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Artificial Intelligence Techniques in Clinical Decision Support Systems in Radiology Using X-ray and MRI

Shubhmehar Singh Dhillon*[1], Sandeep Kaur[2], Satveer Kour[3]

Department of Computer Engineering and Technology, Guru Nanak Dev University, India[1-3]

Abstract: Artificial Intelligence (AI) is changing the Clinical Decision Support Systems (CDSS) in radiology, especially in X-ray and Magnetic Resonance Imaging (MRI). This study involves a qualitative systematic synthesis of 70 relevant publications with PRISMA approach to assess AI approaches, clinical applications and real-world deployment in radiological CDSS. The findings show that deep learning models like CNNs, 3D CNNs, U-Net, transformer-based models dominate in today's applications. The advantage of AI-CDSS based on X-rays are for screening and classification, whilst AI-CDSS based on MRI are better for volumetric analysis, tumour segmentation, and data monitoring. Aidoc, Viz.ai, Qure.ai, Arterys and DeepMind Health demonstrate the therapeutic use of AI in triage, anomaly detection and workflow optimisation. However, challenges remain concerning interpretability, data heterogeneity, generalisability and clinical integration. AI is rapidly evolving as a vital companion in radiological CDSS, improving accuracy and efficiency.

Keywords: Artificial Intelligence, Clinical Decision Support Systems, Radiology, X-ray, MRI, Deep Learning, Explainable AI

I. INTRODUCTION

Radiology is a fundamental part of today's healthcare, offering non-invasive visualisation of anatomical structures and disease processes using imaging modalities such as X-ray and Magnetic Resonance Imaging (MRI) [1], [2]. With the progress of precision medicine, radiological imaging has extended beyond traditional diagnosis to facilitate early disease identification, treatment planning, and patient monitoring [3], [4]. X-ray is still frequently used for its availability, low cost and clinical utility for thoracic and skeletal examination [5], [6]. MRI is vital in neurological and oncological assessment due to its better soft-tissue characterisation and multidimensional imaging [7], [8]. However, the fast growth of imaging data imposes major cognitive and operational problems for radiologists, compromising diagnostic accuracy, efficiency and consistency [9], [10].

Clinical Decision Support Systems (CDSS) have been developed to support clinical reasoning by integrating patient information, imaging data and evidence-based knowledge [11], [12]. Traditional CDSSs, that are frequently based on rule-based or statistical methods, have limited capacity to deal with the complexity and high dimensionality of radiological data [13], [15]. The advent of Artificial Intelligence (AI) with its branches like Machine Learning (ML) and Deep Learning (DL) has greatly increased the ability of CDSS in radiology [16], [17]. AI models can automatically extract features and recognise complicated imaging patterns, which supports accurate classification, detection, segmentation, and prediction [5], [18]. Convolutional Neural Networks (CNNs) have demonstrated impressive performance in X-ray processing. 3D CNNs and transformer-based designs have enhanced MRI interpretation by capturing spatial and contextual correlations [19], [20]. The AI-assisted CDSS not only enhance diagnostic performance but also facilitate process optimisation, decrease inter-observer variability, and allow for swifter clinical decision-making [21], [22]. Real-world technologies like Aidoc, Qure.ai and DeepMind Health show the practical application of AI in automated triaging, alarm generation and integration with healthcare systems [23]. However, these advances are not easily translated into clinical use due to data heterogeneity, limited generalisability to other patient groups, lack of transparency in deep learning models, uncertainty regarding interpretability of models, clinician trust, ethical concerns, and regulatory barriers [23], [24], [25], [26], [27]. Such restrictions highlight the need to evaluate all AI solutions not only by how well they perform the algorithms but also by how they can be practically applied in a trustworthy, scalable and clinically applicable CDSS [8], [28]. Therefore, this paper aims to critically examine the current applications of AI techniques to improve CDSS, particularly with regard to X-ray and MRI imaging. It covers the use of machine learning, deep learning, hybrid techniques and explainable AI methods in classification, detection and segmentation, and predictive scenarios. The paper also examines real-world AI-CDSS platforms and identifies a number of challenges, such as dataset bias, interpretability, scalability, ethical considerations, and clinical implementation. Integrating current research and practical applications, this study offers a

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cohesive view of the intersection of AI and radiological decision-making, underscoring the synergistic role of human expertise and machine intelligence in enhancing diagnostic accuracy and clinical outcomes.

