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Deep Learning-based Recognition of Devanagari Handwritten Characters

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Abstract- Numerous techniques have been used over many years to study handwriting recognition. There are two methods for reading handwriting, one of which is online and the other offline. Image recognition is the main part of the handwriting recognition process. Image recognition gives careful consideration to the picture's dimensions, viewing angle, and image quality. Machine learning and deep learning techniques are the two areas of focus for developers looking to increase the intelligence of computers. A person may learn to perform a task by repeatedly exercising it until they recall how to do it. His brain's neurons begin to work automatically, enabling him to carry out the task he has quickly learned. This and deep learning are fairly similar. It uses a variety of neural network designs to address a range of problems. The convolution neural network (CNN) is a very effective technique for handwriting and picture detection.

Keywords- Deep learning; Devanagari characters; convolutional neural network; handwritten character recognition; adaptive gradient methods, Image processing, Computer vision

I. INTRODUCTION

Handwriting recognition is the ability of a machine to recognise and predict the human handwritten character. It is a very difficult task for machines to make handwritten letters, figures, or characters since they are not always accurate and can be made with a range of tastes. This article offers a way for precisely identifying and anticipating handwritten characters as a consequence. To collect and analyse legible handwriting data from sources including paper documents, touch screens, photo graphs, and more, "handwriting detection" is a computer method or capability. One kind of spatial pattern recognition is the recognition of handwritten text. Using pattern recognition, data or objects are categorised or sorted into one of several groups or categories. The method of handwriting recognition involves converting a language conveyed by graphical markings in space into its symbolic equivalent. A number of symbols collectively referred to as letters or characters make up any script and each of these symbols has a basic structure. Using handwriting, several automated process systems can accurately identify input letters or images for further analysis.

To collect and analyze legible handwriting data from sources like paper documents, touch displays, photo graphs, and more, "handwriting detection" is a computer technique or capability. One kind of spatial pattern recognition is the recognition of handwritten text. Using pattern recognition, data or objects are categorized or sorted into one of many groups or categories. The method of handwriting recognition involves converting a language conveyed by graphical markings in space into its symbolic equivalent. A number of symbols collectively referred to as letters or characters make up any script, and each of these symbols has a basic structure. Handwriting is used to accurately identify input letters or images that are afterwards evaluated by various automated process systems. So that document processing can be facilitated, a computer is needed to read documents or data. Several strategies can be employed to get notoriety. There are several techniques employed, including Convolutional Neural Networks (CNN), Semi Incremental Methods, Incremental Methods, Line and Word Segmentation, and others. One of the most effective and well-known techniques for handwriting recognition (CNN) is convolutional neural networks. It belongs to the deep learning procedure. CNN is most frequently used for visual imagining analysis. Convolutional neural networks (CNNs) are composed of artificial neurons.

II. LITERATURE SURVEY

Using CNN to recognise handwritten Devanagari and Bangla characters online is a deep learning concept. Using CNN (convolution neural network), a deep learning technique, online handwriting detection is possible for Devanagari and Bangla. The model we propose is a fully connected network with two convolution and pooling layers. Instead of creating features manually, the CNN model creates them, automatically reduces their dimension, and then delivers the characteristics

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of a fully linked network for categorization. In the current study, there are 10,000 basic Bangla characters and 1800 Devanagari characters. Convolutional neural networks are used to distinguish handwritten Devanagari characters [2]. A method for identifying handwritten Devanagari letters One of the most extensively used scripts is Devanagari, which is used in several Indian languages. The Hindi language is also written using the Devanagari script. In this article, we study and analyse the use of deep learning techniques like convolutional neural networks to recognise Devanagari characters. CNNs classify characters using neurons linked in different layers for maximum effectiveness, emulating the organisation of the human brain. This study used six layers of neurons to classify Devanagari letters. This technique managed to achieve an accuracy rate of 95.6%. Once identified, other people might easily convert the handwritten Devanagari characters into English or any other language.

