COMPOUND BANGLA HANDWRITTEN CHARACTER DETECTION USING CNN ALGORITHM

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This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering

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APPROVAL

This project titled "**COMPOUND BANGLA HANDWRITTEN CHARACTER DETECTION USING CNN ALGORITHM**", submitted by Sheikh Shamshad Ahmed, Kamrun Nahar, Dipto Saha to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering (BSc) and approved as to its style and contents. The presentation has been held in December 2022.

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DECLARATION

We hereby declare that this thesis has been done by us under the supervision of **, Mr. Md. Aynul Hasan Nahid** Lecturer, Department of CSE, and co-supervision **of Md. Sanzidul Islam**, Lecturer,of **Department of CSE** Daffodil International University. We also declare that neither this thesis nor any part of this thesis has been submitted elsewhere for the award of any degree or diploma.

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ABSTRACT

Handwritten identification has been one of the top study topics for all researchers. Because of the ease and improved comprehension of their own language scalability with technology. For this purpose, we created a model for handwritten compound Bangla character detection from images. As we know in Bangla language, we have almost 320 compound characters. Among them 171 have been listed searching many google sources. Researchers works with about 110 characters out of 171. So we decided to work with rest of the 50 characters in that list which haven't worked before. The acquisition of datasets is essential to this research since the dataset will determine how accurate the model is. We have our own dataset collection with over 4500 pieces of data. Data was gathered using sheets and then converted to images (JPG format). Images have been handled in a way that we were able to develop the box detection algorithm in Python open CV along with other processing methods. We have used a machine learning approach which consists of multilayer CNN model with some convolution layer, maxpooling layer, dense layer and dropout layer. For our model, the accuracy we received was 88.48%, which is good.

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CHAPTER 1

INTRODUCTION

1.1 Introduction

Bangla Due to its several applications, including OCR, which aids in character recognition from images, automatic handwritten recognition has emerged as one of the most significant study areas in recent years. Information has moved from handwritten hardcopy papers over the past few years to more dependable digital file types. However, this system can manage new document formats. However, many older documents still exist today were written by hand. The difficulty comes from attempting to convert them if you use the manual typing method as is customary to copy the material. Because it requires a lot of labor and takes a long time. However, using OCR technology can assist digitize old data more quickly and with fewer resources. Few examples of compound characters are shown in Table 1.1

TABLE: 1.1 EXAMPLE OF COMPOUND CHARACTERS

ফ্ল	স্ফ	স্ত্র	হ্ব	হ্ন
হ্ল	চ্ছ	গ্ব	জ্ব	গ্ন
ব্ব	প্ন	প্স	স্ত	ব্ধ
ত্ত্ব	ন্দ্র	ক্ষ্ণ	শ্ন	স্ম

For the purpose of recognizing handwritten Bangla compound characters, a variety of techniques have been used, including neural networks, handmade features, support vector machines, and deep learning. Deep learning, particularly CNN [2] techniques, are favored among them for OCR-based applications due to their outstanding recognition performance and little pre-processing needs for assessing any input of visual images. A strong handwritten character recognition model is crucial for this reason. Despite this, there is no reliable paradigm for building a good Bangla OCR for handwritten characters. There is currently hardly a model that can accurately classify every type of composite character. In order to acquire information from the general community to train and test handwritten recognition systems, vast databases are a necessity. We have gathered handwritten letters from common people using a form to construct our dataset. There are 50 compound letters in each category. The 4500 forms we have collected contain 229,020 compound characters. Following the image's extraction from the cell, background removal and contour detection are performed. Thresholding and image inversion are also included in our method. A multilayer CNN model with some convolution layers, maxpooling layers, and dropout layers make up the machine learning strategy we utilized. The accuracy we obtained for our model was 89%, which is decent.

1.2 Motivation

One of the most widely used languages worldwide is Bengali. It is currently the most widely spoken language in India and the official language of Bangladesh. Bengali has played a significant role in the ethnic and national pride of Bangladeshis, as evidenced by the fact that many individuals have died trying to establish Bengali as our nation's official tongue. UNESCO proclaims February 21 as International Mother Language Day in honor of the Bangla language martyrs who died in Bangladesh in 1952. Therefore, 337 million people worldwide speak and write in Bangla. In considering the above circumstances, handwritten character recognition in Bangla is crucial in assisting those individuals with various needs like Data extraction from paper forms, automatic ID card reading, automatic document digitization, and traffic number plate recognition in Bangla are just a few examples.. Therefore, there is an urgent need to improve Bangla's computer compatibility. Bangla OCR has therefore received a lot of interest from scholars in recent years. Basic character and numeric identification in handwritten Bangla has been the subject of several investigations. However, handwritten Bangla compound character identification is still a relatively unexplored area of research in this field. Consequently, there is a lot of room for improvement in the recognition of handwritten Bangla compound characters. Because of this, we are motivated to work with Bangla so that it may be used to identify Bangla compound characters in a variety of ways.

1.3 Objective of the Study

The results that researchers want to get from their work are known as research objectives. Many studies have many goals for their study. Strong research objectives can aid an organization in achieving its overarching objectives. Research objectives serve as the direction for the whole research effort, including data collection, analysis, and conclusions. Research objectives also direct us through the study process by helping us to concentrate our research and identify its major components.

- The image processing approach should be designed to fully use the dataset in order to find any compound characters.
- To develop a model for precisely identifying Bangla compound characters from any picture.
- The model was constructed to be used on a huge scale.

1.4 Research Questions

- To fulfill this entire research is authenticity maintained?
- How dataset is collected?
- How dataset has been processed
- Can the machine learning process predict compound Bangla Character correctly?
- Is it possible to implement the gained knowledge and logic in real life in different technology?
- What is the process to help people by your concept?
- In future can this model can be enriched?

1.5 Research Methodology

Research Methodology is about how a researcher plans a study in a methodical way to guarantee that the results are accurate and trustworthy and that the research goals and objectives are met. This section will walk over the workflow we use, which entails data processing, model development, model training, and model evolution.

1.6 Report Layout

The following are the features of our work.

