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Bangla handwritten character recognition using MobileNet V1 architecture

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ABSTRACT

Handwritten character recognition is a very tough task in case of complex shaped alphabet set like Bangla script. As optical character recognition (OCR) has a huge application in mobile devices, model needs to be suitable for mobile applications. Many researches have been performed in this arena but none of them achieved satisfactory accuracy or could not detect more than 200 characters. MobileNet is a state of art (convolutional neural network) CNN architecture which is designed for mobile devices as it requires less computing power. In this paper, we used MobileNet for handwritten character recognition. It has achieved 96.46% accuracy in recognizing 231 classes (171 compound, 50 basic and 10 numerals), 96.17% accuracy in 171 compound character classes, 98.37% accuracy in 50 basic character classes and 99.56% accuracy in 10 numeral character classes.

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1. INTRODUCTION

Convolutional neural network (CNN) has recently been incredibly popular in image recognition. But most of the models are very bulky and need a lot of time to train. But for modern application like in mobile applications need light and fast models. In case of OCR application, models need to provide high precision though having large number of classes to distinguish between. MobileNet is a state of art CNN architecture which is very small in size, very fast and provide very high accuracy. In this paper, we have introduced a MobileNet based architecture that can recognize Bangla handwritten character.

Handwritten character recognition (HCR) is a significant part of OCR system which is also a very popular research area. Handwritten character recognition has achieved advancement in English, Arabic etc. language. Bangla is a very popular language with around 250 million speakers. Bangla is the official language of Bangladesh. So, handwritten character recognition of Bangla alphabets needs to be advanced and accurate.

Shape of Bangla alphabet is very complex. Some of the characters are written in different pattern by different person. Some of the characters are distinguished by a single stroke of line called 'Matra'. Bangla script contains around 50 basic characters and 10 numeric characters. These basic characters also become combined and create compound characters. Bangla script contains more than 300 compound characters. Due to large number of classes, complex and similarity in shape, recognition of Bangla character is a very tough task. Figure 1 illustrates somecomplex shaped basic and compound bangla characters.

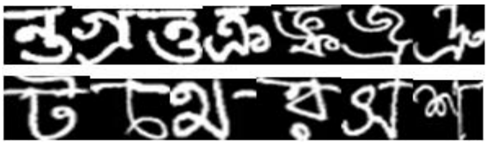

Figure 1. Some Bangla characters

Bangla Handwritten characters are very cursive and complex shaped. There are more than 400 compound characters which are needed to be classified. Even some of the characters can be written in two forms. So, it is really hard to distinguish one from another. A lot of researches have been carried out in English or Arabic handwritten character recognition but its limited in Bangla character set. The model needs to be fast and lightweight to use in low config devices. MobileNet can be a very good solution as it is fast, lightweight and capable of acquiring very high precision in large classification task. We have proposed a lightweight, fast and suitable Bangla handwritten character recognition (BHCR) architecture. Our system can successfully recognize 231 Bangla character classes.

2. RELATED WORKS

Before 2010, research on BHCR was confined in basic and numeral character detection. After 2015, some researchers started to work with compound characters. But still, there is no work which can classify all the characters together. Zhang [1] showed how convolutional neural network can recognize Chinese handwritten characters. Chinese characters are very cursive and complex shaped. The researcher showed how deep CNN can extract higher level features as depth of the convolutional layer increases. He also showed adding a convolutional layer improves performance more than adding an extra dense layer. He also showed more filters help to achieve better performance. He showed deep networks can achieve better performance and adding a convolutional layer after 5^{th} conv layer provides more benefit than adding after $7/8^{th}$ conv layer. He achieved 97.3% accuracy during classifying 200 classes and 95.5% accuracy in 3755 characters classification.

