HCR-Net: A deep learning based script independent handwritten character recognition network

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Abstract Despite being studied extensively for a few decades, handwritten character recognition (HCR) is still considered a challenging learning problem in pattern recognition, and there is very limited research on script independent models. This is mainly because of similarity in structure of characters, different handwriting styles, noisy datasets, diversity of scripts, focus of the conventional research on handcrafted feature extraction techniques, and unavailability of public datasets and code-repositories to reproduce the results. On the other hand, deep learning has witnessed huge success in different areas of pattern recognition, including HCR, and provides an end-to-end learning. However, deep learning techniques are computationally expensive, need large amount of data for training and have been developed for specific scripts only. To address the above limitations, we have proposed a novel generic deep learning architecture for script independent handwritten character recognition, called HCR-Net. HCR-Net is based on a novel transfer learning approach for HCR, which partly utilizes feature extraction layers of a pre-trained network. Due to transfer

learning and image-augmentation, HCR-Net provides faster and computationally efficient training, better performance and better generalizations, and can work with small datasets. HCR-Net is extensively evaluated on 40 publicly available datasets of Bangla, Punjabi, Hindi, English, Swedish, Urdu, Farsi, Tibetan, Kannada, Malayalam, Telugu, Marathi, Nepali and Arabic languages, and established 26 new benchmark results while performed close to the best results in the rest cases. HCR-Net showed performance improvements up to 11% against the existing results and achieved a fast convergence rate showing up to 99% of final performance in the very first epoch. HCR-Net significantly outperformed the state-of-the-art transfer learning techniques and also reduced number of trainable parameters by 34% as compared with corresponding pretrained network. For reproducibility of the results and for further advancements of the HCR research, complete code is publicly released and verified at https: //codeocean.com/capsule/9660931.

Keywords Handwritten character recognition \cdot deep learning \cdot transfer learning \cdot offline handwriting \cdot script independent

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1 Introduction

Handwritten character recognition (HCR) is a widely studied and an important pattern recognition problem, e.g., [1,2,3,4,5,6,7,8,9]. It has a variety of useful applications, e.g., digitizing ancient documents, converting handwritten notes on tablets to text, reading doctor prescriptions and in the automated processing of forms in railways, post-offices and government offices, in developing applications to help visually impaired people, and in classroom teaching etc. [3,5,10,11].

Handwriting recognition, depending upon the type of data as online and offline, can be broadly classified into two categories [11,12] and so need different techniques for recognition. Online data consists of series of points (x,y) where x and y are coordinates, recorded between pen down and pen up on a digital surface. On the other hand, offline data consists of images of characters. Online data can be converted to offline and then offline techniques can be applied to online data which can sometimes give better results, e.g., [13]. So, this paper focuses only on offline HCR but presents examples of online handwriting datasets IAPR-11 and UJIPen-Chars, which are first converted to images and then proposed recognition technique is applied.

Based on research approaches used for HCR, the research can be broadly classified into two categories: conventional approaches and deep learning (DL) based approaches, as shown in Fig. 1 and discussed in detail in Section 2. The conventional approaches focus on development of feature extraction (FE) techniques and classifiers for recognition. FE involves finding distinct elements of characters which help to distinguish it from others. Generally, FE develops handcrafted features based on morphological or structural appearance of characters, which are domain/script specific and are not always available. FE can use statistical features, like zoning, histograms, and moment etc., or structural features, like number of loops, intersections, and endpoints etc. Support vector machine (SVM), hidden Markov model (HMM), decision trees, k-nearest neighbour (k-NN) and multi-layer perceptrons (MLP) are widely used for recognition under the conventional approaches [6, 14, 15, 16, 17, 18, 19, 20]. Unlike conventional approaches, DL provides an end-to-end learning, i.e., performs both automated feature extraction and recognition. The recent success of DL, especially convolutional neural networks (CNN), also referred as ConvNets, have shown impressive results in HCR and have become first choice of the researchers, e.g., [11,8,12,21, 22, 23, 24, 25].

HCR is being studied for a few decades [1] but it is still an unsolved challenging learning problem in pattern recognition [26]. This is mainly because of following reasons: (i) every person has its own writing style and no two persons' handwritings match, and that's why it is considered as a unique biometric identifier of a person, (ii) most of the scripts have characters which are similar in their structure, e.g., 'ta' and 'na' in Devanagari look similar, as shown in Sub-figs. 6e and 6f, (iii) noisy data due to errors in the recording process, such as, unwanted marks in the background of characters or errors in cropping images, e.g., in Sub-fig. 6d 'digit_9' is not cropped properly, (iv) bad handwriting, e.g., in

Sub-fig. 6c 'digit_7' appears as 'digit_0', (v) recursive nature of scripts, e.g., Bangla, and (vi) unavailability of public datasets and code-repositories to reproduce and extend the existing results.

For some scripts, like Chinese, Japanese and Latin etc., there have been extensive research [4,21,27,28,29]. However, for some other scripts, such as Gurmukhi, the research is still in its infancy. Since the research on individual scripts is considered as an open problem and is ongoing [13], so there is a little research on multiscript models. This is due to following reasons: (i) the conventional research was focused on handcrafted features which are domain/script specific and are not always available, (ii) a large variety of scripts and their diversity, and (ii) unavailability of datasets and coderepositories for extending and for reproducibility of results etc.

From the above discussion, it is clear that HCR still remains a challenging pattern recognition problem and lacks development of script independent recognition techniques. Deep learning offers end-to-end learning solution for HCR, however, the existing deep learning techniques are tuned to specific scripts/datasets, are computationally expensive and also lack reproducible code. Thus, the objective of the study is to develop a generic, computationally efficient, faster, robust and publicly available and reproducible script independent deep learning technique for HCR, which could work even with small datasets.

Building on the recent success and capability of endto-end learning of deep learning, and availability of publicly available datasets, this paper proposes a script independent novel deep convolutional network for HCR, called HCR-Net. HCR-Net is a script independent technique as it does not dependent on script specific handcrafted features which might not be available for all the scripts. Moreover, it is based on a novel transfer learning approach and supported by image-augmentation, which make HCR-Net as a powerful generic architecture, unlike deep learning techniques developed for specific scripts [24]. The proposed architecture has advantages of faster and robust learning, computational efficiency and capability of dealing with trivial datasets, i.e., datasets with small number of samples. The proposed model trains in two-phases where first phase initializes some weights from some of lower layers of a pre-trained VGG16 [30] and can get impressive results on most of the datasets. Second phase involves training all weights of the model and is helpful for complex handwriting problems with noisy data or large number of classes etc.

The key contributions of the paper are summarized below.

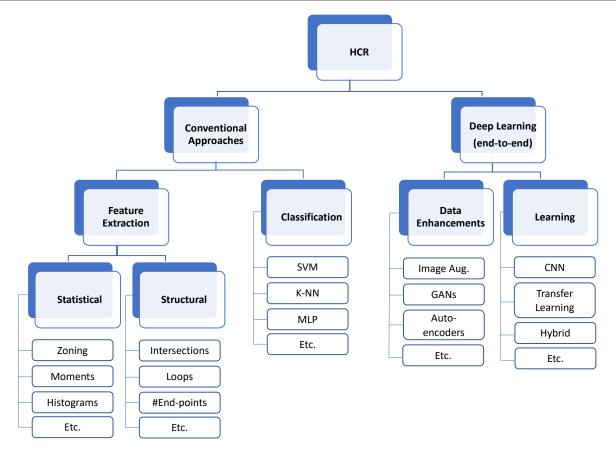


Fig. 1: Handwritten character recognition research

- (a) This paper proposes the first script independent novel deep convolutional network for end-to-end handwritten character recognition, called HCR-Net.
- (b) HCR-Net develops a novel transfer learning approach for HCR research by partly utilizing feature extraction layers of a pre-trained VGG16 to initialize some of its lower layers, unlike the existing research which utilizes all feature extraction layers of the pre-trained models. Transfer learning along with image augmentation helps HCR-Net in faster, computationally efficient and robust learning and learning even on trivial datasets as compared with CNN models developed from scratch.
- (c) HCR-Net is extensively evaluated on 40 publicly available datasets of Bangla, Punjabi, Hindi, English, Swedish, Urdu, Farsi, Tibetan, Kannada, Malayalam, Telugu, Marathi, Nepali and Arabic languages, and established 26 new benchmark results while performing very close to the best results in the rest cases. HCR-Net showed performance improvements up to 11% against the existing results. HCR-Net achieved a fast convergence rate and showed up to 99% of final performance in the very first epoch. HCR-Net also significantly (p-

- value=0.00099 using Student's t-test) outperformed the existing transfer learning techniques and showed 34% reduction in number of trainable parameters as compared with the corresponding pre-trained network
- (d) For reproducibility and advancement of the HCR research, the complete code is released and verified at: https://codeocean.com/capsule/9660931.

