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Deep Learning-Based Detection of Abdominal Diseases Using YOLOv9 Models and Advanced Preprocessing Techniques

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ABSTRACT Artificial intelligence has emerged as a transformative tool in medical imaging, enabling automated diagnosis and analysis across various domains. While significant advancements have been made in abdominal imaging, many studies struggle to achieve robust detection of diseases. The complexity and variability in abdominal structures present unique challenges for traditional machine learning models, necessitating the adoption of more advanced object detection frameworks. Motivated by these challenges, this study focuses on leveraging the YOLOv9 object detection architecture to enhance the identification of abdominal diseases using the TEKNOFEST 2022 Abdomen Dataset. Advanced preprocessing techniques, including CLAHE (Contrast Limited Adaptive Histogram Equalization) and Gaussian noise augmentation, were applied to improve image contrast and model robustness. The dataset was processed into YOLO-compatible formats, and multiple training configurations were evaluated using YOLOv9c and YOLOv9s variants. These configurations included variations in batch size, optimizer type (SGD and Adam), dropout rate, and frozen layers. Among the configurations tested, the YOLOv9s model with 32 batch size, SGD optimizer, and a 35% dropout rate demonstrated the best performance, achieving a Recall of 0.7698, Accuracy of 0.7698, and F1 Score of 0.8228. The highest mAP50 of 0.9385 was observed with the YOLOv9c model trained using the Adam optimizer and a 35% dropout rate. Confusion matrix analysis revealed strong detection capabilities for conditions like acute cholecystitis and abdominal aortic aneurysm. This study highlights the potential of YOLOv9 models in medical imaging and emphasizes the importance of high-resolution datasets and advanced feature extraction techniques for improving diagnostic accuracy in abdominal disease detection. These findings lay a foundation for the development of reliable and efficient AI-driven diagnostic tools.

KEYWORDS
Abdominal disease detection
YOLOv9
Medical image analysis
Preprocessing techniques
Deep learning for diagnosis

INTRODUCTION

Artificial intelligence (AI) has brought about transformative changes in the diagnosis and treatment processes within the medical field. AI technologies, such as machine learning and deep learning, have significantly enhanced accuracy in medical imaging, thereby improving the efficiency of healthcare services (El-Tanani *et al.* 2025). In the analysis and processing of medical data, AI has enabled the early detection of diseases and the development of personalized treatment approaches (Shaikh *et al.* 2025). Moreover, the application of AI in genomic research has deepened the understanding of genetic disorders, offering innovative solutions in treatment strategies (Zhou *et al.* 2025; Chen *et al.* 2025).

The integration of AI into healthcare services through automated machine learning (AutoML) applications has allowed for reduced error rates and faster processing of healthcare workflows (Shujaat 2025). These advancements have not only optimized diagnostic and treatment processes but also increased the overall efficiency of healthcare systems (Donovan *et al.* 2025). Furthermore, the necessity to uphold data privacy and ethical standards in healthcare systems remains a critical priority to ensure the safe and equitable application of AI.

Abdominal diseases, which encompass pathological conditions affecting organs in the abdominal region, involve complex processes in both diagnosis and treatment. AI-based approaches offer significant opportunities to enhance accuracy, save time, and support clinical decision-making mechanisms in these processes. In particular, machine learning and deep learning techniques have demonstrated high performance in analyzing abdominal imaging data, enabling the early detection of conditions such as appendicitis, pancreatic cancer, and abdominal aortic aneurysm. Recent studies show that AI-based image processing algorithms can be utilized not only for diagnosis but also in conjunction with verification systems that ensure the security of patient data. The increasing adoption of these technologies in clinical applications facilitates more precise disease management and drives transformation in healthcare services (Zhou *et al.* 2025; Boyraz *et al.* 2022; Santos *et al.* 2024).

