Devanagari Handwritten Character Recognition using fine-tuned Deep Convolution Neural Network

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Abstract

The swift evolution of automated and accurate image recognition and categorization systems is predominantly propelled by the rapid advancements in deep learning technology. In particular, the classification of handwritten characters has garnered increasing interest owing to its significant contributions to automation, particularly in the development of applications aimed at assisting individuals with visual impairments. Basically, the Devanagari script has 12 vowels, 36 consonant basic forms, 10 numeric characters, and a few special characters. The used dataset comprises 92000 distinct images of handwritten characters of 46 classes containing numerals and consonants of Devanagari script. The dataset is divided into 85% training and 15% test sets, with images stored in Portable Network Graphics (PNG) format at a resolution of 32x32 pixels. Various methods used to improve character recognition, including Deep Convolutional Neural Network (D-CNN) along with different deep learning algorithms such as LeNet, VGG and ResNet to train models. The study's results were presented and compared for each model and promising achieved 99.94 % training accuracy and 99.57% testing accuracy with the training loss of 0.020.

Keywords: Deep Learning; Devanagari character recognition; Deep Convolution Neural Network (DCNN); LeNet; VGG; ResNet;

1. INTRODUCTION

1.1 Background

The Devanagari script, utilized for languages such as Hindi, Marathi, Nepali, and Sanskrit, poses challenges in offline handwritten text recognition due to its complexity and diverse handwriting styles. Handwriting recognition involves interpreting handwritten text using computer algorithms, with two main subdomains: online and offline recognition. Online recognition, performed in real-time using digital pens or styluses, offers dynamic analysis of writing movements. In contrast, offline recognition processes static images of handwritten text, requiring image analysis. Each method has its advantages and challenges; online recognition tends to be faster and more accurate but necessitates specialized input devices, while offline recognition is versatile but computationally intensive. Offline Devanagari Handwritten Recognition (ODHR) has practical applications in digitization, aiding in the conversion of historical documents and manuscripts into digital format and streamlining data entry tasks. Convolutional Neural Networks (CNNs or ConvNets) represent a biologically inspired trainable architecture within machine learning, capable of learning from experiences akin to standard multilayer neural networks. Comprising multiple layers of overlapping tiling collections of small neurons, ConvNets aim to achieve enhanced representation of the original image. The performance of CNN can be changed by alerting the counter hidden layers and the trainable parameters in those layers.

1.2 Related Works

This research explores methods for recognizing offline handwritten changed characters, employing two convolutional neural network (CNN) models and a conventional approach using Histogram of Oriented Gradients (HOG) for feature extraction and Support Vector Machine (SVM) for classification. The study demonstrates satisfactory accuracy in recognizing Hindi consonants from the Matras dataset, with training comprising 70% of the dataset, validation 15%, and testing 15%. As a result, Double-CNN architecture achieves robust performance, achieving an average recognition rate of 90.99% on test data, with a standard deviation of 0.01 [1].

Convolution Neural Networks (CNN) are employed to work with images and train a model on them. The dataset used contains 58 distinct classes of numerals, vowels and consonants from the Devanagari script. The suggested method has a 99.20% accuracy rate and 98.31% accuracy on training data. According to the findings, Adam optimizer outperforms Stochastic Gradient Descent (SGD) optimizer and ReLU outperforms Leaky ReLU for problems of this nature. As a result, the straightforward technique proposed in this paper performs better than complex transfer learning algorithms like VGG16 and Inception V3 [3].

The author presents an overview of previous research on offline handwritten word recognition of the Devanagari script. This includes studies that have used various techniques such as Hidden Markov Models (HMM), Artificial Neural Networks (ANNs), and Support Vector Machines (SVMs). The author also discusses studies that have used pre-processing techniques such as image enhancement and binarization to improve the recognition accuracy [4].

The authors proposes a customized CNN for recognizing handwritten Devanagari words. The system's ability to recognize handwritten Devanagari words accurately and successfully was the main objective of the proposed model. The model's accuracy was 94% for the validation data and 96.05% for the training data, which is better than that of earlier methods, according to the results [5].

The authors present a two-stage VGG16 deep learning model, which is implemented to recognize these characters using two advanced adaptive gradient methods. This two-stage approach is said to enhance the overall success of the proposed Devanagari Handwritten Character Recognition System (DHCRS). The first model is reported to achieve 94.84% testing accuracy with a training loss of 0.18 on the new dataset, while the second fine-tuned model, which requires fewer trainable parameters and notably less training time, is said to achieve 96.55% testing accuracy with a training loss of 0.12 [6].

