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Offline Handwritten Devanagari Numerals Recognition Using Deep Neural Network

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Abstract: In India, a large number of people are using Devanagari Script to write their documents but due to large complexity, research work done on this is very less. Recognizing the text of a document would be useful in many diverse applications like reading medical prescriptions, bank cheques and other official documents. Handwriting recognition can be broken into a number of relatively independent modules. After going through several papers and web pages on handwritten word recognition, we thought of various strategies for each of these modules. We then consider the accuracy and efficiency of these strategies independently and as a whole. Also, we came up with a new idea based on feature extraction and relative position matching with the help of directional graphs. Our paper is aimed at implementing this idea keeping in mind the strategies which we considered best for overall accurate, efficient and scalable handwriting recognition software. In this paper, the offline handwritten Devanagari numerals recognition will be done using deep neural network.

Keywords: ANN, CNN, DEVNAGARI, DEEP NEURAL NETWORK, OCR, SVM.

I. Introduction

In offline handwriting recognition, handwritten text scanned with the help of scanners and provided to the system digitally. The recognition procedure is completed on the last dash of composing. However, in an on line recognition gadget, the spatial arrange estimations of progressive pixels are spoken to utilizing an element of time and spared so as. The recommended notoriety expenses and exactness degree for on-line notoriety structures are superior to anything that for offline recognition frameworks. Notwithstanding, offline notoriety frameworks have great measured effect in specific areas like manually written arrangement with translation, signature confirmation, postal arrangement with ubiquity, bank cheques recognition and writer identification. Further, because of dynamic nature of manually written data, offline penmanship recognition is a vigorous and extreme field of concentrates for investigating the more up to date strategies to improve the recognition precision. In any case, there are some significant inconveniences that ascent up in offline transcribed frameworks which include:

- Distinct writing styles of single person.
- Impact of different conditions on writing styles of single person.

Aside from trademark classification and extraction, the segment of test recognition also comprises of preprocessing and layout of examples. In well known, a transcribed example recognition framework comprises of following 3 chief advances:

- Preprocessing of the input samples.
- Feature extraction from the input samples.
- Classification.

An essential preprocessing step utilized in manually written numeral example notoriety is to symbolize the basic state of such design through bringing down the example to a diagram. This decrease might be accomplished through a system alluded to as diminishing. A diminishing arrangement of principles produces the skeleton for a numeral example. Diminishing makes trademark extraction and prominence technique simple and green by methods for lessening an offered example to unit pixel thickness. Consequently, diminishing is fundamental just as significant for a green recognition methodology.

Deep learning has been widely used to recognize handwriting. In offline handwriting recognition, text is analyzed after being written. The only information that can be analyzed is the binary output of a character against a background. Although shifts towards digital stylus for writing gives more information, such as pen stroke, pressure and speed of writing, there is still a necessity for offline methods, when online is inaccessible. It is particularly necessary for historical documents, archives, or mass digitization of hand-filled forms.

Handwritten text classifiers were first required for classification of postal mail. Using scanning equipment, hardwired logic recognized mono-spaced fonts. The first Optical Character Recognition (OCR) software developed in 1974 by Ray Kurzweil. By reducing the problem domain, the process was more accurate. This allowed for recognition in handwritten forms. Foremost, it lacked efficiency and knowledge of unexpected characters. These classical techniques carried heavy limitations in two key areas:

Character extraction — Individual characters are recognized by ease with OCR. Cursive handwriting, which is connected, poses more issues with evaluation. It is difficult to interpret handwriting with no distinct separation between characters.

Feature extraction — Individual properties of symbols were hard-coded, and matched to input symbols. Properties include aspect ratio, pixel distribution, number of strokes, distance from the image centre, and reflection. This requires development time, as these properties are added manually.

