ARTIFICIAL INTELLIGENCE BASED MODEL FOR HANDWRITTEN RECOGNITION

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ABSTRACT:

An all-encompassing method for improved handwriting recognition is put forward in this project. By speeding up the process of turning documents into letters, handwriting recognition algorithms can lessen the effort. The thesis uses the multi-script handwritten font family, which includes the Latin, MNIST handwritten alphabet series on prescription, and the Bangla font. Genetic algorithms and artificial intelligence tools were used in the creation and development of this stage. This method was created to deliver correct results in the recognition of the Bangla set, which is 54.05 percent, Latin, which is 98.58 percent, and MNIST, which is 98.58 percent.

Keywords — Handwritten, Recognition, SVM algorithm, Artificial Intelligence, Multi-scripts.

1 INTRODUCTION

In the fields of pattern recognition and artificial intelligence, handwritten recognition (HR) is a difficult problem. These techniques make it easier to translate a variety of written materials, including letters, postcards, historical records, inscriptions, novels by Bai Lan, newspaper articles, and other types of documents. There are three categories of handwriting complexity: simple, moderate, and tough. It is difficult to design a handwriting recognition system based on research. then converts the leaves into digital form using over 1,000 lilac picture files. However, it was discovered that there was just a half leaf. much of the textbook on the Bai Lan inscription. Ancient customs, local history, and other important facts are in poor shape or eliminated altogether as a result of storage. Researchers from all across the world understand the significance of acknowledgment for this additional reason. interpreting handwritten characters using evolving techniques and methodologies, such better character categorization systems. the accurate and quick classification for stock price predictions, sound categorization, and accurate information retrieval. the connection between hospital test results, drugs, and patient issues.

In commercial settings, handwritten recognition systems (HRS) are frequently employed for tasks including the identification of postal codes, bank cheques, and postcards. Profit from this study. Identification is the process of locating and analysing authors. Check documents It is often employed, including in courts of law and for the electronic signing of applications for financial transactions. Apart from MNIST handwritten digit we extend our scope to BANGLA handwritten digit recognition. By implementing both machine learning and deep learning Techniques.

Bengali, often known as Bangla, is the fifth most utilised language worldwide and the second most popular language in Bangladesh and India.

The MNIST data set is a portion of the NIST data set, which consists of a digitised picture that has been scaled to the standard and is centred over a handwritten static size image. The handwritten pictures are from the MNIST data collection and are 28 × 28 pixels in size.

PURPOSE OF PROJECT

We created a model to detect handwritten digits for MNIST and BANGLA in this, which is very helpful for many real-time applications (like vehile number plate recognition) The researcher evaluated the effectiveness of the offered algorithms and strategies using the study methodology specified subsequently. By determining the suggested algorithm's accuracy and reporting this part. This research uses artificial intelligence to recognise handwritten characters among three sets of characters from various authors. In certain classes, these characters' problems are the same. In Bangladesh and India, Bangla is the second most widely spoken language. There are 45 classes in the Bangla Handwriting Handbook, 4,627 classes in the training set, and 900 examples in the test suite. Dutch is written in cursive Latin letters. 37,616 handwritten characters, 26,329 practise examples, and 11,287 sample samples are available for 251 authors. Large databases of numbers make up the MNIST data sets. Image processing algorithms are frequently trained using human handwriting. The picture is 28 × 28 pixels in size.

2. LITERATURE SURVEY

Recent advances in handwritten text recovery from collections of scanned historical documents are now possible because to recent advancements in "off-line" writer identification. The outlines of fractured connecting components in free-style handwriting are used in this research to introduce novel algorithms for forensic or historical writer identification. A stochastic pattern generator is thought to represent the author and produce a group of character tiny bits (fraglets). The probability distribution of fraglet outlines for an independent test set was calculated using a code generator of such fraglets from a separate training set. The fraglet histogram was very sensitive in identifying specific writers based on a paragraph of text, according to the results. Large-scale tests on the ideal Kohonen map dimension for fraglet contours were conducted, and the results showed reasonable classification scores within a non-critical range. The suggested automated methodology fills the gap between solely knowledge-based manually character-based methods and image-statistics approaches.

