

OBC306: A Large-Scale Oracle Bone Character Recognition Dataset

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Abstract—The oracle bone script from ancient China is among the worlds most famous ancient writing systems. Identifying and deciphering oracle bone scripts is one of the most important topics in oracle bone study and requires a deep familiarity with the culture of ancient China. This task remains very challenging for two reasons. The first is that it is executed mainly by humans and requires a high level of experience, aptitude, and commitment. The second is due to the scarcity of domain-specific data, which hinders the advancement of automatic recognition research. A collection of well-labeled oracle-bone data is necessary to bridge the oracle bone and information processing fields; however, such a dataset has not yet been presented. Hence, in this paper, we construct a new large-scale dataset of oracle bone characters called OBC306. We also present the standard deep convolutional neural network-based evaluation for this dataset to serve as a benchmark. Through statistical and visual analyses, we describe the inherent difficulties of oracle bone recognition and propose future challenges for and extensions of oracle bone study using information processing. This dataset contains more than 300,000 character-level samples cropped from oracle-bone rubbings or images. It covers 306 glyph classes and is the largest existing raw oracle-bone character set, to the best of our knowledge. It is anticipated the publication of this dataset will facilitate the development of oracle bone research and lead to optimal algorithmic solutions.

Keywords—oracle bone script; dataset; character-level

I. INTRODUCTION

The earliest known form of Chinese writing, oracle-bone script, is found on animal bones or turtle shells and is one of the most famous writing systems in the world [1]. These bones and shells were once used for divination in the Shang dynasty of ancient China, and thus contain rich information about peoples lives during this dynasty and record the development of civilization during that period. The study of oracle-bone inscriptions is of great importance not only for Chinese etymologies but also for learning about the culture and history of the Shang dynasty, ancient China, and even the world.

In the late 1890s, shortly after the first unearthing of the oracle bones, research on oracle bones began. After the raw oracle-bone materials were digitalized [2], recognition and deciphering has gradually progressed [3], [4]. These studies have led to many results and achievements, such as printed oracle rubbings as well as databases of simulated and translated oracle-bone text. In these results, the raw oracle bone materials have been organized and the connotations

of some oracle bone characters have been interpreted to some degree. Nevertheless, these results were completed by experts manually. This manual approach requires a high level of expertise, making such studies very expensive, and furthermore hinders the progress of oracle-bone identification and decipherment.

Thus far, more than 150,000 pieces of bone and turtle fragments have been excavated throughout China, and nearly 4,500 different oracle characters have been discovered on them [5]. Most characters have been recorded [6]–[10]; however, only about 2,200 characters have been successfully deciphered [1]. Hence, there is still a long way to go before this writing system and its relationship to the culture of ancient times can be fully understood. In addition, the set of the oracle bone materials is not stable because new oracle bones may still be excavated and unseen characters could still be discovered. Therefore, an efficient and effective oracle-bone research technique is urgently required for existing and future oracle-bone study.

Recently, the field of computer vision has significantly advanced thanks to deep convolutional neural network (DCNN) methods. Moreover, many oracle-bone characters can be considered as sketches of ancestors of objects in the real world, and raw oracle-bone materials can be presented using images. Therefore, it is reasonable to study oracle bone inscription identification from the perspective of computer vision. The great achievements of DCNNs in the computer-vision community inspired us to adopt them for the identification of oracle-bone characters. However, these DCNN-based methods rely on a large number of labeled training data, which are often unavailable, especially in this specific field. Hence, in this paper, we collected a large dataset called OBC306, containing 309,551 character-level samples that are grouped into 306-character categories.

