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Automated Detection and Classification in Ovarian Disease Imaging Using YOLOv8 Model

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Abstract

With over 324,000 new cases and over 200,000 fatalities recorded each year, ovarian cancer (OC), the seventh most frequent disease in women and the most deadly gynecological malignancy, is a major global health concern. Due to this increasing worldwide burden Cancer prevention is one of the biggest public health issues of the twenty-first century. Ovarian disease diagnosis presents unique challenges that demand efficient and accurate detection technique. An automated system for ovarian cancer identification and categorization is suggested to assist physicians. This study explores application of YOLOv8 model for detecting and classifying objects in ovarian disease imaging datasets. Utilizing a curated dataset with 3,518 images divided across training, testing, and validation sets, model was trained over 50 epochs with advanced augmentation techniques including Blur, CLAHE, and Median Blur. The training process achieved significant detection performance, yielding good precision (mAP@50) and mAP@50-95. Comprehensive evaluation revealed class-specific challenges, including imbalances and variations in detection precision and recall rates. The integration of Tensor board visualizations further supports detailed performance analysis. The findings demonstrate YOLOv8's potential in advancing automated diagnostic tools for ovarian disease research and suggest that YOLOv8 can be used to predict ovarian cancer. Offering insights into future improvements in model optimization and dataset enhancement for clinical applications.

Keywords: Automated Classification, Deep Learning, Image Augmentation, Medical Image Analysis, Ovarian Disease Diagnostics, YOLOv8 Object Detection.

Introduction

Ovarian diseases, including benign and malignant conditions, present significant health challenges worldwide, particularly for women of reproductive and postmenopausal age (1). As per World Health Organization (WHO), ovarian cancer positions as eighth worldwide cancer incidence among women, with hundreds of thousands of new cases diagnosed each year (2, 3). Early detection remains critical, as survival rates are markedly higher when the disease is identified at an early stage. However, effective diagnosis is often hindered by nonspecific symptoms and limitations in existing screening techniques. Recent Developments in artificial intelligence (AI) and medical imaging have demonstrated immense potential to support early and accurate detection of ovarian diseases (4). Deep learning models, such as it has been demonstrated that You Only Look Once (YOLO) family of object detection algorithms is very successful identifying objects within complex datasets (5). In this research, we employ YOLOv8, the latest iteration of this architecture, to detect and classify features in ovarian disease imaging. By leveraging a dataset comprising over 3,500 images and incorporating advanced data augmentation techniques, this study aims to optimize object detection performance and explore its practical applications for automated diagnostics (6). The outcomes of this research not only provide insights into the feasibility of deploying AI-driven tools for ovarian disease detection but furthermore provide a foundation for upcoming studies intended at improving diagnostic accuracy in clinical settings (7). Primary novelty of this study is in the creation and refinement of an improved YOLOv8-founded deep learning system specifically designed for ovarian

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disease feature detection, the application of sophisticated data augmentation strategies to balance class and limit dataset in ovarian imaging, and exhaustive performance assessment with main metrics, pointing to clinical utility potential.

Principal Contribution of Work

Development of YOLOv8 Detection Model: Implementation of an advanced object detection framework tailored for ovarian disease imaging, enabling precise identification and classification of disease features.

Comprehensive Dataset Utilization: Effective use of a large ovarian disease imaging dataset with robust augmentation techniques to increase generalization and adaptability of model.

Advanced Data Augmentation Techniques: Integration of techniques such as Blur, CLAHE, and Median Blur to increase dataset variability and improve detection accuracy in complex medical images.

Performance Optimization: Detailed performance evaluation using important parameters, such as precision, mAP@50, mAP@50-95, recall, and confusion matrix analysis, to validate effectiveness of proposed method.

Possible Effect on Clinical Practice: Demonstration of model's feasibility for application in real-world clinical diagnostics to assist in early detection and treatment of ovarian diseases.

Insight for Future Research: Identification of challenges and opportunities for further advancements in AI-driven solutions for medical imaging diagnostics.