3. METHODOLOGY

3.1 Workflow

Offline Handwritten character recognition (OHCHR) encompasses several steps to transform handwritten text into machine-readable form. Initially, a diverse dataset of handwritten characters is collected and processed to standardize and refine its quality. Feature extraction techniques like Convolutional Neural Networks (CNN) are applied to convert raw pixel data into understandable patterns for machine learning models. These models are trained using the extracted features and corresponding labels. The trained model undergoes validation and tuning to enhance its accuracy. During recognition, the model processes handwritten input by extracting features, predicting characters based on learned patterns. This workflow integrates data pre-processing, feature extraction, model training, and deployment, culminating in a system capable of recognizing handwritten characters effectively.

The Fig 1 represents the working model of this paper. It provides an overall idea how the Devanagari character recognition system works. This methodology flows as in Fig 1 for the handwritten character recognition. The process included the data set collection, pre-processing, cleaning, splitting, model training, evaluation and classify with comparison.

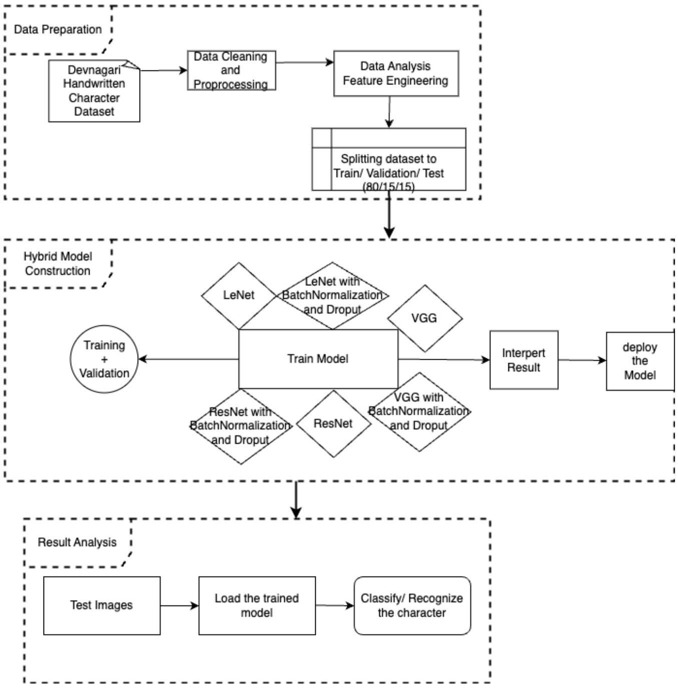

Fig - 1: Proposed Methodology for Offline Devanagari Handwritten Character Recognition

3.2 Proposed System

The high-level handwriting recognition system is divided into five sub-system, image acquisition, pre-processing, feature extraction, convolution neural network, recognition. The high-level model of proposed system is given in Fig 2

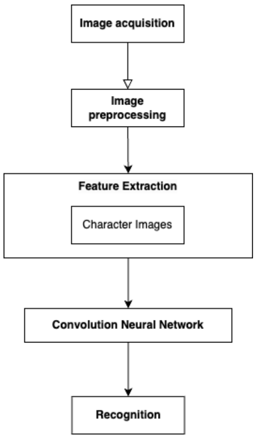

Fig - 2: Off-line Devanagari Handwritten Recognition System

3.3 Datasets

Devanagari Handwritten Character Dataset (DHCD) is created by collecting the variety of handwritten Devanagari characters from different individuals from diverse field. These datasets downloaded from UC Irvine (UCI) Machine Learning Repository [10]. This repository is an image database of Handwritten Devanagari characters. There are 46 classes of characters with 2000 examples for each character and digit. This dataset is split into training (85%) and testing set (15%), showing some of example in Fig 3. This DHCD datasets contains total of 92000 images with 72000 images in consonant dataset and 20000 images in numeral dataset. In this dataset, each character sample in 32x32 pixels ad the actual character is centered withing 28x28 pixels. Padding of 0 valued 2 pixels is done on all four side to make this increment in image size.

3.4 Model Training

The LeNet, VGG, and ResNet architectures represent distinct flavors of convolutional neural networks (CNNs) utilized for training various models. Each architecture offers unique features and capabilities suited to different tasks and datasets. During the training process, appropriate algorithms and hyperparameters specific to each architecture were employed to optimize model performance. Additionally, any necessary data resampling techniques were applied to ensure the quality and representativeness of the training data.

Fig - 3: Example of image from the DHCD.

3.5 Model Evaluation

The performance of the LeNet, VGG, and ResNet used models was evaluated using the test set. A metric is a function that is utilized in the process of evaluating the effectiveness of a model. This problem can be classified as a multi-class problem because the task at hand is to construct a model that can recognize Devanagari characters from the images that are provided.

