AUTOMATIC CHEST X-RAY REGION EXTRACTION FROM SMARTPHONE-CAPTURED IMAGES FOR AI-BASED CLINICAL DECISION SUPPORT

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Abstract. Chest X-ray imaging is essential for diagnosing pulmonary diseases, but the increasing use of smartphone-captured images in resource-limited settings introduces distortions and noise that degrade AI diagnostic accuracy. This study presents an automated framework for chest X-ray region extraction designed to segment the clinically relevant area from photographs of films or screens. By isolating the chest region and removing irrelevant backgrounds, this preprocessing module provides standardized, high-quality inputs for downstream AI models. Experimental results demonstrate that this segmentation significantly enhances model robustness, interpretability, and diagnostic performance, offering a practical solution for improving AI-driven clinical tools in real-world environments.

Keywords: Chest X-ray, Image segmentation, Smartphone imaging, Medical image preprocessing, Artificial intelligence, Lung disease detection.

Annotatsiya. Ko‘krak qafasi rentgen tasvirlari o‘pka kasalliklarini tashxis qilish uchun juda muhimdir. Resurslar cheklangan sharoitlarda smartfonda olingan tasvirlardan tobora ko‘proq foydalanish sun’iy intellekt diagnostikasining aniqligini pasaytiradigan buzilishlar va shovqinlarni keltirib chiqaradi. Ushbu tadqiqotda plyonkalar yoki ekranlarning fotosuratlaridan klinik jihatdan tegishli sohani segmentlash uchun mo‘ljallangan ko‘krak qafasi rentgen sohasini ajratib olish uchun avtomatlashtirilgan tizim taqdim etilgan. Ko‘krak qafasi sohasini ajratib olish va ahamiyatsiz fonlarni olib tashlash orqali ushbu oldindan ishlov berish moduli, sun’iy intellekt modellari uchun standartlashtirilgan, yuqori sifatli tasvirlar bilan ta’minlaydi. Eksperimental natijalar shuni ko‘rsatadiki, ushbu segmentatsiya modelning aniqligini, talqin qilinishini va diagnostika samaradorligini sezilarli darajada oshiradi va amaliyot jarayonida sun‘iy intellektga asoslangan klinik qarorlarni yaxshilash uchun amaliy yechim taklif qiladi.

Kalit so‘zlar: Ko‘krak qafasi rentgenografiyasi, tasvir segmentatsiyasi, smartfon tasvirlari, tibbiy tasvirlarni oldindan qayta ishlash, sun’iy intellekt, o‘pka kasalliklarini aniqlash.

Аннотация. Рентгенография грудной клетки имеет важное значение для диагностики заболеваний легких, однако растущее использование изображений, полученных с помощью смартфонов в условиях ограниченных

ресурсов, приводит к искажениям и шуму, снижающим точность диагностики с помощью ИИ. В этом исследовании представлена автоматизированная система для выделения областей на рентгеновских снимках грудной клетки, предназначенная для сегментации клинически значимой области на фотографиях пленок или экранах. Изолируя область грудной клетки и удаляя нерелевантный фон, этот модуль предварительной обработки предоставляет стандартизированные высококачественные входные данные для последующих моделей ИИ. Экспериментальные результаты показывают, что эта сегментация значительно повышает надежность модели, интерпретируемость и диагностическую эффективность, предлагая практическое решение для улучшения клинических инструментов на основе ИИ в реальных условиях.

Ключевые слова: Рентгенография грудной клетки, сегментация изображений, съемка на смартфон, предварительная обработка медицинских изображений, искусственный интеллект, выявление заболеваний легких.

