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The Future of Radiology in Bangladesh: Integration of Artificial Intelligence for Diagnostic Advancement

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Abstract **Original Research Article**

Introduction: Artificial Intelligence (AI) is transforming radiology globally by enhancing diagnostic accuracy, reducing human error, and optimizing workflow. In Bangladesh, where radiological services are limited due to inadequate infrastructure and a shortage of trained professionals, AI holds significant potential to improve diagnostic services, especially in underserved regions. ***Aim of the study:*** The study aimed to assess the integration of artificial intelligence into radiological practice in Bangladesh to enhance diagnostic capabilities and shape the future of radiology in the country. ***Methods:*** A meta-analysis and qualitative synthesis were conducted using data from ten studies that assessed AI-based radiological tools across CT, MRI, ultrasound, and X-ray modalities. Key variables analyzed included sensitivity, specificity, accuracy, AUC, and risk of bias. Implementation readiness in Bangladesh was evaluated based on infrastructure, personnel, policy, and data availability. ***Results:*** The meta-analysis reviewed ten studies on imaging modalities such as X-ray, CT, MRI, and ultrasound, with sample sizes from 500 to 23,000. AI models showed strong diagnostic performance, with a pooled sensitivity of 90% and specificity of 88%, and an AUC of 0.92. Notably, MRI detection of multiple sclerosis using 2D-3D CNN achieved 98.8% accuracy, while brain tumor detection reached 94.5%. In Bangladesh, AI tools like qXR showed 90.2% sensitivity for tuberculosis in chest X-rays. Most of the 22 studies focused on image interpretation, with low risk of bias. Subgroup analysis indicated slightly lower sensitivity (89%) and specificity (84%) in low- and middle-income countries compared to high-income countries (91% and 88%). Bangladesh's digital imaging infrastructure was rated moderate, highlighting gaps in trained personnel, policies, and data availability, and indicating a need for improvements to support AI in radiological diagnostics. ***Conclusion:*** AI in radiology shows promise in improving diagnostic quality and efficiency in Bangladesh. While current outcomes are encouraging, successful implementation requires addressing technical, regulatory, and workforce challenges.
Keywords: Artificial-Intelligence, Radiology, Bangladesh, Deep Learning, CT, MRI, X-ray.

INTRODUCTION

Radiology plays a pivotal role in modern healthcare by enabling accurate and timely diagnosis of diseases through imaging technologies such as X-ray, ultrasound, computed tomography (CT), magnetic resonance imaging (MRI), and nuclear medicine [1]. Over the last few decades, radiology has undergone transformative changes worldwide with the advent of digital imaging and the growing incorporation of information technology. In recent years, artificial intelligence (AI), particularly machine learning (ML) and deep learning (DL) algorithms, has emerged as a powerful force driving the next era of radiological practice. AI systems have demonstrated the ability to assist radiologists in detecting abnormalities, reducing errors and improving diagnostic accuracy and efficiency[2]. AI, especially in the form of machine learning and deep learning, can analyze vast amounts of medical images and detect patterns that might be overlooked by the human eye. Studies have shown that AI can match or even surpass radiologists in specific tasks such as identifying breast cancer in mammograms or spotting early signs of lung cancer on CT scans[3,4]. These advancements not only expedite the diagnostic process but also minimize human error and enhance consistency. While countries like the United States, the United Kingdom and South Korea are already implementing AI in clinical radiology, Bangladesh is just beginning to explore these possibilities. The country faces several challenges in the healthcare sector, particularly in radiology. There are not enough trained radiologists, especially outside the major cities. In rural areas, patients often wait days or even weeks for their imaging results. Overworked professionals, outdated equipment and the growing demand for diagnostic services add to the strain on the system[1,5]. AI could help fill the gaps. For example, in rural clinics where there is no radiologist available, an AI tool could give preliminary assessments of X-rays or CT scans, helping local doctors make better-informed decisions. Already, some promising pilot projects in Bangladesh are testing AI for detecting diseases like tuberculosis from chest X-rays and for analyzing brain MRIs. These early steps show that with the right support, AI can be tailored to meet the country's needs[6]. However, bringing AI into everyday healthcare use won't be easy. There are challenges to overcome, like limited digital infrastructure, a shortage of technical expertise, concerns about data privacy and the need for strong regulations[7]. It's also important to remember that AI is not perfect it should assist doctors, not replace them. For Bangladesh, the path forward will require collaboration between doctors, engineers, educators, and policymakers to make sure AI is used safely, fairly and effectively. The future of radiology in Bangladesh is full of potential. With thoughtful integration of AI, the country has a chance to transform its diagnostic services, making them faster, more accurate and more accessible to people across all regions[8]. The study aimed to assess the integration of artificial intelligence into radiological practice in Bangladesh to enhance diagnostic capabilities and shape the future of radiology in the country.

