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A STUDY ON HANDWRITTEN DEVANAGARI DIGITS RECOGNITION USING RESIDUAL NEURAL NETWORK

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ABSTRACT. Handwritten digit recognition is a profoundly advanced exploration area 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 modern research trend in this field. ResNet is a deep learning architecture that is computationally expensive and provide high accuracy in classification problems. We assessed our scheme on 16000 Devanagari samples from the UCI database and accomplished 99.40% recognition rate.

1. INTRODUCTION

Computer Vision and Pattern Recognition (CVPR) is a significant developing field in the area of image processing. Handwritten digit recognition system is one of the important fields in pattern recognition. This system can recognize the characters from a digitalized or scanned handwritten document. This framework has become an important part of various applications like office report automation, signature confirmation, manually written postcodes, cheque automation, and numerous different applications [1]. This system becomes complicated because of challenges like characters written by the different writer are not indistinguishable in various viewpoints, for example, textual style, size and shape. Most of the proposed models depend on the customary example

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acknowledgment where human ability is required to highlight extraction. The recent ongoing accomplishment of deep learning, specially Residual Neural Network (ResNet) [4], is used to recognize manually written characters and digits as a computer vision problem. This ResNet is based on deep Convolutional Neural Network (CNN) [8]. This is one of the best models for image classification.

2. LITERATURE REVIEW

In the acknowledgment of handwritten digits, different methodologies have been proposed with exceptionally high precision rates [1, 9, 10]. Different procedures have been applied to this issue like K-NN, SVM, Decision Tree, Neural Network(NN), and CNN [9].

A profound learning method for recognition of Arabic handwritten digits is proposed by Ahmed et.al [1]. The strategy utilizes CNN with LeNet-5 is prepared and tried on the MADBase database that comprises of 60000 training and 10000 testing pictures.

A Telugu printed numeral digits recognition framework is proposed by Ravi et.al, where diverse component extractions procedures like the number of forms, skeleton property, and water repository property are utilized. This strategy prepared and tried on database of 3150 printed Telugu numerals.

U. Pal et.al proposed techniques where disconnected Bengali manually written numerals were perceived which are unconstrained. This technique is applied on their own gathered dataset of size 12000 and acquired an exactness of 92.80%.

A methodology for segregated Digit Recognition framework is proposed by Vijay Kumar et.al [10]. In this methodology highlights from digit picture are separated utilizing Geometrical and Hosts pot highlights. This strategy utilized MNIST database which contains 60,000 preparing and 10000 testing tests.

Manually written Bangla Digit Recognition Using Combination of classifier through Dempster-Shafer (DS) is proposed by Subhadip Basu et.al. In this methodology DS procedure and MLP classifier for characterization is utilized. Their strategy accomplished 95.1 % test exactness.

3. PROPOSED WORK

The proposed strategy comprises of different steps. In the primary step, we have gathered the data from standard dataset which is UCI machine learning database. After collecting the data we converted the gray level values which are 0-255 to 0-1 values using normalization techniques. Then we reshape each image from two dimensions to three dimensions in the second step. In the third step, we used a residual block which consists of convolutional layers 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. In fourth step, we applied an optimization technique (Adam Optimizer) to maximize efficiency. Finally, in the last step, we used real time augmentation to increase diversity of data available for training set. The block diagram for proposed method is shown in figure 2.

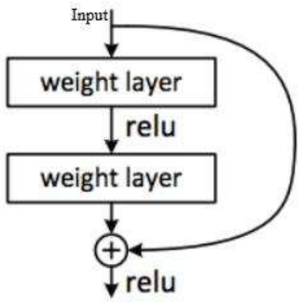

FIGURE 1. Residual Building Block

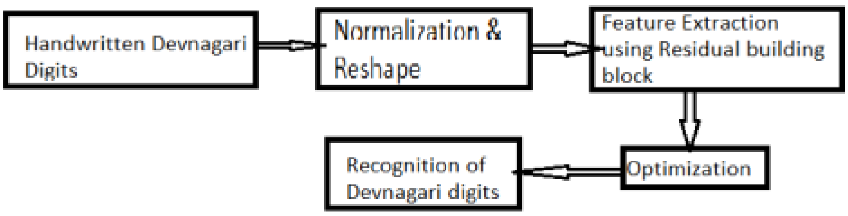

FIGURE 2. Block diagram of Proposed Method

3.1. **Collection of Devnagari Dataset:**

The different handwritten digits of Devanagari numerical are taken from UCI repository. From this dataset we have collected ten classes of numerical characters with total 16000 examples. Resolutions of the images are 32 x 32 and each image is in gray scale. Sample of digits from the database is shown in figure 3.