II. LITERATURE REVIEW

Artificial Intelligence in Radiological The use of Artificial Intelligence (AI) in radiology has significantly improved the interpretation of pictures, diagnostic accuracy and the efficiency of clinical workflow [1], [3]. The research indicates a strong movement from classic machine learning approaches to deep learning (DL) algorithms, which are able to automatically extract complicated hierarchical features from high dimensional imaging data [7], [15]. This is particularly notable because the number and complexity of radiological tests are increasing and are causing a significant workload stress for radiologists [4], [17].

One of the most popular AI models for analysing X-ray images is Convolutional Neural Networks (CNNs) [29; 30]. Architectures such as ResNet, DenseNet and EfficientNet have exhibited high performance for illness identification and classification with diagnostic accuracy nearing or surpassing expert-level interpretation in various chest radiography tasks [5], [6], [31], [32]. The availability of huge annotated datasets has also fuelled the development of multi-label classification systems capable of detecting various thoracic anomalies concurrently, hence enhancing diagnostic efficiency in clinical practice [62], [63].

On the other hand, MRI based AI applications have more computational and methodological obstacles because of the volumetric, multi-parametric and high-dimensional nature of MRI data [7], [8]. To overcome these issues, state-of-the-art designs such as 3D CNNs [19], hybrid deep learning models [21] and attention-based networks [19] have been widely studied. These models can learn spatial and contextual links among the slices of the imaging data, and hence are valuable for tumour segmentation, lesion detection, volumetric analysis, and disease characterisation. Some investigations demonstrated very high performances with accuracy up to almost 99% for specified controlled applications [54]. Moreover, AI is playing an ever-increasing role as a diagnostic and prognostic tool in radiology, with predictive modelling approaches such as brain-age estimation and disease-progression analysis [47], [63].

In addition to diagnostic interpretation, AI has demonstrated tremendous potential in optimising radiological workflow. Automation can help prioritise critical cases, shorten reporting time, reduce inter-observer variability and increase overall clinical efficiency [14], [22]. Recently, developments in self-supervised learning have led to enhanced generalisation of models on various datasets [26], [27]. Methods of Explainable AI (XAI) such as Grad-CAM and attention-based visualisation have also been developed to offer transparency and interpretability. Additionally, new vision-language models and hybrid AI systems are starting to add reasoning, although their clinical robustness still needs more validation [32], [33], [34].

But these achievements have their limitations. One of the key issues is the restricted generalisability of AI models to different clinical contexts as models trained on certain datasets or populations can demonstrate decreased performance in real-world settings [24], [35]. Moreover, data imbalance, inconsistent annotations, limited dataset size and heterogeneity in imaging techniques may influence the robustness and reliability of the models [36], [37]. Additionally, the black box nature of deep learning is a barrier to physician trust and clinical adoption. The absence of standardised reporting and validation processes also impacts repeatability and comparison across research [26], [38]. These problems underscore the need for standardised, interpretable, externally validated, and clinically usable AI frameworks in radiology [49], [57].

AI-Driven Clinical Decision Support Systems in Radiology

Clinical Decision Support Systems (CDSS) are computer systems that can integrate imaging information with patient information and analytical models with the goal of providing information to support the physician in making appropriate evidence based decisions [11], [12]. In the field of radiology, AI-powered CDSS have evolved from a set of rules to data-driven, adaptive platforms that can learn from large volumes of data and provide predictive insights [13], [15]. Modern AI-driven CDSS usually comprise data collection modules, data preprocessing pipelines, analytic engines, knowledge base, and user interfaces, the analytic engine being usually equipped with machine learning or deep learning algorithms [12], [64]. AI-based CDSS can be used to assist with many radiological tasks, including classification, segmentation, anomaly detection, risk stratification and prediction, which enhance the accuracy of diagnosis and improve clinical efficiency [1], [59], [66]. The seamless incorporation of their role in radiology has supported the shift from a