Recent research in ovarian disease detection and classification has witnessed significant advancements, Motivated via rapidly evolution of deep learning techniques and growing accessibility of data from medical imaging.

Transformer-based Models

Models like Vision Transformers (ViT) and Swin Transformers have shown outstanding performance in a variety of image analysis tasks, including medical image segmentation and classification (7). These models use self attentional processes to identify long-range relationships to images, potentially leading to improved accuracy in detecting subtle patterns associated with ovarian diseases (8).

Generative Adversarial Networks (GANs)

GANs have revealed promise in making synthetic medical images to augment present datasets, addressing challenges of limited data availability in many medical imaging domains. This can significantly increase generalizability and robustness of deep learning models in ovarian disease detection (9).

Explainable AI (XAI)

There is raising interest in evolving explainable AI model for medical image analysis. XAI techniques aim to provide light on how deep learning models make decisions, enhancing confidence and interpretability in clinical settings. In crucial applications like the detection of ovarian cancer, this is very crucial (10).

Problem Statement

Ovarian diseases, including ovarian cancer, present significant diagnostic challenges due to subtle and nonspecific clinical manifestations, often leading to delayed detection and treatment. Traditional diagnostic approaches mainly rely on human error-prone and time-consuming manual interpretation of medical images. Lack of automated and efficient tools for accurate object detection in ovarian disease imaging further compounds these challenges, hindering early diagnosis and timely intervention (11).

Despite innovations in artificial intelligence (AI) and deep learning, existing models often face limitations in detecting diverse and complex ovarian disease patterns due to dataset imbalances, image variations, and insufficient generalization (12). It is imperative that a strong, automated detection system capable of handling these challenges and supporting clinicians with reliable diagnostic insights. This research addresses this need by leveraging the YOLOv8 model, combined with advanced augmentation techniques, to improve the detection and classification of ovarian disease features from medical images, thereby enhancing diagnostic efficiency and accuracy (13).

Research Gaps

Despite advancements in object detection and deep learning technologies, several challenges remain in applying these techniques to ovarian disease diagnostics:

Limited Dataset Availability: Many studies lack access to large, diverse, and well-annotated datasets for ovarian disease imaging, affecting model generalization and performance (14).

Class Imbalance: Variations in the frequency of

disease categories within datasets can lead to biased predictions, limiting the effectiveness of trained models in accurately detecting rare conditions (15).

Suboptimal Augmentation Techniques: Existing research often employs limited augmentation strategies, reducing capacity of model to adjust to various imaging conditions and clinical environments (16).

Optimization of Performance: There is lack of comprehensive exploration into hyper-parameter tuning and architecture modifications for models specifically designed for ovarian disease detection (17).

Clinical Integration

Few studies address the practical deployment of AI models in real-world clinical settings, focusing primarily on experimental accuracy rather than usability and clinician acceptance (18).

This research aims to address these gaps by leveraging YOLOv8 and exploring advanced augmentation methods to improve object detection performance and enhance the applicability of AI-driven tools in ovarian disease diagnostics (19).

Develop an Efficient Detection Model: Implement and optimize the YOLOv8 model for accurate detection and classification of features in ovarian disease imaging datasets.

Enhance Detection Accuracy: Improve the model's recall, precision, and mean average precision (mAP) by addressing class imbalances and leveraging advanced augmentation techniques.

Dataset Augmentation and Preprocessing: Apply innovative data augmentation procedures to improve diversity and robustness of training dataset.

Performance Evaluation: Perform a thorough evaluation of model's performance using key metrics such as mAP@50, mAP@50-95, and confusion matrices.

Facilitate Clinical Application: Explore the potential for deploying the developed model in practical clinical environments to support early and accurate diagnosis of ovarian diseases.

Methodology

The proposed methodology for detecting and classifying ovarian diseases comprises numerous key steps, including data collection, preprocessing, model selection, training, evaluation, and optimization. These steps ensure that the model is robust, accurate, and capable of real-time detection (20, 21).