FIGURE 3. Sample images from dataset

3.2. **Residual Neural Network (ResNet):**

Computer Vision and pattern recognition is a major growing domain in the area of image processing. ResNet plays a major role in computer vision. ResNet comprises of Convolutional layers which are the most important layer to extract features from image. To understand ResNet we have to think of it as various residual blocks where each block contains 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. We have used Keras API with Tensor-flow as a backend to implement this model. In this model we have used 50 layers where after the first layer we used max-pool (Maxpool2D) shown in figure 4. After that 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 (figure 5) is used on the output. Model architecture is shown in figure 6. We continued this setting until the last layer where we used Flatten layer and connected dense layer with 10 classes and finally Softmax classifier for probability distribution.

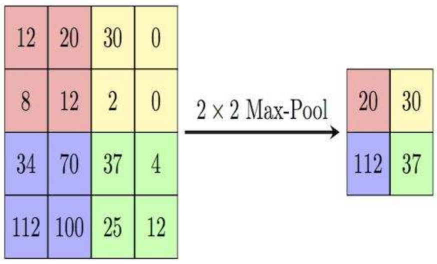

FIGURE 4. Maxpool

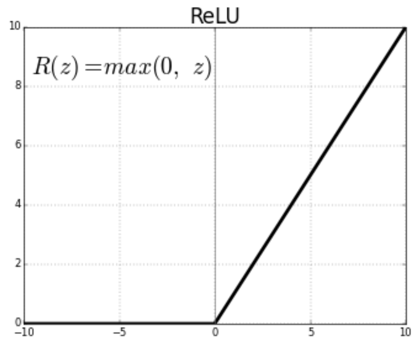

FIGURE 5. Relu Activation

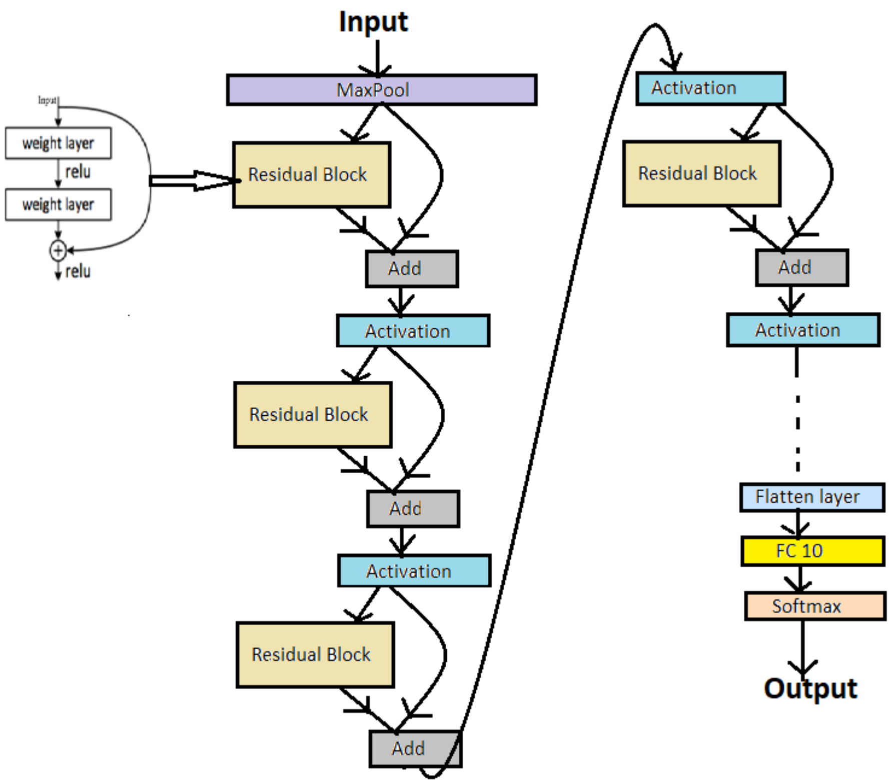

FIGURE 6. Model architecture

3.3. **Softmax Classifier:**

It is a Logistic Regression classifier which gives probabilities for each class label.

