REZCR: Zero-shot Character Recognition via Radical Extraction

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Abstract

The long-tail effect is a common issue that limits the performance of deep learning models on real-world datasets. Character image datasets are also affected by such unbalanced data distribution due to differences in character usage frequency. Thus, current character recognition methods are limited when applied in the real world, especially for the categories in the tail which are lacking training samples, e.g., uncommon characters. In this paper, we propose a zero-shot character recognition framework via radical extraction (REZCR) to improve the recognition performance of few-sample character categories in the tail. Specifically, we exploit radicals, the graphical units of characters, by decomposing and reconstructing characters according to orthography. REZCR consists of an attention-based radical information extractor (RIE) and a knowledge graph-based character reasoner (KGR). The RIE aims to recognize candidate radicals and their possible structural relations from character images. The results are then fed into KGR to recognize the target character by reasoning with a pre-designed knowledge graph. We validate our method on multiple datasets, and REZCR shows promising experimental results, especially on few-sample character datasets.

Introduction

Developments in optical character recognition (OCR) technology offer new solutions for learning, managing, and utilizing character resources. Current OCR methods are mainly based on deep learning models, which place high demands on the quantity and quality of data (Zhang, Bengio, and Liu 2017). Due to differences in character usage frequency, the long-tail effect exists as a common issue in character datasets. Such datasets often contain categories with few samples, especially for un reproduce or inaccessible cases, such as historical character (Huang et al. 2019) and calligraphic character (Lyu et al. 2017) datasets. Fig. 1(a) shows the distribution of character samples for each category in the oracle bone dataset (Wu 2012). The distribution demonstrates a typical long-tail effect, where over half of the character categories have five or fewer samples, and there are even categories with a single sample. These character datasets challenge the validity of OCR methods.

Inspired by studies on general image classification, current research on character recognition mainly focused on methods based on deep convolutional neural networks (CNN). Such OCR methods achieve limited performance on unbalanced datasets, especially when recognizing character categories with few samples (Anderson 2006; Cao et al. 2020). A common solution to alleviate the limitations caused by the few-sample problem is employing data augmentation methods to balance data categories, including re-sampling (Mahajan et al. 2018) and re-weighting (Cui et al. 2019). However, these methods are rarely applied to data categories with few samples or a single sample. Although the compromise solution tends to discard categories with few samples (Géron 2019), we consider such categories valuable and irreplaceable for real-world tasks. For example, many categories in Fig. 1(a) contain only one sample in the unearthed oracle bone dataset, which is unique evidence for understanding this character by archaeologists. Thus, we aim to achieve character recognition on few-sample datasets while keeping data integrity.

The orthography-based strategy of learning East Asian characters in terms of radicals and character structure is the
most frequent and effective way for human beings (Shen 2005). We observe the orthographic peculiarities (Myers 2016) of East Asian characters:

- Characters are composed of a set of radicals organized in a specific structure, where radicals are semantic units of the character.
- Radicals are commonly shared by different characters. Thus, the number of radicals is less than that of characters significantly.

Fig. 1(b), (c) and (d) show our observations on oracle bone, Chinese, and Korean characters, where we highlight radicals by colored boxes. Statistically, 6,763 Chinese characters can be represented by 485 radicals and 10 character structures (Liu et al. 2011). In Fig. 1(a), we demonstrate some characters that contain the same radical “yang” (in red boxes), where such characters tend to distribute randomly in the statistics. As a result, decomposing and reconstructing characters by exploiting radicals help to intensionally analyze characters, which offers the possibility to learn from enough radical samples and recognize character categories with few samples.

According to the above-mentioned discussions, we propose a novel method for zero-shot character recognition via radical extraction, namely REZCR. Specifically, the proposed REZCR consists of a radical information extractor (RIE) and a knowledge graph-based character reasoner (KGR). The former aims to extract semantic information in characters by obtaining candidate radicals and their structural relations in parallel, and the radical attention blocks (RABs) are introduced to handle the radical overlapping issues. The results of RIE are then fed into KGR, where a weight-fusion reasoning algorithm is proposed to reconstruct characters by modeling the radical information as soft labels. We achieve zero-shot recognition by reasoning with the pre-designed character knowledge graph (CKG) that stores information about characters, radicals, and their relations.

The contributions of our paper are summarized as follows:

- We propose a novel zero-shot method (i.e., REZCR) for character recognition, which can effectively handle categories with insufficient training samples by character decomposing and reconstructing.
- REZCR introduces a new strategy to organize candidates for reasoning-based character recognition, where candidate radicals and structural relations are extracted in parallel by RIE, and then characters are recognized by the proposed weight-fusion reasoning algorithm in KGR.
- Our method is validated on multiple datasets, including a newly constructed dataset, namely OracleRC. Compared to state-of-the-art OCR methods, our REZCR achieves promising results, especially on few-sample cases.

**Related Work**

**Zero-shot Learning.** Zero-shot learning aims to classify unseen categories by learning from existing categories and knowledge supplemented by auxiliary resources (Wang et al. 2019b; Sun, Gu, and Sun 2021). In recent years, zero-shot learning has been considered from a variety of perspectives. For instance, embedding-based methods (Akata et al. 2015; Xie et al. 2019) propose to perform image embedding and label semantic embedding in the same space, and extend to unseen categories by a compatibility function. Furthermore, attribute-based methods (Lampert, Nickisch, and Harmeling 2009, 2013) manually design attributes in different ways and represent categories with multidimensional attribute vectors, which are introduced to train the visual classifier by vector mapping. Moreover, reasoning-based methods exploit knowledge graphs (Rohrbach, Stark, and Schiele 2011; Wang, Ye, and Gupta 2018) to guide zero-shot learning since knowledge graphs connect trained categories and unseen categories by pre-defined relations. The success of the above methods brings us inspiration about the usage of auxiliary information from knowledge graphs and the organization of attributes in zero-shot character recognition.