Chapter 1 Beginning with the portion of the study is really essential. This chapter also discusses the rationale for our decision to conduct the study. The summary and the reasoning of this investigation are the two most crucial parts of this chapter. In this section, the expected study results are also addressed.

Chapter 2 It includes an initial evaluation that gives a quick overview of the research done in this field. Here is an explanation of the related machine learning work. Additionally, the difficulties we encountered during this research and the scale of the problem.

Chapter 3 In this section, the topics of data set processing and model construction has been elaborately discussed.

Chapter 4 This section evaluated and examined the results of our model. It includes all the results of the graphical presentation for easier comprehension.

Chapter 5 It represents the study's concluding phase. The results of the model are discussed in this section. This part also covers the execution of the idea and performance. An examination of the work's constraints concludes the chapter. Additionally, the study's possibility was marked.

1.7 Expected Outcome

The major goal of our study is to recognize compound Bangla characters in any handwritten language. We anticipated that our built-up model would be able to reliably identify characters from photographs. In order to do this, we have gathered data via forms, converted it to pictures, and then preprocessed the image data so that it accurately recognized the characters. As a multilayer CNN model with certain convolution layers, maxpooling layers, and dropout layers that function as normalization is what we use to detect compound characters. We anticipate that our model will produce a result that accurately detects the characters.

CHAPTER 2

BACKGROUND STUDY

2.1 Introduction

The background of the study provides context for the information covered in the paper. The study's background therefore piques the reader's curiosity about the research issue and clarifies why it is important. For instance, the backdrop of a study can address how various factors affect the learning styles or academic performance gaps among grade 12 students. This is only an illustration, and you are the best person to decide what information to include in the study's background. This chapter gives a general summary of the associated tasks that many experts in the earlier region successfully completed.

2.2 Related Works

This topic was presented in a variety of ways and languages. Here is the some related works is given that helps us to improve the idea of our work.

For this work, color digital photographs of the Great Isaiah Scroll-based CR system were employed. With the use of image preprocessing techniques, manual segmentation, and tagging, the authors of this article produced a collection of isolated ancient Hebrew letters. Convolutional neural networks are used in this article to address issues with material deterioration, script complexity, and a variety of handwriting styles. In character recognition systems, there are four different CNN model types. AlexNet, VGG16, ResNet50, LeNet-5, and
AlexNet. Accuracy varies between 72, 57%, 78, 21%, and 84, 9%.[4]

The high classification rates from the CNN models in this study that have depths greater than 7 also suggest that deep CNN's are often a good class of models for classifying Japanese handwriting. Convolutional neural networks were able to attain good recognition rates across all categorization challenges. The models shown here outperform the human comparable recognition rate of 96.1% for character categorization. The National Institute of Advanced Industrial Science and Technology's Electro technical Laboratory (ETL) Character Database was used for the experiments (AIST). Test precision improved to 98.33%. [7]

A collection of 166,105 square pictures from 84 different classes (50 basic, 10 numerals, and 32 compound characters) were developed for this study. The greatest recorded accuracy is 97.21%. Using a classifier like CNN, MLP, SVM, etc. This study was carried out either by machine learning techniques or by character structure analysis.[8]

In this study, ECNN outperforms SCNN in terms of accuracy (accuracy=97.1%), whereas SCNN recognizes Persian handwritten letters with tolerable complexity and mediocre accuracy (accuracy=96.3%). Three different neural network types have been applied to the recognition of Persian handwriting in this article. The classification accuracy on the test set is up to 97.1% better thanks to this study's projected labels for 64 networks. With varying heights and widths, the dataset is in binary format. It is transformed to PNG-format pictures during the preparation stage. One of the most straightforward methods for categorizing images is linear classification. [11]

Convex hull-based feature extraction approach (125 features) was suggested in this study to categorize 50 basic characters and 10 numerals. For categorization purposes, MLP with an unique hidden layer was selected. In terms of recognizing handwritten basic characters and numerals, this approach had accuracy rates of 76.66% and 99.45%, respectively. [14]

The recognition of handwriting Japanese letters using deep convolutional neural networks was demonstrated in this article. In this paper, four various categorization problems are examined for various scripts. They work with the millions of handwriting Japanese characters in the Electro technical Laboratory (ETL) Character Database. In terms of total categorization, they received 99.53%. The models they developed surpass the human comparable detection accuracy of 96.1% for character categorization. [15]

This study uses a modified quadratic discriminant function to identify off-line Bangla handwritten compound characters (MQDF). They used the suggested strategy on a dataset of 20,543 examples of Bangla compound characters. They achieved an accuracy of 85.60% using this strategy. [17]

2.3 Scope of the Problem

About 337 million people in Bangladesh and two states in India speak Bangla as their first language. The majority of computer-based materials and technical periodicals available today are written in English. The language barrier presents a significant impediment to the general public's ability to fully benefit from contemporary ICT (information and communication technologies) and the vast, globally enhanced body of English knowledge. The only available technique to overcome this hurdle is language processing in the native tongue. Detecting Bangla compound characters is a very significant area of research, and it has already yielded some useful outcomes. If this research is successful, it might have a significant impact on how easily and effectively the general public can learn and utilize ICT in Bangla. The potential for solving this issue in the near future is enormous.

2.4 Challenges

To conduct this research, just like any other project, we encountered several difficulties. But in order for this to be successful, we overcame everything together.

- collecting or creating a suitable dataset for us to work with is the first and most important challenge.

- Utilizing the dataset is also every crucial and as the dataset is in image format image preprocessing is hard comparative other dataset.

- Due to structural proximity and non-uniform scaled properties, creating a Bangla compound character from the combination of many characters is a difficult operation.

- Our dataset requires a powerful GPU, we must use Colab-Pro which is quite new for us.

- Building the model in a way that we get a good accuracy for our model.

CHAPTER 3
RESEARCH METHODOLOGY

3.1 Introduction

The working method is divided into Different stages. Figure 3.1 depicts a diagram of our work.

