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SOIL LAYER CLASSIFICATION FROM CONE PENETRATION TEST DATA: A CPT-AS-IMAGE PARADIGM

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Abstracts:Soil classification is a fundamental task in geotechnical engineering, providing essential information for various applications such as foundation design, slope stability analysis, and earthwork construction. Traditional soil classification methods, such as borehole logging, are often limited by high costs and the small number of boreholes. Cone Penetration Test (CPT) data offers a more cost-effective and widely available alternative for soil classification. This study proposes a YOLOv8-based deep learning model for classifying soil layer via aCPT-as-Image paradigm, treating CPT data as images. The performance of the model is evaluated using precision, recall, F1 score, and mean average precision (mAP). The established model chieved a mAP of 0.986. The results demonstrate that the proposed model achieves high accuracy in soil classification for different soil type (e.g., clay, silt, and sand).

Keywords: Soil classification; deep learning; CPT data;YOLOv8 model.

1. Introduction

Soil classification is a critical process in geotechnical engineering, providing essential information for foundation design, slope stability analysis, and earthwork construction. Traditional methods of soil classification primarily rely on borehole logging, which involves drilling holes into the ground and analysing the soil samples extracted(Qi et al., 2016, Shi & Wang, 2021; Gong et al., 2020; Zhang et al., 2021). This method, while accurate, is often limited by the high cost and the limited number of boreholes that can be drilled. The interpretation of borehole data is also time-consuming and requires significant engineering experience. In recent years, Cone Penetration Test (CPT) data has emerged as a more cost-effective and widely available alternative for soil classification (Robertson, 1990, 2016). CPT data provides detailed information about the soil layers, including specific penetration resistance, which can be used to infer soil type and layering. However, the interpretation of CPT data for soil classification is often time-consuming and requires significant engineering experience.

To address these challenges, this study proposes a novel approach to soil classification using CPT data. The key innovation of this study is the conversion of CPT data into images, which allows for the application of deep learning techniques to automate the soil classification process. This approach not only improves the efficiency of soil classification but also enhances the accuracy by reducing the reliance on manual interpretation. The use of deep learning models, such as the You Only Look Once(YOLO) architecture, enables the model to learn complex patterns in the CPT data and make accurate predictions about soil types and layering.

The objectives of this study are to develop a deep learning-based soil classification model using CPT data, evaluate the performance of the model in classifying major and subdivision soil layers, and investigate the transferability of the trained model to other sites. The paper is organized as follows: The next section describes the collection and preparation of the CPT data used in this study. This is followed by a detailed methodology section, which explains the deep learning model used and the training process. The results section presents the performance of the model in classifying soil layers, including a comparison of the improved model with the baseline model. Finally, the conclusion summarizes the key findings of the study and outlines future work.

2. CPT Data Collection

In this study, a comprehensive dataset of Cone Penetration Test (CPT) data was collected from engineering reports in Shanghai, totalling 400 data points. The data includes specific penetration resistance (Ps) values at different depths and soil type information. The specific penetration resistance (Ps) values were recorded at intervals of 0.5 meters, providing detailed information about the soil layers. The soil types in the dataset include major soil layers and subdivision soil layers, such as sand, silt, clay, and their combinations. The data was collected from various sites in Shanghai, covering a wide range of geological conditions.