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Object detection algorithms have significantly advanced the field of medical diagnosis by enabling the rapid and accurate identification of diseases in medical imaging data. Deep learning-based models like YOLO have made it possible to identify thyroid nodules in ultrasound images with high accuracy (Wang *et al.* 2025). Moreover, multi-object detection algorithms have contributed to the precise differentiation of reactive lymphocytes in blood samples, playing a crucial role in the diagnosis of hematological diseases (Liu *et al.* 2025). In another study, YOLO-based deep learning models were employed to detect extrahepatic common bile duct obstruction in MRCP images, allowing for the clinical diagnosis of these complex conditions with high accuracy (Tho *et al.* 2025). Additionally, multi-scale feature fusion algorithms used in the staging of occupational diseases such as pneumoconiosis have enhanced diagnostic precision while improving the understanding of disease progression (Ren *et al.* 2025). These studies demonstrate that object detection algorithms not only improve the accuracy of image analysis but also make patient care processes more efficient.

In this study, a YOLOv9-based (Wang *et al.* 2024) object detection model was developed to enable the early and accurate detection of acute abdominal diseases using the Abdomen Dataset presented in the TEKNOFEST 2022 Artificial Intelligence in Health Competition (Koç *et al.* 2024). Detailed preprocessing steps were conducted for the dataset classes, including the enhancement of image contrast through the CLAHE method (Pisano *et al.* 1998) and the addition of noise at varying levels. The model training was performed using the s and c variants of YOLOv9 with different hyperparameter combinations. Furthermore, the model's performance was evaluated using metrics such as precision and accuracy, emphasizing the effectiveness of AI-based methods in medical image analysis.

The main contributions of this paper are as follows:

- An object detection-based model for the detection of abdominal diseases was developed using the Abdomen Dataset from the TEKNOFEST 2022 Artificial Intelligence in Health Competition.
- Image contrast was enhanced through the CLAHE method, and preprocessing techniques such as noise addition at varying levels enriched the diversity of the training data.
- The model was trained using different variants of YOLOv9 (YOLOv9s and YOLOv9c) and hyperparameter combinations, with optimization techniques analyzed in detail.
- The effects of different optimization algorithms (SGD and Adam) and hyperparameters on the classification accuracy of medical image data were thoroughly analyzed.
- The proposed method offers the potential for faster and more accurate diagnosis in medical imaging, making a significant contribution to clinical decision support systems.

The remainder of this paper is organized as follows. The Related Work section reviews previous studies utilizing object detection models for analyzing abdominal medical images and detecting related diseases. The Dataset section introduces the TEKNOFEST 2022 Abdomen Dataset, describing its class structure, annotations, and preprocessing steps. The Methodology section explains the proposed workflow in detail, including preprocessing techniques like CLAHE for enhancing image contrast and noise augmentation, along with the training steps of YOLOv9 models with varying hyperparameters. The Experiments and Results section presents quantitative evaluations of model performance, including precision, recall, and overall accuracy, f1-score across different configurations. The Discussion section interprets these results, highlights the significance of the findings, and compares the proposed approach with existing methods. Lastly, the Conclusion and Future Work section summarizes the study's contributions and provides insights into potential future developments for improving disease detection in abdominal images using advanced object detection techniques.

Object detection algorithms play a crucial role in the diagnosis and classification of abdominal diseases in medical image analysis. Ramamoorthy *et al.* (2024) employed deep learning methods for early cancer detection and ulcer classification in endoscopy videos. In this study, cancer and ulcer lesions were automatically detected. The research demonstrated that object detection models could precisely identify small and ambiguous lesions in endoscopic images. Moreover, this approach ensured the accurate classification of lesions. Maity *et al.* (2024) integrated explainable artificial intelligence (XAI) with object detection methods for the diagnosis of gastroesophageal reflux disease (GERD). The study identified different stages of the disease through segmentation and classification processes. Using object detection models, anatomical abnormalities caused by GERD were automatically detected, thereby supporting clinical decision-making processes.

Su *et al.* (2023) compared Faster RCNN, Cascade RCNN, and Mask RCNN models for the diagnosis of early gastric cancer in gastroscopic images. This study successfully detected and localized cancerous regions using object detection algorithms. The results showed that RCNN-based models achieved high accuracy rates in lesion detection in gastroscopic images. Jin *et al.* (2022) performed segmentation and detection of gastric cancer lesions in endoscopic images using the Mask RCNN model. Object detection algorithms optimized the diagnostic process by accurately identifying cancerous regions. This study demonstrated that Mask RCNN is an effective method for improving detection accuracy in endoscopic images.