Organization of rest of the paper: Section 2 presents literature review and discusses about conventional approaches and recent deep learning based approaches for HCR. Section 3 discusses HCR-Net and Section 4 presents experimental results on different scripts. Finally, Section 5 concludes the paper.

2 Literature review

In this section, literature on HCR is briefly discussed which can be broadly classified into two categories, conventional approaches and deep learning based approaches [31], as depicted in Fig. 1 and discussed in following subsections.

2.1 Conventional approaches

HCR field is studied extensively for more than five decades [1,2,3,4,5,6,7,16,8,9]. Earlier, the focus of research was mainly on developing feature extraction techniques and applying different classification techniques for recognition. FE is the process of finding key features which can distinguish different classes correctly and is a critical factor for the performance of machine learning models. FE can be further broadly classified into statistical and structural FE techniques. Statistical FE considers features based on pixels distribution in an image, e.g., histograms, zoning and moments etc. But structural FE techniques consider features based on the structure of characters, such as loops, intersections, and number of endpoints etc. On the other hand, classification techniques are machine learning tools which learn to classify/recognize a script from a given features/dataset. For example, SVM (for more details refer to [32]), k-NN and MLP are most widely used classifiers in the conventional approaches [6,14,15,19,17, 18]. Few representative conventional approaches are discussed below.

[1] proposed a Fourier transformation based FE along with a non-optimized decision method for recognition of handwritten characters. [3] developed a system for recognition of unconstrained handwritten digits using FE based on geometric primitives containing topological information such as convex polygons and line segments, with a relaxation matching classifier. [33] proposed a novel FE method based on the concept of water overflow from a reservoir as well as statistical and topological features along with a tree based classifier for unconstrained offline handwritten Bangla numerals. [34] used wavelet based multi-resolution features with multilayer perceptron classifiers for digit recognition. [6] proposed genetic algorithm (GA), simulated annealing and hill climbing techniques to sample regions to select local features. They used SVM classifier for handwritten digit recognition. [14] proposed principal component analysis (PCA), modular PCA and quad-tree based hierarchically derived longest-run features with SVM for recognition of numerals of Devanagari, Telugu, Bangla, Latin and Arabic scripts. [15] presented a benchmark offline dataset of isolated handwritten Bangla compound characters, called as CMATERdb 3.1.3.3. The recognition was performed using quad-tree based features with SVM. [35] studied a multi-script numeral recognition for Bangla, Arabic, Telugu, Nepali, Assamese, Gurumukhi, Latin and Devanagari scripts. They used histogram of oriented pixel positions and point-light source-based shadow feature extractors with k-NN, random forest, MLP, simple logistic and sequential minimal optimization as classifiers.

2.2 Deep learning approaches

The recent success of DL models, especially CNN, have revolutionized the artificial intelligence world and have found applications in different fields like, image processing, computer vision, healthcare and natural language processing etc. [36, 37, 38, 39, 40, 41]. The success of DL models can be attributed, mainly to the advancements in the hardware technology, new optimization algorithms and availability of large number of data sources. CNN have shifted paradigm from handcrafted features to automated features learned directly from the input images. CNN also outperform all other machine learning techniques for HCR and have become the choice of researchers [22, 24, 42, 17, 31, 43]. But the main limitations with CNN are that they need large amount of data, great computing resources and large training time, if trained from scratch. These limitations are overcome with the use of image augmentation and transfer learning techniques. The CNN are the state-of-art for HCR research and a few important studies are discussed below.

[44] proposed a CNN based architecture for Hangul HCR and reported results of 95.96% and 92.92% on SERI95a and PE92 datasets, respectively. [17] employed a layer-wise training of CNN based architecture for isolated Bangla compound character recognition. The proposed model was reported to outperform conventional shallow models, like SVM, as well as regular CNN. [27] proposed a cascaded CNN with weighted average pooling for reducing the number of parameters for Chinese HCR. They reported 97.1% results on ICDAR-2013 dataset. [45] also proposed a CNN based architecture utilizing scattering transform-based wavelet filters in the first convolutional layer for Malayalam HCR. [31] designed a lighter multi-channel residual CNN network (similar to GoogLeNet [37]) for handwritten digit recognition and reported results on mnist and SVHN datasets. [46] proposed a CNN based architecture for offline Tamil HCR on HP Labs India dataset and achieved an accuracy of 97.7%. [47] developed a CNN based architecture for low memory GPU for offline Bangla HCR. They used spatial pyramid pooling and fusion of features from different CNN layers. [24] proposed DevNet, a CNN based architecture with five convolutional layers followed by max pooling, one fully connected layer and one fully connected layer as output, for Devanagari HCR. [21] presented a high-performance CNN based architecture using global weighted output average pooling to calculate class activation maps for offline Chinese HCR. [19] introduced Meitei Mayek (Manipuri script) handwritten character dataset. They reported results using handcrafted features such as HOG and discrete wavelet transform (DWT), and image pixel intensities with random forest, k-NN, SVM and also using CNN based architecture. CNN model provided benchmark results of 95.56%. [9] used a CNN based architecture which uses a self-adaptive lion algorithm for fine tuning fully connected layer and weights for Tamil HCR. [48] proposed a three channel CNN architecture using gradient direction, gradient magnitude and greyscale images for Meitei Mayek HCR.

Transfer learning is very successful to work with small datasets, including HCR [49, 24, 22, 13]. For example, [22] used fine-tuned VGG16 in two stages for recognition of Devanagari and Bangla scripts. [49] also used fine-tuning of pre-trained AlexNet and VGG16 on some Indic scripts. Image augmentation (IA), generative adversarial networks (GANs) and auto-encoders also help to work with limited datasets [22,50,38,51,43,52]. IA artificially expands datasets by using operations, such as translation, flip, rotation, shear and zoom etc. on the input images. This helps in developing robust classifier with limited datasets because the model is trained on the modified variants of the training images, e.g., [22, 50,38]. GANs are deep neural networks which are used to generate new, synthetic data, similar to real data. For example, [51] used GANs for Devanagari handwritten character generation. Auto-encoders are also deep neural networks which are used to learn compact representation of the data, like PCA and also for generating synthetic data, e.g., [43] used deep encoder and CNN for recognition of handwritten Urdu characters.

In addition, hybrid of conventional and deep learning approaches are also developed for HCR. For example, [53] used LeNet-5 for FE and SVM as classifier for recognition of Bangla, Devanagari, Latin, Oriya and Telugu. [42] used scattering CNN with SVM for Malayalam HCR. [8] proposed a multi-column multi-scale CNN architecture based on a multi-scale deep quad tree based feature extraction and used SVM as a classifier. They reported their results with Bangla, Tamil, Telugu, Hindi and Urdu scripts.

Thus, from the brief literature review, we find that conventional approaches are not suitable for script independent HCR due to use of handcrafted features or manually designed features based on morphological or structural appearance, which might not be available all the time. On the other hand, recent developments in DL approaches due to its end-to-end learning approach are suitable but are studied a little for multi-script HCR. Moreover, the existing deep learning techniques are computationally expensive, lack reproducible code

and are developed specifically to some scripts and may not work on other scripts.

3 HCR-Net

HCR-Net is a CNN based end-to-end architecture for offline HCR whose lower and middle layers act as feature extractors and upper layers act as classifiers. This is a generic script independent model based on novel transfer learning and image augmentation, which help it in faster and computationally efficient learning, performing on the small datasets and in better generalization. HCR-Net initializes some of its layers using some of lower layers of a pre-trained VGG16, which was originally trained on the ImageNet with 14 million images and 1000 classes [30], and trains in two-phases. Following subsections provide details about HCR-Net.

3.1 Image augmentation (IA)

IA is a data augmentation technique which helps to artificially expand the training dataset by creating modified versions of the training images. For example, an input image can be modified by rotation, shear, translation, flip (vertical or horizontal), zoom and their hybrid combinations etc. This helps to apply DL techniques for problems with limited datasets which otherwise might not be possible to train on such a dataset. IA also helps a model to generalize well on the test dataset because of its training on different variants of training images. Some HCR studies have already used IA and reported improvements in the performance of the model, e.g., [50,22,38].

Fig. 2 presents an example of IA on a character image and applies rotation, shear, translation, zoom and hybrid operations. It is to be noted that IA should be applied carefully to HCR as it is different from other image classification tasks because it can distort the structure of character and change its meaning, e.g., horizontal flip or large translation.

