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Research Article

Performance Analysis of AI-Assisted Chest Radiography for COVID-19 Pneumonia Diagnosis in Resource-Limited Settings

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ABSTRACT

Introduction: Chest radiography (CXR) is commonly used for diagnosing lung and cardiothoracic disorders, including coronavirus disease (COVID-19) pneumonia. However, its diagnostic accuracy during the early COVID-19 stages was limited. Artificial intelligence (AI) can enhance CXR analysis and diagnostic accuracy.

Objective: To evaluate AI in X-ray diagnostics for COVID-19 patients in Kyrgyzstan.

Methods: Three radiologists reviewed CXR reports of pneumonia patients and healthy individuals. An AI system with the MedVit deep learning model identified COVID-19 pneumonia, and its reports were compared to radiologists' interpretations to evaluate diagnostic accuracy.

Results: AI's performance in detecting pneumonia matched that of radiologists, with 88.31% sensitivity and 96.67% specificity. High Youden index values indicated quality. AI can enhance X-ray accuracy, especially in resource-limited settings, though challenges like data quality, standardization, and ethics must be addressed for widespread adoption.

Conclusion: Collaboration between radiologists and AI can enhance radiological reports for patients with COVID-19 pneumonia, particularly in rural areas with staff shortages.

Keywords: Chest Radiography, COVID-19, Pneumonia, Artificial Intelligence, Radiologists

Introduction

Chest radiography (CXR) is the most prevalent imaging method for detecting and analysing lung and cardiothoracic abnormalities,[1–3] accounting for approximately 20% of all radiographic examinations in radiology departments. Traditionally, radiologists interpret CXR images.[4–8]

Coronavirus disease (COVID-19) primarily affects the respiratory system, and CXR is the initial imaging method for assessing uncertain cases[9] and involvement of their lungs. However, the diagnostic effectiveness of CXR in early COVID-19 stages is limited, as early pathological changes may not be visible on radiographs, but can be detected via lung computed tomography.[10] Studies indicate that CXR in confirmed COVID-19 pneumonia cases has a 69% sensitivity.[11] Despite its lower sensitivity, CXR is more accessible than lung computed tomography and can aid in COVID-19 diagnosis.

Radiologist shortages are pronounced in low-income countries, where they are concentrated in major urban hospitals, leaving rural and remote areas underserved.[4,12]

Various techniques are currently being evaluated for chest imaging, particularly for pneumonia detection. CXR is ideal for developing deep learning systems for automated diagnosis that require large annotated datasets.[13]

CXR features indicative of pneumonia include new interstitial infiltrates, lobar consolidation, or cavitary lesions.[14,15] The diagnostic criteria for pneumonia vary. The American Thoracic Society/ Infectious Diseases Society of America and the European Society for Clinical Microbiology and Infectious Diseases base diagnosis on clinical symptoms and CXR findings. The British Thoracic Society recommends CXR for all hospitalised patients when the diagnosis is unclear or the response to treatment is inadequate.[16]

These CXR analysis methodologies enable radiologists to work efficiently and accurately. However, manual X-ray analysis is labour-intensive, time-consuming, and prone to inaccuracies.[17] An automated CXR recognition system can expedite the process and improve diagnostic accuracy. Researchers are currently developing reliable automated alternatives to address these challenges.[18,19]

Artificial intelligence (AI) has a significant potential to enhance medical and healthcare services globally. AI can improve the speed and accuracy of disease detection, including in screening. AI-powered radiography analysis, also known as computer-aided detection, introduces a new tool for evaluating CXR and is expected to have broader diagnostic applications.[14,17,19–21] This study aimed to evaluate the application of AI in X-ray diagnostics for patients with COVID-19 in Kyrgyzstan.