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reactive diagnostic process to a proactive, predictive healthcare process, which can help to minimize diagnostic delays and improve patient outcomes [3], [60]. Indeed, practical examples of real-world implementation support the practical value of AI-based CDSS. In an emergency scenario, platforms like Aidoc are using deep learning algorithms to sort and identify serious cases in real time, helping to reduce response times [23], [55], [58]. Likewise, Qure.ai uses CNN models for large-scale chest X-ray screening, particularly in areas of the healthcare system with few resources [5], [46]. Multimodal systems like IBM Watson Health combine imaging information with electronic health records, and use NLP and machine learning to glean deeper clinical insights [2], [51]. There are also some advanced research programs, such as DeepMind Health, demonstrating the potential of advanced AI architectures for diagnostic use in MRI scanning [7], [41]. However, there are several challenges that prevent the widespread clinical use of AI powered CDSS. Seeking to gain insight into the reasons behind AI decision-making is a significant concern because the black-box approach might erode clinician confidence and accountability [26], [27], [52]. There is a particular need for quality,diversity and representativeness of training data as designing a model with biased or limited datasets may limit generalisability across diverse patient populations [25], [68]. In addition, integration with current clinical infrastructures such as Picture Archiving and Communication Systems (PACS), Radiology Information Systems (RIS) and electronic health records is technically complex, especially in resource-constrained settings [21], [69]. Regulatory, ethical and privacy issues also have to be carefully considered and validated per healthcare standards when deploying [23], [28]. Another major challenge is that, most current AI-CDSS are task specific, which hinders their scalability and wider clinical use [10], [39]. Advanced architectures like as 3D CNNs and transformer-based models also impose practical constraints for real-time clinical usage, owing to high processing needs [40], [41]. In summary, the research shows that AI, particularly deep learning, has greatly boosted the capabilities of CDSS in radiology, notably for X-ray and MRI applications [70]. The development of integrated, explainable, scalable and clinically proven AI-CDSS frameworks that can reliably function across diverse populations and in real-world healthcare contexts, however, is still needed for further advancement [8], [43].

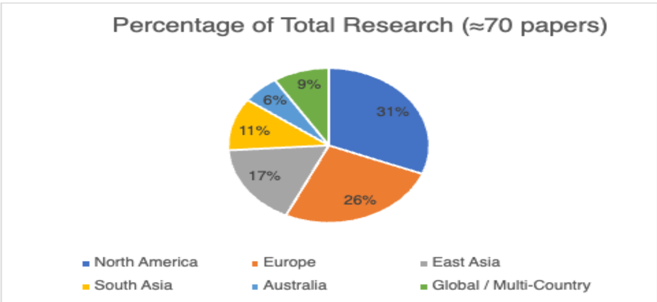

Figure 1: Region-wise distribution of selected studies on AI-based clinical decision support systems in radiology.

The figure 1 highlights global research trends and geographical differences in the adoption of AI techniques, with higher contributions from technologically advanced regions reflecting stronger imaging datasets, computational infrastructure, hospital-based AI networks, and digital health investment. Lower representation from some regions may indicate limited access to annotated radiological data, funding, and AI-enabled clinical infrastructure.

Table 1: Distribution of selected studies according to imaging modality.

Imaging Modality	Number of Papers	Percentage (%)
Chest X-ray (CXR)	35	50.0%
MRI	18	25.7%
CT	10	14.3%
Multi-modal (CXR + CT + MRI + Clinical Data)	7	10.0%
Total	70	100.0%

This table summarizes the imaging modalities used across the 70 selected studies. Chest X-ray was the most frequently studied modality, followed by MRI, CT, and multimodal approaches. The dominance of X-ray reflects its wide availability, lower cost, faster acquisition, and suitability for AI-based screening and classification.

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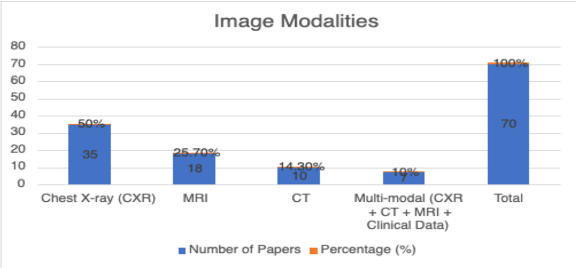

Figure 2: Modality-wise distribution of selected AI-radiology studies.

This figure visually supports the modality pattern shown in Table 1. Chest X-ray-based studies form the largest proportion, indicating their strong role in AI-driven radiological research. MRI and CT studies are fewer but remain important for complex anatomical, volumetric, and disease-specific analysis.

Table 2: Distribution of AI techniques used in the selected radiology studies.