3.2 Transfer learning (TL)

In deep learning, TL is a technique to transfer knowledge learned on one task to another related task. Thus, TL enables the reuse of pre-trained models on a new but related problem. TL is very useful in faster training, mostly better results and learning on small datasets which otherwise will need large amount of data for DL models [22]. For TL, either pre-trained models can be used, or a source model can be trained first where large

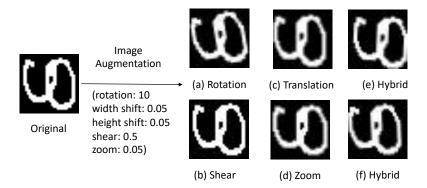


Fig. 2: An example of mage augmentation using rotation, translation, shear, zoom and hybrid operations

amount of data is available and then the source model can be reused on the target problem. In both the cases, either entire model can be reused or part of it. As discussed in Section 2.2, TL has already been studied in HCR and has helped to get better performance, e.g., [49,24,22].

As shown in Fig. 3, HCR-Net architecture partly matches VGG16 up to block4_conv2 layer. HCR-Net initializes those layers with a pre-trained VGG16. Thus, our use of TL is novel in HCR research to the best of our knowledge as it reuses pre-trained model partly, unlike existing research which uses entire pre-trained models [49,22]. Moreover, this approach enables to use TL without using complex models. Details on training of HCR-Net are provided in Subsection 3.4.

3.3 Proposed architecture

Fig. 3 presents the architecture of HCR-Net. It takes input as a greyscale image of 32×32 pixels and produces output as class probabilities, and class with highest probability is predicted as target. The hypothesis behind the proposed architecture is that lower level layers learn the basic features and higher level layers learn combination of those basic features which are specific to learning task. Moreover, handwritten characters do not present complex task as are dealt by the pre-trained complex networks like VGG16. So, use of only some of the lower layers of pre-trained models could be sufficient and could give better results, as is supported by our experiments. This is also the reason for using VGG16 and not using complex and powerful architectures, such as ResNet, DenseNet and Inception etc. having large number of layers, all of which are not very useful in HCR.

The architecture consists of convolutional, pooling, batch normalization (BN), dropout and dense layers. The lower part of the architecture, enclosed inside red square in Fig. 3, is similar to VGG16 architecture up

to block4_conv2 layer, and act as feature extractor. It has four convolutional blocks: first has two convolution layers with 64 filters followed by a max-pooling layer, second block has two convolutional layers with 128 filters followed by max-pooling, third block has three convolutional layers with 256 filters followed by maxpooling, and last convolutional block has two convolutional layers with 512 filters. All the convolutional layers use stride of one and padding as 'same', and all the pooling layers use stride of two and padding as 'valid'. The convolutional blocks are followed by BN and two dense layers each of which has 512 neurons and is followed by BN + dropout (with 35% rate) layers. The last layer is dense layer with neurons equal to number of output classes. All convolutional and dense layers use ReLU as activation function except the output dense layer which uses softmax, because it is faster and helps to avoid gradient vanishing problem. Categorical cross-entropy is used as a loss function with Root Mean Square Propagation (RMSprop)¹ as an optimizer to update weights/parameters of the network. The complexity of a deep CNN, and hence of HCR-Net is $\Omega(n)$, where n is number of pixels in an image.

For an input vector x, label vector p, predicted probability vector \hat{p} and for C classes, ReLU, softmax, categorical cross-entropy and RMSprop's weight update rules are given below.

$$ReLU(x) = \max(0, x), \tag{1}$$

$$softmax(x)_i = \frac{exp(x_i)}{\sum_j exp(x_j)},$$
(2)

$$l(p, \hat{p}) = -\sum_{i=1}^{C} p_i \log(\hat{p}_i),$$
 (3)

¹ http://www.cs.toronto.edu/~tijmen/csc321/slides/ lecture_slides_lec6.pdf

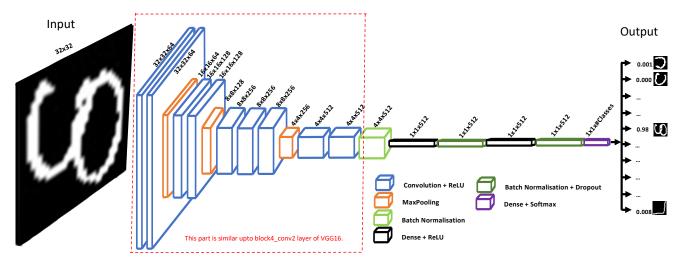


Fig. 3: Proposed architecture of HCR-Net

$$v_{t} = \beta v_{t-1} + (1 - \beta)g_{t}^{2},$$

$$W_{t+1} = W_{t} - \alpha_{t}V_{t}^{-1/2}g_{t}$$
with $V_{t}^{-1/2} = \operatorname{diag}(v_{t} + \epsilon),$
(4)

where $g_t = \nabla f(W_t, \xi_t), \ \beta \in [0, 1], \ \alpha_t$ is learning rate

(also called as step size), W_t , ξ_t are model weights and randomness at step t, and ϵ is very small number for numerical stability. The different layers of HCR-Net are discussed below.

Convolution layers are the heart and soul of CNN and also give the network its name. It applies convolution operation which is a repeated application of a set of weights, called a filter, to the input image and generates a feature map and helps in learning some specific feature during training. So, use of multiple filters generates multiple feature maps, each learning some aspect of the image. Convolutions are very useful for learning spatial relationships in the input and reducing parameters by sharing of weights. Let there are l input feature maps of size m * m, convolutional filter size is n * nwith stride s, padding p, number of feature maps k and output size o * o, then

#Params =
$$(n * n * l + 1) * k$$
,

$$o = \lfloor \frac{m + 2p - n}{s} \rfloor + 1.$$
(5)

Pooling layers (PLs) are commonly inserted after successive convolutional layers. Its function is to down sample the feature maps obtained from convolutional layers. So, it helps in reducing computations and number of parameters, hence it avoids over-fitting and helps in achieving local translation invariance. PL uses filters, smaller than feature maps, on patches of feature maps and summarizes the information. The most commonly used pooling operations are max pooling and average pooling, which returns the most activated feature and average feature, respectively. Let m*m be input size of one feature map, n * n be filter size with stride s and output o * o, then

#Params = 0,

$$o = \lfloor \frac{m-n}{c} \rfloor + 1.$$
(6)

Batch-normalization (BN) layers It is a technique for training very deep neural networks that normalizes inputs of neural network layers coming from previous layers, and since this is done in batches so the name BN [54]. It helps to stabilize the training of deep neural networks and get faster convergence. [55] argued that a combination of BN and dropout outperforms the baselines and gives better training stability and faster convergence. So, we have used combination of BN and dropout with dense layers in HCR-Net. Let B be a mini-batch of size b, then mean and variance over B

$$\mu_B = \frac{1}{b} \sum_{i=1}^b x_i$$
, and $\sigma_B^2 = \frac{1}{b} \sum_{i=1}^b (x_i - \mu_B)^2$. (7)

For d-dimensional input, each dimension is normalized

$$\hat{x}_i^{(k)} = \frac{x_i^{(k)} - \mu_B^{(k)}}{\sqrt{\sigma_B^{(k)^2} + \epsilon}}, \text{ where } k \in [1, d], i \in [1, m],$$
(8)

 ϵ is an arbitrarily small constant added for numerical stability, and transform is given below,

$$y_i^{(k)} = \gamma^{(k)} x_i^{(k)} + \beta^{(k)}, \tag{9}$$

where $\gamma^{(k)}$ and $\beta^{(k)}$ are parameters learned during training. So, BN transform is $BN_{\gamma^{(k)}\beta^{(k)}}: x_{i=1,2,..,m}^{(k)} \to y_{i=1,2,..,m}^{(k)}$, with output equal to input and number of parameters is 2d.

Dropout layers randomly and temporarily remove a given percentage of neurons from the hidden layers. This is one of the regularization techniques in deep leaning and helps neural networks (NN) to avoid overfitting because it helps NN in removing dependency on any specific neuron. This is not a computationally expensive regularization technique as it does not require any specific implementation or new parameters. Output from the dropout layer is equal to input of the layer. Mostly, it is used after dense layer, but it can be used with other layers.

Dense layers This is a most commonly used layer in NN. Dense layer, also called fully connected layer, contains a given number of neurons each of which is connected to all neurons in the previous layer. Output layer is mostly a dense layer which has number of neurons equal to number of classes, representing different class probabilities. Let n_i and n_o be number of neurons in input and output for a dense layer, then

$$#Params = n_i * n_o + n_o,$$
Output size = n_o . (10)

Table 1 presents different layers of HCR-Net along with their types, outputs and number of parameters. In first phase, layers up to block4_conv2 are initialized from pre-trained VGG16 layers and are freezed, i.e., parameters/weights are not updated, and rest of the layers are trained, so number of trainable parameters in first phase are 4,465,674 of total parameters 9,744,202. Moreover, for second phase all layer weights are updated so number of trainable parameters are 9,741,130 while 3,072 are non-trainable. The non-trainable parameters belong to BN layer because for each dimension BN maintains four parameters to keep track of the distributions, out of which two parameters are non-trainable (i.e., moving_mean and moving_variance).

