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HANDWRITTEN DEVANAGARI DIGITS RECOGNITION USING DEEP LEARNING

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ABSTRACT

Character recognition, a subdomain of pattern recognition, has been a subject of research since the early 20th century. Hindi is the common and most popular language in the countries such as India, Nepal etc. People use this language not only for conversation but also in their vehicles license plates, documents, sign boards, handwritten notes etc. In recent years, many approaches have been proposed for Hindi character recognition and various applications such as text to speech translator, automatic license plate recognition etc. are proposed for these. Some computationally expensive approaches have achieved desirable accuracy but for light computing devices, recognition of handwritten characters is still challenging task. This paper proposes an approach for recognition of handwritten Devanagari character recognition.

Keywords: *Handwritten Digit Recognition, Deep Learning, Devanagari Script, CNN, OCR*.

Introduction

In the last few years, deep learning approaches have been successfully applied to various areas such as image classification, speech recognition, cancer cell detection, video search, face detection, satellite imagery, recognizing traffic signs and pedestrian detection, etc. The outcome of deep learning approaches is also prominent, and in some cases the results are superior to human experts in the past years. Most of the problems are also being re- experimented with deep learning approaches with the view to achieving improvements in the existing findings.

Different architectures of deep learning have been introduced in recent years, such as deep convolution neural networks, deep belief networks, and recurrent neural networks. The entire architecture has shown the proficiency in different areas. Character recognition is one of the areas where machine learning techniques have been extensively experimented. The first deep learning approach, which is one of the leading machine learning techniques, was proposed for characters recognition in 1998 on MNIST database .The deep learning techniques are basically composed of multiple hidden layers, and each hidden layer consists of multiple neurons, which compute the suitable weights for the deep network. A lot of computing power is needed to compute these weights, and a powerful system was needed, which was not easily available at that time. Since then, the researchers have drawn their attention to finding the technique which needs less power by converting the images into feature vectors. In the last few decades, a lot of feature extraction techniques have been proposed such as HOG (histogram of oriented gradients) SIFT (scale- invariant feature transform), LBP (local binary pattern) and SURF(speeded up robust features), These are prominent feature extraction methods, which have been experimented for many problems like image recognition, character recognition, face detection, etc. and the corresponding models are called shallow learning models, which are still popular for the pattern recognition. Feature extraction is one type of dimensionality reduction technique that represents the important parts of a large image into a feature vector. These features are handcrafted and explicitly designed by the research community. The robustness and performance of these features depend on the skill and the knowledge of each researcher. There are the cases where some vital features may be unseen by the researcher while extracting the features from the image and this may result in a high classification error.

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Deep learning inverts the process of handcrafting and designing features for a particular problem into an automatic process to compute the best features for that problem. A deep convolutional neural network has multiple convolution layers to extract the features automatically. The features are extracted only once in most of the shallow learning models, but in the case of deep learning models, multiple convolutional layers have been adopted to extract discriminating features multiple times. This is one of the reasons that deep learning models are generally successful. The LeNetis an example of deep convolutional neural network for character recognition. Recently, many other examples of deep learning models can be listed such as Alex Net, ZFNet, VGGNet and spatial transformer networks . These models have been successfully applied for image classification and character recognition. Owing to their great success, many leading companies have also introduced deep models. Google Corporation has made a Google Net having 22 layers of convolutional and pooling layers alternatively. Apart from this model, Google has also developed an open source software library named Tensor flow to conduct deep learning research. Microsoft also introduced its own deep convolutional neural network architecture named ResNet in 2015. ResNet has 152-layer network architectures which made a new record in detection, localization, and classification. This model introduced a new idea of residual learning that makes the optimization and the back-propagation process easier than the basic DCNN model.

Character recognition is a field of image processing where the image is recognized and converted into a machine-readable format. As discussed above, the deep learning approach and especially deep convolutional neural networks have been used for image detection and recognition. It has also been successfully applied on Roman (MNIST), Chinese, Bangla and Arabic languages. In this work, a deep convolutional neural network is applied for handwritten Devanagari characters recognition.

Background

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The first deep learning approach, which is one of the leading machine learning techniques, was proposed for character recognition in 1998 on MNIST database. Deep learning inverts the process of handcrafting and designing features for a particular problem into an automatic process to compute the best features for that problem. A deep convolution neural network has multiple convolution layers to extract the features automatically. The main contributions of our work can be summarized in the following points:

Deep learning approach is time applying on ISI, Kolkata created dataset. CNN is used to recognize the Devanagari digits. Deep learning is a rapidly developing field, which is bringing new techniques that can significantly ameliorate the performance of DCNNs. Since these techniques have been published in the last few years, there is even a validation process for establishing their cross-domainutility.

The proposed handwritten Devanagari character recognition system achieves high classification accuracy, surpassing existing approaches in literature mainly regarding recognition accuracy. A layer-wise technique of DCNN technique is proposed to achieve the highest recognition accuracy and also get a faster convergence rate.