Deep Learning Network Architecture is used to recognise Kannada handwritten characters [3]. The Devanagari character set has 92000 total pictures over 46 classes. On the other hand, the Kannada character set consists of 188 classes, each with 200–500 sample pictures, for a total of 81654 training images and 9401 testing images. 1,23,654 data samples in total were utilised to train the VGG19 NET. For the testing, 9401 samples from 188 classes comprising 40–100 samples each were employed. Over 90% accuracy was achieved. The VGG19 NET validated an accuracy of 73.51% with a loss of 16.18% after 10 evaluations. They developed the concept of transfer learning in response to the need for huge datasets in deep learning systems. Even while deep learning techniques are highly effective and dependable in obtaining higher accuracy, they depend on very big datasets with good training data labelling. Machine learning in Noise for Handwritten Character Recognition in Odia [4]. Offline odia handwritten characters with and without noise are classified using this model, which has been used to prepare the data. This work aims to build a narrative machine learning approach that combines Naive Bayes and Decision Tables to classify Offline Odia handwritten characters in the Waikato Environment for Knowledge Analysis (WEKA) environment. It has been demonstrated that the noiseless character outperforms the noise character in both the Naive Bayes and Decision Table classification algorithms. Identifying Devanagari Handwriting Using Convolutional Neural Networks [5]. The alphabetic letters change when a vowel is added to a consonant. The letters are not capitalised like in Latin languages. The Devanagari script is made up of consonants and modifiers. A collection of 29 consonants and one change form the foundation of the strategy described in this article. It uses a collection of 29 consonants in the Devanagari script that the author produced; there is no header line (Shirorekha) above them. The collection contains 34604 handwritten images. Deep learning techniques are applied to detect letters and extract attributes from images. They employed a Deep Convolutional Neural Network (DCNN) to identify features in the input photos and categorise them. The use of successive convolutional layers in this technique aids in the extraction of higher-level information. The trained model's accuracy percentage is 99.65%.

A deep learning technique called Deep Net Devanagari [6] is used to identify ancient Devanagari characters. The authors suggest using a deep learning model to detect 33 different types of crucial characters in old Devanagari manuscripts as a feature extractor and classifier. A 5484-character dataset was used in an experimental study that was conducted. Numerous studies demonstrate that, compared to other state-of-the-art methods, utilising CNN as a feature extractor improves accuracy. Using the approach outlined in this article, the accuracy of the Devanagari ancient character recognition was 93.73%. For the purpose of creating ground truth for handwritten character recognition, multi-feature representations with density-based semi-automatic labelling are used [7]. The method use the nearest neighbour graph in an iterative procedure to assess samples in different feature spaces. An expert is tasked with selecting a pertinent unlabeled sample at random from the area with the highest concentration of unlabeled samples at the start of each iteration. The manually annotated label is then disseminated to nearby samples safely utilising sample density and multi-views. Continue until all samples that aren't labelled have been done so. The suggested labelling method is evaluated on datasets from MNIST, Devanagari, Thai, and Lana Dhamma, and it yields a 93.73% accuracy rate. The outcomes demonstrate that the proposed strategy performs better than the state-of-the-art labelling methods and attains the maximum level of labelling accuracy. It also supports outlier samples and alphabets with seemingly similar letters. Additionally, the classification performance of the classifier learned using the semi-automatically constructed training dataset is equivalent to the classification performance of the classifier taught using real-world data.