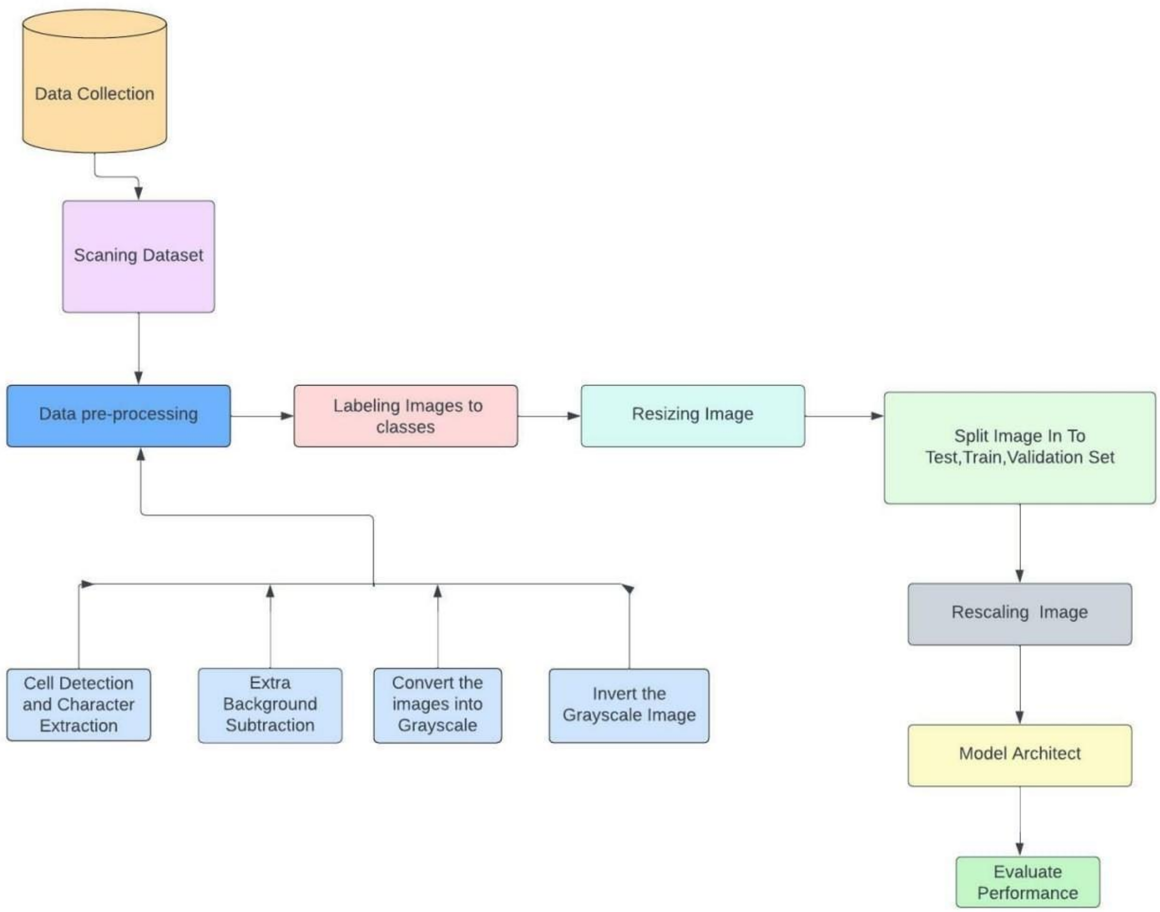


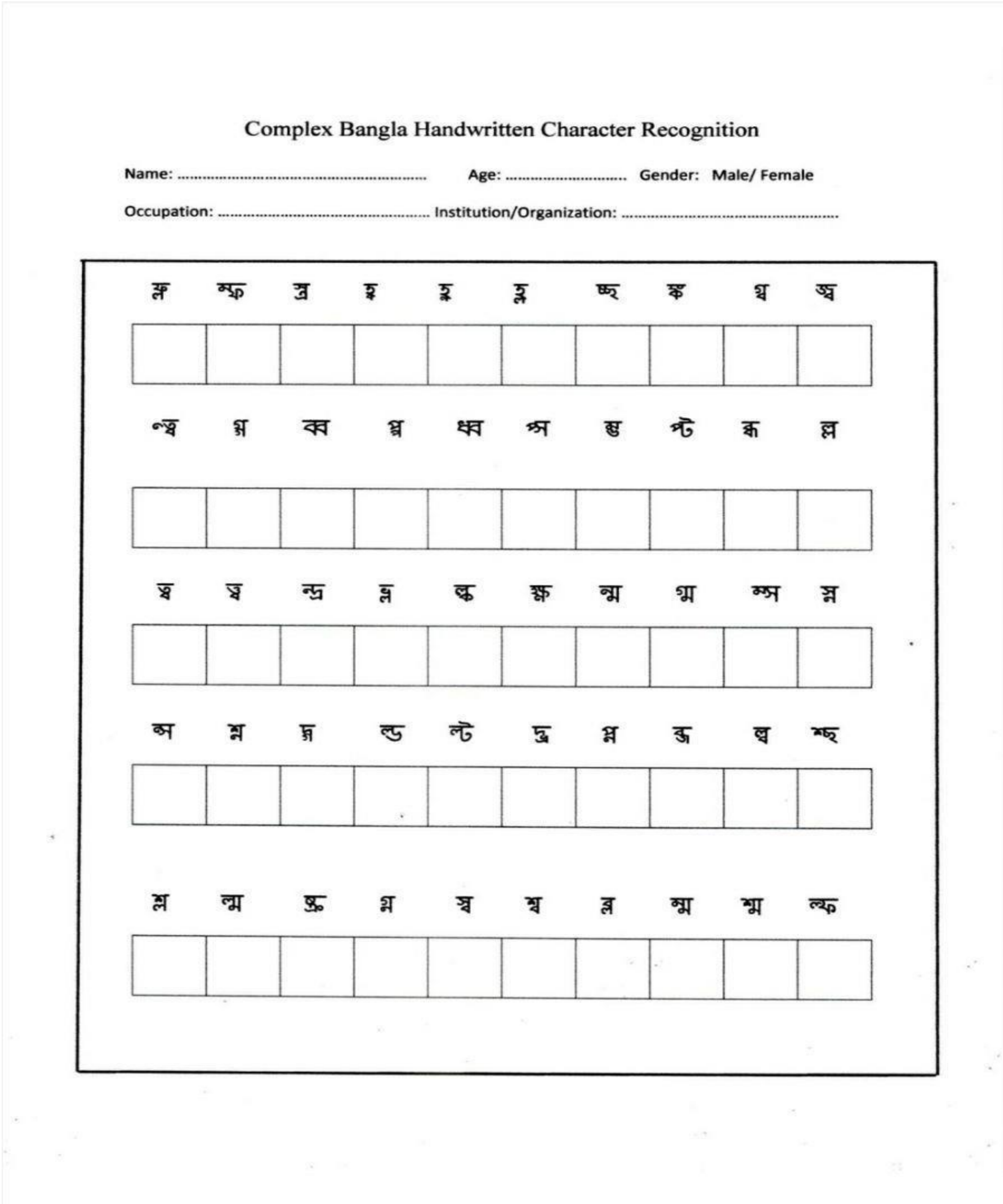
Figure 3.1 Methodology Diagram

3.2 Appropriate Form Creation

Making the research form is the top priority task, which is a little tacky since we will use the form to gather data, analyze the images on the dataset, and then utilize the dataset to determine the correctness of the suggested model. In order for Python OpenCV to identify significant data from the dataset, we have designed this form in a certain way. We have made vacant square-shaped compartments so that they might be filled up by other people. An example casting the character that must be typed in the vacant cells has been made above the empty cells. Anyone can grasp it because it was written in an approachable manner. Additionally, we print the form on a high-quality printer or copier. Because it's possible that if we don't utilize high-quality equipment, the printed label will be fuzzy and the volunteers can fill out the form inaccurately.

There are 5 rows and 10 columns total on this form. In addition to the top of the form, there are blank fields for name, age, and gender collection. The collected dataset can be categorized by occupation or gender in the future for use in other research projects.
Determination of factors which we keep in our mind to create the form.

