Instance Segmentation for Chinese Character Stroke Extraction, Datasets and Benchmarks

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Abstract

Stroke is the basic element of Chinese character and stroke extraction has been an important and long-standing endeavor. Existing stroke extraction methods are often handcrafted and highly depend on domain expertise due to the limited training data. Moreover, there are no standardized benchmarks to provide a fair comparison between different stroke extraction methods, which, we believe, is a major impediment to the development of Chinese character stroke understanding and related tasks. In this work, we present the first public available Chinese Character Stroke Extraction (CCSE) benchmark, with two new large-scale datasets: Kaiti CCSE (CCSE-Kai) and Handwritten CCSE (CCSE-HW). With the large-scale datasets, we hope to leverage the representation power of deep models such as CNNs to solve the stroke extraction task, which, however, remains an open question. To this end, we turn the stroke extraction problem into a stroke instance segmentation problem. Using the proposed datasets to train a stroke instance segmentation model, we surpass previous methods by a large margin. Moreover, the models trained with the proposed datasets benefit the downstream font generation and handwritten aesthetic assessment tasks. We hope these benchmark results can facilitate further research. The source code and datasets are publicly available at: https://github.com/lizhaoliu-Lec/CCSE.

Introduction

Stroke is the basic element of Chinese character and stroke extraction has been an important and long-standing endeavor (Lee and Wu 1998). Given an image of a Chinese character, stroke extraction aims to decompose it into individual strokes (see Figure 1). It serves as a bedrock for many Chinese character-related applications such as handwritten synthesis (Liu and Lian 2021), font generation (Jiang et al. 2019; Zeng et al. 2021; Xie et al. 2021), character style transfer (Xu et al. 2007; Sun et al. 2015), etc. Recently, it has been shown that explicitly incorporating the stroke information boosts the performance of Chinese character-related tasks (Gao and Wu 2020; Huang et al. 2020; Zeng et al. 2021). Though various tasks that leverage the stroke inform-

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points, which inevitably contain fork points due to the complex character structure. Second, these methods are typically tailored to the regular and highly structural standard fonts and may not perform well on handwritten characters due to the large intra-class variance of strokes caused by different handwriting habits. Last, they aim to optimize the stroke extraction task only and may not produce transferable features to benefit downstream tasks.

Moreover, there are no standardized benchmarks to provide a fair comparison between different stroke extraction methods, which is of great importance to guide and facilitate further research. And the lack of publicly available datasets leads to inconsistent evaluation protocols. Specifically, (Cao and Tan 2000; Qiguang 2004; Xu et al. 2016) consider accuracy as the main evaluation metric for the stroke extraction task, which does not consider the spatial location of the extracted stroke, thereby, cannot comprehensively measure the performance of stroke extraction algorithm. (Chen et al. 2016, 2017) leverage Hamming distance and cut discrepancy to measure the consistency of stroke interiors and the similarity of stroke boundaries, respectively. They require the extracted strokes and the ground truth strokes to be strictly aligned by spatial location and categories, which is hard to evaluate the missed and false extraction. Thus, how to effectively evaluate the stroke extraction algorithm with reasonable protocol remains an unsolved question.

To facilitate stroke extraction research, we present a Chinese Character Stroke Extraction (CCSE) benchmark, with two new large-scale datasets and evaluation methods. As the foundation of the CCSE benchmark, the datasets have two requirements: i.e., character-level diversity and stroke-level diversity. Specifically, the datasets should cover as many Chinese characters to represent the structure between strokes, whose relationship can be very complex (see the left of Figure 2). Moreover, since humans with different writing habits will produce very different appearances even for the same stroke (see the right of Figure 2), the datasets should cover this kind of diversity for models to achieve effective extraction. To this end, we harvested a large set of Kai Ti (a kind of Chinese font) Chinese character images and handwritten Chinese character images to achieve character-level diversity and stroke-level diversity, respectively.

With the large-scale datasets, we hope to leverage the representation power of deep models such as CNNs to solve the stroke extraction task, which, however, remains an open question. To this end, we turn the stroke extraction problem into the stroke instance segmentation problem. This change of view not only allows us to take advantage of the state-of-the-art instance segmentation models but also the well-defined evaluation metrics (i.e., box AP and mask AP). We perform experiments with state-of-the-art instance segmentation models to produce benchmark results that facilitate further research. Compared to previous methods of stroke extraction, our approach does not require reference images and in-depth domain expertise. Moreover, the deep models trained on our dataset are able to produce transferable features that consistently benefit the downstream tasks.

