A Review of the Current Status of AI Research in Handwritten Chinese Character Recognition

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Abstract. With the continuous development of artificial intelligence technology, there have been attempts to utilize AI in the field of linguistics. In this context, research and development in AI-based Chinese character recognition technology has spanned 40 years, with its outcomes attracting significant attention. However, in the field of Chinese character recognition, the research into offline handwritten recognition technology is particularly challenging due to the unique characteristics of handwritten Chinese characters. The main issue in current research is the significant decrease in accuracy for characters composed of similar components or characters with similar overall shapes. The focus of research solutions has been on modern mechanical programming and other engineering aspects, while research that integrates the inherent characteristics of Chinese characters themselves has been relatively overlooked. The author believes that combining engineering technology research with a deeper understanding of the nature of Chinese characters can solve many of the current problems. This paper reviews the current state of related domestic and international research to identify areas with significant potential for improvement and progress in research, and finally proposes directions for future research.

1. Introduction

As Artificial Intelligence (AI) technology continues to evolve, its contributions are evident in various aspects of modern life. In the field of linguistics, these include voice recognition, translation tools, text recognition in dictionaries and lexicons, and image-based text recognition capabilities. Among these applications, the author believes that the field with the greatest potential for improvement is the study of Handwritten Chinese Character Recognition (HCCR). There is a considerable history of research on online handwritten Chinese character recognizer, with significant achievements in methods and accuracy. However, recent dictionaries and translators, in addition to online input and translation, have gradually acquired the capability to extract and recognize text from images, and many people also employ camera-based direct translation features. In this context, the recognition accuracy for English characters or other phonetic scripts, as well as printed Chinese characters, is comparatively high. Nevertheless, the recognition of handwritten Chinese characters continues to be a crucial area of research that requires further enhancement. The primary reason for this is the issue of the sheer number of characters. The 'Table of General Standard Chinese Characters', which includes commonly used Chinese characters, contains 8,105 characters. The actual number of Chinese characters exceeds 50,000, with a particularly high number of categories. Additionally, many characters feature complex structures and similar shapes. Coupled with the varied writing habits of individuals, these results in an extremely broad data range. These factors contribute to the phenomenon where the accuracy of handwritten Chinese character recognition remains comparatively lower than other languages and scripts. This study aims to summarize the current state of research in this area, providing a theoretical background and suggesting directions for future improvements.

2. Analysis of Domestic and International Research Status

In researching relevant literature, the author discovered that there is extensive research on English character recognition, while the research on Chinese character detection and recognition in natural scenes is relatively limited and presents more unresolved challenges. The following is a review of relevant literature that is valuable in terms of theory, viewpoints, or research methods:

2.1. Research on Chinese Character Recognition

"A Comprehensive Review of the Application of Deep Learning in Handwritten Chinese Character Recognition" (Jin Lianwen, Zhong Zhuoyao, Yang Zhao, Yang Weixin, Xie Zecheng, Sun Jun, 2016) provides a comprehensive overview of the methods, principles, technical details, and performance indicators of Chinese character recognition, summarizing the overall developments in the field to date. [1] In the 1960s, IBM in the United States began research on pattern recognition of

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printed Chinese characters, successfully recognizing 1,000 printed characters using template matching by 1996. Handwritten Chinese Character Recognition (HCCR) was initially explored by Japan. In the 1980s, China started its own research on handwritten Chinese characters. Since Chinese characters are predominantly used in China and the country has the most comprehensive understanding of their types, connotations, and principles of character formation, China's research in this field is particularly thorough. The in-depth research on handwritten Chinese character recognition is mainly focused in China. Handwritten Chinese character recognition can be divided into two categories: "offline recognition" and "online recognition". Online handwritten Chinese character recognition involves writing characters online using physical devices such as digital pens, digital writing pads, or touch screens. Offline handwritten text recognition is achieved by capturing images through scanners or cameras. Generally speaking, the former contains information arranged in a chronological sequence, while the latter lacks stroke order information. Furthermore, digitization can introduce noise interference due to different factors such as varying lighting, resolution, and writing paper. Hence, offline handwritten text recognition poses greater challenges compared to online handwritten text recognition. The paper discusses the difficulties and problems in machine learning for Chinese character handwriting recognition, such as the arbitrary and non-standardized writing styles, the complexity at the character level, the similarity in appearance that leads to confusion, and the challenges in collecting training data. However, these challenges can be seen as opportunities for significant progress and research value. The recent developments in deep learning are well-suited to meet the demands of handwritten Chinese character recognition and are expected to enhance recognition accuracy.

