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Handwritten Character Recognition Using Convolutional Neural Network

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Abstract: Handwritten character recognition has been one of the active and challenging research areas in the field of image processing and pattern recognition. It has numerous advantages such as reading aid for bank cheques, recognizing character from form applications etc. An attempt is made to recognize handwritten characters for English alphabets using CNN. FKI dataset which consists of English alphabets are made use of to train the neural network. FKI balanced dataset consist of 131,600 images of characters and 47 classes. The feature extraction technique is obtained by normalizing the pixel values. Pixel values will range from 0 to 255 which represents the intensity of each pixel in the image and they are normalized to represent value between 0 and 1. Convolutional neural network is used as a classifier which trains the FKI dataset. The work is extended by adding some more dataset to FKI dataset of characters from English language and training the model. The prediction for the given input image is obtained from the trained classifier.

Index Terms: CNN, Handwritten Characters, Feature extraction

INTRODUCTION

Handwritten character recognition is a field of research in artificial intelligence, computer vision, and pattern recognition. A computer performing handwriting recognition is said to acquire and detect characters in paper documents, pictures, touch-screen devices and other sources and convert them into machine-encoded form. Its application is found in optical character recognition and more advanced intelligent character recognition systems. Most of these systems implement machine learning mechanisms such as neural networks.

After the extraction of individual characters occurs, a recognition engine is used to identify the corresponding computer character. Several different recognition techniques are currently available. Neural network recognizers learn from an initial image training set. The trained network then makes the character identifications. Each neural network uniquely learns the properties that differentiate training images. It then looks for similar properties in the target image to be identified. Neural networks are quick to set up; however, they can be inaccurate if they learn properties that are not important in the target data.

Handwriting recognition has been one of the most fascinating and challenging research areas in field of image processing and pattern recognition in the recent years. It contributes immensely to the advancement of automation process and improves the interface between man and machine in numerous applications. Several research works have been focusing on new techniques and methods that would reduce the processing time while providing higher recognition accuracy.

The rest of this paper is organized as follows: Chapter 2 presents the related work. Chapter 3 presents the proposed work. Chapter 4 presents the module description. Chapter 5 presents the experimental results for handwritten character recognition. Chapter 6 presents the conclusion.

I. RELATED WORK

Toru [6] addresses the problem of reinforcing the ability of the k-NN classification of handwritten characters via distortiontolerant template matching techniques with a limited quantity of data. Three kinds of matching techniques, namely, Conventional Simple Correlation, the Tangent Distance and the Global Affine Transformation (GAT) correlation are compared. The k-NN classification method consumes a lot of time. Therefore, to reduce the computational cost of matching in k-NN classification, the GAT correlation method was accelerated by reformulating its computational model and adopting efficient lookup tables. Recognition experiments performed on the IPTP CDROM1B handwritten numerical database show that the matching techniques achieved recognition rates of 97% to 98% .The computation time ratios of the tangent distance and the accelerated GAT correlation to the simple correlation were 26.3 and 36.5 to 1.0 respectively for each technique.

Nasien [4] proposed a recognition model for English handwritten character recognition which includes upper and lower cases and also letters. Freeman chain code (FCC) was used 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 the location of

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the next pixel. An FCC method that uses 8-neighbourhood that starts from direction labelled as 1 to 8 is used. Randomized algorithm was used to generate the FCC which builds the features vector. The criteria of features to input the classification is the chain code that converted to 64 features. Support vector machine (SVM) was chosen for the classification step. NIST Databases are used as the data in the experiment. By applying the proposed model, a relatively high accuracy for the problem of English handwritten recognition was reached.

Olarik [5] used the local gradient feature descriptors, namely the scale invariant features transform key point descriptor and the histogram of oriented gradients, for handwritten character recognition. The local gradient feature descriptors are used to extract feature vectors from the handwritten images, which were then presented to a machine learning algorithm for the actual classification. As classifiers, the k-nearest neighbour and the support vector machine algorithms were used. The feature descriptors and classifiers had been evaluated on three different language scripts, namely Thai, Bangla and Latin, consisting of both handwritten characters and digits. The results showed that the local gradient feature descriptors significantly out-perform directly using pixel intensities from the images. When the proposed feature descriptors are combined with the support vector machine, very high accuracies were obtained on the Thai handwritten datasets (character and digit), the Latin handwritten datasets (character and digit), and the Bangla handwritten digit dataset.

