Online Handwritten Character Recognition (OHCR) using Deep Learning Convolution Neural Network

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***Abstract*—Online Handwritten Character Recognition (OHCR) is the process of automated recognition of characters written on any digital device. The device tries to recognize the text written by the user by recording the (x,y) coordinate of the surface where the stroke was made. In this paper, a novel approach for extracting characters and digits from English statements using deep neural network is discussed. The dataset used for training and testing the network is UNIPEN database. The performance of the network is evaluated by evaluating the classification accuracy of the system in recognizing 52 English alphabets both upper case and lower case and 10 digits.**

Keyword: deep learning, artificial intelligence, back propagation, Convolution Neural Network (CNN), pattern recognition

I. Introduction

Handwritten Character Recognition (HCR) systems are complex systems built to recognize the text written by a user or from scanned documents. The character recognition efficiency is dependent on how well the system is trained to classify the characters and digits in a written text. HCR systems are widely used in document analysis and also can be used as a tool to help the blind people through text to speech processing. There is a lot of research being done to make machines recognize characters of almost all the languages used globally. Recent research suggests that most of the studies focus on the recognition of individual characters written in regional Indian languages and foreign languages like English, Chinese etc. A community of researchers is actively involved in developing efficient HCR systems and discusses their work through conferences like International Conference on Frontiers in Handwriting Recognition (ICFHR) and the International Conference on Document Analysis and Recognition (ICDAR). The research is done in areas like online recognition, signature verification both online and offline, recognition of offline text, postal-address interpretation, bank check verification and processing and writer recognition.

Handwritten Character Recognition (HCR) system generally deals with recognizing text written by users on an electronic surface using a special device or on a sheet of paper using a normal pen [1]. HCR systems can be classified into two categories: Online HCR and Offline HCR systems. The following Fig 1 shows the general classification of character recognition systems.

Offline HCR systems use scanned documents or images of handwritten text as the input. The input image is processed using image processing algorithms and pattern recognition techniques are applied to recognize the characters from the image. The performance of such systems greatly depends on the quality of the image fed as input. Large amount of handwritten documents available in places like banks, offices, insurance fields needs recognition of characters for verification and validation of the content in the document [2]. A lot of dynamic research is going on in the field of offline HCR. Overlapping of characters, poor quality image and cursive writing are the major challenges in the recognition of offline text.

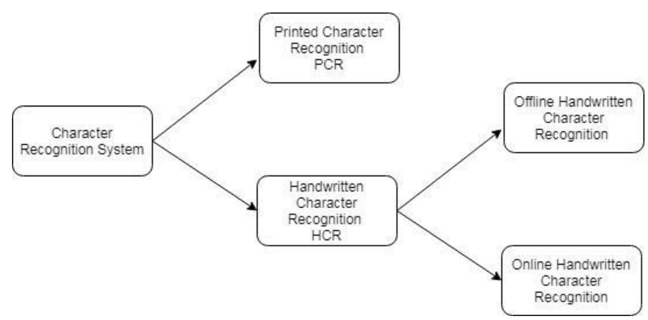

Fig. 1 Classification of Character Recognition System

Online HCR is the automatic recognition of characters as it is written on a computer screen or any handheld device surface. The device uses a sensor to pick up the pen-tip movements and the pen up and down switching. The data from the sensor is the digital representation of the handwritten text which must be converted to character codes for text processing and classification. The components required for OHCR includes a pen or stylus for writing, a touch sensitive surface, and an application which recognizes the characters in the text written by the user.

With the advancements in the handheld devices, OHCR systems are in great demand. It can also be used by visually challenged people to effectively interact with the devices if the recognized characters are read out through speakers using text-to-speech processing. Many researchers have actively been implementing OHCR systems with effective techniques for feature extraction like directional distance feature extraction [3], wavelet based features [4], and convex-hull based feature extraction [5]. Nowadays lot of research is centered on machine learning algorithms and online handwritten character recognition systems are built using deep learning networks.

The objective of this paper is to discuss the methodology of OHCR using Convolution Neural Networks (CNN) for effectively extracting the boundary features of handwritten text and classifying the character accurately. The rest of the paper is organized into three sections. Section 2 explains the methodology used. The experimental framework is discussed in section 3 and section 4 concludes the paper with summary of the result and future work.

