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HANDWRITTEN DEVANAGARI CHARACTER RECOGNITION USING DEEP LEARNING - CONVOLUTIONAL NEURAL NETWORK (CNN) MODEL

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Abstract

Handwritten character recognition is increasingly important in a variety of automation fields, for example, authentication of bank signatures, identification of ZIP codes on letter addresses, and forensic evidence, etc. Handwritten character recognition is the process where the machine detects and recognizes the characters from a text image and converts that processed data into a code which is understood by the machine. It is a fundamental yet challenging task in the field of pattern recognition. In this paper, we used a new public image dataset for Devnagari script character: Devnagari Character Dataset (DCD). This considered dataset consists of 92 thousand images of 46 different classes of characters of Devnagari script segmented from handwritten documents. This paper also explore the challenges in recognition of Devnagari characters. Along with the dataset, a deep learning based convolutional neural network (CNN) architecture is proposed in this paper for recognition of those handwritten characters in an unrestricted environment. Deep Convolutional Neural Network have shown superior results to traditional shallow networks in many recognition tasks. Keeping distance with the regular approach of character recognition by Deep CNN, we focus the use of Dropout and dataset increment approach to improve test accuracy. By implementing these techniques in Deep CNN, we were able to increase test accuracy by nearly 0.98 percent. The proposed architecture scored highest test accuracy of 98.13% on theconsidered dataset. The results indicate that the proposed model may be a strong candidate for handwritten character recognition and automated handwritten Devnagari script character recognition applications.

Introduction

Handwritten character recognition is considered to be one of the most challenging and appealing research areas in the field of pattern recognition and computer vision. It is the natural way of interacting with the computer.(Acharya et al., 2015)Due to the critical factors of differences in writing patterns and cursive text, and the similarity of various characters in Devanagari script characters, recognition research is time-consuming and challenging. It has been a field of great interest for researchers and scientists. Character recognition is the process where the machine detects and recognizes the characters from a text image and converts that processed data into a code which is understood by the machine. It is a fundamental yet challenging task in the field of pattern recognition.Recognition of handwritten Devanagari script characters may be performed online or offline. Online character identification is relatively simple due to the temporal-based character properties such as form, number of strokes, distance, and direction of writing. Offline character recognition implementation is complex due to variations of writers and fonts. Recognition is termed as optical character recognition (OCR) as they deal with characters which are optically processed and not magnetically processed.(Sinha, 2009)The literature shows a high accuracy rate for recognition of characters and isolated words in optical character recognition (OCR) or printed text; however, there is a need for a competent handwritten character recognition system capable of generating a high degree of accuracy in handwritten text recognition.(Fujisawa, 2008)(Plamondon & Srihari, 2000)(Steinherz et al., 1999)(Arica & Yarman-Vural, 2001)

Concept of character recognition was introduced by Carey in 1870 when the researcher developed the retina scanner.(Acharya et al., 2015) Then in 1890, the sequential scanner was introduced which brought in the revolution for reading machines. The advancement of technology in terms of both scanning devices and the computation power has also led to the development in the field of character recognition. Today, a number of OCR's are present in the market which can perform recognition task with minimal error rate. Some of these are also available for handheld and portable devices like cellular phones.

Lately, several such systems have been developed for more complex languages such as Chinese, Korean, Arabic, etc. but the accuracy and consistency are not at par as compared to those for the English language. One of the reasons for this is that English Script is not as complex and complicated as that of Chinese or Devanagari Script. Pertaining to this reason, the existing character recognition faces difficulties in understanding the not so popular languages like Sanskrit, Hindi, and Tamil, and hence are not useful for people whose native language is not English. Another shortcoming of the majority of the OCR's is that they fail to understand the context of the text.

