An Oracle Recognition Method Based on Eigenvalue Preprocessing and YOLOv8 Network

Chun-Yang Zhou[1, 3, 4], Yun-Cong Ge[1, 3, 4], Zhen-Tao Liu[2, 3 ,4 *]

[1]School of Future Technology, China University of Geosciences, Wuhan 430074, China

[2]School of Automation, China University of Geosciences, Wuhan 430074, China

[3]Hubei Key Laboratory of Advanced Control and Intelligent Automation for Complex Systems, Wuhan 430074, China

[4]Engineering Research Center of Intelligent Technology for Geo-Exploration, Ministry of Education, Wuhan 430074, China

* Corresponding author, E-mail: liuzhentao@cug.edu.cn

Abstract: Oracle bone inscriptions, engraved on tortoise shells and animal bones throughout the Yin and Shang dynasties, hold immense importance in refining Chinese cultural history and examining the development and progression of Chinese characters. Image segmentation and detection of authentic oracle bone inscriptions are frequently hindered by three types of interference elements present on the original rubbings: point noise, fake texture, and intrinsic texture. In order to tackle this issue, this research presents a methodology for recognizing oracle bones. Initially, the image undergoes preprocessing by computing customized eigenvalues derived from the writing attributes of oracle bones represented as hieroglyphics. Subsequently, the processed image is sent into the YOLOv8 network for automated identification and categorization. The experimental results demonstrate that the proposed Oracle bone character recognition method in this study achieves a recognition accuracy of 95.31% on the selected dataset of the Oracle Bone Character Collection, indicating excellent recognition outcomes.

Keywords: Oracle, Feature extraction, Image recognition, YOLOv8

1 Introduction

Oracle bone inscriptions mostly pertain to the Yinxu Oracle bone inscriptions, which were engraved on tortoise shells and animal bones during the Yin and Shang Dynasties. These inscriptions, found in China, are the oldest and most comprehensive system of ancient Chinese writing. They hold immense importance in understanding the development of Chinese culture and the evolution of Chinese characters[1]. Due to the prolonged burial and erosion of oracle bones and animal bones, the acquired topographic images of the oracle bones suffer from significant noise, image distortion, and other issues. This poses substantial challenges in the field of oracle bone recognition research[2]. The original topographic image of the oracle bone refers to the initial image acquired from the topography of the excavated tortoise shell, animal bone, and other text-bearing materials by specialists. Oracle single character segmentation and recognition technology involves identifying and extracting the text from the oracle bone topography image[3]. Nevertheless, the process of segmenting and recognizing topographic images on oracle bones is frequently hindered by three types of interference elements in the original topography: point noise, artificial texture, and intrinsic texture. These factors contribute to inadequate segmentation of individual words and ultimately lead to low classification accuracy.

Early methods of recognizing oracle bones focused on feature extraction techniques[3]. These approaches involved manually extracting and analyzing the shape, structure, and other characteristics of the oracle bones. The bones were then identified and interpreted by comparing them to known oracle bone libraries. Machine learning algorithms, such as support vector[5] machines and fractal geometry[6], have been used in oracle bone glyph detection due to their significant achievements in computer vision. These approaches exhibit both low recognition accuracy and limited effectiveness in recognizing unknown oracle bone pictures.

Recently, there has been a growing body of research focusing on the utilization of deep convolutional neural networks for recognizing topographic oracle bone features[7-12]. Some notable examples of this study include: Hao-Bin Wang[13] addressed the issue of uneven distribution of sample data resulting from the challenge of feature extraction by introducing a recurrent generative adversarial network algorithm that enables the network to independently learn the styles of oracle bone characters and generate character images with a wide range of diversity. Zhang Yikang[14] developed a metric learning approach with a ternary loss and adversarial training to align the distribution of different oracle bone characters in a common feature space, addressing the imbalance in their recognition. Liu Fang[15] utilized Mask R-CNN to enhance the accuracy of oracle bone topography recognition to 95%. Yan Sheng [16] further enhanced Mask R-CNN by integrating class masking and automatic identification, achieving the first-ever integration of oracle bone character detection and recognition in topography images.

The YOLO algorithm integrates the responsibilities of detection and classification for processing, utilizing a straightforward model structure and achieving great real-time performance[17]. It has the capability to accomplish both the segmentation of individual words and the recognition of text on oracle bones. YOLOv8 is a target recognition network within the YOLO series introduced in 2023. Compared to prior models in the YOLO series such as YOLOv5 and YOLOv7, YOLOv8 is a superior network model that offers improved detection accuracy and faster detection speed. In recent years, the YOLOv8 network has been used in various target detection and classification efforts: Zhang[18] proposed an improved YOLOv8 model for student behaviour detection in classroom videos. Sumit Pandey[19] combines the YOLOv8 model, the Segment Anything Model (SAM) and the High Quality (HQ) SAM to segment regions of interest (ROIs) in different medical imaging datasets for fully automated and accurate segmentation. Arshleen Kaur[20] presented an improved YOLOv8-based traffic sign recognition model for accurate detection of traffic signs in adverse conditions such as snowy days.

