

BDNet: Bengali handwritten numeral digit recognition based on densely connected convolutional neural networks

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M M Hafizur Rahman³

Abstract

Images of handwritten digits are different from natural images as the orientation of a digit, as well as similarity of features of different digits, makes confusion. On the other hand, deep convolutional neural networks are achieving huge success in computer vision problems, especially in image classification. BDNet is a densely connected deep convolutional neural network model used to classify (recognize) Bengali handwritten numeral digits. It is end-to-end trained using ISI Bengali handwritten numeral dataset. During training, untraditional data preprocessing and augmentation techniques are used so that the trained model works on a different dataset. The model has achieved the test accuracy of **99.775%**(baseline was 99.40%) on the test dataset of ISI Bengali handwritten numerals. So, the BDNet model gives 62.5% error reduction compared to previous state-of-the-art models. Here we have also created a dataset of 1000 images of Bengali handwritten numerals to test the trained model, and it giving promising results. Codes, trained model and our own dataset are available at: <https://github.com/Sufianlab/BDNet>.

Keywords: Bengali Digit Recognition, CNN, Dataset, Deep Learning, Handwritten Numerals, Image Classification.

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1. Introduction

Bangla (Bengali) is the second most spoken language in India. It ranks fifth in Asia and it is also in the top ten spoken languages in the world [1]. So, a huge number of people depend on this language for their day to day communication. Therefore, automatic recognition of Bengali handwritten characters and numeral digits are needed to be digitized for making the communication smoother. Many research works and models have been proposed to recognize Bengali handwritten characters and numeral digits so far, but still, a huge scope is there to improve this task in terms of accuracy and applicability. Most of the previously proposed models are based on traditional pattern recognition and machine learning techniques where human expertise is required for feature engineering [2], [3].

The recent success of deep learning, specially Convolutional Neural Network (CNN) for computer vision [4], [5], [6], [7] [8] has inspired many researchers to use the CNN to recognize handwritten characters and digits as a computer vision task. The BNet, we proposing through this paper, is a target oriented deep CNN based model to classify Bengali numeral digits. This model trained using untraditional preprocessing and data augmentation techniques for trained with generalization. It has achieved new baseline accuracy on benchmark datasets [9]. Here we have also proposing a new dataset of 1000 images of Bengali handwritten numerals. This own dataset used to test the trained model, and it giving promising results but this new dataset not used during training. The working pipeline of the BNet is designed by a inspiration of DenseNet [10] which is one of the state-of-the-art deep CNN algorithm for image classification. The conceptual view of the BNet has shown in figure 1 and details of the model has explained in section 3.

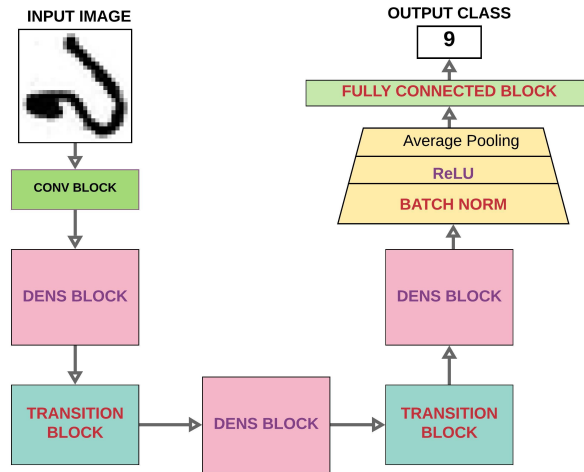


Figure 1: Overview of the BDNet model.

1.1. Contributions of this paper

- A deep CNN working model, called BDNet, is designed to recognize Bengali handwritten numerals.
- The BDNet is trained end-to-end with untraditional data preprocessing and augmentation.
- The proposed model has achieved the highest test accuracy with 62.50% error reduction on baseline result (**99.775%** whereas the previous best was 99.40%) on test data of ISI Bengali handwritten numeral dataset.
- A new dataset is created with 1000 samples of handwritten Bengali numerals for testing performance of the trained BDNet where the model gives promising results.

1.2. Organization of the paper

Rest of the paper is organized as follows: In section 2, literature review has done. Model details of BDNet are explained in section 3. In section 4, dataset and preprocessing of data is explained. Training details are explained in section 5 and result analysis is in section 6. Finally the paper is concluded in section 7.

2. Literature Review

For background analysis, we have reviewed two relevant things: one is existing research works on Bengali handwritten numeral recognition and another is the advancements of deep learning models for image classification. First part of this review is for baseline results and domain knowledge of target application, whereas later part is for idea about latest trends of deep learning based state-of-the-art algorithms. In this section, we have reviewed these two things in following two subsections:

2.1. Existing works on Bengali handwritten numeral recognition

Bengali handwritten numeral recognition is one of the oldest pattern recognition problems. Many researchers have been working in this field since the 90s of the last century [11], [12]. Through this subsection, we have reviewed most notable works on this Bengali handwritten numeral recognition.

Subhadip Basu et al. proposed Handwritten Bangla Digit Recognition using Classifier Combination Through Dempster-Shafer (DS) Technique [13]. They have used the DS technique and MLP classifier for classification and also used 3-fold cross-validation on the training dataset of 6000 handwritten samples. Their scheme achieved 95.1% test accuracy. In [14] U. Pal et al. proposed a scheme where unconstrained off-line Bengali handwritten numerals were recognized. This scheme has recognized different handwritten styles. The scheme selects the required features using the concept of water overflow from the reservoir, and also collect topological and structural features of the numerals. They applied this scheme on their own collected dataset of size 12000 and obtained recognition accuracy of around 92.8%.