Character classification is an important part of handwritten character recognition that plays an essential role in many computer vision problems like OCR, license Plate recognition, etc. Development of a recognition system is an emerging need for digitizing handwritten hindi documents that use Devnagari characters. Optical Character Recognition systems are least explored for Devnagari characters. (Pant et al., 2012)(Dongre & Mankar, 2011) present a few approaches for segmentation and recognition of Devnagari characters. The major challenging task while creating a recognizer and classifier for the Devnagari scripts is that they have a large number of symbols as compared to languages like English. English contains mainly 52 characters while a script like Devanagari consists of more than 200 symbols. Almost all the Indic languages are similar to each other. Some of them have a characteristic of allowing characters to be combined together to form another character, generally referred to as 'sayuktakshar' where Sayukt stands for combined and 'akshar' means word. Another challenge is the identification of vowel modifiers or ‘matras’. Vowel modifiers change the UNICODE value of that character, and hence, in order to identify the correct character and its Unicode value, we need to write script specific rules. These modifiers may be present at the left, right, bottom or top of the character. In some of the cases, the modifier may be present at two positions on the same character.Hence, it is required to identify these modifiers correctly to reduce the error in classification.So this paper considering a publicly availableDevnagari Character Dataset, of 92 thousand images of 46 Devnagari characters. Then, this paper proposinga Deep learning Convolutional Neural Network model to classify the characters in DCD. Introduction of multilayer perceptron network has been a milestone in many classification tasks in computer vision.(Quiles & Romero, 2005) But, performance of such a network has always been greatly dependent on the selection of good representing features.(Ruck et al., 1990)(Yang et al., 2009) Deep Neural Networks on the other hand do not require any feature to be explicitly defined, instead they work on the raw pixel data generating the best features and using it to classify the inputs into different classes.(Lee et al., 2009) Deep Neural networks consist of multiple nonlinear hidden layers and so the number of connections and trainable parameters are very large. Besides being very hard to train, such networks also require a very large set of examples to prevent overfitting. One class of DNN with comparatively smaller set of parameters and easier to train is Convolutional Neural Network.(LeCun et al., 1998)The ability of CNN to correctly model the input dataset can be varied by changing the number of hidden layers and the trainable parameters in each layer and they also make correct assumption on the nature of images.(Krizhevsky et al., 2012) Like a standard feed forward network, they can model complex non-linear relationship between input and output. But CNN have very few trainable parameters than a fully connected feed-forward network of same depth. CNNs introduce the concept of local receptive field, weight replication and temporal subsampling(LeCun et al., 1990) which provide some degree of shift and distortion invariance. CNNs for image processing generally are formed of many convolution and sub-sampling layers between input and output layer. These layers are followed by fully connected layers thereby generating distinctive representation of the input data. Beside image recognition, CNNs have also been used for speech recognition.(Abdel-Hamid et al., 2012)(Sainath et al., 2013) Although deep convolutional neural networks have a small and inexpensive architecture compared to standard feed forward network of same depth, training a CNN still requires a lot of computation and a large labeled dataset. Training such a network was not so effective and did not produce any superior result to traditional shallow network, until recently. With the availability of large labeled dataset like IMAGENET, NIST, SVHN, development of state of the art GPUs and introduction of unsupervised pre-training phase, CNNs have at present proven to surpass traditional feed forward network in a number of classification tasks. In CNNs, initializing the weight randomly and applying gradient descent and backpropagation to update the weights seems to generate poorer solution for a deep network.(Larochelle et al., 2009) So, generally, greedy layer wise unsupervised pre training is applied prior to supervise training. Why such unsupervised training helps is investigated in(Erhan et al., 2010).

Literature review

This section covers the related work on handwritten character recognition of English, Arabic, Meetei Mayek, Bangla, Sanskrit, Hindi, and Chinese etc. handwritten characters is described. These following research work perform character recognition with different algorithms and they also used different deep learning for better accuracy and recognition.

Many studies have been conducted on handwritten English, Arabic, Chinese and Urdu character recognition; however, Devanagari character recognition has not been explored to the same extent. English and Arabic handwritten character recognition can be classified into two approaches, conventional approaches and deep learning-based approaches.

Conventional approaches depend on manual feature extraction by experts whereas deep learning-based techniques automatically extract features from raw images. Conventional techniques cannot extract features from images in their raw form. Machine learning experts have struggled to design feature extractors that extract discriminative features from raw data into vectors as an input to classifiers for pattern recognition.(Abandah et al., 2008)

In a notable early work for isolated handwritten character recognition, Roy et. al., 2017 they developed Supervised Layer Wise training of a Deep Convolutional Neural Network (SL-DCNN) architecture. It had a set a new benchmark of 9.67% error rate on the rather difficult CMATERdb 3.1.3.3 handwritten Bangla isolated compound character dataset. The model represented a lowering of error rated by nearly 10% from the previously set benchmarks on the same and is an excellent result in the area of Bangla compound character recognition.(Roy et al., 2017) Alom et. al., 2017 they have used a combination of dropout and many filters on a dataset CMATERdb 3.1.1 and evaluate the performance of CNN and DBN with the integration of Deep Learning. They perform many experiments and conclude that CNN with Gabor feature and dropout get better accuracy for BANGLA digit recognition to compare to another technique.(Alom et al., 2017) El-sawy et. al., 2017 they had used convolution neural network (CNN) handwritten character recognition for ARABIC character and show the results were promising with a 94.9% classification accuracy rate on testing image scripts.(El-Sawy et al., 2017) Savitha Attigeri, 2018 presented a neural network based offline character recognition from the handwritten script using offline mode without using feature extraction from the scanned image. They had used layers and got accuracy for 90.19/5 from 100 neurons.(Attigeri, 2018) Adnan et. al., 2018 had analyzed different deep convolution neural networks (DCNNs) and concluded that DenseNet can generate more fruitful results in BANGLA character recognition. They also mention that the accuracy could achieve up to 98% for digit, alphabet and special character recognition.(Adnan et al., 2018) Jangid et. al., 2018 have used deep convolution neural network (DCNN) and adaptive gradient methods for DEVENAGRI character recognition. They had also used Network Architecture – 6 and RAMSProp optimizer method. They achieved about 98% recognition accuracy using ISIDCHAR and V2DMCHAR dataset.(Jangid & Srivastava, 2018) D.S. Joshi & Risodkar, 2018 focused on GUJARATI character recognition with the help of K-NN and Neural Network. They also used filtering, edge detection, morphological transformation for image processing and achieved 78.6% accuracy on a dataset.(Joshi & Risodkar, 2018) Das et. al., 2018 had presented a popular CNNs with kernel size, pooling methods and activation function for BANGLA handwritten character recognition. Results proved that CNNs architecture can improve the character recognition accuracy.(Sen et al., 2018) Yu Weng & Chunel Xia, 2019 developed a convolution neural network to handwritten character recognition of SHUI. After performing the different experiments and they concluded that characters can be classified easily using CNN models. They also made a comparison with their developed model and another available model.(Weng &

