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Review:

Offline Handwritten Chinese Character Using Convolutional Neural Network: State-of-the-Art Methods

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Given the presence of handwritten documents in human transactions, including email sorting, bank checks, and automating procedures, handwritten characters recognition (HCR) of documents has been invaluable to society. Handwritten Chinese characters (HCC) can be divided into offline and online categories. Online HCC recognition (HCCR) involves the trajectory movement of the pen tip for expressing linguistic content. In contrast, offline HCCR involves analyzing and categorizing the sample binary or grayscale images of characters. As recognition technology develops, academics' interest in Chinese character recognition has continuously increased, as it significantly affects social and economic development. Recent development in this area is promising. However, the recognition accuracy of offline HCCR is still a sophisticated challenge owing to their complexity and variety of writing styles. With the advancement of deep learning, convolutional neural network (CNN)-based algorithms have demonstrated distinct benefits in offline HCCR and have achieved outstanding results. In this review, we aim to show the different HCCR methods for tackling the complexity and variability of offline HCC writing styles. This paper also reviews different activation functions used in offline HCCR and provides valuable assistance to new researchers in offline Chinese handwriting recognition by providing a succinct study of various methods for recognizing offline HCC.

Keywords: handwritten Chinese characters recognition, convolutional neural network, filtering techniques, activation functions

1. Introduction

Handwritten character recognition (HCR) has been used in several applications, including sorting e-mails, examining bank checks, and automating processes [1, 2]. The earliest studies on character recognition focused on English and number recognition. Over 25% of the world's population, mainly in Asia, use Chinese characters for daily communication [3]. Since then, Chinese character recognition has progressively drawn the interest of researchers as recognition technology advances, bringing significant benefits to social and economic growth.

Handwritten Chinese character recognition (HCCR) can be categorized into online or offline based on real-time writing and recognition. In online HCCR, the recorded pen tip movement trajectory is used to identify the conveyed linguistic content [4]. In contrast, offline HCCR works by analyzing and categorizing sample images of characters in binary or grayscale format [5].

Because of the various forms of sample data, the complexity of distinguishing between online and offline HCCR varies. Online HCCR has achieved successful results in recent decades [6, 7]. Conversely, offline HCCR is significantly slower and less efficient than online HCCR, owing to its complexity. Typically, Chinese characters vary based on subtle distinctions between dialects, thereby influencing the HCCR process. Therefore, this study considers the diversity of Chinese writing styles as one of the problems in offline HCCR. Furthermore, before conducting a convolutional neural network (CNN) for HCCR, the noise removal process represents a significant challenge in the learning process of the CNN on the HCCR.

Before the implementation of deep learning in the HCCR, the traditional HCCR approaches were the primary research approach. Traditional HCCR systems involve data preparation, classification, and feature extraction. Over the past few years, numerous techniques have been developed to enhance the performance of HCCR. These techniques include modified quadratic discriminant function (MQDF), discriminative learning quadratic discriminant function (DLQDF), hidden Markov model (HMM), support vector machine (SVM) [8], and locally smoothed modified quadratic discriminant function (LSMQDF) [9–11]. MQDF and DLQDF are regarded as the most acceptable conventional recognition methods because they produce good accuracy on the CASIA-HWDB dataset; however, there is still a significant gap in human performance [12].

The emergence of deep learning has offered novel insights into HCCR. Since the first implementation of CNNs to recognize the complex and intricate structures of Chinese characters, CNN-based methods have substantially altered HCCR solutions from conventional methods [13]. HCCR has been significantly enhanced using CNN methods, which has assisted in closing the performance gap between recognition systems and humans.

Some studies have developed methods that integrate the depth-image-based rendering (DIBR) procedure with a single picture depth of Chinese characters estimated into a single CNN structure [14].

This paper aims to review the methods and techniques of CNN for offline recognition of handwritten Chinese character (HCC). The remainder of this paper is organized as follows. Section 2 briefly describes the online recognition of HCCR. Section 3 describes the offline recognition of HCCR, including traditional approaches. Section 4 introduces the CNNs in HCCR. Section 5 provides the details of different filtering techniques for data preprocessing noise removal in HCCR. Finally, Section 6 provides the conclusions, including trends, future directions, and factors that hinder improvements in HCCR.

