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Handwritten Ol-Chiki Character Recognition using Convolution Neural Network

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Abstract

The process of recognizing scanned documents or machine printed documents using automated tools are used in different real life domains. Designing a method with cent percent accuracy of character recognition is a challenging and unachievable task. Presence of noise, distinct styles of font under real time environment makes character recognition more difficult.

In this paper, we propose a convolution deep model to recognize Ol-Chiki handwritten characters. Here we describe recognition of handwritten basic characters of Ol-Chiki script, used by more than 10 million tribal people in India mostly from Assam, Bengal, Bihar, Odisha and Jharkhand. There are 30 basic characters and 10 numeral digits in OlChiki. We have used a dataset of 10000 handwritten isolated character samples written by 50 persons. Convolution Neural Network (CNN) architecture has been used for the recognition of handwritten isolated Ol-Chiki characters.

Useful set of features has been extracted using kernels and local receptive fields and an activation function in the CNN architecture has been performed. Our system has been tested on Ol-Chiki isolated dataset and we have achieved 88% accuracy on almost all Ol-Chiki characters.

Key Words: Convolution Deep Model, Convolution Neural Network, Kernels, Activation Function.

1. Introduction

Handwritten character recognition has emerged as one of the major interests for its wide range of applications. The applications range from zip code reading to writer recognition, from recognizing numerals and alphabets in number plate of traffics to bank check processing, and etc. While there is an overwhelming number of works done on english (or alike languages), but no such work has been done so far on Ol-Chiki character.

The Ol-Chiki Script, Also Called Olcemet', Ol-Chiki, Or Simply Ol, was invented by Pandit Raghunath Murmu in the first half of the 20th Century, spoken by ten Million Santali People, mostly in India with a few in Nepal and Bangladesh. The Santali is the language spoken by one of the largest indigenous socio-linguistic Group in the Indian subcontinent and its speakers presently resides mainly in the Indian States of Assam, Bihar, Jharkhand, Orissa and West Bengal, and also in Bangladesh and Nepal. Currently Santali language is written in five different scripts, viz. Ol-Chiki, Bengali, Devnagari, Oriya and Roman Scripts. Out of these scripts, it is only the Ol-Chiki Script that has been devised purely for writing Santali, in particular.

After the invention of Ol-Chiki script during 1930s, a large number of books have been written by various authors in santali using Ol-Chiki script. Therefore, it is of great importance to preserve santali language in its authentic form, and evidently the script plays an important role to perpetuate a language in its true form among the members of its speakers. In other words, the propagating Ol-Chiki for the development of santali language is the only way of carrying forward its heritage. In the year of December, 2002 Ol-Chiki script has been computerized with ASCII code.

Novelty of Ol-Chiki script: One of the interesting features of Ol-Chiki script is that it makes use of

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signs and symbols long familiar to the santals. Letters of Ol-Chiki script are also derived from the physical environment, likes – hills, rivers, trees, birds, bees, plough, sickle etc [1, 2]. A partial list is given below in figure 1 to show some Ol-Chiki alphabets with their meaning and significance.

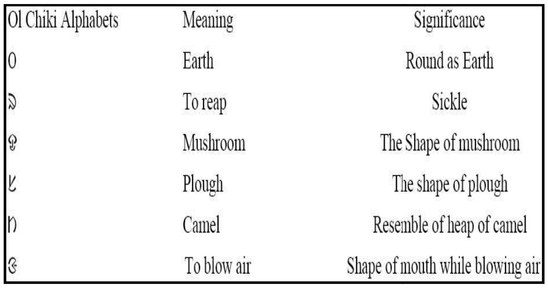

Figure 1: Ol-Chiki alphabets with their meaning and significance

Usefulness of recognition system of Ol-Chiki: Santals are not able to harness the power of the great global phenomenon known as the 'computer'. This paper focuses on the recognition of Ol-Chiki characters and as well as of Ol-Chiki script for the document processing in near future. In Ol-Chiki script, there are 30 characters (Figure 2a (Printed), 2b (Handwritten)) and 10 digits (Figure 3a (Printed), 3b (Handwritten)). Ol-Chiki printed and hand written characters are not similar in shape.