In the study conducted by Koçer *et al.* (2024), the YOLOv5 algorithm was employed to detect and classify various diseases in abdominal CT images. The study was carried out on a dataset containing 11 different disease conditions from 1200 patients. The YOLOv5 algorithm demonstrated high accuracy, particularly in detecting conditions such as acute appendicitis, kidney stones, gallstones, and ureteral stones. The data were converted from DICOM format to formats required by the YOLO algorithm, making them compatible with the deep learning model. The object detection algorithm was equipped with class labels and bounding boxes to pinpoint the exact locations of disease regions. The study highlighted that YOLOv5 is a promising tool for fast and accurate diagnosis in medical imaging and can expedite diagnostic processes while reducing the workload of radiologists. These studies emphasize the significant advantages of object detection algorithms in medical image analysis, particularly in the early diagnosis and accurate classification of abdominal diseases. Models such as YOLO, RCNN, and Mask RCNN have been observed to contribute to faster and more precise diagnostic processes on abdominal images.

DATASET

In this study, the TR_ABDOMEN_RAD_EMERGENCY dataset (Koç *et al.* 2024), used in the TEKNOFEST-2022 Artificial Intelligence in Healthcare Competition, was utilized. The dataset aims to classify abdominal emergencies into six distinct categories: (i) acute cholecystitis, (ii) kidney and/or ureter stones, (iii) acute pancreatitis, (iv) abdominal aortic aneurysm/dissection/rupture, (v) acute appendicitis, and (vi) acute diverticulitis.

The dataset was collected through the infrastructure of the e-Nabız (Pulse) and National Teleradiology System (NTS) managed by the Ministry of Health of the Republic of Türkiye (Koç *et al.* 2024). DICOM-format images recorded between 2019 and 2021 underwent a centralized screening and selection process. These anonymized images were meticulously labeled by 10 radiologists with 5 to 10 years of professional experience. During the labeling process, bounding boxes were used to ensure the accurate classification of radiological data.

The dataset is divided into two distinct parts for training and competition phases:

- Training data: 1,209 cases and 357,428 images.
- Competition data: 308 cases and 98,101 images.

The distributions and detailed information for each class are presented in Table 1.

METHODOLOGY

This section outlines the methodology employed for detecting abdominal diseases using the TEKNOFEST 2022 Abdomen Dataset. The Preprocessing step focuses on enhancing the quality and contrast of medical images by applying CLAHE (Contrast Limited Adaptive Histogram Equalization), which improves visibility in low-contrast regions. To further simulate real-world variability and increase model robustness, various levels of Gaussian noise were added to the dataset. The Training Step involves utilizing the YOLOv9 model, which was trained with multiple configurations, including variations in hyperparameters such as batch size, optimizer type, and dropout rates.

Preprocessing Step

The preprocessing phase is a critical step in preparing the TEKNOFEST 2022 Abdomen Dataset for training. Several preprocessing techniques were employed to enhance the dataset and prepare it for training with the YOLOv9 model. These steps include:

- **DICOM to JPG Conversion:** The medical images in DICOM format were converted to JPG format to ensure compatibility with the YOLO framework.
- **Bounding Box Conversion:** The bounding box annotations provided in the dataset were converted to YOLO-compatible coordinates.
- **Image Resizing:** Each image was resized to a resolution of 640×640 pixels, adhering to the YOLO model's input requirements.
- **Contrast Enhancement (CLAHE):** CLAHE (Contrast Limited Adaptive Histogram Equalization) was applied to improve the visibility of critical details, especially in low-contrast regions.
- **Noise Addition:** Gaussian noise was added at varying levels to simulate real-world variability and increase model robustness. Four variations were tested: CLAHE without noise, CLAHE with 0.03 noise, CLAHE with 0.1 noise, and CLAHE with 0.3 noise.

Among the tested preprocessing methods, CLAHE with 0.03 Gaussian noise yielded the best results in terms of model accuracy, as it provided an optimal balance between noise robustness and enhanced contrast. This highlights the importance of careful tuning of preprocessing parameters to achieve superior performance.