Oracle recognition has been affected by the large amount of noise on the original image. To solve the above problems, this paper proposes to pre-process the image according to the eigenvalues before inputting the original topographic image into the network. This paper introduces four image features for the oracle bone: Equivalent Diameter of Connected Domains (EDCD), Minimum Distance of Connected Domains (MDCD), Point Feature Analysis Matrix (PFAM), and Point Eigenvalue (PE). By comparing and analyzing these four features, the oracle bone image is preprocessed, which leads to the exclusion of interfering elements. Ultimately, the preprocessed image is fed into the YOLOv8 neural network to accomplish the task of segmenting and classifying individual characters.

2 Methodology

This paper presents a method for preprocessing the original topography based on eigenvalues to enhance the accuracy of future single-character segmentation and recognition. Oracle is an archaic Chinese pictograph characterized by a consistent stroke pattern and a meaningful relationship between strokes[21]. Broken or missing strokes could be identified as being a component of the oracle by looking at a binary map of the original terrain. First, the oracle bone strokes are large and close to each other, while most of the noise is small and far away from other connected domains. Concurrently, after the refinement of the strokes in the binarized picture of the oracle topography, the oracle bone strokes create connections and intersections, and point noise, layered textures, and fake textures are transformed into isolated points. This paper introduces four image features for oracle bone characters: Equivalent Diameter of Connecting Domain (EDCD), Minimum Distance of Connecting Domain (MDCD), Point Feature Analysis Matrix (PFAM), and Point Eigenvalues (PE). In a binarized picture, these characteristics are utilized to identify if a white connecting domain corresponds to an oracle bone character. A connected domain is blacked out if its pertinent qualities don't match the grading criteria. In the end, the processed picture is sent to the YOLOv8 network for classification and identification.

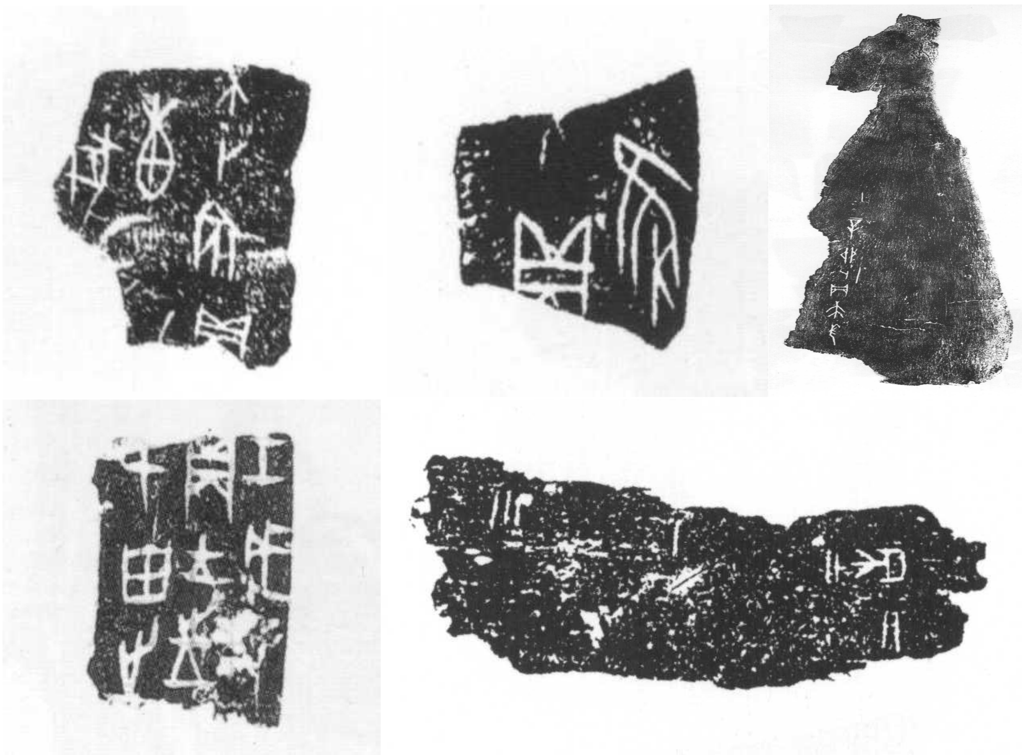


Fig. 1 Original oracle bone topographies filled with dot noise, layered textures and artificial textures