II. Literature Review

In [1,2], around 90000 images of more than 40 different classes of characters of Devanagari script were segmented from handwritten documents. Used deep learning architecture for recognition and CNN for superior result to traditional shallow networks in many recognition tasks and focus the use of Idler and dataset increment approach to improve test accuracy. The base form of consonant characters can be combined with vowels to form an additional character which is not explored in that research. So, they used Deep CNNs with additional Dataset increment techniques and Dropout layer which results in very high test accuracy even for a various and challenging dataset.

In [3], they describe same problem of handwriting recognition. They used holistic approach to identify the handwritten words, each word take is an individual entity so holistic approach is better and used such methods namely density features, long run features and structural features for extraction in the input handwritten document image. After that they apply classification by using Support Vector Machines (SVM). They achieved 88.13% of recognition rate.

In [4], they researched on digit recognition in Arabic with help of CNN. They proposed a novel algorithm based on deep learning neural networks using appropriate activation function and regularization layer, which shows significantly improved accuracy compared to the existing Arabic numeral recognition methods. In the Multi-Layer Perceptron (MLP) model, they implement dropout regularization to reduce over fitting in between fully connected layers. The output layer, consisting of 10 neurons with softmax activation, predicts the probability for 10 individual digit classes (0-9). They apply two methods in it, MLP and CNN but they achieved high accuracy in CNN.

In [5], they propose a workflow and a machine learning model for recognizing handwritten characters on form document. It is based on CNN as a powerful feature extraction and Support Vector Machines (SVM) as a high-end classifier. Based on the experiment results using data, both for training and testing, the proposed method achieves an accuracy rate better than only CNN method. The proposed method was also validated using ten folds cross-validation, and it shows that the recognition rate for this proposed method is still able to be improved.

In [6], they investigate the applicability of Deep Convolution Neural Network (DCNN) using the transfer learning strategies on two datasets; they demonstrated the abilities of satisfactory recognition and done enhanced methods in the field of handwritten Arabic character recognition (HACR). He examined and discussed the use of CNN in the field of off-line HACR. We used the same architecture as Alex-Net, without the pre-processing phase and with a three learning strategy.

In [7], they provide a new system for DCNN Drop Sample, and apply it to a large number of online handwritten Chinese letter identification (HCRR). It is connected to the Quota Function, which is dynamically DCNN, Based on confidence expressed by softmax output. It is with a variety of domain-specific knowledge; the accuracy of HCCR can be improved effectively.

In [8], they recognize handwritten Devanagari digits. They use density and background direction distribution facilities for zones. They use common images of different sizes of 32 * 32, 40 * 40 and 48 * 48. For the purpose of classification, they used the SMS classifier with the RBF kernel. Documents used for handwritten Devanagari numbers are given by the Indian Statistical Institute (ISI), Kolkata. They recommend a 144-size feature vector to identify the test sample. 32 * 32 normally tested, the accuracy of the test by the 144 quake is 98.51%, which is prominent and cost-efficient.

In [9], they used two classification methods to identify handwritten Devanagari numbers. They used two classifiers HMM and ANN to introduce the recognition system. The digital image is classified according to the maximum score obtained by ANN Classifier.

In [10], they introduced a novel offline strategy for recognition of online handwritten characters written in Devnagari entered in an unrestricted manner. They experiment different classifiers like SVM, HMM, ANN and trained on statistical, structural or spectral features but they used CNN because it allows writers to enter characters in any number or arrangement of strokes and is also strong to certain amount of overwriting. They test with 10 different arrangements of CNN and for both Exponential Decay and Inverse Scale Annealing approaches to convergence, show highly promising results. Using a hybrid approach they conclude that character level data is extracted from the collected words and covers all probable variants owing to the different writing styles and varied parent word structures.

In [11], they recognize offline handwritten Guajarati character based on water reservoir and radial histogram. They presented use of structural features based on water reservoir principle and radial histogram for Gujarati character recognition.

They used two-layer feed-forward neural network for classification to train the recognition system. They conclude a two-layer feed-forward network is obtained overall 74.16% of accuracy.