A stacked ensemble neural network may be used to distinguish handwritten Marathi digits [8]. A stacked ensemble meta-learning strategy for tailored convolutional neural networks is described for the aim of identifying Marathi handwritten numerals. The pre-trained base pipelines are stacked to provide multi-head meta-learning classifiers, which supply the final target labels. It performs better than the average ensemble because it takes the maximum and weighted contributions from each pipeline into account. The stacked ensemble meta-learning classifiers are additionally efficient. as output target outcomes are already known to base pipelines,

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which are concatenated rather than averaged to maximise maximum efficiency. A dataset of Marathi handwritten numbers was used for performance evaluation and analysis, and it was discovered that the equipment is frequently more effective than the currently recommended options. An effective offline handwritten word recognition model has been created [9] using CNN-RNN networks and the sequence-to-sequence method. To distinguish handwritten text, the H2TR system employs deep neural networks and the sequence-to-sequence (Seq2Seq) technique. This hybrid model combines the best features of convolutional neural networks (CNN) and recurrent neural networks (RNN) with a long-short-term memory network. CNN is used to extract the properties of the handwritten picture. These returned properties are then modeled using a sequence-to-sequence method and sent to an RNN-LSTM in order to decode the letter sequence and embed visual information in the handwritten picture. The current model is validated using the IAM and RIMES handwritten datasets, and it yields results that are competitive in terms of word and letter accuracy.

Recognising Handwritten Devanagari Characters with CNN and Transfer Learning [10]. Devanagari characters are recognised in handwriting using CNNs and transfer learning. To recognise handwritten Devanagari letters, they compare and evaluate the transfer learning capabilities of VGG16 and DenseNet121. Models are trained under various conditions, and the results are contrasted with those of alternative methods. The study discovered that DenseNet121 performed better utilising a deep fine-tuning strategy than other pre-trained models and additional learning techniques. The learning accuracy further improved with some tweaking of hyperparameters like batch size, learning rate, and other factors. An Effective Method for Recognising Handwritten Devanagari Characters Based on Artificial Neural Networks [11]. How to read Devanagari characters written by hand Devanagari script's fluctuating curves show the character's shifting form. These characters can be separated using a piecewise feature extraction method. Using the image partitioning method, piecewise histograms of oriented gradients (HOG) features are extracted. The neural network is trained using a feature vector that consists of HOG features from all partitions. With enough practise, the recommended approach can recognise a variety of handwritten Devanagari characters with an average recognition accuracy of 97.06% and a maximum classification accuracy of 99.27%. If a blind person wants that handwritten material be read to them, the following procedure could be beneficial. Convolutional Neural Network for Handwritten Devanagari Character Recognition [12]. The categorization and feature extraction stages of any pattern recognition challenge are crucial for precisely defining the patterns. Highlight extraction is no longer a problem thanks to deep learning, which makes software engineers' jobs easier. Slowly but surely, deep learning is displacing earlier pattern recognition methods. The intricacy of systems like character recognition, which need a lot of data as well as inaccurate data, can best be handled by deep learning. Online handwritten word recognition in Bengali and Devanagari scripts using horizontal zoning and RNNs [13]. Two newly developed Recurrent Neural Network (RNN) models, Long-Short Term Memory (LSTM) and Bidirectional Long-Short Term Memory (BLSTM), are the foundation of a novel approach for online handwritten cursive and non-cursive word detection in Bengali and Devanagari scripts. The suggested method minimises changes in the primary stroke order inside such a text by dividing each letter horizontally into three regions: upper, middle, and lower. The primary word segments are then re-segmented into their basic strokes. For each zone, a variety of structural and directional characteristics may be deduced from each word's core letters. The RNN, LSTM, and BLSTM versions are then used to investigate these fundamental stroke characteristics for each zone. The bulk of current word recognition systems use a word-based technique, in contrast to the proposed system's simple stroke-based approach to class labelling. In a rigorous test on large datasets, RNN and HMM were employed to build a comparative performance study to evaluate the efficacy of the recommended strategy. According to experimental data, the proposed RNN-based system outperforms existing HMM-based systems that have been proposed in the literature with accuracy levels of 99.50% and 95.24% in Bengali and Devanagari scripts, respectively.