The paper also lists the application methods and types of algorithms of deep learning in Chinese character recognition. The authors highlight that among the deep learning models and methods, Deep Reinforcement Learning (DRL) deserves special attention. For example, the Deep Q-Network (DQN) proposed by Google DeepMind team in 2015 demonstrates exceptional performance in simulating human intelligence and online reinforcement learning. Finally, the paper summarizes unresolved and research-worthy topics, outlining the following topics that require attention from the academic community. Firstly, the types of characters that can be recognized are primarily based on the 3755 categories of Chinese characters in the National Standard First Level Character Set, with a low recognition rate for characters beyond this set. Beyond the training data, there will eventually be a need to input all Chinese characters. How can one develop a deep learning-based solution that not only processes data rapidly but also remains practical with minimally sized model parameters? The process of constructing ultra-large-scale datasets, developing rapid algorithms for various deep learning models, and finding techniques for compressing parameters in deep learning models presents challenges that require continued exploration and resolution by researchers. The second area of focus is the recognition of content in ancient manuscripts and handwritten documents. The character categories in Chinese ancient texts exceed 30,000, with numerous variant and similar characters. Addressing the issue of insufficient training samples and designing classifiers for extremely large categories are both questions worthy of attention. Thirdly, there is the research on the application of new deep learning models in handwritten Chinese character recognition, as well as the study of the interrelationships and integrated applications of various deep learning models.

Zhang Bin and Jin Lianwen (2017) discussed in their paper titled *"Handwritten Chinese Similar Characters Recognition Based on AdaBoost"* the factors that pose challenges to the improvement of recognition rate in comparison to recognition in other languages. [2] Firstly, the extensive number of Chinese characters with numerous categories (3755 characters in the National Standard First Level and 3008 in the Second Level, exceeding Western characters by two orders of magnitude) hinders the direct application of many established recognition methods and patterns. Furthermore, there are a significant number of visually similar characters within the Chinese character set. Experimental evidence indicates that the errors of traditional distance classifiers mainly arise from distinguishing these visually similar characters. This is more prominent in handwritten Chinese character recognition because handwriting involves deformations, resulting in a greater number of visually similar characters compared to printed characters. Therefore, the paper advocates that improving the recognition rate of visually similar characters can enhance the overall recognition rate of Chinese characters. Since the number of categories within the visually similar character set is relatively small, a new integrated Chinese character recognition system can be proposed through detailed analysis of visually similar handwritten Chinese characters and their components. This paper primarily addresses the limitations and elements of Chinese character recognition and conducts research on improving these limitations using the AdaBoost algorithm. Experimental results demonstrate that this algorithm enhances the recognition rate of visually similar characters compared to traditional distance classifiers.

The paper *"On-line Handwriting Chinese Character Recognition; Comparison and Improvement to Japanese Kanji Recognition"* (1998), published by Japanese scholars in Australia, marked the beginning of active research in Chinese character recognition.[3] It analyzed the differences between handwritten Chinese characters in China and Japan and represents an initial research effort in exploring methods to improve recognition accuracy. While this paper is a relatively early study in online recognition, its descriptions of stroke shape classification and transformation methods aimed at improving accuracy hold academic value. For example, statements such as "A connected stroke is better to be divided into the original strokes. Some feature points are helpful for analysis, such as the end point and break point," represent these valuable insights. (Figure 1)

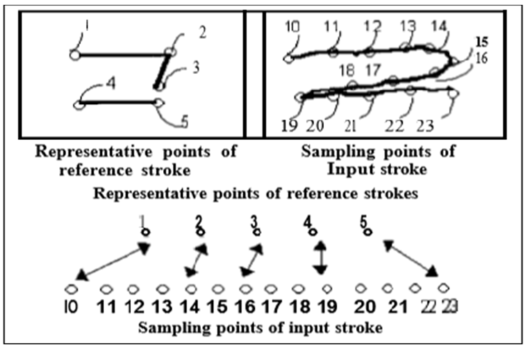

Fig. 1. Example of Stroke Transformation.