Using a specific working process, all the character instances are extracted from oracle bone rubbing images and labeled with the character class. Through statistical and visual analyses, we reveal several difficulties of identifying oracle bone scripts and analyze potential future extensions or challenges. We also present the performance of several baseline DCNN-based methods, demonstrating promising results, although many problems remain. We hope that this work is a step toward overcoming the scarcity of well-labeled oracle bone characters. It also bridges the gap between

Table I
THE SOURCE LITERATURES AND THEIR ABBREVIATIONS

| Literature | Abbr. |
|--------------------------------------------------------------------------------------------------------------------------------------------------------|-------|
| Jiaguwen heji (The Comprehensive Dictionary of Oracle Characters) [6] | h |
| Xiaotun Nandi Jiagu(Oracle Bones from Nandi, Xiaotun) [12] | t |
| Yingguo suocang jiagu ji(Oracle Bone Collection in Great Britain) [20] | y |
| Su-De-Mei-Ri suojian jiagu ji(Oracle-bone Inscriptions Stored in Soviet Union, German, America and Japan) [8] | s |
| Jiaguwen heji bubian (A Supplement to the Comprehensive Dictionary of Oracle Characters) [7] | b |
| Oracle Bones from the White and Other Collections [10] | w |
| Tôkyô daigaku Tôyô bunka kenkyûjo shozô kôkotsu monji(Oracle-bone Script in the Institute of Oriental Studies, Tokyo University) [9] | d |
| Tenri daigaku fuzoku Tenri sankôkan zô kokotsu monji(Oracle-bone Inscriptions Stored in the Tenri Reference library Attached to Tenri University) [11] | l |

information experts and archaeologists or paleographers, further stimulating future work in the study of oracle bones.

II. RELATED WORK

A. Materials of Oracle Bones

Oracle bones have been investigated since the last century and many related studies have been published, including collections of rubbings [6], [7], [9], [11], [12], dictionaries [13], and general explanations of oracle bones [14]. In addition to physical books, many images of oracle bones have been digitized [2], and many oracle-bone characters have been manually depicted and encoded [15], [16]. Despite these projects, there exists no annotated dataset containing raw images at character level for computer-based analysis. This hinders the progress toward automatically identifying and deciphering oracle-bone characters. Hence, we present a large oracle-bone character dataset to address this issue.

B. Oracle-Bone Script Recognition

Several methods for the recognition of oracle bone scripts have been proposed. These methods are mainly based on graph theory and topology. For instance, [17] used graph isomorphism, whereas [18] adopted topological features to recognize scripts. [19] proposed a Fourier descriptor based on curvature histograms to recognize oracle-bone inscriptions. In addition, [3] regarded the question as a sketch recognition task and constructed a hierarchical representation. In addition, [4] adopted support vector machines and block histogram-based features to recognize oracle-bone inscription images. However, most of these methods are complex ensemble systems constructed of features at multiple levels, and they rely heavily on manual feature design. Furthermore, they were designed for and evaluated on small-scale datasets; thus, they are not suitable for large-scale datasets.

C. Deep Learning Methods

Recently, deep neural networks have obtained great success in computer vision tasks such as large-scale image classification. [21] won the ImageNet 2012 competition, leading the adoption of CNNs in computer vision. Moreover, several methods subsequently achieved state-of-the-art performance on ImageNet with improved model architectures, including GoogLeNet [22], VGG [23], and ResNet [24].

Handwritten character recognition has become an active research topic in recent years. Because handwritten characters can be seen as visual objects with specific properties, DCNN methods are increasingly adopted for this task. For instance, [25] extended dropout to the whole DCNN to improve handwritten digit recognition. [26] extracted high-level features with a DCNN to recognize handwritten characters in six languages. [27] designed a streamlined version of GoogLeNet and achieved high accuracy on handwritten Chinese character recognition. Because oracle bone script and modern handwritten fonts have several similar properties (e.g., strokes), using DCNN methods to identify oracle bone script is a feasible approach. We hence evaluate several DCNN methods to provide a baseline for the constructed dataset.

III. CONSTRUCTION OF THE DATASET

To construct the OBC306, published printed matter on oracle bones, which serves as the raw materials for the dataset as well as the source of oracle-bone domain expertise, was first collected. All the pages in the printed publications were scanned for accommodation in an image-based database and encoded using a six character/number code. Further, using an oracle-bone dictionary tool, each character in A List of Oracle Characters [28] was compared with the text in the scanned images and matching character samples were added to the dataset. Further details are given below.