- Variety in institutions.
- Age differences.
- Count occupation.


Complex Bangla Handwritten Character Recognition

Name: .... Age: .... Gender: Male/ Female

Occupation: .... Institution/Organization: ....

ক্ল ম্ফ ত্র হ্ন হ্ম হ্ল চ্ছ্র ঙ্ক থ্ব জ্ব

ন্ত্ব ঘ্ন ব্ব প্ন ধ্ব প্স স্ত প্ট ব্ধ ল্ল

ষ্ব ত্ব ন্দ্র ভ্ল ল্ক ক্ষ ন্ম গ্ম ম্স স্ন

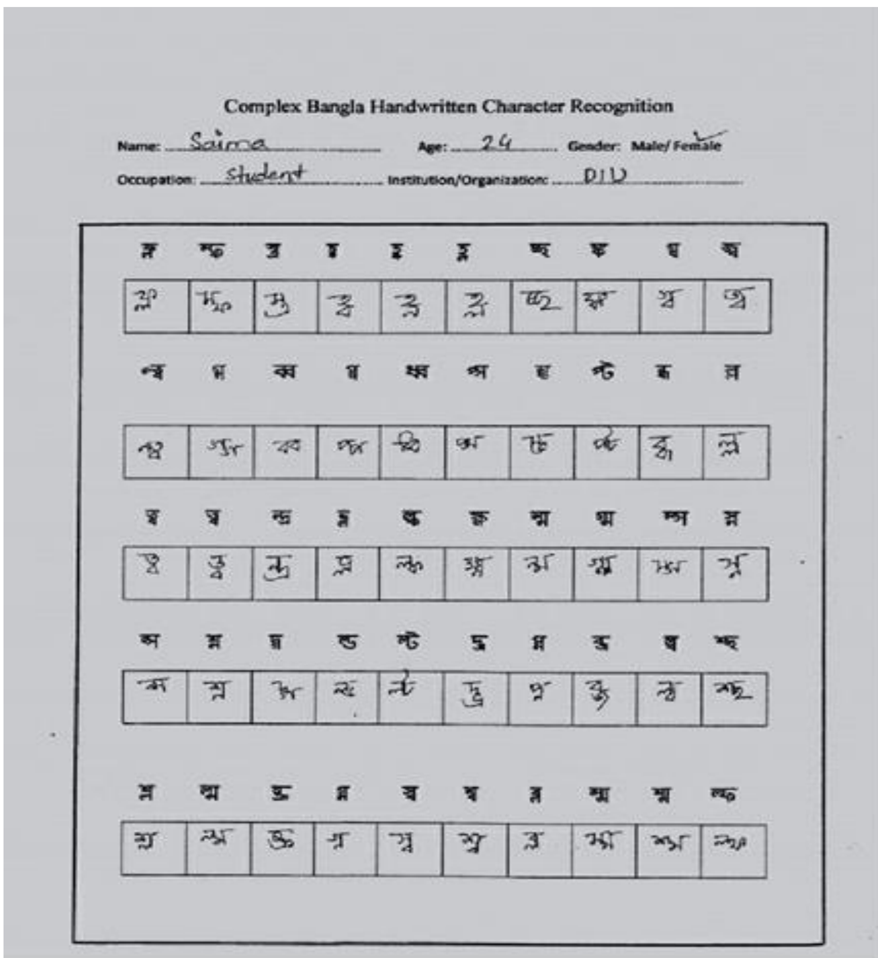
ত্স শ্ন দ্ন ল্ড ল্ট দ্ভ্র প্ন ব্জ ল্ব শ্ছ

শ্ল ল্ম ষ্ক্র গ্ন স্ব শ্ব ব্ল ষ্ম শ্ম ল্ফ

Figure 3.2: Form for Data Collection

3.3 Distribution and Data Collection

The most crucial and difficult element of this research is gathering the data and creating a meaningful dataset since, in order to train an NLP model, we need a decent amount of data in order to acquire excellent accuracy. We have worked on the level of the field to get this dataset ready. In order to enrich our dataset and properly train our model, we spoke with people of all ages and occupations and gave them consideration. By doing this, we can offer variety to our dataset. This dataset contains a sizable amount of information that was gathered from school, college, and university students We can gather 50 compound characters that were written by volunteers or persons from one form. Our dataset, which we have obtained from a total of 4500 forms, has 229,020 compound characters.