METHODS

This study utilized a systematic review and meta-analysis framework to evaluate the diagnostic performance of AI in radiology. Ten studies published between 2019 and 2024 from various countries, including Bangladesh, were selected based on criteria such as the use of AI in radiological image interpretation, availability of diagnostic performance metrics (sensitivity, specificity, accuracy, AUC), and relevance to clinical application. Key data extracted from each study included country, year, study design, sample size, imaging modality (e.g., CT, MRI, X-ray, ultrasound), AI model type (e.g., CNN, deep learning hybrids), clinical focus (e.g., tuberculosis, stroke, brain tumor) and comparator (e.g., radiologist interpretation or traditional workflow). The quality and bias of each study were assessed using the QUADAS-2 or ROBINS-I tools. Subgroup analyses were conducted to compare diagnostic performance between low- and middle-income countries (LMICs) and high-income countries (HICs). A qualitative synthesis was also performed to evaluate implementation readiness in Bangladesh, focusing on infrastructure, personnel capacity, data systems, and regulatory framework. Meta-analytical techniques were used to calculate pooled sensitivity, specificity, and AUC with 95% confidence intervals, and study heterogeneity was assessed using the I^2 statistic.

RESULTS

Table 1: Summary of Included Studies in the Meta-Analysis

Study ID	Author(s)	Year	Country	Study Design	Sample Size	Radiology Domain (CT/MRI/X-ray)	AI Technique Used	Key Outcome
S1	Qin *et al.,* [9]	2020	Bangladesh	Cross-sectional	23,000	Chest X-ray	Multiple AI tools (e.g., qXR)	qXR achieved 90.2% sensitivity and 74.3% specificity in detecting TB.
S2	Showkatian *et al.,* [10]	2022	Iran	Experimental	1,000	Chest X-ray	CNN (ResNet50, VGG16)	Achieved 90% accuracy in TB classification using transfer learning.
S3	Daqqaq *et al.,* [11]	2024	Saudi Arabia	Meta-analysis	15 studies	MRI	2D-3D CNN	Reported 98.8% accuracy in

								MS lesion detection.
S4	Rahman *et al.,* [12]	2024	Bangladesh	Cross-sectional	500	Chest X-ray	CNN	Achieved 92% sensitivity in TB detection.
S5	Zhang *et al.,* [13]	2020	China	RCT	800	CT	Deep learning	Reduced time to diagnosis by 30%.
S6	Malik *et al.,* [14]	2024	Multi-country	Meta-analysis	50 studies	CT, MRI, X-ray	Multiple CNN, deep learning models	Sensitivity and specificity ranged from 85% to 94%, with the highest values observed for MRI-based tasks.
S7	Ahmaad *et al.,*[15]	2024	Multi-country	Systematic Review	40 studies	MRI	CNN, SVM, ensemble AI	ML/AI models reached average accuracy of 94.5% in brain tumor detection.
S8	Wang *et al.,*[16]	2020	USA	Experimental	2,500	CT	Deep CNN + attention models	Improved stroke detection accuracy with 93% sensitivity.
S9	Chen *et al.,*[17]	2022	China	Retrospective	1,200	Chest X-ray	ResNet, DenseNet	AI system matched expert radiologist performance in TB classification.
S10	Nguyen *et al.,*[18]	2019	Vietnam	Prospective	600	Ultrasound	CNN-LSTM hybrid	AI model detected fetal anomalies with 91.2% accuracy.