We summarize our contributions as follows:

- We propose the first benchmark containing two high-quality large-scale datasets that satisfy the requirements of the character-level and stroke-level diversities for building promising stroke extraction models.
- We cast the stroke extraction problem into the stroke instance segmentation problem. In this way, we build deep stroke extraction models that scale to scenarios with highly-diverse characters and stroke variance while producing transferable features to benefit downstream tasks.
- By leveraging the state-of-the-art instance segmentation models and well-defined evaluation metrics, we build standardized benchmarks to facilitate further research.

Related Work

Stroke Extraction

Stroke extraction aims to extract strokes from handwritten image (Lee and Wu 1998), which is very difficult to solve due to the complex character structure (Cao and Tan 2000) and the large intra-class variances (Xu et al. 2016). Existing methods mainly follow stroke extraction from skeletonized character or from original character paradigms. For the first kind of approach, efforts have been put into exploring the relations between strokes by resolving the fork points issues (Fan and Wu 2000), applying affine transformation to strokes (Liu, Jia, and Tan 2006), detecting ambiguous zone (Su, Cao, and Wang 2009) and using additional reference image (Zeng et al. 2010). However, these approaches are limited by the thinning step that introduces stroke distortion and the loss of short strokes. Therefore, stroke extraction from the original image is proposed to conquer this limitation. These approaches focus on leveraging the rich information in characters such as stroke width and curvature by combining multiple contour information in strokes (Lee and Wu 1998), exploring pixel-stroke relationships (Cao and Tan 2000), detecting strokes in multiple directions (Su and Wang 2004) and using corner points (Yu, Wu, and Yuan 2012). The latest approach (Xu et al. 2016) considers the advantages from both worlds to further improve the performance. Nonetheless, these methods typically use handcrafted rules to improve the stroke extraction task only during algorithm design. Therefore, they inherently suffer from extracting strokes from complex characters and with highly irregular shape. Moreover, they can not be trivially employed for downstream tasks such as font generation, limiting their further application.

Instance Segmentation

The goal of instance segmentation is to segment every instance (countable objects) in an image by assigning it with pixel-wise class label. Existing approaches can be broadly divided into two categories: two-stage (He et al. 2017; Hsieh et al. 2021) and one-stage (Bolya et al. 2019). Two-stage methods consist of instance detection and segmentation steps. In Mask R-CNN (He et al. 2017), one of the most important milestones in computer vision, the segmentation head is applied to the detected instances from the Faster R-CNN (Ren et al. 2015) detector to acquire the instance-wise segmentation mask. Approaches based on Mask R-CNN typically demand dense prior proposals or anchors to
obtain decent results, leading to complicated label assignment and post-processing steps. To tackle this issue, one-stage methods such as YOLACT (Bolya et al. 2019) produce instance masks by linearly combining the prototypes with the mask coefficients and do not depend on pre-detection step. In this paper, we benefit from the rapid development of instance segmentation algorithms and focus on applying the instance segmentation models to tackle the stroke extraction task, thus we mainly consider the well-studied two-stage methods such as Mask R-CNN as our baselines.

User-friendly interfaces to access the Kai Ti image stroke-by-stroke. As shown in Figure 3, the results from cnchar have a clear stroke-wise mark with light brown denoting the spatial mask and category of the current stroke. Regarding the stroke category, the database of cnchar contains the most frequently used 25 categories (see Figure 1 (a) for details).

**Proposed Datasets**

**Image Collection and Annotation**

To achieve promising stroke extraction performance, we harvest a large number of samples that cover the complex structures of Chinese characters and different styles of stroke, which are character-level and stroke-level diversity, respectively. Since the frequently used Chinese characters are restricted to a small range, there may not have enough handwritten characters with complex stroke structures. Thus, we collect the frequently used standard font (e.g., Kai Ti) to meet the character-level diversity requirement. Then, to satisfy the stroke-level diversity, we gather handwritten Chinese character images from different writers. We detail the process of collection and annotation below.