Complex Bangla Handwritten Character Recognition

Name: Saima Age: 24 Gender: Male/ Female

Occupation: Student Institution/Organization: DIU

Figure 3.3: Fill Up Form by People

3.4 Scanning the Form

Since we have collected the data via forms, we must scan them in order to turn them into images, from which we can then extract the data by processing the images. There are several techniques for scanning a form. We may use a variety of applications to do that. Any windows scanning program typically needs at least a minute to scan a single form. Additionally, the majority of Windows scan applications do not allow users to save several photos simultaneously. For convenience, we utilize the "Simple Scan" program [1] on "Ubuntu" at 300 dpi. It scans a page in 7–15 seconds and offers the option of storing and trimming the photos to lessen the scanner's excess black area. Figure 3.3 illustrate “Simple Scan” software in Ubuntu.

Figure 3.4 Simple Scan Software In Ubuntu

3.5 Cell Detection and Character Extraction

Preprocessing should always come first when dealing with OCR or any other data or object classification issue. In this context, preprocessing refers to the process of locating the location of our information. Any machine algorithm will be used to that image after extracting the location. Finding things that are in any tables, boxes, or row-column formats might be difficult. It has been designed so that characters may be quickly and readily identified and separated using Python's opencv library. To identify cells (boxes) and separate letters, we have created a box detecting algorithm. Figure 3.5(a) and 3.5(b) respectively depicts row wise cropping and character extraction images.

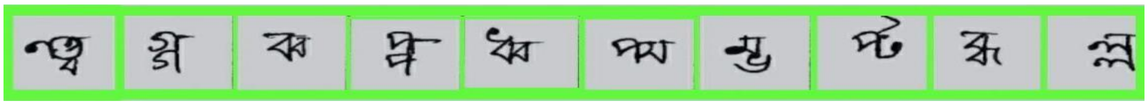


Figure 3.5(a): Rowwise Cropping

The next step is to find boxes. Morphological operations will be used for it. We shall create a rectangle kernel for that purpose, with length determined by the image's width. Two kernels will be defined. 1) A kernel that can find horizontal lines. 2) A kernel that can find vertical lines[23]. Now that kernels have been defined, we'll do morphological operations to find the vertical and horizontal lines. The picture with vertical lines is displayed in the code below. These two photos will now be included. There will only be boxes in this, and the data entered in each box will be deleted. In order to effectively detect the boxes and prevent noise from leading to erroneous box extraction.

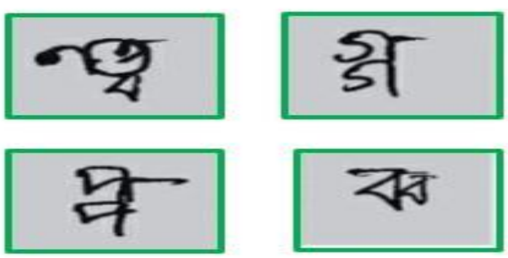


Figure 3.5(b): Character Extraction

3.6 Extra Background Subtraction

We achieve a decent outcome or accuracy in the model by removing additional or unwanted information from our separate photos. We did this by using a contour detection method. And by doing so, we can eliminate the extraneous backdrop and quickly identify the main subject of the photograph. Figure 3.6 depicts extra background subtraction from images.

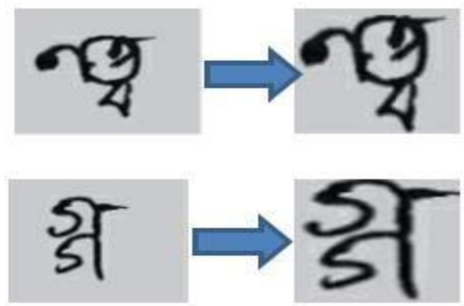


Figure 3.6: Extra Background Subtraction

3.7 Convert the Images into Grayscale and Invert the Images

Gray scaling is the method that transforms a picture from another color space, such as RGB, CMYK, HSV, etc., to various shades of gray. Absolute black and white are both possible. Grayscale images are required for thresholding; otherwise, it won't work. In order to make the photographs more apparent, we utilized OSTU threshold as our threshold. Figure 3.7(a) and 3.7(b) illustrate respectively grayscale and inverted images.

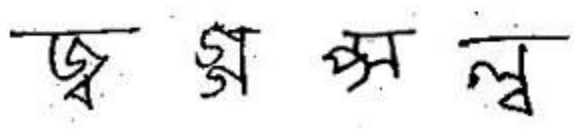


Figure 3.7(a): Grayscale Images

Figure 3.7(b): Inverted Images

Python and several Python libraries have been used for all of the work. The work is entirely automated. These libraries and the importing dataset folder have helped us finish the task.

3.8 Labeling Images to Appropriate Classes

We have 50 categories images. We need to store all our images to their respective classes. This will help to load the images easily during training our model. For a specific image we will get a label which will help to encode our images instances. We save the folder using numerical values. As if we save it in Bangla font it will not encode it appropriate form even may throws error for it. I'm showing some figures for our labeled dataset