**Character Recognition.** Early studies on character recognition mainly contain feature extraction-based (Su and Wang 2003) and statistical-based methods (Shanthi and Duraiswamy 2010), which are poorly performed on datasets with a large number of categories. Then, researchers exploit CNN, e.g., Yuan et al. (2012) applies an improved LeNet-5 model to recognize English characters, and (Cireşan and Meier 2015) first introduces CNN into Chinese character recognition. Zhang, Bengio, and Liu (2017) combines a normalization-cooperated direction-decomposed feature map with deep CNN for handwriting character recognition. To recognize curved or distorted characters in the real world, Zhan and Lu (2019), Yang et al. (2019) introduce trainable models based on symmetry-constrained rectification and line-fitting transformation, respectively. Moreover, deep character recognition models with dedicated improvements achieve promising results in different languages (Balah a et al. 2021; Mushtaq et al. 2021).

The success of the above deep learning-based methods relies on a large number of training samples for each character category. Thus, data augmentation strategies are introduced to solve insufficient data issues. For instance, Qu et al. (2018) combines global transformation and local distortion to effectively enlarge the training dataset, and Luo et al. (2020) designs a set of custom fiducial points to assist in flexibly enhancing character images, both of which alleviate the insufficient training sample issue. Some researchers also introduce domain knowledge related to character attributes to deal with few-sample problems by decomposing characters, i.e., presenting characters as preset sequences. For instance, Cao et al. (2020) introduce CNN-based encoder-decoder frameworks to generate radical sequences for character recognition. Inspired by these methods, Chen, Li, and Xue (2021) decomposes characters into strokes, the smallest units of characters, then perform recognition by looking up generated stroke sequences in a dictionary. However, the above methods require the generated sequences to match the dictionary exactly, both for each element and the order, i.e., hard-matching strategy. As a result, such sequence-based methods perform poorly on the benchmarks, which limits their applications in practice.
Intuitive Discussion

In this section, we provide some intuitive observations to explore the character recognition task and discuss potential performance improvement strategies, driving the motivation of this paper. Then, we model the zero-shot character recognition to clarify the task in this paper.

Decomposition of Characters. According to orthography, characters can be decomposed into a set of radicals organized in specific structures, where radicals are independent characters or evolve from simple-semantic characters (Yeung et al. 2016). Complex-semantic characters usually contain more than one radical since radicals are the smallest units that represent complete semantic information (Ho, Ng, and Ng 2003). A Chinese character is shown in Fig. 2(a) as an example, where the three radicals in the first row represent “house”, “person”, and “mat (evolved)” and constitute the character that means “get an accommodation”. However, the decomposition in the second row shows an opposite example, i.e., the character is decomposed excessively into strokes, where the major semantic information is lost. Meanwhile, we define the structure of character as the relative localization relation between the constituent radicals, namely structural relations, which also contain semantic information. Structural relations are also crucial for characters since the same radical composition points to different candidate characters when the structure changes, as shown in Fig. 2(b). Moreover, as discussed in the introduction, the same radical can be shared by various characters. For instance, 2,374 Korean characters contain 68 radicals (Zatsepin et al. 2019), and over 6,000 common Chinese characters can be composed of less than 500 radicals (Liu et al. 2011), which means a large number of characters can be presented by a small number of radicals.

Motivation and Challenges. Based on the above observations, two ideas are derived for achieving zero-shot character recognition. Firstly, a character can be properly decomposed into a set of radicals and their structural relations, i.e., radical information, which can be extracted from the character image. Since the semantics of characters can be represented by radical information, we aim to extract such semantic information through deep neural networks. Thus, we propose RIE to extract all the radical information in parallel rather than extracting separately since radicals and the structure support each other. Meanwhile, we apply the attention mechanism to deal with the radical overlapping problem for better recognition performance.

Secondly, current sequence-based methods organize character elements in the form of long sequences that are matched by hard-matching strategies. In Table 1 we show accuracy estimation for sequence-based methods at both radical and stroke levels, where $p$ represents the probability of correct character recognition; $r_i, s_i$ are correct recognition probabilities of elements in radical and stroke sequences, respectively; $m, n$ are the lengths of sequences. We find $p$ only achieve 0.48/0.28 maximally under the hard-matching strategy, even if we ideally assume a high recognition probability $r_i=s_i=0.9$. Therefore, we propose KGR to achieve reasoning-based zero-shot recognition by exploiting knowledge graphs to organize characters, radicals, and structural relations in a flexible way rather than in long sequences. Meanwhile, we introduce soft labels into the matching strategy, i.e., the proposed weight-fusion algorithm, to achieve stable recognition performance.