U. Bhattacharya and B. B. Choudhury presented handwritten numeral database along with Devanagari database and proposed a classifier model [9]. Their database contains 23392 handwritten Bengali numeral images. Their classifier model is a multi-stage cascaded recognition scheme where they used wavelet-based multi-resolution representations and multilayer perception as classifiers.

They have mentioned 99.14% training and 98.20% testing accuracy on this dataset. Cheng-Lin Liu and Ching Y. Suen proposed a benchmark model [15] on ISI numeral dataset [9] along with a Farsi numeral database. They preprocessed the dataset into gray-scale images and applied many traditional feature extraction models. This benchmark model achieved the highest test accuracy of 99.40%. Ying Wen and Lianghua He proposed a classifier model [16] for Bengali handwritten numeral recognition. This model tried to solve large dataset high dimensionality problem. They combined Bayesian discriminant with kernel approach with UCI dataset and another dataset such as MNIST [17]. The rate of error is 1.8%, the recognition rate is 99.08% and recognition time is 7.46 milliseconds.

Local region identification, where optimal unambiguous features are extracted, is one of the crucial tasks in the field of character recognition. This idea is adopted by N. Das et al. in their handwritten digit recognition technique [18] based on genetic algorithm(GA). GA is applied on seven sets of local regions. For each set, GA selects a minimal local regions group with a Support Vector Machine (SVM) based classifier. The whole digit images are used for global features extraction whereas local features are extracted for shape information. The number of global features is constant whereas the number of the local features depends on the number of local region. The test accuracy rate was 95.50% for this model. M. K. Nasir and M. S. Uddin proposed a scheme [19] where they used K-Means clustering, Bayes' theorem and Maximum a Posteriori for feature extraction, and for classification SVM is used. After converting the images into binary values, some points are found, which was discarded using a flood fill algorithm. The plinth steps are Clipping, Segmentation, Horizontal, and Vertical Thinning Scan. Here test accuracy rate was 99.33%.

In [20] M. M. Rahaman et al. proposed a CNN based model. This method normalizes the written character images and then employed CNN to classify individual characters. It does not employ any feature extraction method like previously mentioned works. The major steps are pre-processing of raw images by converting them into gray-scale image and then training the model. In this

case, test accuracy was 85.36%. On another paper, we have seen the existence of auto-encoder for unsupervised pre-training through Deep CNN which consists of more than one hidden layer with 3 convolutional layers. Each layer was followed by 2×2 max pooling layer. This scheme [21] was proposed by Md Shopon et al. The layers have $32 \times 3 \times 3$ number of kernels. In the same manner, the decoder has an architecture with each convolutional layer with 5 neurons, rather than 32. The ReLU [22] activation is present in all layers. For training purpose, the model enhanced the training dataset by randomly rotating each image between 0 degree and 50 degree and also by shifting vertically by a random amount between 0 pixels and 6 pixels. This model was trained in 3 various setups SCM, SCMA, and ACMA. They have achieved a test accuracy of 99.50%. Another model [23], proposed by M. A. H. Akhand et al. used pre-processing by using simple rotation based approach to produce patterns and it also makes all images of ISI handwritten database into the same resolution, dimension, and size. CNN structure of this model has two convolutional layers with 5×5 sized local receptive fields and two sub-sampling layers with 2×2 sized local averaging areas along with input and output layers. Input layer contains 784 receptive fields for 28×28 pixels image. The first convolutional operation produces six feature maps. Convolution operation with kernel spatial dimension of 5 reduces 28 spatial dimension to 24 (i.e., $28 + 1 - 5$) spatial dimension. Therefore, each first level feature map size is 24×24 . The accuracy rate of the testing is 98.45% on ISI handwritten Bengali numerals.

In [24], A. Choudhury et al. proposed a histogram of oriented gradient (HOG) and color histogram for selection of feature algorithm. Here, HOG is used as the feature set to represent each numeral item at the feature space and SVM is used to produce the output from input. Test accuracy of this algorithm is 98.05% on CMATERDB 3.1.1 dataset (which is a benchmark Bengali handwritten numeral database created by CMATER lab of Jadavpur University, India). M. M. Hasan et al. proposed a Bengali handwritten digit recognition model based on ResNet [25]. Their ensemble model from their six best models, applied on NumtaDB dataset [26], achieved 99.3359% test accuracy. In [27] R.

Noor et al. proposed an ensemble model based Convolutional Neural Network for recognizing Bengali handwritten numerals. They train their model in many noisy conditions using customized NumtaDB dataset [26]. In all cases, their model achieved more than 96% test accuracy on this NumtaDB dataset. A very recent Bengali handwritten numeral recognition work [28] was there, proposed by AKM S. A. Rabby. Here author used deep CNN model to classify the handwritten numeral digits. This model is trained using ISI handwritten Bengali numeral [9] and CMATERDB 3.1.1 databases with 20% data for validation. The author of this paper claimed their test accuracy as 99.58% on ISI handwritten numerals and 92.65% on CMATERDB 3.1.1.