2.1 Image pre-processing

Calculation of image features. This paper proposes four distinct characteristics: The Equivalent Diameter of the Connected Domain (EDCD), the Minimum Distance of the Connected Domain (MDCD), the Point Feature Analysis Matrix (PFAM) and Point Eigenvalues (PE)：

Equivalent Diameter of the Connected Domain In the binarised oracle bone topography image, each white area is defined as a connectivity domain. The area of each connected domain is denoted as S . To account for the intricate and adaptable nature of the oracle bone, the Equivalent Diameter of the Connected Domain (EDCD) is established. This metric is calculated in the following manner:：

$$EDCD = \sqrt{\frac{4S}{\pi}} \tag{1}$$

This article stipulates that a connected domain is classified as a Valid Connected Domain (VCD) if its equivalent radius exceeds the threshold value of δ.

The Minimum Distance of the Connected Domain. The proximity of connected domains can serve as an indication of the oracle's continuity. The Distance between Connected Domains (DCD) is defined as the measure of distance between the average coordinates of all pixel points within the connected domains：

$$DCD = \sqrt{\left(\frac{\sum_{i=1}^{N} x_{1i}}{N} - \frac{\sum_{i=1}^{M} x_{2i}}{M}\right)^2 + \left(\frac{\sum_{i=1}^{N} y_{1i}}{N} - \frac{\sum_{i=1}^{M} y_{2i}}{M}\right)^2} \tag{2}$$

where *N* and *M* represent the number of pixels in the two connected domains. *n* represents the number of connected domains.

The minimal Distance of the Connected Domain (MDCD) is defined as the minimal distance from other Valid Connected Domains for a certain Connected Domain:

$$MDCD = \min(DCD_1, DCD_2 \ldots DCD_n) \tag{3}$$

Extraction of point eigenmatrix and point eigenvalues. Figure 2 (a) displays the outcome of refining the binarized original topography image. In oracle bone stroke refined pictures, the Point Feature Analysis Matrix (PFAM) is represented as a 3×3 matrix. The focal point of the matrix is the specific location under analysis, while the adjacent 8 points represent the surrounding pixels. In the stroke-refined image, a multi-pixel point is assigned a value of 1 in the point feature analysis matrix of the store if it is white, and a value of 0 if it is black.

Point eigenvalues (PE) refer to the eigenvalues of the point feature analysis matrix:

$$PE = \sum_{k=2}^{8} P_k \tag{4}$$

Determination of connected domain characteristics. Based on the characteristics of the oracle bones, two judgments of the connectivity domain are proposed in the binary image of the original oracle topography.

Judgment 1: In the binarised image, most of the point noise, layered texture and artificial texture are located in the connectivity domain with a small area and generally isolated by the connectivity domain where the oracle is located. Therefore, in this paper, when the equivalent radius of the connectivity domain (DCD) is less than the threshold δ and the minimum distance of the connectivity domain (MDCD) is greater than the threshold γ (the size of the threshold is determined by the resolution of the image), then the connectivity domain is blackened.

$$DCD < \gamma \ and \ MDCD > \ \delta \tag{5}$$

Judgment 2: The pixel points in the refined image are categorized based on their connection with the neighboring points, such as isolated points, end points, bifurcation points, and so on. The value of PE determines the correlation between that point and its neighboring pixels. For instance, an isolated point refers to a pixel point that is not connected to any other points, and its eigenvalue is lower than that of other types of pixel points, which are all greater than 1. The refined oracle bone stroke is a segment of pixelated lines with continuity[17]. If the total sum of the PE of all the pixels within a connectivity domain is less than 1, the connectivity domain will become an isolated point after refinement and it is judged as noise.

$$\left(\sum_{i=1}^{n} PE\right) < 1 \tag{6}$$

If the above judgments are satisfied at the same time, it can be judged that the connected domain does not belong to a part of the oracle script, and it will be blackened in the binarised image of the oracle topography, thus eliminating its influence on the oracle script recognition. The processing effect is shown in Figure 2.

