

Offline Bangla Handwritten Character Recognition with Convolutional Neural Network (CNN)

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Abstract:

Now-a-days Handwritten Character Recognition (HCR) is a remarkable research topic in Bangla language. It is known to be one of the most first-rate classical problems in the field of machine learning and image processing. HCR has been researched extensively during the last few decades with varying level of success. It is so much challenging motive owing to its high variation in individual writing style and structural reflection between characters. Significantly due to lack of large Bangla handwritten character dataset, Bangla handwritten character recognition could not program far. In this field, several types of character recognition policies are going on, however offline handwritten Bangla documents are rarely found. Several approaches such as neural network, handcraft feature, support vector machine, deep learning have employed for handwritten character recognition. In this paper, the proposed approach has been evaluated by using Convolutional Neural Netwok (CNN) and greedy algorithm to recognize Bangla handwritten character and achieve better recognition accuracy. The used dataset are comparatively large and reliable for character recognition. The proposed method gained more than 90% recognition accuracy which is significantly better approach.

Keywords —Handwritten Bangla Character Recognition, Python Open CV Library, Greedy algorithm, Convolutional Neural Network.

I. INTRODUCTION

Bangla is the national and official language of the People’s Republic of Bangladesh. It is the second most popular language in the neighborhood country. Being the language of 270 million people from all over the world, Bangla language is the sixth most frequently spoken native language all over the world. There are rich number of potential applications of Bangla handwritten character recognition such as automatic postal code identification, digitizing and recognizing text on

paper based documents and automatic bank check reading. Majority of those applications have a strong dependency on the performance of BanglaHandwritten Character Recognition. Handwritten Character Recognition has long been an active research area because of its vast potential applications. For this case, it is a crying need to enhance the computer adaptability of Bangla language. Many studies have been conducted on handwritten Bangla basic character and numeral recognition [1, 2, 4, 5]. Most of the known successes in the area of neural networks and deep

learning have come from the application of neural network models to supervised machine learning tasks. Handwritten Bangla character recognition is comparatively a novel task in neural network. Main difficulty of any character recognition system is the shape similarity. It can be noted that because of handwritten style, two different characters in Bangla may look very close [3, 6]. Bangla HCR is considered as a challenging task, particularly three types of challenges can be considered such as i) recognizing convoluted edges, ii) distinguish between the repetition of the same pattern in different characters and iii) different handwritten pattern for the same character. Significantly due to lack of large bangle handwritten character dataset, Bangla handwritten character recognition could not program far. In this paper, a large dataset collected from Ekush [8] is used to train the system and test the performance in the deep learning architecture to solve this problem. It is the idea that a computer can learn and understand to classify patterns and images barring a human to provide proper guidance [1, 3]. In this proposed approach a complete Bangla document can be recognized with the better improvement of this technique. Several possibilities exist which could improve the chances of constructing a practical text recognition device. (i) High standard of scanning quality. ii) Stylized character 28*28 size. And iii) Language simplification.

II. PROPOSED METHODOLOGY

Handwritten Character Recognition has long been an active research area because of its vast potential applications. Several approaches such as neural network, handcraft feature, support vector machine, deep learning have employed for handwritten character recognition. In this paper, proposed approach have been conducted by using CNN, Python's CV Library and Greedy algorithm. In this approach, CNN is used to train this system to recognize characters and for comparing those we used a sequential model. This work uses an alternative approach in which a minimal subset of the data provides the pose estimate, and a robust regression scheme selects the best subset. The

resulting tracker performs very well on the difficult task of tracking a handwritten character, even when the image is partially occluded and OpenCV Library has made a huge impact on the development of image processing and its scope. In this paper, a greedy matching algorithm with geometric constraint is proposed for solving the polygonal arcs matching (boundary line segments matching). The goal of this paper is to find a matching such that (i) the overall costs of matched line segments and the penalties of unmatched line segments is minimum, and (ii) the matching preserves the geometric relation. The proposed greedy matching algorithm consists of two main modules. The first is an optimal matching module, which utilizes the optimization matching method to find an optimal matching without the geometric constraint. The second module is an evaluation and update module, which deletes the matched pair with a geometric relation having the maximum inconsistency after each matched pair has been evaluated, and a new matching is found again.