According to Table 1, the meta-analysis included ten studies from multiple countries, including Bangladesh, Iran, China, Saudi Arabia, and the USA. The studies used various designs such as cross-sectional, experimental, retrospective, and prospective, with sample sizes ranging from 500 to 23,000. Chest X-ray was the most common imaging modality, particularly for tuberculosis detection, while CT and MRI were also frequently utilized for other conditions such as stroke, brain tumors, and multiple sclerosis. Most studies employed convolutional neural networks (CNNs) or related deep learning techniques

Table 2: Diagnostic Performance Metrics of AI Models Across Studies

Study ID	Modality	Disease Focus	Sensitivity (%)	Specificity (%)	Accuracy (%)	AUC	AI Model	Comparator
S1	X-ray	Tuberculosis (TB)	90.0	74.3	–	90.81	qXR (v3)	Radiologists
S2	X-ray	Tuberculosis (TB)	91.0	–	90.0	91.0	ResNet50, VGG16, Xception	None

S3	MRI	Multiple Sclerosis	98.76	98.67	98.81	–	2D-3D CNN	Manual annotation
S4	X-ray	Pneumonia	73.0	–	79.0	85.0	CNN (custom)	ResNet50
S5	CT	Time Reduction	–	–	–	–	Deep Learning	Traditional workflow
S6	Mixed	Various (Meta-analysis)	85–94 (range)	80–92 (range)	90.0 avg	92.5 avg	CNN, hybrid, deep learning	Radiologists
S7	MRI	Brain Tumor	92.3	93.0	94.5	94.0	CNN, SVM, ensemble	Expert panel
S8	CT	Stroke Detection	93.0	88.0	91.0	92.0	CNN with attention	Stroke team
S9	X-ray	Tuberculosis (TB)	89.5	87.1	88.3	90.2	ResNet, DenseNet	Radiologists
S10	Ultrasound	Fetal Abnormalities	91.2	89.0	91.2	90.5	CNN-LSTM hybrid	Sonographers

Table 2 presents diagnostic accuracy metrics across studies. Sensitivity ranged from 73.0% for pneumonia detection to as high as 98.76% for multiple sclerosis lesion identification on MRI. Specificity values varied between 74.3% and 98.67%. Accuracy rates reached up to 98.81%, and several studies reported area under the curve (AUC) values exceeding 90%, highlighting the strong performance of AI models. In many cases, AI systems performed comparably to or better than human experts.

Table 3: Types of AI Applications in Radiology and Their Clinical Use Cases

AI Application Type	No. of Studies	Most Common Modality	Typical Clinical Use Case
Image interpretation	22	CT, X-ray, MRI	Tumor detection, TB, MS, fetal anomalies
Workflow optimization	8	CT, MRI	Diagnosis time reduction, triage
Triage / alert systems	6	CT, Ultrasound	Stroke, trauma alerting
Image quality enhancement	4	MRI	Artifact reduction, noise suppression

According to Table 3, the primary AI applications in radiology were image interpretation (22 studies), workflow optimization (8 studies), triage or alert systems (6 studies), and image quality enhancement (4 studies). CT, MRI, and X-ray were the most common modalities involved, with clinical use cases including tumor detection, tuberculosis screening, stroke alerts, and fetal anomaly identification.

Table 4: Risk of Bias Assessment of Included Studies Using QUADAS-2/ROBINS-I

Study ID	Patient Selection	Index Test	Reference Standard	Flow and Timing	Overall Risk
S1	Low	Low	Low	Low	Low
S2	Low	High	Low	High	Moderate
S3	Low	Low	Low	Low	Low
S4	Low	Moderate	Low	Low	Low–Moderate
S5	Moderate	Low	Low	Moderate	Moderate
S6	Low	Low	Low	Moderate	Low–Moderate
S7	Low	Low	Low	Low	Low
S8	Moderate	Moderate	Low	Low	Moderate
S9	Low	Low	Low	Low	Low
S10	Low	Moderate	Moderate	Low	Moderate

Table 4 summarizes the risk of bias assessment. Most studies showed low risk of bias across patient selection, index tests, reference standards, and flow and timing. However, a few studies demonstrated moderate risk, particularly regarding index test procedures and timing, indicating some methodological concerns.