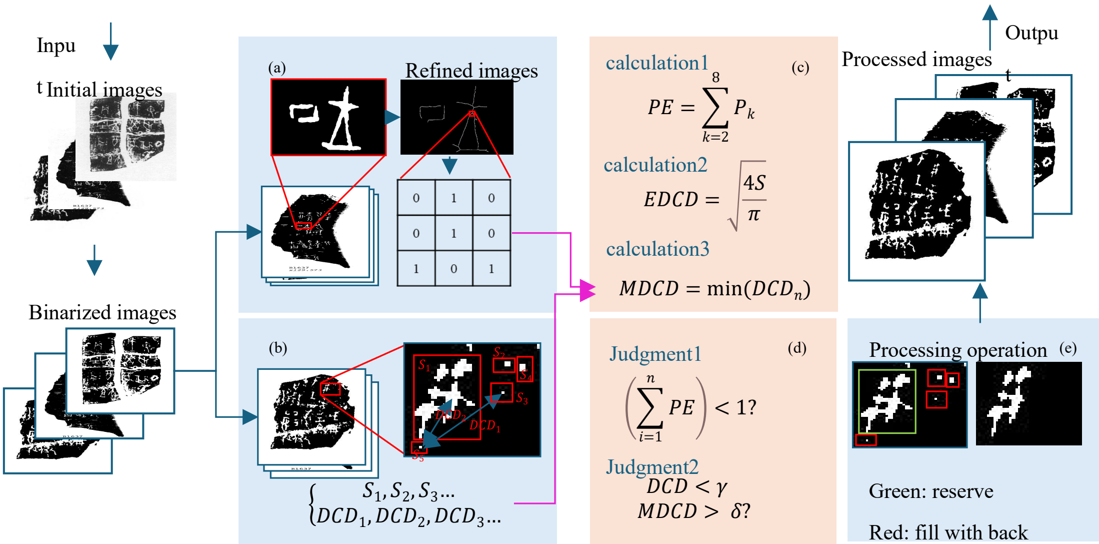


Fig. 2 Pre-processing of oracle according to customised feature values. (a) Stroke refinement and PFAM extraction;(b) Extraction of connected domain area and DCD;(c)Calculation of PE,MDCD,EDCD;(d) Two judgments of the connectivity domain;(e) Processing operation

2.2 YOLOv8 network

Its network structure is partitioned into three components: Backbone, Neck, and Head, as illustrated in Figure 3.

The Backbone component utilizes an enhanced CSPDarknet53 network. The YOLOv8 network undergoes a substitution of all CSP (Cross Stage Partial) modules in YOLOv5 with the C2f (Cross Stage Partial Network Fusion) module. The C2f module is the primary module responsible for residual feature learning. It incorporates more jump-layer connections and more splitting manipulations in comparison to the CSP module[22]. The CBS module, consisting of convolution, batch normalization, and SiLU activation, processes the input data by applying convolution operations, normalizing the batches, and activating the information stream using the Sigmoid Linear Unit (SiLU) function to provide the output results. Spatial Pyramid Pooling Fast (SPPF) pools the input feature mapping into a fixed size mapping, resulting in an adaptive size output.

The Neck component utilizes the Path Aggregation Network with Feature Pyramid Network (PAN-FPN) architecture. Compared with the Neck structure of YOLOv5 and YOLOv7 models,
YOLOv8 eliminates the convolution process after upsampling in the Path Aggregation Network (PAN) structure. This modification allows YOLOv8 to be a lightweight model without compromising its original performance. PAN-FPN utilizes a network architecture that combines top-down and bottom-up approaches. It effectively

combines basic positional information with deep semantic information through feature fusion, resulting in diverse and comprehensive features.

The Head component utilizes a decoupled structure, which is an enhancement over the prior anchor-based approach to anchor-free. The Anchor Free approach primarily utilizes several key or center points and boundary information to depict the object.