2.2. Research on the Image and Structure Analysis of Chinese Characters

In the study *"On-line Handwriting Chinese Character Recognition for PDA Using a Unit Reconstruction Method,"* South Korean scholar Chin Won and Kim Kidoo (2002) conducted a survey on the accuracy and speed of online handwriting recognition for 1,800 basic Chinese characters taught in South Korean middle and high schools. [4] This research, relevant for PDAs (including smartphones, tablets, handheld gaming devices, and other handheld computers), is not only scientifically significant but also valuable in the field of humanities, such as the categorization of Chinese character strokes. It involves the analysis of features of the targeted Chinese characters and the average error rate in stroke order among the surveyed characters. The paper defines the basic unit of writing as a "stroke," categorizing them into basic and special strokes. Basic strokes are linear and come in five types, while special strokes include more than one segment of angle turns and are categorized into seven types. (Figure 2) Generally, strokes are distinguished using seven types, but to enhance the recognition of similar characters, the paper classified strokes into twelve different forms. (Figure 3)

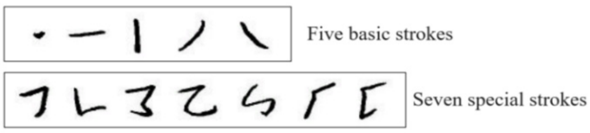

Fig. 2. Classification of Strokes.

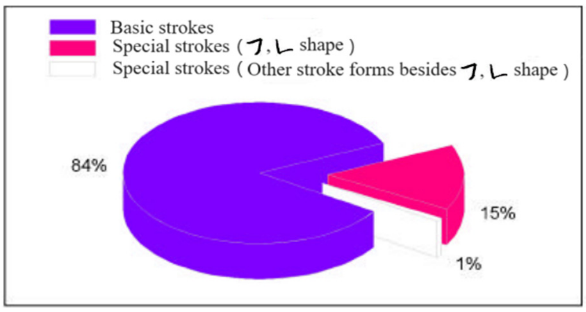

Fig. 3. Proportion of Stroke Forms.

In the paper *"Similar Pattern Discriminant Analysis for Improving Chinese Character Recognition Accuracy"* (2013), authors Wang Yanwei, Liu Changsong, and Ding Xiaoqing focused on developing a method for analyzing and distinguishing similar Chinese characters. [5] They employed a modified quadratic discriminant function (MQDF) in conjunction with Linear Discriminant Analysis (LDA) and Similar Pattern Discriminant Analysis. This approach resulted in a 15.59% lower error rate compared to the Compound Mahalanobis Function (CMF) method. In their research, they calculated the number of recognition errors and created a confusion matrix to illustrate the similarities between two similar characters. They compared the accuracy of LDA and SPDA for similar character combinations, leading to the following results. The variable 'n' represents the number of Chinese characters in the training data. (Table 1)

Table 1. Comparison of Accuracy between LDA and SPDA.

n	LDA(%)	SPDA(%)
128	95.06	96.00
200	95.75	96.28
320	96.39	96.98
400	96.63	97.22
600	97.10	97.55

The authors then presented the structure and procedures of the Modified Quadratic Discriminant Function (MQDF) using charts and compared two distinct approaches: (a) and (b). Structure (a) involves selecting the maximum value between MQDF1 and MQDF2, while structure (b) applies MQDF2 classification to the two characters with the highest probability from MQDF1 when the MQDF1 result is not satisfactory. The results show that the highest accuracy for structure (a) is 98.62%, while the accuracy for structure (b) is 98.15%. (Figure 4)