The specific penetration resistance (Ps) values show significant variability across different soil types, as illustrated in the table. For example, the Ps values for "Filling" range from 0.16 to 7.12 MPa, with a mean value of 1.85 MPa and a standard deviation of 2.72 MPa. This variability reflects the diverse soil conditions in Shanghai and provides a rich dataset for soil classification. The Ps values for "Silty clay" range from 0.2 to 13.22 MPa, with a mean value of 1.09 MPa and a standard deviation of 1.25 MPa, indicating a moderate variability. The Ps values for "Muddy silty clay" range from 0.2 to 18.32 MPa, with a mean value of 0.94 MPa and a standard deviation of 1.18 MPa, showing a similar level of variability. The Ps values for "Muddy clay" range from 0.28 to 4.74 MPa, with a mean value of 0.67 MPa and a standard deviation of 0.17 MPa, indicating relatively low variability. The Ps values for "Clay to Silty clay" range from 0.38 to 26.71 MPa, with a mean value of 1.71 MPa and a standard deviation of 1.68 MPa, showing a moderate level of variability. The Ps values for "Silty clay" range from 0.72 to 16.27 MPa, with a mean value of 2.11 MPa and a standard deviation of 1.29 MPa, indicating a moderate variability. The Ps values for "Sandy silt to Fine sand" range from 1.21 to 32.03 MPa, with a mean value of 14.29 MPa and a standard deviation of 6.63 MPa, showing a high level of variability. The Ps values for "Silty clay with silty sand" range from 2.47 to 20.41 MPa, with a mean value of 4.66 MPa and a standard deviation of 1.74 MPa, indicating a moderate variability.

To utilize the CPT data for soil classification, the data was converted into images. Each image represents a CPT profile, with the x-axis representing the specific penetration resistance (Ps) value and the y-axis representing the depth. The images were generated in batches based on the soil type name, the soil thickness of each layer, and the Ps value of different depths. The dataset was divided into a training set of 360 CPT images and a validation set of 40 CPT images. The images were pre-processed to ensure consistent size and resolution, with each image having a size of 256x256 pixels. The preprocessing steps included normalization of the Ps values and depth information, as well as resizing and cropping of the images to ensure uniformity. The resulting CPT image dataset provides a visual representation of the soil layers, enabling the application of deep learning techniques for soil classification. The dataset was carefully constructed to ensure that the images accurately reflect the soil conditions and provide sufficient information for the model to learn the patterns and features associated with different soil types. The specific penetration resistance (Ps) values were normalized to ensure consistent scales across different images, and the soil type information was used to label the images, allowing the model to learn the relationship between the CPT profiles and the corresponding soil types. The CPT image dataset provides a comprehensive and detailed representation of the soil conditions in Shanghai, enabling the development of a robust and accurate soil classification model.

Table 1 . Specific penetration resistance (Ps) value statistics in Shanghai

No.	Name	P_s value (MPa)		
		Range	Mean	Standard deviation
①	Filling	0.16-7.12	1.85	2.72
②	Silty clay	0.2-13.22	1.09	1.25
③	Muddy silty clay	0.2-18.32	0.94	1.18
④	Muddy clay	0.28-4.74	0.67	0.17
⑤	Clay to Silty clay	0.38-26.71	1.71	1.68
⑥	Silty clay	0.72-16.27	2.11	1.29
⑦	Sandy silt to Fine sand	1.21-32.03	14.29	6.63
⑧	Silty clay with silty sand	2.47-20.41	4.66	1.74

3. Methodology

The methodology section of this study focuses on the development and implementation of a deep learning-based soil classification model using Cone Penetration Test (CPT) data. The core of the methodology is the application of the YOLOv8 model architecture, which is a state-of-the-art object detection model. The following sections provide a detailed explanation of the YOLOv8 model architecture and its application in soil classification. The model architecture is designed to be modular, allowing for efficient model construction and training. The YOLOv8 model primarily consists of three components: Backbone, Neck, and Head.

The Backbone is the foundation of the YOLOv8 model, responsible for extracting features from the input images. It is composed of multiple convolutional layers and modules designed to capture hierarchical features from the data. The Backbone in YOLOv8 includes several key modules: ConvModule (Conv), Bottleneck, C2f (CSP Bottleneck with 2 Convolutions) and Spatial Pyramid Pooling Fast(SPPF). The Neck is responsible for feature fusion and enhancement, bridging the Backbone and the Head. It takes the features extracted by the

Backbone and processes them to improve the model's detection capabilities. The Neck in YOLOv8 includesC2f Modules and Upsample and Contact Layers. The Head is the final component of the YOLOv8 model, responsible for object detection and classification. It takes the processed features from the Neck and predicts the bounding boxes and class probabilities. The Head includes multiple detection layers, each responsible for predicting objects at different scales.