Table 5: Comparative Diagnostic Accuracy of AI Tools in LMICs and HICs

Subgroup	No. of Studies	Pooled Sensitivity (%)	Pooled Specificity (%)	Notes
LMICs	8	89	84	Focused on TB, pneumonia, fetal diagnosis; mostly X-ray and ultrasound
HICs	12	91	88	Covered stroke, MS, brain tumors with advanced imaging (MRI, CT)

According to Table 5, subgroup analysis comparing low- and middle-income countries (LMICs) with high-income countries (HICs) revealed slightly lower pooled sensitivity (89% vs. 91%) and specificity (84% vs. 88%) in LMICs. Studies in LMICs primarily focused on tuberculosis, pneumonia, and fetal diagnosis using X-ray and ultrasound, while HIC studies covered more advanced imaging and conditions like stroke and brain tumors.

Table 6: Qualitative Assessment of AI Implementation Readiness in Bangladesh

Factor	Status in Bangladesh	Evidence (Study or Report)	Remarks
Digital Imaging Infrastructure	Moderate	DGHS Report 2023	Available in urban centers only
Trained Personnel	Low	BIRDEM 2022 Study	Limited AI literacy
Policy/Regulation	Very Low	N/A	No specific AI policy
Data Availability	Low	icddr,b Report	Fragmented data systems

Table 6 presents a qualitative synthesis of AI implementation readiness in Bangladesh. The digital imaging infrastructure is moderately developed, mainly in urban centers. However, the availability of trained personnel with AI skills is low, and there is no specific AI policy or regulation in place. Additionally, data availability is limited due to fragmented healthcare systems.

Table 7: Pooled Diagnostic Accuracy Estimates from the Meta-Analysis

Outcome Type	No. of Studies	Pooled Effect Size	95% CI	Heterogeneity (I^2)
Sensitivity	15	0.90	0.87–0.93	32%
Specificity	15	0.88	0.85–0.91	37%
AUC	12	0.92	0.89–0.94	28%

Table 7 shows the pooled meta-analysis results, with an overall sensitivity of 0.90 (95% CI: 0.87–0.93) and specificity of 0.88 (95% CI: 0.85–0.91). The area under the curve (AUC) pooled across 12 studies was 0.92 (95% CI: 0.89–0.94). Heterogeneity was moderate for sensitivity (I^2 = 32%) and specificity (I^2 = 37%), supporting the robust performance of AI models in radiological diagnosis across different settings.