2. Online HCCR

As mentioned above, HCCR is categorized into online and offline recognitions according to input data types. Online recognition identifies expressed linguistic information by investigating the recorded trajectories of pen tip movements [4]. The online recognition of HCC was initiated by American researchers in the mid-1960s. Japanese researchers subsequently began working on online HCCR (Kanji) in the late 1960s.

Since then, HCCR has attracted the attention of several researchers. Numerous experiments on online HCCR have been reported with impressive performance. For example, the studies in [6, 15] were successfully performed on an online HCCR dataset. Meanwhile, Zheng et al. successfully identified 98.8% of the online HCCR [7]. The focus of research has changed to less-restricted HCR since the 1990s when online HCCR became widely marketed [3].

Online character recognition is more accessible than offline recognition because writers can correct mistakes or change their writing styles in response to recognition results [16]. Thus, online recognition is more flexible. Furthermore, online recognition can achieve higher accuracy than offline recognition owing to the accessibility of information on timing strokes and space shapes [4]. Therefore, researchers have concluded that online HCCR has achieved excellent results with high performance. In contrast, offline HCCR remains an ongoing challenge, owing to its various characters and diverse writing styles.

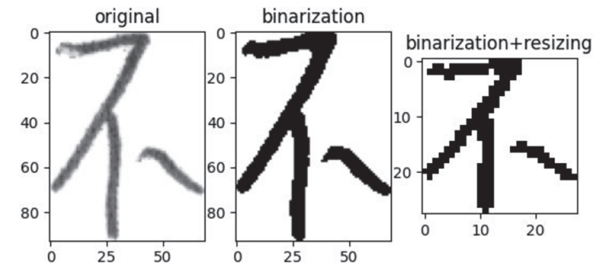

Fig. 1. Example of preprocessed image.

3. Offline HCCR

Offline Chinese character recognition focuses on analyzing and classifying character images (grayscale or binary) into different classes. Offline HCCR approaches are roughly divided into two types: traditional and deep-learning approaches. Traditional recognition methods dominated until deep-learning methods were successfully used. Among deep-learning approaches, CNNs are regarded as the most popular for recognition tasks. In this review, we focused on CNNs.

The three main components of a conventional HCCR system are feature extraction, classification, and data preprocessing. Among them, the former two parts are crucial for the identification system, significantly affecting the recognition accuracy.

3.1. Feature Extraction Methods

Several feature extraction techniques are commonly used in image processing, including histogram of oriented gradient (HOG), Gabor, and gradient features. Research has shown that applying the Gabor feature can achieve competitive results in HCCR [17, 18]. Alom et al. also achieved higher accuracy by applying the Gabor feature [19]. Images that were binarized or converted to grayscale were used to further extract the gradient features [16]. Shi et al. proved that the gradient feature extraction method can increase the effectiveness of HCCR. The HOG feature has been proposed for computer vision as an essential feature for good performance [20, 21]. Zhong et al. proposed the application of the HOG method to enhance the performance of CNN [12]. **Fig. 1** illustrates an example of a preprocessed image.

3.2. Classification Methods

Various statistical classifiers are frequently applied in the last classification step of HCCR, including MQDF, DLQDF, and nearest prototype classifier (NPC) [5]. In recent decades, frameworks with this type of classifier have become the benchmark for HCCR. Many experiments have achieved impressive recognition results by applying standard classification and feature extraction methods [22, 23].

Interestingly, researchers have extensively attempted to enhance HCCR performance [5, 24]. However, traditional approaches based on these classifiers have encountered a bottleneck, as there has been no significant progress in our observations in recent years. Therefore, traditional Chinese character recognition approaches have reached their limits [25, 26], nevertheless still leaving a significant gap in human performance.

4. CNNs in HCCR

Deep learning provides a new method for achieving breakthroughs and narrows the margin between machines and humans. With the success of deep learning in different pattern recognition tasks, such as character recognition [26], image recognition [27], and human face recognition [28], traditional approaches to HCCR have been substantially replaced by deep learning approaches. The CNN is the most well-known deep learning technique and is frequently used in image recognition applications. The primary reasons for this are the two characteristics of the CNN: the weight-sharing method and the local-connection approach [24].