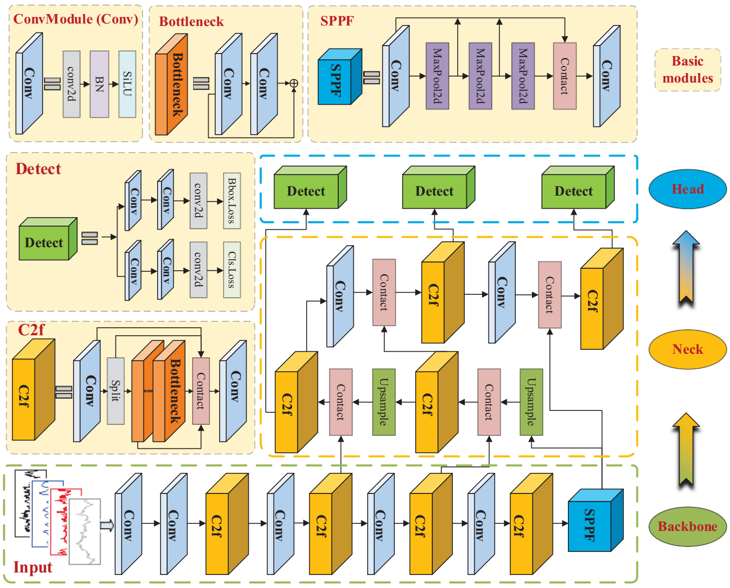


Fig 1. YOLOv8 model architecture

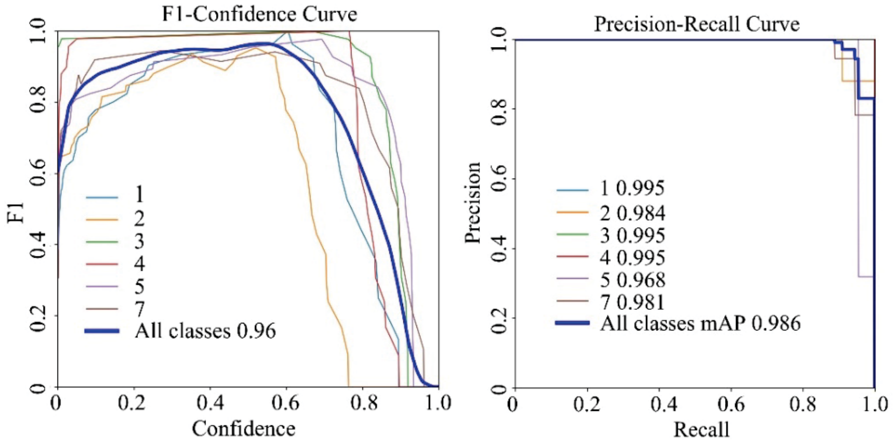
4. Results

The model performance is evaluated using two key metrics: the F1-Confidence Curve and the Precision-Recall (P-R) Curve. These metrics provide a comprehensive understanding of the model's ability to classify different soil types accurately. The F1-Confidence Curve illustrates the relationship between the F1 score and the confidence level for each soil type. The F1 score is a measure of the model's accuracy, combining both precision and recall. The confidence level indicates the model's certainty in its predictions.

Soil Types 3, 5, and 7 show higher F1 scores, indicating better identification performance. The F1 scores for these types are relatively stable across different confidence levels, suggesting that the model is consistently accurate in classifying these soil types.Soil Types 1, 2, and 4have lower F1 scores.

The Precision-Recall (P-R) Curve provides a detailed view of the model's performance in terms of precision and recall for each soil type. Precision is the ratio of true positive predictions to the total number of positive predictions, while recall is the ratio of true positive predictions to the total number of actual positive instances.The mAP (mean Average Precision) value is close to 1, indicating that the model can accurately identify all kinds of soil types. The P-R curves for most soil types are relatively flat and close to the top-right corner, indicating high precision and recall.