**Kai Ti Image Collection and Annotation** Labeling every stroke in an image is time-consuming and labor-intensive. Since Kai Ti is a standard Chinese font commonly used in daily life, our first thought is to collect an annotation-free Kai Ti dataset by retrieving the spatial information from its font design database. However, the coordinates of each stroke are not preserved during the font design process. Thus, we browse the web resources extensively and discover an open source project Make Me A Hanzi¹, which has constructed a stroke database for Kai Ti. Then, this project is further evolved by cnchar², which provides more

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¹https://github.com/skishore/makemeahanzi
²https://github.com/theajack/cnchar

**Handwritten Image Collection and Annotation** Since CCSE-Kai only meets character-level diversity, we target at improving the stroke-level diversity of our dataset by leveraging the handwritten character with various styles. To this end, we further harvest handwritten Chinese characters and label them in a stroke instance manner. Specifically, we leverage the CASIA Offline Chinese Handwrit-
ing Databases\textsuperscript{4}, which has 7,185 kinds of Chinese characters written repeatedly by about 300 humans, resulting in nearly 3M handwritten Chinese images.

However, as shown in Figure 4, some human writers draw a character that is not stroke-separable, which cannot be trivially handled in stroke extraction task. To tackle this issue, we sub-sample the data that is stroke-separable from CASIA. Moreover, considering that human annotation is labor-intensive and time-consuming, we select 10 samples for the top 300 most frequently used Chinese characters and 8 samples for the next 700 Chinese characters, resulting in about 7,600 images in total. Then, we apply extensive human labor to carefully provide annotation for each stroke and finally create a Handwritten CCSE (CCSE-HW) dataset. Note that we adopt the stroke categories used in CCSE-Kai during the stroke annotation process. The visualization results of CCSE-HW are shown on the right of Figure 2, from which we can see that strokes of the same category appear very differently in terms of scale, coverage and curvature etc. So far, we overcome the shortcoming of CCSE-Kai by complementing the stroke-level diversity. With both CCSE-Kai and CCSE-HW, we provide datasets with rich character and stroke-level diversity to build our benchmarks effectively and reasonably.

**Dataset Statistics**

In this section, we analyze the properties of the proposed CCSE-Kai and CCSE-HW datasets. We first compare our datasets to existing datasets with respect to the amount and annotation type. Then, we analyze the proposed datasets and intrinsic difficulties that occurred in our datasets.

| Dataset          | Pub. Ava. | Annotation Type | #Images | #Strokes |
|------------------|-----------|-----------------|--------|---------|
| (Cao and Tan 2000) | ×         | category        | 111    | 849     |
| (Xun et al. 2015)  | ×         | category        | 518    | N/A     |
| (Xu et al. 2016)   | ×         | category        | 1,500  | N/A     |
| (Chen et al. 2016) | ×         | category        | 2,556  | N/A     |
| CCSE-Kai (Ours)    | √         | instance mask   | 9,523  | 112,024 |
| CCSE-HW (Ours)     | √         | instance mask   | 7,628  | 56,722  |
| CCSE-Kai&HW (Ours) | √         | instance mask   | 17,151 | 168,746 |

Table 1: Comparison between different Chinese character stroke datasets. We propose the largest publicly available Chinese stroke datasets with instance mask annotation to date. Pub. Ava. is short for Publicly Available.

**Comparison to Existing Datasets** We analyze the size of the proposed datasets in comparison to several commonly used datasets (Cao and Tan 2000; Xun et al. 2015; Xu et al. 2016; Chen et al. 2016) for Chinese stroke extraction. The summary is shown in Table 1. We have about 4× amount of images compared to the previous largest one (e.g., 9,523 vs. 2,556). Notably, different from existing datasets that only provide category level labels, we provide an instance level mask for each stroke, which contains detailed spatial as well as shape information. Most importantly, we are the first one to provide publicly available datasets for stroke extraction.