As demonstrated in Figure 1, the original image (left) has relatively low contrast, which is significantly improved after applying CLAHE (middle). When Gaussian noise is combined with CLAHE (right), the contrast is further enhanced, with CLAHE + 0.03 noise providing the best results. This combination ensures that the processed images retain their clinical significance while providing robust input for the YOLO model.

Training Step

The training phase involved the application of the YOLOv9 model, specifically using its two variants: YOLOv9c and YOLOv9s. These models were trained using a variety of configurations to identify the best-performing setup for abdominal disease detection. The training process utilized several key hyperparameters and techniques, as summarized in Table 2.

In this study, the models were trained using batch sizes of 16 and 32 to examine the effect of batch size on training stability and performance. Two optimization algorithms, SGD and Adam, were employed to compare convergence rates and generalization. Each model was trained for 90 epochs, with input images resized to 640×640 pixels to meet YOLO requirements.

Additional techniques included applying dropout rates of 35% to reduce overfitting and freezing the first 10 layers in some configurations to leverage pre-trained weights. The models were evaluated using 5-fold cross-validation, ensuring reliable and robust results across different data splits.

This systematic experimentation allowed for the identification of the optimal configuration, which utilized YOLOv9c, a batch size of 32, SGD optimizer, and a dropout rate of 35%, achieving the highest performance with a mean average precision (mAP) of 83.1%.

RESULTS AND DISCUSSION

The results obtained from training YOLOv9c and YOLOv9s models using various configurations are summarized in Table 3. The evaluation metrics, including Precision, Recall, Accuracy, F1 Score, and mAP50, were calculated for each configuration to assess the performance of the models.

As shown in Table 3, the performance of the models varied across different configurations. The following observations can be made:

Performance of YOLOv9c and YOLOv9s Models

The results indicate that the YOLOv9s variant, when trained with 32 batch size, SGD optimizer, and a 35% dropout rate, achieved the highest F1 Score (0.8228) and mAP50 (0.8738) among SGD-based configurations. On the other hand, the YOLOv9c model, trained with the Adam optimizer and a 35% dropout rate, achieved the highest overall mAP50 (0.9385) and Precision (0.9530).

Effect of Dropout and Freezing Layers

Applying a 35% dropout rate improved the generalization performance, as evidenced by higher F1 Scores and mAP50 values compared to configurations without dropout. However, freezing the first 10 layers in the models led to slight reductions in Recall and Accuracy metrics, suggesting that freezing may limit the model's ability to adapt to new data.

Comparison of Optimizers

The Adam optimizer showed superior performance in terms of Precision and mAP50, particularly for the YOLOv9c model. However, SGD provided more balanced results across all metrics, making it a reliable choice for configurations focused on generalizability.

Table 1 Distribution of Dataset

Class	Training Cases	Test Cases	Total Images
Acute Appendicitis	221	83	7,541
Acute Cholecystitis	124	34	6,345
Acute Pancreatitis	146	48	8,841
Kidney/Ureter Stones	283	97	3,488
Acute Diverticulitis	76	16	1,403
Abdominal Aortic Aneurysm	159	49	12,667

