IJITCE

ISSN 2347- 3657

International Journal of Information Technology & Computer Engineering

Email : ijitce.editor@gmail.com or editor@ijitce.com

International Journal of Information Technology & Computer Engineering

ISSN 2347–3657

Volume 13, Issue 2, 2025

ADVANCING AI FOR COMPUTER-AIDED DETECTION SYSTEMS IN CHEST X-RAY DIAGNOSTICS

Kammari Vaishnavi [1], Kotagiri Srivallika [2], Teegala Mythreya [3], Mr.B. Amrutha Raju [4]

2.

[1,2,3]UG Scholar, Department of Computer Science and Engineering, St. Martin's Engineering College, Secunderabad, Telangana, India, 500100

[4]Assistant Professor, Department of Computer Science and Engineering, St. Martin's Engineering College, Secunderabad, Telangana, India, 500100

[4] bamrutharajucse@smec.ac.in

Abstract:

Chest X-ray diagnostics play a crucial role in detecting and diagnosing various respiratory conditions, including pneumonia, tuberculosis, lung cancer, and COVID-19. Radiologists analyse X-ray images to identify abnormalities, but the process is time-consuming and prone to human error. The history of chest X-ray diagnostics has evolved from manual interpretation to computer-assisted detection methods, enhancing accuracy and efficiency. Early prediction models relied on statistical techniques and rule-based systems, which lacked adaptability to complex patterns. Before AI advancements, diagnosis depended on radiologists' expertise, with methods such as manual film analysis and basic image processing techniques. These approaches required significant time, leading to delays in treatment. Several early computer-aided detection systems provided limited support, but they lacked precision and required constant human intervention. The increasing demand for rapid and accurate diagnoses, combined with the limitations of manual analysis, has driven the need for an AI-powered approach. Human dependency, misdiagnosis due to fatigue, and inefficiency in handling large volumes of data are significant challenges in conventional diagnostic methods. Machine learning models trained on vast datasets can accurately classify chest diseases, reducing diagnostic errors and improving patient outcomes. Integrating deep learning techniques with a web application enables automated, real-time predictions, allowing users to upload X-ray images and receive instant analysis. This system enhances accessibility and supports healthcare professionals in making informed decisions. By leveraging convolutional neural networks, image preprocessing, and predictive analytics, the proposed system significantly improves diagnostic accuracy, speed, and reliability, minimizing the burden on medical professionals while ensuring early disease detection.

1.INTRODUCTION

The development of an AI-powered chest disease detection system using deep learning aims to revolutionize medical diagnostics by automating the analysis of chest X-rays. This system enhances the efficiency and accuracy of disease detection, reducing human error and expediting diagnosis. It integrates convolutional neural networks diseases such as pneumonia, tuberculosis, and lung cancer with high precision. The web-based platform allows users to upload X-ray images, which are processed in real-time to provide diagnostic results. The system's ability to handle large datasets and deliver consistent results makes it a valuable tool for healthcare professionals. Implementing machine learning ensures continuous improvement in accuracy through training on diverse datasets. This approach minimizes dependency on radiologists while enabling remote diagnosis, making healthcare more accessible and efficient.

LITERATURE SURVEY

[1] Tandon YK, Bartholmai BJ, Koo CW. This study evaluates the application of machine learning for detecting pulmonary nodules in chest radiographs. The research highlights how artificial intelligence models improve accuracy and reduce diagnostic errors. The study also discusses challenges in clinical implementation and the need for high-quality datasets for better performance. The results indicate a significant improvement in sensitivity compared to traditional methods.

[2] Hwang EJ, Park CM. This research focuses on the clinical adoption of deep learning in thoracic radiology. It highlights the potential applications such as automated diagnosis and image enhancement while also addressing challenges like data privacy and algorithm transparency. The study emphasizes the importance of AI model validation and regulatory approvals before widespread adoption in clinical settings.