3.4 Two-phase training

HCR-Net trains in two-phases due to transfer learning. In first phase, parameters initialized from pre-trained weights of VGG16 are freezed and rest of the parameters are trained. The model trains faster in first phase than the second phase and is quite powerful as most of the time it can achieve up to 99% of the final accuracy in just one epoch and converges in few epochs. In fact,

Table 1: Summary of different layers and parameters of the proposed HCR-Net for an example with 10 classes

Layer (type)	Output Shape	$\# { m Params}$
Input layer	(None, 32, 32, 3)	0
block1_conv1 (Conv2D)	(None, 32, 32, 64)	1792
block1_conv2 (Conv2D)	(None, 32, 32, 64)	36928
block1_pool (MaxPooling2D)	(None, 16, 16, 64)	0
block2_conv1 (Conv2D)	(None, 16, 16, 128)	73856
block2_conv2 (Conv2D)	(None, 16, 16, 128)	147584
block2_pool (MaxPooling2D)	(None, 8, 8, 128)	0
block3_conv1 (Conv2D)	(None, 8, 8, 256)	295168
block3_conv2 (Conv2D)	(None, 8, 8, 256)	590080
block3_conv3 (Conv2D)	(None, 8, 8, 256)	590080
block3_pool (MaxPooling2D)	(None, 4, 4, 256)	0
block4_conv1 (Conv2D)	(None, 4, 4, 512)	1180160
block4_conv2 (Conv2D)	(None, 4, 4, 512)	2359808
$batch_normalization$	(None, 4, 4, 512)	2048
flatten (Flatten)	(None, 8192)	0
dense (Dense)	(None, 512)	4194816
batch_normalization_1	(None, 512)	2048
dropout (Dropout)	(None, 512)	0
dense_1 (Dense)	(None, 512)	262656
batch_normalization_2	(Batch (None, 512)	2048
$dropout_1 (Dropout)$	(None, 512)	0
dense_2 (Dense)	(None, 10)	5130

the model obtained after the first phase is sufficient for most of the datasets like handwritten digit recognition.

In the second training phase of HCR-Net, all the parameters of the network are learned. Although, for the first few epochs learning rate is kept very small to avoid abrupt changes to the parameters and avoid losing information. Then, learning rate is increased, as discussed in Subsec. 4.2. Second phase is useful for complex datasets, is computationally expensive and requires more epochs to converge with little improvements.

Table 2 presents convergence analysis for two phases of HCR-Net. As it is clear from the table, without image-augmentation, first phase can get up to 99% (and more in some cases) of final accuracy in just first epoch. Moreover, there is very slight improvement in the second phase. With image-augmentation, test accuracy in first epoch of first phase training is lower as compared with without-augmentation because training images have more diversity and hence more to learn due to modified variants of the images. Further, with-augmentation second phase shows relatively more improvement over first phase, as compared with without-augmentation.

Fig. 4 presents convergence analysis of two phases, averaged over five runs, of HCR-Net using RMSprop optimizer on Gurmukhi_1.1 dataset, where first phase runs for 30 epochs while second phase runs for 20 epochs.

Dataset	Without aug	gmentation	With augmentation		
Dataset	First phase	Second phase	First phase	Second phase	
	first Last epoch	last epoch	first Last epoch	last epoch	
Gurmukhi_1.1	96.82 99.28	99.31	94.67 99.18	99.47	
Kannada-mnist	84.05 84.90	85.46	84.45 86.43	88.26	
Mnist	99.05 99.42	99.49	98.87 99.31	99.55	
UCI Devanagari	98.04 99.30	99.42	97.71 99.13	99.59	

Table 2: Analysis of two-phase training of HCR-Net

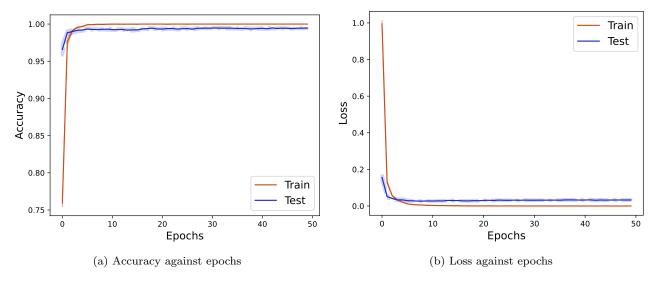


Fig. 4: Convergence analysis of HCR-Net on Gurmukhi_1.1 dataset, where first phase takes first 30 epochs and second phase uses the remaining 20 epochs.

The figure shows how accuracy improves and loss/error reduces with each epoch (i.e., pass through the data), where solid line represent average results and shaded regions around the lines represent standard deviation in the performance. As it is clear from the figure, HCR-Net shows small deviations in the performance over multiple runs. HCR-Net also converges very quickly in a few epochs, and it is difficult to detect the slight improvement in performance obtained in the second phase with bare eyes. Moreover, small gap between test and train performance shows nice convergence of the model without over-fitting, obtained with the use of dropout.

4 Experimental results

This section presents statistics about datasets used in the experiments, provides experimental settings, compares HCR-Net against different benchmark studies and some of the state-of-the-art transfer learning techniques, and also discusses error analysis.

4.1 Datasets

The experiments use publicly available datasets from Bangla, Punjabi, Hindi, English, Swedish, Urdu, Farsi, Tibetan, Kannada, Malayalam, Telugu, Marathi, Nepali and Arabic languages belonging to Bangla, Gurmukhi, Devanagari, Latin, Urdu, Farsi, Tibetan, Kannada, Malayalam, Telugu and Arabic scripts. The statistics of 41 datasets used in the experiments is given in Table 3. The datasets contain two online handwriting datasets (shown with 'O' in the name), namely, IAPR TC-11 and UJIPenChars. The online datasets are first converted to offline images and then proposed model is applied.

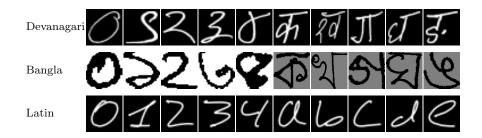
Few samples of some scripts are presented in Table 4, where samples are taken from UCI Devanagari, CMATERdb 3.1.1 & CMATERdb 3.1.2 (Bangla) and UJIPenChars (Latin) datasets. This highlights structural differences in different scripts, e.g., a horizontal line above the character is used in Devanagari and Bangla scripts but not in Latin script. This table also shows some noise (for Bangla) in recording different characters, which makes HCR a challenging task.

Table 3: Statistics for different character datasets

Dataset	Writers	Samples per class	Classes	Training Samples	Testing samples	Total samples
Gurmukhi						
HWRGurmukhi_1.1 [56]	1	100	35	2450	1050	3500
HWRGurmukhi_1.2 [56]	10	10	35	2450	1050	3500
HWRGurmukhi_1.3 [56]	100	1	35	2450	1050	3500
HWRGurmukhi_2.1 [56]	1	100	56	3920	1680	5600
HWRGurmukhi_2.2 [56]	10	10	56	3920	1680	5600
HWRGurmukhi_2.3 [56]	100	1	56	3920	1680	5600
HWRGurmukhi_3.1 [56]	200	1	35	4900	2100	7000
Devanagari						
Nepali (combined) [57]	40	_	58	_	_	12,912
Nepali numeral [57]	40	_	10	_	_	2880
Nepali vowels [57]	40	_	12	_	_	2652
Nepali consonants [57]	40	_	36	_	_	7380
Marathi numerals [22]	100	100	10	800	200	1000
Marathi characters [22]	100	100	48	3840	960	4800
Marathi combined [22]	100	100	58	4640	1160	5800
IICI Davanagani	100					5000
numerals [7]	_	2000	10	17,000	3,000	20,000
HCI Davanagani		a		04	40	-
characters [7]	_	2000	36	61,200	10,800	72,000
UCI Devanagari		a			40	05 -
total [7]	_	2000	46	78,200	$13,\!800$	92,000
CMATERdb_3.2.1						
Devanagari [6,14]	_	_	10	2400	600	3000
Numeral			10	2400	000	300
IAPR TC-11 (O) [58]	25	_	36	_	_	180
Bangla	20		30			100
CMATERAL 3 1 1						
(Bangla numeral) [6]	_	_	10	4089	1019	510
(Dangia numerar)						
CMATERdb_3.1.2 [59]	_	300	50	12,000	3,000	15,00
(Bangla character) [99]				,	,	ŕ
CMATERdb 3.1.3.3						
(Bangla compound [15]	335	_	171	44,152	$11,\!126$	55,278
character)						
Banglalekha-isolated	_	_	10	15802	3946	1974
numerai			10	10002	3340	1314
Banglalekha-isolated [60]			50	79179	19771	9895
character [00]	_	_	50	19119	19771	9090
Banglalekha-isolated [60]			0.4	100014	20101	1,001,0
combined [60]	_	_	84	132914	33191	16610
ISI Bangla [5]	_	_	10	19392	4000	23,39
Latin						- ,
UJIPenchars (O) [61]	11	_	35	1240	124	136
mnist [4]	_	7,000	10	60,000	10,000	70,00
ARDIS-II [62]	_	-,000	10	6602	1000	760
ARDIS-III [62]		_	10	6600	1000	760
			10			
ARDIS-IV [62]			10	6600	1000	760
Malayalam*			0.5	17 000	0.000	90.80
Amrita_MalCharDb [42]	77	_	85	17,236	6,360	29,30
Malayalam_DB [45]	77		85	22,942	6,360	29,30
Telugu						
CMATERdb 3.4.1 [6]	_	_	10	2400	600	300
(Telugu numeral) [0]			10	2400	000	900
Kannada						
Kannada-mnist [63]	_	_	_	10	60,000	10,24
					60,000	10,00
Urdu					-	· · · · · · · · · · · · · · · · · · ·
Urdu [43]	_	_	10	6,606	1,414	802
Farsi				,	,	
Farsi [64]	_	_	10	60,000	20,000	80,00
Tibetan				,	_==,===	
Tibetan-mnist	_	_	10	14,214	3,554	17,76
TINCOUNT HIHIDU	_	_	10	17,414	5,554	11,10
Arabic						

