recognition. It's a recent trend. According to machine learning we are making the machine to learn about particular thing and when they appears again the system itself report as what it is. So for doing CNN we need an accurate dataset for training and testing. Based on the dataset the method is going to perform well. Optical Character Recognition or OCR is an important field in image processing. This is used to reduce much of the overheads, human errors and efforts in different fields. First the number of convolution layers, max pooling layers and fully connected layers needs to be chosen. It is not possible to determine the exact number of layers that will yield the best outcome. Hence it is vital to try several configurations of the network and choose which network best suits. This mainly consists of parameter adjust and design. Final result will be a Net file.

Here for the implementation of CNN it uses the basic LeNet-5 Architecture. The architecture mainly use six layers for implementation. That is three convolutional layers, two average sampling layers and a fully connected layer. The convolutional layer is mainly used for extracting the features. And the average sampling layer is mainly used for avoiding unwanted noise from the input and it is a sub division of pooling or sub-sampling layer. That means pooling layer is divided into two, average pooling and maximum pooling. Pooling layer is also called as down sampling. The fully connected layer will predict the final output. The overall architecture of CNN is demonstrated in fig. 5.

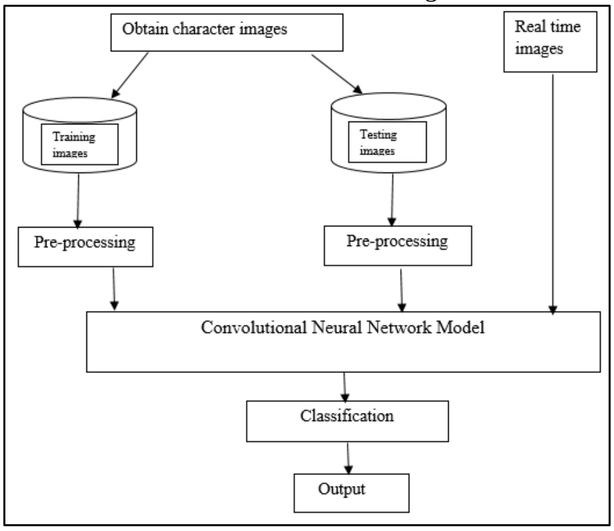

Fig. 5: Architecture of CNN

Convolutional Networks are commonly made up of only three layer types: CONV, POOL and FC. There are several architectures in the field of Convolutional Networks that have a name. The most common are: LeNet, AlexNet, ZF Net, GoogLeNet, VGGNet, and ResNet. Here we follows a basic LeNet Architecture and is shown in fig. 6.

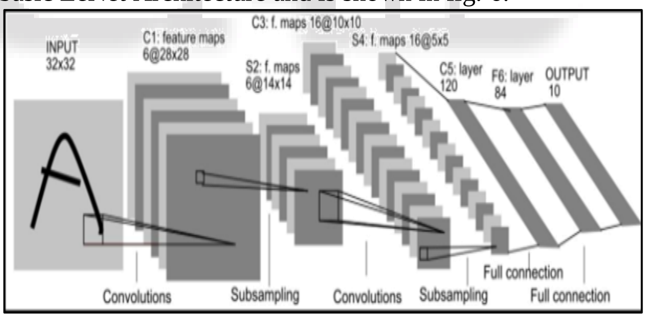

Fig. 6: Basic Architecture of LeNet-5

AdaGrad Optimizer is used for optimization and then training is done and the net result file is saved. AdaGrad is an optimization method that allows different step sizes for different features. It increases the influence of rare but informative features. In this phase the weight and bias is get adjusted for getting better accuracy level.