Xia, 2019) Gan et. al., 2019 used 1-D CNN for CHINESE character recognition with the implementation of the sequential structure of handwritten character and also derived that this model of CNN is very compact and runes faster than other architecture like 2-D CNN and RNN.(Gan et al., 2019) Kavitha & Srimathi, 2019 have used CNNs for TAMIL handwritten character recognition. They achieved a testing accuracy of 97.7% using the HP Lab's dataset. They also proved that the CNNs are a more accurate paradigm for character recognition from the handwritten script.(Kavitha & Srimathi, 2019) Saha & Saha, 2018 introduced a deep convolution neural network with techniques like Divide and Merge Mapping and Optimal Path Finder for BANGLA handwritten character recognition. They achieved the results with the lowest complexity of the provided parameters on a small network as well as a large network of the dataset.(Saha & Saha, 2018) Uki et. al., 2019 used CNN's depth and wavelet transformation on the image. They had used different approached like max-pooling, probabilistic voting, feature extraction, feature correction, etc. with the help of all these methods they found that the accuracy of the character recognition is increased more than 4% with the previous techniques.(Ukil et al., 2019)

Table 1: Detailed comparison of approaches uses by different author for character recognition

Sr. No.	**Author(s)**	**Year Of Publication**	**Approach**	**Dataset**	**Pre-processing**	**Result/ Accuracy**
1	(Roy et al., 2017)	2017	Supervised layer wise training of a deep convolution neural network (SL-DCNN)	CMATERdb 3.1.3.3	The available dataset used, they resized the image to 30 pixels of height and width.	CNN model provides an error rate of 9.67% compared to 15.96% for the DCNN.
3	(Alom et al., 2017)	2017	Deep Belief Network (DBN), CNN with dropout, CNN with dropout and Gaussian filters, CNN with dropout and Gabor Filters.	CMATERdb 3.1.1	Raw images used as input and passed to the next phase (Normalization).	DBN produced 97.20 % CNN + GABOR + DROPOUT achieved an accuracy of 98.78%
4	(El-Sawy et al., 2017)	2017	Convolution Neural Network (CNN)	16800 images 13340 images for Training and 3360 images for testing.	The input to a convolution layer is the M X M X C; where M is the height and width of the image and C is a number of channels per	They achieved an accuracy of 94.9%.

					pixel.	
2	(Attigeri, 2018)	2018	Artificial Neural Network (ANN)	Own dataset of 49 characters and 4840 samples.	Each individual character is uniformly resized to 30 X 20 pixels.	The character recognition accuracy of 90.19% they have achieved.
6	(Adnan et al., 2018)	2018	Deep Belief Network(DBN), Stacked Auto encoder (AE), CNN, DenseNet	CMATERdb 3.11	Each digit has 600 images that are rescaled to 32 X 32 pixels.	Digit-10 --- 99.13%. Alphabet - 50 --- 98.31%. Special Character --- 98.18% accuracy.
9	(Jangid & Srivastava, 2018)	2018	Deep Convolution neural network (DCNN)	ISIDCHAR and V2DMDCHAR database.	A normalization process has to follow for converting the image h X w X c size to m m X m X c size where m represents the height and width of an image.	Using a DCNN layer-wise training model, they obtained 98% recognition accuracy.
10	(Joshi & Risodkar, 2018)	2018	K-NN classifier and Neural Network	Own database with 30 samples	RGB to gray conversion, skew correction, filtering, morphological operation	Got accuracy nearby 78.6%
12	(Sen et al., 2018)	2018	Convolutional Neural Network (CNN) architecture	Own database with 200 samples from 100 different persons.	Resized all images to 28 X 28 pixels.	They have achieved an accuracy of 99.40% for character recognition.

5	(Weng & Xia, 2019)	2019	Deep Neural Network (DNNs)	400 types of pictures used as a dataset.	37500 data are used as a training and 12500 data used as test data. Shui character image normalized to 52 * 52 pixels. The class label is added to the clustering results.	The final test accuracy is around 93.3% achieved.
7	(Gan et al., 2019)	2019	1-D CNN Databases	ICDAR-2013 IAHCC-UC AS2016	Chainese character images rescaled into 60 X 60 pixel size.	98.11 % on ICDAR-2013 and 97.14% on IAHCC-UCA2016 dataset.
8	(Kavitha & Srimathi, 2019)	2019	CNN model total of nine layers; five convolution layers, two max pooling layers, and two fully connected layers.	HPL-taiml-is o-char 156 characters 500 samples for each class 82,928 total samples.	Convert into a grayscale image from the original image.	Testing accuracy of 97.7%.
11	(Saha & Saha, 2018)	2019	Divide and Merge Mapping (DAMM)	Own database with 1,66,105 images	Resize all images to 128 X 128 pixels.	Achieved a training accuracy of 99.13% along with a validation accuracy of 98.87%
13	(Ukil et al., 2019)	2019	Convolutional Neural Networks (CNNs)	PHD_Indic_11 dataset	RGB to grayscale conversion and resized image to 28 X 28 pixels.	CNNprob performed the best with an accuracy of 95.45%, precision of 95.36%, recall of 95.32% and f-measure of 95.33%.