^{*} Both datasets are same but differ in the splitting.

Table 4: Few handwriting samples of some scripts



4.2 Experimental setup

Different hyperparameters of the HCR-Net, e.g., learning rate, mini-batch size, number of layers, neurons and optimizer are selected by trial over a range of values. Each experiment uses mini-batch size of 32 and RM-Sprop as optimizer. Although, RMSprop and Adam (Adaptive Moment Estimation), which are popular in HCR research, show similar test accuracy but RMSprop is selected because it takes lesser time for training. Image-augmentation uses rotation of 10 degree, horizontal and vertical shift of 0.05, shear 0.5 and zoom of 0.05. Experiments use staircase learning rate to better control convergence of the learning algorithms. In first phase, it starts with high learning rate of 1e-4 to get faster convergence up to five epochs, then learning rate is decreased to 5e-5 for rest of the epochs.

In second phase, up to five epochs learning rate is 1e-7 to avoid abrupt changes in weights, then for rest of epochs except last five, learning rate is increased to 5e-6 and then further decreased to 1e-6 in the last five epochs. Number of epochs required to train HCR-Net is dependent on the dataset and trained until test accuracy becomes stable. Generally, without image-augmentation, first phase is run for 30 epochs and second phase is run for at least 20 epochs. With image-augmentation, first phase is run for 10 epochs and second phase is run for at least 50 epochs, this is because training with image-augmentation learns more on diverse images than without-augmentation and takes longer to converge. All the experiments are implemented using Keras library², averaged over five runs and executed on MacBook Pro (RAM 16 GB, Core-i7) and Linux Server (RAM 64 GB, 56 CPUs and 1 GPU).

The datasets are partitioned into 80:20 ratio for train and test, respectively wherever test sets are not separately available. The experimental results are reported on test dataset using accuracy, precision, recall and F1-score. But, as it is clear from experiments with different datasets, all the metrics have almost similar

values due to class balanced datasets, so accuracy is a sufficient metric for HCR. Some authors also present test error/cost as a metric, since cost is dependent on the objective function/model used for recognition so cost is not a good metric and not used. Moreover, test accuracy is reported at last epoch of the network training, unlike some authors reporting the best accuracy which is not the correct way. This is because during the training of a model, there may be a spike in test accuracy, i.e., optimizer may enter the best solution region for a given test set but that might not give best generalization at that epoch because the decision to select the model is based on the test dataset. So, the test accuracy is reported using test accuracy at last epoch and best test accuracy during the training but only test accuracy at last epoch is used to compare with the existing literature. We argue that either the results should be reported at last epoch of training or reports should be reported on a separate dataset not used to decide the model, e.g., dividing the dataset into train, validation and test sets where train and validation may be used for training and final performance should be reported on test set. Similarly, training accuracy is also not a good metric for reporting HCR results because that does not reflect the generalization of the model and the model may be overfitting on the train dataset.

4.3 Preprocessing

This paper does not use extensive preprocessing but simple preprocessing techniques as a generic architecture is developed for different scripts. HCR-Net uses greyscale character images of size 32×32 as inputs, and if image augmentation is turned on, then during the training on the fly applies image augmentation of rotation (10 degrees), translation (0.05), sheer (0.05), zoom (0.05) and hybrid combinations. Wherever possible, the character images are plotted against black background to simplify the computations. All image pixel intensities are scaled to a range of 0 to 1.

 $^{^2}$ https://keras.io

Dataset	Precision	Dogoli	Recall F1-score	Accura	асу
Dataset	Frecision	Recail	r 1-score	At last epoch	\mathbf{Best}
HWRGurmukhi_1.1	99.34 99.48	99.31 99.47	99.31 99.47	99.31 99.47	99.49 99.52
HWRGurmukhi_1.2	99.53 98.31	99.50 98.17	99.50 98.16	99.50 98.17	99.81 98.63
HWRGurmukhi_1.3	96.71 96.02	96.53 95.64	96.53 95.66	96.53 95.64	96.69 95.96
HWRGurmukhi_2.1	98.95 98.91	98.94 98.83	98.93 98.83	98.94 98.83	99.18 99.02
HWRGurmukhi_2.2	94.58 93.85	94.11 93.37	93.95 93.20	94.11 93.37	94.30 93.76
HWRGurmukhi_2.3	93.74 93.52	93.37 93.25	93.19 93.04	93.37 93.25	93.68 93.45
HWRGurmukhi_3.1	97.40 96.90	97.34 96.68	97.33 96.66	97.34 96.68	97.49 96.99

Table 5: Performance of HCR-Net on Gurmukhi script without with augmentation

Table 6: Recognition rates on Gurmukhi datasets

Dataset	Reference	Methodology	Accuracy
HWRGurmukhi_1.1	[56]	Random forest with diagonal features	97.40
	HCR-Net	our work	99.47
HWRGurmukhi_1.2	[56]	Random forest with intersection and open end	93.50
		points features	
	HCR-Net	our work	99.50
HWRGurmukhi_1.3	[56]	MLP with directional features	91.70
	HCR-Net	our work	96.53
HWRGurmukhi_2.1	[56]	Random forest with diagonal features	92.60
	HCR-Net	our work	98.94
HWRGurmukhi_2.2	[56]	MLP with zoning features	91.50
	HCR-Net	our work	94.11
HWRGurmukhi_2.3	[56]	Random forest with intersection and open end	85.30
		points features	
	HCR-Net	our work	93.37
HWRGurmukhi_3.1	[56]	Random forest with diagonal features	90.50
	HCR-Net	our work	97.34

4.4 Comparative study

This subsection provides experimental results and comparisons with the literature. The performance of HCR-Net is reported on test dataset using accuracy, precision, recall and F1-score without and with augmentation, respectively and is separated using '|'. We also present the best accuracy, in addition to accuracy at last epoch just to show that best test accuracy during training is almost all the time more than accuracy at last epoch. Although, we compare only test accuracy at last epoch with the existing results. Following subsections discuss results for different scripts.

4.4.1 Gurmukhi script

Table 5 presents performance of HCR-Net on Gurmukhi script. All the performance metrics for each dataset show similar results because datasets are class-balanced. HCR-Net performs very well despite the fact that the datasets are quite small, and that is because of the power of transfer learning. Moreover, image-augmentation shows improvement only on HWRGurmukhi_1.1 but for rest of the datasets it leads to reduction of performance.

Table 6 presents comparative study of HCR-Net against the state-of-art results. Since these are recently released public datasets so there is not much literature to compare. From the table, it is clear that HCR-Net outperforms existing results and provides new benchmarks on all seven datasets, and shows up to seven percent improvement in the test accuracy. This is because [56] has used traditional machine learning techniques with handcrafted features. Comparison of 1.1 with 1.3 or comparison of 2.1 with 2.3, cases with equal number of samples and classes but 1 and 100 writers, respectively, show decrease in test accuracy with increase in number of writers. This makes the point that different people have different writing styles which impact the performance.