Research [12] was the first to report the successful implementation of CNN for HCCR with the model of multi-column deep neural network (MCDNN) derived from a combination of several deep neural network columns. Subsequently, Graham proposed a spatially sparse CNN, which won the gold medal in Task 3 of the 23rd International Conference on Document Analysis and Recognition (ICDAR 2013) competition [29]. Their model outperformed humans in terms of the performance. Chen et al. introduced a system based on CNN, and it also outperformed humans in recognizing Chinese characters (CASIA) [25].

Researchers have reported several valuable and essential achievements in HCCR using CNN approaches. The recognition performance is a critical criterion for CNN models. In recent years, the accuracy of HCCR has been continually enhanced in various ways.

Xiao et al. developed a nine-layer CNN baseline model which achieved 97.30% recognition accuracy [30]. In contrast, although the accuracy decreased slightly in the modified model with the adaptive drop-weight (ADW) and global supervised low-rank expansion (GSLRE) approaches, it still outperformed the best single network of CNN. It significantly improved the running time and reduced the storage even smaller than the best single network [21]. In addition, they developed a 12-layer CNN model that achieved 97.59% recognition accuracy, indicating that better performance can be obtained with a more extensive and deeper neural network.

Subsequently, Li et al. proposed a cascaded model by applying the global weighted average pooling (GWAP) technique in a fully connected layer [26] and combined it with a fire module [30]. The performance of their model was 97.14%, and the running time required to classify a character image was shorter than that of Xiao et al. [30].

Furthermore, Melnyk et al. developed an improved system [31] based on the study of Li et al. [26]. They utilized global weighted output average pooling (GWOAP), which is optimized from GWAP and enables the calculation of class activation maps (CAMs) to visualize the most diverse areas of a picture. The accuracy increased by 0.02%, and the storage was almost twice as small as the model HCCR-CNN12Layer [30].

Zou et al. proposed several CNN models with three loss functions (cross-entropy, combination of cross-entropy and Euclidean distance, and combination of cross-entropy and average variance similarity), among which the last loss function produced the highest accuracy for HCCR [32]. The results demonstrated that the application of similarity ranking could achieve a much better recognition result, as it could simultaneously decrease intraclass variation and enhance interclass variation.

Bi et al. proposed modified models [33] based on GoogLeNet by the study of Szegedy et al. [34] and made some advanced improvements based on their research. The recognition accuracy of the proposed improved models outperformed those of all the existing CNN models. This improvement was accomplished at the cost of a sizeable number of parameters and extensive storage. However, the network recognition capacity increased, and the training time decreased.

Gan et al. designed a CNN model for an in-air HCCR [35]. Moreover, they developed a modified model based on the baseline model using channel pruning (CP), drop-weights (DW), and incremental network quantization (INQ) techniques. Two models were used for the offline ICDAR 2013 dataset. There was no difference in the recognition accuracy between the two models. However, the results of the modified model demonstrated that the proposed model has obvious advantages over advanced approaches for offline HCCR [30].

Min et al. [36] developed an enhanced shallow GoogLeNet based on the study by Szegedy et al. [34]. They added an error-elimination algorithm to the model to remove erroneous samples. In addition to increasing accuracy, the proposed model also reduces the training parameters. In a recent study, Liu et al. [37] proposed an improved long short-term memory (LSTM)-based deep neural network structure to identify semantic similarities among Chinese sentences of different lengths. **Fig. 2** illustrates an overview of the proposed model, whereby the authors integrate syntactic component features of words, such as word vector similarity, syntactic dependency tree similarity, and semantic role labeling information.

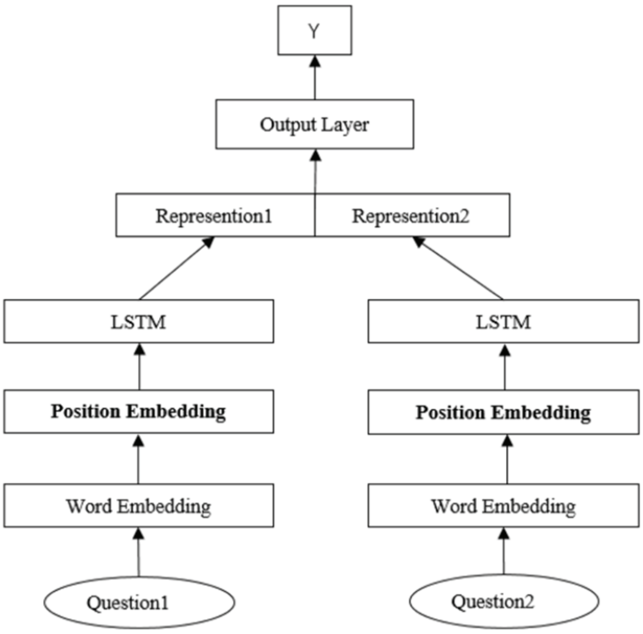

Fig. 2. Overview of the proposed model [37].