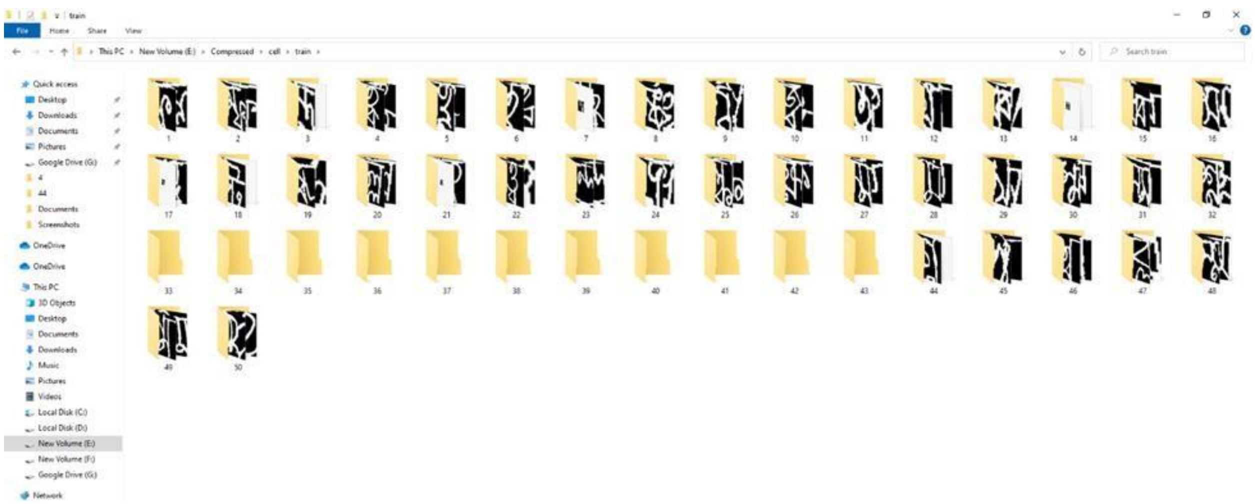


Figure 3.8 Folders of Classes

3.9 Resizing and Rescaling

We convert our data to a 28x28 pixel size. It aids in reducing the computing effort and accelerating model learning. There are variety of importance of rescaling and resizing for our model.

- Improve model accuracy
- Less computational power consumption
- Reduce time and space complexity
- Easy weight updating

Sometimes we take pictures with varied sizes and formats. If we supplied that into our algorithm, it would accept it as input but would not provide the optimal outcome. Because of this, we require a base size for all picture data. One channels are being used. Figure 3.7(a) shows the resizing code for our model.

```
input_folder="cell/test/50"
folderlen=len(input_folder)
os.mkdir("50")
i=0
for img in glob.glob(input_folder + "/*.jpg"):
    #image = cv2.imread(img)
    image = cv2.imread(img, cv2.IMREAD_UNCHANGED)
    #print('Original Dimensions : ',img.shape)
    width = 28
    height = 28
    dim = (width, height)
    # resize image
    resized = cv2.resize(image, dim, interpolation = cv2.INTER_AREA)
    cv2.imwrite("50/image%04i.jpg" %i,resized)
    i=i+1
```

Figure 3.8(a): Resizing Code for Images

Rescaling the data is necessary to make it simpler to calculate the model. Each pixel cell has a value between 0 and 255. Because the range of values is so wide, it was spread from 0 to 255 units. Which will be restricted to 0 and 1 if we rescale the value. Figure 3.7(b) shows the rescaling code for images.

```
ImageFile.LOAD_TRUNCATED_IMAGES = True

train_datagen = ImageDataGenerator(rescale = 1./255)
val_datagen = ImageDataGenerator(rescale = 1./255)
test_datagen = ImageDataGenerator(rescale = 1./255)
```

Figure 3.8(b): Rescaling Code for Image

3.10 Splitting Data into Test, Train and Validation

229020 images in all, found in 50 instances. We divided the total data set into three 7:2:1 portions. 70% (187080) of the data are used to train the model. 10% of the data (14019) were retained to assess the model, leaving 20% (27921) for validation. Fig 3.10 depicts graphical picture of splitting dataset.

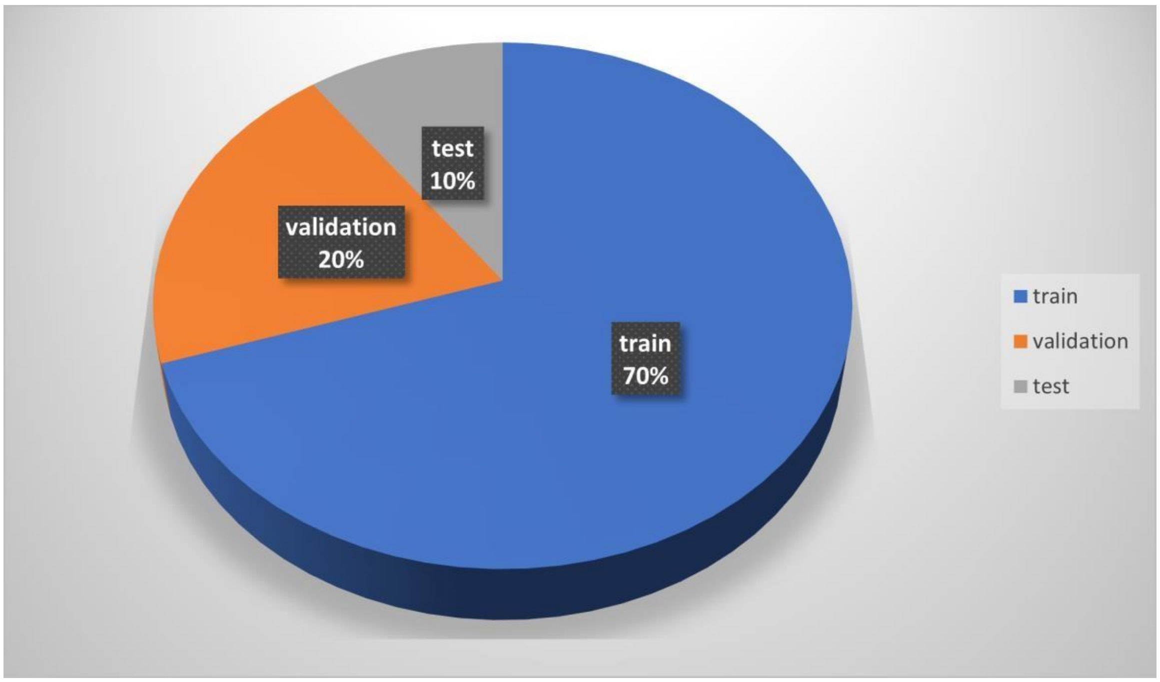


Figure 3.10; Splitting Dataset

3.11 Optimizer and learning Rate

To minimize the error we need optimizer. Optimizer helps to update weight such a way that will reduce accuracy errors and increase our accuracy. As optimizer we used ADAM optimizer. It performs really well It is the updated version of stochastic gradient descent optimizer algorithm. Here our learning rate is 0.001.