It is used at the last dense layer. Mapping function is derived using

$$f(x_i; W) = Wx_i.$$

Here, x is input data items and w is weight.
Cross Entropy loss can be defined as

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

or equivalently,

$$L_i = -f_{y_i} + log\sum_j e^{f_j}.$$

Interpretation of probability can be defined as

$$P(y_i|x_i : w) = \frac{e^{f_{y_i}}}{\sum_j e^{f_j}}.$$

The final Loss function is

$$L_i = -log\left(\frac{e^{s_{y_i}}}{\sum_j e^{s_j}}\right).$$

Cross-entropy can be defined as

$$L = \frac{1}{N}\sum_{i=1}^{N} L_i.$$

3.4. **Adam Optimizer:**
In our model we have used Adam optimizer. It is a method which uses an adaptive learning rate. It is used to update network weight depending on training data. 1st and 2nd moments of gradient for estimation are utilized by Adam to adjust the learning rate for each weight of the neural system. Random variable of N-th moment is defined as

$$m_n = E[X^n],$$

where m is the moment and random variable is represented as X. The first moment is mean, and uncentered variance is the second moment. Adam utilizes exponentially moving averages to estimates moments. It can be defined as

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1)g_t,$$

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_t^2,$$

where m and v are characterized as moving averages, g is gradient on current mini-batch, and β is hyper-parameters of the calculation.

3.5. **Proposed Algorithm:**

Input: Devnagari Numerical image

Output: Devnagari Numerical image recognition

Method: Handwritten Devanagari Digits Recognition Using Residual Neural Network

Step1: Images of Handwritten Digits are taken.
Step2: Resize images into 32×32 pixels.
Step3: Normalize the gray scale images
Step4: Convert the images from 2D to 3D.
Step5: One hot encoding is done. i.e. 1 is represented as [0100000000].
Step6: Flatten layer is used with fully connected dense layers.
Step7: Softmax classifier is used to classify input images.
Step8: Adam optimizer is used to improve accuracy.
Step9: Real time augmentation technique is used to increase diversity of training data.
End

4. Results and Discussion

We evaluated the performance of our model using Google Colaboratory, which is a free platform to evaluate various deep learning models. We have selected 10 classes of numerical with a total 16000 images from UCI dataset. Further the data set was split into train and test set where 12800 & 3200 images are selected randomly for the training and testing set. 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 graph for training and validation data are given in figure 7 & 8.

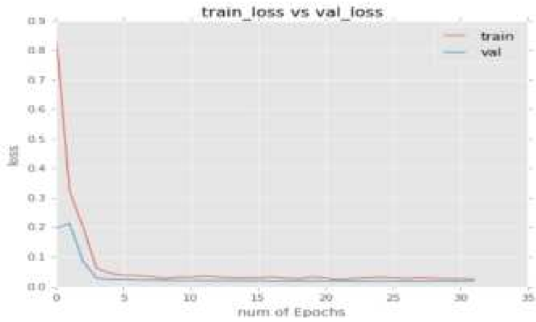

FIGURE 7. Train & Validation Loss

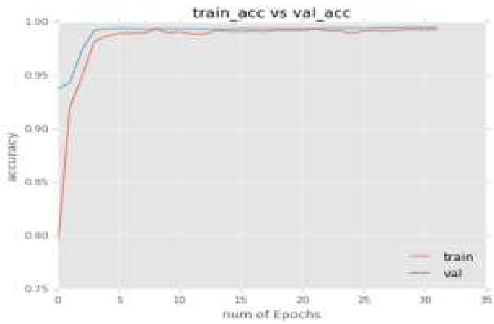

FIGURE 8. Train & Validation Accuracy

TABLE 1. Performance Comparison With Existing Work

Authors	Sample Size	Recognition Rate(%)
Dongre,V.J et.al	3000	93.17
Singh, P.K et.al	6000	95.02
C.Vasantha Lakshmi et.al	9800	94.25
G.G.Rajput et.al	13000	97.85
Ujjwal Bhattacharya et.al	18794	99.04
U. Pal et.al	22546	98.36
Proposed Method	16000	99.40

5. CONCLUSION

A Devnagari Numeral Digit Recognition system using deep learning approach is been proposed in this paper. We assessed our model using ResNet on a standard dataset. From the outcomes, it is observed that ResNet achieved the best accuracy for Devnagari Numeral Digit Recognition compared to the alternative techniques. Our method accomplished 99.40% recognition rate.

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