ABSTRACT

A computer can read and interpret intelligible handwritten input from sources like paper, photos, and other devices, known as Handwriting recognition (HWR). Besides, handwritten recognition is an interesting challenge in machine learning and deep learning. Because several strategies and approaches have been followed already to solve this challenge, machine learning and deep learning provided the best results. Handwritten digit recognition is a part of HWR. It is getting popular day by day because many applications could be made using this system like OCR, postal code recognition, license plate recognition, bank checks recognition, etc. Besides, the importance of recognizing the Bangla digit from the document is increasing. But the works available in Bangla handwritten digit recognition are very few.

Similarly, none of them are robust, and some of them are overfitted. Therefore, we need to make some improvements to this system considering its importance. This paper explores the presentation of transfer learning with the help of some best-in-class profound CNN strategies for the acknowledgment of manually written Bangla digits. It considers two deep CNN architectures, such as Mobile Net and Residual Network (ResNet) based on performance and accuracy. This model was trained and tested with the CMATERdb dataset. The study suggests that transfer learning provides 97% accurate results, where traditional CNN provides 86-92%.

Keywords - Bangla Handwritten Digit, CNN, MobileNet, ResNet50, Transfer learning.
Several approaches and strategies have been made to solve the digit recognition problem. In 2000, Pal and Chaudhury made some attempts to solve digit recognition problems for Bangla numerals using the water reservoir concept, dependent on the extracted features. T. Hassan and A.H. Khan used the Local Binary Pattern (LBP) approach in three different schemes. LBP has been generally used for face recognition. The writers of the paper used the K-nearest neighbor classifier to classify characters. This paper proposed an OCR system on a dataset from the CMATERdb3.1.1 database, which accurately recognized 96.7% of characters [1]. Researcher U. Bhattacharya of this paper worked on Devanagari handwritten database. This database has 22,556 data points collected from 1049 individuals. The researcher also used Bangla handwritten numerical database with 23,392 samples collected from 1106 individuals. He had chosen the nearest neighbor classifier to do his research and got results for $k = 1, 3, 5, 7, 9,$ and 15. In the case of resizing, he used Daubechies wavelet filters to classify the images, and he used the Multistage Recognition System. In the Devanagari dataset, he trained 1,657,940 images and got 99.27% accuracy, and for validation, 20,000 data points were used, and he got 99.02% accuracy. In the Bangla dataset, he used 173920 images for training and 20,000 images for validation.

Table 1: Example of Bangla Digits

| ০ | ১ | ২ | ৩ | ৪ | ৫ | ৬ | ৭ | ৮ | ৯ |
|---|---|---|---|---|---|---|---|---|---|
| 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |

To recognize Bangla, handwritten digits have used traditional CNN and two deep CNN architectures (MobileNet and ResNet50) along with transfer learning. We have used CNN because it is preferable for image recognition and transfer learning with CNN architecture to a better result with less computational power. Though there are many other ways, two build this digit recognition system, water reservoir scheme, autoencoder, some other CNN architecture (AlexNet, CapsuleNet), etc.

II. BACKGROUND ANALYSIS AND RELATED WORK

We have used TensorFlow and two deep CNN architectures (MobileNet and ResNet50) for our study. TensorFlow is a python library, and it is used for fast numerical computation [13] [14] [15][16]. On the other hand, MobileNet is used for image classification, and its specialty is that it takes less computational power when applying transfer learning compared to other models. ResNet is a 50-layer deep convolutional neural network, and we can load pertained versions of the network trained on more than a million images from the ImageNet database [17][18][19].

This paper's researchers used the CMATERdb dataset and tried some combinational approach of deep learning and traditional algorithms to build a Bangla handwritten digit recognizer. Their applied techniques are SVM, deep belief network, CNN + Gaussian, CNN + Gabor, CNN + Gaussian + Dropout, CNN + Gabor + Dropout. The highest accuracy they got using the CNN + Gabor + Dropout approach was 98.78% [12].

III. DATASET

We have used the CMATERdb 3.1.1 database for our study. It is a popular dataset and preferred by many researchers for the handwritten digit recognition challenge. It is handwritten and a balanced dataset of a total of 6000 Bangla numerals (32x32 RGB colored, 6000 images), each having 600 images per class (per digit) [7]. In the CMATERdb, the Bangla handwritten dataset ids are level from 0 to 9. We have divided the data set for training and testing to avoid the same subject in both segments. This database has created in the Jadavpur University research lab in Kolkata.

IV. METHODOLOGY

Modern technology provides a vast number of multimedia devices, simulation software, network technologies. People use them rapidly and are increasing amounts of information in the forms of images. This massive number of images needs to organize effectively. These images
contain several complex and logical information, so they needed to be labeled accurately. In general, the images are labeled in multiple labels to classify, predict, and group them. Some traditional supervised algorithm helps to retrieve and process the images, but now, in the recent year, researchers are more interested in deep learning to solve the problems.