2.2. Advancements of deep learning for image classification

After the success of AlexNet [5], a deep learning based model for image classification, many researchers shifted to this area of research of computer vision and pattern recognition. Therefore, many successive state-of-the-art models came within a short span of time since 2012 [8], [29]. In this subsection, we briefly reviewed the development of deep learning especially Convolutional Neural Networks in the field of image classifications.

CNN is a special type of multi-layer neural network inspired by the vision mechanism of the animal [4]. Hubel and Wiesel experimented and said that visual cortex cells of animal detect light in the small receptive field [30]. Kuniyuki Fukushima got motivation from this experiment and proposed multi-layered neural network, called NEOCOGNITRON [31], capable of recognizing visual patterns hierarchically through learning. This model is considered as the inspiration for CNN. A classical CNN model is composed of one or more blocks of convolutional and sub-sampling or pooling layer, then single or multiple fully connected layers, and an output layer function as shown in figure 2. The benefits of using CNN are automated features extraction, parameter sharing and many more [32], [5], [33]. Classical CNN is modified in many different ways according to target domain[8], [34], [35], [36].

Yann LeCun et al. introduced the first complete CNN model, called LeNet-5

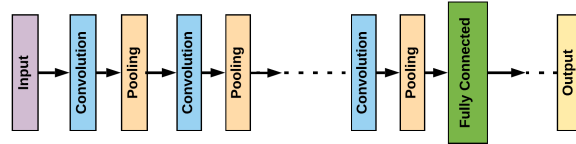


Figure 2: Building blocks of a classical CNN model [8]

[32], to classify English handwritten digit images. It has 7 layers among which 3 convolutions, 2 average pooling, 1 fully connected, and 1 output layer. They used SIGMOID function as the activation function for non-linearity before an average pooling layer. The output layer used Euclidean Radial Basis Function(RBF) for classification of MNIST [17] dataset. The weights of each layer were trained using back-propagation algorithm [37]. AlexNet [5] was the first CNN based model which won the ILSVRC challenge [38] in 2012 with a significant reduction of error. AlexNet’s error rate was 16.4% whereas the second best error rate was 26.17%. This model was proposed by Alex Krizhevsky et al. and it is trained by using ImageNet dataset [39], this dataset contains 15 million high resolution labeled images over 22 thousand categories. AlexNet has 11 trainable layers, and the structure is almost similar to LeNet-5, but here max-pooling used instead of the average pooling, ReLU activation in place of the SIGMOID function, softmax function in place of RBF, and 11×11 in-place of 5×5 filter size in the first layer. In addition, for the first time dropout strategy [40] and GPU were used to train the model. In [41] Zeiler and Fergus presented ZFNet which was the winner of ILSVRC challenge in 2013. The building blocks of ZFNet is almost similar to AlexNet with few changes such as first layer filter size is 7×7 instead 11×11 in AlexNet. Authors of ZFNet explained how CNN works with the help of Deconvolutional Neural Networks (DeconvNet). DeconvNet is just the opposite of CNN. The error rate of ZFNet was 11.7%. K. Simonyan and A. Zisserman proposed VGGNet [42], which is like a deeper version of AlexNet. Here, authors used small filters 3×3 sizes for all layers. They have used total 6 different CNN configurations with different

weight layers. This VGGNet secured 2nd place in ILSVRC challenge in 2014 with an error rate of 7.3% just 0.6% more than the error rate of the winner GoogLeNet [43].

GoogLeNet, Going Deeper with Convolutions [43], is proposed by Christian Szegedy et al. which was a research team of Google. The Structure of GoogLeNet is different from traditional CNN, it is wider and deeper than previous models but computationally efficient. Through inception architecture, multiple parallel filters with different sizes are used, and for this, problems of vanishing gradient and over-fitting were tackled. Fully connected layers are not used in GoogLeNet but average pooling layer is used before the classifier. This model won ILSVRC challenge 2014 with error rate of 6.7%. The increasing layer could give more accuracy but will suffer from vanishing gradient problem. To tackle this problem, Kaiming He et al. from Microsoft Research proposed ResNet [25]. ResNet is a very deep model where each layer has a residual block with skip connection to the layer before the previous layer. ResNet is the winner of ILSVRC challenge with error rate of 3.57% and this is a success of beyond human level. Gao Hunag et al. proposed DenseNet [10], where every layer is connected to all previous layers of the model. DenseNet overcomes the vanishing gradient problem as well as it collects required features of all layers and propagates to all successive layers in feed-forward fashions for features reuse. Therefore, this model requires less number of parameters to achieve accuracy, so it is computationally efficient. Inspired by the success of ResNet, Jie Hu et al. proposed SENet [44] with the main focus to increase channel relationship between successive layers. SENet has added “Squeeze-and-Excitation” (SE) block into each block (ResNet Block), and for this, the model adaptively re-calibrates channel wise feature responses between channels. SENet has won ILSVRC-2017 challenge with error rate of 2.252%.