4.4.2 Devanagari script

Table 7 presents performance of HCR-Net on Nepali, Hindi and Marathi languages which share Devanagari script. All the performance metrics for each dataset show similar results because datasets are class-balanced. Image-augmentation shows slight improvement on most of the datasets. It is to be noted that datasets with low performance, e.g., Marathi character and IAPR TC-11 (O) etc., show better improvements

Datasat	Precision	Darrell	E1	Accur	acy
Dataset	Precision	Recall	F1-score	At last epoch	Best
UCI Devanagari numeral	99.97 99.99	99.97 99.99	99.97 99.99	99.97 99.99	99.99 100.00
UCI Devanagari character	99.33 99.45	99.33 99.45	99.33 99.45	99.33 99.45	99.34 99.48
UCI Devanagari combined	99.42 99.59	99.42 99.59	99.42 99.59	99.42 99.59	99.45 99.61
Marathi numeral	99.05 98.86	99.00 98.80	99.00 98.80	99.00 98.80	99.20 99.30
Marathi character	94.36 95.34	94.12 94.97	94.10 95.00	94.12 94.97	94.33 95.20
Marathi combined	95.02 95.80	94.77 95.51	94.76 95.52	94.77 95.51	94.96 95.84
$CMATERdb \ 3.2.1$	98.67 98.26	98.63 98.23	98.64 98.24	98.63 98.23	99.03 98.57
Nepali combined	95.03 95.20	94.68 94.80	94.66 94.77	94.99 95.10	95.17 95.28
Nepali numeral	99.79 99.59	99.79 99.58	99.79 99.58	99.79 99.58	99.89 99.82
Nepali vowel	98.37 97.54	98.26 97.39	98.26 97.39	98.26 97.39	98.86 97.92
Nepali consonants	93.98 94.07	93.56 93.60	93.50 93.53	93.56 93.60	93.96 94.09
IAPR TC-11 (O)	95.05 95.71	94.39 95.28	94.24 95.19	94.39 95.28	95.22 96.00

Table 7: Performance of HCR-Net on Devanagari script without with augmentation

with image augmentation than others because others, like UCI Devanagari, have already reached high level of performance.

Table 8 presents comparative study of HCR-Net against the state-of-art results. From the table, it is clear that HCR-Net performs quite well and provides new benchmarks on Marathi numeral, UCI Devanagari (numeral and character) and Nepali (numeral, vowel consonants and combined). For Nepali combined dataset, there is no reported result so there is not any literature to compare. IAPR TC-11 dataset is a small online handwriting dataset, where HCR-Net is able to beat the baseline model. So, HCR-Net can be used to recognize online handwriting and can perform better if datasets are larger. The experiments were able to achieve perfect score of 100% test accuracy on UCI numeral dataset for four times out of five, which averaged to 99.99%.

4.4.3 Latin script

Table 9 presents performance of HCR-Net on Swedish and English languages sharing Latin script. All the performance metrics for each dataset show similar results because the datasets are class-balanced. Image-augmentation shows slight improvement on all of the datasets except ARDIS-III where there is very slight drop in performance. The performance on UJIPenchars (O), which is an online handwriting dataset, is low compared to other datasets. This is because it has only 1240 training points with 35 classes which are much smaller than rest of the datasets.

Table 10 presents comparative study of HCR-Net against the state-of-art results. From the table, it is

clear that HCR-Net performs quite well and provides new benchmarks on ARDIS dataset (II, III and IV). mnist is a widely used benchmark dataset in computer vision and has an extensive literate but here, we have presented some representative studies only. HCR-Net shows good performance on mnist with a very low error. ARDIS dataset is present in three different formats with different preprocessing and noise levels. HCR-Net outperforms on all datasets, including results given in literature without name of the exact variant of ARDIS. Our proposed method shows large improvements as compared with the existing literature for ARDIS. Moreover, there is no result reported in literature for ARDIS-IV dataset so there is nothing to compare. HCR-Net does not perform well on UJIPenchars dataset because it is a very small online handwriting dataset but the performance is still comparable to the existing literature.

4.4.4 Telugu, Malayalam and Kannada scripts

Table 11 presents performance of HCR-Net on Telugu, Malayalam and Kannada scripts' datasets. All the performance metrics for each dataset show similar results. Image-augmentation shows slight improvement on most of the datasets except CMATERdb 3.4.1 where there is very slight drop in performance. Kannadamnist comes with two test-sets, one of which is out-of-distribution noisy test-set, called Dig-mnist. Interestingly, image-augmentation shows sharp improvement of around three percent in the test accuracy for Dig-mnist, this is because image-augmentation produces modified variants of images which are not present in the training set and helps in better generalization, which is

Table 8: Recognition rates on Devanagari datasets

Dataset	Reference	Methodology	Accuracy
Marathi character	[22]	fine-tuned VGG16	97.20
	HCR-Net	our work	94.97
Marathi numeral	[22]	fine-tuned VGG16	95.50
	HCR-Net	our work	99.00
Marathi combined	[22]	fine-tuned VGG16	96.55
With a compliance	HCR-Net	our work	95.51
IAPR TC-11 (O)	[58]	hierarchical stroke clustering and stroke-matching technique	95.00
IAI It 10-11 (0)			
	[65]	hierarchical stroke clustering and stroke-matching technique	97.00
uci p	HCR-Net	our work	95.28
UCI Devanagari numeral	[7]	Deep CNN	98.47
		LeNet	98.26
	[66]	Back-propagation neural network with projection histogram	92.20
		Back-propagation neural network with chain code histogram	92.70
		Deep Auto-encoder network	98.20
	[8]	a multi-column multi-scale CNN architecture + SVM	99.50
	[22]	fine-tuned VGG16	99.40
	HCR-Net	our work	99.99
UCI Devanagari charac- ter	[67]	CNN	93.00
	[18]	Multi-objective (recognition accuracy, redundancy of local regions and average recognition time per image) optimization to find the informative regions of character image. Histogram of	94.15
		gradients (HOG) features+Convex hull features + quad-tree based Longest run features + SVM	
	[22]	fine-tuned VGG16	97.80
	HCR-Net	our work	99.45
UCI Devanagari com- bined	[7]	deep CNN architecture	98.47
	[68]	CNN architecture with 8 Layers	96.90
	[69]	GAN + CNN Classifier	97.38
	[24]	deep CNN architecture	99.54
		DenseNet-121	99.60*
	HCR-Net	our work	99.59
CMATERdb 3.2.1 (De-	[35]	Histogram of Oriented Pixel Positions and Point-Light Source-	98.01
vanagari numeral)	[90]	based Shadow with random forest	30.01
vanagari numerar)	[94]	deep CNN architecture	98.70
	[24]	*	
	[14]	modular Principal Component Analysis + quad tree based Longest-Run (QTLR) features + SVM	98.70
	[8]	a multi-column multi-scale CNN architecture + SVM	99.50
	HCR-Net	our work	98.63
Nepali numeral	[57]	directional features, moment invariant features, Euler number, centroid of image, eccentricity and area of character skeleton + MLP and radial basis function	94.44
	[35]	Histogram of Oriented Pixel Positions and Point-Light Source- based Shadow with k-NN	98.60
	HCR-Net	our work	99.79
Nepali vowel	[57]	directional features, moment invariant features, Euler number,	86.04
vepair vower	[01]	centroid of image, eccentricity and area of character skeleton + MLP and radial basis function	00.04
	HCR-Net	our work	98.26
Nepali consonants	[57]	directional features, moment invariant features, Euler number, centroid of image, eccentricity and area of character skeleton +	80.25
		MLP and radial basis function	
	HCR-Net	our work	93.60
Nepali (combined)	HCR-Net	our work	95.10

no averaging

more helpful in this case because Dig-mnist is a outof-distribution noisy dataset. Moreover, best accuracy values are missing for Kannada-mnist test-set because

^{*} it appears authors have reported the max accuracy obtained during the training + no averaging

Accuracy Dataset Precision Recall F1-score At last epoch Best 99.49|99.55 99.50|99.55 99.48|99.54 mnist 99.49 99.55 99.54|99.61 99.68 99.78 99.68 99.78 99.68 99.78 99.80 99.96 ARDIS-II 99.68|99.78 ARDIS-III 99.84 | 99.80 99.84 | 99.80 99.84 | 99.80 99.84|99.80 100.00|99.96 ARDIS-IV 99.40 | 99.49 99.40 | 99.48 99.40|99.48 99.40 | 99.48 99.56|99.62 85.70 | 86.05 86.86|87.71 84.76 | 85.20 87.74 | 88.23 89.19|89.68 UJIPenchars (O)

Table 9: Performance of HCR-Net on Latin script without with augmentation

Table 10: Recognition rates on Latin datasets

Dataset	Reference	Methodology	Accuracy
mnist	[45]	CNN based on scattering transform-based wavelet filters	99.31
	[18]	Multi-objective (recognition accuracy, redundancy of local re-	98.92
		gions and average recognition time per image) optimization to	
		find the informative regions of character image + SVM	
	[70]	CNN based architecture with DropConnect layer	99.79
	HCR-Net	our work	99.55
ARDIS	[62]	CNN	98.60
	[71]	pre-trained LeNet	98.20
ARDIS-II	[35]	Histogram of Oriented Pixel Positions and Point-Light Source-	94.27
		based Shadow with random forest	
	HCR-Net	our work	99.78
ARDIS-III	[35]	Histogram of Oriented Pixel Positions and Point-Light Source-	94.27
		based Shadow with sequential minimal optimization	
	HCR-Net	our work	99.84
ARDIS-IV	HCR-Net	our work	99.48
UJIPenchars (O)	[61]	Microsoft Tablet PC SDK recognition engine	91.60
` ,	[72]	approximate dynamic time warping	89.10
	HCR-Net	our work	88.23

it was used for final evaluation and Dig-mnist was used for evaluation during the training.

