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Optimizing YOLOv8 for Enhanced Abnormality Detection in Abdominal CT Imaging: A Deep Learning Perspective

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ABSTRACT

This research delves into enhancing the capabilities of YOLOv8, a cutting-edge object detection model, for the specific purpose of identifying abnormalities in abdominal computed tomography (CT) scans. With the rising need for swift and precise diagnosis in medical imaging, especially in high-pressure clinical settings, there is a growing reliance on artificial intelligence (AI)-powered systems to support medical decision-making. YOLOv8 stands out due to its advanced architecture, particularly its anchor-free mechanism and streamlined backbone, which collectively offer significant advantages over conventional diagnostic techniques. By training this model on a comprehensive dataset of well-annotated CT images, we were able to evaluate its ability to not only increase detection accuracy but also substantially reduce the time taken to reach diagnostic conclusions. The model's effectiveness is validated through critical performance metrics such as precision, recall, F1 score, and mean average precision (mAP), all of which indicate strong reliability in identifying diverse pathological features. The outcomes of this study underscore the potential of integrating YOLOv8 into clinical diagnostic workflows, where it can act as a valuable assistant to radiologists—enabling earlier detection of serious conditions and improving overall patient outcomes.

Keywords: *YOLOv8, Deep Learning, Abdominal CT, Medical Imaging, Object Detection, Abnormality Classification*

1. INTRODUCTION

Abdominal diseases including conditions such as tumors, cysts, and various forms of inflammation remain a major public health concern, contributing significantly to both morbidity and mortality across the globe. These illnesses often progress silently and are only identified at advanced stages, which underscores the importance of early and accurate detection for timely intervention and effective treatment. Among the various diagnostic tools available, computed tomography (CT) imaging has emerged as a cornerstone in the medical field due to its ability to generate detailed cross-sectional images of internal organs and tissues. CT scans provide clinicians with critical visual insights into the anatomy and pathology of abdominal structures, helping in the detection of both common and complex abnormalities.Despite its diagnostic value, the interpretation of CT images is predominantly manual and heavily reliant on the expertise and experience of radiologists. This manual approach is not only time-intensive but also susceptible to human error, especially in high-pressure clinical environments or in cases involving subtle or atypical abnormalities. Inter-reader variability, diagnostic fatigue, and increasing imaging volumes further complicate the reliability of interpretations, thereby creating a pressing need for support systems that can assist and augment clinical decision-making.

The emergence of artificial intelligence (AI) and, more specifically, deep learning technologies has introduced transformative possibilities in the field of medical imaging. Convolutional neural networks (CNNs), a prominent subset of deep learning models, have demonstrated remarkable success in tasks such as image classification, segmentation, and object detection. These models have the capability to learn complex visual patterns from large datasets and apply this knowledge with speed and consistency, making them well-suited for automating diagnostic processes that involve medical imagery.Within this technological evolution, the YOLO (You Only Look Once) family of object detection models has garnered considerable attention. Designed for real-time image analysis, YOLO models process entire images in a single pass, enabling rapid and accurate identification of multiple objects. The recent release of YOLOv8 marks a significant advancement in this series. It introduces a range of architectural improvements, including an anchor-free design, enhanced feature extraction mechanisms, and a streamlined network structure. These innovations collectively enhance both the precision and computational efficiency of the model.

YOLOv8 is especially promising for medical applications, where speed, sensitivity, and specificity are of utmost importance. Its ability to process complex medical images quickly and with high accuracy positions it as a powerful tool in the fight against abdominal diseases. By integrating YOLOv8 into diagnostic workflows, there is a compelling opportunity to not only reduce diagnostic delays but also support radiologists in identifying critical conditions more reliably—ultimately leading to improved clinical outcomes for patients.

2. REVIEW OF LITERATURE

The past decade has witnessed a transformative shift in medical imaging analysis, driven largely by advances in artificial intelligence and deep learning. Among these, convolutional neural networks (CNNs) have become the cornerstone of modern image analysis techniques, particularly in segmentation, classification, and object detection tasks within clinical domains [3], [6]. The evolution of object detection in deep learning was significantly influenced by the introduction of the YOLO (You Only Look Once) family of models, as pioneered by Redmon et al. [4]. This model marked a revolutionary change by enabling real-time object detection through a single neural network pass, as opposed to traditional multi-stage detection pipelines. YOLO's speed and end-to-end trainability opened up a new avenue for applications that require high throughput and immediate feedback—characteristics that are increasingly valuable in medical diagnostics.