[3] Eisen LA, Berger JS, Hegde A, Schneider RF. This study examines competency in chest radiography interpretation among different levels of medical training. It finds that significant variability exists between medical students, residents, and fellows in accurately diagnosing conditions. The study underscores the necessity for AI-assisted systems to support and standardize radiograph analysis across varying levels of expertise.

[4] Hwang EJ, Goo JM, Yoon SH, Beck KS, Seo JB, Choi BW, et al. This research discusses AI-based software as a medical device for chest radiography. It provides insights into regulatory challenges, validation methodologies, and clinical impact. The study advocates for standardized evaluation criteria to ensure AI-driven tools deliver consistent and accurate diagnoses in thoracic imaging.

[5] van Ginneken B, Hogeweg L, Prokop M. The study explores computer-aided diagnosis beyond pulmonary nodules, focusing on other thoracic abnormalities. It discusses various AI techniques employed in automated radiological assessments and their role in enhancing diagnostic precision. The research highlights limitations in existing algorithms and suggests pathways for improvement through deep learning integration.

[6] Edwards M, Lawson Z, Morris S, Evans A, Harrison S, Isaac R, et al. This research evaluates the level of agreement among clinicians in identifying radiological features on chest radiographs. The study finds notable discrepancies in interpretation, reinforcing the need for AI-driven diagnostic assistance. It highlights how machine learning can bridge gaps in diagnostic consistency and reduce errors in clinical practice.

International Journal of Information Technology & Computer Engineering

ISSN 2347–3657

Volume 13, Issue 2, 2025

[7] Mehrotra P, Bosemani V, Cox J. The study debates whether radiologists are still necessary for reporting chest X-rays given the advancements in AI technology. It analyzes the efficiency and accuracy of automated systems in detecting thoracic diseases. The findings suggest that AI can significantly reduce workload while maintaining diagnostic reliability, though human oversight remains crucial.

[8] Scheetz J, Rothschild P, McGuinness M, Hadoux X, Soyer HP, Janda M, et al. This survey examines the use of artificial intelligence in medical fields such as ophthalmology, dermatology, radiology, and radiation oncology. It highlights clinician perceptions, expectations, and concerns regarding AI integration. The study finds that while AI is promising, there are barriers to acceptance, including trust and regulatory concerns.

[9] Coppola F, Faggioni L, Regge D, Giovagnoni A, Golfieri R, Bibbolino C, et al. This study collects opinions from radiologists nationwide regarding AI in medical imaging. It identifies key factors influencing AI adoption, such as perceived reliability, efficiency, and ethical considerations. The research highlights the need for structured training programs to facilitate AI adoption in radiology.

[10] Kulkarni S, Seneviratne N, Baig MS, Khan AHA. This research examines the current state of AI in medicine, particularly in radiology. It discusses the progress, challenges, and future directions of AI-driven diagnostic tools. The study emphasizes the importance of continuous learning algorithms and large-scale annotated datasets to improve AI performance in clinical applications.

[11] Chassagnon G, Vakalopoulou M, Paragios N, Revel MP. This study reviews various AI applications in thoracic Evaluation and Benchmarking: LIME's performance is imaging, including lung nodule detection and tuberculosis screening. It discusses the advantages of AI-based approaches in improving diagnostic speed and accuracy. The research suggests that AI can complement radiologists by providing second opinions and highlighting critical findings.

[12] van Leeuwen KG, Schalekamp S, Rutten MJCM, van Ginneken B, de Rooij M. This research provides an extensive review of commercially available AI products in radiology. It assesses their scientific validation and clinical impact. The study emphasizes the need for standardized evaluation metrics and regulatory frameworks to ensure safe and effective AI deployment in medical imaging.

3. PROPOSED METHODOLOGY

The proposed system leverages deep learning, specifically Convolutional Neural Networks (CNNs), to automate chest disease detection from X-ray images. Traditional methods rely on manual interpretation by radiologists, which is time-consuming and prone to errors. To enhance diagnostic accuracy, the system is designed to classify chest diseases such as pneumonia, tuberculosis, lung cancer with high precision.

