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Typewritten Gurmukhi Character Recognition using Deep Learning Architecture

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Abstract
In this era of digitalization, most businesses, work, and even daily life activities are influenced by technology. Nowadays, most textual data, including books, novels, old thesis/ dissertation books, and holy books, are available in digital form. Moreover, millions of pages containing typewritten text and images have been digitally preserved thanks to the ever-increasing availability of scanning and storage equipment, which has inspired archivists and historians to digitize many historical data. However, they rapidly understood that making historical records accessible to the academic community and the public requires more steps than just digitalization, even if that step is perhaps the simplest. Moreover, most historical documents are in the typical native languages, so systems need to recognize the characters. In this paper, the dataset of typewritten Gurmukhi characters is used to develop a Gurmukhi typewritten text recognition system. This dataset is collected from various typewritten thesis documents, books, etc. The recognition method is based on deep learning architecture called a deep convolutional neural network. The performance of the proposed system is tested in terms of accuracy, and it achieved an overall accuracy of 97.47%, which is suitable for the text recognition system.
Keywords: Gurmukhi, Deep Learning, CNN, Character Recognition

1. Introduction

Optical character recognition (OCR) technology encodes input text for computer use. An innovation that makes it possible to recognize text in pictures and scanned documents in OCR. The accuracy and efficiency of OCR technologies have significantly increased with the development of deep learning. OCR is now used to transform typewritten texts into digital format and assist in digitizing medieval manuscripts written by hand [1]. Since one no longer needs to shift through mountains of documents and files to get what they are looking for, retrieving the necessary information is now simpler. In addition, companies are meeting demands for the digital preservation of historical material, legal papers, educational persistence, etc. [2] [3]. Moreover, India is a very culturally and linguistically diverse nation. Every 100 kilometers in India, the language might entirely or partially change due to political and cultural factors. As a result, research on the OCR of Indian characters has not yet attained the same accuracy and precision as that of non-Indian scripts. While there are several techniques for recognizing characters for scripts other than Indian, such as Devanagari, Gurmukhi, Tamil, Kannada, Bangla, and Oriya, there have only been a few efforts [4]. Gurumukhi character recognition is among the most difficult OCR challenges. The Punjabi language, which is largely spoken in the Punjab region of India, is written using the Gurmukhi script. It is challenging to identify typewritten Gurmukhi characters using conventional OCR techniques because of the script's intricacy. In this work, Gurmukhi typewritten text documents are used for character recognition.

Due to the rapid growth of smart devices, AI has utilized deep Learning to represent and build internet services, sensor devices, decision-making, information transfer, etc. [5]. Deep Learning may be used for object recognition, information extraction from media, object identification, multi-aspect data analysis, and speech-to-text conversion. Over the past few years, character recognition has extensively used deep Learning [6]. Deep learning architectures have, nevertheless, proven to be useful in dealing with this issue. A branch of machine learning called "deep learning" uses artificial neural networks as its foundation. These networks may be trained to spot patterns in images and are created to replicate how the human brain functions. So, the main aim of this work is to propose a system that utilizes a deep

learning-based architecture to recognize Gurmukhi typewritten characters.

Similar to the text recognition systems for handwritten, machine-printed, or other recognition systems, typewritten text recognition also functioned. The initial stage in the recognition system is the acquisition of samples, where scanned papers or images of the documents obtained by cameras may be used. The subsequent phases are pre-processing, segmentation, feature extraction, and classification. Finally, when the recognition system demands it, post-processing is also occasionally used [7]. In this work, the dataset of the segmented character of Gurmukhi typewritten text is already pre-processed, and deep learning architecture is used for feature extraction and classification. The main contribution of this paper is given as follows:

(a) The first main contribution is the proposed deep convolutional neural network architecture that automatically extracts the feature maps from the given image samples based on which the recognition of the characters is done.

(b) The second contribution is towards the Gurmukhi typewritten data, collected from the hard copy of the dissertation files, books, etc., and all the images are captured by mobile phone camera, and the two datasets, manual and automated, are prepared. All the characters are cropped in the manual dataset, but the automated dataset automatically contains segmented characters using different approaches.

(c) The third and final contribution is to test the proposed deep learning architecture's performance with both datasets.

The next part of the paper presented the existing deep learning-based text recognition system on different text types and languages. Further, the proposed deep convolution neural network architecture designed for typewritten character recognition is elaborated along with the proposed system and its experimentation analysis based on accuracy.