Mubarok[1] proposed Hierarchical graph matching for handwritten character recognition. Handwritten character was transformed into graphs based on its underlying skeleton structure. Edges of the extracted graph were categorized into shape types and vertices were extracted from each of the edges using line simplification algorithm. Matching procedure of the graph was performed in hierarchical approach and followed sub-graph isomorphism principals. Performance evaluation of the proposed method was conducted using validated CEDAR dataset and the method reached a recognition rate of 93.40%.

Bautista[2] investigated the accuracy and precision of the proposed system by cross examining the values solved using the proposed system with the values solved manually. The feature extractor and classifier directly influenced the accuracy and precision of Optical Character Recognition, hence considered choosing the combination of Feature Extractor-Classifier combination for handwritten characters which is the Projection Histogram and Support Vector Machine (SVM) combination. The model included three stages. The Pre-Processing or Feature extraction stage then the Recognition stage using SVM. The last stage was Solving Equations and Accuracy measurement. The SVM is trained with Linear, Polynomial and RBF as its kernel, using 90 training images per each character (a total of 5580 images) and a database was created which contained the unique features that represents a specific character.

Lei [3] explains the current status of handwritten character recognition and problems for research and feature selection. On the basis of existing research results, a new feature named direction string is proposed for handwritten character recognition. It uses stroke trend and integrate the properties of both the traditional statistical features and structural features. A measure of distance between different direction strings is proposed and a classifier for handwritten character recognition is implemented using nearest neighbour matching algorithm based on the proposed direction strings and their distances. It explains the application of handwritten character recognition in handwritten calculator. Direction string is proposed to represent the key features of handwritten symbol strokes and distance between direction symbols and direction strings are also defined for nearest neighbour string matching algorithm. Experiments have shown that this method could perform quite well.

II. PROPOSED SYSTEM

In proposed system, FKI dataset is extended by adding some more characters from English language. First the input image is provided and is converted into a gray-scale image and normalized in such a way that it represents the same resolution (28 x 28) as that of FKI dataset. CNN is trained using FKI dataset and use it as a classifier which will yield better results when compared with other machine learning algorithms. The feature vectors are extracted from the input image and provided to the trained model of Convolution Neural Network which recognizes and provides the desired output. Figure 3.1 presents the handwritten character recognition architecture diagram.

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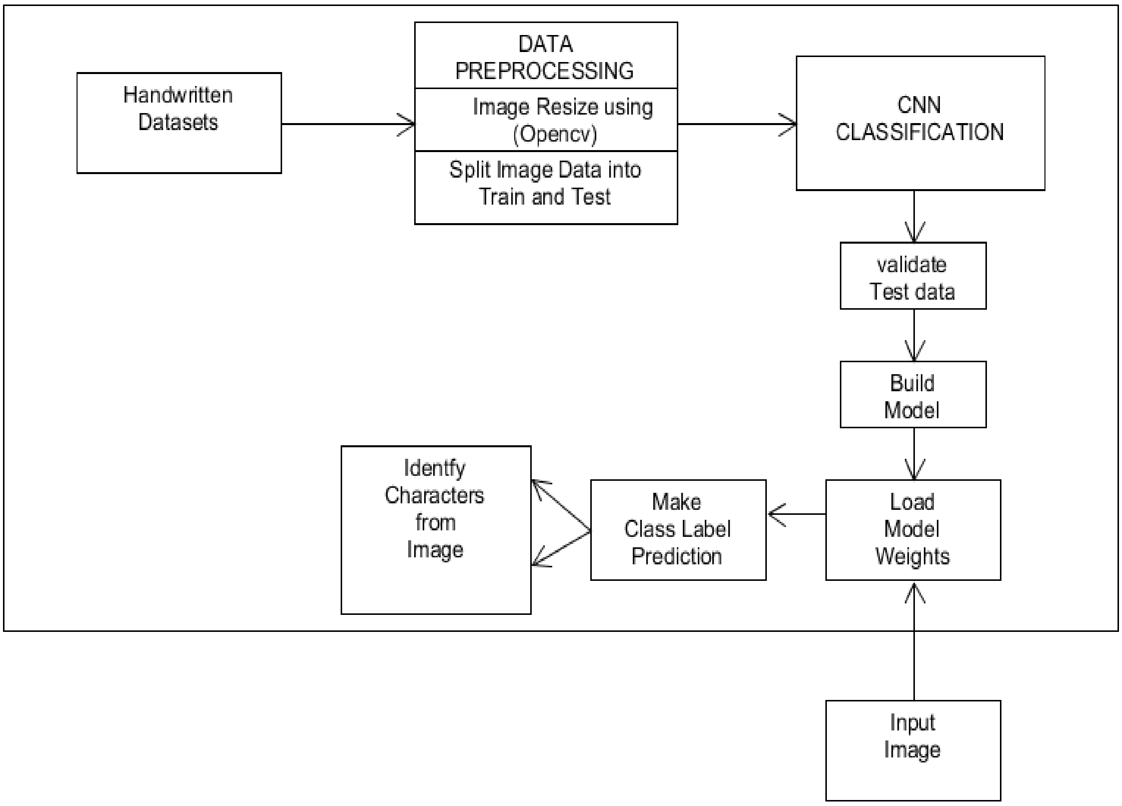