A. Source of Raw Images

An oracle-bone repository of full images was first constructed. To this end, we selected eight authoritative oracle-bone publications as the source of raw images (Table I). These selected publications cover nearly all the oracle bones discovered globally and are well known. [6] contains 41,956 pieces of oracle bones and is the largest collection of oracle bones. It was published during the years 1978-1983 and covers nearly all the oracle bones known at that time. An exception is the oracle bones excavated in 1973 from the village of Xiaotun (located in the city of Anyang, Henan Province, China). These oracle bones are included in [12] as a total of 4,589 rubbing images. This set of oracle bones was discovered in one place and contains many new contents that do not appear elsewhere, thus increasing their academic value. In addition, [7] collected 13,450 fragments of oracle bones, which serve as an important supplement to the study of [6]. [7] additionally included some oracle bone materials,

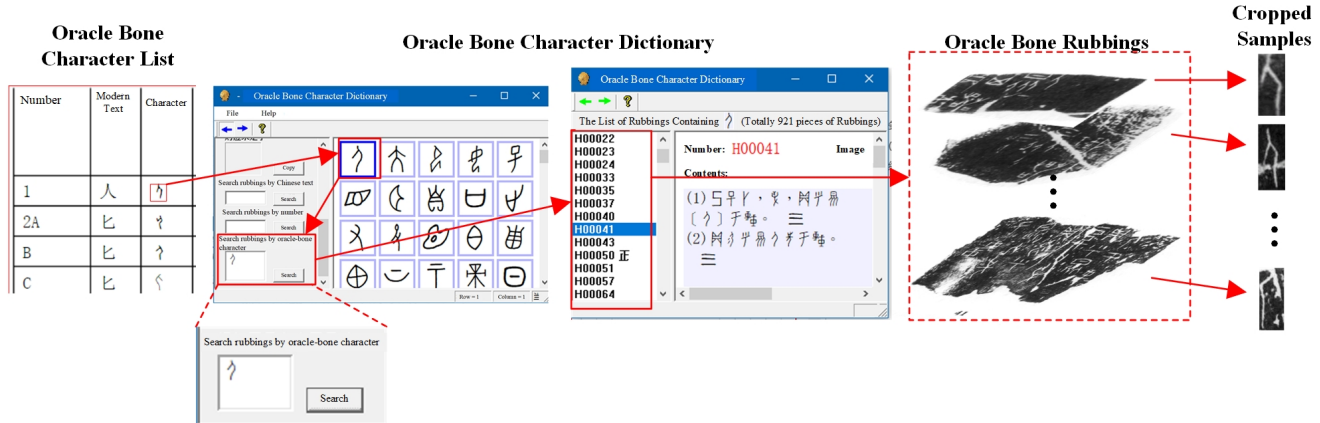


Figure 1. Overview of processing procedure of OBC306 construction. For each character in the Oracle-Bone Character List, all the occurrences can be found by means of Oracle-Bone Dictionary and cropped out to be instances.

