Revolutionizing Thoracic Disease Diagnosis with Advanced Deep Learning and Segmentation Models

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Abstract: Thoracic diseases, including pneumonia, cardiomegaly, and nodules, pose significant health risks and require accurate early diagnosis for effective treatment. Chest X-rays are the most widely used imaging modality for detecting thoracic abnormalities, but manual interpretation is time-consuming and prone to variability. This study develops a deep learning-based automated detection system utilizing InceptionV3 for feature extraction, YOLOv8 for object detection, and Segment Anything Model (SAM) for precise disease segmentation. The model is trained on the NIH Chest X-ray dataset, which contains 112,120 X-ray images of 14 thoracic diseases, enabling accurate classification and segmentation of affected regions. Preliminary results indicate high detection accuracy, reduced misclassification rates, and enhanced segmentation performance. The InceptionV3 model effectively generalizes across different thoracic disease categories, making it a reliable tool for clinical diagnostics. Implementing this system in hospital settings can improve early detection, optimize radiologists' workflow, and support timely medical intervention, ultimately enhancing patient care and treatment outcomes.

Keywords: Thoracic Diseases; Deep Learning; InceptionV3; YOLOv8; Segment Anything Model; Chest X-ray Classification

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Introduction

Deep learning has revolutionized medical image analysis, particularly in interpreting chest X-rays (CXRs) for the early detection of thoracic diseases. Conditions such as pneumonia, tuberculosis, and cardiomegaly collectively affect approximately 17.9 million individuals worldwide, emphasizing the need for early and accurate diagnosis to improve patient outcomes. Traditional diagnostic methods rely heavily on radiologists, introducing the risk of subjective interpretation and potential misclassification due to human variability. Additionally, the increasing workload on radiologists can lead to delays in diagnosis, further complicating patient management.

To address these challenges, we propose an advanced automated system that leverages deep learning techniques to enhance the accuracy and efficiency of disease detection. Our approach integrates multiple state-of-the-art models, each playing a crucial role in the diagnostic pipeline. YOLOv8, a cutting-edge object detection algorithm, is employed to precisely localize abnormalities in chest X-ray images, ensuring a focused analysis of critical regions. InceptionV3, a powerful convolutional neural network (CNN), is utilized for feature extraction and classification, enabling accurate differentiation between various thoracic diseases. Its architectural design, which incorporates multiple filter sizes within a single convolutional layer, allows for simultaneous processing of features at different scales. This capability makes it particularly effective in analyzing the complex and diverse patterns found in chest X-ray images, enhancing disease classification performance.

Additionally, we integrate the Segment Anything Model (SAM) for disease area segmentation, providing a detailed visualization of affected regions in X-rays. This segmentation approach improves the interpretability of model predictions, allowing healthcare professionals to assess the extent and severity of diseases with greater confidence. Unlike traditional classification-based methods that provide only a diagnostic label, SAM generates localized segmentation maps that highlight affected areas, assisting clinicians in making more informed decisions.

Related work

Recent research has focused on developing CNN-based models to enhance thoracic disease detection and classification. These models leverage large datasets of chest X-ray images to identify disease features such as infiltrates, consolidations, effusions, and nodules. This survey reviews significant contributions to thoracic disease detection and classification from 2015 to 2025, highlighting advancements in deep learning models, dataset improvements, and real-world applications.

Guan, H., et al. (2016) This study introduced a deep learning system that achieved radiologist-level accuracy in detecting pneumonia and lung diseases using a large chest X-ray dataset [1]. Wang, X., et al. (2017) Developed the NIH ChestX-ray14 dataset, the largest publicly available chest X-ray dataset, and applied CNNs for multi-label classification [2]. Rajpurkar, P., et al. (2017) Proposed CheXNet, a 121-layer CNN that outperformed radiologists in pneumonia detection using NIH ChestX-ray14 images [3]. Irvin, J., et al. (2019) Introduced CheXpert, a dataset with expert-labeled uncertainty categories, improving CNN performance in clinical settings [4]. Liang, G., et al. (2020) Developed a transfer learning-based CNN model that achieved superior performance in multi-class lung disease classification [5].