Das *et al.* [2] used MLP & SVM classifier and shadow, longest and quad tree feature set to classify 50 basic, 43 compound characters total 93 characters. This method achieved 80.86% precision by using SVM classifier. Sarkhel *et al.* [3] classified around 231 characters using a region sampling method where most discrimination portion of the image was selected to distinguish with other characters and SVM was used as classifier. It achieved 72.87% precision in 384 classes classification. Pramanik [4] introduced a shape decomposition-based architecture where compound characters were converted into basic characters. It reduced complexity and MLP was used as classifier. They recognized 171 compound characters and obtained 88.74% accuracy. Das *et al.* [5] used a convex hull-based feature extraction method for classifying 50 basic characters and 10 numerals. Das *et al.* [6] proposed an improved feature set containing 132 features. Modified shadow features, quad tree based longest run feature, distance-based features, octant and centroid features were added in proposed feature set. MLP with one hidden layer was used for classification. Accuracy improved from 75.05 to 85.40% on 50 basic character classes. Basu [7] proposed a word segmentation process to extract characters. Anew feature descriptor was also proposed for this purpose. Bhowmik *et al.* [8] used SVM, RBF and MLP based method for classifying 45 basic character classes. Image was classified in a group and then the original class label was extracted. This architecture was more effective than traditional SVM based methods. Parui [9] proposed a hidden Markov model and tried a stroke-basedtechnique where 54 groups of strokes were identified, 6 groups of strokes were generated and a distinct HMM was assigned for each stroke. They achieved 87.7% classification accuracy in test set. Roy [10] introduced a process for generating database of strokes on the basis of handwritten characters. Construction of characters from its stroke was used in this proposed method. The classification precision was 96.85% for the isolated strokes. Sazal *et al.* [11] implemented a deep belief network which took raw images as input and it was processed through unsupervised learning and a supervised fine tuning for classifying 50 basic and 10 numeral character at 90.27% accuracy.

Tapotosh Ghosh *et al.* [12] reviewed existing works on bangla handwritten character recognition (BHCR). He showed CNN based methods achieved better result than other architectures. Roy *et al.* [13] introduced a neural network architecture where a layer wise training method and RMSprop optimizer was used. RMSprop optimizer is capable of achieving faster convergence. They obtained 90.33% precision in recognizing 173 Bangla handwritten character classes. Ashiquzzaman *et al.* [14] stated a CNN architecture. Overfitting problem was reduced in this architecture by dropouts and gradient vanishing problem was decreased by ELU filter. They classified 171 characters and obtained 93.68% precision. Fardous *et al.* [15]

developed a CNN model which is consist of 8 conv layer, 2 fully connected layer, and 4 pooling layers. They used ReLU as activation function which is able to introduce non-linearity. They also used dropout in order to reduce overfitting. They achieved 95.5% precision in 171 compound character classification. Saha *et al.* [16] stated a CNN model where different number of filters were used in every layer to acquire necessary features from the image. They followed GOOGLENET architecture. They only classified 84 characters with 97.21% precision. Rabby *et al.* [17] introduced a 22 layered CNN architecture to classify 122 classes. They classified 50 basic characters, 52 compound characters, 10 numerals and 10 modifiers. They obtained 97.73% accuracy in the mixed set. Alif *et al.* [18] experimented Resnet architecture to recognize 173 characters. Dropout between layers and Adam optimizer was used with Resnet. They acquired 95.18% precision using this Resnet model. Alom *et al.* [19] evaluated different state-of-the-art DCNN model for BHCR. They used CMATERdb [19] for testing purpose and got the best accuracy using DenseNet [20].

3. MOBILENET V1 ARCHITECTURE

MobileNet is a light weight model with 4,253,864 parameters. It takes 224x224x3 images as input and uses depthwise separable convolution block rather than standard convolutional block to extract feature [21]. Depthwise convolution uses 1 filter to each channel during convolution. Pointwise convolution is 1x1 convolution. Pointwise convolution merges the output of depthwise convolution. Depthwise seperable convolution contains a smaller number of parameters than traditional standard convolution. Depthwise convolution is used to extract features from images and pointwise convolution is used to combine the features. These layers also have a ReLU activation layer and Batch Normalization layer. But in standard convolution, filtering the image and combining output is done by one layer [22] which is computationally more expensive.So, depthwise separable convolution is more efficient than standard convolution layer. Figure 2 shows the difference between depthwise separable convolution and standard convolution. MobileNet architecture is provided in Figure 3.