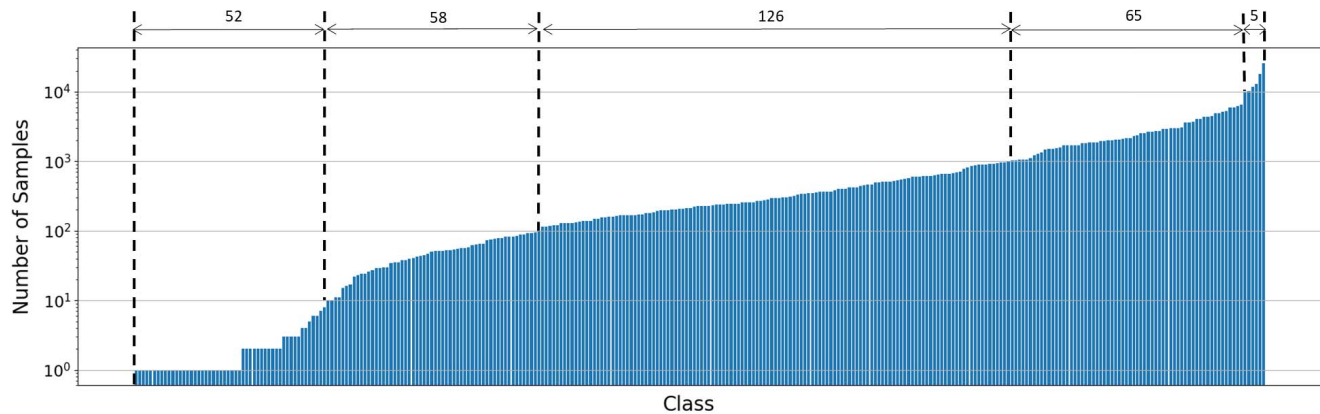


Figure 2. The number of samples in each class sorted in an ascending order.

rubbings, and photos that were not included by [6] partly because of their seriously degraded quality. All materials were edited using the same process used by [6].

Apart from the collections in China, nearly 26,700 pieces of oracle bones are stored in other countries [29]. Five publications [8]–[11], [20] cover nearly all the overseas collections of oracle bones. [20] covers the oracle bones residing in Britain. Although it records only 2,735 fragments of oracle bones, it contains a variety of character instances and is rich in content. [8] recorded 692 fragments of oracle bones kept in the Soviet Union, Germany, the USA, and Japan, and all of the images are hard copies of the original oracle bones taken by experts. [9] describes 1,315 rubbings of oracle bones stored at Tokyo University, Japan. Many oracle bones in this paper are fragments or contain unclear script, thus increasing the difficulty of deciphering them. Another Japanese study [11] records the oracle bones housed in the Tenri Reference Library of Tenri University, Japan, and it contains 747 pieces of rubbings. [10] recorded 1,915 fragments of oracle bones collected by several Canadian

scholars, some of which provide information about ancient military establishments, making them academically valuable.

Several of these publications contain duplicate images, e.g., [7] includes the contents published in [12] and [20]. Therefore, we minimize the chance of near-duplicate images existing across multiple sources by explicitly removing them. Because the oracle bones were buried for a long time before discovery and many were damaged during excavation, their records are of low quality. Moreover, oracle bone data were collected as rubbings, photographs, or hand copies, yielding highly different images in the literature. These factors increase the diversity of the samples, making the identification of oracle-bone script a challenging task.

All the pages in the included publications were scanned, arranged, and indexed according to the source material. Thanks to the adequacy of the oracle bone publications produced from several long-term oracle-bone digitization projects [15], [30], we inherited a rich prior knowledge about oracle-bone scripts and thus were able to investigate the oracle bone identification and deciphering using this volume