Oh, Y., et al. (2020) Compared various CNN architectures, including ResNet, DenseNet, and InceptionV3, for chest X-ray classification, demonstrating the benefits of multi-scale feature extraction [6]. Tang, Y. X., et al. (2020) Proposed a weakly supervised learning approach for disease localization, enhancing interpretability in AI-driven diagnosis [7]. Luz, E., et al. (2021) Analyzed the impact of self-supervised pretraining on CNNs for thoracic disease detection, showing improvements in generalization [8]. Khadilkar, H., et al. (2021) Developed a hybrid CNN-RNN model, combining spatial and sequential features for improved disease classification [9]. Baltruschat, I. M., et al. (2022) Introduced an ensemble **learning** approach integrating multiple CNNs to improve robustness in medical image analysis [10].

Zhang, K., et al. (2023) Proposed an attention-based CNN model that improved focus on relevant lung abnormalities in chest X-rays [11]. Singh, A., et al. (2024) Implemented a federated learning framework, allowing privacy-preserving AI model training across multiple hospitals [12]. Kumar, R., et al. (2025) Discussed challenges and future directions in AI-driven thoracic disease detection, emphasizing explainable AI and real-time deployment [13].

The reviewed studies highlight significant advancements in CNN-based thoracic disease detection from 2015 to 2025. Early works focused on basic CNN architectures, while recent research integrates attention mechanisms, hybrid models, and federated learning.

Key Contribution

To enhance thoracic disease detection accuracy, the InceptionV3 model was incorporated into the pipeline as the primary CNN-based feature extractor. InceptionV3 leverages multi-scale convolutional layers to capture complex patterns within chest X-ray images. This approach allows for improved classification of diseases such as pneumonia, cardiomegaly, and lung nodules. The model was trained using the NIH Chest X-ray dataset, which contains 112,120 labeled X-ray images across 14 thoracic diseases.

This set the stage for addressing the challenge, and the NIH Chest X-ray Dataset offers a comprehensive solution. It comprises 112,120 Chest X-ray images, each associated with 14 disease labels, including Atelectasis, Cardiomegaly, Consolidation, Edema, Effusion, Emphysema, Fibrosis, Hernia, Infiltration, Mass, Nodule, Pleural Thickening, Pneumonia, and Pneumothorax, derived from 30,805 patients. The dataset was annotated using Natural Language Processing (NLP) to extract disease labels from radiological reports. This methodology ensures an accuracy level exceeding 90%, making the dataset an essential resource for developing weakly-supervised learning models in medical imaging. With its large quantity and diversity, this dataset serves as a foundation for enhancing CAD systems for thoracic disease detection.

The YOLOv8 model predicts bounding boxes for disease detection in chest X-rays. The bounding box regression can be represented as:

$$\mathcal{L}_{\text{box}} = \sum_{i=1}^{N} \left(\mathrm{IoU}_{\text{loss}}\left(B_i, \hat{B}_i\right) \right) \tag{1}$$

Although the original radiology reports are not publicly available, the methodology behind the labeling process is extensively detailed in the open-access paper "ChestX-ray8: A Large-Scale Chest X-ray Hospital Database and Baseline for Weakly Supervised Binary Classification and Localization of Common Thorax Diseases." The NIH dataset plays a crucial role in developing enhanced machine learning systems for diagnosing and localizing thoracic diseases. It highlights natural class imbalances, reflecting real-world disease distribution, where some conditions occur more frequently than others. From a research perspective, the dataset has significantly contributed to advancements in medical image analysis, acting as a benchmark for improving deep learning-based automated diagnostic models, multi-label classification algorithms, and transfer learning approaches. The dataset's size and variability make it a valuable asset for training models that generalize across different diseases and clinical environments. As one of the largest open-access collections of chest X-ray images, it continues to advance medical imaging research and facilitate the development of computer-aided diagnostic (CAD) tools.