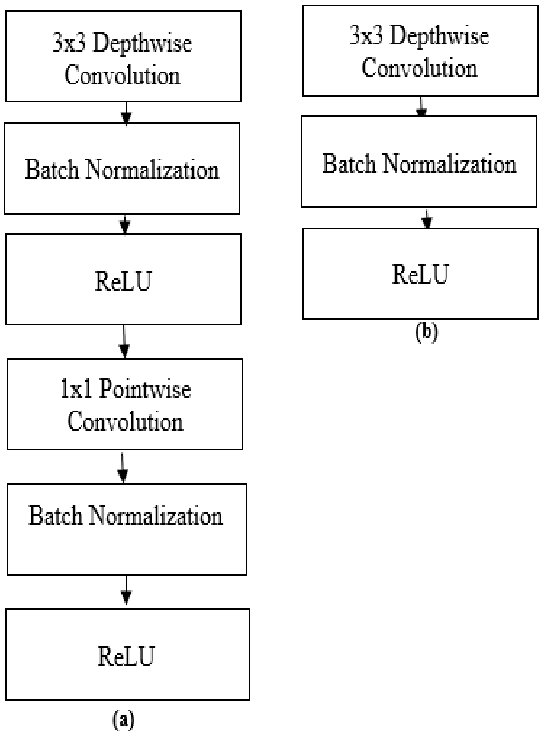

Figure 2. (a) Depthwise convolution [21], (b) Standard Convolution [22]

Type/Stride	Filter Shape	Input Size
Conv / s2	3 × 3 × 3 × 32	224 × 224 × 3
Conv dw / s1	3 × 3 × 32 dw	112 × 112 × 32
Conv / s1	1× 1 × 32 × 64	112 × 112 × 32
Conv dw / s2	3 × 3 × 64 dw	112 × 112 × 64
Conv / s1	1 × 1 × 64 × 128	56 × 56 × 64
Conv dw / s1	3 × 3 × 128 dw	56 × 56 × 128
Conv / s1	1 × 1 × 128 × 128	56 × 56 × 128
Conv dw / s2	3 × 3 × 128 dw	56 × 56 × 128
Conv / s1	1 × 1 × 128 × 256	28 × 28 × 128
Conv dw / s1	3 × 3 × 256 dw	28 × 28 × 256
Conv / s1	1 × 1 × 256 × 256	28 × 28 × 256
Conv dw / s2	3 × 3 × 256 dw	28 × 28 × 256
Conv / s1	1 × 1 × 256 × 512	14 × 14 × 256
Conv dw / s1 5 × Conv / s1	3 × 3 × 512 dw 1 × 1 × 256 × 512	14 × 14 × 512 14 × 14 × 512
Conv dw / s2	3 × 3 × 512 dw	14 × 14 × 512
Conv / s1	1 × 1 × 512 × 1024	7 × 7 × 512
Conv dw / s2	3 × 3 × 1024 dw	7 × 7 × 1024
Conv / s1	1 × 1 × 1024 × 1024	7 × 7 × 1024
Avg Pool / s1	Pool 7 × 7	7 × 7 × 1024
FC/ s1	1024 × 1000	1× 1 × 1024
Softmax / s1	Classifier	1× 1 × 1000

Figure 3. MobileNet architecture [21]

4. RESEARCH METHOD

The whole work is conducted in the manner mentioned in Figure 4. At first a large Bangla handwritten dataset has been collected. The dataset required cleaning and then it was fed to MobileNet model for training. Around 20% images were kept aside for testing purpose. The model was then tested with testing dataset.

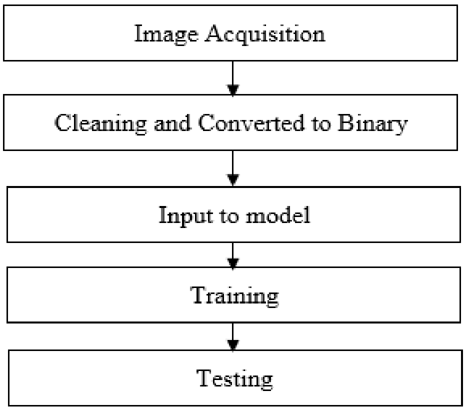

Figure 4. Workflow followed in this research

4.1. Dataset preparation

There are four large databases containing Bangla handwritten cahracters [19, 23-25]. Among them, CMATERdb [11] has the largest amount of classes. We used CMATERdb [19] 3.1.1, 3.1.2 and 3.1.3 databases for acquiring images of 231 classes. The images were mostly in grey background and size of the images were different. The dataset was divided into train & test. At first, we cleaned the dataset in order to remove misclassed images. Then, we converted the images to binary and later we converted the images to a same shape (28*28). Figure 5(a) shows some of the samples of original dataset. Figure 5(b) shows the result of preprocessing. Table 1 provides a statistics of training, testing and validation images used for evaluating this model.