Materials and Methods

This retrospective analysis was conducted at healthcare facilities in Kyrgyzstan and approved by the Bioethics Committee (Protocol No. 11, July 25, 2023), where study is conducted from June 2023 to October 2024. All participants provided signed informed consent. Initially, three radiologists from different clinics assessed the completeness, substance, and spirit of the chest X-ray reports for patients with pneumonia and healthy individuals. Subsequently, an advanced AI system was developed to detect COVID-19 pneumonia using digital X-rays. AI was then used to diagnose COVID-19 pneumonia. Finally, a comparative evaluation of the AI diagnostic results and the reports from the three radiologists was performed.

Radiologist Analysis

The average experience of the radiologists was 26.6 years. Each radiologist received digitised images of respiratory organs in the PNG format, with each image assigned a unique identification number to ensure research integrity (Figure 1). The radiologists worked independently without discussing their analyses. The study team adapted the template for describing respiratory organ radiographs. Non-digital radiographs of inadequate quality were excluded to prevent interpretation errors.

Using a retrospective database of approximately 700,000 X-ray images,[22] this study employed a deep machine learning model to identify COVID-19 pneumonia in healthy individuals. Deep learning, especially Convolutional Neural Networks (CNN), is gaining traction in medical image processing because CNNs are highly effective in computer-vision tasks.[23]

The web application was set up to provide access to the X-ray room of a primary healthcare facility in Kyrgyzstan.

This study employed a neural network with a MedVit architecture (Figure 2).[24] Vision transformer-based neural networks yield superior results in medical-image classification.[22] The MedViT_large model, trained on multiple extensive open datasets of chest X-rays, ChestX-ray8 (NIH, United States),[25] CheXpert (Stanford University, United States),[26] RSNA Pneumonia Challenge,[27] and MIMIC-CXR (MIT, United States),[28] was used in all experiments.

X-ray images of patients with pneumonia and healthy individuals were selected based on the initial radiologist reports. The images were sourced from a clinic at the Bishkek Family Medicine Center, comprising 77 digital X-rays of confirmed COVID-19 pneumonia cases and 90 from healthy patients (2021–2022).

We compared the AI-generated X-ray reports with radiologists' interpretations of pneumonia and healthy

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subjects. Both the AI and radiologists were evaluated under identical conditions, without additional clinical laboratory data. The results were recorded based on the criterion "pneumonia/ not pneumonia and without features/ with features."

A web application was developed for model use and deployed on a server in a data centre. Users needed a personal computer with Google Chrome and at least 512 Kbps Internet connectivity. The application was tested on Chrome versions 120 and above, requiring a minimum of 4GB RAM for optimal performance.

Statistical analysis was performed using MedCalc software (version 22.021, MedCalc Software Ltd, Ostend, Belgium).[29] ROC curves were plotted, and the area under the curve (AUC) with 95% confidence intervals (CI) was analyzed. The Youden index was used to determine the optimal cutoff values, and the DeLong test was applied to compare the AUC values across models.[30] Higher AUC values indicate better diagnostic performance.

Results

The AI performance in detecting pneumonia matched that of radiologists, demonstrating the predictive capability of machine analysis (Figure 2).

The ROC curves illustrate the performance of both radiologists and artificial intelligence. The data revealed that the areas under the curves for radiologists and AI were nearly identical, with all four scenarios showing high specificity and sensitivity.

This study calculated the ROC curve characteristics and AUC to assess diagnostic effectiveness (Table 1). Table 1 indicates that radiologists 1 and 2 had the highest AUCs, while doctors 3 and AI had slightly lower AUCs. The substantial overlap in the CIs suggests that these differences are likely not statistically significant, as supported by the comparisons in Table 2.