Task Formulation. The goal of the character recognition task is to classify character image $I_C \in \mathbb{R}^{H \times W \times C}$ into character category $Z$, where $H \times W$ represents the spatial resolution, and $C$ is the number of channels. We model character recognition as a zero-shot classification task, defined as follows. The training data is defined as $I_{seen} = \{(x, y)|x \in X, y \in Y\}$, where $x$ is the input image from the training image set $X$, $y$ refers to the label(s) of $x$ annotated based on radical information, and $Y$ is the label set of the radical categories. Note that there are one or more radicals in an image. Similarly, the test set can be defined as $I_{unseen} = \{(x, z)|x \in \hat{X}, z \in Z\}$, where $x$ belongs to images from unseen categories $\hat{X}$, i.e., character categories, $Z$ represents the set of labels for unseen categories. In this task, the training is based on radical categories and finally outputs the target character category, as $f: x \rightarrow Z$.

The Proposed REZCR

In this section, we detail the proposed REZCR and its key components RIE and KGR, as shown in Fig. 3.

Radical Information Extractor

RIE aims to obtain candidate radicals and structural relations from an input character image $I_C$. We observe that character images usually contain overlapping and unclear boundaries

| Method | ASL | Accuracy Calculation | Example ( $r_i, s_i = 0.9$) |
|--------|-----|----------------------|-----------------------------|
| Radical | 7.76 | $p = \prod_{i=0}^{n} r_i$ | $0.9^7 = 0.4783$ |
| Stroke  | 12.88 | $p = \prod_{i=0}^{m} s_i$ | $0.9^{12} = 0.2824$ |
between radicals (Shi et al. 2022b), especially for handwritten characters, which challenges the performance of radical recognition. Thus, we propose a set of radical attention blocks (RABs) to extract deep features from the input image, where the attention mechanism is applied to concentrate on the target radicals. The RAB consists of a dual spatial attention layer (DSAL) and two consecutive CBR blocks (including a $3 \times 3$ convolutional layer, a batch normalization operation, and a ReLU operation), as shown in the green blocks of Fig. 3. Each DSAL obtains the attention weights by two calculations, in which the foreground information is retained for radical feature selection via MaxPool, and the background information is processed via AvgPool to maintain integrity. Element-wise multiplication is applied to compute the correlation of two spatial vectors: the larger the vector product, the stronger the correlation between two vectors. The process in DSAL can be defined as:

$$
A_i' = \sigma(\text{Conv}(\text{MaxPool}(F_i))) \odot F_i,
$$

$$
A_i = \sigma(\text{Conv}(\text{AvgPool}(A_i'))) \odot F_i,
$$

where $A_i'$ and $A_i$ denote the intermediate and final output features of the DSAL in the $i$-th RAB; $\sigma$ refers to the sigmoid function; $\text{Conv}$ refers to the convolutional layer; $F_i$ is the feature map fed into the corresponding DSAL.

As a result, RABs output the deep feature $F_i$ that contains semantic information to perform radical detection and structural relation extraction in parallel. Thus, we have two output projectors $OP_r$ and $OP_s$ in RIE that aim to recognize radicals and structural relations, respectively. The output projector $OP_r$ consists of an FC layer whose size is $K \times K \times M \times (n_r + n_c)$, where $K \times K$ refers to the number of divided grids of an input character image, $M$ represents the number of anchor boxes in each grid, $n_r$ is the number of radical categories in the datasets, and $n_c$ records the coordinates of the radical location $(x, y, w, h)$ and the confidence of radical detection, thus $n_c = 5$. Therefore, the output projector $OP_r$ constrains RIE training by predicting radical categories and radical location. Parallely, we apply $OP_s$ to predict the structural relations between candidate radicals, where both shallow features (the output features of RAB$_1$) and deep features $F_i$ (containing radical location information) are exploited to capture the global and local structural information. $OP_s$ consists of two convolutional layers and an FC layer to further handle the concatenated shallow-deep features. Correspondingly, $OP_s$ constrains RIE training by classifying structural relations.

### Loss Functions

RIE contains two output projectors $OP_r$ and $OP_s$. Thus, we have corresponding loss functions $\mathcal{L}_R$ and $\mathcal{L}_S$, respectively. $\mathcal{L}_R$ consists of three components, $\mathcal{L}_r$, $\mathcal{L}_{\text{coo}}$, and $\mathcal{L}_{\text{isR}}$. We define $\mathcal{L}_r$ as the cross-entropy loss (De Boer et al. 2005) of radical classification:

$$
\mathcal{L}_r = \frac{1}{K^2} \sum_{i=0}^{K^2} \sum_{j=0}^{M} \| i_{i,j}^R \| p_i(r) \log(\hat{p}_i(r)) + (1 - p_i(r)) \log(1 - \hat{p}_i(r)),
$$

where $r$ is a category from radical set $R$; $i_{i,j}^R$ is assigned 1 or 0 to indicate whether the target radical exists in the proposal coordinates; $p_i(r)$ and $\hat{p}_i(r)$ refer to the probability of target and predicted results, respectively. We also define $\mathcal{L}_{\text{coo}}$ as the loss function of the radical coordinates:

$$
\mathcal{L}_{\text{coo}} = \frac{1}{K^2} \sum_{i=0}^{K^2} \sum_{j=0}^{M} \| i_{i,j}^R \| 2 (w_i - \hat{w}_i)^2 + (h_i - \hat{h}_i)^2,
$$

$\mathcal{L}_{\text{isR}}$ is the loss function of the radical detection confidence:

$$
\mathcal{L}_{\text{isR}} = \frac{1}{K^2} \sum_{i=0}^{K^2} \sum_{j=0}^{M} \| i_{i,j}^R \| (c_i - \hat{c}_i)^2 + \lambda \sum_{i=0}^{K^2} \sum_{j=0}^{M} \| i_{i,j}^R \| (c_i - \hat{c}_i)^2,
$$

where we consider both cases of radical existence and absence. Thus, we also set $\lambda = 0.05$ to present if there is no radical covered by proposal coordinates; $c_i$ refers to the confidence of radical prediction, and $\hat{c}_i$ is the existence of radical; $\lambda$ is the weight of absence cases, and we set $\lambda = 0.05$ in the experiments. Then we define $\mathcal{L}_S$ as the loss function of $OP_s$. 