Technique Category	Number of Papers	Percentage (%)
CNN-based Models (ResNet, DenseNet, VGG, EfficientNet, etc.)	42	60.0%
Segmentation Models (U-Net, nnU-Net, V-Net, Mask R-CNN)	12	17.1%
Transformers / Vision Transformers (ViT)	4	5.7%
Hybrid Models (CNN + LLM / CNN + ML / Multi-task DL)	5	7.1%
Classical ML (SVM, Random Forest, Logistic Regression)	3	4.3%
Self-Supervised / Unsupervised Learning (MoCo, Barlow Twins, GANs)	2	2.9%
Explainable AI (XAI, Grad-CAM, CAM-based Methods)	2	2.9%
Total	70	100.0%

The table 2 categorizes the selected studies according to the major AI techniques applied in radiological image analysis. CNN-based models were the most commonly used, followed by segmentation networks, transformers, hybrid models, classical machine learning, self-supervised approaches, and explainable AI methods. This reflects the central role of deep learning in classification, detection, segmentation, and clinical decision support.

Pre-processing, Model Evaluation, and Validation

The review also explored typical reported steps of picture pre-processing, as these have a substantial effect on the performance and generalisability of models. The common pre-processing techniques used in X-ray investigations were image normalisation, scaling, contrast enhancement, and region-of-interest segmentation [79]. Preprocessing in MRI investigations typically involves intensity normalisation, slice alignment, volumetric reconstruction and integration of several sequences. Model evaluation was carried out by employing clinically relevant performance parameters including accuracy, sensitivity, specificity, AUC and Dice Similarity Coefficient [79]. In several investigations, model robustness was evaluated using k-fold cross-validation, and in some studies, generalisability was evaluated using external datasets. Moreover, Grad-CAM and other explainability methodologies were investigated, notably in research that improved the transparency, trust, and clinical interpretability of AI-assisted choices [80].

Comparative and Descriptive Synthesis

A descriptive and comparative analysis was done for the trends in imaging modalities, AI architecture, clinical application and geographical distribution of investigations. The most reported approaches were CNN-based models, followed by segmentation networks, hybrid models and the upcoming.

III. METHODOLOGY

Study Design

The study took a qualitative systematic review approach to critically analyze the application of Artificial Intelligence (AI) techniques in Clinical Decision Support Systems (CDSS) in radiological imaging and specifically in X-ray and Magnetic Resonance Imaging (MRI) [71]. We followed PRISMA principles in our review methodology ensuring a transparent and reproducible process of locating, screening and selecting eligible papers. The investigation was made on imaging modality, AI technique, clinical application, model performance and CDSS integration. This gave a comprehensive picture of the potential of AI in radiological decision making. A standardised data extraction approach

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was utilised to retrieve critical information from each selected study [76], [77]. The extracted data were imaging modality, artificial intelligence technique, dataset Transformer-based architectures [81], [82]. The availability and clinical usage of the radiography made the X-ray investigations more frequent while the MRI studies often involved more detailed anatomical and tissue level analysis features, clinical application, evaluation metrics, validation strategy, and reported limitations. The AI approaches used were traditional machine learning models, Convolutional Neural Networks (CNNs), U-Net based segmentation models, Transformer based architectures, hybrid frameworks, and explainable AI approaches [77].

The selected studies were analysed through thematic and comparative syntheses. This allowed comparison of performance of AI in X-ray and MRI applications, models of different architectures, and clinical utility in CDSS processes. The investigation went beyond a descriptive review to identify common themes, methodological strengths and limitations, and research gaps in AI-driven radiology [78].

Data Sources and Study Selection
A complete literature search was performed utilising major scientific databases including PubMed, IEEE Xplore, ScienceDirect, arXiv and Google Scholar [72], [72]. We also searched reference lists of relevant papers for further studies. Keywords: artificial intelligence, machine learning, deep learning, clinical decision support systems, radiology, X-ray, MRI, diagnosis, segmentation, predictive analysis.

More than 100 articles were initially obtained. Duplicates were removed and titles and abstracts were screened before full text articles were appraised for eligibility against pre-defined eligibility criteria. Finally, 70 high-quality studies were selected for comprehensive analysis based on their relevance to AI-based radiological imaging, clinical or experimental validation, and applicability in the context of CDSS or diagnostic decision support.