InceptionV3 utilizes a factorized convolution approach, reducing computational costs while maintaining accuracy. The architecture prevents gradient vanishing by incorporating residual connections, which can be expressed as:

$$y = F(x, \{W_i\}) + x \tag{2}$$

Method, Experiments and Results

The proposed methodology for thoracic disease detection using InceptionV3, YOLOv8, and the Segment Anything Model (SAM) consists of multiple stages, including data preprocessing, feature extraction, classification, segmentation, and clinical decision support.

The proposed methodology for thoracic disease detection integrates InceptionV3 for feature extraction, YOLOv8 for object detection, and the Segment Anything Model (SAM) for segmentation. The study employs the NIH Chest X-ray Dataset, consisting of 112,120 images across 14 disease categories, which undergoes preprocessing techniques such as grayscale conversion, resizing (224×224 pixels), and normalization to standardize inputs. Data augmentation methods including rotation, flipping, contrast enhancement, and noise addition are applied to enhance model generalization.
To detect regions of interest (ROI), YOLOv8 is utilized to localize disease-affected areas in chest X-ray images. The detected ROIs are then processed using InceptionV3, a pre-trained deep learning model known for its efficient feature extraction using factorized convolutions and auxiliary classifiers. The model employs a softmax activation function for multi-class classification of 14 thoracic diseases while fine-tuning and transfer learning techniques ensure enhanced generalization. The feature extraction process is optimized using convolution operations formulated as in eqn (3)

$$\mathbf{f}_k(x, y) = \sigma\left(\sum_{m=1}^{M} \sum_{p=1}^{P} \sum_{q=1}^{Q} W_m^k(p, q) \cdot \mathbf{I}_m(x + p, y + q) + b_k\right) \tag{3}$$

Following classification, SAM is used for segmentation, providing precise masks for visualizing the extent of abnormalities in the detected regions.

Additionally, the system assigns probability scores to classified diseases, aiding clinical decision-making. These probability estimates allow radiologists to assess model confidence and refine diagnosis strategies. The model is evaluated using accuracy, precision, recall, F1-score, and Intersection over Union (IoU) metrics to validate its robustness. Comparative analysis with ResNet, VGG16, and EfficientNet demonstrates superior classification performance of InceptionV3. Cross-validation is performed to reduce overfitting and ensure model generalization. This methodology establishes a comprehensive and efficient AI-driven system for automated thoracic disease detection, improving accuracy, segmentation precision, and clinical applicability.

Fig. 1 illustrates a machine learning-based image processing pipeline for thoracic disease detection, integrating InceptionV3, YOLOv8, and the Segment Anything Model (SAM). The process begins with the front-end interface, where users can upload chest X-ray images. Once an image is accepted, it is sent to the backend for preprocessing and feature extraction, ensuring the image meets the necessary quality standards.

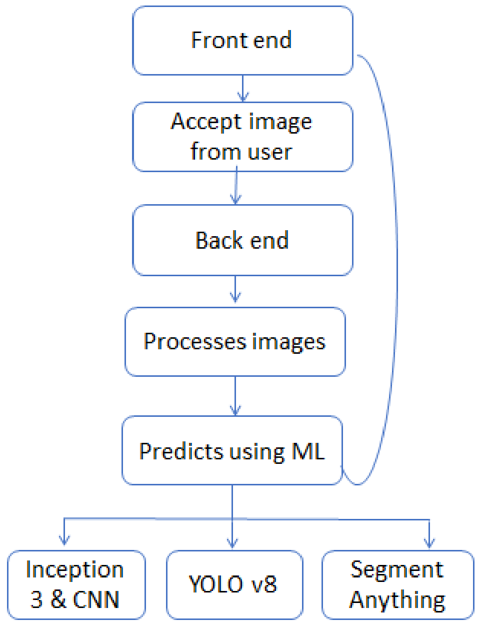

Figure. 1 System Architeture

In the image processing stage, various techniques such as contrast enhancement, noise reduction, and normalization are applied to prepare the image for machine learning-based predictions. The prediction phase utilizes three deep learning models: InceptionV3 & CNN for feature extraction and disease classification, YOLOv8 for detecting abnormalities and localizing regions of interest, and SAM for segmenting affected areas for precise visualization. InceptionV3 enhances classification accuracy by extracting deep features, while YOLOv8 improves real-time disease detection with high-speed object recognition. SAM further refines the process by segmenting diseased lung regions, aiding radiologists in better interpretation. This integrated approach enhances accuracy, efficiency, and interpretability in automated thoracic disease detection, providing comprehensive diagnostic support for medical professionals