**Analysis on CCSE-Kai and CCSE-HW** We mainly perform quantitative analyses on our datasets in terms of instance level and category level. The results are shown in Figure 5. From Figure 5a and Figure 5b, we observe that CCSE-Kai provides more strokes in one image in averaged as we expected since complex stroke structures typically introduce more strokes and categories in one character. This shows that CCSE-Kai indeed improves the character-level diversity for our benchmark datasets. Moreover, as depicted in Figure 5c, we find that CCSE-HW covers a wider range in an image, which suggests that the handwritten character is able to improve the stroke-level diversity by including strokes with various scales. These results verify that our datasets fulfill the diversity requirements for achieving promising stroke extraction performance.

We then reveal the intrinsic difficulties of our datasets by analyzing the number of strokes per category and the scale statistics of our bounding box, where the results are shown in Figure 6 and Figure 7, respectively. From Figure 6, we observe that the stroke extraction task faces a severe class imbalance problem, which may result in impeded performance for classifying strokes with few data points. Moreover, we also find out from Figure 7 that: 1) strokes are often in a strip shape, which is a major difference from the common object detection. 2) the shape of stroke also occurs a class imbalance problem, making it difficult to locate the stroke with a very strip shape. Solving these difficulties is out of the scope of this paper and we leave them to our future works.

**Algorithmic Analysis**

**Baseline.** To build stroke detection baselines\textsuperscript{5}, we consider widely used detectors Faster R-CNN (Ren et al. 2015), Cascade R-CNN (Cai and Vasconcelos 2018) and FCOS (Tian et al. 2019). For constructing stroke instance segmentation benchmark results, we employ Mask R-CNN (He et al. 2017) and its cascade version (Cai and Vasconcelos 2018). The overview of stroke instance segmentation workflow is depicted in Figure 8. For simplicity, we use $K$ and $H$ to denote CCSE-Kai and CCSE-HW datasets, respectively.

**Implementation details.** Our implementation is based on detectron2 (Wu et al. 2019) framework. Since the training cost for our datasets is low due to low image resolution, we apply the 3× training schedule by default. All ex-

\textsuperscript{4}http://www.nlpr.ia.ac.cn/databases/handwriting/Home.html

\textsuperscript{5}Results are in the supplementary.
In this section, we present the results of stroke instance segmentation. The quantitative results are in Table 2. We also provide the qualitative results in Figure 9. As can be seen in Table 2, we achieve promising results for stroke instance segmentation for both CCSE-Kai and CCSE-HW. The AP\textsubscript{mask} is low for CCSE-Kai. We attribute it to the complex characters with many strokes that highly overlapped with each other in CCSE-Kai. It may be further improved by tailoring the model with complex character structure prior. Notably, as depicted in Figure 9, we are able to produce stroke instance segmentation results with a high confidence score, indicating the effectiveness of our datasets and applying instance segmentation for stroke extraction. Due to the space limit, we put the failure case analysis in the supplementary.

**Transferability Results on Standard Fonts** One may ask whether the proposed dataset can contain character images in more printing font styles that are also stroke-separable. Simply labeling more frequently used printing font styles will fulfill this goal but also be time-consuming and labor-intensive. Considering the highly similar structure and appearance of commonly used font styles (e.g., Kai Ti, Song Ti, Hei Ti), we thus leverage the model trained by our CCSE-Kai dataset to automatically label character images of other font styles. As shown in Figure 10\textsuperscript{6}, minor effort is required to adjust the bounding box and mask to use the labels derived by the model trained by our CCSE-Kai.

**Effect of the Background** Since the proposed datasets have no background, training a model under this setting may not be suitable for real-life applications with noisy backgrounds. Thus, we conduct experiments to verify and remedy this issue. As shown in Figure 11, we add complex backgrounds to character images\textsuperscript{7} and use them to test the model trained with our original datasets. As shown in Table 3, the performance drops considerably. To compensate for this, we propose to train the model with complex background augmented images, which boosts the performance substantially.

| Train set | Test set | AP\textsubscript{box} | AP\textsubscript{mask} | Test set | Train set | AP\textsubscript{box} | AP\textsubscript{mask} |
|-----------|---------|----------------------|----------------------|---------|---------|----------------------|----------------------|
| K         | K       | 78.73                | 44.89                | H       | H       | 72.09                | 68.27                |
| K + BG    | K + BG  | 76.66                | 39.83                | H + BG  | H + BG  | 24.40                | 14.91                |
|           |         | 61.20                | 57.06                |         |         |                      |                      |

Table 3: Experiment results of Mask R-CNN on images with a complex background. BG denotes adding a complex background to the images in the dataset.