Handwritten Devnagari script is converted using CNN [14] into a Word-editable version. Devanagari numerals had an accuracy rate of 89%, whereas the English set had a recognition rate of 78.4%, a perplexity frequency of 4.5%, and a risk of confusion of 18%. Even though HOCR has undergone a lot of work, the accuracy rate is between 94 and 97%. A Convolutional Neural Network will be used in my study to translate handwritten Devanagari script into editable text form. Old handwritten characters need to be translated into machine editable form so that important historical documents, like manuscripts, may be easily kept and available. I choose this subject to research. With the aid of a strong and powerful dataset and a combination of different neural network techniques, they can increase the accuracy rate and we can preserve more historical records for our access.Digit Recognition of Handwriting on CNN [15]. A particular type of neural network is the convolutional neural network (CNN). The outcomes demonstrate that, without compromising performance, the CNN classifier surpassed the Neural Network in terms of computational efficiency. can distinguish handwritten numbers using a convolutional neural network

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from machine learning. My project's development is based on the KAGGLE (Modified National Institute of Standards and Technologies) database and compilation, which is also a CNN resource. Therefore, in order to run the model, we will need libraries like NumPy, Pandas, TensorFlow, and Keras. These act as the principal cornerstones on which my major undertaking is built. On KAGGLE, there are over 70,000 photos of handwritten numerals from 0 to 9. Consequently, it is a classification model of class 10. This dataset is divided into training and testing sections. The image is represented as a 28*28 matrix with grayscale pixel values in each row and column.

III. PROPSOED SYSTEM DESIGN

In order to recognise handwritten characters or letters, we created a technique called Convolutional Neural Networks (CNN). There are two parts to this process. The first is model learning, where a model is created, trained, and then saved before being used when recognition is necessary. The model's real functioning is done in the second stage, when we employ a graphical user interface to obtain the desired result.

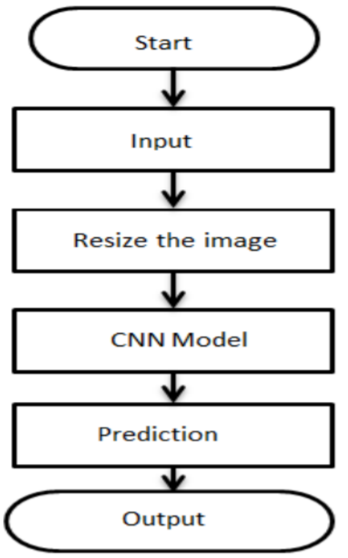

Figure 1: proposed system flowchart

To optimise recognition accuracy and processing speed for the task of handwritten digit recognition, a model of a convolutional neural network is created and assessed for the best variable learning parameters. We advise researching both three- and four-layer CNN designs (CNN 4L) and CNN 4L architectures. Six instances (cases 1 through 6) were looked at for CNN architecture with three layers, however only five examples (cases 1 through 5) were looked at for CNN design with four levels. For each instance, there are different numbers of feature maps, stride sizes, padding, dilation, and received receptive fields.

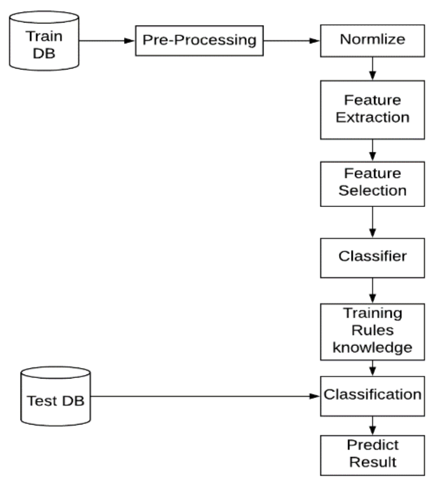

Figure 2: Proposed system architecture

The following steps are necessary for our suggested model to recognise handwritten characters. In the paragraphs following, we discuss each phase. To obtain or collect handwritten digit images from KAGGLE and divide the input images into training and test groups. Use the pre-processing procedure to prepare the training and test datasets. Normalise the data such that it lies between 0 and 1 after preprocessing it, and then divide the training dataset into manageable halves. Train the CNN model and its variants using the tagged data, and then categorise the data using the learned model. The processing time and recognition accuracy for each version should then be calculated.