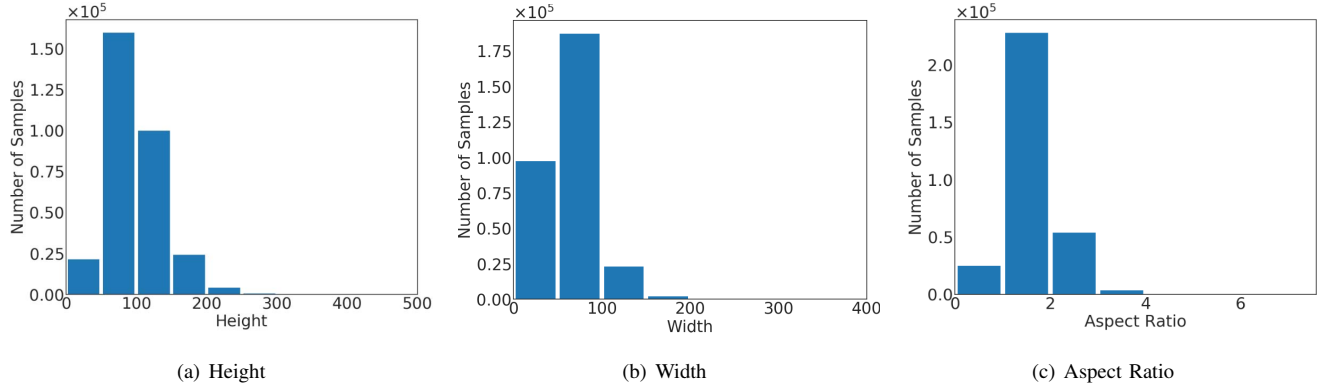


Figure 3. Distribution of image sizes including height, width and aspect ratio

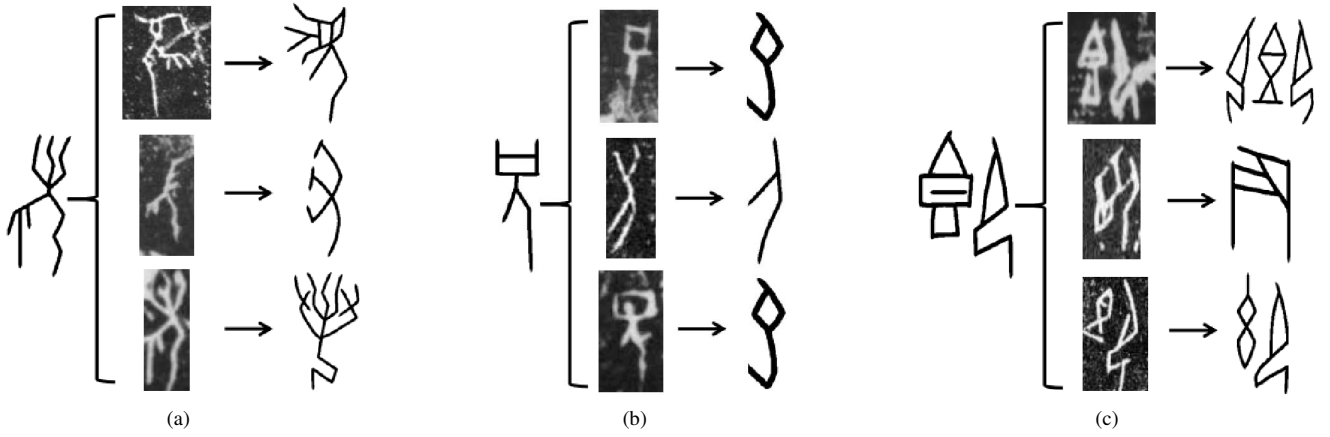


Figure 4. Examples of Oracle Bone characters with several variants. The samples in each brace belong to the glyph class on the left, but they are recognized to the ones pointed by arrows by mistakes during the evaluations of the baseline methods in Section V.