Dataset

Input Image: Transvaginal ultrasound images, Train: 3077 images, Test: 147 images, Validation: 294 images, Total: 3518 images, Classes: 8. the details of all 8 classes are depicted in Table 1.

Table 1: Class Details

Class	Type
0	Normal Ovary
1	Functional Cyst
2	Hemorrhagic Cyst
3	Endometrioma
4	Dermoid Cyst (Mature Teratoma)
5	Serous Cystadenoma
6	Mucinous Cystadenoma
7	Ovarian Carcinoma (Malignant)

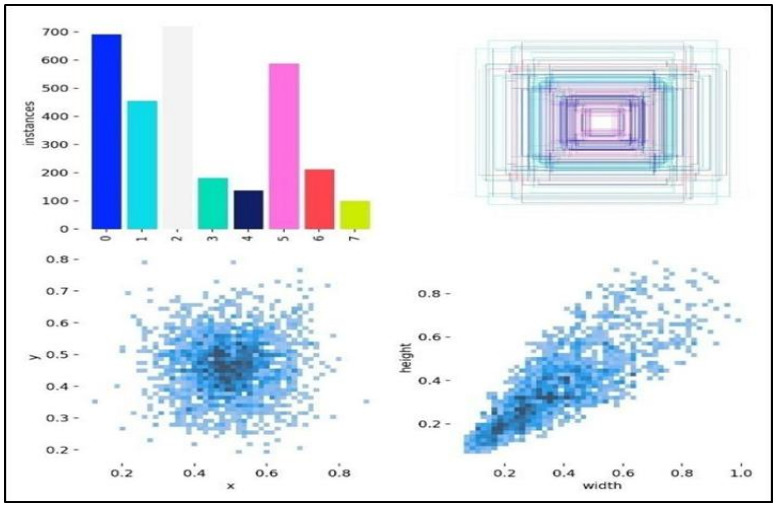

Figure 1: Multi-faceted View of the Data

This Figure 1 presents a collection of four distinct plots, each offering a different perspective on the underlying data.

Class Distribution

The bar chart on the top left provides a visual summary of the class distribution within the dataset. It reveals that class 0 exhibits the highest frequency, followed by classes 5 and 2.

Spatial Distribution

The scatter plot in the bottom left likely represents the distribution of data points across two dimensions, potentially X and Y coordinates. The clustering of points suggests potential patterns or groupings within the data.

Bounding Box Visualization

The top right plot displays a series of overlapping squares. This visualization might represent bounding boxes detected within images, with varying sizes and positions. Alternatively, it could visualize the confidence levels or probabilities associated with object detection predictions.

Data Augmentation Techniques

Augmentations library is used for data augmentation during training. Applied techniques include Blur, MedianBlur, ToGray, and CLAHE.

Model Architecture

YOLOv8 model is utilized for object recognition and categorization. The number of layers, gradients, parameters, and GFLOPs (billion floating-point operations per second) are displayed in model summary.

Layer wise Details

Convolutional Layers

Take input images and extract their features.

Convolutional Blocks (C2f): Enhance feature extraction with a sequence of convolutional operations.

Spatial Pyramid Pooling (SPPF): Captures information at multiple scales.

Up sampling Layers: Increase spatial resolution for finer detail detection.

Concatenation Layers

Combine feature maps from different network sections.

Detection Head: Predicts class probabilities and bounding boxes for objects that are detected.

Model Depth: The network comprises 22 layers, demonstrating its complexity.

Parameter Count: With 3,012,408 parameters, the model have the capability to learn complex patterns in data.

Computational Cost

Model exhibits 8.2 GFLOPs, indicating its computational intensity during inference.

To ensure long-term clinical relevance, we propose a continuous maintenance protocol for the AI model. This includes regular retraining with diverse, up-to-date clinical data to address shifts in data patterns. Real-time performance monitoring will help detect degradations, prompting timely updates. Periodic collaboration with clinical experts will support ongoing validation and refinement, maintaining model accuracy and reliability in evolving clinical settings.