The identification of handwritten character using our suggested model involves the subsequent phases. Below are the paragraphs that outline each step. Obtaining or collecting handwritten digit images from KAGGLE, and dividing the input images into two categories: training and test. The pre-processing procedure should be used to prepare both the training and test datasets. After preparing the data, normalise it such that it ranges from 0 to 1 and divide the training dataset into manageable portions. Train the CNN model and its variants using the tagged data, and then use the trained model to categorise the data. Lastly, to figure out how long each version will take to process and how accurately it will be recognised. A convolution layer with 28 kernel/filter/patches with kernel sizes of 5 5 and 3 3 is used to extract the features. The structural information of a picture is included in each patch. For instance, a concatenation is produced by sweeping a 5 x 5 filter across the input picture. In order to change the input data, a patch/filter of locally coupled neurons from the original picture is employed in this layer. In a summary, the current research examines the effects of parameter amount, gradient descent optimisation techniques, and CNN architectures on handwritten digit recognition.

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IV. ALGORITHM DESIGN

Input: Multiple-instance test dataset train dataset instances as trainDB[], testDB[], and threshold T.

Output: HashMap <Instanceid, Weight> contains all instances higher which weight higher than threshold.

Step 1: Read all Test instances, the A[i] is the respective attribute after the data preprocessing

$$testF(x) = \sum_{x=1}^{n} \left(.\frac{Normalize[A[i] \ldots \ldots . A[n]]}{\sum testDB}\right)$$

Step 2 : Split the testF(x) using below formula, here m is number of attributes has selected from test instances likewise

$$\text{FeatureSetx[]} = \sum_{x=1}^{m}(t) \leftarrow \text{testF}(x)$$

Each (t) in this case represents an attribute value that was taken from the test dataset and stored in Feature Set x.

Step 3: Read Train instances, the A[i] is the respective attribute after the data preprocessing

$$trainF(y) = \sum_{y=1}^{n} \left(.\frac{Normalize[A[i] \ldots \ldots . A[n]]}{\sum trainDB}\right)$$

Step 4 : Split the testF(x) using below formula, here m is number of attributes has selected from test instances likewise

$$\text{FeatureSety[]} = \sum_{x=1}^{m}(t) \leftarrow \text{tainF}(x)$$

Each (t) in this example represents an attribute value that was taken from the train dataset and put in FeatureSety.

Step 5 : Now map each test feature set to all respective training feature set

$$CorrectInstances + 1 = if\ (\text{FeatureSetx} \mid\mid == \mid\mid \geq \mid\mid \leq \sum_{i=1}^{n} \text{FeatureSety[y]})$$

Step 6 : Calculate the current weight for each instances

$$weight = \frac{CorrectInstances}{Featuresety.length} * 100$$

Step 6 : Evaluate the current weight with desired threshold

$$if(weight >= Th)$$

Step 7 : $Hashmap.add\ (trainF.class, weight)$

Step 8 : Go to step 1 and continue when$testF(x) ==$ null

Step 9 : Return $Hashmap$

V. RESULTS AND DISCUSSION

The table below demonstrates how several convolutional layers may be tuned to increase training, testing, and validation accuracy. With various convolutional layers, the error rate is also shown for all phases. 95.2% accuracy rate with planned CNN for testing archives.

No. of Hidden layers	No. of Steps	TA	VA	TEA	AL
125	25000	90.3	91.50	93.3	0.56
250	25000	91.2	92.5	93.8	0.52
500	25000	90.65	92.4	94.1	0.66
750	25000	90.15	92.0	94.0	0.52
1000	25000	91.6	92.7	94.3	0.60
1200	25000	92.3	92.4	96.3	0.48
1400	25000	93.45	92.9	95.2	0.52

- TA- Training Accuracy, VA- Validation Accuracy, TEA – Testing Accuracy, AL- Average Loss.