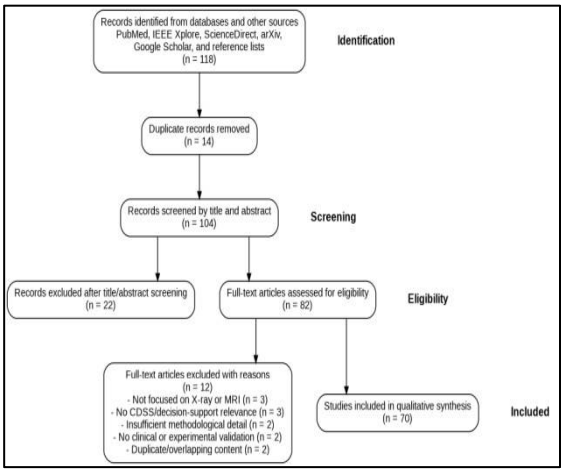

Figure 3. PRISMA flow diagram of study identification, screening, eligibility, and inclusion.

This figure 3 presents the systematic process followed to select studies for qualitative synthesis. Articles were identified from major scientific databases, screened for relevance, assessed for eligibility, and finally included based on predefined criteria. The PRISMA flow improves transparency and reproducibility of the review methodology.
Inclusion and Exclusion Criteria

Studies were included if they focused on applications of AI in X-ray or MRI imaging, especially for clinical decision support, diagnostic improvement, classification, detection, segmentation, or prediction [73], [74]. Articles which reported the model performance on criteria like accuracy, sensitivity, specificity, Area under the Curve (AUC) or Dice Similarity Coefficient were also included. We preferred well reviewed journals and high quality conference papers.

Studies were excluded if they were confined to non-radiological imaging modalities, were not relevant to CDSS, did not report experimental or clinical validation or did not report adequate methodological detail [75]. The review dataset was cleaned by removing duplicate, duplicated and low quality research to ensure the reliability and originality of the review dataset.

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Methodological Contribution

The methodological originality of the review consists in the global evaluation of AI strategies in the CDSS context rather than its algorithmic performance [83]. The study aims to provide a more comprehensive overview of the clinical applications and the architecture of the AI tools used in radiology, as well as the analysis of different modalities like X-ray or MRI. This is a way to get closer to the real world clinical deployment, and to the technical model development.

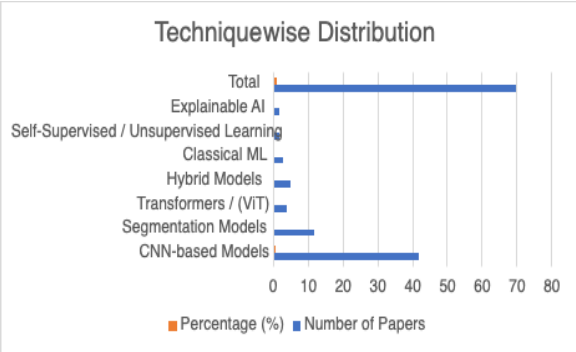

Figure 4: Distribution of AI techniques across the selected studies.

This figure illustrates the relative use of different AI techniques in the reviewed studies. CNN-based models dominate the selected literature, confirming their importance in radiological image classification and abnormality detection. The presence of segmentation networks, transformers, hybrid models, and XAI methods shows the growing shift toward advanced and clinically interpretable AI systems.