On a common dataset, this approach produces results that are more accurate than conventional approaches while maintaining the effectiveness of the reasoning process [13].

Meanwhile, Li et al. designed a unique technique for HCCR, template matching, which enables the discovery of how closely character images resemble template images [38]. Their research results suggested that the proposed approach can recognize the "open set" or the characters that are not used for training. In other words, it can identify characters that were not utilized in the training stage.

Aleskerova and Zhuravlev designed a two-stage hierarchical deep CNN [39]. Although the accuracy was not as high as the prior results in HCCR, the proposed hierarchical model produced a recognition accuracy that was considerably higher than that of the traditional CNN, indicating that the hierarchical technique may be employed in this field to improve model performance. Furthermore, the research suggested that the hierarchical approach could perform better than the conventional one-stage CNN in handling the categorization issue with many categories [39].

Liu et al. proposed a CNN-only model for handwritten Chinese text recognition (HCTR) [40]. All the convolutional layers of the model architecture were based on the official VGG-16 network [40], whereas the fully connected layers are different. The CNN + connectionist temporal classification (CTC) method was first used for HCTR. CTC was used as the loss function, and the CNN-only + CTC technique was the first to be reported for HCTR. The proposed model achieved the best results in the benchmark of the character error rate in ICDAR 2013 without a language model. The results also suggested that the CTC loss function is helpful for categorization problems and that CNN is powerful for representing a model with many classes.

Wang et al. proposed a residual-attention fully CNN-based model [41]. The application of residual attention can extract representative features and decrease the importance of unnecessary features. In addition, a word-embedding matrix based on attention was utilized to expand text information and reduce the impact of noise information on the model [42]. A large amount of data was required to train the CNN. Moreover, manually shifting a genuine handwritten system into various stances to capture images is challenging and time-consuming [43].

Ameri et al. proposed a customized CNN model using minimal layers (two convolutions, two pooling layers, and one fully connected layer) for handwritten Chinese number classification [44]. The proposed model can achieve competitive performance compared with other deep CNN models with large-size architecture, such as SqueezeNet [45], MobileNet [46], and GoogLeNet [36], as well as appearance-based methods [47].

Furthermore, Li and Li developed a "private customized" recognition model based on CNN [48]. They used CASIA-HWDB 1.1 to train the model and manually corrected the character labels that were incorrectly pre-identified to build a user-specific dataset. The recognition accuracy of their system could achieve over 98% for English letters, Chinese characters, Arabic numerals, and punctuation marks.

Liu et al. designed an enhanced CNN model to recognize visually similar HCC [49]. The accuracy of the proposed model reached 97%, demonstrating that the CNN model performed better than other classification techniques in recognizing visually similar characters, such as SVM [50], regular neural networks, and logistic regression.

Xu et al. proposed a model that combined the attention features spatial aggregation (ASA) and multiple scale convolution shuffle (MSCS) modules, among which the MSCS module was mainly used for feature extraction, whereas the ASA module was mainly used for model compression [51]. Although machine vision technology has been successfully used to recognize characters, significant experimental testing remains necessary to identify pertinent algorithmic parameters and decision-making criteria [52]. The proposed model achieved competitive results, reaching the best result in single networks in terms of inference time and storage.

Table 1 summarizes the aforementioned research regarding current performance improvement.

5. Filtering Techniques for HCCR

Filtering is a common approach for noise removal during data preprocessing, particularly image preprocessing. It performs several practical operations, modifications, and enhancements on the image or extracts representative information from it. Filtering is a technique for removing unwanted features from an image with modifications or

Table 1. Summary of literature for CNNs in Chinese character recognition.