Figure 3.1: Handwritten Character Recognition Architecture

III. MODULES DESCRIPTION

The various modules of the proposed system include Pre-processing, Segmentation, Feature Extraction, Classification, Post-preprocessing.

A. **Pre-processing:** The goal of pre-processing is to discard irrelevant information that can negatively affect the recognition. Generally, the irrelevant information includes duplicated points, wild points, hooks, noise etc. Pre-processing aims to produce data that are easy for the HCR system to operate accurately.

B. **Segmentation:** After pre-processing a clean document is obtained. In this stage, segmenting the document into its sub components. It separates the logical parts, like text from graphics, line of paragraph, and characters of a word. Segmentation is important phase in HCR system.

C. **Feature Extraction**: A set of rules stored on HCR engine comparing against characters shape and its features that distinguishes each character identify a character. The main part of recognition system design is the selection of a stable representative set of features. It is most consequential issue in the designing issues involved in building an HCR system.

D. **Classification:** The main decision-making stage of HCR system is classification. Classification uses the features extracted in the feature extraction stage to identify the text segment.

E. **Post Processing**: It is the final stage, post processing refining the decisions taken by the previous stage, improves the recognition and recognizes words using context. It is ultimately responsible for outputting the best solution and is often implemented as a set of techniques that rely on character frequencies, lexicons, and other context information.

Convolutional Neural Networks have a different architecture than regular Neural Networks. Regular Neural Networks transform an input by putting it through a series of hidden layers. Every layer is made up of a set of neurons, where each layer is fully connected to all neurons in the layer before. Finally, there is a last fully-connected layer — the output layer — that represent the predictions.

Convolutional Neural Networks are a bit different. First of all, the layers are organized in 3 dimensions: width, height and depth. Further, the neurons in one layer do not connect to all the neurons in the next layer but only to a small region of it. Lastly, the final output will be reduced to a single vector of probability scores, organized along the depth dimension.

A. **Module 1:** Region Proposal. Generate and extract category independent region proposals, e.g., candidate bounding boxes.

B. **Module 2:** Feature Extractor. Extract feature from each candidate region, e.g., using a deep convolutional neural network.