IV. RESULTS

Performance of AI Techniques Across X-ray and MRI Modalities

Analysis of selected studies and real-world AI-based Clinical Decision Support Systems (AI-CDSS) indicates that the success of Artificial Intelligence in radiology is strongly reliant on the interplay of the imaging modalities, model architecture, clinical job and deployment scenario [84]. The data point to a modality-specific trend rather than a general performance trend across all radiological applications. For example, CNN-based models are great for X-ray interpretation, while for MRI applications, it's more segmentation networks, 3D architectures, transformers, and multimodal frameworks. CNN-based models remain the most widely used and clinically scalable AI solution for X-ray imaging, especially in the setting of chest radiography [85]. They are able to efficiently extract spatial features in 2D radiographic images for high performance classification, anomaly detection and multi-label disease prediction. This is consistent with the examined dataset where the most dominant part of AI techniques are based on CNN based architectures and are common in thoracic disorders, tuberculosis, COVID-19, lung nodules and multi-disease screening. This is also found in industrial systems like Qure.ai, Infervision, Zebra Medical Vision and Riverain Technologies, which use deep learning models for large-scale screening, quick anomaly diagnosis and process prioritisation in chest X-ray processing. AI applications based on MRI have mixed results, as MRI data are volumetric, multi-parametric and anatomically complex [86]. Thus MRI-based CDSS demand models which are able to capture 3D spatial relationships and subtle tissue variations. MRI tasks, such as tumour segmentation, cardiac imaging, neurological assessment, and longitudinal disease monitoring, are becoming more amenable to segmentation models, e.g., versions of U-Net, 3D CNNs, Mask R-CNN, and transformer-based approaches [87]. Other examples are the use of cloud-based deep learning, volumetric analysis and advanced predictive modelling in radiology processes based on MRI, such as Arterys and DeepMind Health. One main observation is that there is no consistently efficient AI method across radiological CDSS. CNNs perform very well for scalable 2D X-ray classification but for MRI applications architectures with higher capacity for spatial modelling are needed [88]. Transformers and hybrid CNN-LLM or multimodal models have the potential for contextual reasoning and integrating imaging with clinical data, but their clinical relevance is limited by computational burden, interpretability issues, and deployment complexity. Classical ML methods are now mostly obsolete and used to a lesser extent for smaller datasets or radiomics settings [89]. Overall, the results indicate that the usefulness of AI for radiological CDSS is not solely dependent on the accuracy of the model but also on the alignment of the model with the imaging modalities and clinical workflows [90]. This is key for high-level clinical translation as it shifts the evaluation of AI from accuracy reporting to task-specific appropriateness, interpretability, scalability and integration into therapy.

Impact of AI-CDSS on Clinical Decision-Making

AI in Clinical Decision Support Systems has greatly enhanced radiological decision making, by allowing for quicker interpretation, minimising diagnostic variations, and helping in the prioritisation of critical situations. Most noticeable is use in emergency radiology where systems like Aidoc and Viz.ai can automate triage, coordinate workflows and alert in real time to essential findings like stroke, PE and CH [91], [92]. AI-CDSS also act as a second-reader to further improve decision-making. In high-volume imaging centers, tools such as Infervision, RADLogics, Riverain Technologies and Qure.ai assist radiologists in identifying subtle abnormalities, categorizing the disease severity and increasing detection sensitivity [93]. This is particularly true when dealing with interpreting chest x-rays on a fast pace and has larger loads of the radiologists. Another key effect is that AI is becoming more and more crucial in streamlining procedures. AI technology can take over monotonous tasks like anomaly detection, lesion segmentation, image labelling, prioritisation and preliminary reporting [94]. This provides more time for radiologists to more thoroughly interpret the films instead of blindly screening them.Cloud-based technologies such as Arterys also provide collaborative interpretation, longitudinal tracking, and better visualisation, notably for applications on MRI and CT. However, the clinical benefits of AI-CDSS are not free from downsides. Solutions are available to address specific scenarios but there are not many that can offer general radiological decision support. Say, viz.ai is very good for stroke triage but not much value beyond that. Qure.ai is scalable and works well in low-resource settings but has limited multimodal integration. Similarly, the high-performance MRI-based systems are often built on expensive infrastructure that may be challenging to deploy in institutions with limited resources. The results clearly show that AI-CDSS are most beneficial to improve clinical decision making when embedded in existing radiological workflows, associated with PACS/RIS systems and designed to assist, not replace, the opinion of the radiologist.

Comparative Analysis of Real-World AI-CDSS Platforms

The comparative examination of real AI-CDSS platforms is classified into three broad types of clinical deployment in practice. For one, emergency triage systems like Aidoc and Viz.ai are designed for quick diagnosis [95]. These strategies are mostly used to quickly recognise relevant imaging findings and to alert care staff. These platforms have a high therapeutic utility since they directly influence therapy timing and patient outcome. Second, screening and detection systems (such as Qure.ai, Zebra Medical Vision, Infervision, RADLogics and Riverain Technologies) are working on high throughput image interpretation. Such systems are extremely useful in chest X-ray and CT based lung disease detection where scalability, sensitivity and speed are of utmost importance [96], [104]. Their contribution is particularly important for low-resource healthcare settings and population-based screening.