Method	Accuracy [%]	Dataset	Ref.
CNN-9Layer; CNN-12Layer	97.30; 97.59	ICDAR-2013 offline HCCR competition	[30]
Cascaded CNN Model + WAP	97.14		[26]
CNN15Layer + GWOAP + CAMs	97.61		[31]
CNN + CP2 + DW + INQ(8-bit)	96.97		[35]
Siamese network + CNN-based + template matching	92.31		[37]
Two-stage hierarchical CNN	92.10		[13]
CNN-only + CTC	93.19		[40]
MSCS + ASA	97.63		[51]
CNN + similarity ranking function	95.58	CASIA-HWDB 1.1	[32]
GoogLeNet + several adjustments	98.2		[1]
Improved shallow GoogLeNet + error elimination algorithm	97.48		[36]
Residual-attention + fully CNN	97.32		[41]
Data collection + label image + CNN	98.137		[48]
Enhanced CNN + Adam	97	Self-collected dataset	[49]

Table 2. Performance comparisons of different activation functions.

Model	Dataset	Accuracy [%]				Ref.
		Sigmoid	*Tanh*	*ReLU*	*Mish*	
LeNet-5 CNN	MNIST	84.16	N/A	94.55	98.09	[5]
CNN-based	HWDB	10	85	87	90	[58]
CNN3Conv Layer	MNIST	N/A	98.35	98.75	98.81	[59]
CNN5Conv Layer	Fashion MNIST	N/A	89.79	89.56	90.37	
CNN5Conv Layer	CIFAR-10	N/A	67.85	68.29	69.38	
ResNet-v1-56		36.47	63.88	69.64	69.88	
ResNet-50	CIFAR-10	88.8	87.5	89.6	92.4	[32]
DenseNet-201		79.82	81.84	86.89	88.17	
SE-Inception-ResNet-V2		76.38	74.23	76.12	80.71	
ResNet	MNIST	98.87	99.07	98.91	99.04	
DenseNet		98.42	99.07	98.91	99.04	
SENet		98.81	98.64	98.01	98.994	
MobileNet	CIFAR-10	N/A	N/A	84.12	85.27	[60]
Resnet32		N/A	N/A	91.78	92.29	
ShuffleNet		N/A	N/A	87.05	87.31	
MobileNet	CIFAR-100	N/A	N/A	49.21	51.93	
Resnet32		N/A	N/A	68.45	69.44	
ShuffleNet		N/A	N/A	57.98	59.19	

enhancements, which can enhance the quality of an image by deleting certain features or highlighting other features.

Standard filtering techniques for removing image noise include Wiener, median, and average (mean) filters. In recent years, researchers have compared the performance of these filtering approaches on different image noise removal tasks.

Patidar and Srivastava conducted their research by comparing the effects of different filters on removing various kinds of noise [50]. Their research suggested that the Wiener filter performed better than the median and average filters for all Gaussian, Poisson, and speckle noise types. In contrast, the median filter achieves the best performance in terms of salt-and-pepper noise compared to the other two filters.

The same conclusion can be drawn from Shetti and Patil [53], who implemented the MRI Image research. Dass and Saini also concluded that the Wiener filter is the most effective for Gaussian noise among several filters applied to MRI images [54].

Srinivas and Panda compared several filtering methods [55]. They concluded that the standard median filter efficiently removed the low-density noise for salt-and-pepper noise. Simultaneously, the averaging filter performs well for high-density salt-and-pepper and Gaussian noise.

Arya and Semwal began their research using lung images to compare the performance of each filtering method [56]. Their results suggest that the Wiener filter is more effective in eliminating noise than the average and median filters.

Zhang et al. [57] introduced the Mish function into the LeNet-5 CNN for the mixed National Institute of Standards and Technology (MNIST) dataset and compared the model's performance with standard activation functions in this neural network: the sigmoid and rectified linear unit (ReLU) functions [57]. Their study showed that the ReLU activation function had higher accuracy and convergence speed than the sigmoid function. In contrast, the Mish activation function had the highest accuracy and fastest convergence speed among the other two functions. The accuracy of the Mish activation function was 13.93% higher than that of the sigmoid function and 3.54% higher than that of the ReLU function. These results suggest that the Mish activation function is efficient and accurate.

