

Handwritten Devanagari Digits Recognition Using Residual Neural Network

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Abstract. Handwritten digit recognition is a highly evolved research domain of pattern recognition. It is used to classify pre-segmented handwritten digits. The Devanagari script is one of the writing systems of various Indian languages including Sanskrit and Hindi. In this paper, an efficient Handwritten Devanagari numeral digit recognition using ResNet is proposed. Deep learning is a recent research trend in this field. Architectures like Residual neural Networks (ResNet) are being used. ResNet is an architecture that is computationally expensive and normally used to provide high accuracy in classification problems. The structural design of the network consists of stacks of two convolutional (Conv2D) layers with Batch Normalization and an activation function called Relu. We evaluated our scheme on 16000 handwritten samples of Devanagari numerals from the UCI machine learning database and from the experiment we have achieved 99.40% recognition rate.

Keywords. CNN; ResNet; Handwritten digits recognition; Devanagari; Hindi; Sanskrit; UCI

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1. Introduction

In the area of image processing, Computer Vision and Pattern Recognition (CVPR) is a major growing field, where pattern recognition is one of the most important needs in Natural language processing (NLP). Handwritten digit recognition is a system that can recognize the characters from a digitalized or scanned handwritten document. This system has become an important part of various applications like office document automation, signature authentication, handwritten postcodes, cheque automatic, immigration data processing, health data record into digital format and many other applications [1]. this system, becomes complicated because of challenges like characters written by the different writer are not identical in different aspects such as font, size, shape, and styles. Most of the previously proposed models are based on traditional pattern recognition where human expertise is

required for feature engineering [2], [3]. The recent success of deep learning, specially Residual Neural Network (ResNet) for computer vision [4], [5], [6] [7] is used to recognize handwritten characters and digits as a computer vision problem. This ResNet is a deep Convolutional Neural Network (CNN) based model [8]. This is one of the current state-of-the-art deep learning models for image classification.

2. Literature review

2.1. Several approaches in current decade

In the recognition of handwritten digits, various approaches have been proposed with very high accuracy rates [1, 9-12]. Various sets of classification techniques have been applied to this problem like Linear K-Nearest Neighbour, Random forest, Decision Tree, SVMs, Neural Network, and Convolutional Neural Network [9]. A deep learning technique for recognition of Arabic handwritten digits is proposed by Ahmed et.al [1]. The method uses CNN with LeNet-5 is trained and tested on the MADBase database that consists of 60000 training and 10000 testing images. U. Pal et.al [14] proposed a method where off-line Bengali handwritten numerals were recognized which are unconstrained. This method is applied on their own collected dataset of size 12000 and obtained an accuracy of 92.80%. An approach for isolated Digit Recognition system is proposed by Vijay Kumar et.al [10]. In this approach features from digit image are extracted using Geometrical and Hosts pot features. This method used MNIST database which contains 60,000 training and 10000 testing samples.

3. Proposed Method

The proposed method consists of 4 steps. In the primary step, we have collected the numerals data from the UCI machine learning database. After collecting the data which is in grayscale we used normalization techniques to convert the gray level values to the range of 0 to 1 values. In the second step, we reshape it from 2 dimensions to 3 dimensions. In the third step, we used a residual block which consists of 3×3 convolutional layers with the same number of output channels followed by a batch normalization layer and a ReLU activation function. In the residual block, we skip two convolution operations and add the input directly before the final ReLU activation function shown in figure 1. In this step, we extracted the features of image data atomically and used the algorithm for recognition of handwritten numerals. Finally, in the last step, we applied an optimization technique to get promising results. The proposed method block diagram is shown below in figure 2.

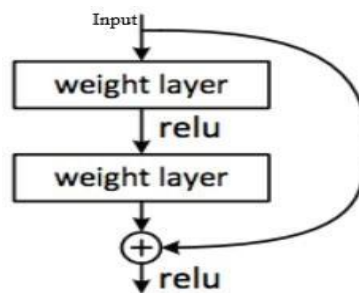


Figure 1: Residual Building Block.