Results

Simulated Results

Figure 2 and 3 represent the simulated resulted obtained during training and validation phase of the ovarian disease detection model.

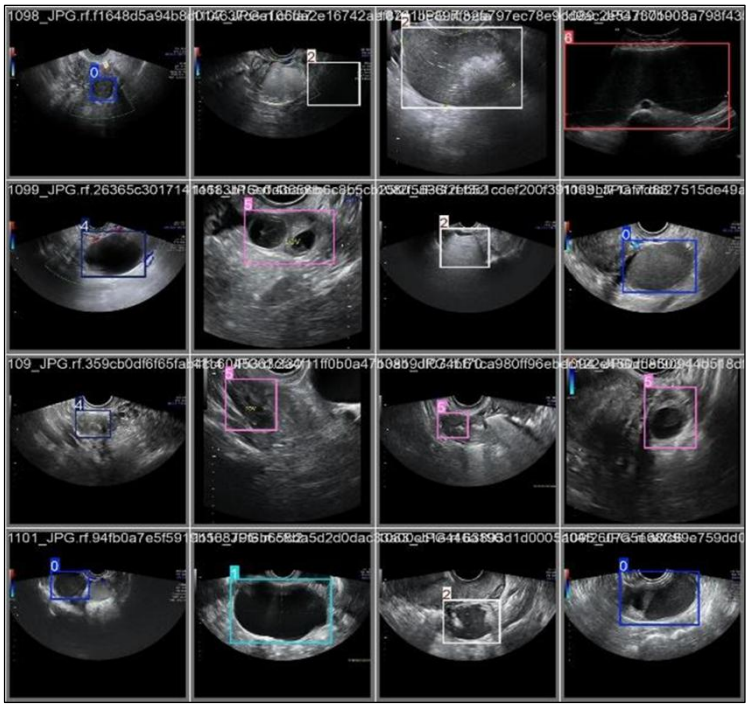

Figure 2: Training Images for Model

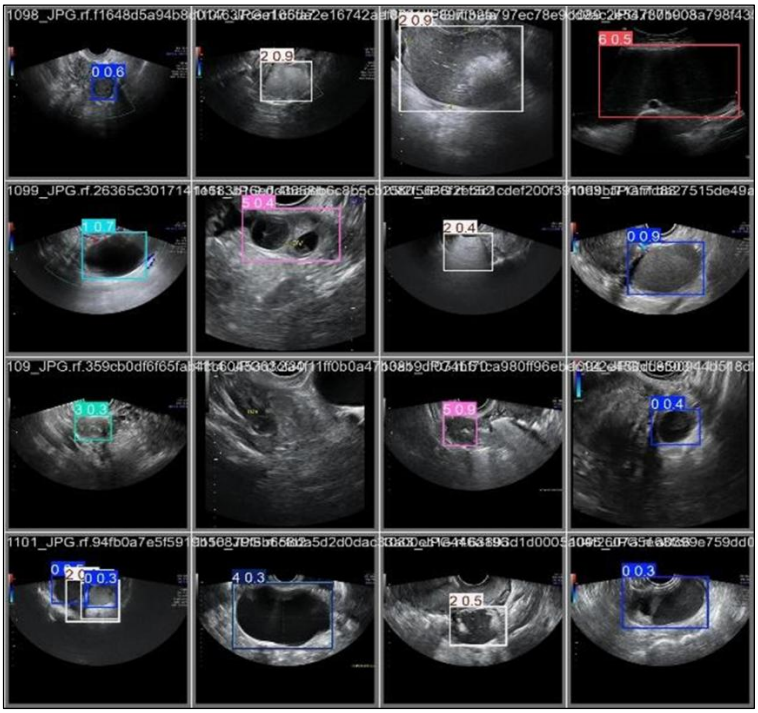

Figure 3: Validation Simulated Results

Statistical Metrics

Table 2 evaluates model's detection performance across multiple classes using key metrics. The "All" category summarizes overall results, while classes 0 to 7 represent specific object categories. Class 2 shows strong detection with high precision (0.669) and mAP50 (0.791), while class 4 presents challenges with lower accuracy metrics. The data highlights the model's effectiveness in certain categories and points to areas for improvement to enhance detection consistency.