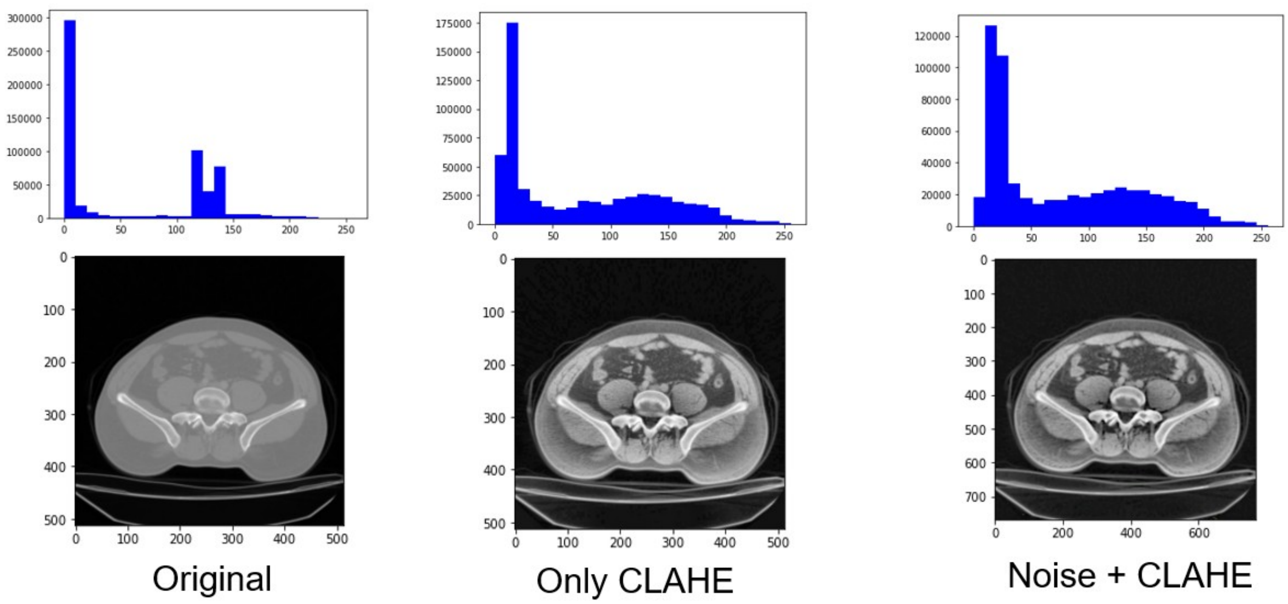

Figure 1 The comparison of original, CLAHE-applied, and Gaussian noise + CLAHE-applied abdominal images

Table 2 Training Parameters and Configurations

Parameter	Values Used
Batch Size	16, 32
Optimizer	SGD, Adam
Epochs	90
Input Size	640×640 pixels
Dropout	0%, 35%
Frozen Layers	0, 10
Model Variants	YOLOv9c, YOLOv9s
Cross-Validation	5-fold

Best Configuration Performance Evaluation

The best-performing configuration in terms of Recall, Accuracy, and F1 Score was achieved using the **YOLOv9s model** with a batch size of 32, the SGD optimizer, and a 35% dropout rate. This configuration produced a Recall of **0.7698**, an Accuracy of **0.7698**, and an F1 Score of **0.8228**, demonstrating its robust ability to detect and classify abdominal diseases effectively. The mAP50 value of **0.8738** further supports the strong generalization of this model across all test cases.

Figure 2 presents the normalized confusion matrix for this configuration, providing a detailed view of the model's performance across different classes. Notably, the model achieved high classification accuracy for categories such as **"Compatible with acute cholecystitis"** (0.78) and **"Abdominal aortic aneurysm"** (0.89), indicating its capability to identify larger and more distinct features associated with these conditions. However, the matrix reveals that the classification performance for **"Kidney stone"** was notably lower, with a Recall of **0.48**.

The low performance for the **"Kidney stone"** category can be attributed to the small size of these stones, which makes them challenging to detect even with advanced object detection mod-

Table 3 Training Results and Metrics for YOLOv9 Configurations

Configuration	Precision	Recall	Accuracy	F1 Score	mAP50
YOLOv9c, 16 Batch, SGD, No Dropout	0.8758	0.7619	0.7619	0.8149	0.8651
YOLOv9c, 16 Batch, SGD, 35% Dropout	0.8781	0.7639	0.7639	0.8170	0.8689
YOLOv9c, 16 Batch, SGD, 35% Dropout, 10 Freeze	0.8658	0.7564	0.7564	0.8074	0.8574
YOLOv9c, 32 Batch, SGD, No Dropout	0.8713	0.7583	0.7583	0.8109	0.8628
YOLOv9c, 32 Batch, SGD, 35% Dropout	0.8744	0.7609	0.7609	0.8137	0.8665
YOLOv9c, 32 Batch, SGD, 10 Freeze	0.8603	0.7637	0.7637	0.8091	0.8532
YOLOv9c, 32 Batch, SGD, 35% Dropout, 10 Freeze	0.8594	0.7629	0.7629	0.8083	0.8531
YOLOv9s, 32 Batch, SGD, No Dropout	0.8795	0.7662	0.7662	0.8190	0.8672
YOLOv9s, 32 Batch, SGD, 35% Dropout	0.8836	**0.7698**	**0.7698**	**0.8228**	0.8738
YOLOv9s, 32 Batch, SGD, 35% Dropout, 10 Freeze	0.8790	0.7574	0.7574	0.8137	0.8715
YOLOv9c, 32 Batch, Adam, No Dropout	0.9499	0.7002	0.7002	0.8061	0.9347
YOLOv9c, 32 Batch, Adam, 10 Freeze	**0.9551**	0.6871	0.6871	0.7992	0.9372
YOLOv9c, 32 Batch, Adam, 35% Dropout	0.9530	0.7024	0.7024	0.8088	**0.9385**