III. ENUMERATIVE ALGORITHM

In this work, we use a greedy matching algorithm with geometric constraint in order to solve the polygonal arcs matching (boundary line segments matching). The Greedy algorithm takes every sample in the training profile and places it on a three-dimensional grid. The X and Y coordinates directly correspond to the X and Y coordinates of the points within the normalized bounding box while the Z coordinate is the distance along the arc from the pen down point. If graphed in three dimensions, our representation should appear to be growing along the +Z axis from the start point of the stroke to the finishing point. Our recognition algorithm simply takes points from an unknown glyph and finds their distances (errors) to the closest points on every glyph in the training data. The process is then reversed and training glyphs are matched against the unknown glyphs. The total distances/errors are summed up. We choose the symbol represented by the training glyph with the least total error as the best match.

The steps of proposed algorithm are shown in the following Fig. 1.

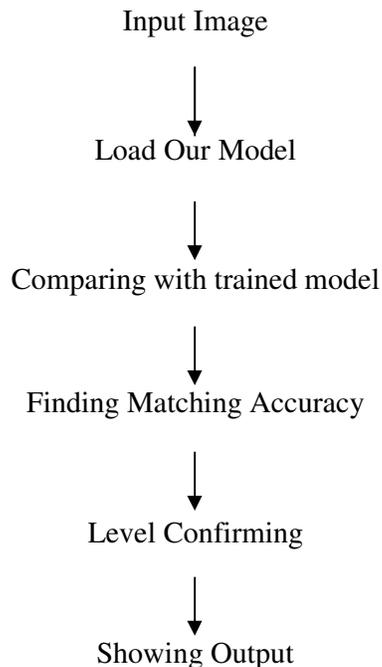


Fig 1: The proposed algorithm

This proposed approach follows the following steps to describe CNN model layers to manipulate the data and train system to recognize Bangla handwritten characters.

- step 1: we called our model sequential ()
- step 2: added conv 2d using activation Relu here we decided our input shape
- step 3: more conv 2d layer for finding more nodes
- step 4: max pooling 2d at size 2*2 for compressing image
- step 5: two more conv 2d layer for finding nodes where filter size 3*3
- step 6: again, max pooling for more data collection
- step 7: use .5 dropout
- step 8: flatten ()

- step 9: dense layer as node value with Relu activation
- step 10: dropout .5
- step 11: dense of filters activation SoftMax
- step 12: compile using adam method

Fig. 2 shows character recognition flowchart that disclose how proposed model works to recognize any character of local input data.

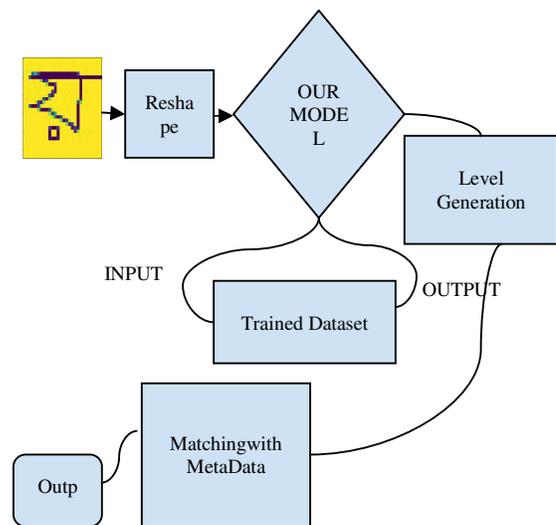


Fig. 2: Character Recognition Flowchart

IV. DATASET PREPROCESSING

In this paper, a large dataset collected from Ekush [8] is used to train the system and test the performance in the deep learning architecture to solve this problem. It is the idea that a computer can learn and understand to classify patterns and images barring a human to provide proper guidance [7]. The proposed dataset contains 120 different types of compound characters that consist of 74,663 images written handwritten Bangla characters. Preprocessing steps for used dataset for implementing the proposed approach are listed below:

- Import Dataset
- Data Preprocessing (28 x 28 pixel)

- Build CNN Model
- Import Handwritten Image
- Recognizing Image data
- Converting data using trained model to text
- Text to translate data

Fig. 3 shows the input data and separation of those data as training, testing and verification where 47 thousand images and 28*28 dimensions have been obtained with one channel.