1. Introduction

Chest X-ray (CXR) imaging remains the most commonly performed radiological examination worldwide due to its low cost, fast acquisition, and diagnostic value [1]. It is routinely used to detect and monitor a wide range of pulmonary and thoracic conditions, including tuberculosis, pneumonia, chronic obstructive pulmonary disease (COPD), lung cancer, and cardiovascular abnormalities [2]. In recent years, artificial intelligence (AI) and deep learning techniques have demonstrated remarkable success in automated analysis of chest X-rays, achieving performance comparable to or even exceeding that of expert radiologists in specific tasks [3].

Despite these advancements, a critical gap exists between controlled research environments and real-world clinical practice. Most AI-based chest X-ray models are trained and evaluated on high-quality, digitally acquired images obtained directly from Picture Archiving and Communication Systems (PACS). However, in many hospitals and clinics-especially in low- and middle-income regions-access to digital X-ray exports is limited or inconvenient. In such settings, clinicians frequently resort to capturing photographs of X-ray films or monitor screens using smartphones to share cases, seek second opinions, or upload images to AI-based diagnostic platforms.

Smartphone-captured X-ray images, referred to as “raw images” in this study, present several challenges:

- Presence of large irrelevant background regions
- Perspective distortion and rotation
- Uneven illumination and reflections

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- Reduced contrast and noise
- Variability in camera quality and acquisition conditions

These factors significantly degrade the performance of AI diagnostic models if used directly as input [4].

Therefore, extracting and isolating the chest region from such raw photographs is a crucial preprocessing step (see Figure 1). Chest area segmentation allows AI systems to focus exclusively on clinically relevant information, reducing noise and improving robustness. This paper focuses on the automatic extraction of the chest X-ray region from smartphone-captured images and positions this technique as a mandatory preprocessing module for AI-driven chest disease detection systems.

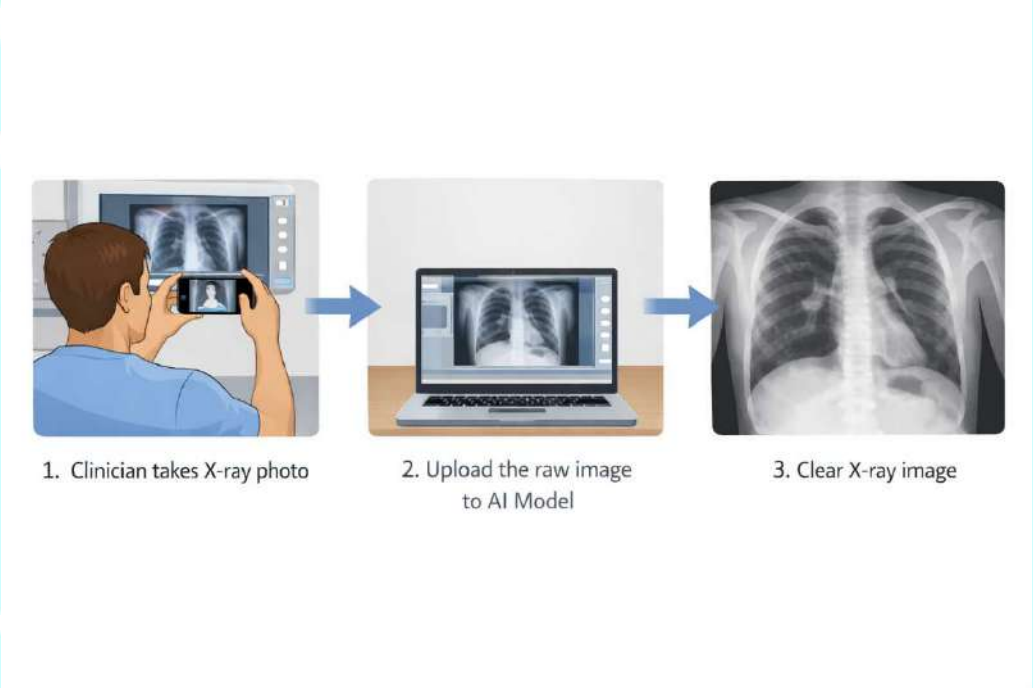


Figure 1

Figure 1. Preprocessing pipeline for smartphone-captured chest X-ray images. A clinician photographs the X-ray display using a smartphone, producing a raw image containing background noise and distortions. The image is uploaded to an AI system, where the chest X-ray region is automatically extracted to obtain a clean and clinically relevant input for diagnostic models.