1.1 CONVOLUTION NEURAL NETWORK (CNN)

In the 1960s, Hubel and Wiesel [8] first proposed the Convolution neural network during a study of neurons in monkey cortexes. CNN's work by sharing weights and extracting some essential features from the images. CNN's take images as input, process them, and classify them under specific categories. For image resolution computer considers an image as an array of pixels, and it sees h x w x d [height x weight x dimension]. In the RGB value, dimension assigns to 3, whereas in grayscale, it assigns to 1. Each image passes through a series of layers during training and testing. The combination of a convolutional layer, pooled layer, and fully connected layer builds the CNNs. In the output layer, the Softmax activation function is applied to classify objects with probabilistic values 0 to 1 [9][20][21][22].

The convolution layer works for extracting features from an input image, and in this layer “relu” activation function works well. It takes two inputs, a matrix of pixels of the input image and a filter or kernel. The mathematics behind this is –

- An image dimension (h x w x d)
- A filter (f_h x f_w x d)
- Output dimension (h - f_h + 1) x (w - f_w + 1) x 1

Rectified Linear Unit (ReLU) uses for non-linearity in our ConvoNet. ConvoNet should learn the non-negative linear value, and that’s what ReLU does [2][23][24][25].

The pooling layer reduces the number of parameters in the case of a large image. Spatial pooling reduces the dimensionality of each map, which is also known as subsampling or downsampling. Different types of pooling can be:

- Max pooling
- Average pooling
- Sum pooling

After pooling the feature, the matrix is converted into vectors [x1, x2, x3, …..] and fed it to the fully connected layer. Finally, as output, it becomes a complete model able to classify the images [2].

1.2 RESIDUAL NETWORK (RESNET)

CNN has different types of architecture that participate in the ImageNet challenge, and one of them is ResNet, which stands for Residual Network. A classic neural network works behind it. This model won first place in the ILSVRC 2015 competition, competing with a top-5 error rate of 3.57%. The model that helps to train with 150+ layers deep neural network is developed by Kaiming [3].

This model has a concept called skip connections. With the ReLU activation function in classic CNN, the input matrix calculates the linear transformation one after another. Still, in RestNet it skips the first transformation and directly passes the input matrix to the second transformation output, and finally, all the outputs sum up in the final ReLU function [10].

The pooling layer reduces the number of parameters in the case of a large image. Spatial pooling reduces the dimensionality of each map, which is also known as subsampling or downsampling. Different types of pooling can be:

- Max pooling
- Average pooling
- Sum pooling

After pooling the feature, the matrix is converted into vectors [x1, x2, x3, ....] and fed it to the fully connected layer. Finally, as output, it becomes a complete model able to classify the images [2].

1.3 MOBILE NET

A CNN class is MobileNet that Google publicly released, and hence, this gives us a fantastic beginning stage for preparing our classifiers that are madly little and madly quick. This model is designed for a mobile application that uses depth-wise separable convolution. The model is used to do transfer learning. This ImageNet classification model is defined to meet the resource limitations of different cases [11].

In our research, we have used an end-to-end machine learning open-source platform, TensorFlow. It has several libraries and resources that help developers build a model in a short time.
1) Preprocessing: This step holds the most crucial part during the research as a result, it mostly depends on the preprocessing of the dataset. We did resize the dataset and then grayscaled them, and finally sharpen them.

   a) resizing: Though the sizes of images in the database were mentioned as 32x32 pixels, we took a little initiative to confirm the image size.

   b) Grayscale: The images were in RGB scaling, so we needed to convert the images into Gray scaling. We have changed the color channel also to 1 so that our model can be built properly. Initially, the color channel was 3, which was a restriction.

   b) Normalizing: To make it computationally efficient, we need to reduced the grayscaled values by 0 to 1. It uses a pixel intensity value.

   Fig 3: Random image before preprocessing
   Fig 4: Random image after Gray scaling
   Fig 5: Random image after a normalization

The whole process of our work-

```
images
Gray-Scaling
Normalize
```

Table 2: A short summary of three models

| Model Name | Total parameters | Trainable parameters | Non-trainable parameters |
|------------|------------------|----------------------|--------------------------|
| CNN        | 61,706           | 61,706               | 0                        |
| MobileNet  | 3,228,864        | 3206976              | 21888                    |
| ResNet50   | 23,587,712       | 23,534,592           | 53,120                   |

V. RESULTS

We have used 83% of the training dataset and 17% of the dataset for testing, 1000 data points, and ten classes. As our PC configuration was not much good and the experiments typically take so much time to train a model, we set epochs 5. We first trained the model with traditional CNN and found that the model predicts Bengali handwritten digits with 91% accuracy. Figure 6 shows that for digits 1, 3, 6, and 9, recall and f1-score are less than 90%.