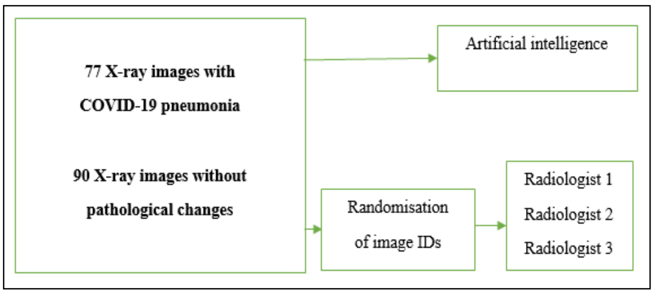

Figure 1.Scheme of Processing Digital X-Ray Images by AI and Radiologists

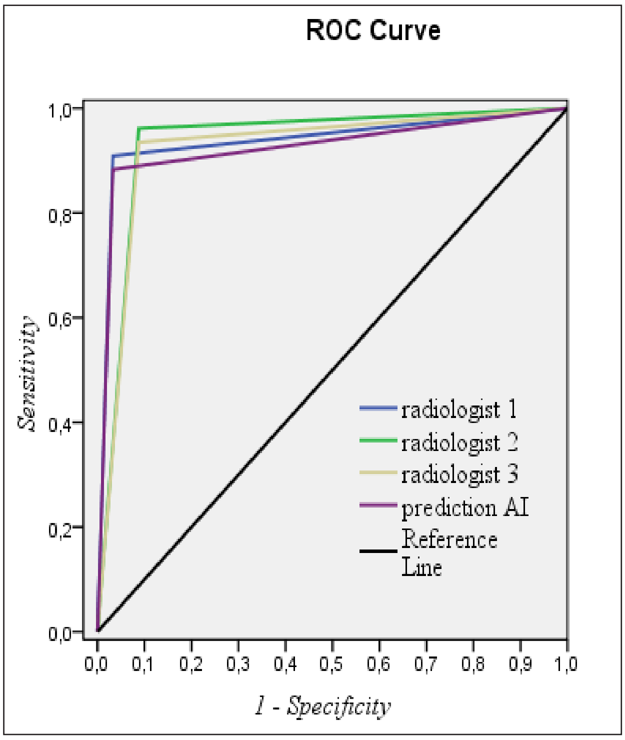

Figure 2.Comparison of ROC Curves of Radiologists and AI

A similar conclusion can be reached from the analysis of the sensitivity and specificity of predictors. Table 3 shows that although the specificities of all four predictors are similar, the sensitivity of AI is slightly lower but not statistically significant because of overlapping CIs with the other predictors. The Youden index was also computed based on the sensitivity and specificity values.

The Youden index values for all predictors are near one, indicating the high quality of all predictors, including AI.

Table 1.Characteristics of ROC Curves

Variable	AUC	SE[a]	95% CI
radiologist_1	0.923	0.0242	0.871–0.958
radiologist_2	0.931	0.0208	0.881–0.964
radiologist_3	0.892	0.0296	0.835–0.935
AI	0.916	0.0237	0.863–0.953

aDelong et al. 198830, AUC: Area Under the Curve, AI: Artificial Intelligence, SE - standard error, CI: Confidence Interval