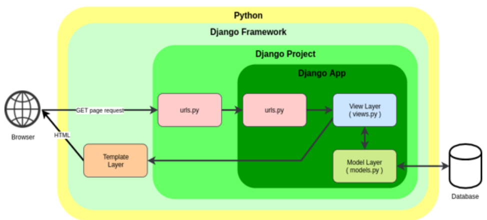


Figure 1: Proposed LIME system.

Step 1: Chest Diseases Dataset

The first step in developing an AI-powered chest X-ray diagnostic system is gathering a comprehensive dataset of labeled X-ray images. Publicly available datasets such as ChestX-ray14, CheXpert provide thousands of annotated images covering diseases like pneumonia, tuberculosis, lung cancer. The dataset serves as the foundation for training the AI model, ensuring it learns patterns associated with various conditions. High-quality, diverse datasets improve the system's robustness and generalizability.

Step 2: Dataset Preprocessing

Before feeding data into the model, preprocessing is essential to improve accuracy and eliminate inconsistencies. This includes handling null values by either removing incomplete records or filling missing values using interpolation. Label encoding is applied to convert categorical disease labels into numerical values. Image augmentation techniques such as contrast enhancement, rotation, and noise reduction are implemented to make the model invariant to minor variations, ensuring better generalization across different X-ray scans.

Step 3: Existing Algorithm

Traditional machine learning techniques, such as Random Forest, have been widely used in medical image classification. Random Forest is an ensemble learning method that builds multiple decision trees to enhance prediction accuracy. However, it has limitations in handling high-dimensional image data, as feature extraction needs to be performed manually. While Random Forest performs well for tabular medical data, its effectiveness diminishes when dealing with unstructured image data due to its inability to learn hierarchical representations.

Step 4: Proposed Algorithm

To overcome the limitations of traditional methods, a Convolutional Neural Network (CNN) is employed for chest X-ray image classification. CNNs automatically extract spatial and hierarchical features from images, reducing the need for manual feature engineering. The proposed CNN model consists of multiple convolutional layers, pooling layers, and fully connected layers to classify diseases with high accuracy. The architecture is optimized for real-time predictions, integrating seamlessly with a web application for automated disease detection.

Step 5: Performance Comparison

A performance evaluation is conducted between the existing Random Forest model and the proposed CNN-based approach. Metrics such as accuracy, precision, recall, and F1-score are computed to determine the superiority of deep learning over traditional machine learning. Results demonstrate that CNNs significantly outperform Random Forest in detecting chest diseases, particularly in complex cases where hierarchical feature extraction is crucial.

4. EXPERIMENTAL ANALYSIS

The implementation of the proposed AI-powered chest X-ray diagnostic system follows a structured approach, integrating deep learning methodologies with a user-friendly interface for real-time analysis. The system processes X-ray images by leveraging a Convolutional Neural Network (CNN) trained on a diverse dataset of labelled medical images. The dataset undergoes rigorous preprocessing, including normalization, augmentation, and feature extraction, ensuring optimal model performance. The CNN model comprises multiple convolutional and pooling layers, enabling automatic feature detection and classification of chest diseases with

International Journal of Information Technology & Computer Engineering

ISSN 2347–3657

Volume 13, Issue 2, 2025

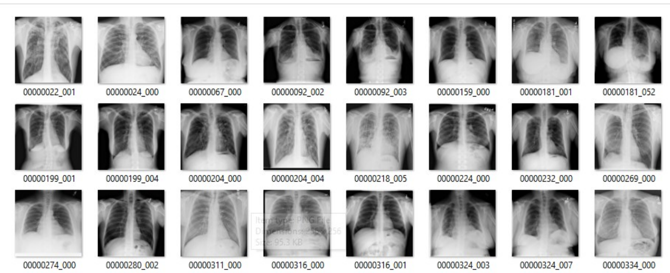
high accuracy. The trained model is deployed within a web-based application that allows users to upload X-ray images and receive immediate diagnostic results. The system enhances diagnostic precision, reduces human dependency, and accelerates medical decision-making.