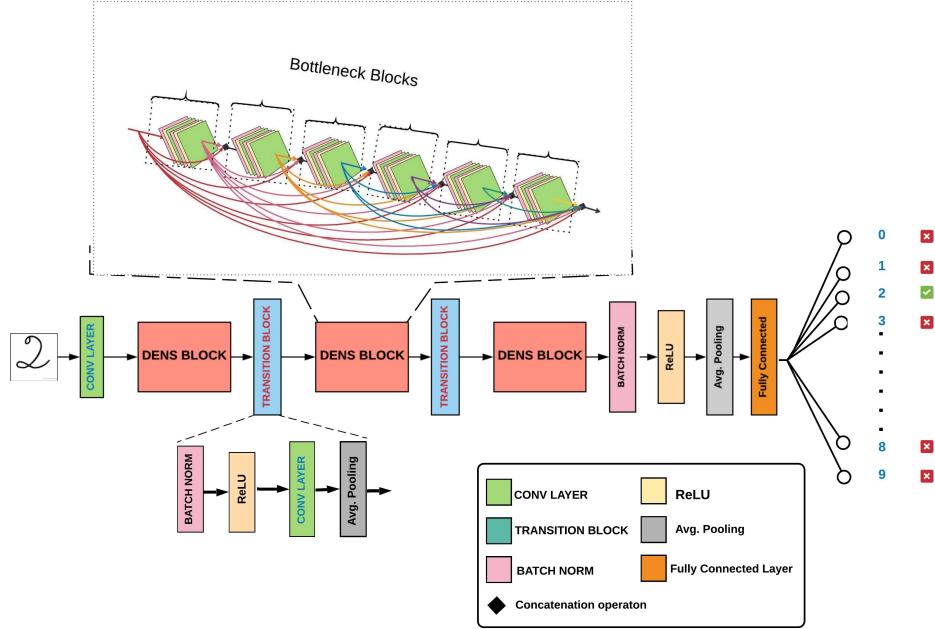


Figure 3: Structure of the BDNet

3. BDNet Model Details

The network architecture of the BDNet model has shown in figure 3. The BDNet consists of three Dense Blocks and two Transition Blocks followed by Batch Normalization(BN), Rectified Linear Unit(ReLU) activation, Average Pooling(Avg. POOLING), Fully Connected(FC) Layer, Softmax Function with Output Layer. Each Dense Block is made up of 6 bottleneck blocks. Structure of each bottleneck block is as follows: $\dots \rightarrow BatchNorm \rightarrow ReLU \rightarrow Conv2d(1 \times 1) \rightarrow BatchNorm \rightarrow ReLU \rightarrow Conv2d(3 \times 3) \rightarrow \dots$. The number of bottleneck blocks(NBL) per dense block has calculated using equation 1.

$$NBL = \frac{1}{2} \left\lfloor \frac{n-4}{3} \right\rfloor \quad (1)$$

where n is the number of layers of the network model. Dense connectivity is present among bottleneck blocks of each dense block i.e. output of each bottle-

neck block is forwarded to all other successive blocks for features propagation. The number of feature maps that will be forwarded depends on the growth rate, and here the growth rate is 12. In between two dense blocks, we have used one transition block which consists of: *BatchNorm* \rightarrow *ReLU* \rightarrow *ConV.* \rightarrow *Avg.Polling.* To make the model compact we reduce the number of feature maps.

4. Dataset and Preprocessing of the Dataset

The Bengali language is mainly derived from the Brahmi script and Devanagari script in the 11th Century AD. The structural view of each character and numeral of this language are very complex. So, train a model using Bengali digit is more difficult compared to English numeral digit as the English digits has a less complex structure. In addition, English numerals datasets are easily available in terms of quantity and quality such as MNIST [17] but it is not easy for Bengali numeral datasets. Bengali digit also has some high similarity features for different numerals such as numeral 1 (in Bengali) and numeral 9 (in Bengali) has high similarity features, similarly numeral 5 (in Bengali) and 6 (in Bengali) has high similarity features. The typical Bengali handwritten numerals and corresponding printed values has shown in figure 4.

		Digits									
Different forms of literals	Bengali Handwritten Numerals	০	১	২	৩	৪	৫	৬	৭	৮	৯
	Bengali Printed Font	০	১	২	৩	৪	৫	৬	৭	৮	৯
	Standard English Font	0	1	2	3	4	5	6	7	8	9

Figure 4: Typical Bengali handwritten numeral digits and corresponding printed values.

4.1. Used Dataset

The ISI Bengali numeral off-line handwritten dataset [9] is one of the largest popular datasets of handwritten Bengali numerals. This dataset consists of

Variation in ISI dataset Images	
ZERO	0 0 0 0 0 0 0 0 0 0
ONE	1 1 1 1 1 1 1 1 1 1
TWO	2 2 2 2 2 2 2 2 2 2
THREE	3 3 3 3 3 3 3 3 3 3
FOUR	4 4 4 4 4 4 4 4 4 4
FIVE	5 5 5 5 5 5 5 5 5 5
SIX	6 6 6 6 6 6 6 6 6 6
SEVEN	7 7 7 7 7 7 7 7 7 7
EIGHT	8 8 8 8 8 8 8 8 8 8
NINE	9 9 9 9 9 9 9 9 9 9

Figure 5: Sample handwritten ISI numeral image data

23392 black and white image data written by 1106 persons collected from postal mail and job application forms. Among these 23392 data, 19392 are training data and 4000 are testing data. The entire dataset represents 10 classes for numeral 0 to 9. Some typical data items of this dataset shown in figure 5.