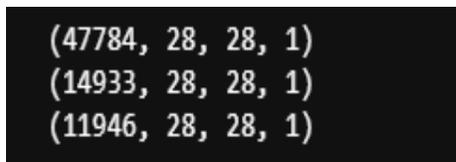


Fig. 3: Separation of inputted data as training, testing and verification

Fig. 4 shows the processed image (Thresholding image) to get output from our model.

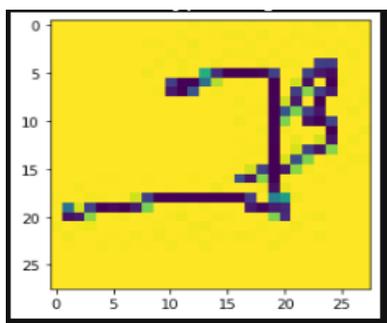


Fig. 4: Input Image (processed image) for recognition

V. IMPLEMENTATION

To train this proposed model, more than seventy-four thousand image data of various categories of Bangla characters have been used. After importing those images, the system reshaped them as 28*28 size image where width and height are the same. After that those data are separated as random to train, test, and validate this training. Here, the ratio of testing data was .2% of all data and validation data was .2% after separating test data. After that, using the remaining data, the proposed model has been started training. Before training, custom

sequential model is used to train the system where there was 60 filters. The filters were 5*5 and 3*3 and for activation the Relu function and four Conv. layer with two 2*2 max pooling used. Then the proposed system used dense as five hundred nodes with activation of Relu function and also used SoftMax activation using as filter counts.

Fig. 5 shows the details of the proposed model where branch of conv. 2d layers using Relu. and max pooling then Flatten that data, have been taken.

```
Model: "sequential_3"
Layer (type)                Output Shape                Param #
-----
conv2d_12 (Conv2D)          (None, 24, 24, 60)         1560
conv2d_13 (Conv2D)          (None, 20, 20, 60)         90060
max_pooling2d_6 (MaxPooling2 (None, 10, 10, 60)         0
conv2d_14 (Conv2D)          (None, 8, 8, 30)           16230
conv2d_15 (Conv2D)          (None, 6, 6, 30)           8130
max_pooling2d_7 (MaxPooling2 (None, 3, 3, 30)           0
dropout_6 (Dropout)         (None, 3, 3, 30)           0
flatten_3 (Flatten)         (None, 270)                 0
dense_6 (Dense)             (None, 500)                 135500
dropout_7 (Dropout)         (None, 500)                 0
dense_7 (Dense)             (None, 60)                  30060
-----
Total params: 281,540
Trainable params: 281,540
Non-trainable params: 0
```

Fig. 5: Details of proposed sequential model.

VI. EXPERIMENTAL RESULTS

Some necessary steps are listed below which are required to fulfil system requirements:

- i) Handwritten dataset importing
- ii) Reshape data to train
- iii) Training the Model
- iv) Verify the model training
- v) Using test data that tested the proposed machine
- vi) Taking handwritten character to recognize that

Fig.6 shows the data Training and Verifying policy of proposed model with accuracy.

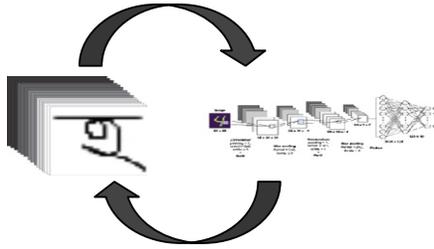


Fig. 6: Data Training and Verifying

Fig. 7 shows the period of giving the testing data in this model to test that model accuracy.