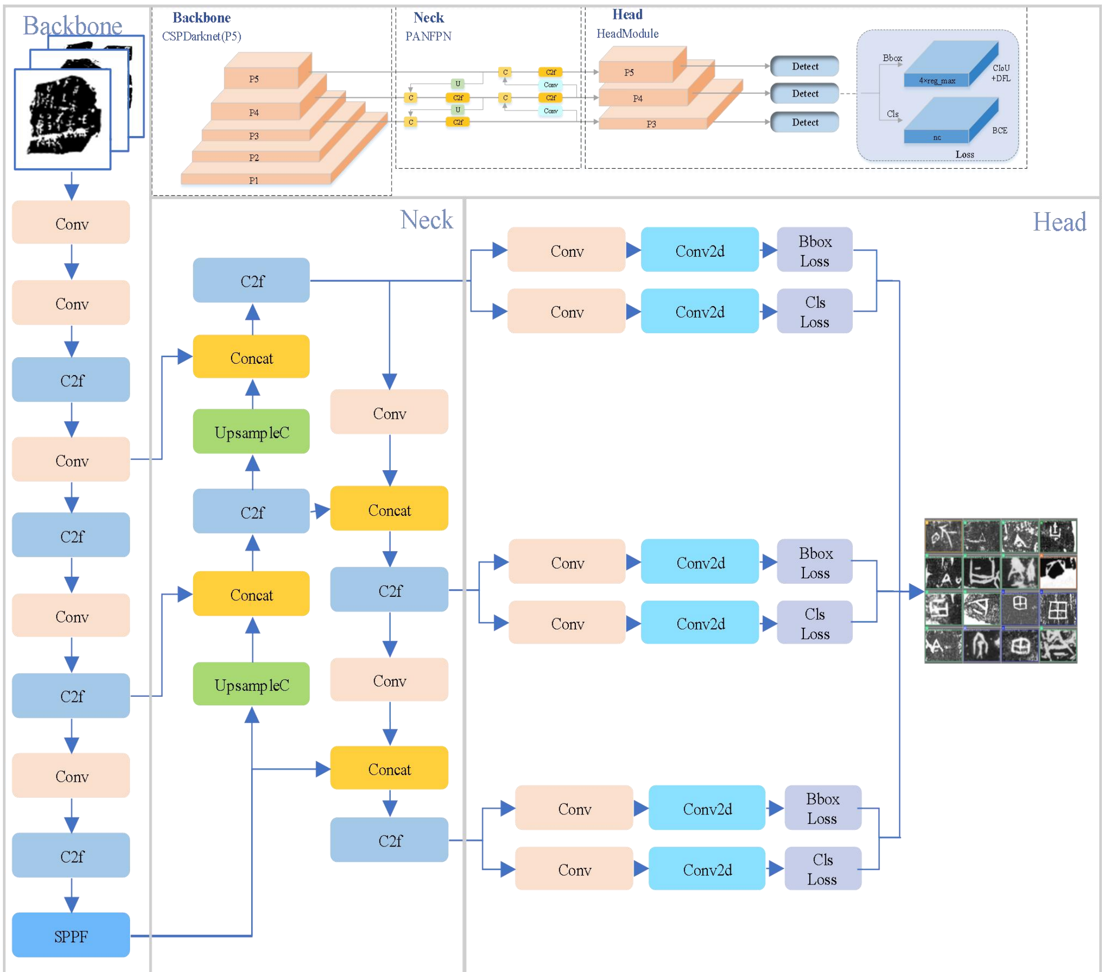


Fig. 3 Network of YOLOv8

3 Expriment

To validate the efficacy and progress of the novel research described in this paper, two experiments were primarily conducted.

(1) Validate the efficacy of the oracle bone automatic recognition and classification model provided in this research work;

(2) Validate the superiority of the improved oracle recognition method by comparison experiments between the method proposed here and two existing methods that currently have high recognition performance.

3.1 Dataset Selection

The main source of the dataset selected for the training of this paper is The Oracle Bone Collection[23]. The Collection of Oracle Bones contains 39,476 topographies unearthed in Yinxu selected from more than 150,000 oracle bones at home and abroad. A team of professionals meticulously annotated the rubbings to ensure the accuracy and reliability of the experimental data, including both the rubbing data and the interpretation data. The dataset utilized in this work contains images with varying resolutions as a result of segmentation. To enhance the dependability of the data, the photos are consistently resized to a resolution of 1024×1024. During the experiment, the dataset was partitioned into a training set and a test set using a random division at a ratio of 4:1. The training dataset has 31,581 photos, whereas the test dataset comprises 7,895 images.

3.2 Experimental Setting

The experiments were performed on a computer equipped with an NVIDIA RTX A6000 GPU, which has 48GB of video memory. The computer runs on the Windows operating system and utilizes the Pytorch deep learning framework. The training batch size was set to 20A. The training process consisted of 50 epochs, and it took a total of 20 hours. Simultaneously, to enable the model to continually experiment with data during the learning process, this work opted for the Adam optimizer, which dynamically adjusts the learning rate.

$$G_t = \beta_1 G_{t-1} + (1 - \beta_1) {g_t}^2 \tag{7}$$

$$\widehat{G}_t = \frac{G_t}{1 - \beta_1^t} \tag{8}$$

$$\Delta\theta = -\frac{\alpha}{\sqrt{\widehat{G}_t + \epsilon}} \tag{9}$$

where the iterative gradient G_t and the custom decay rate β_1 which is set at 0.33. The value of α, referred to as the initial learning rate, is set to 0.001 in this paper. The symbol ϵ represents a minute constant that is used to ensure numerical stability. The term $\widehat{G}_t$ refers to the exponentially weighted average.