In CNN it uses tiny – dnn. It is a header only, dependency free deep learning library written in C++. It is designed to be used in the real applications, including IoT devices and embedded systems. Here it uses the training and test files. Training files contains 45 samples and test file contains 10 samples. The trained files is read from the database and is pass through the page segmentor. Then the exact character portion is cropped and resized into 38x38. Then the image in MAT format is convert into floating format. Normalization is done between -0.5 to +0.5. It uses the activation functions like tanh and softmax. Then pre-processing is applied to avoid unwanted noise from the character image. Finally CNN modelling is done and it is based on 6 layers. The result in the form of net file is saved. Again the test file is taken and after all the primary steps the net file is loaded for prediction. Calculation is done to show the percentage value out of 10samples (in test file per folder) which one went wrong and correct. And the final result is displayed.

Here a deep machine learning algorithm is used and the features are not needed to extract. The CNN itself extract the features. The OCR using ANN is also implemented to show the performance evaluation. Artificial Neural Network (ANN) based handwritten character recognition method implementation procedure is stated in above of literature survey.

D. Module Description

There is no standard dataset for handwritten English characters. CNN requires a large set of training images. The functional block diagram of CNN is demonstrated in fig. 7. CNN achieves a high accuracy rate only if it is trained with a substantially large training set. This is one of the biggest challenge. The input is first scanned using a scanner or taken as a photograph using a smart phone. The modules wise explanation of CNN based English handwritten character recognition are as follows:

1) Database Building and Image Acquisition

Database consisting of 88 folders is created. This mainly consists of capital letters (A to Z), small letters (a to z), digits (0 to 9) and also contains 26 special symbols such as ! @ # $. , % & * ( ) - _ + = / [ ] { } ; : " ? . Each character and digits contains mainly 45 samples. So there are total of 45*62 = 2790 samples is there for training. And there are 10 samples per folder for testing. That is 10*62= 620 samples of total for testing. The accuracy of the character recognition depends on number of datasets available for training. If there are so many samples of hand written character the result will be of good quality.

2) Pre-processing

In the pre-processing stage, the character image is processed for removing all the undesirable entities from an image to make the process of recognizing easier. The input images are resized to a suitable format of 32x32x1. It must not be too large or too small. If the image is too large, the amount of computation required will be high. If the image is too small, it will be difficult to fit it into a large network. Larger images are cropped and some methods will be applied to smaller images to achieve a standard size.

3) CNN Training and Net file Creation

This is the most important step. CNN modelling means modelling the structure of CNN. The number of convolution layers, max pooling layers and fully connected layers needs to be chosen. It is not possible to determine the exact number of layers that will yield the best outcome. Hence it is vital to try several configurations of the network and choose which network best suits. This mainly consists of parameter adjust and design. Page segmenter is used for reading the lines and characters. Final result will be a Net file.

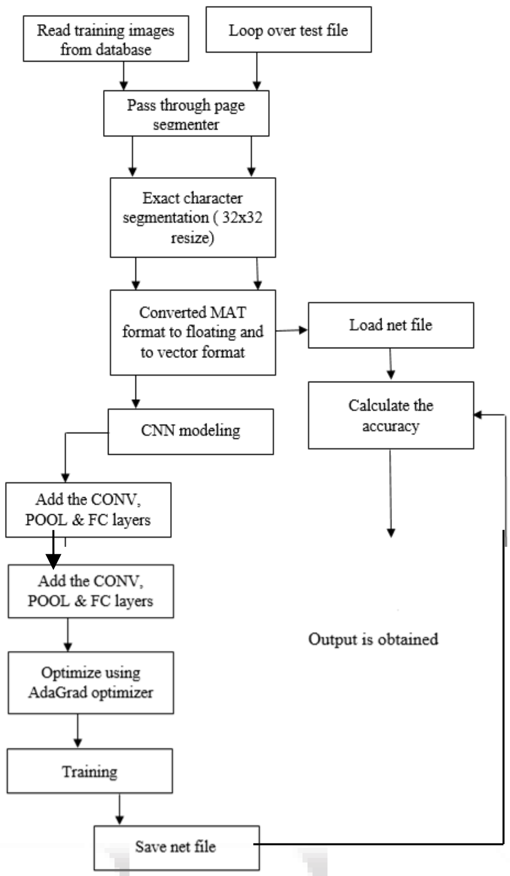

Fig. 7: Block diagram of CNN

4) Load Net file and Testing

Net file is loaded for Testing. Testing module deals with the test images. It will first pre-process the input image. Labels are assigned to each of test images by the network and then the accuracy is measured. In the post processing stage of the system, produced classifier output is mapped to the character Unicode. The output of the classifier will be some integer labels. This integer label should be converted into corresponding character Unicode. The Unicode is written in a text file.