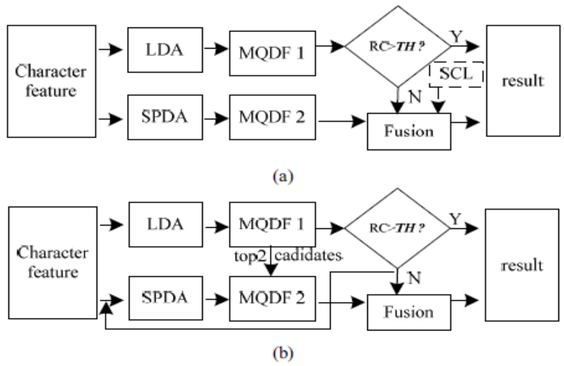

Fig. 4. Structures and procedures of Two Types of Cascade MQDF.

Finally, the authors confirm that the accuracy of the algorithm combining MQDF with CMF (98.62%) is slightly higher than that of using MQDF alone (98.53%).

Yang Chen, Wang Qing, Du Jun, Zhang Jianshu, Wu Changjie, Wang Jiaming (2021) introduced an advanced method in Chinese character recognition using a transformer-based radical analysis network, emphasizing improvements in recognizing complex and low-frequency characters. [6] A transformer-based radical analysis network is a type of neural network architecture used in machine learning, particularly in the field of Chinese character recognition. This network leverages the transformer model, which is known for its effectiveness in handling sequential data, like language. In the context of Chinese characters, the network analyzes the radicals, which are the building blocks of Chinese characters. This approach differs from traditional character recognition methods by emphasizing the underlying structure and components of the characters, leading to improved accuracy and efficiency in recognition tasks. By focusing on these radicals, the network can more effectively learn and recognize the vast array of characters, and this approach can address the challenges of recognizing characters that appear less frequently and have more complicated structures. The integration of a dense encoder and a transformer decoder was a key innovation, enhancing the model's ability to interpret a wide range of character styles and contexts, particularly in difficult scenarios like character occlusion and distortion. The authors' comprehensive experimental validation highlighted the model's superior performance in various datasets, demonstrating a significant leap in the field of Chinese character recognition technology, especially in terms of adaptability and accuracy.

Kim Woo-jeong and Choi Ji-yeon (2023) introduced a three-step process—'Character Analysis,' 'Character Review,' and 'Character Confirmation'—in the Database Management System of the Han-Character Education Research Institute, affiliated with Dankook University. [7] They also classified the types of errors in Chinese character recognition identified during the data verification process as follows:

1) Cases where the Chinese character image is not fully extracted: Mainly occurs in Chinese characters that include components which are also used as independent characters.

2) Cases where adjacent, different Chinese characters are additionally extracted.

3) Cases of mistaking noise for Chinese characters.

4) Cases involving poor printing quality.

5) Cases where character shapes are similar.

6) Cases where artificial intelligence training is not progressing well due to insufficient training data.

2.3. Applied Research of Various CNN Architectures in Chinese Character Recognition

"DenseRAN for Offline Handwritten Chinese Character Recognition" (2018) is an applied research of the DenseRAN algorithm in offline handwritten Chinese character recognition. [8] This paper introduces a novel radical analysis network based on the DenseRAN algorithm, which can analyze the radicals and their two-dimensional structures within Chinese characters. In traditional methods, the process of handwritten Chinese character recognition typically includes image normalization, feature extraction, data dimensionality reduction, and classifier training. With the advancement of deep learning, the Multi-Column Deep Neural Network (MCDNN) emerged as the first convolutional neural network (CNN) used for handwritten Chinese character recognition.

However, these algorithms can only recognize Chinese characters that have appeared in the training dataset. Moreover, they treat each character as a whole, without considering the similarities and sub-structures between characters. The distinctive aspect of this paper is its identification of Chinese characters as logograms composed of basic radicals. Previous research largely treated each character as a whole, without explicitly considering the internal two-dimensional structure and component radicals of the characters. Unlike the algorithms mentioned above, DenseRAN employs an attention-based encoder-decoder model to automatically learn and detect the segmentation of radicals. [9] Here, 'attention' refers to the concept of assigning more 'weighted value' to specific parts (components) in the image. The primary idea behind DenseRAN is to decompose Chinese characters into 'descriptors' that detail the radicals and their structure. When these descriptors match with the actual data, handwritten Chinese characters are successfully recognized.