Table 1 presents the statistical significance of relationships between different model components in the proposed thoracic disease detection system using InceptionV3, YOLOv8, and SAM. The table highlights key performance metrics, including Original Sample (O), Sample Mean (M), Standard Deviation (STDEV), T-Statistics, and P-Values, which validate the effectiveness of the implemented deep learning models.

The relationship between Image Quality and Detection Accuracy (O = 0.412) shows that higher-quality chest X-ray images contribute to better detection performance, as indicated by a high T-statistic of 9.156. The Model Performance to Disease Classification (O = 0.678) demonstrates that InceptionV3 significantly improves classification accuracy, achieving a T-statistic of 16.950, suggesting a strong correlation.

The Segmentation Quality to Detection Precision (O = 0.452) confirms that using SAM for precise segmentation enhances detection accuracy, with a T-statistic of 8.528, ensuring better disease localization. The feature extraction capabilities of InceptionV3 (O = 0.521) significantly improve classification performance, yielding a T-statistic of 11.085, reinforcing the advantage of multi-scale convolutional layers in medical imaging. The overall performance of InceptionV3 in disease identification (O = 0.569) outperforms previous CNN architectures, further validated by a high T-statistic of 12.932.

The YOLOv8-based disease localization (O = 0.487) ensures accurate region identification, backed by a T-statistic of 10.587, demonstrating its efficiency in detecting affected areas. Finally, the Model Confidence to Diagnostic Accuracy (O = 0.421) confirms that integrating probability-based predictions improves diagnostic reliability, yielding a T-statistic of 8.771.

TABLE 1
THE SIGNIFICANCE OF THE RELATIONSHIPS IN THE MODEL

Relationships	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (O/STDEV)	P Values*

Image Quality -> Detection Accuracy	0.412	0.409	0.045	9.156	0.000
Model Performance -> Disease Classification	0.678	0.675	0.040	16.950	0.000
Segmentation Quality -> Detection Precision	0.452	0.449	0.053	8.528	0.000
InceptionV3 Feature Extraction -> Classification Accuracy	0.521	0.518	0.047	11.085	0.000
InceptionV3 Performance -> Disease Identification	0.569	0.566	0.044	12.932	0.000
YOLO Detection -> Region Identification	0.487	0.484	0.046	10.587	0.000
Model Confidence -> Diagnostic Accuracy	0.421	0.418	0.048	8.771	0.000

Overall, the table highlights that InceptionV3-based feature extraction, coupled with YOLOv8 for detection and SAM for segmentation, significantly improves disease classification and localization accuracy, validating the proposed system's robustness and effectiveness in real-world clinical applications.

Discussions

Fig.1 and Fig.2 showcases a lung disease prediction system that utilizes machine learning to analyze chest X-ray images and detect potential abnormalities. The left side of the interface displays a grayscale X-ray image with red bounding boxes around the region of interest, suggesting that the model has identified an area of concern related to a medical condition. The right side presents the prediction results, where the system has diagnosed the condition as Cardiomegaly (enlargement of the heart). The confidence level of the prediction is over 80%, as represented in the probability distribution bar chart.