Third, more advanced AI-CDSS development stages are multimodal and advanced analytics systems like as IBM Watson Health, Arterys and DeepMind Health. These systems expand the analysis of single images to incorporate clinical data, longitudinal imaging, cloud computing, natural language processing or transformer based modelling. They are powerful in tailored diagnostics and integrated decision help but remain technically tricky to accomplish [97]. The main benefits of AI-CDSS in these domains include rapid diagnosis speed, increased detection accuracy, reduced effort and improved prioritisation of workflow [98]. Major limitations include black box decision making dependence on imaging data quality, restricted generalisability, limited task design, regulatory complexity and infrastructural requirements.

Integrated Interpretation of Results

The findings indicate that Artificial Intelligence (AI) techniques are changing Radiological Clinical Decision Support Systems (CDSS) from passive assistance tools to active and intelligent systems that perform abnormality detection, case prioritisation, image segmentation, predictive analysis and workflow management [99]. The most sophisticated and scalable CDSS systems based on X-ray are mostly based on Convolutional Neural Networks (CNNs) for screening and abnormality detection. On the other hand, such complex and high-dimensional data have a great promise for MRI-based CDSSs in 3D segmentation, multimodal learning and predictive analytics [100].

One of the main take-aways from this analysis is that performance of AI-driven CDSS should not be measured on diagnostic accuracy alone [101]. Beyond the technical validation, the successful application of AI systems in the clinic involves assessment of other translational elements such as model-modality compatibility, integration with clinical processes, interpretability, scalability, external validation and usability in the real world [102], [103]. Thus, the findings indicate a dramatic shift from pure algorithm-based AI research towards clinically integrated, explainable and multimodal decision support systems in radiology [105]. This change is needed to construct AI-CDSS that are not only technically efficient, but also trustworthy, transparent and acceptable in real healthcare settings.

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Table 3: Comparison of real-world AI-based CDSS platforms in radiology.

System	Modality	Application	AI Model	Key Capability	Pros / Cons
Aidoc	CT, CXR	Stroke, PE, ICH	CNN	Triage, alerts, PACS/RIS integration	+ Fast emergency detection; − Black-box, image-quality dependent
Zebra Medical Vision	CT, X-ray	CVD, liver disease, osteoporosis screening	ML/CNN	Automated reporting, screening	+ Scalable, multi-disease detection; − Limited explainability
Qure.ai	CXR, CT	TB, COVID-19, stroke	CNN, Transfer Learning	Rapid screening, offline support	+ Low-cost, suitable for low-resource settings; − Limited multimodal support
Arterys	MRI, CT	Cardiology, oncology	3D CNN, Segmentation	3D visualization, longitudinal tracking	+ High accuracy; − Expensive infrastructure
Viz.ai	Brain CT	Stroke (LVO)	CNN, Segmentation	Real-time alerts, workflow automation	+ Faster treatment decisions; − Stroke-specific
IBM Watson Health	Imaging + EHR	Diagnosis, oncology	NLP, ML, DL	Multimodal decision support	+ Broad integration; − Complex deployment
DeepMind Health	MRI, OCT, Multimodal	Retinal & neurological disorders	DL, Transformers	Disease prediction	+ State-of-the-art accuracy; − Limited clinical deployment
RADLogics	CT, CXR	COVID-19, lung disease	CNN, Segmentation	Lesion detection, severity scoring	+ Rapid deployment; − Limited interpretability
Riverain Technologies	CXR	Lung nodule detection	CAD + DL	Bone suppression, lesion enhancement	+ Improves detection rate; − X-ray only
Infervision	CT, CXR	Lung cancer, COVID-19	CNN	Multi-lesion detection	+ High sensitivity; − High computational cost

This table 3 compares major AI-CDSS platforms according to imaging modality, clinical focus, AI technique, regulatory status, advantages, and limitations. Emergency triage systems such as Aidoc and Viz.ai mainly support rapid detection and prioritization, while platforms such as Qure.ai, Infervision, Riverain Technologies, and Zebra Medical Vision focus more on screening and abnormality detection. Advanced systems such as Arterys, IBM Watson Health, and DeepMind Health demonstrate broader potential for multimodal analysis, segmentation, prediction, and workflow integration.