A particularly difficult task is automated handwriting recognition. Without it, there is currently no algorithm that can detect handwriting; instead, there are presumptions that must be made in order to make the process easier. A handwritten text may include lowercase, capital, stick, and digitised letters. Therefore, it is crucial to understand how to isolate and differentiate all of these individual components in order to process them according to the class handwriting's specialised algorithms. We describe a system for unrestricted handwritten text recognition in this research, which enables this operation through intelligent classification based on recursive cutting in a multi-script context. The findings of the test indicates that there is a "equal error rate" (EER) that is close to 6%. These calculations used a base that was rather modest, however a larger base might result in a lower rate. For the mere fact that our technique is located in a more generic framework as opposed to other approaches that establish various non-rigid assumptions, which certainly makes the problem smoother and may even make it easy, our results are quite encouraging.

A generic approach for more effective handwriting recognition was suggested in this study. In order to lighten the effort, handwriting recognition algorithms can speed up the process of converting documents into letters. Multi-script, which includes the Latin, Bangla, and MNIST handwritten alphabet succession on prescription, are the handwritten typefaces utilised in this thesis.

Artificial intelligence and genetic algorithms were used in the creation and development of this stage. This method was created and developed to deliver high accuracy in the identification of the Bangla set, which is 94.05% correct, Latin, which is 98.58% accurate, and MNIST, which is 100% accurate.

The use of biology in law enforcement is known as forensic biology. One type of biometric that may be used to determine owners is handwriting habit. This article suggests an algorithm for document handwriting verification in Thai. This effort was done to demonstrate the experiment's handwriting. This paper's fundamental problem is broken down into three processes: data preparation, classification, and outcomes. Consequentially, a two-step neuron network approach is employed to accurately handle classification tasks. The handwriting models are then made. Finally, we provide criteria for comparing unidentified handwritten writing to our model. Height accuracy is 90.00 percent according to the findings.

Historical document transcriptions are a great resource for obtaining labelled handwriting pictures that may be used to train handwriting recognition software. The Saint Gall database, which contains photographs and a transcription of a Latin text from the 9th century written in Carolingian script, is introduced in this work. The supplied transcription is of excellent quality for a human reader, however when compared to the handwriting image, the grammar of the words is incorrect. As a result, there are a number of alignment issues with the transcription, such as line spacing, abbreviations, and capitalization. Our alignment solution, which is centered on character Invisible Markov Models and can handle these difficulties, effectively aligns all of the pages in a manuscript. On the Saint Gall database, we show that even with poorly trained character models, a respectable alignment accuracy may be attained.

3 MATERIALS AND METHODS

The Convolutional Neural Networks (CNN) are used to extract the features of the images using several layers of filters.

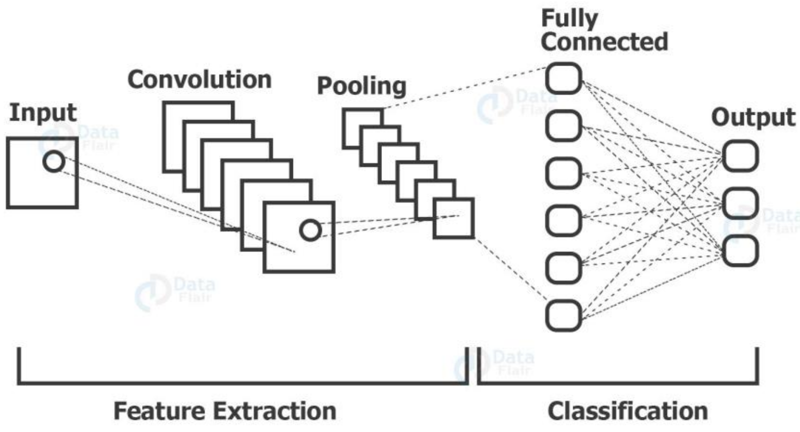

Fig : Methodology for image recognition

The convolution layers are generally followed by maxpool layers that are used to reduce the number of features extracted and ultimately the output of the maxpool and layers and convolution layers are flattened into a vector of single dimension and are given as an input to the Dense layer (The fully connected network).