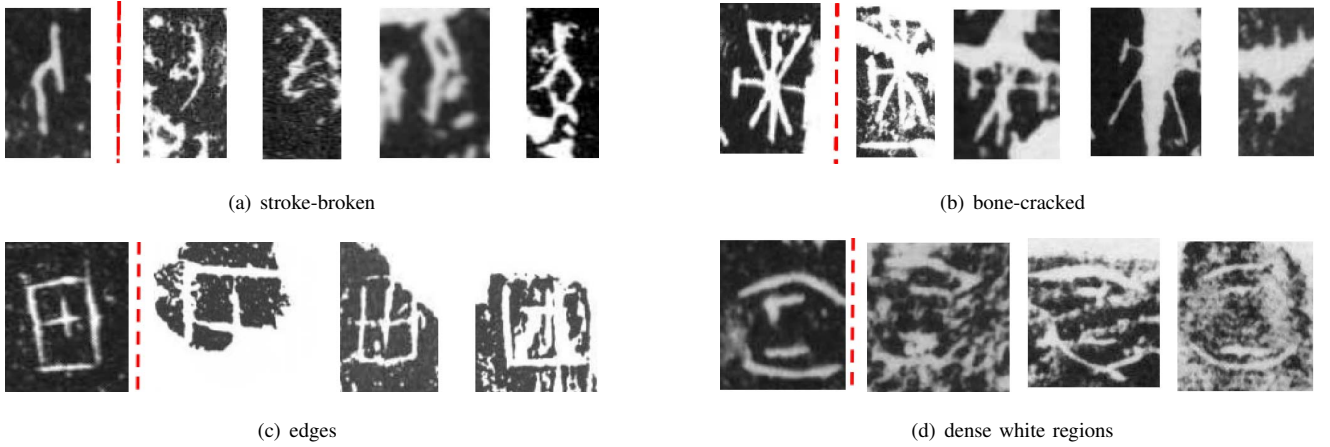


Figure 5. Examples of samples with several types of noises, and all these samples polluted by noises are failed to recognize during the evaluations of the baseline methods in Section V. **Left**: the normal samples in the dataset. **Right**: the samples with specific type of noises.

of oracle-bone data.

B. Main Data Processing

We now describe how the per-character images were obtained from the scanned full-image repository and annotated.

Because we employ two important tools in the procedure, i.e., the list of oracle-bone characters [28] and a digital dictionary tool, we describe them first.

1) *Oracle-Bone Character List*: A List of Oracle-Bone Character [28] was compiled in 2008 and collects a total of 4,024 distinct oracle characters along with their variants and has been widely used for retrieval in this field. This list relies on the bilingual Computerized Database of Oracular Inscriptions on Tortoise Shells and Bones, which was established by the Chinese University of Hong Kong and is a relatively universally accepted list of oracle bone characters [16].

2) *Oracle-Bone Character Dictionary*: This dictionary is a digital dictionary tool published by the research group at Anyang Normal University to facilitate the retrieval of oracle-bone materials for scholars, and was constructed using historical sources alone [16]. This dictionary integrates the simulated oracle-bone characters and their translated modern Chinese text (if it exists), as well as full-image retrieval information that indicates in which oracle bone piece each oracle-bone glyph can be found. All the contents of the dictionary coincide with those in [16]. It is an easy program to use and enables us to avoid working with the hardcopies of oracle bone materials, making dataset construction easier. Thanks to this tool, we constructed the dataset within a reasonable budget and obtained a cost-efficient yet high-quality annotation.

With the help of the above two tools, we found all occurrences of glyphs in the full oracle-bone images and extracted them. All the occurrences of each character are assigned to the corresponding glyph category and each class is given a 6-digit code or class name. Figure 1 presents an overview of the procedure. In the annotation procedure, the character class is first determined, and then all occurrences are searched for to generate class samples. This procedure ensures high annotation quality because we employ information taken from oracle-bone experts. Over a period of several years, we built the large character-level oracle-bone database called OBC306, and Figure 6 presents several samples of this dataset. Although it is incomplete because it does not yet include all the discriminative oracle-bone character classes included in [28], it now includes several hundred thousand images and is the largest set in existence, to the best of our knowledge. We also expect to expand the dataset using algorithmic solutions in future.

IV. PROPERTIES

A. Dataset Statistics

The OBC306 dataset contains 309,551 samples classified into a total of 306 classes, where each class represents a unique oracle bone glyph character. The number of instances per category is shown in Figure 2. Overall, the average number of samples in each character class is slightly over 1,000; however, the number of samples in each class varies

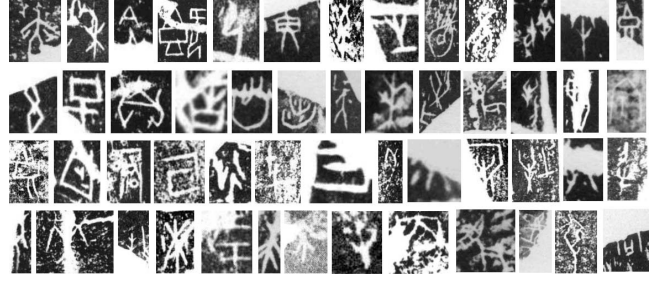


Figure 6. Examples of samples in the dataset OBC306.