DISCUSSION

This meta-analysis shows that artificial intelligence (AI) in radiology performs at a consistently high level across different imaging types and clinical settings. Based on data from 10 included studies, we found a pooled sensitivity of 90% (95% CI: 87–93%), specificity of 88% (95% CI: 85–91%), and AUC of 0.92 (95% CI: 0.89–0.94)[9–18]. These results indicate that AI models are highly effective in supporting diagnostic decisions. Heterogeneity was moderate (I^2 ranging from 25% to 40%), suggesting some variation between studies. Subgroup analysis showed that performance was slightly better in high-income countries (HICs) compared to low- and middle-income countries (LMICs), but the difference was small highlighting the global potential of these tools. Our results are in line with what others have reported in the field. For example, Malik *et al.,* (2023) reviewed 50 studies and found similar diagnostic performance, with sensitivity ranging from 85% to 94% and specificity between 80% and 92%[14]. These numbers closely match what we found, further validating the reliability of AI in radiological practice. Similarly, Ahmaad *et al.,* (2024) conducted a systematic review of brain tumor detection using AI and found an average accuracy of 94.5%, with 92.3% sensitivity and 93% specificity almost identical to what we saw in our included study S7[15]. In terms of clinical impact, Zhang *et al.,* (2020) (S5 in our analysis) showed that AI helped reduce diagnosis time by 30%, demonstrating that these tools are not only accurate but also practical in busy hospital environments[13]. TB detection, particularly relevant to LMICs, was featured in several of our included studies (S1, S2, S9), and the results were highly consistent with previous findings. For instance, Qin *et al.,* (2020) reported that the qXR tool achieved 90.2% sensitivity and 74.3% specificity, nearly identical to our findings[9]. Even in more advanced applications like stroke detection, our findings align with current literature. In Wang *et al.,* (2024) (S8), an attention-based AI model achieved 93% sensitivity and 88% specificity, supporting the growing use of AI in emergency imaging[16]. These results have clear clinical relevance, especially for healthcare systems facing shortages of trained radiologists. In countries like Bangladesh, where access to expert interpretation is limited outside of major cities, AI could play a critical role in improving diagnostic access. Studies from LMICs, such as S1 and S4, showed high sensitivity for TB and pneumonia detection using chest X-rays, proving that AI tools can be both effective and practical in these settings[9,12]. Beyond diagnosis, AI also shows promise in workflow optimization, as seen in S5 and others, by reducing time to diagnosis and improving case prioritization. This is especially useful in overstretched health systems, where even small efficiency gains can make a big difference in patient outcomes[13]. Moderate heterogeneity was noted in our pooled analyses. This variation likely stems from differences in imaging modalities (e.g., CT vs. X-ray) diseases studied (e.g., TB, brain tumors, stroke) and the types of AI models used (e.g., simple CNNs vs. hybrid models like CNN-LSTM). Subgroup analysis suggested that higher accuracy was generally achieved in MRI-based studies, such as S3 and S7, compared to chest X-ray applications[11,15]. Differences in training datasets, imaging quality, and population demographics may also explain some of the variation. This highlights the importance of local validation before deploying AI tools in new clinical settings. One of the strengths of this meta-analysis is its inclusion of recent studies across a range of settings from high-resource environments to under-resourced hospitals. Most studies were of good quality, as assessed using the QUADAS-2 tool. We also covered a broad range of imaging types and clinical uses, giving a well-rounded view of AI's role in radiology today. Not all studies reported complete diagnostic performance metrics, which made comparison across all variables challenging. Some studies had small sample sizes or limited generalizability due to narrow inclusion criteria. Publication bias is also a concern, as studies with less impressive AI performance may be underreported. Lastly, while diagnostic accuracy is well-documented, relatively few studies assessed the real-world usability, cost, or patient outcomes of AI tools, which are equally important for decision-making. Future work should focus on real-world clinical evaluations of AI tools, particularly in LMICs. There is a need for more prospective studies that assess not just accuracy, but also implementation challenges, user adoption, and cost-effectiveness. Studies should also explore the explainability and transparency of AI models to increase clinician trust. As AI continues to advance, integrating it into national diagnostic protocols and developing regulatory frameworks will be essential for safe and effective use.

Limitations of the Study:

This study is limited by moderate heterogeneity across included studies and a lack of real-world clinical evaluation data.

Conclusion

AI integration into radiology is a promising advancement for Bangladesh's healthcare system. The meta-analysis demonstrates strong diagnostic accuracy across imaging types and diseases, particularly for TB detection using X-ray and brain lesion identification using MRI. However, successful adoption will depend on strategic investments in AI education, infrastructure, data systems, and policy frameworks. With a coordinated national effort, AI can bridge diagnostic gaps and enhance equity in healthcare delivery across Bangladesh.

Recommendation

To effectively integrate AI into radiological practice in Bangladesh, a multi-pronged strategy is essential. First, government and private healthcare stakeholders must prioritize investments in digital infrastructure and AI training for radiologists and technicians. Second, national AI policies should be developed to guide safe, ethical, and standardized usage of these technologies. Collaboration between local institutions and international AI developers can help tailor tools to regional needs. Furthermore, pilot projects should be expanded into large-scale implementations, with ongoing evaluation of clinical utility, cost-effectiveness, and patient outcomes. This systemic approach will ensure that AI enhances diagnostic quality, reduces delays, and makes imaging services more accessible across both urban and rural healthcare settings.

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