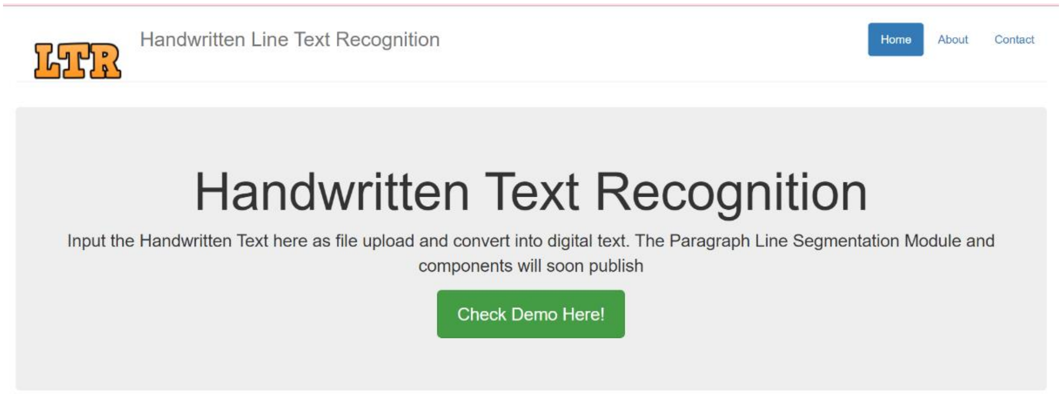
C. **Module 3:** Classifier. Classify features as one of the known classes

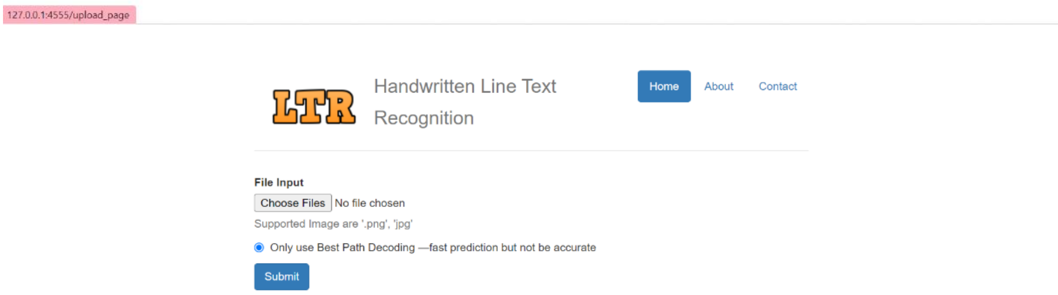
IV. EXPERIMENTAL RESULTS

The CNN algorithm was implemented in Anaconda Jupiter Notebook under Windows 7 operating system. The implemented program was run on intel core i7-2640 CPU with 2GB RAM. The test results are given in Table 1. The table provides three columns – in which the first column provides number of training images; the second column presents the number of testing sets and the last column lists the accuracy obtained by the CNN method for correctly classified images. It can be noticed from the experiment that the average accuracy increases with higher number of training images, since the higher number of images in the training produces more accurate information on the training parameters, which subsequently improves the accuracy in classification during testing phase. One checks that the accuracy obtained from 200 training images as 65.32% is improved gradually with increasing training images. The accuracy reaches to 92.91% with the 1000 training images. Thus, further increment of training images will continue to enhance the accuracy towards to certain limit – which cannot be exceeded due to numerical errors, and the constraints on the CNN capability of image differentiability for labels.

Table 1: Test Results for Handwritten Character Recognition with FKI dataset

No. of Training Images	No. of Testing Images	Average Accuracy (%)
200	200	65.32%
300	200	74.43%
500	200	80.84%
600	200	85.21%
800	200	87.65%
1000	200	92.91%





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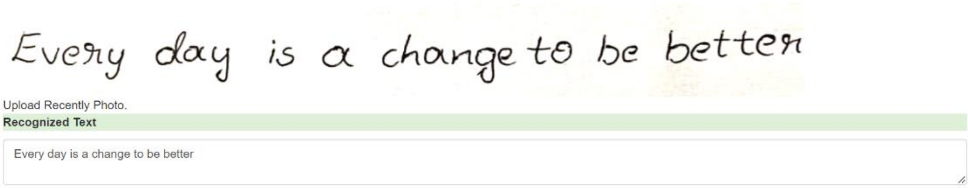

V. CONCLUSION

Handwritten character recognition has been a challenging task in the past few years. But due to development of machine learning domain in recent years and creation of huge amount of data from our day-to-day life, image recognition for computer vision has seen enormous improvement. FKI dataset provides about 132,000 images of 47 characters to be trained and recognized. The convolution neural network was used to train FKI dataset to obtain high accuracy. The FKI dataset is extended to support the 12 characters from English language and the recognition of these character are tested. The input image is pre-processed, standardized normalized and given to the classifier to predict the character. The model improves the true positive rate and reduces the false positive rate.

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