**Cross-domain Evaluation** To evaluate the robustness of a trained stroke extraction model, we perform experiments

\textsuperscript{6} More results are put in the supplementary.

\textsuperscript{7} More results are shown in the supplementary.
under the cross-domain settings. To be specific, we train the model on the source ($S$) training set and evaluate it on the target ($T$) test set. Thus, as shown in Table 4, we perform experiments with $(S, T) \in \{(H, K), (K, H)\}$. The cross-domain evaluation results show that the model is unable to deliver satisfactory performance due to the domain discrepancy caused by unmatched character-level and stroke-level diversities. Thus, we propose a simple remedy by combing source and target datasets to train the model. In this way, the overall performance is improved compared to using only one dataset. We think there is a more data-efficient way to tackle the domain discrepancy issue such as unsupervised domain adaptation (Ganin and Lempitsky 2015).

### Comparison to Previous Approach

**Experiment Protocols.** Most of the previous approaches (Sun, Qian, and Xu 2014; Xu et al. 2016) can only deliver results on extracted stroke locations without corresponding categories. In this way, with no access to external databases, they can only benchmark their results on 100 images with human evaluation (Sun, Qian, and Xu 2014). Specifically, given the extracted stroke images, a human is required to evaluate whether the extracted results contain the desired strokes. Then, accuracy is used as the evaluation metric\(^8\). We follow these protocols for fair

| Method          | $D$  | Acc. | Prec. | Rec. | F1  |
|-----------------|------|------|-------|------|-----|
| Traditional     | $K_s$ | 35.53 | 65.22 | 25.94 | 34.18 |
| Mask R-CNN $k_{s0} \geq 0.9$ | $K_s$ | 49.52 | 90.68 | 66.76 | 74.78 |
| Traditional     | $K_s$ | 41.98 | 86.36 | 42.17 | 53.99 |
| Mask R-CNN $k_{s0} \geq 0.9$ | $K_s$ | 68.08 | 90.21 | 72.55 | 79.34 |
| Mask R-CNN $k_{s0} \geq 0.8$ | $K_s$ | 90.57 | 90.15 | 80.39 | 84.42 |
| Mask R-CNN $k_{s0} \geq 0.7$ | $K_s$ | 94.97 | 90.17 | 81.89 | 85.27 |
| Traditional     | $H_s$ | 36.75 | 72.00 | 35.60 | 45.52 |
| Mask R-CNN $k_{s0} \geq 0.9$ | $H_s$ | 59.54 | 78.25 | 56.71 | 64.78 |
| Mask R-CNN $k_{s0} \geq 0.8$ | $H_s$ | 82.07 | 80.35 | 73.94 | 79.00 |
| Mask R-CNN $k_{s0} \geq 0.7$ | $H_s$ | 90.52 | 90.36 | 83.78 | 86.51 |

\(\text{Table 5: Comparison between the traditional stroke extraction method in (Xu et al. 2016) and our stroke instance segmentation approach via accuracy, precision, recall and F1.} \)

\(\text{$K_s$ and $H_s$ are the subsets with 100 randomly sampled datapoints from $K$ and $H$, respectively.} \)

\(\text{$K_s$ denotes the 100 datapoints with the most strokes in $K$.} \)

\(^8\text{More details are put in the supplementary.}\)
### Transferring Features to Downstream Tasks

**Font Generation** We investigate whether our trained features can be transferred to the font generation task (Jiang et al. 2019; Liu and Lian 2021). We conduct experiments using FontRL (Liu and Lian 2021), which uses a stroke Boundary Box Network (BBoxNet) to put each stroke of a character in the desired position before character rendering. Hence, we use different pretrained models to initialize the BBoxNet and the results are shown in Table 6. IoU and MAE are used to evaluate the structural alignment and the appearance difference between the generated font and the GT font respectively. Using the model pretrained on our datasets, we achieve better performance than other pretrained models, especially on IoU, showing that our pretrained model better understands the character structure to facilitate this task.