3.3 Model validity and analysis

To validate the efficacy of the oracle bone inscription recognition method proposed in this paper, a comparison and analysis are conducted between the accuracy of the recognition method that implements the preprocessing operation proposed in this paper and the accuracy of the method that directly inputs the oracle bone inscription image into the YOLOv8 network. This comparison aims to ascertain the effectiveness of the preprocessing method proposed in this paper. The evaluation metric employed in this study is the model's accuracy.

$$A = \frac{\sum_{k=1}^{N} a_k}{M} \tag{10}$$

where M is the total number of images in the test set, N denotes the number of categories of images in the test set, and a_k denotes the number of photos of the kth category that the model accurately identifies in the test set. As the value increases, the model's recognition effect improves. Table 1 displays the model's accuracy when subjected to various sizes of the thresholds of EDCD (Equivalent Diameter of the Connected Domain) and DCD (Distance between Connected Domains), denoted as γ and δ respectively. Additionally, the table also showcases the recognition accuracy of the model without the preprocessing method proposed in this paper.

Table 1. Model performance analysis

γ	δ	Accuracy
40	10	90.92%
35	30	93.82%
30	50	95.31%
20	60	92.42%
No pre-processing		88.34%

Table 1 shows that when compared to the YOLOv8 recognition technique without preprocessing, the model with preprocessing obtained a better accuracy. At various thresholds, the accuracy increase varied from 2.58% to 6.97%. Peak accuracy of 95.31% was attained by the model with \gamma and \delta set to 30 and 50, respectively. Nevertheless, the accuracy of the model declines when parameter \delta is too big and parameter \gamma is too little. This might be as a result of the deletion of essential information about the features of the oracle bone seen in the picture due to the values of delta and gamma being excessively tiny and big, respectively. In the end, this results in a decrease in the model's recognition accuracy. The link between the number of iterations and the model's accuracy is shown in Figure 4. A few of the Oracle recognition findings are shown in Figure 5.

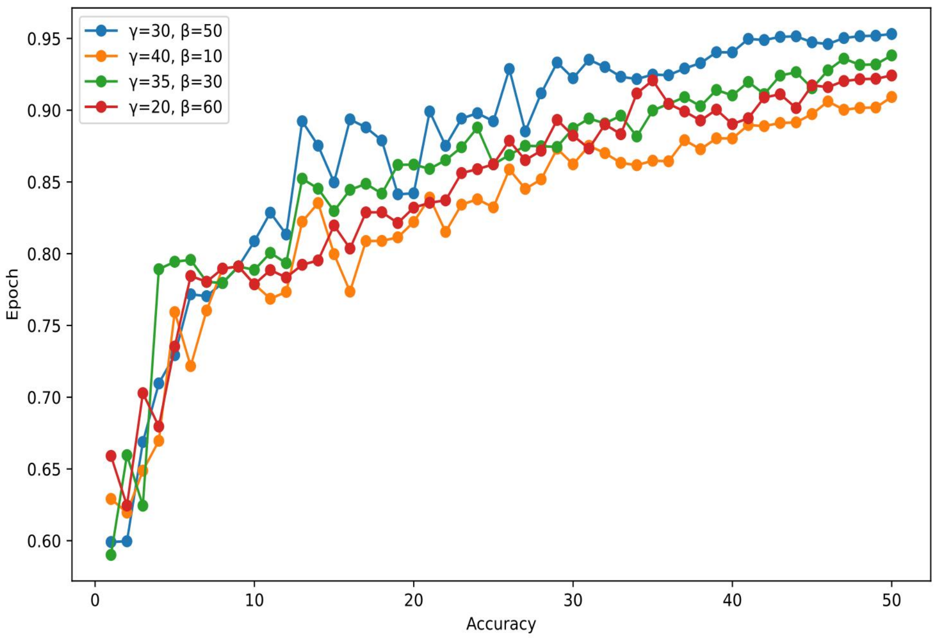
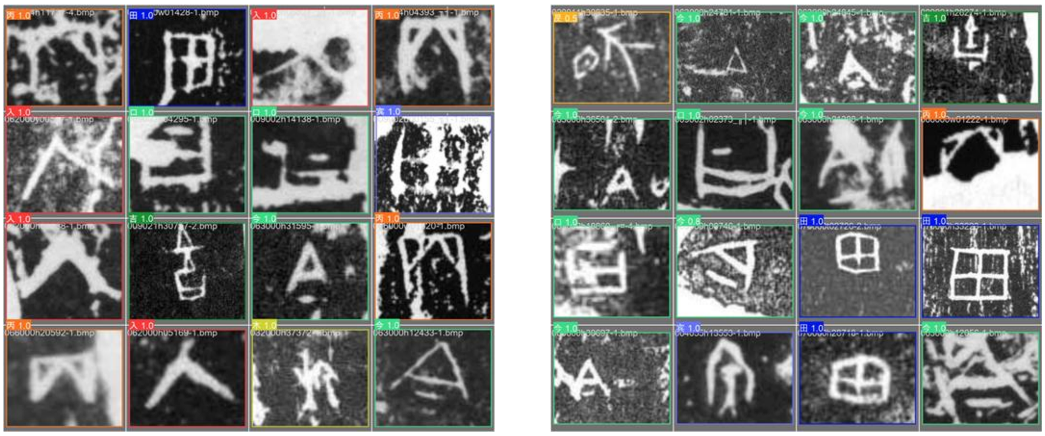


Fig. 4 The accuracy curve of the model varies with the amount of iterations.