Compared to the vast number of Chinese characters, the total number of radicals is limited. According to the GB13000.1 standard published by the Working Committee for National Language and Text, nearly 500 radicals form over 20,000 Chinese characters. The following presents thirteen common spatial structures of Chinese characters along with corresponding examples, as provided by the author. (Figure 5)

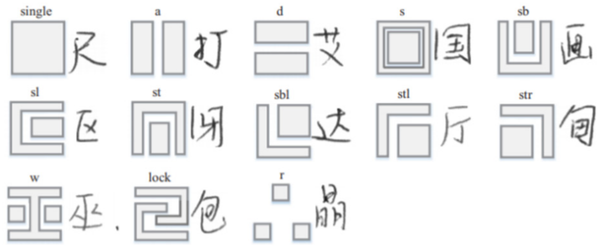

Fig. 5. Thirteen Common Spatial Structures of Chinese Characters and Their Examples.

Then, the author used images to provide a detailed description of how DenseRAN recognizes Chinese characters. (Figure 6), (Figure 7)

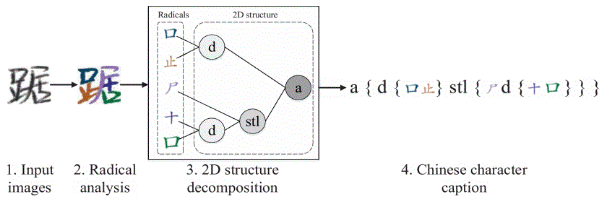

Fig. 6. Illustration of DenseRAN to recognize Chinese characters by analyzing the radicals and two-dimensional structures.

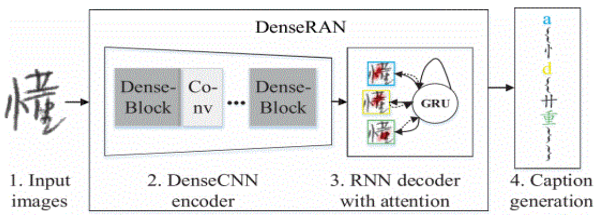

Fig. 7. The overall architecture of DenseRAN for HCCR.

Pavlo Melnyk, You Zhiqiang, Li Keqin (2020) introduced a novel deep CNN architecture for offline handwritten Chinese character recognition, focusing on enhancing network interpretability. [10] The authors developed a CNN with bottleneck layers, reducing computational demands while preserving expressiveness. They innovated with Global Weighted Output Average Pooling (GWOAP) to calculate class activation maps (CAMs), highlighting crucial input character image regions. This approach led to a 0.83% error reduction and a 49% parameter reduction compared to existing methods, without increasing computational costs. Their comprehensive experiments and comparisons showcased the model's superior recognition accuracy and interpretability, marking a significant advancement in the field of HCCR.

"Deep matching network for handwritten Chinese character recognition" (2020) introduced a Deep Matching Network that employs features from template character images, mimicking the human approach to learning Chinese characters. [11] Feature extraction is achieved through CNNs, which map these template images to a feature space. The network utilizes local softmax regression with a subset of template images for each training iteration, enhancing focus and efficiency. A significant advantage of this method is its ability to generalize to new characters by generating template images for characters not included in the training set. The architecture is compact yet effective, featuring several convolutional and pooling layers tailored for both image batches and template image processing. This approach marks a significant advancement in HCCR, particularly in terms of generalization and template-based feature extraction.

Nina Aleskerova and Aleksei Zhuravlev (2020) presented a novel two-stage hierarchical Convolutional Neural Network (CNN) for recognizing handwritten Chinese characters. [12] As mentioned above, one of the major challenges in the study of Chinese character recognition is the extensive quantity of patterns associated with Chinese characters. This method with two-stage hierarchical Convolutional Neural Network (CNN) is designed to effectively manage a large number of target classes, a significant challenge in Chinese character recognition due to the extensive character set. The model involves dividing training samples into clusters, with each cluster representing a subset of character classes. A first-level classifier identifies the cluster, and a second-level classifier, trained specifically on that cluster, performs the final recognition. This hierarchical approach results in improved accuracy and efficiency compared to traditional single-network CNN methods.