It means the model correctly identifies the digits less than 90% of the actual digits. Figure 6 clearly shows that our CNN model accurately trained up to 92% within four epochs and validation accuracy up to 91%. Figure 8 establishes evidence of training and validation loss. The
validation loss is less than 25%, whereas training loss is an exact 25% within four.

|         | precision | recall | f1-score | support |
|---------|-----------|--------|----------|---------|
| 0       | 0.94      | 0.95   | 0.96     | 100     |
| 1       | 0.89      | 0.88   | 0.91     | 100     |
| 2       | 0.88      | 0.86   | 0.87     | 100     |
| 3       | 0.87      | 0.85   | 0.87     | 100     |
| 4       | 0.85      | 0.83   | 0.84     | 100     |
| 5       | 0.83      | 0.81   | 0.82     | 100     |
| 6       | 0.81      | 0.80   | 0.81     | 100     |
| 7       | 0.80      | 0.79   | 0.80     | 100     |
| 8       | 0.79      | 0.78   | 0.79     | 100     |
| 9       | 0.78      | 0.77   | 0.78     | 100     |
| accuracy| 0.91      |        |          | 100     |
| macro avg | 0.91     | 0.91   | 0.91     | 1000    |
| weighted avg | 0.91 | 0.91   | 0.91     | 1000    |

Fig 6: Classification report of CNN model

Fig 7: Training and validation accuracy of CNN model

Fig 8: Training and validation loss of CNN model

Fig 9: Classification report of MobileNet model

After CNN, we have built a MobileNet model to see the performance of our dataset. The model gives an accuracy of 88%, which is less than the CNN model. The precision of digit 1 is 60%, meaning the model can accurately identify the digit 60%. The recall of the digit 0 only 28% means the model can identify the digit 28% of all the 0 digits. As the precision and recall affect the f1-score, f1-score for these two digits is so low. All of this information can be seen in figure 9.

|         | precision | recall | f1-score | support |
|---------|-----------|--------|----------|---------|
| 0       | 1.00      | 0.26   | 0.44     | 100     |
| 1       | 0.60      | 0.00   | 0.07     | 100     |
| 2       | 0.94      | 0.99   | 0.97     | 100     |
| 3       | 0.94      | 0.97   | 0.95     | 100     |
| 4       | 0.94      | 0.97   | 0.95     | 100     |
| 5       | 0.92      | 0.95   | 0.93     | 100     |
| 6       | 0.99      | 0.86   | 0.92     | 100     |
| 7       | 1.00      | 0.82   | 0.90     | 100     |
| 8       | 1.00      | 0.91   | 0.95     | 100     |
| 9       | 0.82      | 0.99   | 0.90     | 100     |

| ACCURACY |           |        |          |         |
| macro avg | 0.91     | 0.86   | 0.87     | 1000    |
| weighted avg | 0.91 | 0.86   | 0.87     | 1000    |

Fig 10: Classification report of ResNet50 model

Finally, we have tried ResNet50 to see the performance on our dataset, and yet, we have got satisfied with the result, and it has given 97% accuracy, which is more convenient to predict our digit. Precision, recall, f1-score for all digits is above 90%, and this model predicts our digits above 90% accurately.

VI. CONCLUSION

Recognizing Bengali handwritten characters are becoming more and more important day by day. As mentioned before, systems like OCR can be highly benefited from it. This study proposed two different methods for recognizing Bengali handwritten digits using Convolutional Neural Network (CNN) and Transfer Learning with ResNet50 and MobileNet. As it suggests, the transfer learning approach produces a better result. The traditional CNN provides an accuracy of 91%, MobileNet 88%, and ResNet50 offers the best accuracy, 97%. We can conclude that conventional CNN is not enough to recognize handwritten...
digits, and we can use deep CNN architecture to build a robust digit recognition system.

There were a few limitations that we faced when we proceeded with this study. We have shortlisted the crucial elements. The dataset we used to train and implement our model was relatively small. A larger dataset would increase efficiency and accuracy for the tests results. We used to run out test models with limited computation power; therefore, we had to resort to fewer models for optimum results. Our work has a vast field to contribute if power; therefore, we had to resort to fewer models for optimum results. Our work has a vast field to contribute if worked on for an extended time, leading to more efficient outputs. The test can be implemented through different data models to regulate and find more efficient solutions among the models and define a better approach. A different dataset with a larger size will increase the accuracy of the results, which can be obtained from an existing source or be collected by personal research means. The dataset we used only contained numerals. This study can be extended further if we incorporate letters from the Bengali alphabet to change the dynamic and bring the research work into a broader perspective.

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