Table 12 presents comparative study of HCR-Net against the state-of-art results. From the table, it is clear that HCR-Net performs quite well and provides new benchmarks on Amrita_MalCharDb, Malay-alam_DB and on Kannada-mnist (Dig-mnist) datasets. CMATERdb 3.4.1 has few versions and it appears that [14] used different version as the dataset statistics is different than the one used in our work. We obtained a huge improvement of over 11% on Dig-mnist, which is an out-of-distribution noisy dataset collected from a practical situation, because of image-augmentation (as reported in Table 11) and transfer learning. Thus, the proposed HCR-Net is suitable to practical applications.

4.4.5 Bangla script

Bangla is one of the widely studied Indian scripts and it has several public datasets which further enhances the research of this script (refer to [73] for survey on Bangla handwritten numeral recognition). Table 13 presents performance of HCR-Net on Bangla script datasets. All the performance metrics for each dataset show similar results. Image-augmentation shows slight improvement on most of the datasets except 3.1.1 and 3.1.2 where

there is slight drop in performance and 3.1.3.3 shows large improvements.

Table 14 presents comparative study of HCR-Net against the state-of-art results. From the table, it is clear that HCR-Net performs quite well and provides few new benchmarks on Banglalekha-isolated (numerals, characters and combined). It is observed that HCR-Net lags by a large gap for complex problems with large number of classes, like CMATERdb 3.1.3.3 which have 171 classes, and also trains slowly and takes large number of epochs, 180 in this case. Moreover, it is observed that a multi-column multi-scale CNN architecture proposed by [8] performs exceptionally well for Bangla script.

4.4.6 Few other scripts

Table 15 presents performance of HCR-Net on Farsi, Urdu, Tibetan and Arabic scripts' datasets. All the performance metrics for each dataset show similar results. Image-augmentation does not show consistent improvements on most of the datasets as there are slight changes in the performance which could be because of randomness associated with the experiments. Although, other reason for slight changes could be that the model

Datasat	Precision	Recall	E1	Accura	асу
Dataset	Precision	Recall	F1-score	At last epoch Best	\mathbf{Best}
CMATERdb 3.4.1	98.80 98.40	98.77 98.30	98.77 98.30	98.77 98.30	99.13 98.57
Amrita_MalCharDb Malayalam_DB	94.98 95.32 95.12 95.45	94.73 94.99 94.87 95.16	94.77 95.05 94.91 95.20	94.84 95.15 94.95 95.32	94.87 95.28 95.02 95.42
Kannada-mnist (test-set)	98.08 98.30	98.05 98.27	98.05 98.26	98.05 98.27	
Kannada-mnist	86.00 88.57	85.46 88.26	85.45 88.28	85.46 88.26	86.61 88.72

Table 11: Performance of HCR-Net on Telugu, Malayalam and Kannada scripts

Table 12: Recognition rates on Telugu, Malayalam and Kannada datasets

Dataset	Reference	Methodology	Accuracy
CMATERdb 3.4.1	[14]	Modular Principal Component Analysis + quad tree based Longest-Run (QTLR) features + SVM	99.20
	[8]	a multi-column multi-scale CNN architecture + SVM	99.50*
	[35]	Histogram of Oriented Pixel Positions and Point-Light Source-	99.03
	[00]	based Shadow with random forest	00.00
	HCR-Net	our work	98.77
Malayalam_DB	[45]	CNN based on scattering transform-based wavelet filters	93.77
·		SmallResnet based on scattering transform-based wavelet filters	92.85
		SmallResnet based on scattering transform-based wavelet filters	95.27
		+ image augmentation	
	HCR-Net	our work	95.32
$Amrita_MalCharDb$	[42]	CNN based on scattering transform-based wavelet filters as fea-	91.05
		ture extractor and Linear SVM as classifier	
	HCR-Net	our work	95.15
Kannada-mnist (test set)	[63]	End-to-end training using CNN based architecture	96.80
	[69]	GAN + CNN Classifier	98.70
	[25]	deep residual network ResNeXt	97.36
	HCR-Net	our work	98.27
Kannada-mnist (Dig- mnist)	[63]	End-to-end training using CNN based architecture	76.10
•	[25]	deep residual network ResNeXt	79.06
	HCR-Net	our work	88.26

^{*} authors used different training dataset

Table 13: Performance of HCR-Net on Bangla script without with augmentation

Dataset	Precision	Recall	F1-score	Accura	acy
Dataset	Precision	Recall	r 1-score	At last epoch	\mathbf{Best}
CMATERdb 3.1.1	98.86 98.52	98.84 98.49	98.84 98.49	98.84 98.49	98.98 98.74
CMATERdb 3.1.2	97.46 96.69	97.42 96.61	97.42 96.60	97.42 96.61	97.59 96.77
CMATERdb 3.1.3.3	89.09 92.53	88.75 92.17	88.81 92.21	88.73 92.19	88.81 92.35
ISI Bangla	99.26 99.44	99.26 99.44	99.25 99.43	99.26 99.44	99.33 99.51
Bangalalekha_isolated numerals	99.24 99.40	99.24 99.40	99.24 99.40	99.24 99.40	99.30 99.50
Bangalalekha_isolated characters	96.96 97.32	96.94 97.30	96.94 97.30	96.95 97.30	96.99 97.31
Bangalalekha_isolated combined	95.74 96.21	95.69 96.18	95.69 96.18	95.70 96.19	95.74 96.20

is already showing good results so there is less scope for improvements.

Table 16 presents comparative study of HCR-Net against the state-of-art results. From the table, it is clear that HCR-Net performs quite well and provides new benchmarks on Urdu, Tibetan-mnist and on MAD-Base datasets. For FARSI, DenseNet based model per-

forms the best followed by HCR-Net with a very small margin.

Thus, from these experiments, we conclude that HCR-Net is a generic architecture which can handle different scripts. It performs very well and establishes several new benchmarks. It is observed that HCR-Net shows very high performance on datasets with smaller

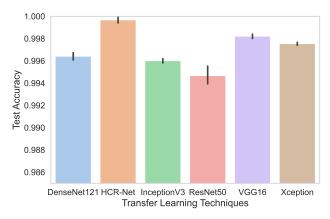
Table 14: Recognition rates on Bangla datasets

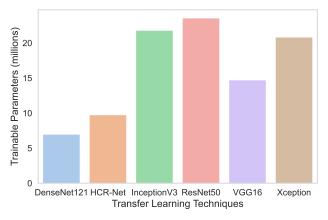
Dataset	Reference	Methodology	Accuracy
CMATERdb 3.1.1 (Bangla numeral)	[6]	SVM classifier using GA for region subsampling of local features	97.70
,	[14]	Modular Principal Component Analysis and Quad-tree based hierarchically derived Longest-Run features + SVM	98.55
	[74]	Axiomatic Fuzzy Set theory to calculate features' combined class separability + quad-tree based longest-run feature set and gradient based directional feature set + SVM	97.45
	[8]	a multi-column multi-scale CNN architecture + SVM	100.00*
	[47]	spatial pyramid pooling and fusion of features from different layers of CNN	98.80
	[22]	fine-tuned VGG16	97.45
	[35]	Histogram of Oriented Pixel Positions and Point-Light Source- based Shadow with random forest	98.50
	HCR-Net	our work	98.84
CMATERdb 3.1.2 (Bangla basic character)	[75]	local chain code histograms $+$ SVM	92.14
,	[8]	a multi-column multi-scale CNN architecture + SVM	100.00
	[50]	CNN based architecture	93.37
	[47]	spatial pyramid pooling and fusion of features from different layers of CNN	98.56
	[22]	fine-tuned VGG16	95.83
	HCR-Net	our work	97.42
CMATERdb 3.1.3.3 (compound character)	[76]	Genetic algorithm based Two pass approach $+$ SVM	87.50
	[15] [17]	A convex hull and quad tree-based features $+$ SVM	79.35 90.33
	[8] [77]	a multi-column multi-scale CNN architecture + SVM	98.12 * 88.74
	[47]	spatial pyramid pooling and fusion of features from different layers of CNN	95.70
	HCR-Net	our work	92.19
ISI Bangla	[71]	pre-trained LeNet	97.05
	[34]	multilayer perceptron classifiers using wavelet based multi- resolution features	98.20
	[78]	Multi-objective (recognition accuracy and recognition cost per image) optimization to find the informative regions of character image + SVM	98.23
	[18]	Multi-objective (recognition accuracy, redundancy of local regions and average recognition time per image) optimization to find the informative regions of character image + SVM	98.61
	[38]	densely connected CNN and image augmentation	99.78
	HCR-Net	our work	99.44
Banglalekha-isolated combined	[50]	CNN based architecture (2 Conv2D)	95.25
	HCR-Net	our work	96.19
Banglalekha-isolated numbers	[71]	pre-trained LeNet	94.86
	HCR-Net	our work	99.40
Banglalekha-isolated characters	HCR-Net	our work	97.30