"Zero-shot Handwritten Chinese Character Recognition with hierarchical decomposition embedding" (2020) focused on encoding the hierarchical structure of Chinese characters into a semantic vector space for recognizing a large vocabulary of characters, their complex hierarchical structures, various writing styles, and the scarcity of training samples for uncommon characters. [13] This innovative approach involves decomposing characters into smaller components, such as radicals and strokes, and then embedding this decomposed structure hierarchically. By doing so, HDE captures the essence of Chinese character formation, which is not just about the individual strokes but also about how these strokes are combined to form meaningful units. This detailed decomposition and embedding enable the model to understand and recognize characters it has never seen before, by leveraging its learned knowledge of character structures and components. This method is particularly effective for characters that are rare or have few training samples, as it relies on structural understanding rather than rote memorization of character appearances.

Shi Pingping, Lou Yuansheng and Xia Rui (2023) presented a novel approach with character segmentation and classification. [14] Character segmentation uses a morphology-based algorithm for character enhancement and segmentation. It involves steps like binarization, centerline extraction, adaptive dilation, central line erosion, geometric center calculation for positioning, and adaptive bounding box segmentation. These steps are designed to effectively separate adhesive characters and improve the clarity of segmented characters. Character classification employs a pre-trained ResNet101 model, leveraging transfer learning for feature extraction and classification. The use of pre-trained weights, data augmentation techniques like label smoothing and Mixup, and the efficient architecture of ResNet101 contribute to the high accuracy in character recognition.

The specific recognition methods and test results of this study will be elaborated in the next section.

2.4. Research on Handwritten Chinese Character Recognition Methods and Algorithms

Chin Won and Kim Kidoo's (2002)[4] paper introduces the preprocessing steps for recognition data:

1) Smoothing: A filtering process to eliminate discontinuities in the data caused by hand tremors or writing surface issues.

2) Dehooking: The process of removing traces unrelated to strokes, such as traces of pen pressure, incorrect writing habits, or intentionally hooked strokes.

3) Distance filtering

4) Size normalization

Therefore, in the data preprocessing phase of online recognition, some aspects are also essential for offline recognition, rendering research in offline recognition a valuable reference. The author also mentions common stroke classification methods, including the use of neural networks, fuzzy functions, elastic matching, and dynamic programming matching. However, these methods are not well-suited for devices such as PDAs, whose central processing units (CPUs) are slower than those of PCs, due to their high computational demands. Thus, further research is necessary to analyze which algorithms are appropriate for specific functionalities and which are not suitable for certain circumstances.

When reconstructing text into units, it is necessary to represent the positional relationship parameters within the text domain. This is a characteristic of offline handwritten recognition data. However, in this paper, a method was developed and utilized to lessen the computational burden, rather than focusing on the precision of domain feature parameters, due to issues related to computational capacity. Since this research pertains to PDA mobile devices, it prioritizes computational capacity and processing speed over positional parameters. Yet, this aspect is an important part of offline handwritten recognition and should not be overlooked. Furthermore, the author anticipates that processing unhandled similar characters could significantly improve the average recognition rate. The final experimental results are as follows (Table 2):

Table 2. Recognition Experiment Results.

Five DB set	Average recognition rate	Average speed of recognition	
		First experiment	Second experiment
JJH	92.32	0.009	0.164
KJY	93.59	0.009	0.164
WON	96.65	0.009	0.162
JYS	94.70	0.009	0.168
SKB	94.19	0.009	0.163
Average	94.29	0.0088 sec	0.164 sec

Additionally, the experimental results from the paper *"DenseRAN for Offline Handwritten Chinese Character Recognition"* (2018)[8] are as follows: When training with 500 Chinese characters (356,553 handwritten character images) and testing with 1,000 characters, the accuracy was only 1.70%. With 1,000 characters (712,254 handwritten character images) used for training data, the accuracy rate tested with the ICDAR 2013 COMPETITION dataset was 8.44%. Training with 3,755 characters (2,674,784 handwritten character images) resulted in an accuracy of 40.82%. The results show that accuracy increases with the number of Chinese characters used in training. However, the accuracy remains low for characters that were not included in the training set. (Table 3)

Table 3. Test Results for Untrained Data.