$$w_{t+1} = w_t - \widehat{m_t}\left(\frac{\alpha}{\sqrt{\widehat{v_t}+\epsilon}}\right)$$

Learning rate is very important factor for neural network. We will get more accuracy if the learning is low but our optimizer will consume more time to reach the global optima to minimize the loss. For the high learning rate it works reversely. Selecting a suitable learning rate is challenging. To overcome the difficulties we choose learning rate reducing automatically that will decrease our selective learning rate from 0.001 to downgrade or adjust it automatically with validation accuracy.

3.12 Loss Function

Loss Function will calculate the loss during model training and evaluating our test result according to our loss value the optimizer try to update their value and reach to global optima. In our model we used loss Function "Categorical Cross Entropy". Here cross entropy works well than other algorithm for finding error such as mean square error, square mean error.

$$L = -\frac{1}{m} \sum_{i=1}^{m} y_i \cdot \log(\hat{y}_i)$$

3.13 Model Architecture

As a multilayer CNN model, our model includes several convolution layers, maxpooling layers, and dropout layers that serve as normalization methods. Figure 3.8 illustrate different layer of our model.

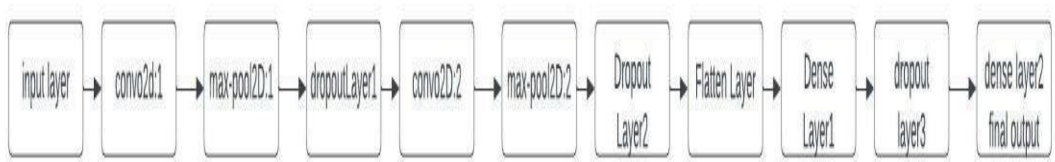


Figure 3.12: Architecture layers of Model

Convolution is a layer found in layers 1 and 4. We utilized filter numbers 64 for layer 1 and filter size (3,3) in the first convolution layer, which is identical to layer 4.That means we use same parameters for our two convolutional layers

In layers 1 and 4, relu has been employed for the activation function. Layers 2 and 5 function as a maxpooling layer, with case pooling sizes of 2*2 and 0.2 dropout layers 3 and 6 in between.

Value in layer 7 has been flattered the output's last three levels. Out of these three layers, two are dense and one is a dropout layer with a ratio of about 0.20. A activator function is used in the first dense layer's 128 output nodes. The thick final layer, which represents the output for 44 classes, It uses the softmax activation function on 44 nodes as a result. We employ the ADAM optimizer throughout the model, and "Catagorical crossentropy" is used to count losses.Model summary is shown in table 3.8

TABLE: 3.13 MODEL SUMMARY

Layer	Type	Output Shape	Param #
conv2d	(conv2D)	(None, 26, 26, 64)	640
Max_pooling2d	(Maxpooling2D)	(None, 13, 13, 64)	0
dropout	(Dropout)	(None, 13, 13, 64)	0
conv2d_1	(Conv2D)	(None, 11, 11, 64)	36928
Max_pooling2d_1	(Maxpooling2D)	(None, 5, 5, 64)	0
Dropout_1	(Dropout)	(None, 5, 5, 64)	0
flatten	(Flatten)	(None, 1600)	0
dense	(Dense)	(None, 128)	204928
dropout_2	(Dropout)	(None, 128)	0
Dense_1	(Dense)	(None, 50)	6450

Total params: 248,172

Trainable params: 248,172

Non-trainable params: 0

CHAPTER 4
RESULT ANALYSIS

4.1 Introduction

Results Analysis (RA) function evaluates ongoing, incomplete operations such as service orders, production orders, internal orders, or projects. One type of outcomes analysis is resource-related results analysis. The repercussions segment should be structured so that the outcomes are stated without any interpretation or evaluation. The guidance is also accessible in the academic papers area. The results are announced, and the test is shown.

4.2 Model Accuracy, Loss, and Overall performance

As we executes 50 epochs in our model, we obtained 90.03% accuracy on our training set and 89.67% accuracy on our validation dataset. We customized our test dataset on that our model perform very well, it is 88.48% and loss 0.427.

Analyzing model accuracy and confusion matrix, our model works pretty well to identify our handwritten Bangla character. Because our handwritten differs from person to person, it has curvy shapes and also joint alphabets makes compound character. So it is much more tough to identify in our neural network, even human finds it difficult to identify it. Considering all situations, it can be said that our model perform really well. I am giving a figure which will show the training, validation accuracy and loss. A comprehensive comparison is shown in the figure 4.2 bellow.