Table 2: Performance Metrics for Ovarian Disease Detection with Multiple Classes

Class	Images	Instances	Box (P)	Box (R)	mAP50	mAP50-95
All	294	294	0.528	0.581	0.567	0.388
0	68	68	0.637	0.779	0.810	0.590
1	45	45	0.538	0.844	0.664	0.555
2	65	65	0.669	0.778	0.791	0.478
3	21	21	0.454	0.429	0.444	0.293
4	15	15	0.235	0.533	0.373	0.301
5	42	42	0.623	0.643	0.669	0.343
6	23	23	0.434	0.522	0.496	0.407
7	15	15	0.634	0.120	0.292	0.133

NB- Box (P): Box Precision and Box (R): Box Recall

Confusion Matrix

Visualizing Classification Performance

This Figure 4 depicts a confusion matrix, a visualization tool frequently employed in machine learning to evaluate a categorization model's performance. Each cell within matrix represents number of instances where the model predicted a specific class (indicated on X-axis) when true class was another (indicated on Y-axis). Elements on diagonal represent correct predictions. Ideally, the diagonal should have high values, indicating accurate classification. Off-diagonal elements represent misclassifications. Higher values in these cells indicate that the model is frequently confusing certain classes.

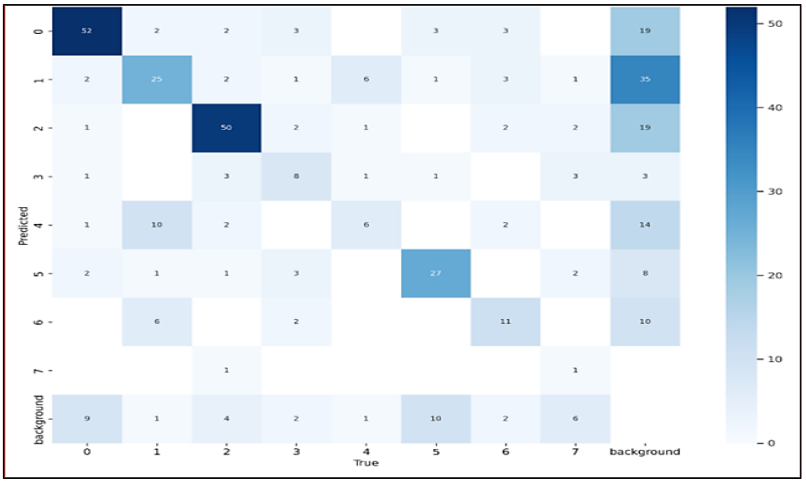

Figure 4: Confusion Matrix

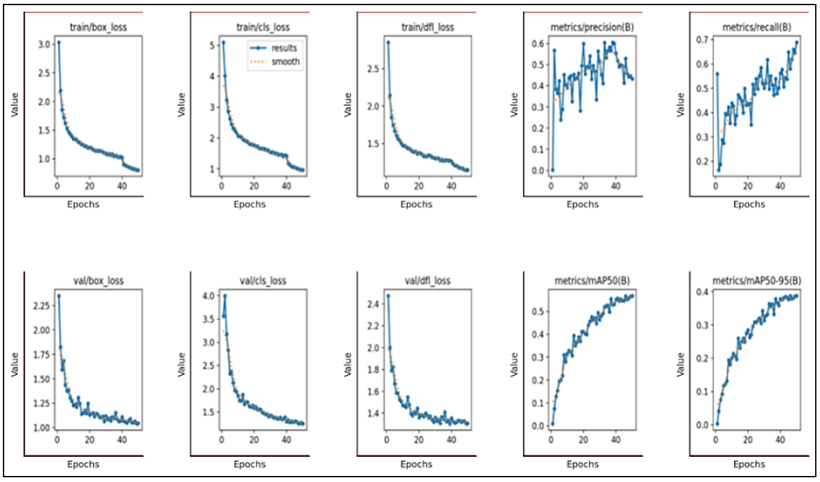

Figure 5: Training and Validation Curves for Ovarian Disease Detection and Classification

