Feature Recognition and Vectorization of Historical Maps of Taiwan Using YOLOv8

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***Abstract*—The "Historical Map of Taiwan," published in 1904 during the Japanese colonial period, provides comprehensive records of topography, administrative divisions, historical toponyms, and land use from over a century ago. Traditionally, the extraction of information from these maps has relied heavily on manual interpretation, a process that is labor-intensive and difficult to scale. To enhance the value-added application of historical cartography and address spatial information challenges across disciplines, this study employs deep learning techniques for the highly automated feature recognition and vectorization of these maps.**

Specifically, this research utilizes "You Only Look Once v8" (YOLOv8), a state-of-the-art Convolutional Neural Network (CNN) framework. We employ the segmentation variant, YOLOv8-Seg, which integrates object bounding box prediction with segmentation mask generation to achieve pixel-level semantic segmentation. The model was trained to identify and segment four key features: settlements, grasslands, cemeteries, and fields within the Taishō Era Historical Map. Using a dataset of 400 training images, 50 validation images, and 50 test images (8:1:1 ratio), the model demonstrated robust performance upon convergence, achieving both precision and recall rates exceeding 80%. These results indicate that the proposed method effectively automates the differentiation of map features and their spatial extents, significantly reducing the manual labor required for vectorization. This automated approach facilitates the reconstruction of historical economic and social environments, enabling advanced spatial and temporal analysis. Future work will explore integrating geometric constraint algorithms to extend vectorization capabilities to complex terrains, such as mountainous regions.

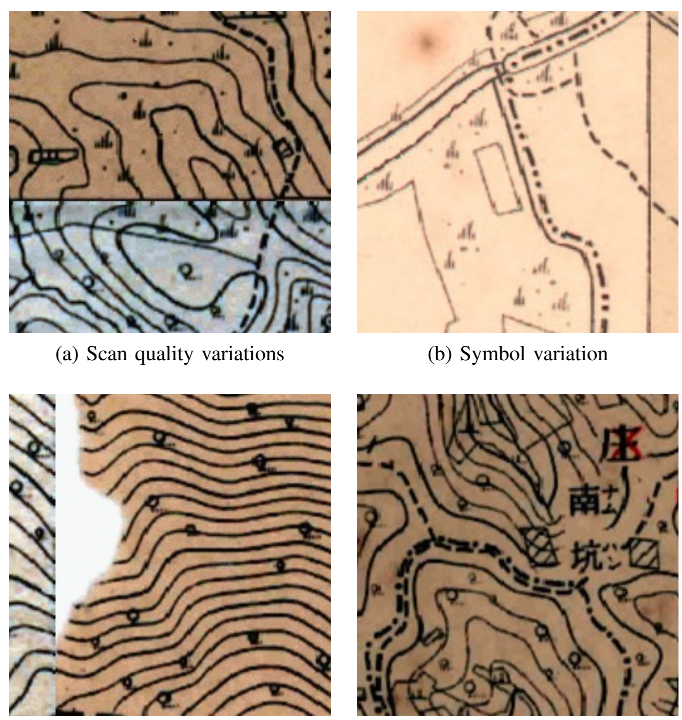
***Index Terms*—Semantic Segmentation, GeoAI, Historical GIS, YOLOv8, Map Vectorization**

I. Introduction

Before the 20th century, Taiwan lacked systematic geographic and spatial information records. This changed with the creation of the first thematic map of Taiwan between 1900 and 1904, following extensive surveys during the Japanese colonial period. This map provides detailed documentation of land use, administrative divisions, topography, and hydrology, serving as a critical resource for modern researchers to reconstruct the lifestyles and movement patterns of that era.

Currently, the Historical Map of Taiwan is available as Open Data through the Center for Geographic Information Science at Academia Sinica. Despite this accessibility, researchers in historical and geographical fields often face the bottleneck of manually interpreting and vectorizing map data to convert it into a numerical format suitable for analysis. This labor-intensive process frequently forces researchers to compromise on the spatiotemporal scope and resolution of their studies.