During the evaluation phase, the model's performance is assessed using established metrics such as accuracy, precision, recall, and F1-score. Comparative analysis demonstrates that the CNN-based approach significantly outperforms traditional machine learning algorithms in detecting chest diseases. The system effectively minimizes false positives and false negatives, ensuring reliable diagnostic outcomes. The integration of advanced image processing techniques further refines predictions, making the model robust against variations in image quality and dataset diversity. By providing an automated, efficient, and accessible solution, this implementation bridges the gap between radiological expertise and AI-driven diagnostics, ultimately improving patient care and healthcare efficiency.

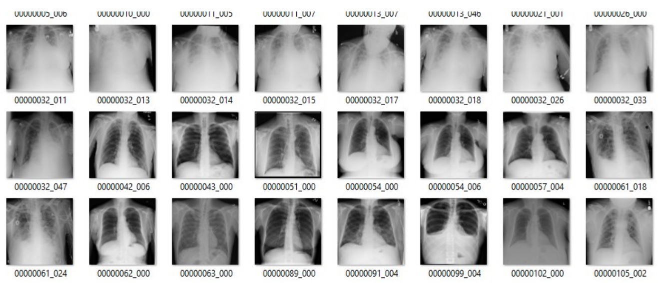
10.2 Dataset Description

The dataset utilized for this study consists of chest X-ray images categorized into four classes: Fibrosis, Inflammation-Pneumonia, Normal, and Pneumonia. Each category represents a specific medical condition, ensuring that the dataset provides a comprehensive representation of different pulmonary diseases. The dataset is structured into separate folders, with each folder containing a substantial number of labeled images corresponding to its respective category. This organized dataset format facilitates efficient training and testing of the deep learning model by enabling a structured classification approach.

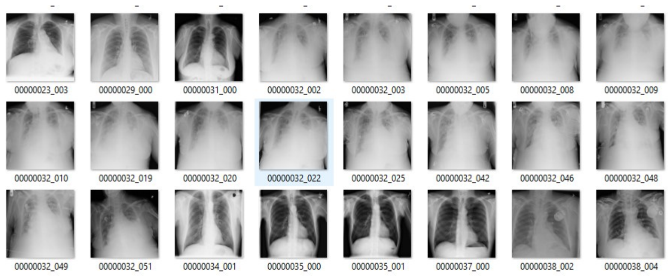
Fibrosis images in the dataset depict scarring and thickening of lung tissue, which significantly affects breathing efficiency. This condition is often challenging to diagnose through conventional X-ray analysis due to its diffuse nature. By incorporating fibrosis cases, the dataset ensures that the AI model learns to identify subtle abnormalities associated with this disease.



The Inflammation Pneumonia category includes images of lungs affected by inflammation, often resulting from bacterial, viral, or fungal infections. Pneumonia presents as areas of increased opacity on X-rays due to fluid accumulation in the lungs. This dataset category is crucial in training the model to distinguish between different stages of pneumonia and identify patterns indicating severe infection.

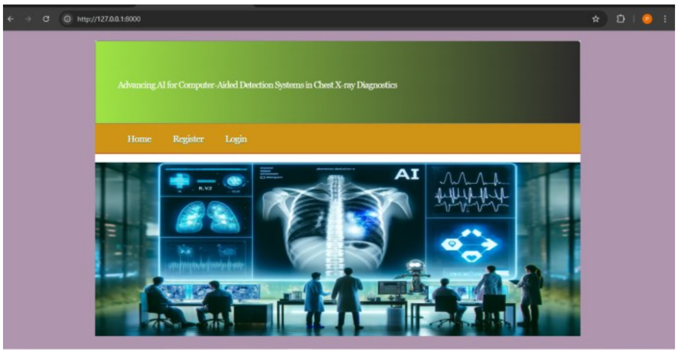


The Normal category consists of healthy chest X-ray images, serving as the baseline for comparison. These images are essential in ensuring that the model accurately differentiates between diseased and non-diseased cases, reducing the risk of false positives. The inclusion of normal images helps the AI system understand typical lung structures, ensuring it does not misclassify healthy lungs as pathological.