The model created is as follows:

```
model = Sequential()
model.add(Conv2D(filters=32, kernel_size=(3, 3), activation='relu', input_shape=(28,28,1)))
model.add(MaxPool2D(pool_size=(2, 2), strides=2))
model.add(Conv2D(filters=64, kernel_size=(3, 3), activation='relu', padding = 'same'))
model.add(MaxPool2D(pool_size=(2, 2), strides=2))
model.add(Conv2D(filters=128, kernel_size=(3, 3), activation='relu', padding = 'valid'))
model.add(MaxPool2D(pool_size=(2, 2), strides=2))
model.add(Flatten())
model.add(Dense(64,activation ="relu"))
model.add(Dense(128,activation ="relu"))
model.add(Dense(26,activation ="softmax"))
```

4. RESULTS AND DISCUSSION

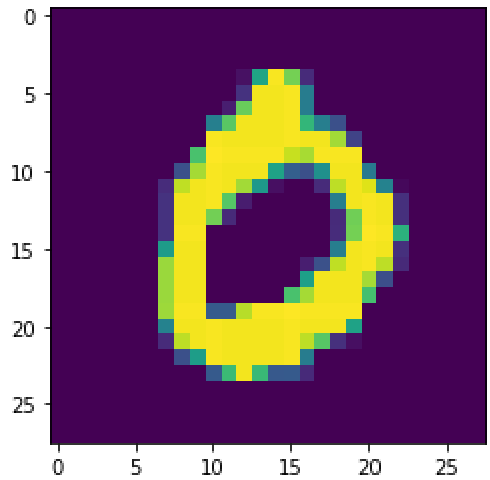

Fig : Digitalized image of input

```
Train Data: [ 6000  6001  6002 ... 59997 59998 59999] validation data: [    0     1     2 ... 5997 5998 5999]
Train Data: [    0     1     2 ... 59997 59998 59999] validation data: [ 6000  6001  6002 ... 11997 11998 11999]
Train Data: [    0     1     2 ... 59997 59998 59999] validation data: [12000 12001 12002 ... 17997 17998 17999]
Train Data: [    0     1     2 ... 59997 59998 59999] validation data: [18000 18001 18002 ... 23997 23998 23999]
Train Data: [    0     1     2 ... 59997 59998 59999] validation data: [24000 24001 24002 ... 29997 29998 29999]
Train Data: [    0     1     2 ... 59997 59998 59999] validation data: [30000 30001 30002 ... 35997 35998 35999]
Train Data: [    0     1     2 ... 59997 59998 59999] validation data: [36000 36001 36002 ... 41997 41998 41999]
Train Data: [    0     1     2 ... 59997 59998 59999] validation data: [42000 42001 42002 ... 47997 47998 47999]
Train Data: [    0     1     2 ... 59997 59998 59999] validation data: [48000 48001 48002 ... 53997 53998 53999]
```