In the case of deep learning approaches, the use of convolutional neural networks for the recognition of Modified national institute of standards and technology(MNIST) and Extended modified national institute of standards and technology (EMNIST) datasets has attracted the attention of numerous researchers, who have applied these models to languages with handwritten character recognition, including English (Deng, 2012), Hangul (Draman et al., 2009), and Chinese (Faraoun & Boukelif, 2006). Arabic-related research studies using deep learning models and techniques have been reported in this research.(Weng & Xia, 2019) The authors first designed an image processing module, and constructed a data set, for mobile devices. They proposed a lightweight CNN for optical character recognition for the dataset. Another work addresses the variability in writer's handwriting (Cilia et al., 2019), in which a feature-ranking technique was adopted. The authors considered different univariate measures to produce a feature ranking and proposed a greedy search approach for choosing the feature subset able to maximize the classification results. Raymond et al. (Ptucha et al., 2019) presented a fully convolutional network architecture that outputs arbitrary length symbol streams from handwritten text. A preprocessing step normalizes input blocks to a canonical representation, which negates the need for costly recurrent symbol alignment correction. The authors introduced a probabilistic character error rate to correct errant word blocks.

A recent study by Chaouki Boufenar et al. (Boufenar et al., 2018), investigated the use of convolutional neural networks for offline Arabic handwritten character recognition. Their architecture consisted of five layers in which three convolutional layers with a max pool were connected to two fully connected layers. They used OIHACDB-28 for training and evaluation of the model, gained a result of 97.32% accuracy. The CNN model was trained with a dropout technique under the Theano framework. Ahmed El-Sawy et al. (El-Sawy et al., 2016) suggested the Deep convolutional neural networks (DCNN)model for the recognition of isolated handwritten Arabic characters. They proposed a dataset referred to as Arabic handwritten characters dataset AHCD. The model was trained with an optimization method for 30 epochs that resulted in a significant increase in performance and a 94.9% classification accuracy.

The available literature shows unsatisfactory research results compared to other languages. In (Decerbo et al., 2004), the Byblos Pashto OCR system was proposed for script-free OCR using HMMs. This system was also subsequently tested for Chinese, English, and Arabic text with success. As previously mentioned, Devanagari Intelligent character recognition and Optical character recognition (OCR) area are the least explored to date. Based on this discussion, it can be concluded that there is a lack of a Devanagari handwritten character dataset. In addition, a research gap exists for classification of Devanagari handwritten characters based on deep learning techniques, such as the CNN. The current research fills this gap by proposing a CNN model and a Devanagari handwritten character dataset. For this purpose, a model was developed and extensive experimentation conducted. These are described in detail in Sections 3 and 4.

Devanagari Handwritten Character Dataset

Devanagari Script

Devanagari is part of the Brahmic family of scripts of Nepal, India, Tibet, and South-East Asia.(Fischer, 2004)(Gaur, 1992) The script is used to write Nepali, Hindi, Marathi and similar other languages of South and East Asia. The

Nepalese writing system adopted from Devanagari script consists of 12 vowels, 36 base forms of consonant, 10 numeral characters and some special characters. Vowel characters are shown in Table2, consonants characters in Table 3 and numeral characters in Table 4. Moreover, all 36 consonants could be wrapped with the vowels generating 12 other derived forms for each branch of consonant character. One such example for “ta (tabala)” and “pa” is shown in Table 5.

Devanagari Character	अ	आ	इ	ई	उ	ऊ	ए	ऐ	ओ	औ	ऑ	ऒ
UNICODE	905	906	907	908	909	090A	090F	910	913	914	911	912

Table 2: Devanagari vowels with UNICODE

Devanagari Character	क	ख	ग	घ	ङ	च	छ	ज	झ	ञ	ट
UNICODE	915	916	917	918	919	091A	091B	091C	091D	091E	091F
Devanagari Character	ठ	ड	ढ	ण	त	थ	द	ध	न	प	फ
UNICODE	920	921	922	923	924	925	926	927	928	092A	092B
Devanagari Character	ब	भ	म	य	र	ल	व	श	ष	स	ह
UNICODE	092C	092D	092E	092F	930	932	935	936	937	938	939
CHARACTER	क्ष	त्र	ज्ञ	These three consonants have no specific UNICODE							

Table 3: Devanagari consonants with UNICODE

०	१	२	३	४	५	६	७	८	९
966	967	968	969	096A	096B	096C	096D	096E	096F

Table 4: Devanagari numerals

त	ता	ति	ती	तु	तू	ते	तै	तो	तौ	तं	तः
प	पा	पि	पी	पु	पू	पे	पै	पो	पौ	पं	पः

Table 5: Derived forms of consonant “ta (tabala)” and “pa” when wrapped with vowels.

Devanagari Handwritten Character Dataset

Devanagari Handwritten Character Dataset is created by collecting the variety of handwritten Devanagari characters from different individuals from diverse fields. Handwritten documents are than scanned and cropped manually for individual characters. Each character sample is 32x32 pixels and the actual character is centered within 28x28 pixels. Padding of 0 valued 2 pixels is done on all four side to make this increment in image size. The images were applied gray-scale conversion. After this the intensity of the images were inverted making the character white on the dark background. To make uniformity in the background for all the images, we suppressed the background to 0 value pixel. Each image is a gray-scale image having background value as 0.

Devanagari Handwritten Character Dataset contains total of 92,000 images with 72,000 images in consonant datasest and 20,000 images in numeral dataset. Handwritten Devanagari consonant character dataset statistics is shown in Table 6 and handwritten Devanagari numeral character dataset statistics is shown in Table 7.