2. Related Work

This section of the paper deliberates the existing text recognition systems designed for different languages, documents, and approaches. So, the related work studied is divided into three sub-sections that explore the text recognition systems for typewritten text, text recognition systems designed for Gurmukhi text, and deep learning-based existing text recognition systems.

2.1 Typewritten Text Recognition Systems

Typewritten Text recognition systems take typewritten text as input and convert it into electronic form. The typewritten documents mostly contain a similar font in terms of shape and size. However, the most challenging task is recognizing old typewritten documents with low-quality or degraded text. The typewritten text's quality is low and non-uniform, but many of these documents have also deteriorated due to the age of the paper and ink used. Usually, the typewritten text contains non-uniform characters, some darker or faint than others, depending on the force used to strike the typewriter key. In addition, it is more challenging to work with typewritten documents than machine-printed documents because it requires pre-processing due to degradation in the text. Some researchers considered this challenge and developed approaches to recognize typewritten text. For example, a semi-supervised clustering-based framework was developed with the constraints of links between the characters [8]. Further, a system was developed for Tamil typewritten text data based on decontextualization, segmentation, and classification model [9]. The other approaches, including the hidden Markov method proposed for Arabic handwritten and typewritten text [10] [11], threshold-based segmentation [12], and template matching based method [13] for English & Indian Language Odia [14], edge detection-based segmentation for Urdu [15], Feature extraction based method for different traditional Arabic fonts [16] was proposed for typewritten text recognition.

2.2 Gurmukhi Text Recognition Systems

The Gurmukhi language is popular in the northern region of India, specifically in Punjab, and many holy books and historical literature are available in typewritten form. Earlier, typewritten text was not considered, so most of the Gurmukhi text recognition systems are available for machine-printed and handwritten text. For instance, Zone based method for segmenting the Gurmukhi

characters into three zones was designed and tested for around 1100 image samples of machine-printed text [17] [18]. The algorithm accuracy is quite impressive and is more than 90%. The other segmentation-based approaches [19] and [20] achieve a reasonable accuracy rate. Further, a feature extraction-based approach was developed that finds the presence of loops, headlines, sidebars, etc., in the data [21] [22]. Moreover, Learning based approaches like KNN, Binary tree, and SVM were also developed for Gurmukhi typewritten text recognition [23].

2.3 Deep Learning-based Text Recognition Systems

This section of the paper discusses the existing text recognition system designed based on deep Learning, as it is a hot research issue in machine learning and pattern recognition. It has also succeeded in various applications, including speech recognition and image processing. An overview of some of the deep learning approaches for text recognition systems is also given in table 1. Deep Learning [24] was utilized to create an accurate method for reading handwritten Gurmukhi letters, including those with damaged characters. The study's main objective was to identify offline handwritten scripts using deep Learning. The revolutionary diagonal-based feature extraction method in the last layer of a convolutional neural network [25] was created with a genetic algorithm to streamline feature extraction. It uses a neural network based on deep Learning to categorize and identify texts. Another CNN-based approach for offline handwritten Gurmukhi character recognition was presented [26] in which a character skeleton was built to extract feature information. Further, a CNN-RNN and Tensorflow - Keras Functional API-based offline handwriting recognition system was proposed [27]. The recommended technique employs a segmentation-free methodology to build a handwritten letter recognition system. Based on CNN's properties, an image processing module [28] was created for a mobile device.

"DetReco," a unique object-text detection and recognition system was proposed to identify items and texts and recognize the text contents [29]. The text recognition task was handled by CRNN, while YOLOv3 handled the object-text detection task. As an online handwritten Gurmukhi word recognition method, a hidden Markov model was suggested [30]. CNN-RNN model with an attention mechanism [31] was presented a for Arabic picture text recognition. An open-source line recognizer [32] has been implemented in PyTorch using CUDA kernels for performance. It mixes deep convolutional networks and LSTMs. Further the issue of handwriting recognition in Kazakh and Russian [33] was examined using CNN and a fully connected multilayer perceptron neural network. The second model, SimpleHTR, uses CNN and recurrent neural network (RNN) layers to extract data from images [34].