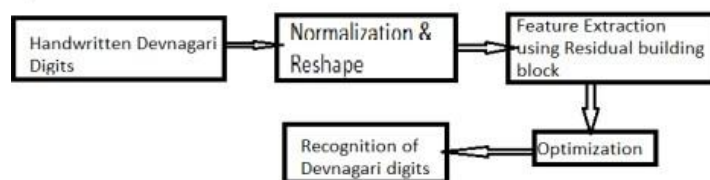


Figure 2: Block diagram of Proposed Method.

3.1. Collection of Devnagari Dataset

The different handwritten digits of Devanagari numerical datasets are taken from UCI Machine Learning repository databases of centre for machine learning and intelligent systems [15].



Figure 3. Different samples extracted from UCI database

In this dataset we have collected 10 classes of numerical characters with total 16000 examples. These images are in grayscale and resolution size is 32 x 32. Where the actual character is centered with 28x28 pixels with padding of 2 pixels on all four sides of the actual character. Sample of digits from the UCI machine learning database is shown in figure 3.

3.2. Residual Neural Networks(ResNet)

Computer Vision and pattern recognition is a major growing field in the area of image processing. ResNet plays a major role in computer vision. ResNet consists of Convolutional layers which are the core of most Computer Vision and pattern recognition systems today [16]. To understand ResNet we have to think of it as various residual blocks where each block contains a convolutional layer followed by batch normalization and Relu activation function. There is also a skip layer in ResNet which helps us to overcome the vanishing gradient problem [17]. We have used Keras API with Tensorflow as a backend. In this model we have used 50 layers where after the first layer we used maxpool (Maxpool2D) shown in figure 4. Then three residual blocks are used and the output is added with the output of the first layer which is also called skip connection and finally activation function Relu shown in figure 5, is used on the output. We continued this setting until the last layer where we used Flatten layer and connected Dense layer with total no of classes. In our case it is 10.

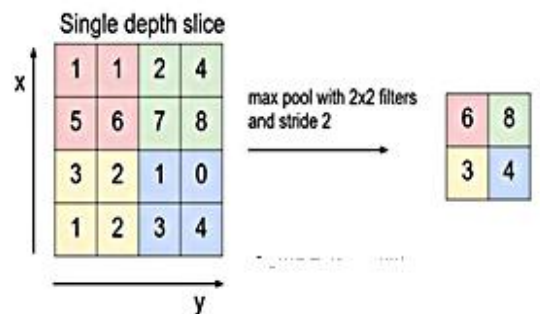


Figure 4: Maxpool.

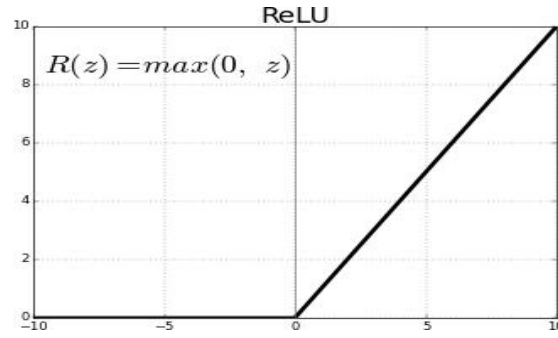


Figure 5: Relu activation function.

3.3. Softmax classifier

It is a Logistic Regression classifier which is a simplification of the binary form of like hinge loss or squared hinge loss. It is used at the last dense layer. Mapping function is derived using

$$f(x_i; W) = Wx_i \quad (1)$$

Where x is input data items and w is weight [18].

Cross Entropy loss has the form

$$L_i = -\log\left(\frac{e^{f_{y_i}}}{\sum_j f_j}\right) \quad \text{or equivalently} \quad L_i = -f_{y_i} + \log \sum_j e^{f_j} \quad (2)$$

Probabilistic interpretation can be defined as

$$P(y_i | x_i; W) = \frac{e^{f_{y_i}}}{\sum_j e^{f_j}} \quad (3)$$

Final loss function is yield form a single data point

$$L_i = -\log\left(\frac{e^{f_{y_i}}}{\sum_j f_j}\right) \quad (4)$$

Cross-entropy loss is compute over a total dataset is done by taking the average

$$L = \frac{1}{N} \sum_{i=1}^N L_i \quad (5)$$

3.4. Adam optimizer

In our model we have used Adam optimizer [19]. It is an adaptive learning rate method, which means, it computes individual learning rates for different parameters. Adam uses estimations of first and second moments of gradient to adapt the learning rate for each weight of the neural network. N-th moment of a random variable is defined as

$$m_n = E[X^n] \quad (6).$$

Where m is the moment and X is a random variable. The first moment is mean, and the second moment is uncentered variance. To estimates the moments, Adam utilizes exponentially moving averages which can be defined as

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t \quad (7a)$$

$$v_t = \beta_2 m_{t-1} + (1 - \beta_2) g_t^2 \quad (7b)$$

Where m and v are moving averages, g is gradient on current mini-batch, and β is new introduced hyper-parameters of the algorithm.