Table 6: Consonant Character Dataset

Devanagari Character (Class)	क	ख	ग	घ	ङ	च	छ	ज	झ	ञ	ट
Individual statistics	2,000	2,000	2,000	2,000	2,000	2,000	2,000	2,000	2,000	2,000	2,000
Devanagari Character (Class)	ठ	ड	ढ	ण	त	थ	द	ध	न	प	फ
Individual statistics	2,000	2,000	2,000	2,000	2,000	2,000	2,000	2,000	2,000	2,000	2,000
Devanagari Character (Class)	ब	भ	म	य	र	ल	व	श	ष	स	ह
Individual statistics	2,000	2,000	2,000	2,000	2,000	2,000	2,000	2,000	2,000	2,000	2,000
Devanagari Character (Class)	क्ष	त्र	ज्ञ								
Individual statistics	2,000	2,000	2,000								
Total	**72,000**										

Table 7: Numeral Dataset

Devanagari Character (Class)	०	१	२	३	४	५	६	७	८	९
Individual statistics	966	967	968	969	096A	096B	096C	096D	096E	096F
Total	**20,000**									

Challenges in Devanagari Character Recognition

There are many pairs in Devnagari script that has similar structure differentiating each with structure like dots, horizontal line etc. Some of the examples are illustrated in Table 8. The problem becomes more intense due to unconstrained cursive nature of writings of individuals. Two such examples are shown in Table 9.

छ	६	Difference being horizontal line at top
ड	ङ	Difference being presence of single dot on right side
द	ढ	Difference being presence of small circle and small down stroke line

Table 8: Structural formation of characters

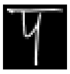
	प		य
	ध		घ

Table 9: Different characters written similarly

Proposed Model for Devanagari handwritten character recognition

This section proposed a means of Devanagari handwritten character classification and recognition model as shown in Figure 1. This recognition model relies on a CNN applied for the Devanagari handwritten character dataset with a feature mapped output layer. This suggested CNN model classifies Devanagari characters into 46different classes. A detailed explanation of the suggested model is presented in the following subsections.

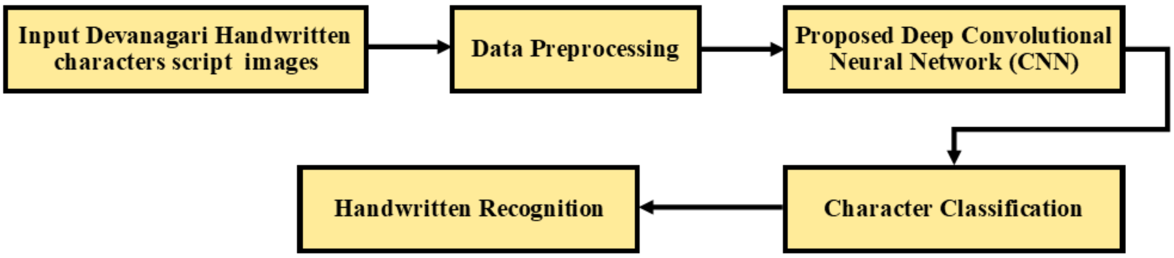


Figure 1: Block diagram of proposed model framework

Devanagari handwritten characters scripts images dataset

A data-enriched dataset plays a vital role in the generation of accurate results in research activities related to deep learning. A concise and precise dataset is required for a true evaluation of mathematical models that are applied to it. Moreover, to achieve benchmark results in deep learning, a standard publicly available dataset is mandatory. During the experimental phase of this research, we considered dataset named Devanagari Handwritten Character Dataset publically available on UCI repository. Detailed description about the data is described in previous section.

Data Preprocessing

Preprocessing steps were applied to the proposed dataset to prepare images for subsequent phases. Image preprocessing consisted of operations on images at the lower abstraction level with the aim of improving the image data. This improvement suppresses undesired distortions in the image dataset, or enhances important details or features that are essential for further processing.

The first step of the preprocessing phase was the removal of noise from images using Gaussian blur. The digital scanner induced spikes of noise into the scanned images, as shown in Figure 2(a). These spikes of noise were removed using the notable work of Soman.(Ganga Gowri & Soman, 2018) The second step was smoothing of the image using the Gaussian function. This can be considered to be low-pass filtering in a non-uniform manner, which conserves the low frequency, and decreases the noise and insignificant details in an image. This was accomplished by convolving the Gaussian kernel with an image.

$$G_{2D}(x, y, \sigma) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}$$

where σ is the standard deviation, and x and y are location indices. The standard deviation controls the variance around the Gaussian distribution mean value, and establishes the blurring effect around certain pixels. In our study, we used $\sigma = 2.8$, which generates a good smoothing effect to suppress the scanner-induced noise. The images were then converted to gray-scale and, finally, the images were resized to 32 × 32 pixels and the aspect ratio was held constant. A CNN was subsequently used for detection and classification of features.

(a) **(b)** **(c)** **(d)**

Figure 2: Image dataset denoising steps: (a) scanner-induced noise; (b) denoised image; (c) Binarized Image; (d) application of Gaussian blur filter

Convolutional Neural Networks

Convolutional Neural Network (CNN or ConvNet) is a biologically-inspired trainable machine leaning architecture that can learn from experiences like standard multilayer neural networks. ConvNets consist of multiple layers of overlapped tiling collections of small neurons to achieve better representation of the original image. ConvNets are widely used for image and video recognition. There are three main types of layers used to build a ConvNet architecture.

1) **Convolution Layer:** The convolution layer is the core building block of a convolutional neural network. It convolves the input image with a set of learnable filters or weights, each producing one feature map in the output image.
2) **Pooling Layer:** The pooling layer is used to progressively reduce the spatial size of the representation to reduce the amount of parameters and computation in the network. The pooling layer takes small rectangular blocks from the convolution layer and subsamples it to produce a single output from that block. There are several ways to do this pooling, such as taking the average or the maximum, or a learned linear combination of the neurons in the block.
3) **Fully-Connected Layer:** The fully-connected layer is used for the high-level reasoning in the neural network. It takes all neurons in the previous layer and connects it to every single neuron it has. Their activations can be

computed with a matrix multiplication followed by a bias offset as a standard neural networks.