^{*} authors used a different version of dataset

Table 15: Performance of HCR-Net on few other scripts without |with augmentation

Dataset	Precision	Recall	F1-score	Accuracy	
				At last epoch	\mathbf{Best}
Farsi	99.38 99.29	99.38 99.28	99.38 99.28	99.38 99.28	99.39 99.35
Urdu	98.63 98.83	98.66 98.83	98.64 98.83	98.66 98.84	98.95 99.01
Tibetan-mnist	99.37 99.26	99.37 99.27	99.37 99.26	99.35 99.24	99.43 99.41
MADBase	99.21 99.26	99.21 99.25	99.21 99.25	99.21 99.25	99.32 99.33





- (a) Comparison in terms of test accuracy
- (b) Comparison in terms of trainable parameters

Fig. 5: Performance comparison of HCR-Net against state-of-the-art transfer learning techniques for HCR

Table 16: Recognition rates on some other datasets

Dataset	Reference	Methodology	Accuracy
FARSI	[79]	PCA+SVM	99.07
	[80]	CNN based archi-	99.34
		tecture	
	[81]	DenseNet + data	99.49
		augmentation	
	HCR-Net	our work	99.38
Urdu	[71]	pre-trained LeNet	97.31
	[80]	CNN based archi-	96.57
		tecture	
	[43]	autoencoder and	97.00
		CNN architecture	
	HCR-Net	our work	98.84
Tibetan-	[71]	pre-trained LeNet	98.31
mnist			
	HCR-Net	our work	99.35
MADBase	[71]	pre-trained LeNet	98.93
	[82]	LeNet + LSTM	98.47
	HCR-Net	our work	99.25

number of classes, like numerals. Image-augmentation component of HCR-Net shows great performance improvement when the test dataset is out-of-distribution and noisy, e.g., Dig-mnist (Table 11). Transfer learning helps HCR-Net to get faster convergence and better generalization (Fig. 4 and Table 2).

4.4.7 Comparison with transfer learning techniques

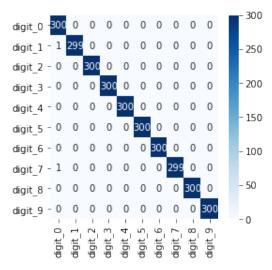
Here, we compare HCR-Net against some of the popularly used state-of-the-art transfer learning techniques for HCR as: VGG16 [30], Xception [83], ResNet50 [84], InceptionV3 [85] and DenseNet121 [86]. Fig. 5 presents the comparative study in terms of test accuracy and number of trainable parameters to measure the computational performance using UCI Devanagari Numeral dataset. The experimental setup for HCR-Net

and other transfer learning techniques is exactly same. All methods train in two phases, where first phase trains only the classifier layer while second phase trains the entire network. From the figure, it is clear that HCR-Net significantly (p-value=0.00099 using Student's t-test) outperforms the rest of the transfer learning techniques, and VGG16 is the second best technique. ResNet50 is the worst performer in terms of test accuracy. However, all the transfer learning approaches show impressive performance and that is why they are widely used in the HCR research. It is also observed that only HCR-Net shows fast convergence and could achieve high performance immediately after the first epoch (please refer to Subsec. 3.4 for HCR-Net convergence, however, convergence of rest of the techniques is not shown here). In terms of computational efficiency, DenseNet121 and HCR-Net are the first and second best techniques, respectively, and have large gap from rest of the techniques. HCR-Net reduces number of trainable parameters of corresponding VGG16 by 34%, and thus is a computationally efficient technique.

4.5 Miss-classification analysis

In this subsection, the causes of miss-classifications are analysed by taking examples of UCI Devanagari numeral dataset and IAPR-11 Devanagari dataset, where HCR-Net outperforms and lacks, respectively.

Sub-fig. 6a presents confusion matrix which shows only two miss-classifications where 'digit_1' and 'digit_7' are classified as 'digit_0'. For 'digit_1', this is due to deviations in the structure by writer, i.e., due to bad handwriting and for 'digit_7', this appears to be noise in the recording process as some part of the charac-



(a) Confusion matrix of UCI Devanagari numeral dataset, showing only two miss-classifications.

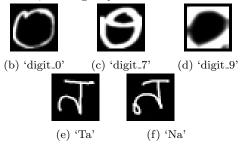


Fig. 6: Miss-classification analysis: (a) confusion matrix of UCI Devanagari numeral dataset, (b) actual 'digit_0' in UCI Devanagari numeral dataset, (c) and (d) show 'digit_7' and 'digit_9', respectively, miss-classified as 'digit_0' on UCI Devanagari numeral dataset, (e) and (f) actual 'ta' and 'na' which is mis-classified as 'ta' on IAPR-11 (O) Devanagari dataset.

ter seems to be cropped, and it is impossible even for humans to find class of the character.

Sub-figs. 6e and 6f study miss-classifications on IAPR-11 dataset, which is a small dataset. Here, one reason for the miss-classifications is due to similarity in the structure of characters. As it is clear from the figures, the character 'na' is miss-classified as 'ta' because they look quite similar, in fact this is the major cause for miss-classifications. Thus, as observed in the literature [22], bad handwriting, errors/noises in the recording process and similarity in the structure of characters cause miss-classifications.

5 Conclusion and future scope

An HCR is a widely studied challenging learning problem in pattern recognition, which has a variety of applications, like in the automated processing of documents. But, there is a lack of research on script independent HCR. This is mainly because of the focus of conventional research on handcrafted feature extraction techniques, diversity of different scripts and unavailability of existing datasets and code-repositories. Moreover, deep learning, especially CNN, provides great opportunity to develop script independent models, however, deep learning research in handwriting is still in its infancy and models developed for HCR are focused on specific scripts.

This paper proposed a novel deep learning based architecture for HCR, called as HCR-Net, and is the first generic architecture for script independent HCR. HCR-Net uses a novel transfer learning approach for HCR, which partly utilizes a pre-trained VGG16 network to initialize some parts of HCR-Net. Powered by transfer learning and image-augmentation, HCR-Net is a computationally efficient technique which can learn faster, learn on small datasets, unlike standard deep learning techniques which need large amount of data, and provides better generalizations across several scripts. This work is reproducible, verified and publicly released at https://codeocean.com/capsule/9660931.

The experimental results proved the efficacy of HCR-Net on 40 publicly available datasets of Bangla, Punjabi, Hindi, English, Swedish, Urdu, Farsi, Tibetan, Kannada, Malayalam, Telugu, Marathi, Nepali and Arabic languages. HCR-Net established 26 new benchmark results while performed close the best results in the rest cases, and showed performance improvements up to 11% against the existing results, which presents HCR-Net as a generic architecture for HCR. HCR-Net also significantly outperformed state-of-the-art transfer learning techniques for HCR, and was able reduce number number of trainable parameters of corresponding VGG16 by 34%. In addition to that, among the transfer learning techniques, HCR-Net have a fastest convergence rate as it can achieve up to 99% of final performance in the very first epoch. From miss-classification analysis, it is observed that errors occur mainly due to noisy datasets, bad handwriting and similarity in different characters.

HCR-Net is a generic deep learning technique for HCR and the main limitation of the technique is that it does not perform well on languages with large number of classes, such as Chinese, as it lags and learns slowly. In future, HCR-Net will be specialized and extended for languages with large number of classes. Since some of the miss-classifications are due to similarity of characters so hierarchical version of HCR-Net will be explored to address the issue. Moreover, as we are heading towards data-centric artificial intelligence from model-centric artificial intelligence, so there are possibilities to improve HCR by developing specialized preprocessing pipelines.

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