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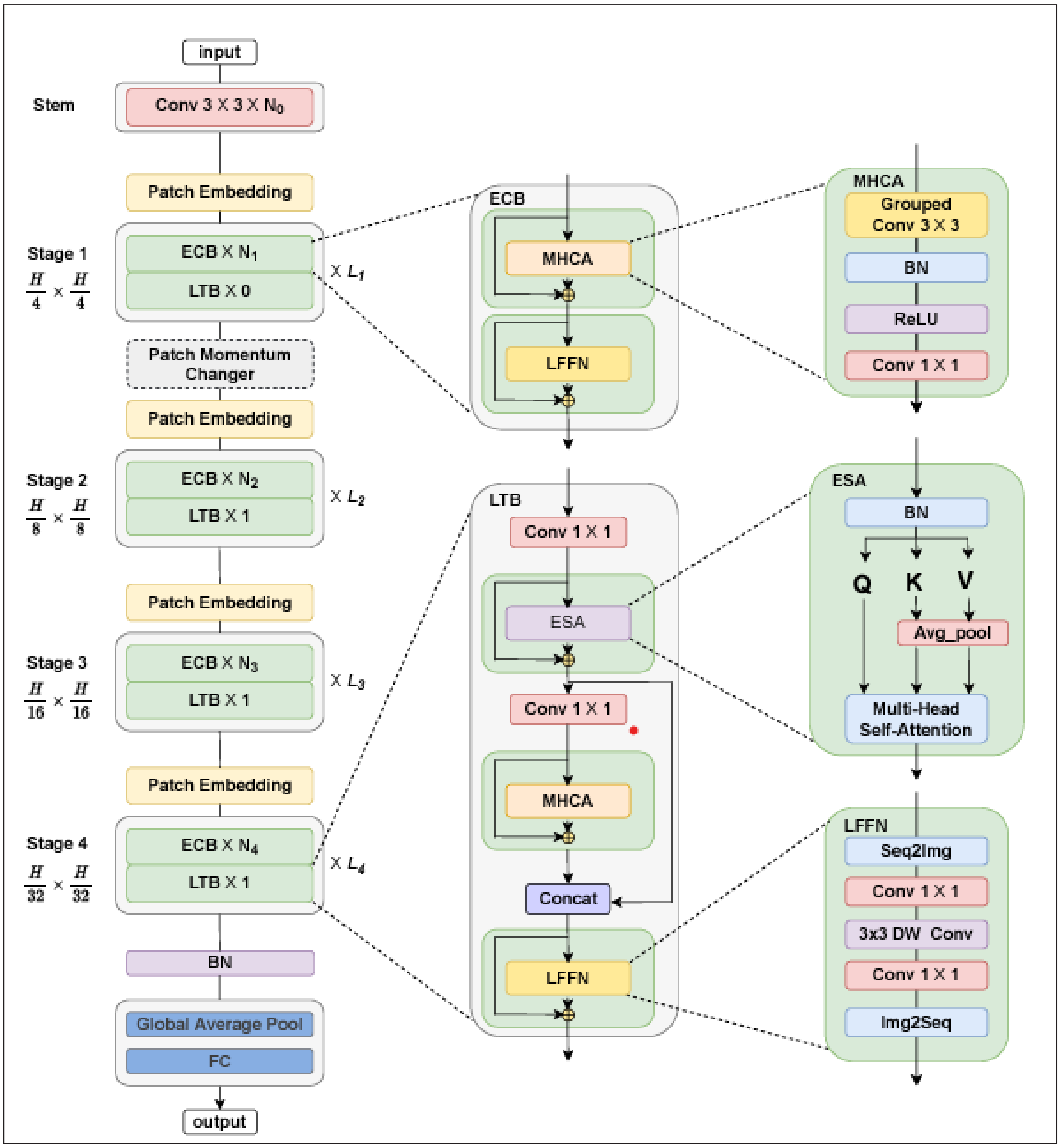

Figure 3.Architecture of the MedVit Neural Network

Table 2.Pairwise Comparison of AUC of ROC Curves

radiologist_1 ~ radiologist_2	
z-statistic	0.292
Significance level	p = 0.7704
radiologist_1 ~ radiologist_3	
z-statistic	1.137
Significance level	p = 0.2557
radiologist_1 ~ AI	
z-statistic	0.206
Significance level	p = 0.8371
radiologist_2 ~ radiologist_3	
z-statistic	1.148
Significance level	p = 0.2508
radiologist_2 ~ AI	
z-statistic	0.469
Significance level	p = 0.6392
radiologist_3 ~ AI	
z-statistic	0.653
Significance level	p = 0.5135

AI: Artificial Intelligence, *p > 0.05.