Soil Types 3, 5, and 7 have obvious morphological characteristics, such as fluctuations in the CPT data. These characteristics make them easier for the model to recognize and classify accurately.Soil Types 1, 2, and 4 are relatively stable with no obvious characteristics, making them more challenging to classify accurately.



(a) F1-Confidence Curve (b) Precision-Recall Curve

Fig 2.Model performance of YOLOv8

As shown in Fig 3,the model's performance in classifying major soil layers is generally good, as indicated by the comparison between the ground truth and prediction images. The model can accurately identify the major soil layers in most cases, with the predicted soil layers closely matching the ground truth.The phenomenon of missed and false detection does exist, but it mainly occurs at the end of the curve, where mutations may occur. This is likely due to the complexity of the soil layers and the limitations of the model in capturing these sudden changes. The changes in the middle of the 5th soil type are still relatively large, with three subdivisions. This indicates that the model has some difficulty in accurately classifying these more complex soil layers.

To improve the model's performance, several strategies can be employed: (1) Optimize Label Quality: Improving the quality of the labels used to train the model can help the model better understand the soil layers and their characteristics. This can be achieved by using more accurate and detailed labels, as well as by increasing the number of labelled data points. (2)Subdivision Soil Type: Focusing on the subdivision of soil types can help the model better capture the complexities of the soil layers. This can be done by creating more detailed labels for the subdivision soil types and training the model to recognize these finer distinctions. (3)Focus on Small Samples: Paying more attention to small samples can help the model better handle the variations in the soil layers. This can be achieved by increasing the number of small samples in the training data and by using techniques such as data augmentation to generate more diverse training examples.

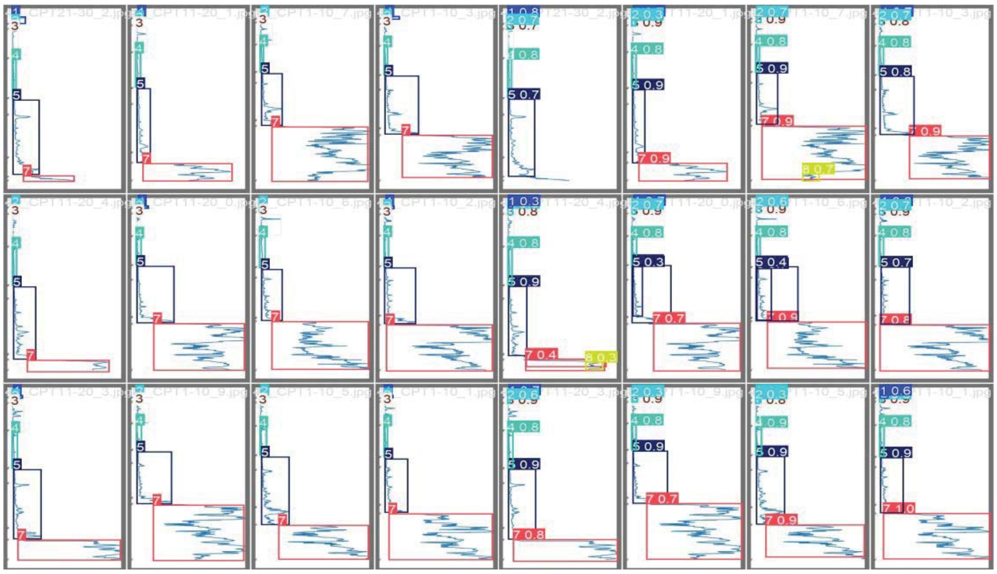


Fig 3.Prediction of soil layer classification based on proposed model

4. Conclusion

The YOLOv8 model demonstrated excellent performance in classifying major soil layers, achieving high accuracy with a mean average precision (mAP) of 0.986. The model's performance was consistent across different soil types, indicating its robustness and reliability. The results suggest that the proposed CPT-as-Image driven soil classification paradigm is a promising approach for soil classification, providing a cost-effective and efficient alternative to traditional methods. Future work will focus on improving the model's performance in classifying subdivision soil layers and investigating its transferability to other sites.

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