**Handwritten Aesthetic Assessment** We study this task (Sun et al. 2015) with different pretrained models. Given a handwritten character image, this task requires the model to output a classification result (from good, medium and bad) and a regression result (range from 0 to 150) to indicate the aesthetic level of the handwritten. We initialize the ResNet-50 with different pretrained models. Moreover, we also employ the linear probing protocol that freezes the pretrained models and trains the classification and regression layer only to further inspect the features’ effectiveness. In Table 7, the model pretrained with our CCSE-HW dataset performs much better than the model pretrained with ImageNet that has more than 1M images, showing that a compact dataset with domain-specific character structure knowledge is more suitable than a large-scale general vision dataset for the handwritten aesthetic assessment task.

### Conclusion

In this work, we propose the first large-scale Chinese Character Stroke Extraction (CCSE) benchmark to improve stroke extraction task and facilitate further research. To this end, we effortlessly harvest a large number of Chinese character images and provide stroke-level annotation for them to create CCSE-Kai and CCSE-HW datasets. The proposed datasets satisfy both character-level and stroke-level diversities for achieving promising stroke extraction. We carry out a series of analyses on the properties of the proposed datasets and point out their intrinsic difficulties. Last, we conduct extensive experiments with stroke instance segmentation models to analyze the influential factors in delivering...
promising results and show that pretraining the model with the proposed datasets benefits the downstream tasks. Our future works will focus on improving the stroke segmentation performance under strict IoU condition.

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Instance Segmentation for Chinese Character Stroke Extraction, Datasets and Benchmarks (Supplementary Materials)

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We organize our supplementary materials as follows.

- In Section “More Analysis on Stroke Detection”, we provide a detailed analysis of the stroke detection process.
- In Section “More Transferability Results on Standard Fonts”, we provide more qualitative results on other standard fonts.
- In Section “More Failure Cases”, we provide more failure cases on the stroke instance segmentation.
- In Section “More Details on the Previous Methods”, we provide more details on previous stroke extraction approach (Xu et al. 2016).
- In Section “More Details on the Downstream Tasks”, we provide more experimental details on the downstream tasks, i.e., experimental settings, evaluation metrics and more results.
- In Section “More Results on the Background Effect”, we provide more qualitative results on the effect of the background.

More Analysis on Stroke Detection

Since we adopt the Mask R-CNN (He et al. 2017) model for stroke instance segmentation, which first performs stroke detection and then segmentation, we analyze the stroke detection process of Faster R-CNN (Ren et al. 2015) (the detection part of Mask R-CNN) process by tuning important hyper-parameters: the number of stages, anchor box, backbone, and image resolution.

Effect of the Number of Stages  In this section, we provide experiments on widely used one-stage, two-stage as well as multiple-stage detectors to see how they perform on our proposed datasets. The results are in Table 1. Note that we set the number of stages of Cascade R-CNN to 3, resulting in a 4-stage model (RPN contributes 1 stage). The results conclude that as the number of stages increases, we obtain better stroke detection results.

| Detector       | #Stage | APbbox | APbox50 | APbox75 | APbox100 |
|----------------|--------|--------|---------|---------|----------|
| Faster R-CNN   | Two    | 90.83  | 82.48   | 71.07   |          |
| Cascade R-CNN  | Multiple | 88.39  | 83.58   | 74.15   |          |

Table 1: Stroke detection results of one-stage, two-stage, and multiple-stage detectors.

Effect of the Anchor Box  As shown by previous researches (Ren et al. 2015), the ratios of the anchor box have a great effect on the final results. Due to the strip shape property of the stroke, we analyze how the choices of anchor box affect the stroke detection performance. Specifically, we gradually add anchor boxes with higher ratios into Faster R-CNN. The results are in Table 2, which conveys that incorporating anchor boxes with higher ratio indeed improve the stroke detection performance.

| Anchor Ratios | APbbox | APbox50 | APbox75 | APbox100 |
|---------------|--------|---------|---------|----------|
| S1 = {1:1}    | 89.91  | 81.37   | 69.12   |          |
| S2 = S1 ∪ {1:2:2:1} | 90.19  | 80.87   | 69.60   |          |
| S3 = S2 ∪ {1:4:4:1} | 88.24  | 79.18   | 69.52   |          |
| S4 = S3 ∪ {1:8:8:1} | 90.75  | 80.33   | 71.03   |          |

Table 2: Stroke detection results in different anchor ratios.