Table : Trained input with validation of data

```
Epoch 1/10
 - 13s - loss: 0.2444 - accuracy: 0.929
Epoch 2/10
 - 13s - loss: 0.0723 - accuracy: 0.978
Epoch 3/10
 - 13s - loss: 0.0471 - accuracy: 0.985
Epoch 4/10
 - 13s - loss: 0.0352 - accuracy: 0.989
Epoch 5/10
 - 13s - loss: 0.0262 - accuracy: 0.992
Epoch 6/10
 - 13s - loss: 0.0193 - accuracy: 0.994
Epoch 7/10
 - 13s - loss: 0.0152 - accuracy: 0.995
Epoch 8/10
 - 13s - loss: 0.0116 - accuracy: 0.996
Epoch 9/10
 - 13s - loss: 0.0090 - accuracy: 0.997
Epoch 10/10
 - 13s - loss: 0.0065 - accuracy: 0.998
6000/6000 [============================
Test loss: 0.05234152577305698
Test accuracy: 0.9869999885559082
```

Table : Testing accuracy with loss level after validation

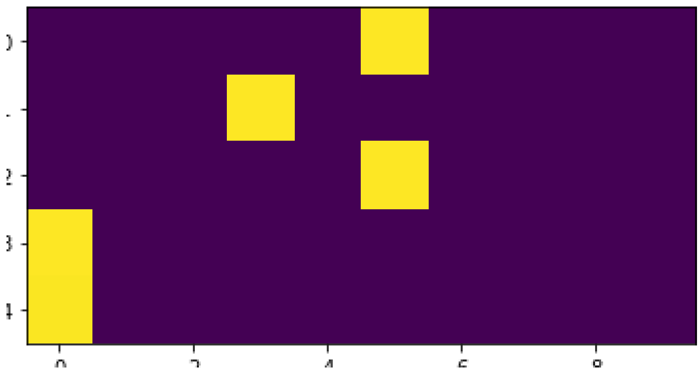

Fig : Test input images output with digitilized plots

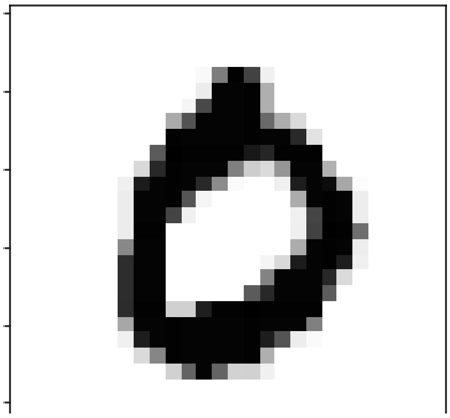

Fig : Recognised image by the model

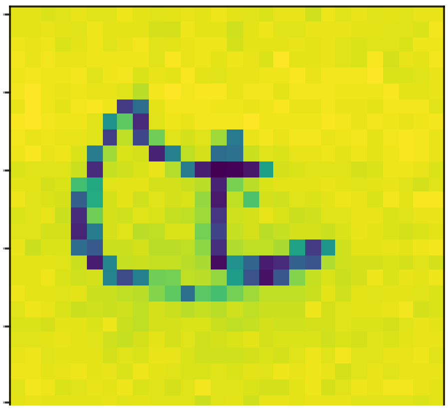

Fig : Recognised sample image

CONCLUSION

The goal of this research is to create fresh handwriting recognition algorithms. In this investigation, a collection of alphabetical photographs was utilised, which is often done in this situation for character recognition. Popular handwritten scripts like Bangla Latin and MNIST are included in the three sets of data. algorithm for recognition based on the outcomes of this algorithm for handwriting recognition. To supply picture data for processing, researchers have created and constructed an algorithm based on the theory of digital image processing. Series have been created from different images utilised in this investigation. In order to assess the efficacy of this investigation, the initial set was the Bangla Latin MNIST font set. The test image has a well-formed typeface sandwiched between both the content and the background, as you can see. The image's backdrop is white as well. Following that, the extraction procedure was carried out in order to calculate the pixel density using the image processing approach. Before include handwriting features in the recognition task, genetic algorithms were employed to examine the extraction of such features.

Following that, the extraction procedure was carried out in order to calculate the pixel density using the image processing approach. Prior include handwriting characteristics in the recognition process, genetic algorithms were employed to examine the retrieval of such features.

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