(a) (b)

Fig. 5 Partial Oracle Segmentation Recognition Results

Furthermore, to validate the sophistication of the enhanced algorithm presented in this research, a comparative experiment was performed, comparing it with the four most recent algorithms that exhibit superior overall recognition performance. The comparison results with other methods are displayed in Table 2.

Table 2. Comparison results with other methods

Model	Accuracy	Number of character categories
[24]	93.51%	277
[25]	86.70%	241
[26]	91.53%	247
[27]	87.43%	300
Our method	95.31%	277

Table 2 shows that the minimum number of recognition categories identified by the various comparison algorithms on oracle recognition categories is 241 and the maximum is 300. A total of 277 recognition categories were selected in this study, which is second only to the references[24]. In terms of recognition effectiveness, the highest recognition accuracy of the various compared algorithms is 95.31% and the lowest is 86.70%. The method proposed in this paper achieves a higher recognition rate. Compared to the method with the highest number of identified categories, the proposed method achieves 7.88% improvement in recognition accuracy.

In summary, the simulation experiments in two aspects prove that the improved model proposed in this paper is effective and advanced。

4 Conclusion

This paper suggested a preprocessing technique for enhancing the accuracy of recognizing oracle bone writings on rubbings. The method is based on eigenvalue calculation and establishes judgment conditions for preprocessing by considering the properties of oracle bone inscriptions as pictographic characters. Next, the preprocessed image is fed into the YOLOv8 network for object recognition. Furthermore, to validate the efficacy of the oracle bone inscription recognition method proposed in this paper, the paper gathered a dataset consisting of 277 original rubbings from The Oracle Bone Collection. The model was then trained and tested using the Adam optimizer. The model described in this study attained a precision of 95.31% after undergoing testing. Ultimately, this paper evaluated this model against the existing model that demonstrates superior performance, hence substantiating the advanced characteristics of this model. Nevertheless, despite the advancements made in this research on oracle bone inscription recognition, there remain unresolved issues. For instance, several kinds of oracle bone inscriptions contain limited data, making them susceptible to overfitting and significant classification errors. A method for recognizing oracle text with very little sample data needs to be investigated. Future work will involve conducting research on all of these difficulties.

Acknowledgements. Firstly, gratitude is extended to the Undergraduate Innovation Training Program for the invaluable support provided throughout this research project. The funding and resources offered were instrumental in enabling the exploration of new ideas and the development of skills. The opportunities provided have significantly contributed to the successful completion of this study. At the same time, deep gratitude is expressed to the Future Technology College of China University of Geosciences (Wuhan) for the unwavering support and resources that have been instrumental in the completion of this research. Immense gratitude is also extended to the seniors who have provided invaluable technical and academic assistance throughout this journey. Their expertise and guidance have been a source of inspiration and learning. Last but not least, heartfelt thanks are extended to Lirong Liu, whose constant encouragement and support during the writing process have been a source of strength. Her belief in this work has been a driving force that has kept the momentum going during challenging times. Thanks are extended to all for their contributions, without which this work would not have been possible.

Disclosure of Interests. The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

5 Reference

1. Xie, N.H.: Research on Oracle Bone Script from Yin Ruins to the World: Review of the "120th Anniversary of the Discovery of Oracle Bone Script International Academic Seminar" in Busan, Korea. Journal of Guanzi Studies, **3**(3), 125–128 (2020)
2. Mao, Y.F., Bi, X.J.: Oracle Bone Script Recognition with Improved ResNeSt Network. Journal of Intelligent Systems, **18**(3), 450-458 (2023)
3. Song, C.M., Qiao, M.Z., Hong, T.: Oracle Bone Script Restoration Algorithm Guided by Edge Gradient Covariance. Journal of Liaoning Normal University (Natural Science Edition), **46**(2), 194-207 (2023)
4. Liu, Y., Lu, Y., Wei, Y.C., et al.: Current Status and Prospects of Oracle Bone Script Recognition Technology. Knowledge Management Forum, **8**(2), 115-125 (2023)