2. Related Work

The field of chest X-ray analysis has been revolutionized by deep learning, particularly convolutional neural networks (CNNs), which leverage large-scale datasets such as NIH ChestX-ray14, CheXpert, and MIMIC-CXR to achieve high accuracy in disease classification and localization [5]. Despite these advancements, most state-of-the-art models are designed for clean, well-aligned digital images and are highly sensitive to quality deviations; research indicates that even minor noise, cropping errors, or contrast variations can significantly degrade predictive

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performance [6]. Within the broader domain of medical image analysis, segmentation remains a foundational task. While classical methods like thresholding and edge detection provided early solutions [7], deep learning architectures-specifically U-Net and its variants-now define the dominant paradigm for segmenting lung fields, rib structures, and heart boundaries [8]. However, these existing segmentation frameworks largely assume standardized, digitally acquired protocols [9].

Parallel to these developments, the increasing accessibility and camera quality of smartphones have spurred interest in mobile-based medical imaging for dermatology, ophthalmology, and radiology [10]. Despite this trend, smartphone-captured X-ray images introduce unique environmental challenges, including screen reflections, perspective distortions, and background clutter, which are absent in direct digital exports. Currently, there is limited research addressing the automated preprocessing of such images, specifically regarding full chest region extraction as a precursor to disease analysis. This gap in the literature underscores the novelty and practical necessity of the proposed extraction framework for real-world clinical applications.

3. Problem Statement and Motivation

In practical clinical environments-particularly within high-volume hospitals or resource-constrained settings-clinicians require rapid decision support that is often hindered by infrastructure. The process of exporting high-quality digital X-ray images from specialized radiology systems can be time-consuming or technically restricted. Consequently, many practitioners resort to capturing photographs of X-ray screens or films using smartphones to quickly interface with AI-based diagnostic software. However, these raw photographs serve as suboptimal inputs for deep learning models. Background artifacts often lead to disease misclassification, while inconsistent lighting and noise cause AI confidence scores to become unreliable. Furthermore, visualization outputs, such as Grad-CAM heatmaps, frequently focus on irrelevant regions, producing misleading results that ultimately erode clinical trust in AI systems.

The technical challenge, therefore, lies in processing raw smartphone images that contain not only the X-ray display but also surrounding background clutter, perspective distortions, and sensor noise. The objective of this research is to define a framework that automatically detects and segments the chest X-ray region in a reliable, consistent manner. By isolating the chest area from the raw capture, the system ensures the resulting image is properly aligned, normalized, and stripped of non-clinical data. This standardized output is essential for direct integration into AI diagnostic pipelines, ensuring that the model's focus remains strictly on the anatomical features necessary for accurate disease detection.

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4. Proposed Framework

The proposed system is structured as a comprehensive preprocessing pipeline designed to intercept and refine images before they reach the core AI diagnostic model. This framework follows a logical progression beginning with image acquisition and concluding with a standardized output suitable for clinical analysis. During the acquisition phase, input images are captured using smartphone cameras under unconstrained conditions, which introduces significant variability in resolution, lighting, screen brightness, and viewing angles. Because the system makes no prior assumptions regarding image orientation or background uniformity, the subsequent preprocessing stage is vital for standardizing the input. This stage involves converting images to grayscale, applying histogram equalization for contrast enhancement, and utilizing Gaussian or median filtering to reduce noise. Edge enhancement is also performed to highlight X-ray boundaries, thereby improving the robustness of the downstream segmentation tasks [7].