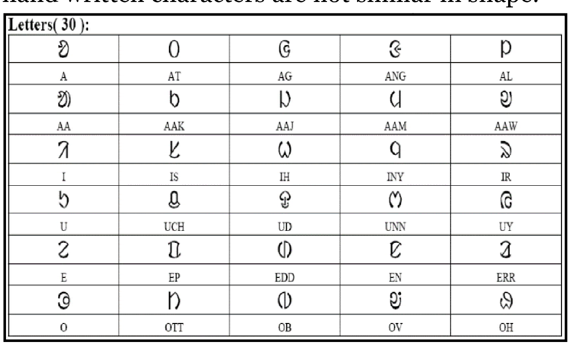

Figure 2a: Ol-Chiki basic printed characters

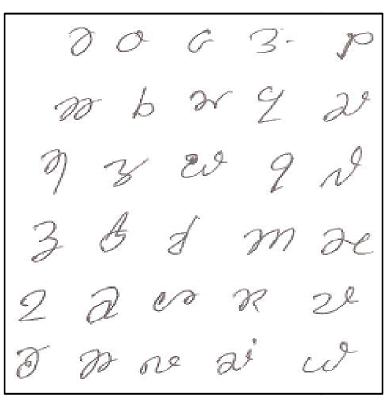

Figure 2b: Ol-Chiki basic handwritten characters

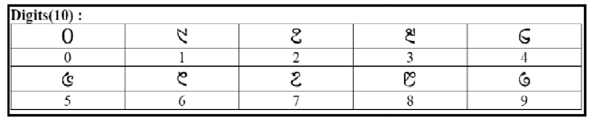

Figure3a: Ol-Chiki digits (Printed)

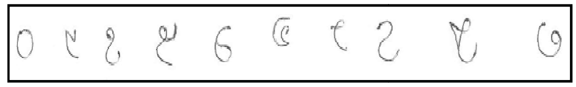

Figure 3b: Ol-Chiki digits (Handwritten)

Convolution neural networks were first recognized for their potential in digit recognition task in [3]. CNNs are good with image inputs because they are significantly insensitive to both translational variance and scale variance of the features in the images. The key challenge in any visual recognition task to a machine is how the appropriate set of features is extracted from the image [4], [5]. There are some other methods like the support vector machines (SVMs) that have also been used in the literature [5], [6], [7]. But they turned out to be effective when CNNs, at the lower layer, extracted necessary features for them [8]. Actually the accuracy of the recognition task largely depends on adaptability to variance of local features. CNNs achieve this adaptability by using kernel feature detectors. CNNs have also been used for Bengali character recognition [9], [10], [11]. To our knowledge, no work till date has worked on Santali literature.

2. Methodology

In this work we used a model in deep convolution neural network with two convolution layers, followed by three densely connected layers (Figure 4).

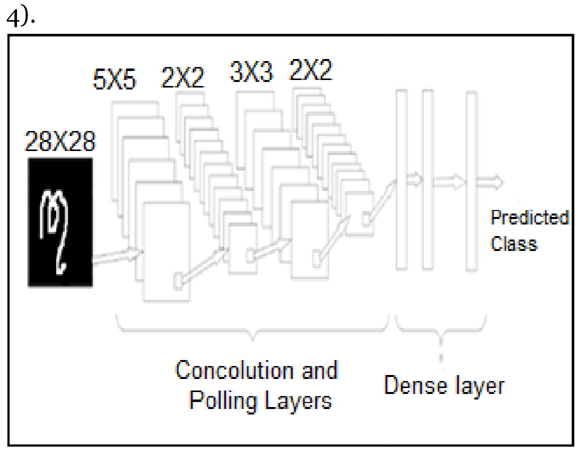

Figure 4: CNN for Character Recognition

The final dense layer is a softmax layer. The standard softmax function in CNN is denoted by σ and formula is as follows:

$$\sigma(\mathbf{z})_i = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}}$$

The layer provides a probability distribution over a predefined number of categories. We pick the category that has the highest probability assigned by the network. The first convolution layer extracts features directly from the image so that they may be used in discrimination task later. This layer scans for 5X5 receptive fields throughout the image. These fields would contain the features. After scanning for the receptive fields the features are then passed through ReLu activation function.

ReLu(x)=max(0,x)

Outputs produced by the ReLu layer are afterwards passed to a max-pooling layer of size 2X2. We slide for the maximum value of the 2X2 adjacent cells' for a cell (Table I). The resulting max-pooled feature maps are then again passed to a convolution layer where we have employed 64 kernels each looking for 3X3 receptive fields. The extracted features are likewise passed first to the ReLu activation function, and then to a 2X2 max-pooling layer. This second max-pooling layer actually embarks the features that would be used for the classification task. The feature extraction task ends with this layer. The next task is of recognizing the true class from these features.