5. Liu, Y.G., Liu, G.Y.: Oracle Bone Script Recognition Based on SVM. Journal of Anyang Normal University, **2**, 54–56 (2017)
6. Gu, S.T.: Oracle Bone Script Shape Recognition Method Based on Fractal Geometry. Chinese Journal of Information, **32**(10), 138–142 (2018)
7. Liu, M.T., Liu, G.Y., Liu, Y.G., et al.: Oracle Bone Inscriptions Recognition Based on Deep Convolutional Neural Network. Journal of Image and Graphics, **8**(4), 114–119 (2020)
8. Yang, Z., Fu, T.: Oracle Detection and Recognition Based on Improved Tiny-YOLOv4. In: ICVIP 2020: The 4th International Conference on Video and Image Processing, pp. 128−133. ACM, New York (2020)
9. Sun, W.J., Zhai, G.T., Gao, Z.P., et al.: Dual-view Oracle Bone Script Recognition System via Temporal-Spatial Psychovisual Modulation. In: 2020 IEEE Conference on Multimedia Information Processing and Retrieval, pp. 193−198. IEEE, Shenzhen (2020)
10. Gao, J.H., Liang, X.: Distinguishing Oracle Variants Based on the Isomorphism and Symmetry Invariances of Oracle-Bone Inscriptions. IEEE Access, 8: 152258–152275 (2020)
11. Liu, M.T.: Research on Oracle Bone Script Recognition Based on Deep Convolutional Neural Network. Zhengzhou: Zhengzhou University (2020)
12. Wang, Q.Q.: Precise Recognition of Oracle Bone Script Based on Deep Convolutional Neural Network. Nanchang: Jiangxi Science & Technology Normal University (2020)
13. Wang, H.B.: Research on Oracle Bone Script Detection and Recognition Based on Deep Learning. Guangzhou: South China University of Technology (2019)
14. Zhang, Y.K., Zhang, H., Liu, Y.G., et al.: Oracle Bone Script Recognition Based on Cross-modal Deep Metric Learning. Acta Automatica Sinica, 47(4): 791–800 (2021)
15. Liu, F., Li, H.B., Ma, J., et al.: Research on Automatic Detection and Recognition of Oracle Bone Script Rubbings Based on Mask R-CNN. Data Analysis and Knowledge Discovery, **5**(12), 88-97 (2021).
16. Yan, S., Liu, F., Sun, D.M., et al.: Popularization and Revitalization of Oracle Bone Script Knowledge in Museums Based on Artificial Intelligence. China Museum, 03, 110-116+144 (2021).
17. Xu, Y.W., Li, J., Dong, Y.F., et al.: A Review of YOLO Series Object Detection Algorithms. Computer Science and Exploration, http://kns.cnki.net/kcms/detail/11.5602, lasted accessed 2024/06/14
18. B. -Y. Zhang, Z. -T. Liu and X. -Y. Zeng: An Online Education Effect Assessing Method Based on YOLOv8 and Vision Transformer. In: 2023 China Automation Congress (CAC), pp. 6228-6233. IEEE, Chongqing (2023)
19. S. Pandey, K. -F. Chen and E. B. Dam: Comprehensive Multimodal Segmentation in Medical Imaging: Combining YOLOv8 with SAM and HQ-SAM Models. In: 2023 International Conference on Computer Vision Workshops (ICCVW), pp. 2584-2590. IEEE/CVF Paris, (2023)
20. A. Kaur, V. Kukreja, N. Thapliyal, M. Aeri, R. Sharma and S. Hariharan. An Improved YOLOv8 Model for Traffic Sign Detection and Classification. In: 2024 3rd International Conference for Innovation in Technology (INOCON), pp. 1-5. IEEE, Bangalore, India, (2024)
21. Wang, J.Z., Hu, B.B.: Research on the Application of Normalization Algorithm in Text Recognition Systems. Computer Applications and Software, 3: 95-97 (2011)
22. Quan, Y., Wang, P., Wang, Y., Jin, X.: GUI-Based YOLOv8 License Plate Detection System Design. In: 5th International Conference on Control and Robotics (ICCR), pp. 156-161. IEEE, Tokyo (2023)
23. Guo, M.: Oracle Collection. Book Bureau, Beijing (1982)
24. Mao, Y.F., Bi, X.J.: Oracle Bone Script Recognition with Improved ResNeSt Network. Journal of Intelligent Systems, 18(03): 450-458 (2023)

25. Zhang, Y.K., Zhang, H., Liu, Y.G., et al.: Oracle Bone Script Recognition Based on Cross-modal Deep Metric Learning. Acta Automatica Sinica, 47(4): 791–800 (2021)
26. Liu, D.Z. Random polygon cover for oracle bone character recognition. .In: 5th International Conference on Computer Science and Artificial Intelligence, pp. 138−142. ACM, New York (2021)
27. Gao Xu. Research and Application of Oracle Bone Script Recognition Based on Convolutional Neural Network. Changchun: Jilin University (2021)