A simple convolutional neural network similar to the one used in our recognition system is shown in Figure3. The input layer consists of the raw pixel values from the 32x32 grayscale image and has no trainable parameters. The first convolution layer has 4 feature maps with 784 units/neurons each (28 x 28). Each feature map is shown in figure as 2D planes and they have different set of weights. All the units in a feature map share the same set of weights and so they are activated by the same features at different locations. This weight sharing not only provides invariance to local shift in feature position but also reduces the true number of trainable parameters at each layer. Each unit in a layer receives its input from a small neighborhood at same position of previous layer. So the number of trainable weights associated with each unit in a convolutional layer depends on the chosen size of the neighborhood of previous layer mapped to that unit. Since all the units are activated only from the input taken from a local neighborhood they detect local features such as corners, edges, end-points. This concept of local receptive field is inspired from study of the locally-sensitive, orientation selective neurons in the cats visual system.(Hubel & Wiesel, 1962)

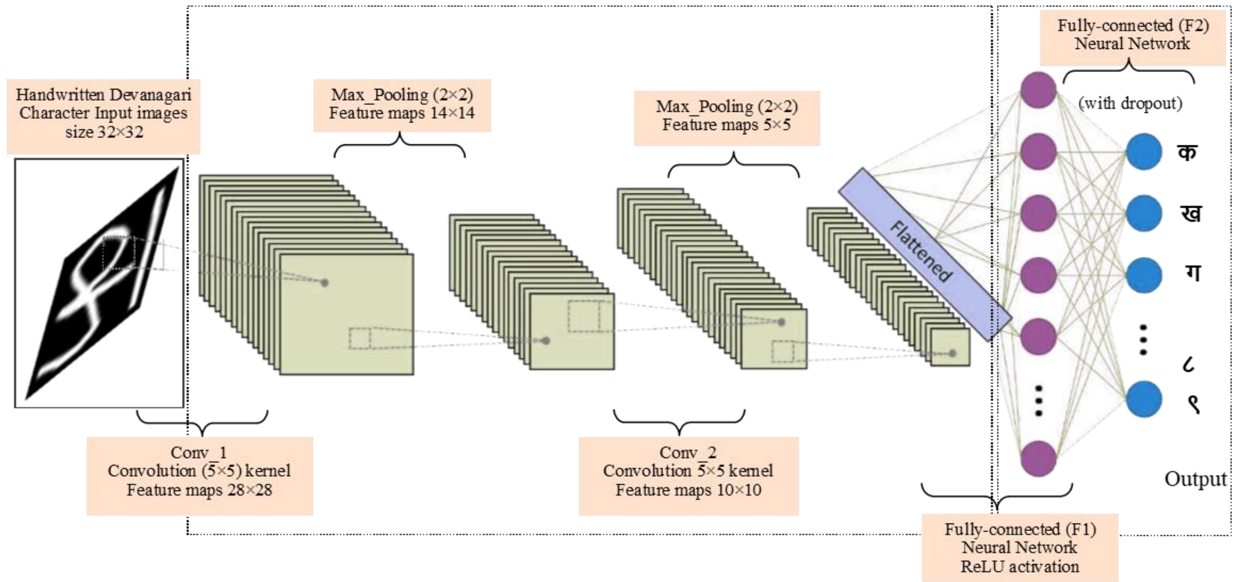


Figure 3: Proposed Convolutional Neural Network

For a 5x5 kernel as shown in Figure3 the number of input weights for each unit is 25. In addition the units also have a trainable bias. The total number of units in a layer depends upon the size of kernel in the previous layer and overlap between the kernels.

The convolutional layer is followed by a subsampling/pooling layer. Sub sampling layer reduces the resolution of the feature map from convolution layer by averaging the features in the neighborhood or pooling for a maximum value. Because the exact position of features vary for different images of the same character, it is more desirable that the system does not learn the absolute position of feature but instead learn the relative position among the features. The pooling layer helps achieve this goal and makes the classifier more immune to shift and distortion. It aggregates the information within a set of small local regions and produces a pooled feature map as output. The number of units in a pooling layer thus depends upon the local region of the previous convolution layer feeding input to the units in pooling layer. So for a non-overlapping scheme and a 2x2 region from previous layer connected to units in pooling layer the dimension of feature maps reduce to half of the convolution layer. The max pooling method checks for the maximum value on its local receptive field, multiplies it by a trainable coefficient, adds a trainable bias and generates output.

The second convolution layer follows this sub-sampling layer. Each feature map in C2 layer is generated by taking input from S1. The units in C2 get their input from the 5x5 neighborhood at identical position of some layers in S1 and not all. The reason for not connecting C2 feature maps to all feature maps of S1 layer is to reduce the total number of trainable parameters and, this also introduces randomness in providing input to different feature maps with the assumption that this will help them to learn complementary features with one another. The output of this convolution layer is subsampled, convolved and forwarded to fully connected layer. From this point we obtain a 1D feature vector. The fully connected layers model the input by applying non-linearity like in a traditional feed-forward network. The type of nonlinearity used is ReLU-non linearity

$$f(x) = \max(0, x)$$

The reason for using it instead of the widely popular nonlinear functions like

$$f(x) = \tanh(x)$$

and

$$f(x) = (1 + exp^{-x})^{-1}$$

is because training with gradient-descent is comparatively much faster for ReLU than the other non-linearities.(Nair & Hinton, 2010) The depth of the network and the size of different layers to be used depends greatly on the dataset and the problem domain. Furthermore, the number of feature maps in a layer, the size of the kernel on each layer and the choice of non-overlapping or overlapping kernel and the extent of overlap also produces different results. So, in our case we tested different architectures by varying these parameters and presented results of the architecture producing the highest accuracy on the test data set. The result of the tests are summarized on the Experimental setting and results section.