E. Algorithm

1) Step 1: Start
2) Step 2: Add the library tiny-dnn. It is a header only, dependency free deep learning library written in C++. It is designed to be used in the real applications, including IoT devices and embedded systems.
3) Step 3: Get training files.
4) Step 4: Image passing through page segmenter.
5) Step 5: Crop exact character portion.
6) Step 6: Converting the image in MAT format into floating format and then to vector Format.
7) Step 7: Training in CNN mainly consists of four steps:
   a) Adding layers such as convolution, sampling and fully connected layers.
   b) Declare optimization algorithm such as AdaGrad optimizer.
   c) Training
   d) Save the net file
8) Step 8: load the net file.
9) Step 9: Loop over testing files.

10) Step 10: Repeat the same steps from 3 to 6 for test file also.
11) Step 11: Calculate recognition accuracy and print the output.
12) Step 12: Stop

F. *Screen Shots of Results*

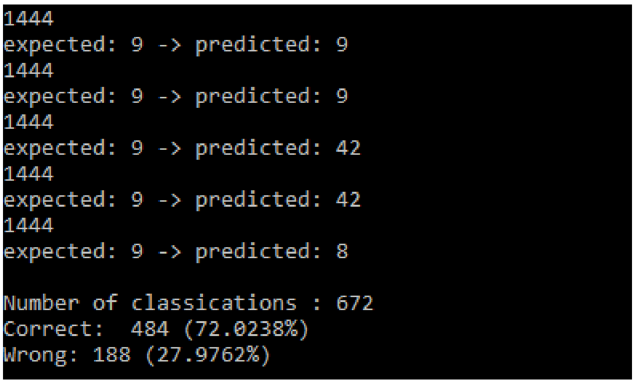

Fig. 8: (a) CNN accuracy including special symbols

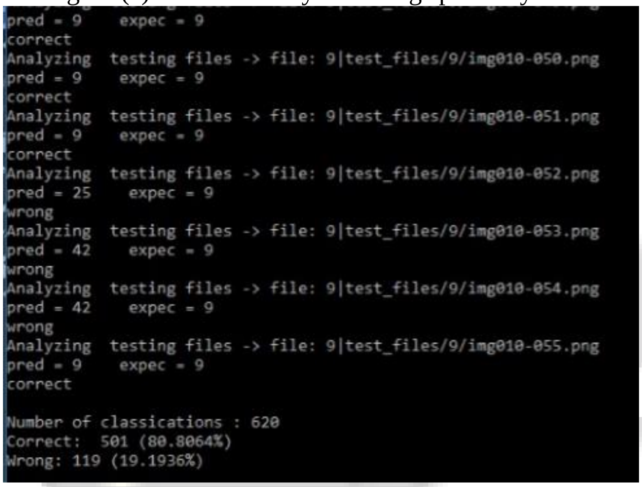

Fig. 8: (b) Recognition accuracy of ANN

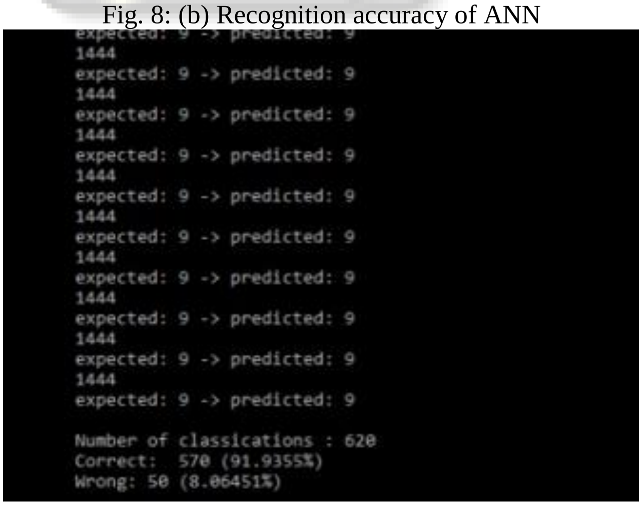

Fig. 8: (c) Recognition accuracy of CNN

Here in this paper handwritten character recognition using CNN is implemented and that method is evaluated based on Artificial Neural Network (ANN). CNN is a deep machine learning algorithm which doesn’t wants to extract the features manually. ANN is one of the existing system which also get implemented for comparing its performance with CNN. Both the CNN and ANN uses the same set of samples for training and testing. By running both the programs separately we get a result of accuracy out of 100 percentage. From that we can get a result of CNN is the best method than ANN. Because CNN have more accuracy and the features need not to be extracted. The algorithm itself do that procedure. But in ANN the features extracted manually and have less accuracy compared to CNN. For both ANN & CNN it uses training files of 45 samples per 62 folders and there are 10 samples for testing per folder. This mainly support English characters (both small and capital letters), digits and 26 special symbols.

Method Used	No. of Classification	True count	True percent	False count	False percent
ANN	620	501	80.8064 %	119	19.1936%
CNN	620	570	91.9355 %	50	8.06451%
CNN with Special Symbol	672	484	72.0238 %	188	27.9762%

Table 1: Recognition Accuracy

The performance evaluation metrics used here are based on testing set as how many characters went wrong and correct out of total samples per folder. For example in this paper CNN uses 10 test samples per folder and there are 62 such folder. So 10 x 62= 620 is the no. of classification and based on that we are going to predict the percentage of accuracy out of 100. It also shows the counts of samples which went wrong and correct out of total samples plus the percentage out of 100.