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**Figure 3:** The overall architecture of REZCR. (left) RIE extracts candidate radicals and structural relations from input character images; (right) KGR recognizes the target character by reasoning with the CKG, where blue, orange, and green nodes represent characters, radicals, and structural relations, respectively, and lines in CKG represent different relations between nodes.
to learn from categories of structural relations:

$$
\mathcal{L}_\text{S} = \frac{\lambda_1}{N} \sum_{i=0}^{N} q_i(s) \log(\hat{q}_i(s)),
$$

where $N$ is the number of categories, $q_i(s)$ is the probability of target structural relation, while $\hat{q}_i(s)$ is the predicted one. To sum up, the full loss function of RIE can be represented as:

$$
\mathcal{L}_{\text{RIE}} = \mathcal{L}_t + \mathcal{L}_{\text{con}} + \mathcal{L}_{\text{inR}} + \mathcal{L}_S.
$$

### Knowledge Graph Reasoner

Inspired by graph-based recommendation methods (Wang et al. 2020; Shi et al. 2020), we propose KGR, which aims to achieve zero-shot character recognition via a reasoning-based strategy rather than hard-matching strategies. A weight fusion-based reasoning algorithm is proposed to obtain better recognition performance, where a character knowledge graph (CKG) is exploited to organize character information. We also utilize the predictions from RIE as soft labels to improve the adaptive ability of the reasoning process.

#### Character Knowledge Graph.

We intend to reuse existing knowledge graphs of characters in various languages, including Oracle, Bronze (Chi et al. 2022), Korean, and simplified Chinese where we can find the radical composition of characters and structural relations. To achieve reasoning-based character recognition, we focus on three kinds of entities in these large-scale CKGs, i.e., character, radical, and structure. Note that characters are associated with the corresponding radicals by the relation contain, and the structures are connected with characters by compose, which provides the possibility of more flexible reasoning via CKG.

#### Weight Fusion-based Reasoning.

The inputs of the weight fusion-based reasoning algorithm $\text{CharReason}(\cdot)$ are CKG, radical predictions ($\text{RPs}$), and the structural relation prediction ($\text{SP}$). The predictions of radical categories $\text{RPs} \in \mathbb{R}^{\text{num} \times n_r}$ are extracted from the output of the projector $\text{OP}_r$, where $\text{num}$ is the number of radicals recognized by RIE and $n_r$ is the length of each prediction. $\text{SP}$ is the output of the projector $\text{OP}_p$, with the length $n_s$ which is the number of predefined structural relations.

As shown in the Algorithm 1, firstly, we map the predictions in each $\text{RP}$ to generate the candidate radical mappings $M$, where the confidence of each $m_i \in M$ is calculated by:

$$
{m_i, \text{conf}} = \frac{1}{\text{num}} \sum_{i=1}^{\text{num}} p_r,
$$

where $p_r$ is the prediction confidence $\text{conf}$ of each candidate radical in the mapping $m_i$. We search for candidate characters $C_r$ that match the radicals in $m_i$ via $\text{searchRad}(\cdot)$ and candidate characters $C_s$ that match the relations $\text{sp}_j$ via $\text{searchStr}(\cdot)$ in CKG, where $\text{sp}_j \in \text{SP}$. Note that we sort $M$ and $\text{SP}$ via $\text{maxSort}(\cdot)$ based on the value of prediction confidence before searching to speed up the reasoning process. As a result, we have candidate character $C_t$ that satisfies both radical mapping and structural relation. Its confidence $p_c$ is calculated by a weighted fusion of the $m_i$ and $\text{sp}_j$ in line 7, where $\theta=0.7$. The obtained $C_t$ and the corresponding confidences $p_c$ are stored in the character prediction $PC$. The algorithm outputs the sorted $PC$ as the final recognition result, where we have the confidence of all candidates $C_t$ to maximize the possibility of correct recognition.

Our proposed KGR comprehensively considers the extracted character information from RIE, which effectively alleviates the low-precision character reasoning issue caused by hard-matching strategies. Note that KGR supports adding new character categories by updating CKG without additional model training. Thus, we consider REZCR as a zero-shot method that is able to recognize unseen character categories by exploiting CKG with radical information and reasoning-based strategy.

### Experiments

#### Experimental Setup

**Datasets.** To evaluate our method on real-world character image sets which suffer from the few-sample problem, we introduce a new character image dataset called OracleRC. We collect oracle rubbing images from (Wu 2012) and normalize images by a denoising method (Shi et al. 2022a). OracleRC includes 2,005 character categories that can be decomposed by 202 radicals and 14 structural relations, where the number of character samples ranges from 1 to 32. Radicals and structural relations were manually annotated by 8 linguists. We also validate on handwritten Chinese datasets ICDAR2013 (Yin et al. 2013), HWDB1.1 (Liu et al. 2013), scene character dataset CTW (Yuan et al. 2019), and Korean dataset PE92 (Kim et al. 1996) for a comprehensive evaluation. To increase the adaptability of REZCR, we propose a radical splicing-based synthetic character strategy to enlarge the training set and reduce the cost of human annotations.