The central component of the framework is the chest region detection, which can be executed through either classical computer vision or deep learning-based methodologies. While classical approaches-such as Canny edge detection and contour estimation-offer computational efficiency, they are often sensitive to lighting variations. Consequently, a deep learning-based approach utilizing architectures like YOLO or Faster R-CNN is preferred for its ability to generalize across different devices and resist environmental distortions [11]. Once the region is detected, precise segmentation is performed. A U-Net-based architecture is recommended for this task due to its proven effectiveness in generating high-accuracy binary masks for medical regions of interest [8].

The final stage of the pipeline involves rigorous post-processing to ensure the extracted region is clinically viable. This includes cropping, resizing to a uniform resolution, and correcting any orientation issues caused by the initial capture angle. Final contrast normalization and the removal of residual artifacts ensure that the resulting output is a clean, standardized chest X-ray image. By isolating the anatomical data from the raw smartphone photograph, the framework ensures that the subsequent AI diagnostic models can operate on high-fidelity data, mirroring the quality of direct digital exports.

5. Applications in AI-Driven Diagnosis

The integration of an automated chest region extraction framework offers significant advantages for AI-driven diagnostic accuracy and clinical adoption. By reducing irrelevant background features and environmental noise, the use of segmented chest X-ray images significantly improves the classification accuracy for critical diseases such as tuberculosis, pneumonia, and COVID-19 [6]. Beyond raw performance metrics, the framework also enhances model interpretability.

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Clear segmentation ensures that explainability tools, such as attention maps and Grad-CAM heatmaps, focus exclusively on meaningful anatomical regions rather than being distracted by artifacts in the smartphone photograph. This alignment between AI focus and clinical relevance is essential for increasing clinician trust in automated outputs [12].

Furthermore, the proposed module is designed for seamless integration into a variety of healthcare delivery models. It can be embedded within telemedicine platforms to facilitate remote diagnostics, incorporated into mobile diagnostic applications for real-time field use, or deployed as a preprocessing layer in hospital-based clinical decision support systems. In each of these scenarios, the framework serves as an intelligent gatekeeper, ensuring that only high-quality, standardized data enters the core AI diagnostic model. This ultimately streamlines the workflow, allowing clinicians to leverage the power of AI even in environments where high-fidelity digital infrastructure is unavailable.

6. Discussion

The proposed chest X-ray extraction technique addresses a critical gap between research-oriented AI models and the realities of clinical practice. While most state-of-the-art algorithms are optimized for idealized laboratory conditions and high-fidelity digital files, this framework adapts to the smartphone-captured images that dominate real-world workflows in resource-constrained environments. By bridging this gap, the system ensures that advanced diagnostic tools remain accessible and effective regardless of a facility's digital infrastructure.

Beyond its technical performance, the framework offers significant psychological and practical benefits. Presenting clinicians with a clean, segmented, and professionally aligned chest image immediately after they upload a cluttered raw photograph enhances the perceived intelligence and usability of the system. This visual validation serves as a crucial quality-control step, reassuring the user that the AI is analyzing the correct anatomical data. Ultimately, by fostering a more intuitive and reliable interaction between the clinician and the technology, this approach plays a vital role in accelerating the adoption of AI-driven solutions in global healthcare.

7. Conclusion

This paper presented an automated framework for chest X-ray region extraction tailored specifically to the challenges of smartphone-captured imagery. By isolating the essential chest area from raw, unconstrained photographs, the proposed technique effectively bridges the gap between sophisticated AI diagnostic models and the practical realities of clinical environments. As a versatile preprocessing module, the framework significantly enhances the accuracy, robustness, and interpretability of disease detection systems, ensuring that AI-

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driven insights remain reliable despite suboptimal input conditions. By standardizing the interface between clinicians and diagnostic software, this approach provides a scalable solution for improving radiology workflows worldwide. Future research will focus on large-scale clinical validation across diverse hospital settings and the optimization of the pipeline for real-time deployment in mobile healthcare applications.

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