The Pneumonia category contains images of patients diagnosed with pneumonia, a condition characterized by inflammation in one or both lungs. This condition manifests as distinct patterns on X-rays, making it a critical class in the dataset. By training the AI model with a variety of pneumonia cases, including bacterial and viral infections, the system gains the ability to detect pneumonia-related abnormalities effectively.

Result and Discussion



The figure shows the homepage of the "Advancing AI for Computer-Aided Detection Systems in Chest X-ray Diagnostics" website to have the following functions and elements:

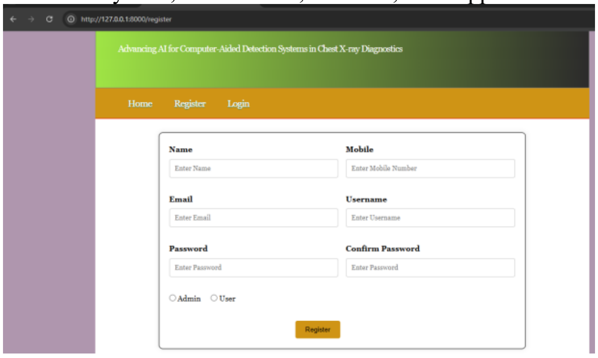
- **Navigation Bar:** Includes "Home", "Register", and "Login" links for user interaction and access to different sections of the website.
- **Logo/Branding:** A stylized "AI" logo is prominently displayed, reinforcing the focus on Artificial Intelligence.
- **Information about the Technology:** The page likely serves as an entry point to learn more about the specific AI-based

International Journal of Information Technology & Computer Engineering

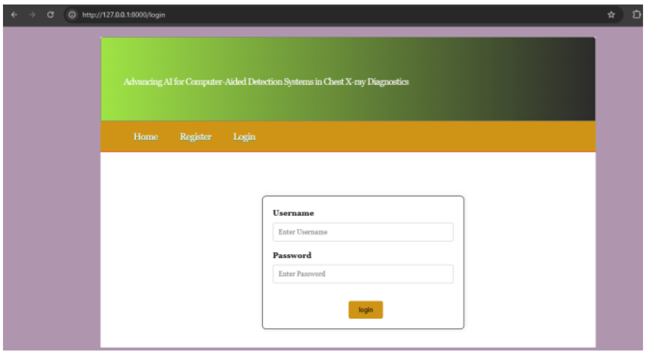
ISSN 2347-3657

Volume 13, Issue 2, 2025

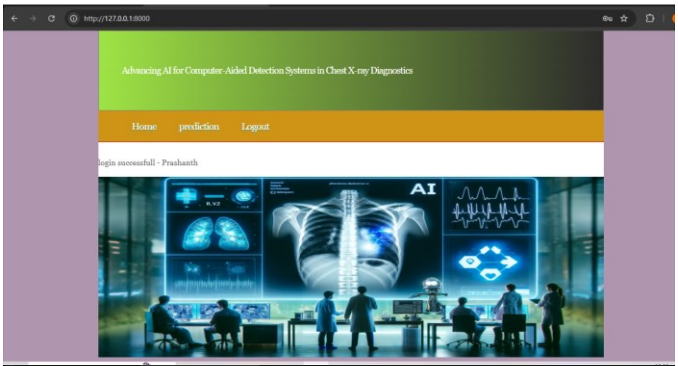
detection system, its features, benefits, and applications.