Moreover, a semantically enhanced encoder-decoder system was designed to identify low-quality scene texts reliably [35]. Finally, a unique HTR design based on Gated-CNN with fewer parameters and layers that surpasses the most recent state-of-the-art HTR architectures was proposed [36]. The other CNN-based text recognition system for Arabic handwritten text was designed and achieved 97% accuracy [37]. Moreover, CNN-based EfficientNet B3 [38] for machine-printed Gujarati text achieved an accuracy of 98.92%.

Author Name	Language	Type of Text	Classification	Recognition Rate
Kumar and Gupta/2017	Gurmukhi	Handwritten	DNN	97.30%
Kaur and Rani/2017	Gurmukhi	Handwritten	CNN	92.08%
Yadav et al./ 2017	English	Machine Printed	CNN	85%
Weng and Xia/2020	Shui Character	Handwritten	CNN	93.30%
Vyavahare et al./2020	English	Handwritten	DCNN-RNN	95.90%
Zhang et al./ 2020	English	Machine Printed	CRNN	72.8 AP
Singh et al./ 2021	Gurmukhi	Handwritten	Deep Learning	97%
Nurseitov et al./2020	English	Handwritten	Deep CNN	75%
Wan et al./ 2020	English	Machine Printed	RNN-attention-based	92.60%

Wang et al./ 2020	English	Machine Printed	decoupled attention network	94.30%
Qiao et al./ 2020	English	Machine Printed	SE-ASTER	93.80%
Neto et al./ 2020	English	Handwritten	Gated-CNN	-
Alheraki/2022	Arabic	Handwritten	CNN	97%
Sharma/2023	Gujarati	Machine Printed	EfficientNet B3	98.92%

Table 1: Observations of Existing Deep Learning Approaches

3. Data Preparation and Experimentation

The main aim of this proposed work is to design a system that utilizes deep learning architecture and performs character recognition. Deep learning architectures such as convolutional neural networks (CNNs) have been demonstrated to perform very well on image recognition tasks. CNNs are made up of many layers of connected nodes that have been trained to spot patterns in images. So, the typewritten text data is the foremost requirement of this proposed system. Further the deep learning architecture is designed using the existing layers of CNN. This section describes the data collection, methodology, and experimentation in detail.

3.1 Data Collection and preparation

The typewritten text is collected from various typewritten dissertations and books written in Gurmukhi language. The image samples are taken using a mobile camera, which contains a full image picture having number of lines. The need of this character recognition system is the images of typewritten characters, so dataset is prepared in two different methods. The first method used is the manual segmentation, where characters are manually segmented from the images and the second method is auto-segmentation in which projection profile-based method is used to segment lines, words, and characters from the images [37]. The sample images for both characters retrieved by auto-segmentation and manual segmentation are given in the following figure 1:

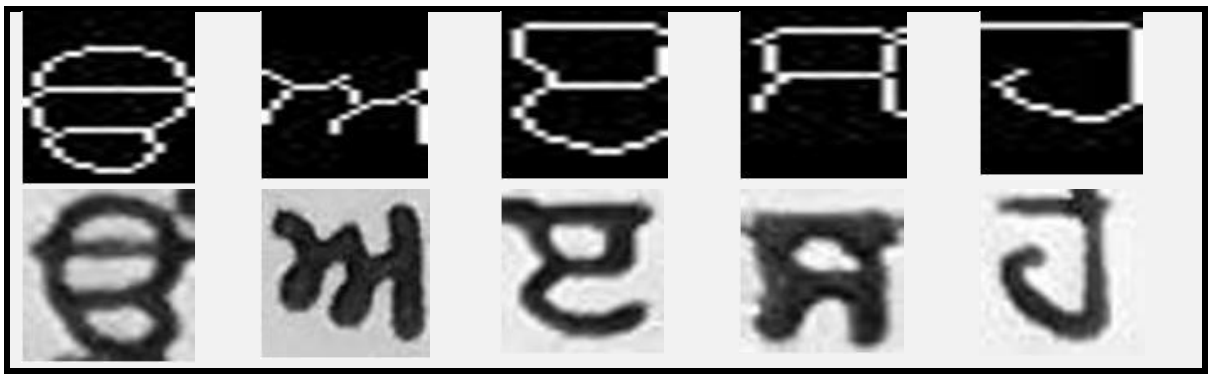


Figure 1. Dataset Used

3.2 Methodology

A deep learning neural network called a convolutional neural network, or CNN is made to process organized arrays of input, like images. The state-of-the-art for many visual applications, such as image classification, and convolutional neural networks, are widely employed in computer vision [40]. Convolutional neural networks are incredibly effective because of their quality. It does not require any preparation and may function immediately on a raw image, in contrast to older computer vision methods. A feedforward neural network with up to 20 or 30 layers is known as a convolutional neural network [41]. The convolutional layer is a unique layer that gives convolutional neural networks their strength. Each of its convolutional layers, piled on top of one another, can recognize increasingly complex forms. For example, convolutional layers are used in CNN to mimic how the human visual brain is organized, where several layers work together to analyze an incoming image and recognize more complicated elements [42].

The character images in this research design are fed into a Deep Convolution Neural Network (DCNN) for training and testing. The human brain's visual cortex and neuronal pattern are the foundation for DCNN design [43]. A three-dimensional framework made of neurons analyses the characteristics of the sample image. The predictions made by the layer are used to construct the final output, which shows how the layer relates to the class. Convolution, pooling, fully connected, and softmax layers are only a few of the layers that make up DCNN. As shown in figure 1, this work's suggested architecture comprises six convolution layers, five average pool layers, a fully connected layer, and a softmax layer. As detailed below, each of these divisions serves a specific function:

- **Input Layer:** Specify the input image size first, then set dimensions such as height, width, and channel size.
- **Convolution Layer:** The main purpose of this layer is to use smaller squares of inputs i.e. image matrix and filter and to preserve the connections between pixels when learning image features. The creation of a feature map is the responsibility of this layer. The probability of the classes over which a filter scans a few pixels is then estimated using this feature map. The primary objective of this layer is to extract high-level characteristics.
- **Pooling Layer:** In this layer, the output of the convolution layer is reduced, which lowers the processing power. Two pooling techniques—Max Pooling and Average Pooling—deliver maximum and average returns, respectively. Average pooling performs substantially better than Max since it also performs denoising.

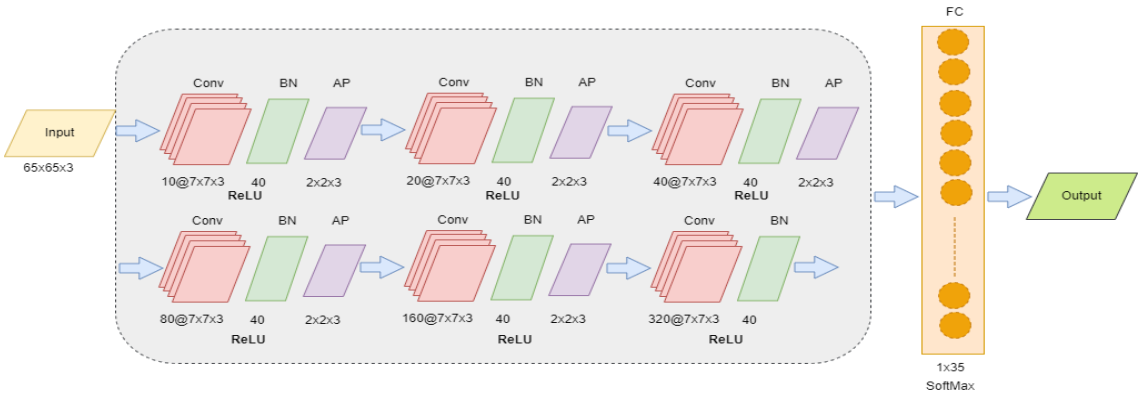


Figure 2. Proposed Deep Convolution Neural Network Architecture

- **Fully Connected Layer:** This layer, which is a classification layer, is where the final probabilities are determined. This layer employs a neural network with feedforward and backpropagation for each iteration.
- **SoftMax Layer:** Most problems involving many classes are solved using this layer. In this layer, a decimal probability is calculated for each class.

The proposed CNN architecture is based on LeNet architecture [44] with different layers of different sizes. Each convolution layer (Conv) extracts the feature, whereas the Average Pooling (AP) layer performs feature reduction. Finally, the batch Normalization (BN) layer divides the data into batches to reduce the load on the system. Here, the ReLU activation function selects only positive values with each convolution. Finally, the Fully Connected (FC) layer performs the classification where SoftMax activation helps to compute the class probabilities.