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1. [http://humanum.arts.cuhk.edu.hk/Lexis/lexi-mf/](http://humanum.arts.cuhk.edu.hk/Lexis/lexi-mf/)
2. CKGs record structure of a character, which is considered equal to our defined structural relation.

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3. More details can be found in the supplementary document.
Table 2: Quantitative comparisons with state-of-the-art methods on four datasets. The best and second-best results are highlighted in red and blue colors, respectively.

| Method                            | OracleRC       | ICDAR2013      | CTW          | HWDB1.1       |
|-----------------------------------|----------------|----------------|--------------|---------------|
|                                   | Top-1 | Top-3 | Top-5 | Cat\_Avg | Top-1 | Top-3 | Top-5 | Cat\_Avg | Top-1 | Top-3 | Top-5 | Cat\_Avg |
| AlexNet (Krizhevsky, Sutskever, and Hinton 2012) | 26.93% | 36.45% | 40.03% | 21.74% | 89.99% | 80.14% | 76.49% | 61.28% | 88.74% | 85.32% |
| VGG16 (Simonyan and Zisserman 2014) | 27.75% | 38.12% | 41.53% | 20.38% | 90.68% | 82.76% | 79.38% | 68.34% | 89.67% | 84.60% |
| HCCR (Zhong, Jin, and Xie 2015) | 28.52% | 36.75% | 39.86% | 18.81% | 96.26% | 88.97% | 82.28% | 71.21% | 94.85% | 90.36% |
| DropSample-DCNN (Yang et al. 2016) | 29.19% | 39.27% | 42.03% | 19.59% | 97.23% | 89.10% | 82.37% | 71.21% | 96.57% | 91.42% |
| ResNet (He et al. 2016) | 28.50% | 33.02% | 40.66% | 21.98% | 92.18% | 85.68% | 79.46% | 69.82% | 90.98% | 86.06% |
| DenseNet (Huang et al. 2017) | 27.85% | 38.63% | 47.48% | 19.20% | 95.90% | 90.36% | 78.98% | 68.48% | 94.32% | 89.72% |
| DirectMap (Zhang, Peng, and Liu 2017) | 30.48% | 44.89% | 54.72% | 23.59% | 97.37% | 90.42% | 86.78% | 72.50% | 96.25% | 91.28% |
| M-RBC + IR (Yang et al. 2017) | 30.53% | 42.74% | 49.32% | 20.72% | 97.37% | 88.70% | 83.65% | 73.06% | 94.16% | 97.06% |
| RAN (Zhang et al. 2018) | 35.37% | - | - | 32.48% | 93.79% | 88.10% | 82.37% | 71.21% | 96.57% | 91.42% |
| DenseRAN (Wang et al. 2018) | 36.02% | - | - | 32.16% | 96.66% | 91.02% | 85.56% | 72.50% | 96.25% | 91.28% |
| FewshotRAN (Wang et al. 2018a) | 33.1% | - | - | 30.90% | 96.97% | 90.42% | 83.65% | 73.06% | 94.16% | 97.06% |
| HDE-Net (Cao et al. 2019) | 37.95% | - | - | 33.10% | 96.74% | 88.75% | 82.28% | 71.21% | 94.85% | 90.36% |
| Stroke-to-Character (Chen, Li, and Xue 2012) | 27.30% | - | - | 20.09% | 96.28% | 89.11% | 85.29% | 77.14% | 93.97% | 89.83% |

REZCR (Ours) 60.28% 69.74% 72.66% 58.17% 96.35% 91.24% 86.64% 82.11% 95.72% 91.99%

Table 3: Comparisons with zero-shot character recognition methods.

| Method                            | OracleRC       | Combined dataset | CTW          |
|-----------------------------------|----------------|------------------|--------------|
|                                   | c-500 | c-1000 | c-1205 | c-1000 | c-2000 | c-2755 | c-1000 | c-2000 | c-3150 |
| DenseRAN (Wang et al. 2018)       | 5.28% | 10.67% | 11.58% | 8.44% | 19.51% | 30.68% | 0.54% | 1.95% | 5.39% |
| HDE-Net (Cao et al. 2020)         | 7.12% | 9.76% | 10.51% | 12.77% | 25.13% | 33.49% | 2.11% | 6.96% | 7.75% |
| Stroke-to-Character (Chen, Li, and Xue 2021) | 3.37% | 7.48% | 7.97% | 13.85% | 25.73% | 37.91% | 2.54% | 6.82% | 8.61% |
| REZCR (Ours)                      | **38.56%** | **51.80%** | **53.74%** | **65.26%** | **72.65%** | **77.91%** | **49.42%** | **60.96%** | **63.55%** |

Table 2: Quantitative comparisons with state-of-the-art methods on four datasets. The best and second-best results are highlighted in red and blue colors, respectively.