The table below shows a comparison of the suggested system and its assessment using several state-of-the-art techniques. As a consequence of this trial, the suggested system records superior results than all already in use systems.

System	TA	TEA	Error Rate
CNN based spatial classification	89.8	90.2	1.23
Text alignment CNN	88.45	87.90	1.02
BHCR based CNN	86.8	91.10	0.60
DBN	89.5	90.30	0.92
Character-level CNN	85.6	86.9	0.77
Proposed Hybrid CNN	93.45	95.2	0.52

- TA- Training Accuracy, TEA – Testing Accuracy.

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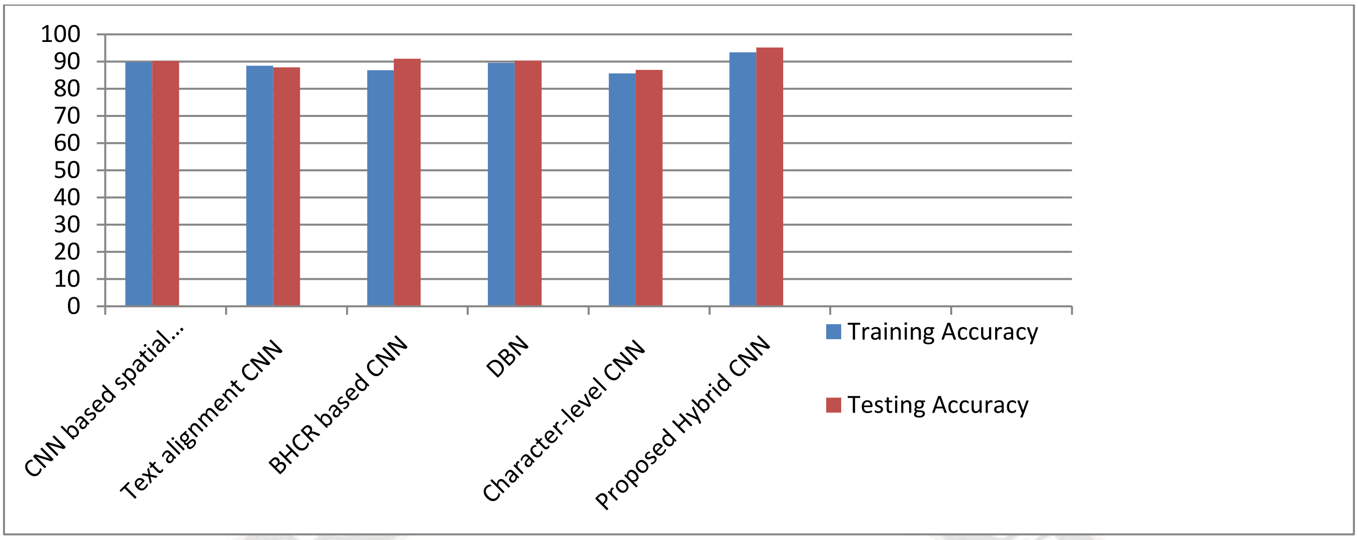
Comparative Analysis



VI. CONCLUSION

Due to a special feature selection via pooling layer, our system will be more accurate and memory efficient than other traditional approaches. The suggested technique also increases the accuracy of Marathi character identification for both synthetic and real-time pictures. With different character identification optimization techniques, the system may produce a range of experiment outcomes in terms of memory and time use. We achieve good classification accuracy using KNN for both heterogeneous and homogeneous datasets. It is a cost-effective solution since it makes use of Tenserflow libraries and works with low-cost hardware.

a) Reassign number of columns: Place your cursor to the right of the last character of the last affiliation line of an even numbered affiliation (e.g., if there are five affiliations, place your cursor at end of fourth affiliation). Drag the cursor up to highlight all of the above author and affiliation lines. Go to Format > Columns and select “2 Columns”. If you have an odd number of affiliations, the final affiliation will be centered on the page; all previous will be in two columns.

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