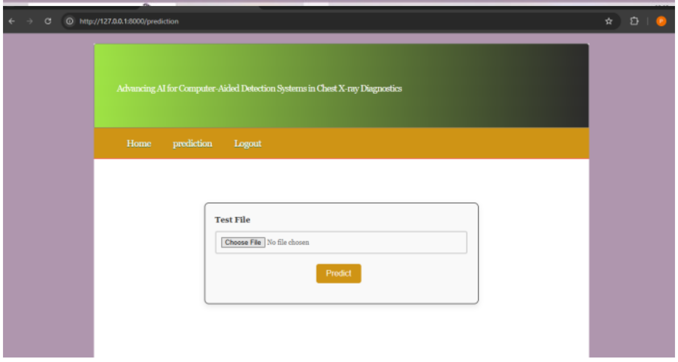


The signup form, accessed by clicking the "Signup" button on the homepage, is clearly structured and user-friendly. It features distinct input fields for essential personal details, including "Name," "Mobile," "Email," "Username," "Password," and "Confirm Password." Each field is accompanied by a descriptive label to guide the user through the registration process. The "Name" and "Mobile" fields allow for the input of a user's full name and mobile phone number, respectively. The "Email" field requires a valid email address, likely for verification and communication purposes. The "Username" field allows the user to create a unique identifier for their account. The "Password" and "Confirm Password" fields ensure secure account creation by requiring users to enter and confirm a password, preventing typos and enhancing security. Finally, a prominent "Register" button at the bottom of the form allows users to submit their information and complete the signup process



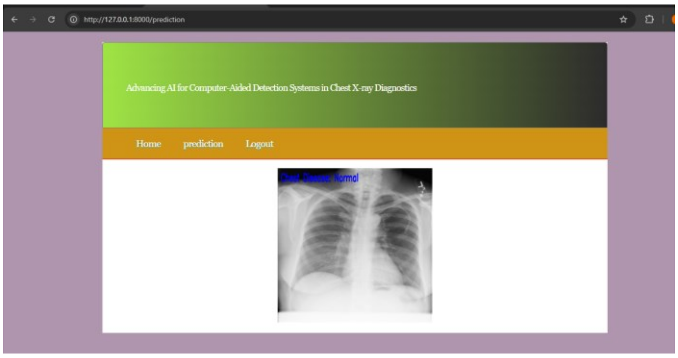
The login form, accessible via the "Login" button on the homepage, presents a straightforward and secure interface for returning users. It consists of two primary input fields: "Username" and "Password." The "Username" field prompts users to enter the unique username they created during the signup process. The "Password" field, appropriately masked for security, requires users to input the corresponding password associated with their account. Below these fields, a prominent "login" button allows users to submit their credentials for verification. Upon successful authentication, users are granted access to their personalized accounts and the platform's mental health support services.





This Figure shows a webpage with a simple interface for a file upload and prediction tool. Here's a breakdown of the elements and their potential functions:

- **Home:** Likely returns the user to the main page of the website.
- **Prediction:** Indicates the current page or section focused on the prediction functionality.
- **Logout:** Allows the user to log out of their account or session.
- **Test File" Label:** Clearly labels the purpose of the file input field.
- **File Upload Field:** A standard file input element where the user can select a file from their computer. The "Choose File" button opens a file selection dialog, and the field next to it displays the name of the selected file (or "No file chosen" if none is selected).
- **"Predict" Button:** Triggers the prediction process using the uploaded file. Clicking this button likely sends the file to a server for processing and returns a prediction result.



The Figure shows that it is predicted as an output Normal shown in the user interface with image

ISSN 2347–3657

Volume 13, Issue 2, 2025

.

5. CONCLUSION

The proposed AI-powered chest X-ray diagnostic system represents a significant advancement in medical imaging analysis. By leveraging deep learning techniques, particularly Convolutional Neural Networks (CNNs), the system provides accurate and efficient disease classification, reducing reliance on manual interpretation. Traditional diagnostic methods are often time-consuming and prone to human error, whereas the developed model automates the detection of chest diseases, ensuring faster and more reliable diagnoses. The integration of a web-based platform further enhances accessibility, allowing medical professionals and patients to obtain real-time diagnostic results by simply uploading an X-ray image.