Implementation Details. The resolution of the input image is 256 × 256. We exploit data enhancement strategies, including translation, rotation, scaling, and background transformation. Parameters $K=7$ and $M=3$ are set in RIE. All experiments are conducted with Adadelta optimization where the hyperparameters are set to $\rho=0.95$ and $\varepsilon=10^{-6}$.

Experimental Results

We compare REZCR with state-of-the-art character recognition methods on four datasets, and the results are shown in Table 2. We output Top-n prediction by confidence to present the average classification accuracy based on samples. Considering a few categories with more samples are not enough to reflect the overall recognition performance in an unbalanced dataset, we also calculate average accuracy for each category and then average over all categories, i.e., Cat\_Avg. Note that in Table 2 general OCR methods are presented in the former rows, and the latter are zero-shot recognition methods. For all four datasets, we select 80% of the samples in each character category as the training set and the remaining as the test set. Note that categories containing only one sample are not included in this experiment since general recognition methods are not able to train on these categories.

For the few-sample dataset OracleRC, we can find REZCR significantly outperforms all general OCR methods and zero-shot methods on Top-n accuracy and Cat\_Avg. We also find zero-shot methods except Stroke-to-Character gain higher accuracy than general methods on Top-1 accuracy and Cat\_Avg. Compared to Top-1 accuracy, lower Cat\_Avg obtained by general OCR methods means that these methods poorly perform on categories with few samples.

The main reason for this disparity is that an insufficient amount of training data limits their performance. In contrast, for zero-shot recognition methods, decomposing characters into elements brings an increasing number of training samples and a decrease in training categories, which alleviates the few-sample issue. Meanwhile, the better performance of REZCR among zero-shot methods benefits from the powerful KGR with a flexible reasoning strategy, as we discussed before. We also evaluate REZCR on ICDAR2013, CTW, and HWDB1.1 to demonstrate its adaptability, where the same training and testing setup are conducted for all methods. As shown in Table 2, both general and zero-shot methods are competitive in these cases with sufficient training samples, where our REZCR also gains promising results. We find REZCR performs better than others on metric Cat\_Avg, which proves our method is less influenced by categories with different numbers of samples during recognition.

Then, we conduct an additional experiment to demonstrate the validity of REZCR on zero-shot character recognition, and the results are presented in Table 3. Only zero-shot recognition methods are included in this experiment since general methods are not able to recognize unseen character categories. Three datasets are applied, including OracleRC, CTW, and a combined dataset by two handwritten character datasets ICDAR2013 and HWDB1.1. We follow the experimental setting introduced by previous zero-shot methods (Wang et al. 2018; Chen, Li, and Xue 2021), where we fix the test categories at the beginning and gradually increase the number of training categories. Thus, in this experiment, 800 out of 2,005 categories in OracleRC are unseen categories used for testing. Similarly, 1,000/3,755 and 500/3,650
categories are applied for testing on the combined dataset and CTW, respectively. Meanwhile, as shown in Table 5, character categories are applied testing on the combined dataset and CTW, respectively. Meanwhile, as shown in Table 5, c-m refers to the comparing group which applied m training categories, m∈{500, 1000,...}. We can find that our proposed RIE significantly surpasses other sequence-based zero-shot methods in each set of datasets, which further shows the superiority of our reasoning-based recognition strategy. More specifically, RIE benefits from the CKG-based knowledge organization and a flexible reasoning algorithm, which results in the possibility of correct character recognition even with incorrect Top-1 radical prediction. Thus, we can conclude that our proposed RIE, as a generic character recognition method, is effective for different character datasets, particularly for few-sample datasets.

Ablation Study

Impact of Reasoning Strategies in KGR. We also conduct experiments to validate the effectiveness of reasoning-based character recognition. Firstly, we change the radical information and matching strategy in KGR. In Table 4, "Top-1 RPs" refers to a hard-matching strategy which considers only radicals with the highest confidence in RPs, while "Top-1 RPs & SP" utilizes both radicals and structural relations with the highest confidence in RPs and SP, respectively. "RPs" considers all candidate radicals in RPs for reasoning, while "RPs & SP" exploits all candidates in both RPs and SP, i.e., our reasoning-based algorithm. We see that the character recognition accuracy Acce of the latter two are significantly higher than that of the former two, which shows our reasoning-based algorithm surpasses hard-matching strategies. We can also find the increasing number of elements limits the performance of the hard-matching strategy, while the accuracy of our algorithm increases when adding structural relations. A similar phenomenon can also be found in Table 5, where character recognition results by KGR are higher than radical recognition results by RIE since the reasoning-based KGR can maximize the possibility of correct recognition.

Impact of Baseline Networks in RIE. RPs and SP are output by OP and OPv via a single baseline network in RIE, which should be obtained by two separate networks intuitively. As shown in Table 6, we apply an ablation test to present the superiority of the proposed RIE. “Separate Networks” output RPs and SP by two baseline networks, respectively. “Single Network” indicates two output projections stacked on a single network, i.e., RIE. ACC and Acce refer to the recognition accuracy of the radical categories and structural relations. We find that RIE obtains better performance in both metrics. This indicates that the feature extraction of radicals and structures can be improved mutually since the structural relation is relevant to the radical location.