The vectorization of historical maps presents unique technical challenges. Chiang et al. (2014) identified four primary difficulties:



(a) Scan quality variations
(b) Symbol variation
(c) Effects of aging
(d) Overlapping symbols

Fig. 1. Challenges in vectorizing historical maps (Source: Taishō Historical Map of Taiwan, 1921)

a) Variations in graphical quality across map scans.
b) Inconsistency of cartographic symbols.
c) Degradation effects due to aging (e.g., discoloration, wear).
d) Overlapping text and symbols.

Taking the Taishō Historical Map of Taiwan (1921) as a case study (see Fig. 1), researchers encounter inconsistent scan colors, mixed layers of contour lines, text, and land use symbols, and physical deterioration. Furthermore, symbol stylization, such as the representation of trees, lacks uniformity.

To address these challenges, we adopt the YOLOv8-Seg model. YOLOv8 is a cutting-edge deep learning framework based on Convolutional Neural Networks (CNN). Its segmentation variant, YOLOv8-Seg, combines traditional object detection with mask generation, enabling pixel-level semantic segmentation. This study aims to establish an efficient digital cartography pipeline using YOLOv8, focusing on the Taishō Historical Map (post-1920 municipal reforms) due to its relative clarity. Our objective is to lower the technical barrier for using historical maps, providing a quantitative, scientific method for understanding Taiwan's past socio-geographic context.

II. Research Methodology

A. Model Architecture

This study employs YOLOv8-Seg for semantic segmentation. The architecture utilizes a single neural network that partitions the image into grids, with each grid responsible for object detection and segmentation. The model incorporates an enhanced backbone and head structure, integrating attention mechanisms and multi-scale feature fusion to optimize both accuracy and inference speed.

B. Target Features

Given the complexity of the historical maps, this research initially focuses on four distinct, densely packed features: **grasslands, cemeteries, fields, and built-up areas** (settlements). These features were selected to test the model's generalization capabilities: cemeteries appear sporadically, built-up areas vary significantly in size, grasslands are infrequent, and fields are ubiquitous.

C. Data Preprocessing

We utilized high-resolution scans of the maps. To prevent the model from failing to detect features at the edges of individual map sheets—a common issue when high resolution leads to a larger scale—we stitched together and annotated four adjacent images. Furthermore, to mitigate false positives caused by the map's varying tones and crowded information, the dataset included an equivalent number of background images (containing no foreground targets) for training. The dataset was partitioned into training, validation, and test sets with a ratio of 8:1:1 (Fig. 2).

III. Results

A. Training Performance

The training dataset underwent data augmentation (Fig. 4) to enhance robustness. The model was trained for 500 epochs. As shown in Fig. 5, the loss function for both validation and training sets demonstrated clear convergence. Training was early-stopped at the 458th epoch to prevent overfitting.