4.2. Preprocessing of the Datasets

As mentioned we have used ISI Handwritten numeral dataset to train the BDNNet. But the data items that we have chosen for this task is very untidy and cannot be used directly for our purpose. All the data were raw images in **.tif** format of different sizes. First, we have converted the raw images into gray-scale images of size 28×28 , then inverted the colors in a way that the background became black and the font became white. After that gray-scale images are converted to RGB images of size 32×32 for better feature extraction using 3 channels. For the convenience to use the BDNNet, we have created a CSV file to access the data samples. Figure 6 is showing steps of preprocessing, and how converted data looks different from actual data after the preprocessing. Distribution of entire ISI handwritten numerals database as shown in table 1.













Steps	Stepwise pre-processing outcome of Bengali numeral samples		
	০	১	২
Step 1			
	Size: 47x51	Size: 50x43	Size: 51x51
	Raw sample of ISI handwritten Bengali numeral images in tif format		
Step 2			
	Size: 28x28	Size: 28x28	Size: 28x28
	Converted into Gray Scale images and resized into 28x28 dimension		
Step 3			
	Size: 28x28	Size: 28x28	Size: 28x28
	Inverted the color of images (black for background and white for digit)		
Step 4			
	Size: 32x32	Size: 32x32	Size: 32x32
	Converted into RGB format and resized into 32x32 dimension and then adjust the contrast(with factor 1.5)		

Figure 6: Step by step pre-processing of training images

Among the training datasets, 10% data is used for 10-fold cross-validation.

Table 1: Used Dataset Distribution

Digit	Training Sets	Test Set
0	1933	400
1	1945	400
2	1945	400
3	1956	400
4	1945	400
5	1933	400
6	1930	400
7	1928	400
8	1932	400
9	1945	400

4.3. Own dataset

We have also created our own dataset of 1000 images. Among these 1000 images, 100 images per digit are there for each Bengali numeral digit from digits zero to nine. This dataset is created by 5 laboratory members of this work with the help of some students. It has done by writing the digits in standard pages

using black or blue pens. Then we have scanned the written digits using the mobile phone camera. Datasets are created with the focus to make it as natural as the common people write the Bengali numerals in their daily life. Each image of the dataset are then set to 28×28 pixels. We have used this dataset only for testing to check generic performance of the trained BDNNet.

5. Training Details

We have started our experiment by training the model using preprocessed labeled dataset mentioned above. Before describing the training details, we have presented the system environment and resources used for our work in table 2. The design of BDNNet is inspired by the state-of-the-art algorithm DenseNet. A

Table 2: Used system specifications

Resources	Specifications
CPU	<i>Intel^R Xeon^R CPU @2.3GHz</i> with 45 MB Cache
RAM	12.72 GB available
DISK	1 TB (Partially used)
GPU	1 × Nvidia Tesla T4 having 2560 CUDA cores, 16GB(14.72GB available) GDDR6 VRAM
Languages & Packages	Python with PyTorch[45]
Training & Validation Time	37.68 Seconds per Epoch

new set set of hyper-parameters here established and setting required value for each required hyper-parameter is a very difficult task. It could be done by trial and error method with careful observation of the pattern of the data as well as by some mathematical analysis. In a similar fashion, we have done hyper-parameter tuning of required hyper-parameters of BDNNet and the details are described below:

Number of hidden layers and units: It is preferably good to add more layers when the test error is no longer decreasing in existing layers. Small number of layers may lead to under-fitting, on the other hand, having more layers is usually not suitable with appropriate regularization. But adding more number of layers

make the model more complex and computation time will increase. After careful experiments, we have used 39 hidden layers, one fully connected(FC) layer in our mode. Then we have used softmax function to output 10 classes. Model details are shown in figure 3. Here, softmax function transforms predicted scores to predicted probability scores using the following equation 2.

$$\hat{y}_i = \frac{e^{z_i}}{\sum_{j=1}^{10} e^{z_j}} \quad (2)$$

Where \hat{y}_i denotes prediction score of i-th digit or class.

Number of Epochs: As it is the number of time the entire training dataset passes through the model network. So, we could increase the number of epochs until the training error becomes small and the validation error is noticeable. For BDNNet model, the number epoch was set to 150 but the model converges around 125 epochs, and it took 37.68 seconds per epoch to train and validate simultaneously(in our system mentioned in table 2).

Optimizer: BDNNet trained through back-propagation [37] using optimizer. Here, weights updated using SGD (Stochastic Gradient Descent) [46]. The mathematical loss function $J(w)$ as in equation 3 and it is basically the difference between the updated internal parameters of a model which are used for computing the values (y_i) from the set of inputs (x_i) used in the model and the desired output (\hat{y}_i).

$$\begin{aligned} J(w) &= \frac{1}{n} \sum_{i=1}^n J_i(w) \\ &= \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \end{aligned} \quad (3)$$

The working flow of optimizer for BDNNet is as follows:

Step 1: Initialization of the vector of parameters w and learning rate η .

Step 2: Repeat until an approximate minimum is found:

Step 2.1: Randomly shuffle items in the training set.

Step 2.2: for $i = 1$ to n do:

$$w = w - \eta \nabla J_i(w)$$

BDNet used random order of the training dataset. As the coefficients are updated after each training data-sample, so the updates, as well as the lost function will be randomly jumping all over the place. By this randomized updates to the coefficients, it reduces random walk and avoids distraction.

Weight initialization: We have initialized the weights with small random numbers (between 0 and 1) to prevent dead neurons, but not too small numbers to avoid zero gradients. Uniform distribution usually works very well. Here, we have used `seed(1)` as python function to initialize the weights randomly.