Effect of the Image Resolution  Currently, most of the detectors are evaluated on COCO (Lin et al. 2014) benchmark that has a relatively large image resolution i.e., (800~1000). However, the resolution of Chinese character images is typically small i.e., (80~120). It is not clear whether the detectors are biased by the image resolution. Thus, we provide experiments on different resolutions to see their effect. Specifically, we apply the equal scaling strategy while resizing the short size into one of {112, 120}, {224, 240} and {448, 480} to see the performance of the Faster R-CNN detector. Note that we also accordingly scale the anchor boxes. In Table 3, we achieve the best APbbox at resolution {448, 480} but also bring higher computation cost.

Effect of the Backbone  We provide experiments on different backbone settings for Faster R-CNN to show how they affect the final performance. Specifically, we consider two settings e.g., different backbone architectures and pretrained
or not on ImageNet (Deng et al. 2009). For backbone architecture, we use ResNet-{50,101} (He et al. 2016) and FPN-
{50,101} (Lin et al. 2017). Table 4 shows the experiment results, which show that pretrained and deeper models boost
the performance.

More Transferability Results on Standard Fonts
In Figure 1, we show more transferability results on the other standard font styles. Specifically, we leverage the model
trained by our CCSE-Kai dataset to automatically label character images of other font styles. Most of the results share
the competitive performance as the result of the source font style (i.e., Kai Ti). We attribute this strong performance to
the highly similar stroke styles shared by these font styles. We notice that in some cases the stroke extraction other
than Kai Ti are inaccurate. We believe this could be addressed by weakly supervised instance segmentation ap-
proach (Zhou et al. 2018) since the stroke categories and the stroke composition of each character are identical across
different font styles. We leave it to future work.

More Failure Cases
We analyze more failure cases in our stroke instance seg-
mentation model. In Figure 2, we observe that the follow-
ing situations may lead to the failure of stroke extraction:
(1) Two separate strokes are connected and thus similar to
another stroke. As shown in Figure 2a, the connection be-
tween shu and heng happens to be similar to heng zhe; (2)
Missed detection caused by the bad hyper-parameter
choices such as high confidence score (Figure 2b); (3) Some
strokes are so similar that they are sometimes indistinguish-
able, such as shu wan and shu ti in Figure 2c; (4) One
stroke is detected as multiple strokes, as shown in Figure 2d;
(5) The stroke has a thin and long shape, as shown in Fig-
ure 2e; (6) A small fraction of one stroke is falsely detected
due to the occlusion by another stroke, as seen in Figure 2f.
We believe these issues can be resolved by incorporating
the stroke instance segmentation model with more charac-
ter structure information and the occurrence relationship
between strokes.

More Details on the Previous Methods
We provide the workflow of the latest traditional stroke ex-
traction method ACSE (Xu et al. 2016) in Figure 3, which
consists of three steps: character decomposition, cross area
extraction and slope-based stroke combination. In ACSE,
the character is first decomposed into several independent
components according to the connectivity. Then, the skele-
tons and contours are extracted to compute the cross point
sets and end point sets. If a skeleton’s cross point set is
empty, the corresponding stroke will be directly output as
a simple stroke. According to the cross point set and end
point set, each component is departed into several stroke
segments. Last, several stroke segments are combined into
one stroke if they share a similar slope.

Font Generation
Dataset. Following the previous approach (Liu and Lian
2021), we conduct the font generation task on the digital
handwritten font FZHSXJW. The training set includes 775
Chinese characters with 7,004 strokes. The test set is consist

| Resolutions | A_P^box_{50} | A_P^box_{75} | A_P^box_{box} |
|-------------|--------------|--------------|---------------|
| 112, 120    | 90.83        | 82.48        | 71.07         |
| 224, 240    | 90.20        | 80.72        | 72.14         |
| 448, 480    | 90.68        | 81.36        | 72.74         |

Table 3: Experiments on different image resolutions.