Impact of Attention Layer Schemes. In RIE, we aim to utilize the attention mechanism to refine the radical information extraction on character images with overlapping radicals and unclear boundaries. As shown in Fig. 4, we design five possible schemes to stack attention layers, where three schemes are proposed based on the single spatial attention layer (SSAL) and the remaining two are based on the DSAL. The results of the radical recognition by different schemes are shown in Table 7. We conduct this experiment on the OracleRC dataset, where we record the radical recognition accuracy Acc. It is easy to find that DSAL-based schemes outperform three SSAL-based schemes. That is because DSALs consider both foreground information for radical feature selection and background information to maintain the integrity of radicals. Thus, we select better-performed DSAL-b as the attention layer in RABs.

Conclusion

In this paper, we first introduce the importance of radical information for character recognition and discuss two character decomposition strategies. Then, we propose RIE, a novel zero-shot character recognition method, to deal with unbalanced character datasets with few samples. Two novel modules are introduced, where RIE exploits attention mechanism to extract radical information and KGR recognizes characters by reasoning on the prediction results from RIE. RIE obtains promising experimental results on multiple character datasets, especially on few-sample datasets.
References

Akata, Z.; Perronnin, F.; Harchaoui, Z.; and Schmid, C. 2015. Label-embedding for image classification. *IEEE TPAMI*, 38(7): 1425–1438.

Anderson, C. 2006. *The long tail: Why the future of business is selling less of more*. Hachette Books.

Balaha, H. M.; Ali, H. A.; Saraya, M.; and Badawy, M. 2021. A new Arabic handwritten character recognition deep learning system (AHCR-DLS). *Neural Computing and Applications*, 33(11): 6325–6367.

Cao, Z.; Lu, J.; Cui, S.; and Zhang, C. 2020. Zero-shot Handwritten Chinese Character Recognition with hierarchical decomposition embedding. *Elsevier PR*, 107: 107488.

Chen, J.; Li, B.; and Xue, X. 2021. Zero-Shot Chinese Character Recognition with Stroke-Level Decomposition. In *IJCAI*.

Chi, Y.; Giunchiglia, F.; Shi, D.; Diao, X.; Li, C.; and Xu, H. 2022. ZiNet: Linking Chinese Characters Spanning Three Thousand Years. In *Findings of the Association for Computational Linguistics: ACL 2022*, 3061–3070.

Cireşan, D.; and Meier, U. 2015. Multi-column deep neural networks for offline handwritten Chinese character classification. In *IJCNN*.

Cui, Y.; Jia, M.; Lin, T.-Y.; Song, Y.; and Belongie, S. 2019. Class-balanced loss based on effective number of samples. In *CVPR*.

De Boer, P.-T.; Kroese, D. P.; Mannor, S.; and Rubinstein, R. Y. 2005. A tutorial on the cross-entropy method. *Annals of operations research*, 134(1): 19–67.

Géron, A. 2019. *Hands-on machine learning with Scikit-Learn, Keras, and TensorFlow: Concepts, tools, and techniques to build intelligent systems*. O'Reilly Media.

He, K.; Zhang, X.; Ren, S.; and Sun, J. 2016. Deep residual learning for image recognition. In *CVPR*.

Ho, C. S.-H.; Ng, T.-T.; and Ng, W.-K. 2003. A “radical” approach to reading development in Chinese: The role of semantic radicals and phonetic radicals. *Journal of literacy research*, 35(3): 849–878.

Huang, G.; Liu, Z.; Van Der Maaten, L.; and Weinberger, K. Q. 2017. Densely connected convolutional networks. In *CVPR*.

Huang, S.; Wang, H.; Liu, Y.; Shi, X.; and Jin, L. 2019. OBC306: A large-scale Oracle Bone character recognition dataset. In *ICDAR*.

KIM, D.-H.; Hwang, Y.-S.; Park, S.-T.; Kim, E.-J.; Paek, S.-H.; and BANG, S.-Y. 1996. Handwritten Korean character image database PE92. *IEICE TOIS*, 79(7): 943–950.

Krizhevsky, A.; Sutskever, I.; and Hinton, G. E. 2012. Imagenet classification with deep convolutional neural networks. In *NeurIPS*.

Lampert, C. H.; Nickisch, H.; and Harmeling, S. 2009. Learning to detect unseen object classes by between-class attribute transfer. In *CVPR*.

Lampert, C. H.; Nickisch, H.; and Harmeling, S. 2013. Attribute-based classification for zero-shot visual object categorization. *IEEE TPAMI*, 36(3): 453–465.

Liu, C.-L.; Yin, F.; Wang, D.-H.; and Wang, Q.-F. 2011. CSAIA online and offline Chinese handwriting databases. In *ICDAR*.

Liu, C.-L.; Yin, F.; Wang, D.-H.; and Wang, Q.-F. 2013. Online and offline handwritten Chinese character recognition: benchmarking on new databases. *Elsevier PR*, 46(1): 155–162.

Luo, C.; Zhu, Y.; Jin, L.; and Wang, Y. 2020. Learn to Augment: Joint Data Augmentation and Network Optimization for Text Recognition. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*.

Lyu, P.; Bai, X.; Yao, C.; Zhu, Z.; Huang, T.; and Liu, W. 2017. Auto-encoder guided GAN for Chinese calligraphy synthesis. In *ICDAR*.

Mahajan, D.; Girshick, R.; Ramanathan, V.; He, K.; Puluri, M.; Li, Y.; Bharambe, A.; and Van Der Maaten, L. 2018. Exploring the limits of weakly supervised pretraining. In *ECCV*.