Batch size: Mini-batch is usually preferable in the place where a dataset is very large. It is usually used to create a partition in between the dataset. Batch size doesn't contribute much to the precision but helps controlling the training speed. We have used the batch size as 32 and the batch size was 64 for testing.

Learning rate: In BDNet we have used learning rate as 0.009 and after 80 epoch it has been changed as in equation 4.

$$\eta = (\text{Initial } \eta) \times (0.15) \tag{4}$$

Weight decay: This is another hyper-parameter tuning where each step's current weights(W) are multiplied by a number slightly less than 1. Weight decay is a regularization term that prevents growing the number of parameters in to a large number. It is updated as equation 5

$$W_i = W_i - \eta \frac{\partial J}{\partial W_i} - \eta \lambda W_i \tag{5}$$

Where J is the current loss, η is the learning rate and λ is the weight decay. After an experiment with several values, finally, the value of the weight decay was set **1e-5**.

Momentum: The concept of momentum is that previous changes in the weights should influence the current direction of movement in weight space. Sometimes these weights changes stuck in a local minimum. To avoid these local minima,

BDNet has used momentum in the objective function, which is a value between 0 and 1 that increases the size of the steps taken towards the minimum by trying to jump from a local minimum. Here the momentum value set is 0.9, and for this reason speed and accuracy improves.

Activation Function: We have used Rectified Linear Unit (ReLU) [22] as activation function. ReLU function as in equation 6 works for non-linearity.

$$f(x) = \max(0, x) \tag{6}$$

Here x denotes the value of a pixel. ReLU removes negative values from an activation map by setting them to zero. It increases the nonlinear properties of the decision function and removes the chances of vanishing gradient of BDNet without affecting the receptive fields of the convolution layer.

Dropout for Regularization: Few techniques ideas make deep learning popular and usable, and the dropout for regularization [40] is one of them. Dropout is used for BDNet to avoid over-fitting during training. The method simply drops out some neurons randomly in neural network in each iteration of training according to a threshold probability. Here we used the dropout threshold probability as 0.09 which is a small probability i.e. only 9% neuron dropout in each epoch.

Data Augmentation: Data augmentation is one of the important parts which gives more versatility to extracted features and helps to train the deep learning model more accurately. Here, we have used data augmentation as the size of the dataset is not as large as required. But the idea has been used with slightly non-traditional way as shown in figure 7. As an image of the handwritten numeral digits have some problems as we can not crop or rotate largely. Here, we did augmentation on the training set for each epoch as follows: adjusted the contrast of training samples by choosing adjusting factor randomly from the list [1, 0.2, 0.3, 0.5, 0.6, 0.7, 0.8, 0.9, 1.3, 1.5], random rotation of training images from -15 to +15 degrees, and random zooming up to 9.1%. For this type of data augmentation, a slightly new dataset is passed through the network in every it-













Steps	Stepwise augmentation outcome of Bengali Numeral training samples		
	০	১	২
Step 1			
	Size: 32x32	Size: 32x32	Size: 32x32
	Sample images of ISI handwritten Bengali numeral after pre-processing		
Step 2			
	Size: 32x32	Size: 32x32	Size: 32x32
	Adjust contrast by choosing factor randomly from list:[1,0.2,0.3,0.5,0.6,0.7,0.8,0.9,1.3,1.5]		
Step 3			
	Size: 32x32	Size: 32x32	Size: 32x32
	Randomly rotate training images upto -15° to 15°		
Step 4			
	Size: 32x32	Size: 32x32	Size: 32x32
	Randomly zoom upto 9.1%		

Figure 7: Data augmentation steps.

eration or epoch.

Cross-Validation: To train BDNet 10-fold random cross-validation are used. We used 10% of training data only for 10-fold cross-validation to validate the model during training for generalization without over-fitting. After one epoch, training set are re-sampled with 10-fold cross-validation. The cross-validation result is mentioned in section 6.

6. Result Analysis

It has mentioned that the BDNet is trained using pre-processed ISI handwritten Bengali numeral database with data augmentation and 10-fold cross-validation. BDNet is tested using test dataset from the same database mentioned in section 4. The trained model also tested using our own dataset described in that section. Following subsections are showing some results of the BDNet, found during training and testing.

6.1. Number of Epoch vs Training Loss

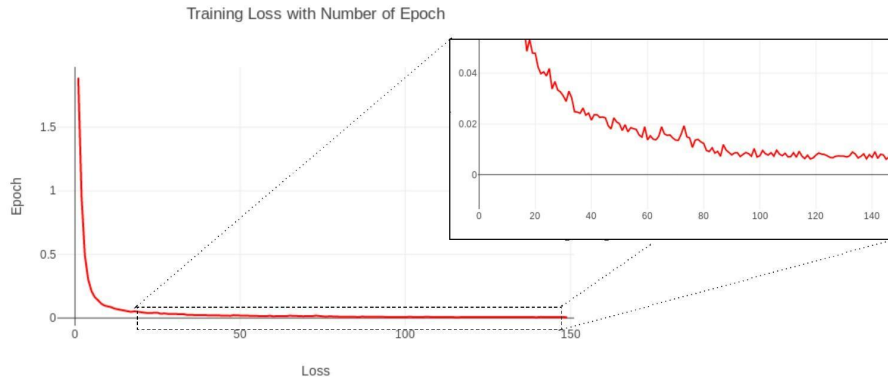


Figure 8: Number of epoch vs training loss

At first, when the training started, the amount of error or training loss was very high and the value of error rate was between 0.95 to 1.88. But with the increasing number of training epochs, the value of training loss decreased drastically and later it slowed down as shown in figure 8. After 120 epochs, the error rate became very small almost between 0.008 to 0.006.