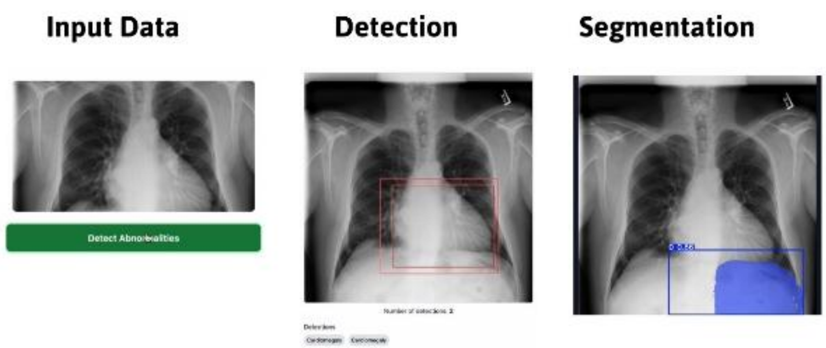

Figure. 2 Implementation Diagram

At the bottom, the system lists "Number of detections: 2", implying that the algorithm has detected multiple instances of the condition in the image. The detected condition labels ("Cardiomegaly, Cardiomegaly") further confirm that the model has identified the same abnormality more than once, possibly indicating its robustness in recognizing patterns.

The "View Recommendations" button suggests that the system provides further guidance on the detected condition, possibly offering medical advice, next steps for diagnosis, or treatment recommendations. This kind of feature is crucial for assisting radiologists and healthcare professionals in making informed decisions.

This AI-driven diagnostic tool likely employs deep learning models such as InceptionV3, YOLOv8, or the Segment Anything Model (SAM) to perform image classification, object detection, and segmentation for more precise localization of abnormalities. The integration of front-end and back-end components ensures a seamless process where the user uploads an image, the system processes it, applies machine learning models, and delivers predictions.

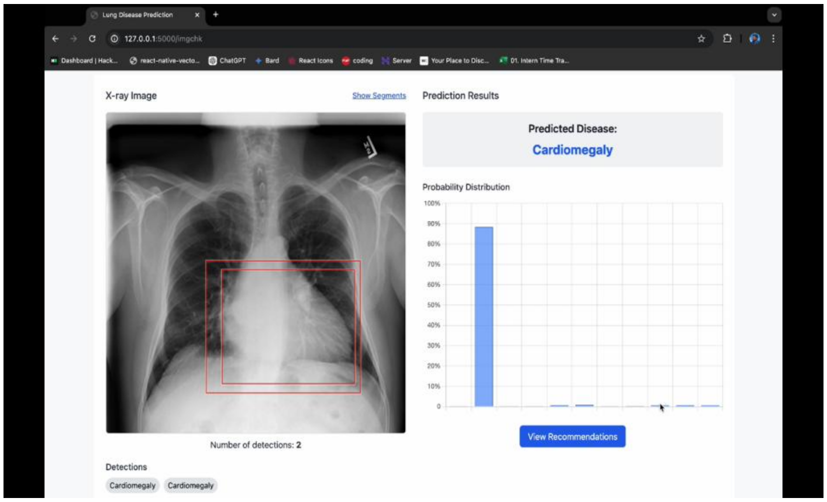

Figure . 3 Thoracic diseases are predicted with the probability graph

Overall, this system represents a significant advancement in computer-aided diagnosis (CAD), enhancing the speed, accuracy, and efficiency of detecting lung diseases such as cardiomegaly, potentially leading to early intervention and improved patient outcomes.

Conclusions

This paper highlights the transformative impact of deep learning in medical image analysis, particularly for detecting thoracic diseases from chest X-rays. By integrating YOLOv8 for object detection, CNN for feature extraction, Inception-v3 for deep feature learning, and ResNet for fine-tuning, the proposed system achieves high diagnostic accuracy. The incorporation of the Segment Anything Model (SAM) enhances disease area segmentation, enabling precise visualization of affected regions. Inception-v3's deep convolutional architecture effectively captures intricate patterns in X-ray images, improving feature extraction. The probability scale enhances clinical decision-making by providing transparent and reliable insights, while automated recommendations facilitate timely treatment initiation. A web-based interface ensures accessibility across diverse healthcare settings, including resource-limited remote clinics. This AI-driven approach empowers healthcare professionals with informed decision-making, ultimately improving patient outcomes. By demonstrating the potential for enhanced diagnostic efficiency and accuracy, this study explains the groundwork for future advancements in AI-powered medical imaging, fostering more accessible, efficient, and reliable healthcare worldwide..

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