| Backbone   | Depth | Pretrained | A_P^box_{50} | A_P^box_{75} | A_P^box_{box} |
|------------|-------|------------|--------------|--------------|---------------|
| ResNet     | 50    | ✓          | 86.10        | 67.93        | 58.03         |
| ResNet     | 50    | ×          | 90.63        | 81.30        | 71.15         |
| FPN        | 50    | ×          | 84.59        | 63.72        | 55.14         |
| FPN        | 50    | ✓          | 90.83        | 82.48        | 71.07         |
| ResNet     | 101   | ✓          | 88.70        | 81.86        | 71.05         |
| FPN        | 101   | ✓          | 90.00        | 81.04        | 70.90         |

Table 4: Stroke detection results with different backbones and whether pretrained.
Figure 3: The overall workflow of the previous method (Xu et al. 2016). Using only the decomposed component 1 for simplicity.

of 6,763 Chinese characters with annotated stroke skeletons and the corresponding mean font styles. For evaluation, both the generated font and GT font are first converted into a binary mask with 1 denoting the pixel with stroke and 0 denoting the background. Then the Intersection over Union (IoU) and Mean Absolute Error (MAE) between the generated and GT fonts are used as the metrics

Implementation details. We leverage the fontRL in (Liu and Lian 2021) as our baseline method to test font generation performance with different pretrained datasets. The font generation process is as follows: given a stroke trajectory in a mean font style, 1) a Modification Parameter Network (MPNet) is applied to bend it into the stroke trajectory in a target font style; 2) a Bounding Box predicting Network (BBBoxNet) is used to predict the location of the bent stroke in a canvas; 3) the above process is repeated for all strokes to form the complete skeleton of the target font; 4) an Image Rendering Module (IRM) is final employed to convert the complete skeleton into a glyph font image in an image-to-image translation manner. The MPNet, BBBoxNet and IRM are trained sequentially. We conduct experiments by initializing the BBBoxNet with parameters pretrained from different datasets: None, ImageNet (Deng et al. 2009), our CCSE-Kai and CCSE-HW while keeping other modules identical. The L1 loss is used as loss function to train BBBoxNet. For optimization, we use Adam optimizer with (lr, weight decay, momentum) = (5e−3, 1e−2, 9e−1). We train all models for 120 epochs and the learning rate is decay by 0.1 every 40 epochs. We use batch size = 64. For image augmentation, random five crops and centre crop to size 224×224 are applied during training and testing, respectively.

Results. We provide the evolution of end-to-end training process w.r.t. classification training loss, regression training loss, test accuracy and test mean absolute error (MAE) in Figure 5. Compared to models pretrained on None and ImageNet (Deng et al. 2009), the model pretrained on our CCSE-HW converges more stable and much faster, achieving strong results over them in test accuracy and MAE. These results verify that pretraining the model using our dataset is able to benefit the downstream handwritten aesthetic assessment task, demonstrating the effectiveness of our datasets and the proposed stroke instance segmentation model. We believe there is a more effective way to improve the downstream tasks and we leave it to future works.

More Results on the Background Effect

In order to evaluate the effect of the background added to CCSE-Kai and CCSE-HW, we conduct more experiments. We leverage the models trained with the pure datasets and the complex background augmented datasets to evaluate their performance on the noisy images. In Figure 6, when using the models trained on the pure CCSE-Kai and CCSE-HW, we unsurprisingly observe that there are a lot of false detections on the complex background. We speculate this is because the complex background contains stroke-like structures and some color interference, which was not taken into account during the training stage. To compensate for this, we propose to train the model with complex background aug-
Figure 4: Results on font generation task using different pretrained models. From left to right: (a) training loss, (b) test intersection over union and (c) test mean absolute error.

Figure 5: Results on handwritten aesthetic assessment task using different pretrained models. From left to right: (a) training loss on aesthetic classification task, (b) test accuracy on aesthetic classification task, (c) training loss on aesthetic regression task and (d) test mean absolute error on aesthetic regression task.

...image added. *+BG*: add complex background. “Trained-Pure”: the model used for inference is trained with the complex background augmented datasets. Best view with zoom-in.

Figure 6: From left to right, “Pure”: no complex background added, “+BG”: add complex background. “Trained-Pure”: the model used for inference is trained with pure datasets. “Trained +BG”: the model used for inference is trained with the complex background augmented datasets. Best view with zoom-in.

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