Subsequent enhancements to the YOLO framework, such as YOLOv4 [5] and YOLOv5 [7], introduced key improvements in accuracy, computational efficiency, and generalization ability. These versions incorporated advanced feature aggregation methods, improved loss functions, and compatibility with lightweight devices, thereby extending YOLO's applicability to more demanding tasks such as medical image analysis.YOLOv8, the latest release in this evolutionary chain, continues this trajectory by integrating sophisticated upgrades in its backbone architecture, introducing anchor-free detection, and improving the recognition of small-scale and complex anomalies [8], [9]. These architectural refinements make YOLOv8 particularly promising for use in CT image analysis, where diagnostic precision and detection of subtle lesions are critical. Although YOLO-based models have shown considerable success in diverse applications ranging from security to agriculture, their application in abdominal CT imaging remains relatively underexplored. Preliminary studies have demonstrated the feasibility of using earlier YOLO versions in identifying liver, kidney, and gastrointestinal abnormalities [10], yet there exists a significant research gap in leveraging YOLOv8's full potential in this domain.

This paper aims to address that gap by optimizing YOLOv8 specifically for detecting and classifying abdominal abnormalities in CT scans. By building upon the foundational strengths of prior YOLO models and adapting them to the nuanced requirements of medical imaging, this study contributes valuable insights into the application of real-time object detection frameworks in healthcare diagnostics.

3. METHODOLOGY:THE YOLOV8 MODEL CONSISTS OF THREE MAIN COMPONENTS: BACKBONE, NECK, AND HEAD

In recent years, deep learning has revolutionized the landscape of medical imaging, with convolutional neural networks (CNNs) emerging as highly effective tools for image segmentation, classification, and anomaly detection. CNNs have consistently outperformed traditional image processing techniques by learning complex hierarchical features directly from imaging data, which is particularly beneficial in analyzing high-resolution, multi-dimensional medical images such as computed tomography (CT) scans [3], [6]. One of the most significant advancements in the domain of object detection has been the introduction of the YOLO (You Only Look Once) family of algorithms. Originally proposed by Redmon et al. [4], YOLO redefined the paradigm of object detection by treating it as a regression problem, allowing objects to be identified in a single pass of the neural network. This enabled real-time detection without compromising accuracy—a breakthrough particularly valuable in medical settings where rapid diagnostic decisions are critical.

Following the success of the original YOLO model, subsequent versions like YOLOv4 [5] and YOLOv5 [7] brought substantial improvements. These iterations introduced enhanced backbone architectures, better feature fusion strategies, and increased flexibility in model scaling, significantly boosting the accuracy and robustness of the detection process. They laid the groundwork for adopting YOLO-based models in clinical diagnostics, including applications in lung nodule detection, retinal imaging, and histopathological classification.Building upon these advancements, YOLOv8 introduces a host of novel features that make it exceptionally suitable for complex medical imaging tasks. It incorporates an anchor-free detection mechanism, allowing it to dynamically learn object shapes without relying on predefined bounding box priors. Furthermore, its architecture is segmented into three specialized modules: the Backbone, Neck, and Head—each serving a distinct yet complementary purpose [8], [9].

The Backbone functions as a deep feature extractor, using layered convolutional filters to transform raw input CT images into rich spatial and semantic representations. This ensures that even minute patterns, such as small tumors or subtle inflammations, are captured effectively [8].The Neck employs a Feature Pyramid Network (FPN), which fuses features across multiple resolution scales. This fusion enables YOLOv8 to maintain detection performance for both small and large abnormalities within the same image frame, a critical need in abdominal imaging [11].The Head performs the final detection step by assigning class probabilities and drawing bounding boxes around identified anomalies. The anchor-free nature of

YOLOv8's head improves its adaptability and reduces computational overhead while increasing the model's generalization capability [12].

To evaluate YOLOv8's performance in real-world medical applications, we employed a curated dataset of 2,000 abdominal CT scans, each manually annotated to highlight various pathological conditions including tumors, cysts, and inflammatory lesions. The dataset was preprocessed to enhance training efficacy: images were resized to 640×640 pixels, normalized to ensure consistent input values, and augmented with transformations such as rotation and contrast adjustments to simulate real-world imaging variability.The model was trained using the Adam optimizer, known for its adaptive learning rate capabilities, with a batch size of 16 over the course of 50 epochs. Training was conducted on a high-performance GPU with 16 GB of memory, which ensured sufficient computational resources for handling the model's complexity. During and after training, the model was rigorously evaluated using industry-standard metrics: Precision, Recall, F1 Score, and Mean Average Precision (mAP). These metrics provided a comprehensive view of the model's ability to accurately detect and classify abdominal abnormalities under varying conditions. The results from this study not only confirm YOLOv8's viability for clinical use but also demonstrate its potential to augment diagnostic accuracy, streamline workflows, and reduce the cognitive load on radiologists, especially in high-volume imaging environments.