--- =validation

--- =train

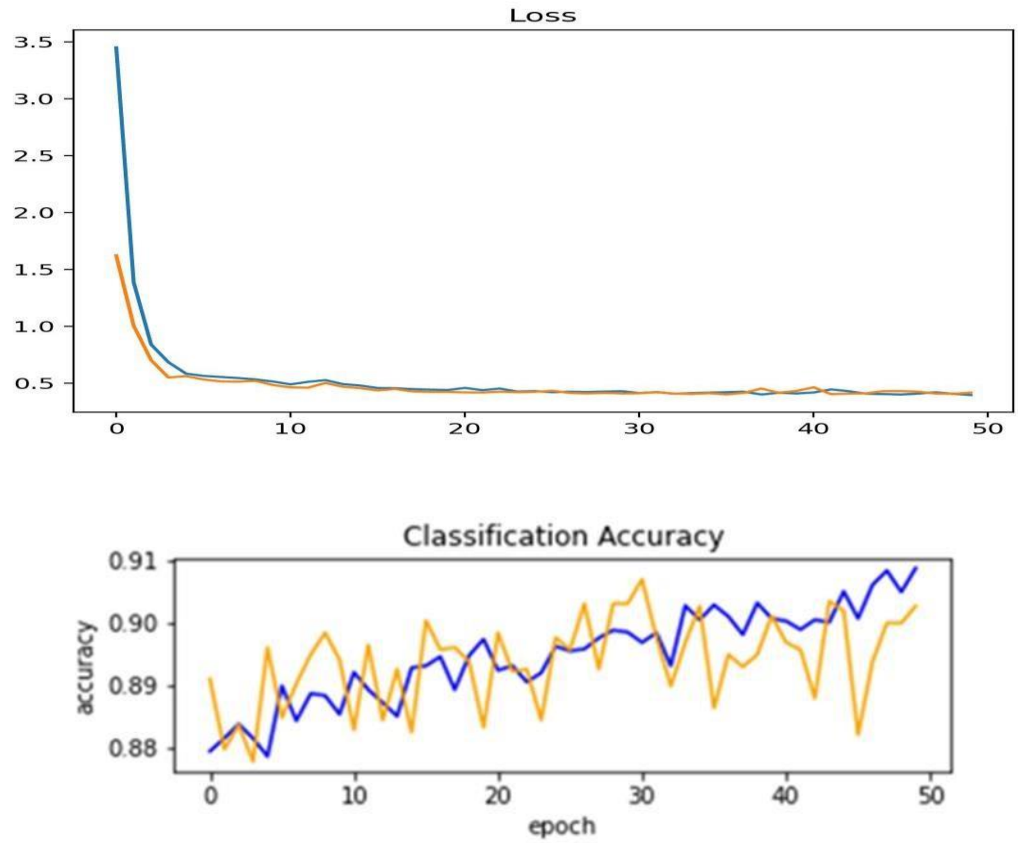


Figure 4.2: Loss and accuracy from Train and validation

4.3 Predicted Label

As our mode gives 88.48% accuracy on our test value that means it gives accurate result for 12,336 separated characters and showing wrong prediction for 1682 character in testing dataset. Some figures has been attached below that will show the prediction label for our testing dataset. Also showing some figure that will not predict true result. Some correct prediction from the test set are presented on Table. 4.3(a), and errors from the cross-validation are shown on Table. 4.3(b). It is evident from these photos that the model works well, with the biggest mistake coming from datasets with inaccurate labels.

TABLE: 4.3(a) CORRECT PREDICTION

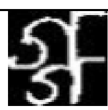
Images	Predicted Label	True Label
	ল্ট	ল্ট
	গ্ল	গ্ল
	ব্ব	ব্ব
	ল্ব	ল্ব

TABLE: 4.3(b) ERROR

Images	Predicted Label	True Label
	শ্ন	চ্ছ
	ত্ত্ব	জ্ব

4.4 Comparison with Other Works

We only came across a very small number of publications that used bangla compound characters; using those papers, we created a comparison. In table the comparison of our study with other papers is shown.

TABLE: 4.4 COMPARISON WITH SOME PREVIOUS WORK

Reference	Year	Method	Accuracy	Findings
Nibaran et al.[1]	2010	SVM,MLP	79.25% using MLP and 80.510% using SVM	Accuracy can be enriched
Akm Ashiquzzaman et al. [7]	2014	SVM	79.35%	Despite using fewer compound characters, their accuracy isn't very excellent.
U.Pal et al.[18]	2007	Modified Quadratic Discriminant Function (MQDF)	85.90%	Image processing may be improved significantly to obtain high accuracy.
Saikat Roy et al.[20]	2017	Deep Convolutional Networks (DCNN)	90.33%	Their Dataset only compares a limited number of compound characters instances to ordinary characters. So, based on their dataset, they obtained their accuracy.
Not Published	Not Published	CNN with Relu and Dropout	88.50%	As we work with a large number of dataset we got a good accuracy.

CHAPTER 5

SUMMARY, CONCLUSION AND FUTURE WORK

5.1 Summary of the Study

The gathering of data serves as the beginning of our path. In order to obtain a diversity of data for our dataset, we created an appropriate form and sent it to all types of people. Preprocessing of images is included later. Scanning our really large form. Extraction of the picture from the cell is followed by contour detection and background subtraction. Our approach includes thresholding and picture inversion as well. The implementation of the algorithm follows. Finally, we assess the output of our model.

5.2 Conclusion

A standard method for processing any language's handwritten character database has been developed thanks to the study presented here. For every language, handwritten character recognition systems may be developed using that database. Researchers will gain knowledge in a variety of study areas by using the suggested methods, which will also aid in the development of automated recognition of the writer's age, gender, location, and other characteristics. The processing of data is essential for all research objectives since the forensic database is a key source of information. Convolutional Neural Networks perform better at classifying and identifying Bangla handwritten letters, numbers, and complex characters, therefore it makes sense to take this into account while analyzing the model. If we had additional resources, such as a bigger dataset, a high-end computer, or a GPU, the accuracy would have been higher when this model produced the results. Researchers can provide better results and advance the state-of-the-art scale for recognizing Bangla handwritten compound characters in the future with more resources and a larger CNN architecture.

5.3 Future Work

The following is future direction on the development of this work:

- We want to utilize it with any program in the future since this approach makes it possible to identify Bangla compound characters.

- We also aim to improve the dataset in order to run our model and improve model accuracy.

- The model may be enhanced to make it simple to separate character detection.

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APPENDIX

The initial step included outlining the analysis's processes, which offered a number of challenges. It was the first report. Furthermore, there hasn't been much advancement in this field in the past. Indeed. It wasn't a standard job, either. We were unable to locate somebody who could be that helpful. Data collecting also proven to be a significant challenge for us. Because we were unable to find an open source Bangladeshi text pre-processing application, we constructed a data collection corpus. We have started manually gathering data. Furthermore, it is challenging to categorize the varied posts. We may be able to do it after a long period of hard work.

PLAGIARISM REPORT

ORIGINALITY REPORT

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