Table 1: work done on handwritten recognition

Script	Data type	Classifier	Accuracy	Reference
Devanagari	Numeral	SVM	98.62%	[8]
Devanagari	Numeral	ANN HMM	1) 92.83%, 2) 87.69%	[9]
Devanagari	Character	CNN	98.19%	[10]
Devanagari	Character	DCNN	98.47%	[2]
Gujarati	Character	Neural Network	74.16%	[11]
Gujarati	Character	Binary tree and KNN	63.1%	[12]
Chinese	Character	DCNN	97.737%	[7]
Arabic	Numeral	DCNN	97.4%	[4]
Arabic	Character	DL technique : CNN from scratch CNN as fixed feature extractor CNN fine-tuned	With preprocessing 99.97% 70.77% 96.19%	[6]

III. Proposed System

The proposed system shown in figure 1 will be gone through the following steps to achieve the defined objectives of the work.

Begin

1. Prepare the database for handwritten text samples.
2. Input the offline/online handwritten Devanagari script image samples.
3. Apply Pre-processing Steps on input handwritten images (CNN will automatically perform following tasks)
   a) Resize image to 64x99 pixels.
   b) Smooth image contour by Apply Gaussian filter of 5x5 with sigma= 0.5.
   c) Binarization of the input blurred image.
4. Generate the training dataset by considering.
5. The test data set consisting of test images on which trained neural network is applied to generate the offline handwritten Devanagari script images.
6. Design neural network structure by determining CNN network architecture and parameters.
7. Train the proposed system network using optimal selection of network parameters. The weights generated from the training process are collected.
8. Develop and apply a deep learning methodology for generating thinned image using the generated weights.
9. Applying post-processing step for testing and validation of the results.
10. Performance analysis of the obtained results.