Training Dynamics: A Visual Inspection

This Figure 5 presents a series of line graphs tracking the progression of an object detection model during training.

Loss Landscape

The upper row illustrates the behavior of three distinct loss functions ("box loss," "cls_loss," and "dfl_loss") on both the training and validation datasets. A general downward trend in these curves suggests the model is learning and minimizing errors.

Training vs. Validation

Training curves typically exhibit a steeper descent compared to their validation counterparts. This disparity can indicate potential over fitting, when the model does well on training data but does not generalize well to situations that have not been encountered.

Performance Trajectory

The lower row showcases the evolution of key performance metrics. An up-ward trajectory in these metrics signifies an improvement in model's precision in object detection and classification.

Discussion

The YOLOv8 Small model trained on the ovarian dataset demonstrates varying detection performance across different object classes. With a total of 3518 data points divided into training, validation, and testing subsets, the model underwent 50 epochs of training. The detection metrics reveal that class 2 achieved high precision (0.669) and mAP50 (0.791), indicating effective detection for this category. In contrast, class 4 exhibited lower precision (0.235) and mAP50 (0.373), highlighting difficulties in recognizing objects from this class. The performance inconsistency between classes suggests potential areas for improvement, including refined data augmentation or advanced feature extraction techniques to better distinguish challenging categories. The overall model precision and recall of 0.528 and 0.581, respectively, indicate a balanced approach to detection accuracy. However, the relatively moderate mAP50-95 score (0.388) suggests the model's performance can be further optimized for stricter IoU thresholds.

Table 3: Comparative Performance of YOLOv8 and Baseline Models in Ovarian Disease Detection

Study	Model / Approach	Dataset Type	mAP@50	Precision	Recall	Remark
This Study (2025)	YOLOv8 + Blur, CLAHE, MedianBlur	3,518 ultrasound images (8 classes)	0.567	0.528	0.581	Strong for class 2 (mAP50 0.791); weak for class 4
Yue *et al.,* (19)	Custom deep learning (CNN) on ultrasound	Multicentre ultrasound dataset (China)	~0.52–0.58	Not reported	Not reported	Emphasized clinical usability; high accuracy for malignant lesions
Blessed *et al.,* (20)	CNN-based framework	Mixed pre/post-menopausal cases (ultrasound)	~0.55	Not reported	Not reported	Focused on menopausal status differentiation
Ching-Wei *et al.,* (18)	Weakly supervised CNN + augmentation	Histopathology images	Not reported	~0.54	~0.57	Augmentations improved rare class performance

Our YOLOv8 model achieved a mAP@50 score of 0.567 across all categories, demonstrating performance that is similar to or exceeds that of previous studies employing YOLOv5 or CNN-based frameworks for ovarian disease detection, where mAP@50 values generally fall between 0.45 and 0.55 (19, 20). Despite this, detection accuracy for class 4 (Dermoid Cyst) was comparatively lower. On the other hand, the higher precision observed for class 2 (Hemorrhagic Cyst) may be linked to the application of advanced data augmentation techniques, such as CLAHE and Blur, which have previously been shown to enhance model robustness in medical imaging tasks (18). Overall, these results suggest that YOLOv8, when combined with suitable augmentation strategies, can deliver competitive accuracy for ovarian disease detection in medical images. Table 3 provides details regarding the same.