Before Pooling				
0.68	0.69	0.09	0.28	1.78
1.04	-1.33	0.72	0.92	0.98
1.73	0.84	-0.85	1.98	1.35
-0.83	0.89	0.12	-0.83	0.56
-1.46	-0.84	0.85	1.03	1.32

After Pooling	
1.04	1.78
1.73	1.32

Table 1: Pooling of a 5X5 filter by a 2X2 max-pool with stride size 2

These features are then passed to three densely connected layers sequentially. These layers are concerned with the actual classification task. We have applied dropout at each layer as not to over fit the data. Dropout is a regularization technique where we randomly omit some of the units of a layer in a given iteration [12]. This introduces weight sharing among (nearly) exponential models. Thus it inhibits the combined model from over fitting. The final layer is a softmax layer which outputs a probability distribution over the classes for a given input.

3. Experimental Results And Analysis:

We have tested our model on our dataset. The dataset consists of 10000 isolated handwritten Ol-Chiki Characters and Digits. Dataset contents 30 Ol-Chiki basic characters and 10 digits. The dataset is summarized in Table II. Each data example is given as an image file. We first brought all the images to a uniform size (28X28 pixels). Thus we represented each character data as a 28 X 28=784 dimensional input. As each data example comprised of 784 dimensions, we linearly projected them to a 2-dimensional plane to have a more insight of it. Figure 5 shows the distribution of each type of character classes. We have randomly picked 1000 examples from each category. The distribution reveals that the classes are strongly interleaved.

Type		Dataset	Total
Ol-Chiki Character	30 Characters	50 Persons, each 5 Times	7500
Ol-Chiki Digits	10 Digits	50 Persons, each 5 Times	2500

Table 2: Dataset of Ol-Chiki Handwritten Data

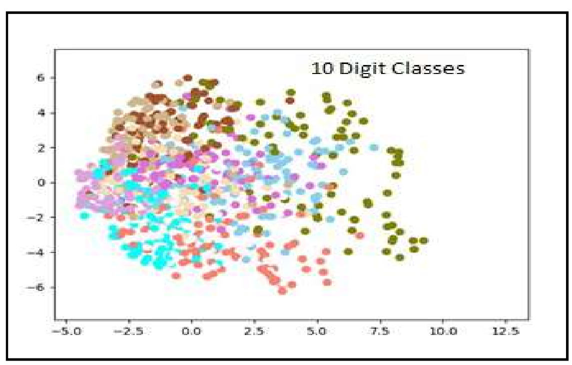

Figure 5a: Distribution for Digit classes

The final output produced by our network is a probability distribution over predefined number of classes.

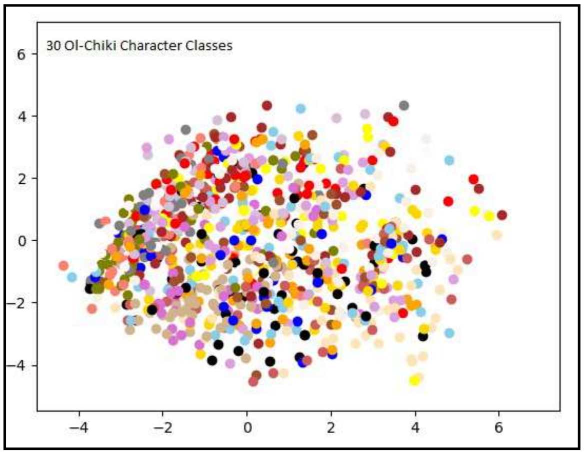

Figure 5b: Distribution for Character Classes

We actually have tested our system on several combinations of the character types. The probability distribution produced by our network makes sense. The distribution reveals that the network is really very confident.

We had shuffled the dataset randomly and then divided it into three parts. The first 85% examples from the whole dataset were used for training purpose, next 5% were used for validation purpose, and the rest were used for testing. After our model had finished training, we ran our system on the test set. The output of the test runs is given in Table III. The types of errors that our model makes are diverse. Although there are some genuine errors in our prediction, most of the errors would be very perplexing for humans too. Again there are some errors, which are due to mislabelling of the dataset; i.e., the preparers of the dataset in advertently labelled the images to wrong categories (or even to wrong types). There are some images that contained invalid structures, and even some contained no character at all. Obviously, our network got produced wrong predictions on those images.

Type	Classes	Accuracy
Ol-Chiki Digits	10	91%
Ol-Chiki Character	30	85%
Overall Accuracy		**88%**

Table 3: Accuracy of the Model

Our network predicts the true character categories, but they are wrongly labelled. The second image in the first row is labelled as numeral 0, but it is equally interpretable as an Ol-Chiki Character. Such examples would perturb even humans.

4. Conclusion:

A deep convolution neural network is really effective for recognizing handwritten characters. The recognition of Ol-Chiki character has done for the first time. It turns out that more distinctive features can be extracted by increasing the capacity of the networks. Later, the discrimination task becomes straight forward by plugging in those features into a classifying network with a proper regularization technique; otherwise the network would seriously over fit.

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