II. METHODOLOGY

The process of online handwritten character recognition involves the following phases: preprocessing, feature extraction, classification and recognition. Fig.2 shows the methodology followed in recognizing online handwritten character recognition.

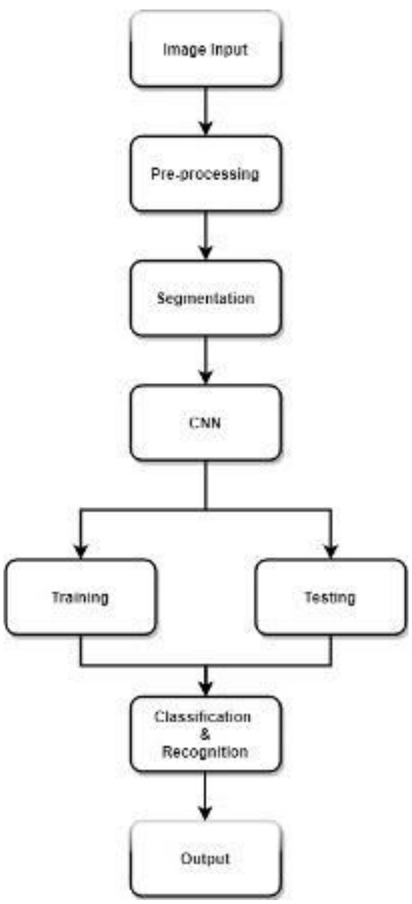

Fig. 2 OHCR Methodology

The purpose of preprocessing is to discard irrelevant information in the input data, that can negatively affect the recognition.[6] This concerns speed and accuracy. Preprocessing usually consists of binarization, normalization, and sampling, smoothing and denoising. The pre-processed image is segmented into individual character regions using projection techniques. Several segmentation algorithms [7] are studied and used for the extraction of individual characters from the handwritten text.

Getting character's rectangle boundary is started from the first left pixel of the character. The boundary is expanded step by step from left to right, from top to bottom until the boundary can wrap the character. A similar algorithm can be applied to get the character's boundary from the topmost pixel. By changing horizontal and vertical steps, the system can get not only isolated characters but also words or sentences without changing algorithm

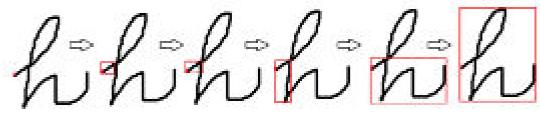

Fig. 3 Character segmentation using boundary detection

The next step is feature extraction. Feature extraction is an important step in character recognition since the effectiveness of recognition and classification accuracy greatly depends on the features extracted [8]. The purpose of this step is to highlight important information for the recognition model. This data may include information like pen pressure, velocity or the changes of writing direction.

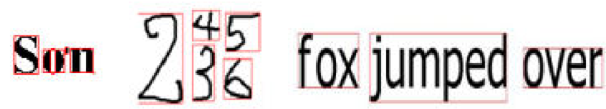

Fig. 4 Segmented characters and words in handwritten text

The last big step is classification. In this step various models are used to map the extracted features to different classes and thus identifying the characters or words the features represent. In the proposed methodology, Convolution Neural Network (CNN) is used for classification and recognition of characters. The classification process involves the training and testing phase. The proposed model is trained with already recognized image samples until an expected accurate classification is done and tested with images to check whether the system is recognizing the characters properly.

III. EXPERIMENTAL RESULTS

The proposed OHCR system is implemented using CNN for feature extraction mapping and character classification. The CNN is a deep neural network which uses back propagation algorithm for training with the dataset. The feature extraction and classification modules are placed in different layers and integrated into a single neural network. The CNN used for OHCR is given in Fig. 5.

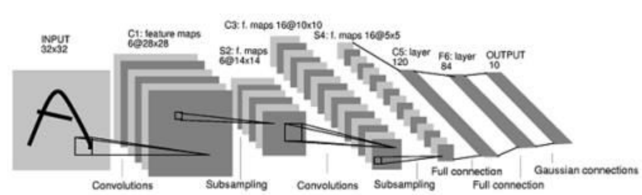

Fig. 5 Convolution Neural Network for OHCR

The CNN consists of five layers. The first layer is the input layer of size 32 x32 and receives the gray-level image containing the digit to recognize. The output of the first layer is forwarded to the first hidden layer C1 which consists of six feature maps each having 25 weights, constituting a 5x5 trainable kernel, and a bias. The values of the feature map are computed by convolving the input layer with respective kernel and applying an activation function to get the results. All values of the feature map are constrained to share the same trainable kernel or the same weights values. Because of the border effects, the feature maps' size is 28x28, smaller than the input layer.