Actually humans communicate in a natural way from eras and that way is known as handwriting. It’s an essential part of one’s daily doings like mark letters, shimming forms, categorization of mails and many more. Automatically processing of handwritten documents and their mounting demands from last few eras works as a complement to human life. Adding to this it also proposes intelligent systems and beheld the work of stylus on hand held devices accepting handwritten inputs. To accept those inputs it requires applications to perform this recognition task. Due to this handwriting recognition is always become important and major research directions and led area of computer vision to new heights.

Handwriting Recognition

An aptitude of computer to collect and construe handwritten input logically is called handwriting recognition (HR) and can also be well-defined as a chore that convert text represented in spatial form of graphical marks to its symbolic depiction. The extreme goalmouth of this study is to evolve structures that can recite any manuscript with the same recognition precision as humans, but with faster rate. When problems dimension is large having numerous sub-tasks then it will become a hard job because of unequivocal nature of handwriting itself. HR can be either “offline” or “online”.

- **Handwritten Digit Recognition**

Identifying single handwritten digit images is a vintage issue of machine learning. Handwritten digit recognition (HDR) has been deeply studied in arena of HR and researchers get various results by using number of classifiers, such as OCR, ZIP Code etc.

- **Handwritten Character Recognition**

Handwritten character recognition (HCR) is based on the identification of cursive document and hand printed characters in a document. It is challenging to draw a fair characteristic between them, as usually their blending is shown.

- **Data Classification**

Data is gained by numerous techniques to the computers from its sources. Type of equipment used for collecting data is the central dependency of automatic character recognition (ACR) and text type being another factor. Further classification of ACR techniques are shown in sub-sections given below.

  - **Classification based on Data Acquisition**

When documents typed or written on low quality papers earlier then problems arise but now with texts keyed on a high quality paper with current printing machineries results in good recognition rates. On another side, HCR systems have finite aptitudes even for identification of the Latin characters. Broadly, classified areas in character recognition are:

  - **Offline Handwritten Recognition**

The off-line recognition systems processes as follows as firstly digits need to be written on a slice of paper then it is scanned and digitized by an optical scanner. After scanning it is captured in computer and each get positioned and segmented. The resultant array matrix is then served into preprocessor for ironing (i.e. smoothing), noise abolition, extent normalization and others, to simplify facet abstraction process in succeeding phase. Assisting in automated processing handwritten documents reveals its importance in man-machine communication by being a subtask of Optical Character Recognition (OCR) that is required for machine-print or HR.

  - **Online Handwritten Recognition**

When characters are directly written on hand-held devices by human and no contour extraction is needed than accessing information progressively from those strokes comes under the category of online recognition system. Storing of 2-d coordinates of succeeding points as a utility of time is obtainable. This system opens new doors in field of human-computer interaction.

- **Classification based on Manuscript**

When documents typed or written on low quality papers earlier then problems arise but now with texts keyed on a high quality paper with current printing machineries results in good recognition rates. On another side, HCR systems have finite aptitudes even for identification of the Latin characters. Broadly, classified areas in character recognition are:

Printed Character Recognition (PCR)

Handwritten Character Recognition

  - **Printed Text**

Printed resources like newspapers, documents, books, magazines etc… that contain all printed resources are the output of typewriters, plotters and printers.

Based on intricacies printed characters are differentiated in three main categories:

Fixedfont CR (recognizing a special font)

Multifont CR (recognizing more than one font))

Omnifont CR (recognizing any font)

Identification degree of commercially accessible stuffs almost depends on the age of the manuscripts and trait of paper and ink that results in major data gaining noise

  - **Handwritten Text**

Although many influential and ancient methods are offered for the identification of printed leaflets, HR still remains an unresolved problem. It is the most challenging area of ACR because characters vary in extent and shape in strokes and reflects dynamic variation as it depends on panache of the writer and its speed of writing. Human eyes are doesn’t sense the location orientation and extent change in characters.

- **Benefits of Handwritten Digit Recognition**

  Handwriting recognition (HR) plays significant part in storage and retrieval of crucial handwritten info.

  - **Data Storage**

Many contracts, files and personal records contain typed and handwritten information. This means that storing such information requires physical space because those original signatures and notes cannot be electronically stored. HR application allows users to interpret those signatures and notes into electric words

  - **Data Retrieval**

Data repossession necessitates manual work to sort through physical replicas of old info. The data is needed to be correctly packed and organized for proper maintenance.

  - **Historical Preservation**

A wealth of historical papers exists in a physical format. This includes genealogical information, written manuscripts, personal diaries and many other pieces of a shared past. Consistent review of this information damages the original paper and can lead to physical data corruption

  - **Textual Studies**

Textual studies are a branch of literature studies that involves rereading the unique manuscripts of literature when compared with printed texts. This form of study is intended as a means of delving into the author's original intentions for a story before it touched an editor's hands. Original manuscripts are well cared for; however, this study requires an intensive review of the manuscript. Handwriting recognition allows for these original manuscripts to be saved in an electronic format, giving access to reviewers without damaging the original copy.

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