substantially. In detail, the most frequent characters (those that appear at least 1,000 times) encompass 70 classes and cover 83.82% of the 309,551 oracle-bone character-level images. Of these 70 characters, exactly five characters have more than 10,000 samples, and comprise 78,963 samples in total. The largest number of samples in a class is 25,898. Hence, only a small number of high-frequency characters account for a large proportion of the oracle bone inscriptions excavated so far. Moreover, exactly 126 characters were found between 100 to 999 times, comprising 15.21% of the corpus, and 58 characters were found between 10 to 99 times, comprising 0.94% of the corpus. The remaining 52 characters were found 1 to 9 times, comprising 0.02% of the corpus, of which 29 classes only had one sample. Hence, a large number of low-frequency characters account for a large proportion of all distinct character classes; however, only a small fraction of these characters are commonly found on oracle bones. The distribution of the dataset classes is hence quite imbalanced. This distribution is often called a long-tail distribution, and it must be carefully handled in large-class classification. We also show the distributions of the height, width, and aspect ratio of the samples, respectively, in Figures 3. The mode of the heights is between 50 and 150 pixels, whereas most widths fall between 0 and 100 pixels. Most of the samples are hence tiny images and have an aspect ratio between 1 and 2.

B. Visual Analysis

In addition to the challenges of the OBC306 dataset described above, there are two key challenges in oracle-bone character recognition that are derived from the visual analysis of the OBC306 samples.

The first challenge is that many oracle-bone characters have several possible variants. Because oracle-bone script is a kind of irregular hieroglyph, emphasizing the description of the objects features, the number of strokes and relative position of radicals are changeable. Figure 4 shows some examples of intra-class confusion.

The second challenge is that the oracle-bone character images are heavily deteriorated by several types of noise. Figure 5 shows sample images from the dataset illustrating the diversity of degraded oracle-bone characters. In detail,

Table II
AVERAGE ACCURACY OF THE DIFFERENT METHODS

| Method | Top-1 | Top-3 | Top-5 | Top-10 |
|--------------|--------|--------|--------|--------|
| HOG + SVM | 14.29% | 25.93% | 32.15% | 41.26% |
| AlexNet | 66.75% | 75.31% | 77.46% | 80.56% |
| VGG16 | 67.20% | 76.21% | 78.57% | 81.51% |
| ResNet-50 | 69.09% | 78.06% | 80.50% | 83.00% |
| ResNet-101 | 69.50% | 77.92% | 80.00% | 81.66% |
| Inception-v4 | 70.28% | 78.74% | 80.28% | 82.28% |

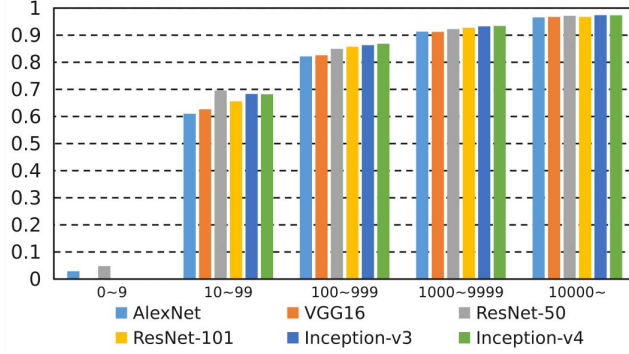


Figure 7. The average accuracy using different methods for classes with different number of samples.

Figure 5(a) shows stroke-broken characters in which some carved strokes on the oracle bones are broken. Figure 5(b) presents bone-cracked images, in which cracks passed through the oracle-bone character when the oracle bones were broken during divination. Moreover, because of their long burial and careless excavation, oracle bones are usually fragmenting and their surfaces are damaged. Therefore, instances are incomplete or covered by noisy regions, as shown in Figures 5(c) and 5(d).