(a) (b)

Figure 5. (a) Before preprocessing, (b) After preprocessing

Table 1. Dataset splitting

Dataset	No of classes	Training images	Validate images	Test images
Basic + Compound + Numeral	231	38,807	9,612	11,503
Compound	171	27,486	6,793	8,123
Basic	50	9,411	2,345	2,896
Numeral	10	1,910	474	484

4.2. Training and testing

We trained the MobileNet architecture four times for mixed set, compound set, basic set & numeral set. Each time we set neurons number of the last dense layer according to the number of classes. We trained the model with Adam optimizer, Learning rate=0.001, loss=categorical crossentropy and epoch=80. This model converged after 60 epochs which can be visualized from Figure 6. After training, we tested the model with completely isolated test set. Table 2 describes the time required to complete an epoch using MobileNet. Figure 6 shows the validation & training accuracy with respect to number of epochs.

Table 2. Time required to train

Classification task	Seconds per epoch
Numerals (10 classes)	15
Basic (50 classes)	70
Compound (171 classes)	212
Mixed (231 classes)	276

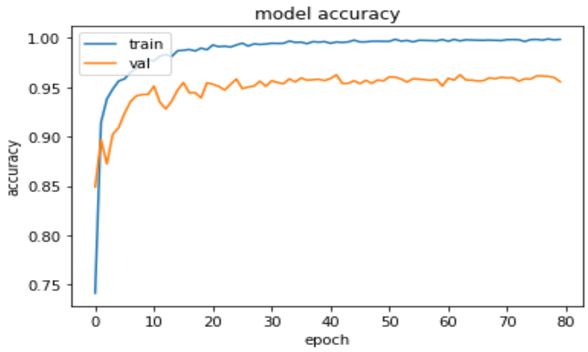

Figure 6. Training and testing accuracy vs epoch

5. RESULT AND DISCUSSION

The trained MobileNet model is tested with completely isolated dataset. During 231 classes classification, this model acquired 96.56% in validation set and 96.46% in testing set. This model obtained 96.26% precision in validation set and 96.17% precision in test set during 171 compound character classification. It provided 98.47% accuracy in validation set and 98.36% accuracy in testing set in basic character recognition. For numeral classification, it acquired 99.80% and 99.56% in validation and testing set respectively. Table 3 illustrates the precision acquired in different classification task.

Table 3. Accuracy of proposed model in different classification task

Classification task	Number of classes	Validation accuracy	Testing accuracy
Numeral	10	99.80%	99.56%
Basic	50	98.47%	98.37%
Compound	171	96.26%	96.17%
Mixed	231	96.56%	96.46%

From the result, we can visualize that the proposed model was pretty good in classifying the numerals but it became more confusing and provided most errors in the case of compound characters as their structure is more complex, similar to each other than numeral characters and some of them can be written in different structure. We can compare the proposed model with existing model according to the number of classes classified and accuracy. Table 4 shows comparison between existing models and proposed model.

Table 4. Comparison between existing models and proposed model

Models	Number of classes	Accuracy
Nibaran Das *et al.* (2010) [2]	93	80.86%
Rahul Pramanik *et al.* (2018) [4]	171	88.74%
Saikot Roy *et al.* (2017) [13]	173	90.33%
A. Ashiquzzaman *et al.* (2017) [14]	171	93.68%
A. Fardous *et al.* (2019) [15]	171	95.5%
M. A. R. Alif *et al.* (2017)[18]	173	95.18%
Rabby *et al.* (2018) [17]	122	97.73%
Sourajit Saha *et al.* (2018) [16]	84	97.21%
Proposed Model	**231**	**96.46%**

Rabby *et al.* [17] acquired around 97.73% accuracy in classifying 122 classes and Saha *et al.* [16] acquired 97.21% accuracy in classifying 84 classes. Both of them achieved better accuracy than MobiletNet model but they classified a smaller number of classes than this model. So, in case of number of classes this model beats all the existing models. Figure 7 shows a comparison between existing models and our proposed model according to accuracy and number of classes. Among these models, five of them used CMATERdb as database. Among them, MobileNet model provided the best accuracy and was able to classify the largest number of classes. A comparison between existing models which used CMATERdb and MobileNet model is provided in Figure 8.