Also included some 26 special characters to this in order to show the accuracy level. The special characters are: = > < - ? ” / * _ ! # $ % &) (; , [@] { } + . so there are 88 folders. That is 62 plus 26 special symbols. There is no standard dataset available for special symbols as result we need to create the dataset manually. So I created the training files consists of 5 samples per 26 folders and the test files consists of 2 samples per 26 samples. This is not actually enough for better accuracy. Because when we use more datasets the recognition accuracy is more.

By including special characters also the accuracy is predicted. So for that it uses 88 folders including 26 special symbols. This 26 special symbols have no any dataset is available and it is made manually by downloading the fonts of handwritten character. So for example in test file it includes 2 samples and in train files it includes 5 samples per 26 folders. So there are total of 2920 (i.e 62*45+26*5=2920) samples in 88 folder. From above two result it is very clear that the number of dataset is very much essential for good accuracy result. Here without using special symbols have much accuracy. If there are more number of datasets then the result is of good quality.

From the above Table: 1 it is very clear that English handwritten character recognition using Convolutional Neural Network (CNN) is having more accuracy than Artificial Neural Network (ANN).

IV. CONCLUSION

OCR is an important field in image processing and pattern recognition. It is used for many real time applications. It can be used for office automation. Here a handwritten English character recognition system using Convolutional Neural Network (CNN) is used. Here mainly six layers of CNN is used. It uses the basic LeNet-5 Architecture. That is three convolutional layer, two average pooling layer and a fully connected layer. CNN has better accuracy in character recognition and also the features need not to be extracted because the method itself extract features from the character during training phase. And the final result will be in an editable format. This is done to reduce burden on large volume of paper work on various fields and also reduce much of human efforts and errors. CNN is also compared with Artificial Neural Network (ANN) to show which one has better accuracy in character recognition. The result shows that CNN have better accuracy than ANN. Here in this paper it supports only 62 English characters, 10 digits and 26 special symbols. Later this work may also be extended to implement multiple languages in a single system.

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