V. BASELINE DCNN METHOD EVALUATION AND FUTURE CHALLENGES

A. Evaluation

We evaluated five popular DCNN models on our dataset: AlexNet [21], Inception-v4 [31], VGG16 [23], Resnet-50 and Resnet-101 [24]. The method of “HOG+SVM” [32] is a typical non-deep learning method and is used as a comparison with the DCNN methods. The experiments of DCNN models were implemented under the PyTorch [33] framework whereas the experiments of the HOG+SVM were implemented using Sklearn [34]. In the experiments of the HOG+SVM, we use the probability calibration algorithm of [35] to map the SVM outputs towards the predicted probabilities and thus obtain Top-K predictions. All of them ran on a PC with an Intel i7-6700K CPU, Nvidia TITAN X GPU, and 32 GB RAM.

We randomly selected 75% of the samples from each class for training and reserved the rest for testing. Exceptions were made for the 29 character classes with only one sample

each. We reserved the single sample for those categories for testing, and therefore these classes do not have a training sample, i.e., it is a zero-shot learning problem for these classes. All the DCNNs models were pre-trained using the ImageNet dataset [36] and fine-tuned on the proposed training set to reach the convergence state.

In consideration of the long tail effect, we measured the performance of each class by determining the fraction of test examples that were correctly classified as belonging to a certain class. The cumulative performance was then calculated by averaging the per-class accuracy.

Table II summarizes the results. Compared to the DCNN methods, the “HOG + SVM” method performs significantly worse. Of the five DCNN methods, Inception-v4 performs the best in terms of the accuracy of Top-1 and Top-3, although its improvement is marginal. Whereas in terms of Top-5 and Top-10 accuracy, it just ranks the second. In contrast, ResNet-50 puts up a slight advantage. In summary, DCNNs demonstrate promising ability to recognize oracle bone characters, which is particularly true when compared to the traditional method. However, the overall performance is still weak and far from satisfactory. Figure 7 indicates the relationship between the number of class samples and average accuracy of the character classes. The figure shows that all methods improve their accuracy as the number of samples per class increases, and the lack of samples in some classes will be a challenge for improving classification performance. In addition to the long tail effect of the distribution of class samples, variant oracle-bone characters (Figure 4) and high noise levels (Figure 5) are also challenges.

B. Future Challenges

In this paper, we emphasize glyph-based oracle-bone character recognition, however, this should not be our only purpose. Developing a recognition system that can handle unseen oracle-bone character classes will be an important challenge in future. It is one of zero-shot learning problem to recognize unseen oracle-bone character classes, in which no associated instance has been seen during training. Thus far, no work focuses on handling unseen oracle-bone character classes, however, some researchers study the problem of classification when the training and test classes are disjoint [37], [38]. We leave this for future work to adapt the zero-shot learning for unseen oracle-bone character recognition. If we succeed in solving it, we can recognize the new variants of existing glyph classes and even recognize a new glyph class, and thus automatically expand our OBC306 dataset to contain the full list of 4,024 distinct oracle characters [28].

Besides, an oracle-bone recognition system based on our dataset can be helpful with the characters detection in oracle-bone rubbing images, for example, recognition-based detection refining or providing the semantic classes for the ground truth boxes of detection datasets, and etc. Moreover, we can develop a comprehensive end-to-end oracle bone

recognition system capable of detecting a single character and recognizing its glyph classification or a semantic class associated with translated modern Chinese text. Further understanding to reveal the semantic meaning of oracle-bone rubbing pieces is also required. One promising approach that we and other researchers have been pursuing is automating the oracle bone deciphering system. This allows us to speed up the study of oracle bone field, pushing it toward digitalization and automation.

VI. CONCLUSIONS

We presented a large dataset of oracle bone scripts to support the advancement of oracle-bone script analysis. This dataset consists of 309,551 oracle character images covering 306 classes, which are drawn from a broad range of sources spanning many authoritative oracle-bone publications to generalize oracle-bone character recognition study. Because the dataset has highly imbalanced classes and several variants are found for each oracle bone character, it is a challenging dataset. We also provide results for several state-of-the-art DCNN algorithms as baseline results and compare them with a traditional method. We hope that our dataset will help future studies on deciphering oracle-bone characters.

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