3.3 Proposed System

A deep neural network is based on a multi-layer neural network and its design is flexible to solve a wide variety of problems. The basic steps to build a simple classification network are: First, load sample image data as input and determine the network architecture. Second, specify training options as well as train the network. Third, predict the labels of new data and compute the classification accuracy. The design of the proposed DCNN defined in the previous sub-section is

utilized in this proposed system to recognize the characters. This proposed system works in two phases: (a) Training and (b) Testing, as shown in figure 3. The details of these phases are as given below:

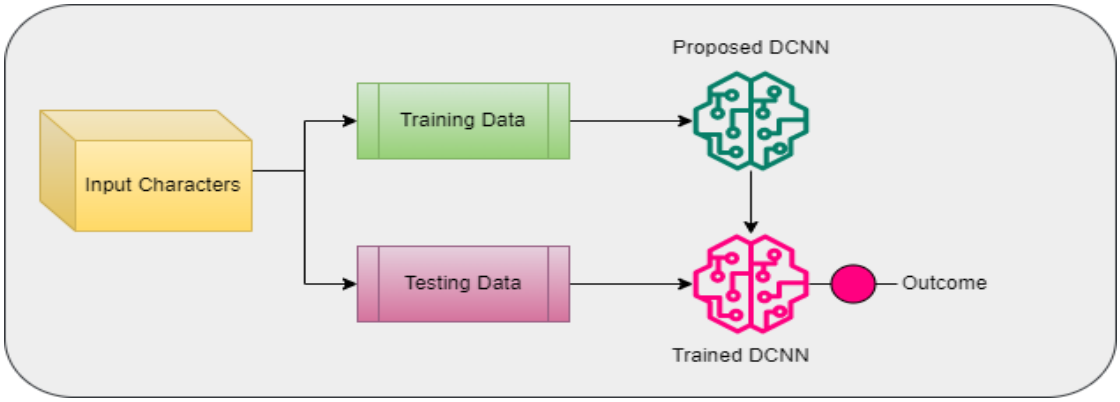


Figure 3. Proposed System

- *Training Phase:* In the training phase, training data, the data images with class labels, are given to the proposed DCNN, and the model is trained with the proposed DCNN using the given training parameters. Once the model is trained, it can be further used for testing.
- *Testing Phase:* The testing data is separately used for testing for which class labels are predicted using the trained model for final prediction or recognition. The final classification is performed with the test data to give the required outcome.

3.4 Experimentation and Result Analysis

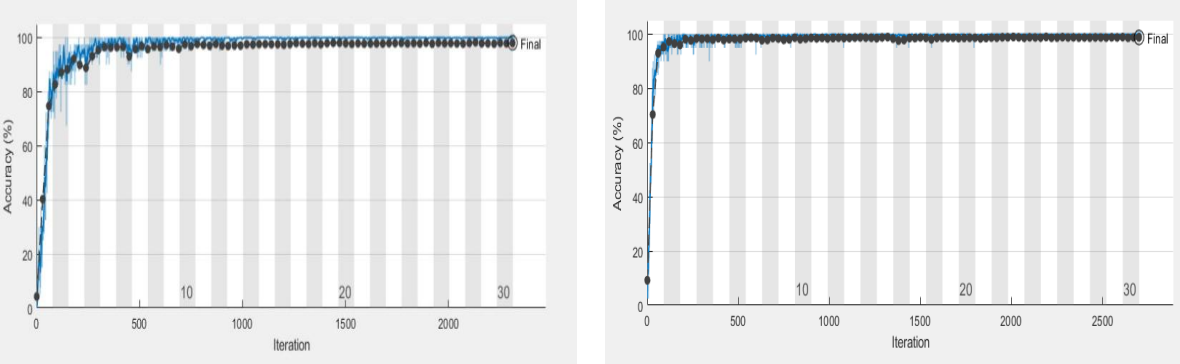
The proposed system uses a deep learning model that utilizes the proposed DCNN architecture. In this proposed model, 60% of the data is used for training and 40% for testing purposes for Gurmukhi typewritten characters. As mentioned earlier, the auto-segmented characters dataset has been created by using Gurmukhi typewritten automated algorithms of line, word, and character images to generate datasets of the composite of pixels size in .JPG format. On the other hand, the manual dataset consists of segmented character images of Gurmukhi typewritten of pixels size in .JPG format and in .MAT. In this process, first, a sample image is selected, then characters from the extracted words are also extracted, and finally, the cropped images are saved. Each segment character image is manually and automatically collected from full-text images. Further, in the dataset, there are 35 characters that, so the system is developed for 35 class classifications using DCNN. The other training options are described in the table below:

Training Options	**Values**
Solver Name	'sgdm'
Learning rate	0.01
Epoch Size	30
Minimum Batch Size	40
Shuffle	Every epoch
Dataset Size	6800-character images
Training Size	4080-character images
Testing Size	2720-character images

Table 2: Training Details

Using the above training parameters, the model is trained with the training dataset with 30 epochs. The accuracy of training and validation is represented by the following figure for both

manual and auto-segmented data using proposed architecture.



(a) **(b)**

Figure 4: Accuracy using Proposed DCNN (a) segmented dataset (b) manual dataset

The accuracy of the proposed model with the test data is 98.06% for auto-segmented characters, and for the manual dataset, it is 96.87%. Further, the performance of the proposed system is compared with the existing Gurmukhi text recognition system, which uses handwritten text. These existing recognition systems were developed for the Gurmukhi text recognition system using deep learning, but all the systems were developed for handwritten text. Also, these architectures have a different number of layers as compared to the proposed architecture. Moreover, it is clear from the graph in figure 5 that the accuracy achieved by the proposed DCNN is impressive and is more than the existing approaches.

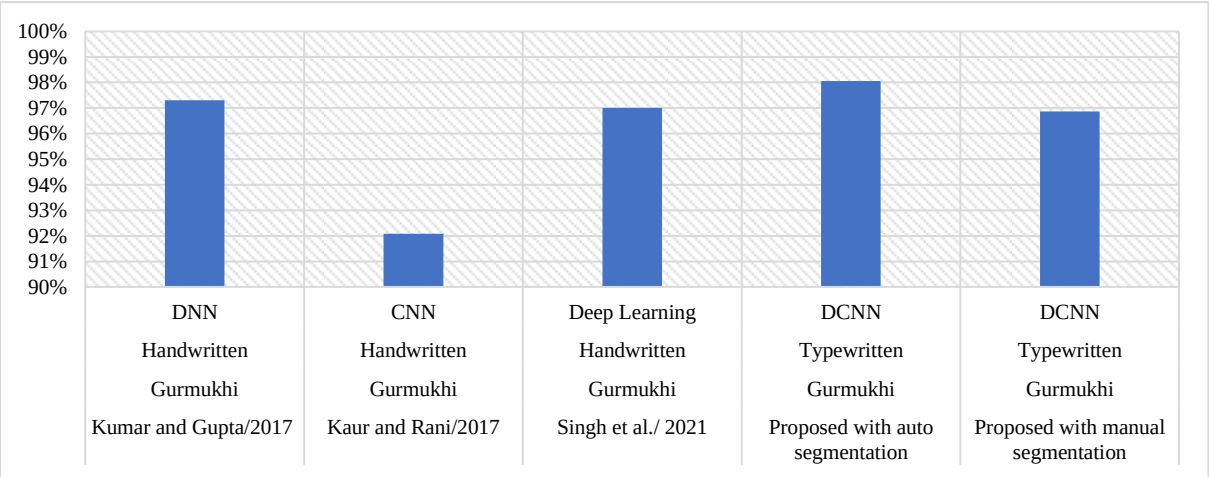


Figure 5. Comparative Analysis

The above results demonstrate that the accuracy of the typewritten auto-segmented characters is higher with the proposed DCNN architecture than with manually segmented characters and the other deep learning architectures.

4. Conclusion and Future Work

Gurmukhi character recognition is challenging, especially when the characters are typewritten and have different degradations. The main aim of this work is to propose a system that utilizes a deep-learning architecture for character classification. So, for this work, a deep convolution neural network was proposed, based on LeNet, and has six convolutional, five pooling, and 01 fully connected layers. The proposed architecture is tested with the Gurmukhi typewritten character dataset, which is prepared manually and automatically using the dataset of text images. The performance results in terms of accuracy define the effectiveness of the proposed system, and hence it can be used for the Gurmukhi character

recognition system. In future, the work can be extended with the large and multi-scale data. Additionally, several CNN-based models are available nowadays which can help to enhance the performance of the proposed system. Similar to that, handcrafted features also provide the scope to enhance the present model.

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