Layer (type)	Output Shape	Param #
input_3 (InputLayer)	[(None, 32, 32, 3)]	0
sequential_10 (Sequential)	(None, 32, 32, 3)	0
conv2d_26 (Conv2D)	(None, 30, 30, 32)	896
conv2d_27 (Conv2D)	(None, 28, 28, 64)	18496
batch_normalization_8 (BatchNormalization)	(None, 28, 28, 64)	256
max_pooling2d_6 (MaxPooling2D)	(None, 14, 14, 64)	0
conv2d_28 (Conv2D)	(None, 14, 14, 64)	36928
conv2d_29 (Conv2D)	(None, 14, 14, 64)	36928
batch_normalization_9 (BatchNormalization)	(None, 14, 14, 64)	256
add_4 (Add)	(None, 14, 14, 64)	0
conv2d_30 (Conv2D)	(None, 14, 14, 64)	36928
conv2d_31 (Conv2D)	(None, 14, 14, 64)	36928
batch_normalization_10 (BatchNormalization)	(None, 14, 14, 64)	256
add_5 (Add)	(None, 14, 14, 64)	0
conv2d_32 (Conv2D)	(None, 12, 12, 64)	36928
global_average_pooling2d_2 (GlobalAveragePooling2D)	(None, 64)	0
dropout_4 (Dropout)	(None, 64)	0
dense_12 (Dense)	(None, 46)	2990

Total params: 207790 (811.68 KB)
Trainable params: 207406 (810.18 KB)
Non-trainable params: 384 (1.50 KB)

Fig - 4: CNN model architecture.

4. RESULT, ANALYSIS AND COMPARISON

This research explores the application of various convolutional neural network (CNN) architectures, such as LeNet, VGG, and ResNet, for recognizing handwritten Devanagari characters. Each architecture possesses distinct features suitable for character recognition tasks. The study evaluates different classifiers to validate the developed models. Experiments involve analysing offline isolated Devanagari handwritten characters, including alphabets and numerals, across two datasets: one for consonants and another for numerals. The system undergoes supervised training using random samples from each dataset, followed by testing with new samples to assess accuracy. Data within each dataset are divided into subsets for training, validation, and testing, with samples selected randomly. Multiple rounds of experimentation are conducted, and accuracy and efficiency metrics are calculated as averages from all experimental results within each dataset.

A comparison of the of six models and their accuracy v/s epoch graph is given in Table-1 and in Fig - 5.

Table -1: Models with Training and Testing accuracy

Sequence	Model Names	Testing Accuracy (%)	Training Accuracy (%)	No of Epochs
1	LeNet	97.48	99.63	28
2	LeNet_BD	98.62	99.72	28
3	VGG	98.64	99.79	28
4	VGG_BD	99.25	99.89	28
5	ResNet	99.27	99.88	20
6	ResNet_BD	99.57	99.92	20

Fig - 5: Models with Training and Testing accuracy

Table - 2: Top three best performing model

Model Name	Model Accuracy (%)
Model-6 ResNet+BatchNormalization+Dropout	99.57
Model-5 ResNet	99.27
Model-4 VGG + BatchNormalization+Dropout	99.25

Table - 3: Comparison with State-Of-Work Literature

Model	Model	Model Accuracy %	Dataset
Patnaik, S., Kumari [13] DCNN	DCNN	97.49	DHCD
Patnaik, S., Kumari [13] ResNet	ResNet	99.38	DHCD
Gupta et al [14] CapsNet	CapsNet	99.02	DHCD
Sonawane et al [15]	AlexNet (Transfer Learning)	95.4	Self-Dataset
ResNet with BathNormalizational and Drooput of this work	ResNet with added components	99.57	DHCD

The hybrid model, namely Model-6, which integrates ResNet with BatchNormalization and Dropout, has been selected for the research work. This decision is based on its notable performance, as evidenced by thirteen out of the 46 classes achieving a classification prediction accuracy of 100%. Furthermore, this model boasts the highest overall accuracy rate of 99.57%. It is noteworthy that this exceptional accuracy was attained with training limited to only 20 epochs.

5. CONCLUSIONS

This study evaluated various flavors of Convolutional Neural Network (CNN) architectures for Devanagari Handwritten Character Recognition System (DHCRS), including LeNet, VGG, and ResNet with additional components. Among these models, the ResNet architecture augmented with BatchNormalization and Dropout emerged as the top performer in terms of prediction accuracy. It achieved an impressive 99.94% training accuracy and 99.57% testing accuracy, with a minimal training loss of 0.020. These results underscore the effectiveness of ResNet with added components in accurately recognizing Devanagari handwritten characters, showcasing its potential for practical deployment in real-world applications. Moreover, this research underscores the significance of thoughtfully evaluating various models and methodologies for Devanagari character recognition, as they play a pivotal role in determining prediction accuracy. The comparative analysis conducted in this study offers valuable insights for guiding future investigations in this domain.

One possible avenue of improvement is to explore different techniques of data normalization. This could help to improve the prediction accuracy of the models.

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