6.2. Training and Validation Accuracy

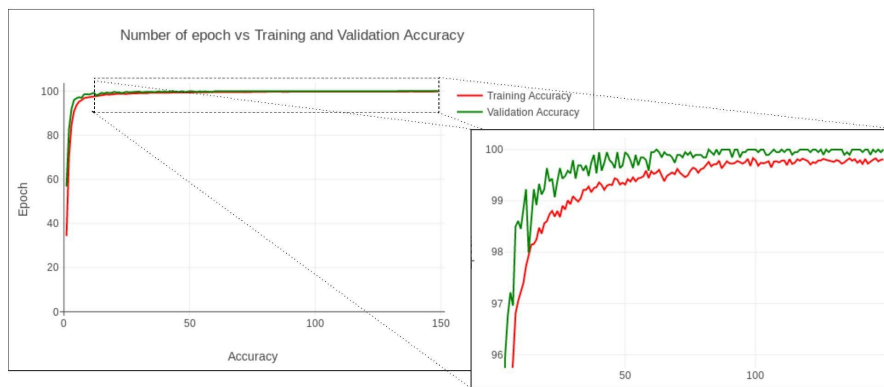


Figure 9: Number of epoch vs Training and Validation Accuracy

The training and validation accuracy has been observed simultaneously. As we can see in figure 9, the increasing rate of accuracy was very high during the

initial training period and it gradually became very low. After 125 epochs, it was almost saturated. We can also see from this figure that the training accuracy was mostly dominated by validation accuracy, and it is happened because of data augmentation. Maximum training accuracy was recorded **99.82%** after epoch number 118, and maximum validation accuracy was recorded **100%** in many times such as after 97th, 107th, 118th, 120th epoch.

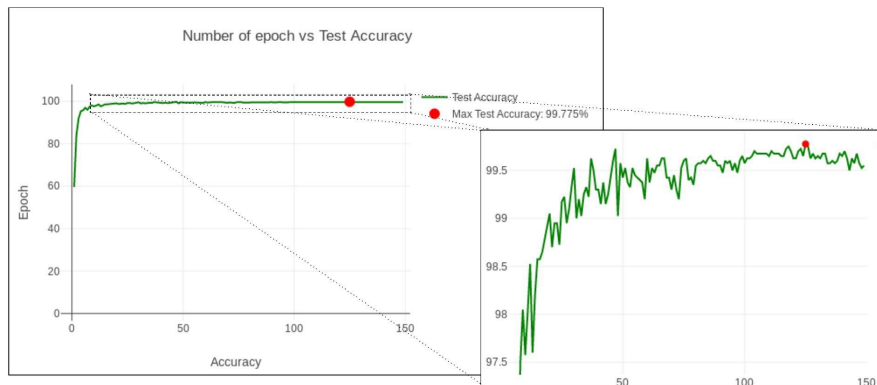


Figure 10: Number of epoch vs Test Accuracy

6.3. Test Accuracy

It is mentioned that BNet has achieved record-breaking test accuracy on ISI Bengali handwritten numeral test dataset. BNet achieved 99% test accuracy after 45 epochs, and at 125th epoch it achieved **99.775%** test accuracy as shown in figure 10 , which is the current best result on the ISI handwritten numeral dataset.

6.4. Analysis through Confusion Matrix

Testing result of the BNet on the test dataset of ISI handwritten Bengali numeral can be presented in the confusion matrix as shown in table 3. Clearly, we can see that among 10 numeral digits of 4000 test images, only 9 were wrongly predicted or classified. Among 400 test images of the digit 0, one is incorrectly predicted as 3, and one is 7. Similarly, 3 images of the digit 1, 1 images of

Table 3: Confusion matrix of the test result of the ISI handwritten Bengali numerals test dataset

		Predicted Class										Accuracy (%)	
		0	1	2	3	4	5	6	7	8	9		
Actual Class	Numerals	0	1	2	3	4	5	6	7	8	9		
		0	398	0	0	1	0	0	0	1	0	0	99.50
		1	0	397	1	0	0	0	0	0	0	2	99.25
		2	0	0	399	0	0	1	0	0	0	0	99.75
		3	0	0	0	400	0	0	0	0	0	0	100.00
		4	0	0	0	0	400	0	0	0	0	0	100.00
		5	0	0	0	0	1	398	1	0	0	0	99.50
		6	0	0	0	0	0	0	400	0	0	0	100.00
		7	0	0	0	0	0	0	0	400	0	0	100.00
		8	0	0	0	0	0	0	0	0	400	0	100.00
	9	0	0	0	0	0	1	0	0	0	399	99.75	

the digit 2, 2 images of the digit 5, and 1 image of the digit 9 were predicted incorrectly. The details of wrong predictions are shown in the confusion matrix in table 3. The **F1** score for this confusion matrix is 0.99775.










Total 9 images are wrongly classified among all the test images of the dataset which are shown in table 4. In the confusion matrix, it has shown that which wrongly predicted image is classified to which class. After careful observation of the patterns of these 9 images, possible reason behind these wrong classification could be understood.