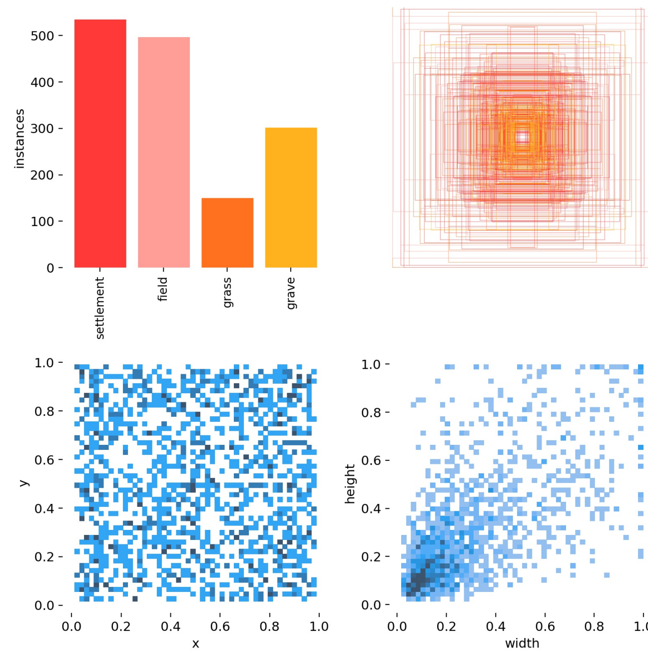


Fig. 3. Histogram of Annotation Quantities

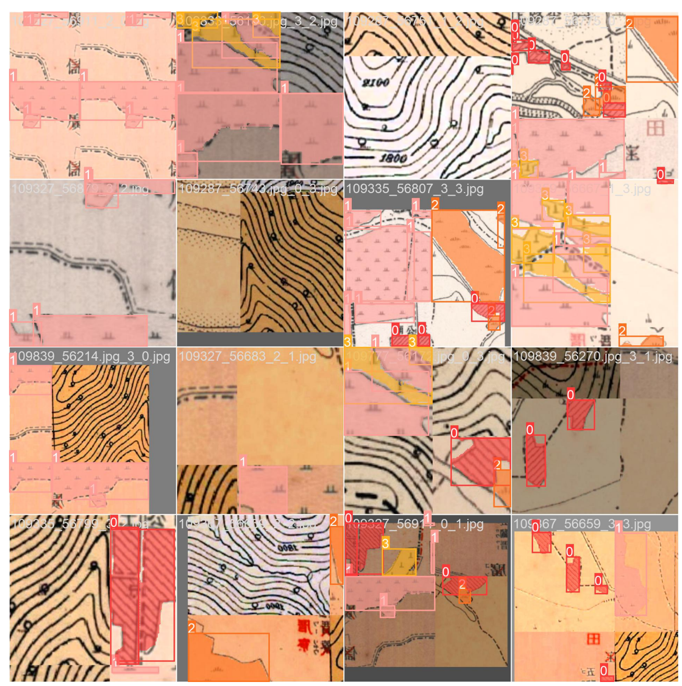


Fig. 4. Visualization of Training Data After Data Augmentation

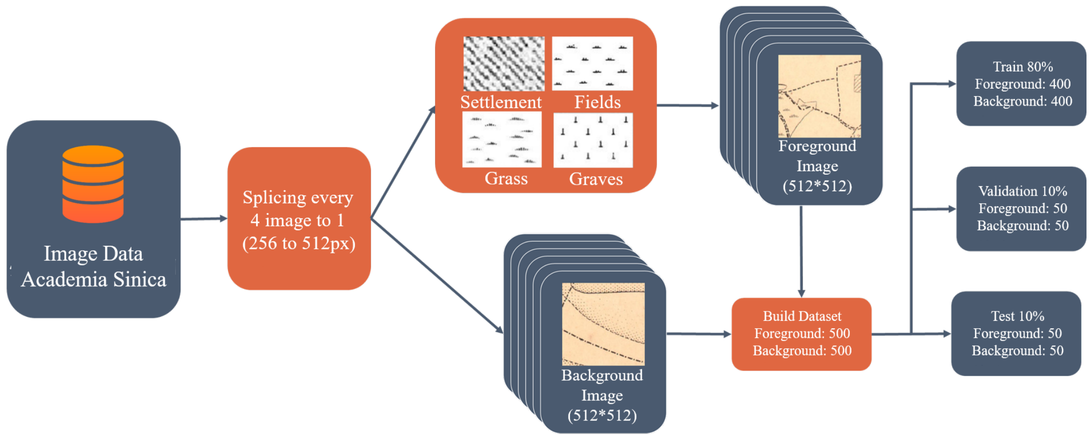


Fig. 2. Research Workflow Diagram

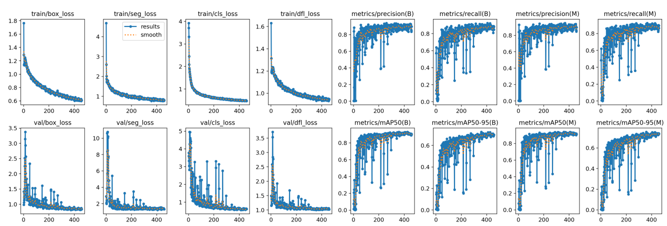


Fig. 5. Training Metrics: Loss, Precision, and Recall vs. Epochs

B. Test Set Evaluation

The evaluation results on the test set are presented in Table I. The model achieved an overall Box Precision (P) of 0.86, Box Recall (R) of 0.88, and a Box mAP50 of 0.90. For segmentation masks, the Precision was 0.86, Recall 0.88, and mAP50 0.90. Performance was consistent across all four categories (settlements, fields, grasslands, cemeteries), indicating high stability and generalization capability.

TABLE I
TEST SET RESULTS BY CLASS

Class	Count	Bounding Box			Mask		
		P	R	mAP50	P	R	mAP50
All	186	0.86	0.88	0.90	0.86	0.88	0.90
Settlements	62	0.82	0.86	0.85	0.81	0.84	0.84
Fields	58	0.79	0.86	0.85	0.82	0.90	0.88
Grasslands	26	0.96	0.87	0.97	0.91	0.82	0.92
Cemeteries	40	0.87	0.93	0.93	0.90	0.95	0.95

Qualitative results (Figs. 6 and 7) show that the model's predictions align closely with ground truth labels. While minor overlaps and confusion exist in complex areas, the low variance between predicted and labeled data suggests minimal overfitting.