Mushtaq, F.; Misgar, M. M.; Kumar, M.; and Khurana, S. S. 2021. UrduDeepNet: offline handwritten Urdu character recognition using deep neural network. *Neural Computing and Applications*, 33(22): 15229–15252.

Myers, J. 2016. Knowing Chinese character grammar. *Elsevier Cognition*, 147: 127–132.

Qu, X.; Wang, W.; Lu, K.; and Zhou, J. 2018. Data augmentation and directional feature maps extraction for in-air handwritten Chinese character recognition based on convolutional neural network. *Pattern recognition letters*, 111: 9–15.

Rohrbach, M.; Stark, M.; and Schiele, B. 2011. Evaluating knowledge transfer and zero-shot learning in a large-scale setting. In *CVPR*.

Shanthi, N.; and Duraiswamy, K. 2010. A novel SVM-based handwritten Tamil character recognition system. *Springer Pattern Analysis and Applications*, 13(2): 173–180.

Shen, H. H. 2005. An investigation of Chinese-character learning strategies among non-native speakers of Chinese. *Elsevier System*, 33(1): 49–68.

Shi, D.; Diao, X.; Shi, L.; Tang, H.; Chi, Y.; Li, C.; and Xu, H. 2022a. CharFormer: A Glyph Fusion based Attentive Framework for High-precision Character Image Denoising. In *Proceedings of the 30th ACM International Conference on Multimedia*.

Shi, D.; Diao, X.; Tang, H.; Li, X.; Xing, H.; and Xu, H. 2022b. RCRN: Real-world Character Image Restoration Network via Skeleton Extraction. In *Proceedings of the 30th ACM International Conference on Multimedia*.

Shi, D.; Wang, T.; Xing, H.; and Xu, H. 2020. A learning path recommendation model based on a multidimensional knowledge graph framework for e-learning. *Knowledge-Based Systems*, 195: 105618.

Simonyan, K.; and Zisserman, A. 2015. Very deep convolutional networks for large-scale image recognition. In *ICLR*. 
Su, Y.-M.; and Wang, J.-F. 2003. A novel stroke extraction method for Chinese characters using Gabor filters. *Elsevier PR*, 36(3): 635–647.

Sun, X.; Gu, J.; and Sun, H. 2021. Research progress of zero-shot learning. *Applied Intelligence*, 51(6): 3600–3614.

Wang, T.; Shi, D.; Wang, Z.; Xu, S.; and Xu, H. 2020. MRPR2Rec: Exploring multiple-step relation path semantics for knowledge graph-based recommendations. *IEEE Access*, 8: 134817–134825.

Wang, T.; Xie, Z.; Li, Z.; Jin, L.; and Chen, X. 2019a. Radical aggregation network for few-shot offline handwritten Chinese character recognition. *Elsevier PRL*, 125: 821–827.

Wang, W.; Zhang, J.; Du, J.; Wang, Z.-R.; and Zhu, Y. 2018. Denseran for offline handwritten Chinese character recognition. In *ICFHR*.

Wang, W.; Zheng, V. W.; Yu, H.; and Miao, C. 2019b. A survey of zero-shot learning: Settings, methods, and applications. *ACM TIST*, 10(2): 1–37.

Wang, X.; Ye, Y.; and Gupta, A. 2018. Zero-shot recognition via semantic embeddings and knowledge graphs. In *CVPR*.

Wu, Z. 2012. *Shang and Zhou Bronze Inscriptions and Image Integration*. Shanghai Classics Publishing House. ISBN 9787532564231.

Xie, G.-S.; Liu, L.; Jin, X.; Zhu, F.; Zhang, Z.; Qin, J.; Yao, Y.; and Shao, L. 2019. Attentive region embedding network for zero-shot learning. In *CVPR*.

Yang, M.; Guan, Y.; Liao, M.; He, X.; Bian, K.; Bai, S.; Yao, C.; and Bai, X. 2019. Symmetry-constrained rectification network for scene text recognition. In *Proceedings of the IEEE/CVF international conference on computer vision*, 9147–9156.

Yang, W.; Jin, L.; Tao, D.; Xie, Z.; and Feng, Z. 2016. DropSample: A new training method to enhance deep convolutional neural networks for large-scale unconstrained handwritten Chinese character recognition. *Pattern Recognition*, 58: 190–203.

Yang, X.; He, D.; Zhou, Z.; Kifer, D.; and Giles, C. L. 2017. Improving offline handwritten Chinese character recognition by iterative refinement. In *2017 14th IAPR International Conference on Document Analysis and Recognition (ICDAR)*, volume 1, 5–10. IEEE.

Yeung, P.-s.; Ho, C. S.-h.; Chan, D. W.-o.; and Chung, K. K.-h. 2016. Orthographic skills important to Chinese literacy development: The role of radical representation and orthographic memory of radicals. *Reading and Writing*, 29(9): 1935–1958.

Yin, F.; Wang, Q.-F.; Zhang, X.-Y.; and Liu, C.-L. 2013. ICDAR 2013 Chinese handwriting recognition competition. In *ICDAR*.

Yuan, A.; Bai, G.; Jiao, L.; and Liu, Y. 2012. Offline handwritten English character recognition based on convolutional neural network. In *DAS*.

Yuan, T.-L.; Zhu, Z.; Xu, K.; Li, C.-J.; Mu, T.-J.; and Hu, S.-M. 2019. A large chinese text dataset in the wild. *Springer JCST*, 34(3): 509–521.