els. Their subtle appearance in medical images often results in misclassification or lower detection confidence. This observation highlights the need for higher-resolution datasets or more advanced preprocessing techniques tailored to enhance the visibility of smaller objects.

In summary, the YOLOv9s model with the aforementioned configuration provided strong results for most abdominal disease categories, but certain challenges, such as detecting small-sized features like kidney stones, emphasize the necessity for further dataset improvements and potential model fine-tuning.

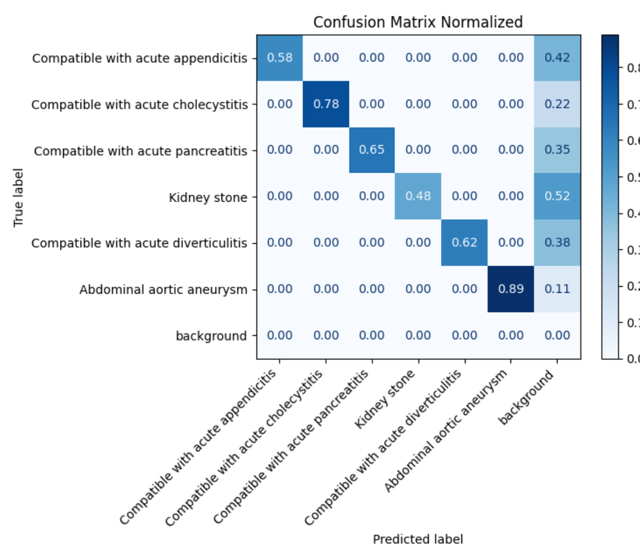

Figure 2 Normalized Confusion Matrix for YOLOv9s, 32 Batch, SGD, 35% Dropout Configuration.

CONCLUSION

In this study, a YOLOv9-based object detection approach was implemented to identify abdominal diseases using the TEKNOFEST 2022 Abdomen Dataset. The dataset was enhanced through advanced preprocessing techniques, including CLAHE and Gaussian noise augmentation, to improve image contrast and robustness. Multiple training configurations were evaluated using YOLOv9c and YOLOv9s variants, with variations in batch size, optimizer, dropout rate, and frozen layers. The results demonstrated that the YOLOv9s model, trained with a batch size of 32, the SGD optimizer, and a 35% dropout rate, provided the best performance in terms of Recall (0.7698), Accuracy (0.7698), and F1 Score (0.8228). Additionally, the highest mAP50 (0.9385) was achieved using the YOLOv9c model with the Adam optimizer and a 35% dropout rate.

The confusion matrix analysis highlighted the strong performance of the proposed approach in identifying diseases such as acute cholecystitis and abdominal aortic aneurysm. However, the detection of smaller objects, such as kidney stones, remained challenging due to their subtle appearance in medical images. This observation emphasizes the need for higher-resolution datasets and advanced preprocessing methods in future studies.

As part of future work, several enhancements can be considered. First, incorporating higher-resolution medical images and exploring multi-scale feature extraction techniques could improve the detection of small-sized objects. Second, leveraging ensemble learning by combining YOLO models with other object detection frameworks could enhance overall performance. Lastly, expanding the dataset with diverse samples and annotating additional classes would further strengthen the model's robustness and applicability in clinical settings.

Availability of data and material

TEKNOFEST 2022 Abdomen Dataset were used in this study.

Conflicts of interest

The author declares that there is no conflict of interest regarding the publication of this paper.

Ethical standard

The author has no relevant financial or non-financial interests to disclose.

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