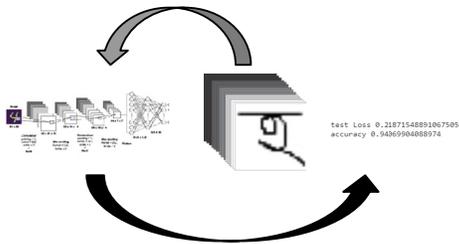
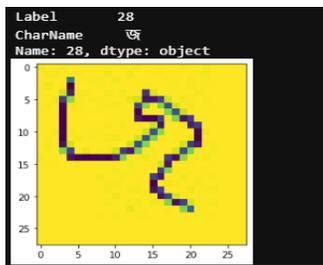


Fig. 7: Testing data and having accuracy of proposed model

Fig. 8(a) 8(b) and 8(c) show the input and output policy of proposed approach during detection and recognition of some specific character.



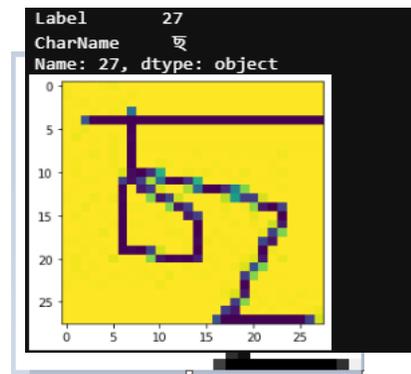
(Input)



(Output)

Fig. 8(a): Character Detection (ॐ)

(Input)



(Output)

Fig. 8(b): Character Detection (ॐ)



(Input)

(Output)

Fig. 8(c): Character Detection (ॐ)

Fig. 9(a) shows, the train and validation accuracy rate up to 90% of the proposed model.

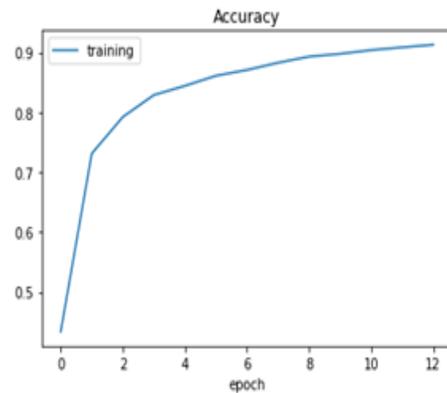


Fig. 9(a): Train and Validation accuracy rate of proposed model.

Fig. 9 (b) shows, the train and validation loss rate less than 10% of the proposed model.

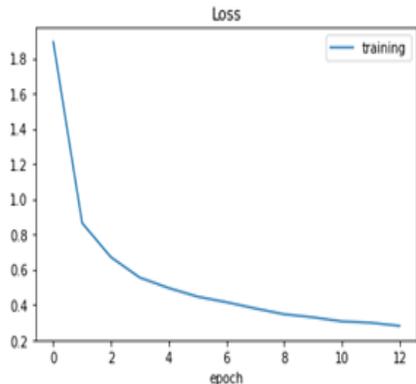


Fig. 9(b): Train and Validation loss rate of proposed model.

VII. CONCLUSIONS

In the field of artificial intelligence and machine learning dataset is the most crucial component. Significantly due to lack of large Bangla handwritten character dataset, Bangla handwritten character recognition could not program far. For some limitations, the proposed method only can recognize a single simple character not a branch of characters or a word in general. The proposed method is tested on different handwritten Bangla documents written by different individuals. This paper has presented CNN sequential models for training the proposed system and recognizing the input local character data to giving output. The performance of this model is superior compared to other implemented models for handwritten character recognition.

Experiment demonstrates that the proposed model obtained up to 90% accuracy on test dataset. In future, in order to improve the achieved performance, we need to investigate the problem further for finding better solution by designing a completely new architecture for Bangla handwritten character recognition including recognizing words, sentences and translating them into other languages.

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