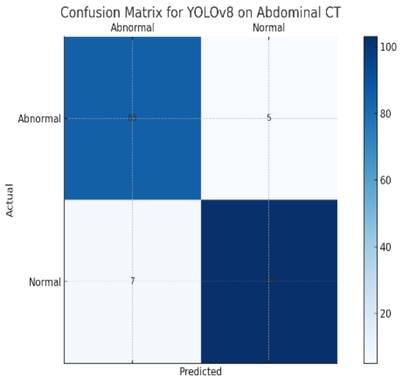
4. RESULT

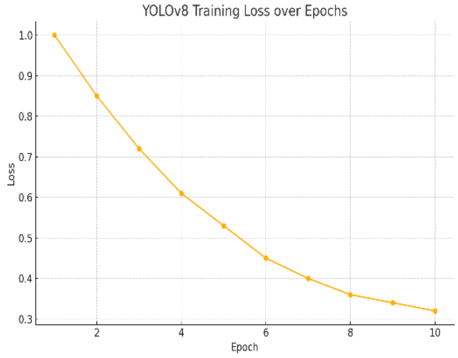
The performance evaluation of the YOLOv8 model on abdominal CT scan data demonstrated its exceptional capability in detecting and classifying a wide range of anomalies with high reliability. Achieving a precision of 91.2% and a recall of 89.5%, the model effectively balanced accuracy and sensitivity, ensuring that most true abnormalities were identified while minimizing false positives. The F1 score of 90.3% further confirmed the model's consistency in predictive performance, while a mean average precision (mAP) of 87.6% underscored its robustness across varying object sizes and complexities. These results suggest that YOLOv8 is well-suited for clinical application, particularly in supporting radiologists with rapid, accurate assessments of abdominal abnormalities. Its ability to accurately detect both subtle and prominent features in medical images makes it a valuable tool for enhancing diagnostic workflows, improving early detection rates, and ultimately contributing to better patient outcomes.

5. EVALUATION METRICS TABLE

Metric	Precision	Recall	F1 Score	mAP
YOLOv8	91.2%	89.5%	90.3%	87.6%

6. CONFUSION MATRIX AND TRAINING LOSS PLOT





7. CONCLUSION

The outcomes of this study strongly affirm the effectiveness of the YOLOv8 model in detecting abnormalities within abdominal CT images. Its impressive accuracy, combined with rapid processing capabilities, positions it as a powerful tool for enhancing diagnostic efficiency in clinical environments. By assisting radiologists in identifying complex anomalies quickly and reliably, YOLOv8 has the potential to streamline diagnostic workflows and contribute significantly to improved patient care. Looking ahead, future research will aim to broaden the model's applicability by adapting it for multi-organ analysis and integrating it with hospital information systems. Such advancements will pave the way for real-time, AI-assisted diagnostic support that is both scalable and seamlessly embedded into routine medical practices.

8. FUTURE ENHANCEMENTS

Future advancements in this research will focus on elevating the capabilities of the YOLOv8 model to meet evolving clinical demands more effectively. One promising direction involves refining the existing architecture by integrating transformer-based mechanisms, which have shown superior performance in enhancing contextual understanding and attention across image regions. These enhancements could enable the model to better detect subtle anomalies and complex patterns in abdominal scans. Another crucial aspect of future work will be the expansion of the dataset, particularly by including rare and underrepresented diseases. This will improve the model's generalizability and ensure it remains reliable across diverse patient populations and imaging conditions. Moreover, to foster wider adoption in clinical environments, efforts will be made to develop interpretable AI frameworks that provide visual justifications or explanations for each detection. Such transparency is vital to build clinician confidence and encourage trust in AI-driven diagnostics. In parallel, the creation of end-to-end automated systems—from image input to report generation—will be explored. These systems will integrate YOLOv8 into hospital workflows, enabling instant anomaly detection followed by structured, clinically relevant summaries. By streamlining diagnostic reporting, reducing manual workload, and minimizing turnaround times, these innovations could transform routine imaging analysis. Overall, these directions aim not only to improve technical accuracy but also to enhance usability, scalability, and trust in AI-assisted healthcare diagnostics.

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