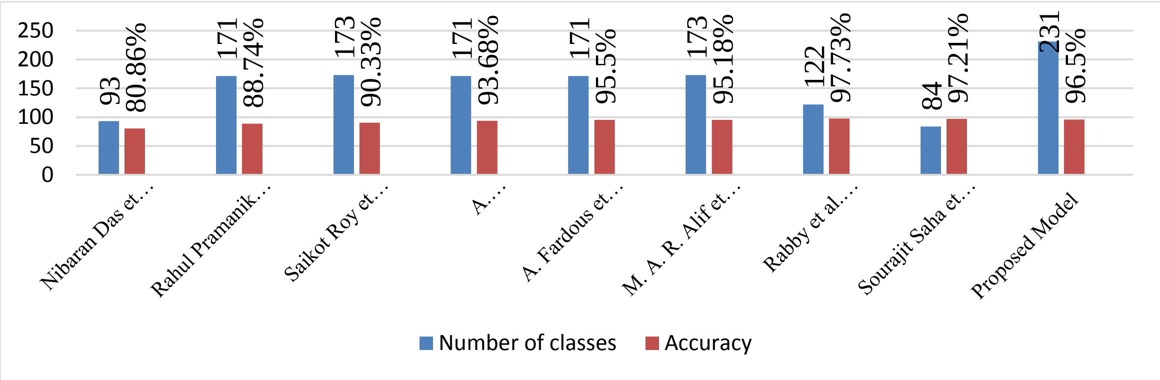

Figure 7. Comparison of different models

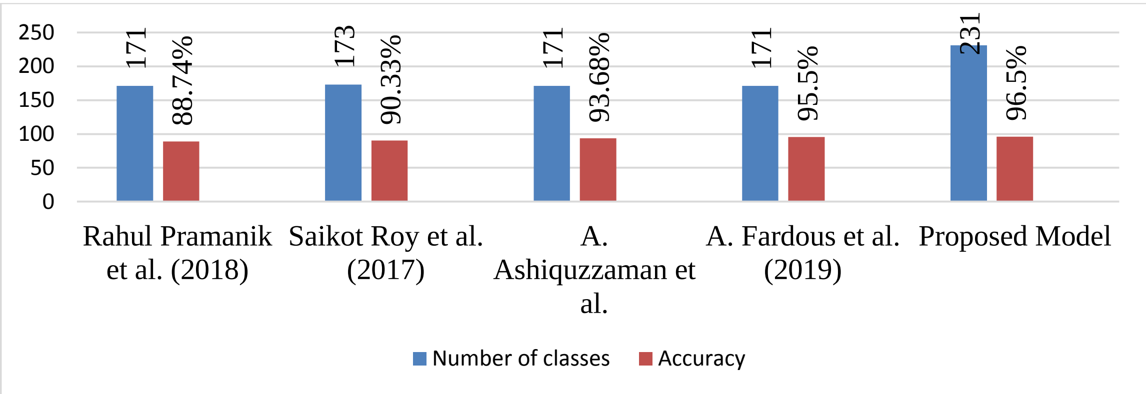

Figure 8. Comparison of different models which are evaluated using CMATERdb

6. CONCLUSION AND FUTURE SCOPE

Bangla handwritten character recognition is much necessitated in order to establish an efficient Bangla OCR. A better model capable of classifying more than mostly used 400 Bangla handwritten characters with higher accuracy is to be found out for establishing a good OCR system for Bangla Characters. MobileNet architecture can be a solution to BHCR because of its lightweight and fast computation. In this regard, other state of art CNN architectures like InceptionNet or ResNet50 can also be applied, however, they must be both efficient and lightweight as well. In this paper, we have tried to illustrate the usefulness of lightweight models and we have also demonstrated that a low-cost model like MobileNet can be a great solution to accomplish recognition task for a very cursive and large character set.Yet an unsupervised technique can be considered where the handwritten characters will be translated to a digitally readable form and the system can easily recognize the handwritten characters from this newly translated form. This can be an advantageous approach to save the heritage of Bangla literature which will be capable of establishing an efficient and computationally inexpensive system to convert Bangla handwritten document to a formatted printed document automatically.

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