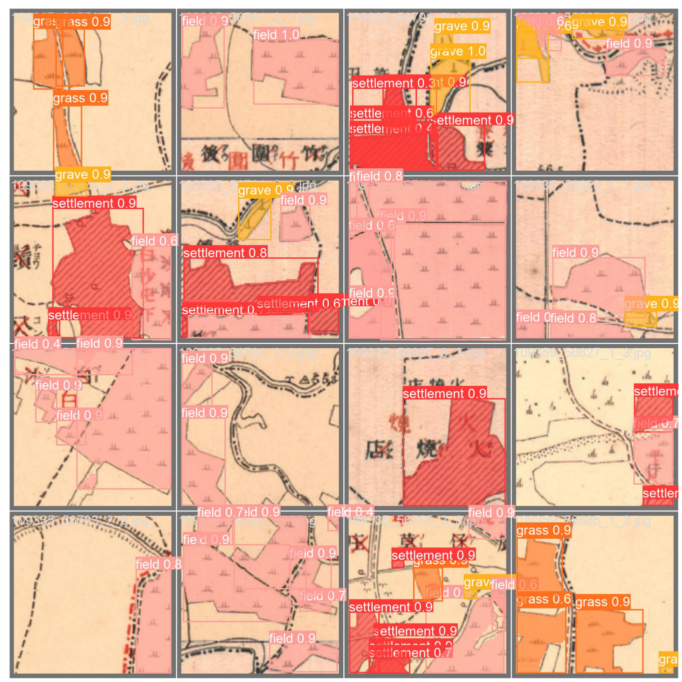


Fig. 6. Ground Truth (Labeled) Test Set Image

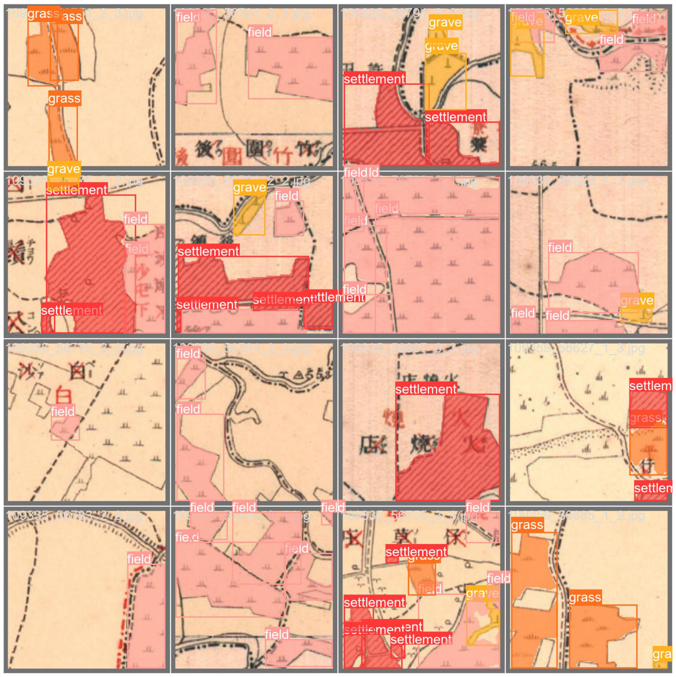


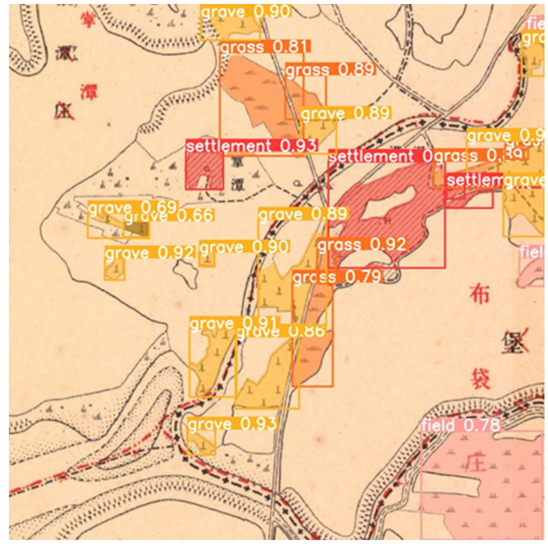
Fig. 7. Model Predicted Test Set Image

IV. Conclusion and Future Work

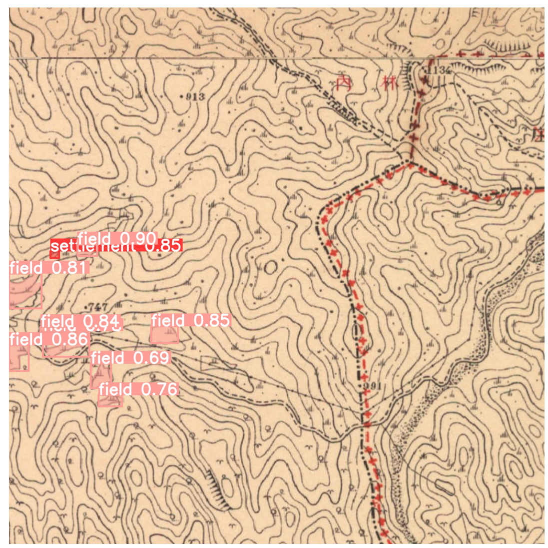
This study demonstrates that a YOLOv8-Seg model trained on settlements, fields, grasslands, and cemeteries can achieve nearly 90% accuracy in boundary detection for the Historical Map of Taiwan. The inclusion of background images effectively reduced false positives, proving that the proposed data augmentation strategy is sufficient for handling diverse cartographic features.

Future work will address three limitations:

1) **Data Diversity:** Current models struggle in mountainous regions with dense contour lines. We plan to expand annotations to include these complex terrains and increase image input size (Fig. 8) to better capture feature contours.
2) **Category Expansion:** We aim to extend the model to recognize forests, tea plantations, and water bodies.
3) **Hybrid Approaches:** For features lacking clear contours (e.g., specific forest types), we plan to combine YOLOv8 object detection with geometric algorithms like Voronoi diagrams (Thiessen polygons) for efficient point-to-surface vectorization.



(a) Correct Boxes, Incomplete Masks



(b) Complex Mountainous Areas

Fig. 8. Prediction analysis on upscaled images (4x size)

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