Each convolution layer is followed by a sub-sampling layer which reduces the dimension of the respective convolution layer's feature maps by factor two. The first two layers are termed as trainable feature extractors and the remaining layers in the network constitute the trainable classifier.

The process of each layer is clearly shown in the following figure. The Convolution Neural Network consists of five layers: Input layer, convolutional layer, sub-sampling layer, fully connected classification layer, output layer. Each convolutional layer is followed by a sub-sampling layer. These two layers together form the i-th layer of a Convolutional Neural Network. The number of these layers is increased depending on the complexities in the images. More the complexity in the input, the number of such layers are increased to capture low-level details which provides a better feature set, but at the cost of more computational power.

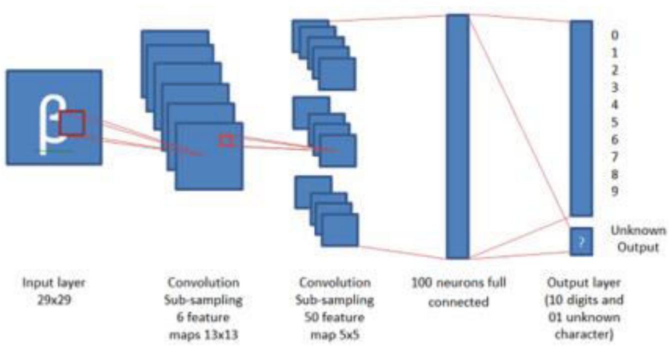

Fig. 6 Layers in the Convolution Neural Network

The UNIPEN [9] dataset is used to train the proposed OHCR and the classification accuracy is found to be around 97% for digits and 89% for upper case and lower case English alphabets. There are around 2000 samples for training and 800 samples used for testing the system. Because of the variations in the writing style of the users, the dataset contains more than one sample for the same character [10]. The network performance is tuned by configuring the various network parameters as listed in the figure 7. The network is trained by changing the number of epochs each time till the Mean Square Error becomes negotiable small The output layer consists of n units where n=10 if digits data alone is used as the knowledge base, n=23 if lower case or upper case alphabets dataset is used for training. If all the data together is used as the training data set then the output layer contains 62 units.

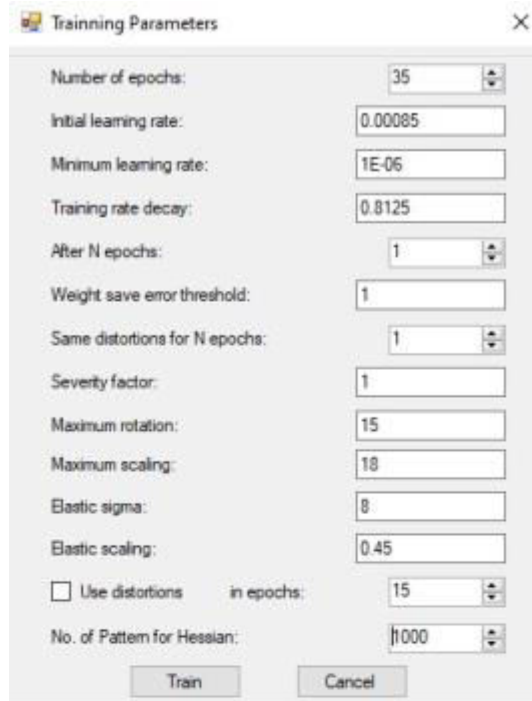

Fig. 7 Neural Network training parameters

IV. CONCLUSION

The experimental results show that the use of CNN for online handwritten character recognition produces better result compared to the existing gradient-based and convex-hull feature extraction models. With the advancements in the human computer interface an automated fast efficient online handwritten character recognition system becomes essential. The current proposed system cannot recognize characters if the text is written in continuous cursive form. In future a spell-checker can be incorporated into the system for efficient recognition of the characters in a text. From touch input to gesture based interaction is becoming very popular. Hence the research can be extended to input real-time gestures [11] and online handwritten characters for effective communication with the advanced PDAs' available in the market.

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