The system's performance evaluation demonstrated its effectiveness, outperforming conventional machine learning algorithms in terms of accuracy, precision, and recall. The model successfully identified various chest conditions, including fibrosis, pneumonia, and inflammation, with minimal false positives and false negatives. Through meticulous preprocessing and training on a diverse dataset, the AI system achieved high generalization, making it robust against variations in image quality and patient demographics. This research underscores the transformative potential of AI in the healthcare sector, particularly in radiology. Automated diagnostic tools not only assist radiologists in making more informed decisions but also alleviate the burden on healthcare infrastructure, especially in resource-limited settings. The implementation of this system contributes to the ongoing evolution of AI-assisted medical diagnostics, ultimately improving patient outcomes and reducing diagnostic errors.

REFERENCES

[1]. Tandon YK, Bartholmai BJ, Koo CW. Putting artificial intelligence (AI) on the spot: machine learning evaluation of pulmonary nodules. J Thorac Dis. 2020; 12:6954–6965. doi: 10.21037/jtd-2019-cptn-03.

[2]. Hwang EJ, Park CM. Clinical implementation of deep learning in thoracic radiology: potential applications and challenges. Korean J Radiol. 2020; 21:511–525. doi: 10.3348/kjr.2019.0821.

[3] .Eisen LA, Berger JS, Hegde A, Schneider RF. Competency in chest radiography. A comparison of medical students, residents, and fellows. J Gen Intern Med. 2006; 21:460–465. doi: 10.1111/j.1525-1497.2006.00427. x.

[4]. Hwang EJ, Goo JM, Yoon SH, Beck KS, Seo JB, Choi BW, et al. Use of artificial intelligence-based software as medical devices for chest radiography: a position paper from the Korean Society of Thoracic Radiology. Korean J Radiol. 2021; 22:1743–1748. doi: 10.3348/kjr.2021.0544.

[5]. van Ginneken B, Hogeweg L, Prokop M. Computer-aided diagnosis in chest radiography: beyond nodules. Eur J Radiol.2009;72:226–230.doi: 10.1016/j.ejrad.2009.05.061.

[6]. Edwards M, Lawson Z, Morris S, Evans A, Harrison S, Isaac R, et al. The presence of radiological features on chest radiographs: how well do clinicians agree? Clin Radiol.2012;67:664–668. doi: 10.1016/j.crad.2011.12.003.

[7]. Mehrotra P, Bosemani V, Cox J. Do radiologists still need to report chest x rays? Postgrad Med J. 2009; 85:339–341. doi: 10.1136/pgmj.2007.066712.

[8]. Scheetz J, Rothschild P, McGuinness M, Hadoux X, Soyer HP, Janda M, et al. A survey of clinicians on the use of artificial intelligence in ophthalmology, dermatology, radiology and radiation oncology. Sci Rep. 2021; 11:5193. doi: 10.1038/s41598-021-84698-5.

[9]. Coppola F, Faggioni L, Regge D, Giovagnoni A, Golfieri R, Bibbolino C, et al. Artificial intelligence: radiologists' expectations and opinions gleaned from a nationwide online survey. Radiol Med. 2021; 126:63–71. doi: 10.1007/s11547-020-01205-y.

[9]. Kulkarni S, Seneviratne N, Baig MS, Khan AHA. Artificial intelligence in medicine: where are we now? Acad Radiol. 2020; 27:62–70. doi: 10.1016/j.acra.2019.10.001.

[10]. Chassagnon G, Vakalopoulou M, Paragios N, Revel MP. Artificial intelligence applications for thoracic imaging. Eur J Radiol. 2020; 123:108774. doi: 10.1016/j.ejrad.2019.108774.

[11]. van Leeuwen KG, Schalekamp S, Rutten MJCM, van Ginneken B, de Rooij M. Artificial intelligence in radiology: 100 commercially available products and their scientific evidence. Eur Radiol. 2021; 31:3797–3804. doi: 10.1007/s00330-021-07892 z.