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Table 3.Estimates of Sensitivity and Specificity of Predictors and Youden Index

Variable	Sensitivity	95% CI	Specificity	95% CI	Youden Index Value
Radiologist 1	90.91	82.2–96.3	96.67	90.6–99.3	0.8758
Radiologist 2	96.10	89.0–99.2	91.11	83.2–96.1	0.8722
Radiologist 3	93.51	85.5–97.9	91.11	83.2–96.1	0.8462
AI	88.31	79.0–94.5	96.67	90.6–99.3	0.8498

AI: Artificial Intelligence, CI: Confidence Interval

Discussion

In COVID-19 diagnostics, AI has significantly improved X-ray analysis, enhancing its accuracy and efficiency. Advanced AI systems using deep learning techniques effectively examine chest X-ray images to detect COVID-19 signs, offering a quick, non-invasive, and scalable diagnostic option, which is especially useful in resource-limited healthcare settings lacking conventional tools.[31,32]

AI systems show high accuracy in identifying COVID-19-related abnormalities on chest X-rays, surpassing traditional evaluations by rapidly processing numerous images and alleviating radiologists' workloads, thus speeding up decision-making.[31,32] However, variations in image quality and symptoms similar to those of other respiratory illnesses present challenges that could affect AI performance. To address these issues, advanced texture-based classification models such as those using Gray-level co-occurrence matrix (GLCM) and wavelet transform methods have been developed to achieve better classification by utilising unique texture features in various datasets.[32]

Integrating AI into clinical protocols improves diagnostics by providing a reliable second opinion and boosting diagnostic confidence. AI tools can categorise cases by severity, enhance triage, and optimise resource use. Effective implementation requires resolving issues related to system compatibility, data protection, and user-friendliness, ensuring AI complements, rather than disrupts existing healthcare practices.[31,33] In this study, we included the web application was set up to provide access to the X-ray room of a primary healthcare facility in Kyrgyzstan (Figure 3).

Challenges to widespread AI adoption in X-ray diagnostics for COVID-19 include the need for extensive, diverse, and high-quality datasets for proper training and validation of AI models. Biases can arise if the training data does not represent the full range of populations affected by the virus. Additionally, the lack of standardisation in AI methodologies and performance evaluation metrics hinders inter-study comparisons and complicates regulatory approval.[32,34]

AI use in healthcare also raises ethical and legal concerns such as patient data privacy and informed consent. Regulatory bodies must set clear criteria for assessing the safety and efficacy of AI-driven diagnostics and ensure compliance with standards before clinical deployment.[33,35]

Advancements in AI for X-ray diagnostics are driven by continuous model development and refinement. Collaboration among researchers, clinicians, and technologists is essential for creating comprehensive datasets and for improving model generalisability. Progress in explainable AI can build trust and acceptance among healthcare professionals by offering transparent insights into AI decision-making processes.

This study assessed the efficacy of an AI system trained to detect pneumonia on chest X-rays, using real-world data. We observed occasional low-quality radiographs owing to variations among centres, such as differences in softness, hardness, and contrast, and some images had errors leading to incorrect patient positioning.

Previous studies on AI models for pneumonia detection in chest X-rays used a class decomposition method with a deep convolutional neural network (Detrac ResNet), achieving 97.9% sensitivity on a small dataset.[36–39] These methods require machine learning expertise, posing challenges for clinical applications.

This study analysed the interpretations of the three radiologists and compared them with the model's performance. AI demonstrated strong predictive ability, with 88.31% sensitivity and 96.67% specificity, making it a potential tool for screening and triaging COVID-19 pneumonia cases. The model is accessible to radiologists for uploading chest X-ray images and is trained with digital images stored in MicroDicom, the primary format in Kyrgyzstan, thus facilitating its use in resource-limited clinical settings.

Conclusion

Emerging technologies in radiation diagnostics are promising for radiologists. Artificial intelligence (AI) benefits diagnostics by saving radiologists' time and facilitating swift pneumonia treatment. Radiologists consider disease patterns, medical history, clinical data, and laboratory

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results in their decision-making. Collaboration between radiologists and AI can improve radiological reports for patients with COVID-19 pneumonia, especially in rural Kyrgyzstan with staff shortages. Future AI advancements will integrate clinical and laboratory data to enhance diagnostic precision.

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