3.5. Proposed algorithm

The proposed algorithm follows as:

Input: Devnagari Numerical image

Output: Devnagari Numerical image recognition

Method: Handwritten Devanagari Digits Recognition Using Residual Neural Network

Step 1: Gray scale images of fixed size is taken.

Step 2: Pre-processing the gray scale images.

Step 3: Normalize the gray scale images i.e. from 0 to 255 into 0 to 1.

Step 4: Reshape the images from 2D to 3D.

Step 5: One hot encoding is done. i.e. 1 is represented as [0100000000].

Step 6: Proposed model is used with Flatten layer and Fully connected layers.

Step 7: Input image is classified into suitable class using softmax classifier.

Step 8: Adam optimizer is used to improve accuracy.

Step 9: Augmentation technique is used to increase number of training data.

End

4. Results and Discussion

The Performance comparison with existing work has been given in Table 1. We also evaluated the performance of our model on a UCI Machine Learning repository dataset. We have selected 10 classes of numerical with a total 16000 images from the repository dataset. Further the data set was split into a training set and a test set where 12800 images selected randomly for the training set and 3200 images selected randomly for testing. Our model reaches 99.40% accuracy on the validation dataset after 32 epochs. In our model total no of trainable parameter is 23,555,082 and non-trainable parameter is 53,120. Loss and accuracy curves for training and validation is given below in figure 6 & 7.

Table-1: Performance comparison with existingwork.

Authors	SampleSize	Rec.Rate (%)
Dongre, V.J et.al [20]	3000	93.17
Singh, P.K et.al [21]	6000	95.02
C. Vasantha Lakshmi et.al [13]	9800	94.25
G. G. Rajput et.al [26]	13000	97.85
Ujjwal Bhattacharya et.al [13]	18794	99.04
U. Pal et.al [14]	22546	98.36
Proposed Method	16000	99.40

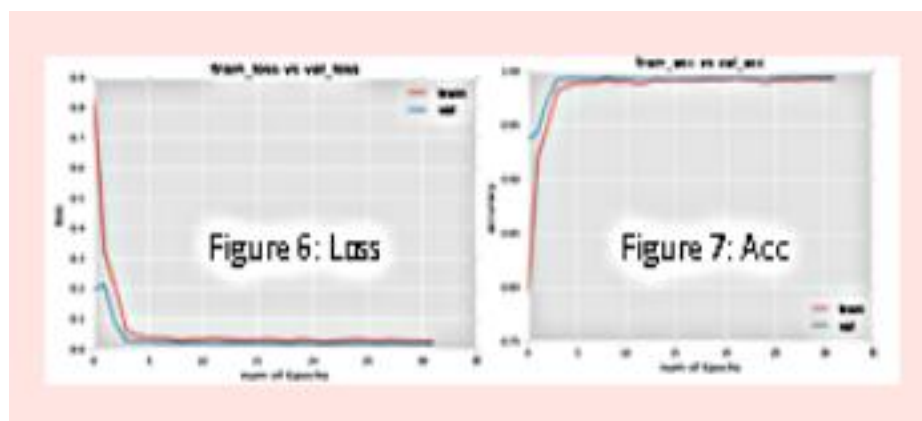


Figure 5. Loss.

Figure 6. Accuracy curves.

5. Conclusions

A deep learning approach for Devnagari Numeral Digit Recognition is been proposed in this paper. We evaluated the performance using ResNet on a standard UCI Machine Learning repository dataset. From the results, it is observed that ResNet yields the best accuracy for Devnagari Numeral Digit Recognition compared to the alternative techniques. Our method achieved 99.40% recognition rate.

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Conflicts of Interest

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