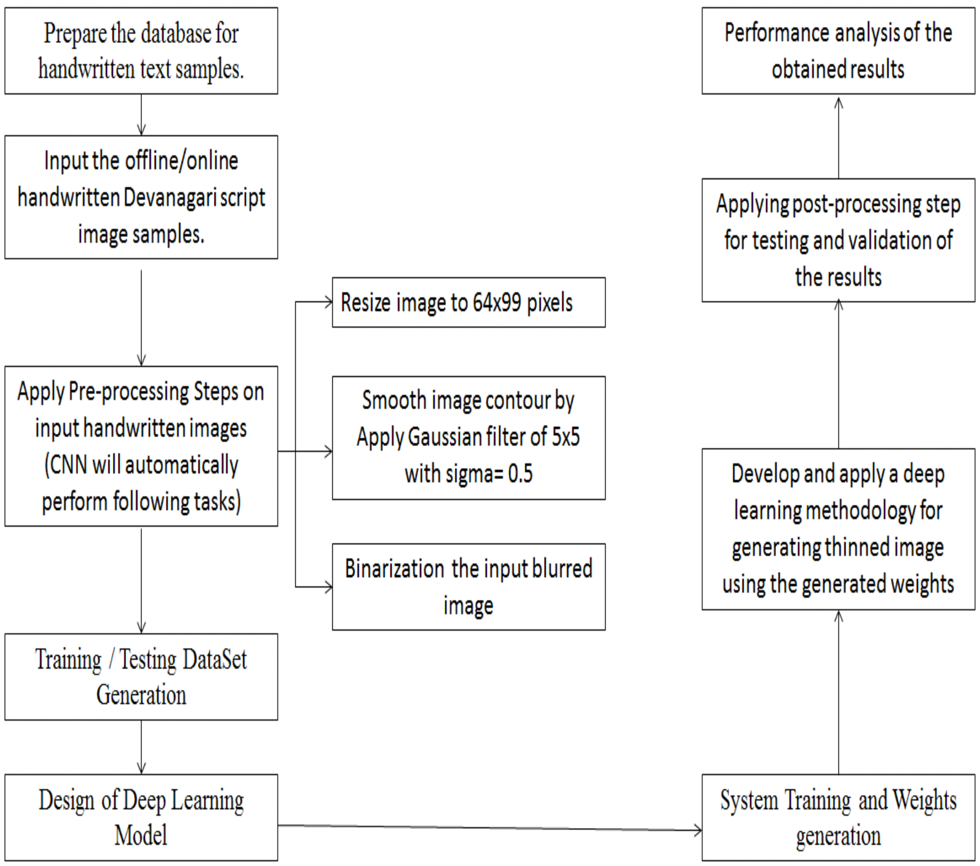

Figure 1: Proposed System

IV. Conclusion and Future Scope

In the scope of proposed work, the focus is on deep learning based neural networks to recognize the handwritten scripts. Therefore, a recognition system using proposed neural based deep neural algorithm can be developed to check improvement in recognition accuracy. The proposed neural based deep learning algorithm will be tested on different image datasets. Possibility of applying other soft computing techniques can be explored. Parameter based improvements can be done.

References:

[1]. Shailesh Acharya, Ashok Kumar Pant, Prashnna Kumar Gyawali," Deep Learning Based Large Scale Handwritten Devanagari Character Recognition", 9th International Conference on Software, Knowledge, Information Management and Applications (SKIMA), 2015.

[2]. Jenis J. Macwan, Mukesh M. Goswami, Archana N. Vyas, "A Survey on Offline Handwritten North Indian Script Symbol Recognition", International Conference on Electrical, Electronics, and Optimization Techniques (ICEEOT) – 2016.

[3]. Shruthi A , M S Patel," Offline Handwritten Word Recognition using Multiple Features with SVM Classifier for Holistic Approach" , International Journal of Innovative Research in Computer and Communication Engineering, June 2015.

[4]. Akm Ashiquzzaman and Abdul Kawsar Tushar," Handwritten Arabic Numeral Recognition using Deep Learning Neural Networks", 2011.

[5]. Darmatasia and Mohamad Ivan Fanany," Handwriting Recognition on Form Document Using Convolutional Neural Network and Support Vector Machines", 2017 Fifth International Conference on Information and Communication Technology (ICoICT), 2017.

[6]. Chaouki Boufenar , Adlen Kerboua, Mohamed Batouche," Investigation on deep learning for off-line handwritten Arabic character recognition", Cognitive Systems Research, 2017.

[7]. WeixinYang , LianwenJin , DachengTao , ZechengXie , ZiyongFeng, "A new training method to enhance deep convolutional neural networks for large-scale unconstrained handwritten Chinese character recognition".

[8]. Jangid, Mahesh, et al. "SVM classifier for recognition of handwritten Devanagari numeral." Image Information Processing (ICIIP), 2011 International Conference on. IEEE, 2011.

[9]. Bhattacharya, U., et al., "Neural combination of ANN and HMM for Handwritten Devanagari numeral recognition." Tenth International Workshop on Frontiers in Handwriting Recognition. Suvisoft, 2006.

[10]. Mehrotra, Kapil, et al., "Unconstrained handwritten Devanagari character recognition using convolutional neural networks." Proceedings of the 4th International Workshop on Multilingual OCR. ACM, 2013.

[11]. Jitendra V. Nasriwala, Dr. Bankim C. Patel, "Offline Handwritten Gujarati Character Recognition Based on Water Reservoir and Radial Histogram", International Journal of Electrical Electronics & Computer Science Engineering, 2016.

[12]. C. Patel, and A. A. Desai, "Gujarati Handwritten Character Recognition Using Hybrid Method Based On Binary Tree-Classifier And K-Nearest Neighbor". International Journal of Engineering Research and Technology, ESRSA Publications. (Vol. 2, No. 6). June-2013.

[13]. Jenis J. Macwan, Mukesh M. Goswami, Archana N. Vyas, "A Survey on Offline Handwritten North Indian Script Symbol Recognition", International Conference on Electrical, Electronics, and Optimization Techniques (ICEEOT) – 2016.