The large and deep architecture of CNN with large bank of trainable parameter makes it susceptible to overfitting. While training the deep networks, it is very difficult to find optimal hyper parameters of the functions that share the parameters. These networks being large, require large amount of training data. Below given are some approaches we used to prevent our model from overfitting.

1.**Dataset augmentation:** For the better recognition models, we require to have more training samples while training the system.(Kobetski & Sullivan, 2013) This can be achieved by augmenting available dataset by mirroring, rotation, jittering, noise injection and random crops.
2.**Dropout:** Dropout simply refers to dropping out units; units representing both hidden and visible in the deep network.(Srivastava et al., 2014) We temporarily remove the random units from the network along with all its inlet and outlet connections. For each training iterations, there will be new lighter network that remains after dropping the random units from the common denser architecture which will be sampled and trained. Each unit is retained with the fixed probability of p independent of other units and we set 0.5 for p, the number being optimal choice for most of the cases.

Experiments and Result

We tested the dataset with different architectures by varying depth, width and number of parameters of network. The results of two of those experiments are presented in the coming sections. The first model is very wide and deep and consists of a large number of parameters. It will be referred to as model A in the coming section. It consists of three convolution layers and one fully connected layer. The sequence of the layers in model A is shown in Figure4., where model consist of three convolution layer, three Rectified Linear Unit Layer, two Normalization layer implementing Local Response Normalization, two pooling layer implementing max pooling, one Dropout layer and one Fully Connected Layer and a accuracy layer for test set and a Softmax Loss layer that computes multinomial logistic loss of the softmax of its input.

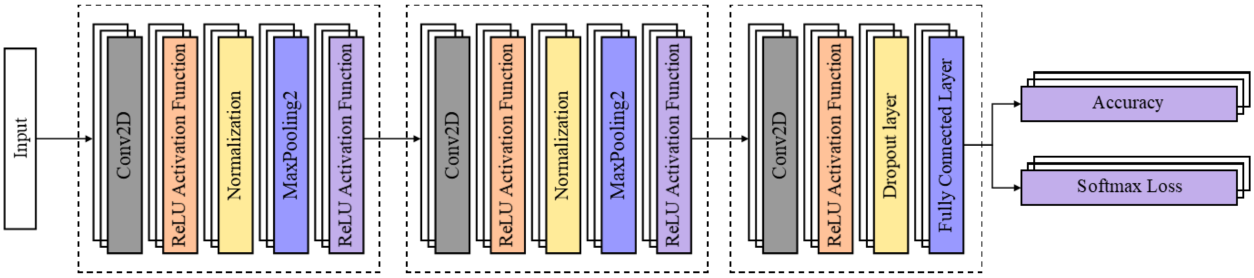


Figure 4: Architecture of model A- deep CNN model for handwritten character recognition.

The second model is derived from the lenet family. It has a shallower architecture and consists of fewer number of parameters than model A.It will be referred to as model B in the coming section. It consists of two convolutional layers followed by two fully connected layers. The sequences of layers in model B is shown in Figure5 where each notation holds similar meaning as discussed for model A.

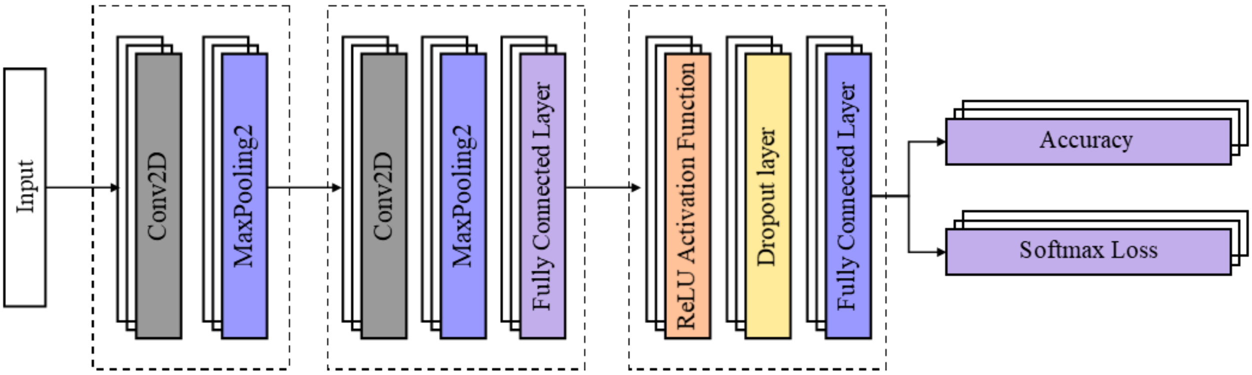


Figure 5: Architecture of model B- deep CNN model for handwritten character recognition.