Train set	Train class	Train samples	Test set	Test class	Accuracy
HWDB 1.0+1.1	500	356553	ICDAR 2013	1000	1.70%
	1000	712254		1000	8.44%
	1500	1068031		1000	14.71%
	2000	1425530		1000	19.51%
	2755	1962529		1000	30.68%
HWDB 1.0+1.1	3755	2674784	HWDB 1.2	3277	40.82%

The author also demonstrated how the DenseRAN algorithm recognizes radicals and two-dimensional structures, and analyzed examples of recognition errors through the visualization of weighted values. (Figure 8)

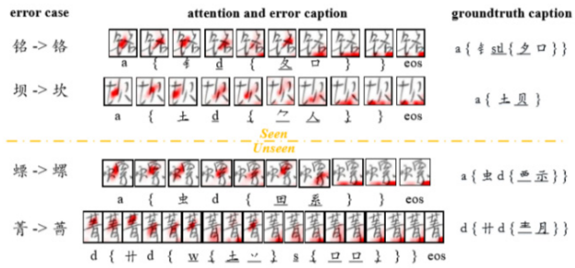

Fig. 8. Examples of Recognition Errors Visualized through Weighted Values.

"Fast and Robust Online Handwritten Chinese Character Recognition with Deep Spatial and Contextual Information Fusion Network" (2022) introduces advanced models for recognizing online handwritten Chinese characters.[15] The Vanilla Compositional Network (VCN) and the Deep Spatial & Contextual Information Fusion Network (DSCIFN) stand out for their methodological approach. DSCIFN employs a transformer-based autoregressive framework combined with multi-layer fusion modules. This approach effectively handles complex character recognition tasks, including characters that are poorly written or have missing strokes. DSCIFN model operates by intricately combining the spatial attributes of handwritten Chinese characters with their preceding contextual information. Spatial features include aspects like stroke order and character shape. The model analyzes these to understand each character's unique structure. Simultaneously, it considers the characters that come before the current one, acknowledging that their meanings and forms can influence the character in question. This dual approach, merging physical attributes (spatial features) with linguistic context (previous contextual information), significantly enhances the model's accuracy in character recognition.

"Chinese character recognition with radical-structured stroke trees" (2023) introduces a unique method for recognizing Chinese characters by first breaking them down into radicals using a Feature-to-Radical Decoder, and then further decomposing these radicals into strokes through a Radical-to-Stroke Decoder.[16] This process forms a structure known as the Radical-Structured Stroke Tree (RSST). The RSST is then interpreted by a Tree-to-Character Translator that employs a Weighted Edit Distance algorithm, enabling the system to effectively handle complex scenarios like zero-shot cases and visual distortions, such as blurring or occlusion, which challenge traditional single-level character recognition methods.

"A Novel Multilevel Stacked SqueezeNet Model for Handwritten Chinese Character Recognition," (2023) introduces model with multilevel stacked feature group extraction to analyze data at different scales, enhancing the model's ability to understand complex character structures. [17] Down-sampling is utilized to reduce feature map dimensions, maintaining essential information while lowering computational demands. Channel amplification is applied to highlight critical features and suppress less relevant ones, aiding in distinguishing similar characters. Lastly, feature information refinement is conducted to ensure only the most pertinent and distinct features are

considered, thereby improving recognition accuracy. These techniques collectively enhance the model's efficiency and precision in recognizing diverse handwritten Chinese characters within computational constraints.