6.5. Standard Deviation of test results

To find how spread out the test accuracy in case of training the model multiple times with same hyper-parameter configurations, we calculate the standard deviation (σ) by using equation 7.

$$\sigma = \sqrt{\frac{1}{N} \sum_{i=1}^N (x_i - \mu)^2} \quad (7)$$

Table 4: Wrongly Classified Images

Digit Images	Actual Class	Predicted Class
	0	3
	0	7
	1	2
	1	9
	1	9
	2	5
	5	4
	5	6
	9	5

Where μ is the mean of N values.

Now, we run our model 5 times with same hyper-parameter configurations and the achieved test accuracy has shown in table 5 and we get $\mu = 99.75$. So finally we get the standard deviation (σ) of test accuracy as 0.015. Codes along with training details of all those 5 cases are available at: <https://github.com/Sufianlab/BDNet>.

Table 5: Test accuracy of our model in 5-classes cases when we run the model with same hyper-parameter configurations.

		Test Accuracy (%)
Cases	1	99.750
	2	99.725
	3	99.750
	4	99.775
	5	99.750

6.6. Comparison of Test Results with Base-line-models

The most notable models proposed by researchers for Bengali handwritten numerals recognition has been discussed in subsection 2.1. We have compared BDNet with some notable models which are also worked on this benchmark

dataset [9]. Before BDNNet, previous two best models [15] and [28] achieved the test accuracy of 99.40% and 99.58%(authors of [28] claimed it) respectively whereas BDNNet achieved 99.775%. All the notable models and corresponding test accuracies are shown in table 6. Graphical comparison of said models has shown in figure 11 where X-axis presents the models and Y-axis shown the corresponding test accuracy in the benchmark dataset [9].

Table 6: Notable Bengali handwritten numerals recognition models and corresponding test accuracy in the benchmark dataset [9].

Models	Test accuracy
U. Bhattacharya & B. B. Choudhury(2009)[9]	98.20%
C-L. Liu & C.Y. Suen(2009) [15]	99.40%
N. Das et.al(2012) [18]	97.70%
Y. Wen and L. He(2012) [16]	99.40%
M. A. H. Akhand et.al(2016) [23]	98.98%
Md. Shopon et.al(2017) [21]	99.35%
AKM S. A. Rabby et.al(2019) [28]	99.58%
BDNNet(Proposed in this paper)	99.775%

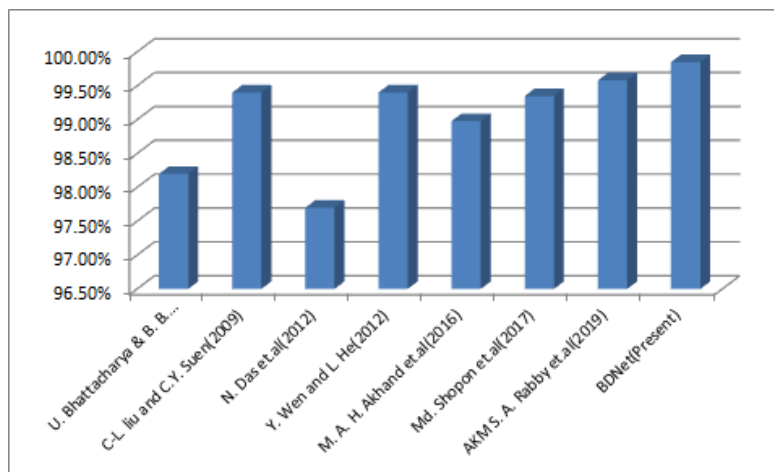


Figure 11: Comparison of notable models and corresponding test accuracy.

6.7. Test Result on Our Own Dataset

Our own test dataset is described in subsection 4.3 which has 10 classes with 100 images per class. This test dataset is not used during training for evaluating the generalization capability of the trained BDNet on new dataset. As a result, the BDNet has got 98.80% test accuracy. The entire result has been shown in the confusion matrix mentioned in table 7.

Table 7: Confusion matrix of the test result on own test dataset

		Predicted Class										Accuracy (%)	
		0	1	2	3	4	5	6	7	8	9		
Actual Class	Numerals	0	1	2	3	4	5	6	7	8	9	Accuracy (%)	
	0	100	0	0	0	0	0	0	0	0	0	0	100
	1	0	100	0	0	0	0	0	0	0	0	0	100
	2	0	0	100	0	0	0	0	0	0	0	0	100
	3	0	0	0	98	0	0	1	0	1	0	0	98
	4	0	0	0	0	100	0	0	0	0	0	0	100
	5	1	0	0	0	0	95	3	1	0	0	0	95
	6	0	0	0	0	0	0	100	0	0	0	0	100
	7	0	0	1	1	0	0	0	98	0	0	0	98
	8	0	0	1	0	0	0	1	0	98	0	0	98
9	0	1	0	0	0	0	0	0	0	0	99	99	

7. Conclusion

Aim of the work was to propose a practical model to recognize Bengali handwritten numerals, and through this paper we are proposing BDNet. BDNet is a densely connected deep CNN model for handwritten Bengali numeral recognition through image classification. The BDNet is trained using ISI Bengali handwritten numerals dataset and the trained model has achieved a new benchmark accuracy on a test dataset. The trained BDNet also tested using our own dataset to see the generalization of the model, where a good result has been found.

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