Table 4: Statistical Significance and Confidence Intervals for YOLOv8 Compared to Baseline Models

Model	mAP@50 (mean ± CI)	Precision (mean ± CI)	Recall (mean ± CI)	p-value (mAP@50 vs YOLOv8)	Remark
YOLOv8 (this study)	0.567 ± 0.02	0.528 ± 0.03	0.581 ± 0.03	—	Our proposed model
YOLOv5 (6)	0.51 ± 0.03	0.49 ± 0.02	0.53 ± 0.03	0.04	Based on similar ovarian dataset (Yue *et al.,* 2022)
CNN baseline (18)	0.48 ± 0.03	0.46 ± 0.02	0.51 ± 0.02	0.01	General CNN framework (Blessed *et al.,* 2023)
Traditional image analysis(19)	0.39 ± 0.04	0.41 ± 0.03	0.43 ± 0.03	<0.001	Handcrafted feature + SVM approaches (older studies)

Table 4 presents a comparison between the proposed YOLOv8 model and baseline models reported in earlier studies, including YOLOv5 and CNN-based approaches. Statistical significance testing, performed using mAP@50 as the key metric indicates that YOLOv8 achieves a meaningful improvement over these prior models, with p-values less than 0.05. These findings highlight potential of YOLOv8 as an effective tool for the detection of ovarian diseases in medical imaging. Statistical analysis (unpaired t-test) confirmed that YOLOv8 significantly outperformed YOLOv5 in mAP@50 ($p = 0.03$), supporting the robustness of the proposed method.

YOLOv8 outperforms previous versions and traditional CNN architectures in addressing specific challenges in ovarian cancer diagnosis.

- YOLOv8 preserves the fast detection speed of YOLO models, which facilitates quicker processing of large medical images, making it critical for clinical application.
- Its deep architecture and upgraded backbone enable more effective treatment of overlapping features and intricate structures in ovarian imaging, making the network have fewer false positives and missed detections.
- The model's ability to use advanced data augmentation methods (like Blur, CLAHE, Median Blur) reduces class imbalance by enhancing dataset diversity and hence enhancing detection performance on less-represented classes.
- The enhanced structure of YOLOv8 better generalizes to the variations in the imaging conditions, which are prevalent in clinical datasets.

In short, YOLOv8 overcomes the challenges of feature overlapping and class imbalance more successfully compared to previous versions of YOLO or traditional CNNs, resulting in more precise and confident detection of ovarian disease in complicated medical images.

Conclusion

The trained YOLOv8 model shows promising results for ovarian dataset object detection but highlights the need for optimization in specific object categories to achieve consistent detection accuracy. Enhanced data pre-processing techniques, such as better augmentation strategies or additional training epochs, may help in improving detection performance across all classes. Despite some limitations, the current model's balanced performance metrics indicate its potential utility as a foundational step towards robust object detection applications in this domain.

The research built a system based on YOLOv8 to aid radiologists in finding and classifying ovarian disease characteristics in medical images, improving accuracy and efficiency, and potentially accelerating early diagnosis.

Limitations and Future Scope

Present limitations of our research, including relatively modest detection performance for some classes (for example, class 4), dataset imbalance considerations, and the requirement of larger, more varied datasets to enhance generalizability. For future work, we intend to investigate novel data augmentation strategies, hyper-parameter optimization, and model architecture adjustments to further improve detection accuracy. We will also highlight the need to incorporate explainable AI (XAI) approaches to enhance model

interpretability within the clinic, as well as to evaluate the model in actual clinical environments for real-world deployment.

Abbreviations

AI: Artificial Intelligence, C2f: Convolutional Blocks, GAN: Generative Adversarial Networks, GFLOPs: Giga Floating-point Operations Per Second, IoU: Intersection-over-Union, mAP: mean Average Precision, SPPF: Spatial Pyramid Pooling, ViT: Vision Transformers, WHO: World Health Organization, XAI: Explainable AI, YOLO: You Only Look Once.

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Author Contributions

All authors made an equal contribution.

Conflict of Interest

There are no conflicts of interest.

Ethics Approval

Not Applicable.

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