Guo et al. laid the foundation for future research, which studied the effect and further analyzed the reason for essential functions and parameters on the performance of CNN, including the activation functions, loss functions, and learning rate of the CNN model [58]. Regarding the activation functions, their research on the HWDB dataset suggested that the Mish activation function has the best recognition rate and stability among the sigmoid, tanh, ReLU, and Mish functions.

Apart from the studies mentioned above, some researchers have compared the performances of different network activation functions for various datasets. **Table 2** provides further details on the performance comparisons of several activation functions in additional research.

6. Discussion

More than 25% of the world's population, mainly in Asia, uses Chinese characters for daily communication. Since it was first proposed [3], scholars have delved deeply into the issue of HCCR for more than 40 years. Since the 1980s, the recognition of HCC has been a significant area of study in pattern recognition, and has received extensive research and attention from the academic community.

However, compared with other characters, the development of HCCR technology presents a relatively slower speed, and its accuracy rate is lower than that of other characters. This is one of the most challenging research subjects in the field of HCCR because of its sophisticated character structure, availability of identical characters, and variety of writing styles.

By reviewing the literature on offline HCCR, we found that the trend in HCCR has shifted toward deep-learning approaches. Traditional methods, which include feature extraction and classification, have achieved impressive recognition results by applying state-of-the-art methods such as Gabor, gradient, HOG, and NPC. Although researchers have extensively attempted to enhance the performance of HCCR, no significant progress has been made in narrowing the gap between machines and humans.

Therefore, current research has focused on applying deep-learning approaches, mainly CNN, to enhance the performance of HCCR. Most of the research on offline HCCR reviewed herein has used network-based methods (CNN). It has been observed that with a more extensive and deeper neural network, the performance of HCCR improves considerably.

However, these approaches have certain limitations, including the need for vast data for training classifiers, long processing times, and slow training speeds. Moreover, the current literature has limitations in terms of extremely scribbled handwriting and distorted lines of text present in offline handwritten data.

As shown in **Table 1**, Xiao et al. [30] performed CNN of various layers. Both the CNN-9Layer and CNN-12Layer were used in their approach. Their findings indicated that utilizing the CNN-12Layer slightly increases the accuracy by 0.29%. This suggests that a greater accuracy is a result of using higher layers.

An experiment on CNN-based picture labeling was conducted in [48]. To construct the test dataset for CNN, their study consists of gathering images. In addition to punctuation, the study materials were in Arabic, Chinese, and English scripts. This demonstrated how well CNNs are versed in both punctuation and other languages.

Compared with the sigmoid, tanh, and ReLU functions, the Mish function showed the best results, as shown in **Table 2**. However, the difference between the Mish and ReLU functions in [60] was minor. This suggests that the ReLU function can be replaced with the Mish function to obtain reliable results.

Model size plays an important role in the overall computational cost owing to the various parameters and experimental setups used in many of the modified HCCR methods and techniques that have been applied in the literature. It has also been reported that the assessment of class activation maps in terms of offline HCCR is highly subjective because of the unavailability of numerical measures.

A lengthy training period was necessary for a limited number of training character examples. Consequently, future research will focus on exploring and applying optimal algorithms and architectures to the proposed CNN to reduce the computing costs while improving the computational efficacy of the model. A future study path might be using hybrid approaches to minimize the network processing complexity, such as hybridizing with machine-learning classifiers or hybrid feature extraction methods. Additionally, a combination of other top methods or algorithms in a single pipeline design framework can help overcome the various limitations of the current literature.

7. Conclusion

Since the first successful implementation of CNN for HCCR [13], many types of research for HCCR based on CNN have been conducted by scholars in recent years. Most of them are dedicated to enhance the performance of the system. The accuracy of the CNN model is significantly affected by its structure, including the depth of the CNN architecture, functions, and meaningful parameters. Appropriate network architecture significantly affects the performance of the recognition model.

In this review, we began with a description of online and offline HCCRs in Sections 2 and 3. Owing to the high performance of online HCCR, we focused on offline HCCR. Furthermore, we also provided descriptions of CNNs in HCCR. Filtering techniques are crucial for denoising image data. We recommend including several additional filtering techniques to make meaningful data processing comparisons in future research. Furthermore, we included reviews of the different activation functions used for HCCR. Moreover, one of the key of future development is to expand the character samples for the suggested model.

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