"Characters as graphs: Interpretable handwritten Chinese character recognition via Pyramid Graph Transformer" (2023) presents a novel approach for recognizing handwritten Chinese characters by representing them as skeleton graphs and processing them with a Pyramid Graph Transformer (PyGT). [18] This method integrates the benefits of Transformers and graph convolutional networks, capturing global information through graph attention and local adjacency structures with graph convolutions. The first graph construction process for Chinese characters is transforming the strokes of a character into a graph structure. Each stroke is represented as a node, and the connections between strokes are represented as edges. The process focuses on accurately capturing the spatial relationships and structural characteristics of the strokes within each character. This graph representation forms the basis for the Pyramid Graph Transformer (PyGT) to analyze and recognize the characters. The PyGT is shown to be superior in interpretability and robustness compared to existing methods like 2D-CNN, RNN/1D-CNN, and Vision Transformer (ViT). It achieves state-of-the-art performance for online handwritten Chinese character recognition and is extendable to offline recognition and text recognition.

In conclusion, the accuracy comparison of studies within the last 5 years is as follows (Table 4):

Table 4. Performance comparisons of Chinese character recognition models over the last 5 years.

Dataset	Method	Accuracy (%)
ICDAR2013	**FewshotRAN (Wang et al., 2019) [19]**	96.97
	Template + Instance (Xiao et al., 2019) [20]	97.45
	SAE (Chen et al., 2023)[21]	97.19
	Hierarchical CNN (Aleskerova et al., 2020)[12]	92.10
	HDE (Cao et al., 2020)[13]	97.14
	Melnyk-Net (Melnyk et al., 2020)[10]	97.61
	Chen et al. (2021)[22]	96.74
	ACPM (Zu et al., 2022)[23]	97.80
	RSST (Yu et al., 2023)[16]	96.05
CASIA-HWDB+ ICDAR2013	**ROA (Wang et al., 2021)[24]**	95.77
	PageNet (Peng et al., 2022)[25]	92.19
	SON (Xu et al., 2022)[26]	93.45
	HHCR (Huang et al., 2022)[27]	94.87
	SqueezeNet (Du et al., 2023)[28]	98.65
CASIA-HWDB	**ResNet101 + transfer learning (Shi et al., 2023)[14]**	92.61

The current accuracy of online handwritten Chinese character recognition and offline printed Chinese character recognition is already relatively high. However, offline handwritten Chinese character recognition, due to certain inherent features, has the lowest accuracy in Chinese character recognition systems. Therefore, it is essential to identify the Chinese characters that current CNN algorithms misrecognize along with the various reasons for these errors. This includes analyzing deformations during handwriting, stroke features of similar characters, and the cognitive processes of the human brain in recognizing these characters. Subsequently, integrating these principles into the current algorithms can help improve and develop more accurate algorithms for handwritten Chinese character recognition.

3. Conclusions

Although the study of handwritten Chinese character recognition (HCCR) has a history of over 40 years, the author has identified several shortcomings and unresolved issues in the course of reviewing the literature on this subject. First, while online handwritten Chinese character recognition has achieved a certain level of accuracy, the accuracy of offline handwritten character recognition remains low. Second, the author believes that specialized research is needed for the analysis of the form and structure of Chinese characters specifically for HCCR. Third, the issue of discriminating between similar-looking characters has not been sufficiently resolved. The academic community should address these existing deficiencies to explore how artificial intelligence (AI) can more accurately and effectively learn and recognize handwritten Chinese characters. The author suggests that current Chinese character recognition algorithms and theories of text recognition in other languages can be referenced and integrated with ontological research in Chinese character studies, such as theories on Chinese character structure, stroke order, and analysis of radicals and components, thereby developing more effective and sophisticated recognition methods. [29] Additionally, insights can be gained from artificial intelligence-based image recognition systems, as their engineering designs for image recognition are currently more intricate and specialized. There have been many algorithms used for image recognition in the past. Among them, the recently utilized Convolutional Neural Network (CNN) algorithm for image recognition takes the pixel values of an image as input data. It recognizes images through feature maps calculated by filters. Currently, research involving the use of Convolutional Neural Networks (CNNs) is being conducted across various fields. This research has demonstrated considerable performance in numerous areas of image recognition and continues to improve through a variety of methods. The author believes that research in this area could consider the principles of Chinese characters and the structure of handwritten characters to enhance the accuracy of handwritten Chinese character recognition.

The author intends for this paper to contribute a theoretical basis to AI Chinese character recognition research and also aims to inspire studies that seek to enhance offline Chinese character recognition capabilities.

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