In all cases, Convolution is implemented with overlapping Filter(Kernel) of Size 5∗5 and stride 1 on both direction. Pooling is implemented with a non-overlapping Filter of size 2 ∗ 2 and stride 2 on both directions. Local response Normalization is achieved by dividing each input value by the expression

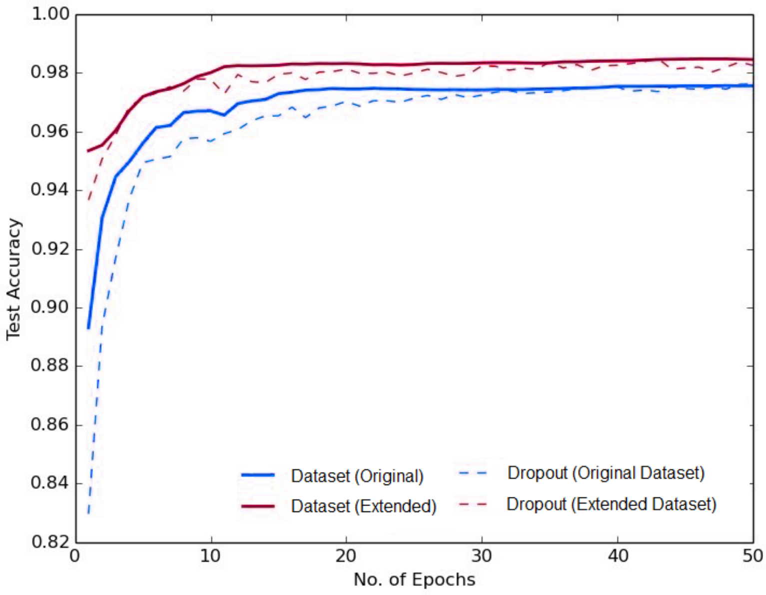
$$\left(1+\left(\frac{\alpha}{n}\sum_{i} x_i^2\right)\right)^{\beta}$$

,where n is the size of each local region, and the sum is taken over the region centered at that value. The value of αparameter used is 0.001 and β-parameter is 0.75.

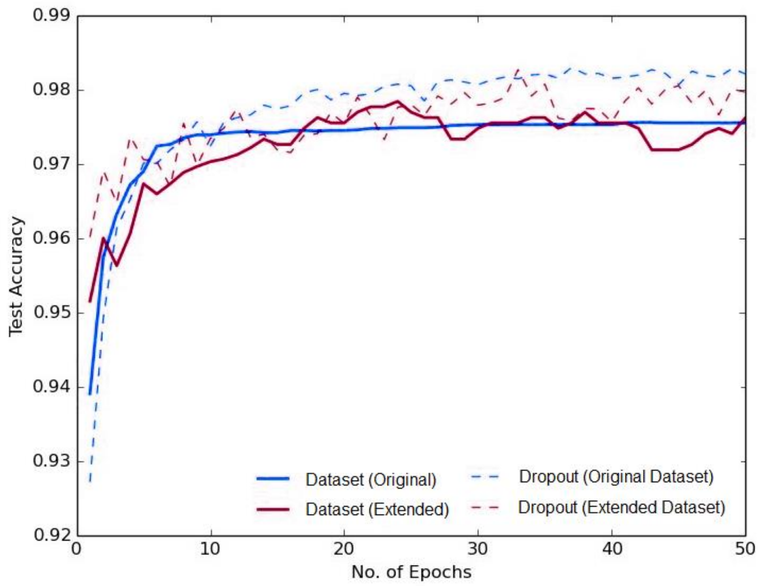
Our deep neural network was trained on the DCD as a multi-class classification problem. For both the models, the standard back-propagation on feed-forward net is implemented by stochastic gradient descent(SGD) with momentum of 0.9. The mini-batch size is 200 and the network was trained for 50 epochs. The base learning rate was initialized for all trainable parameters at 0.005 for Model A and 0.001 for Model B. The learning rate was updated by an inverse function using the relation

$$LR = BLR \times (1 + \gamma \times iterations)^{-power}$$

Where BLR is the Base Learning Rate and iterations is the number iterations completed. The value of γ was set to 0.0001 and power was set to 0.75.



Performance of Model A



Performance of Model B

Figure (a)

Figure (b)

Figure 6: Accuracy testing of the models

The result of training for 50 epoch is presented in Figure6. Test Accuracy remained nearly constant after 50 epochs. For modelA, Extending Dataset showed superior result in Test Accuracy. So, increasing number of training sample is effective to increase performance of wide and deep network with large bank of parameters. The highest testing accuracy obtained for Model A is 0.98471. For model B, addition of dropout showed better improvement in Test accuracy. However, extending dataset also resulted slight improvement in Test accuracy. The highest value of Testing Accuracy obtained for this model is 0.981326.

Conclusion

The presented research work proposed a deep learning CNN model that provide a high accuracy rate $\approx 98.13\%$to recognizing handwritten Devnagari Character, the model is trained using the publically available Devnagari Character Dataset for any researcher. It consists 92 thousand images of 46 different characters of Devnagari script. The proposed model explored the challenges in classification of characters in Devnagari Dataset. The challenges result due to the fact that the dataset consists many characters that are visually similar or written in a similar way by most people. Also, In Devnagari script, the base form of consonant characters can be combined with vowels to form additional characters which is not explored in this research. For recognition, we proposed two deep learning models to train the dataset. We also analyzed the effect of dropout layer and dataset increment to prevent overfitting of these networks. The experimental results suggested that Deep CNNs with added Dropout layer and Dataset increment technique can result in very high test accuracy even for a diverse and challenging dataset like ours.

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