V. DISCUSSION

The outcomes of this study suggest the increasing importance of Artificial Intelligence (AI) in the transformation of Clinical Decision Support Systems (CDSS) in radiology. AI is transforming radiological interpretation from a largely subjective process to a more data-driven, reproducible and workflow-integrated process. The research reviewed suggests that AI can help in illness diagnosis, prioritisation, segmentation, prediction and clinical decision making in

X-ray and Magnetic Resonance Imaging (MRI). However, its efficacy depends on the imaging modalities, clinical objective, model architecture, and level of integration into healthcare systems. X-ray based AI-CDSS displayed more maturity and scalability, particularly in chest radiography. CNN-based models are commonly employed in this domain since they can interpret two-dimensional pictures rapidly and detect thoracic pathologies such as tuberculosis, pneumonia, COVID-19, lung cancer, and other lung disorders. These systems are better ideal for high-volume screening, emergency triage, and everyday clinical practice because of the availability of huge annotated datasets, lower computational needs, and widespread usage of X-ray imaging. The existence of commercial platforms such as Qure.ai, Infervision, Riverain Technologies, and Zebra Medical Vision also suggests that AI-enabled X-ray systems are being deployed in real-world radiology.

In contrast, AI-CDSS based on MRI require more sophisticated computational models due to the volumetric, multi-sequence and anatomically complicated nature of MRI data. 3D CNNs, U-Net models, transformer-based networks, hybrid systems etc. are increasingly used for tumour segmentation, neurological assessment, cardiac imaging, tissue characterisation and disease monitoring. Platforms like Arterys and DeepMind Health show the promise of AI in advanced MRI applications. MRI-based systems have great potential in terms of analysis and prognosis, but their practical translation is additionally dependent on the availability of high quality datasets, computational infrastructure and rigorous external validation. Hence, MRI-based AI-

CDSS offer a deeper level of analysis but are less scalable than X-ray-based systems.
A key finding from this analysis is that the clinical success of AI-CDSS cannot be judged based only on diagnosis accuracy. Metrics like as accuracy, sensitivity, specificity, Area Under the Curve (AUC) and Dice Similarity Coefficient are helpful to assess technical performance but they do not reflect clinical value. Explainability, workflow compatibility, real-time usability, scalability, external validation, and clinician trust are also required for successful adoption. AI can assist urgent healthcare decisions via automated triage and alarm production, as demonstrated by Aidoc and Viz.ai. Thus, AI-CDSS is not meant to replace radiologists, but to assist them in their decision making by minimising reporting time, helping in prioritising cases, decreasing inter-observer variability and enhancing diagnostic consistency.

The present work extends the field by unifying modality-specific and system-level analysis. The results demonstrate that X-ray and MRI should not be viewed as interchangeable inputs for AI systems. X-ray based AI-CDSS are better suitable for fast screening, triage in emergencies, and deployment at the population level, whereas MRI-based systems are more appropriate for precise anatomical segmentation, predictive analysis, and personalised clinical decision-making. This difference also translates into a difference in deployment maturity: X-ray AI-CDSS is closer to routine clinical use, due to simpler image structure, faster processing, and fewer infrastructure requirements.

While promising, there are significant impediments to wider implementation of AI-CDSS in radiology. Many deep learning models are "black boxes" reducing interpretability and potentially clinician trust. Data heterogeneity is a serious challenge, since models trained on specific datasets may not generalise well across diverse demographics, scanners, imaging techniques or healthcare contexts . This is especially essential in MRI where variability in acquisition can have a large effect on model performance. Challenges also include interaction with PACS, RIS and electronic health records, regulatory approval, cybersecurity, cost of deployment and high computational requirements, especially in resource-limited settings.

VI. CONCLUSION

This paper critically analysed the role of Artificial Intelligence techniques in Clinical Decision Support Systems (CDSS) for radiology with specific focus on X-ray and MRI applications. The results indicate that AI has evolved from an experimental tool for image analysis to a clinically applicable decision-support tool that improves diagnostic accuracy, lesion detection and segmentation, process prioritisation, and predictive evaluation. A clear pattern specific to the modality was discovered. X-ray based AI-CDSS is more scalable, cost-effective and ideal for high-volume screening, especially in chest radiography. AI-CDSS based on MRI, on the other hand, provide a higher analytical value for complicated anatomical interpretation, volumetric assessment, tumour segmentation, neurological evaluation, and disease monitoring. The clinical success of AI in radiology depends not only on model performance but also on its adaptability with imaging modalities, clinical job and workflow integration .AI has been used in triage anomalydetection, risk classification, and process. open framework for point-of-care optimisation. Real-world platforms include Aidoc, Viz.ai, Qure.ai, Arterys, and DeepMind Health. However, widespread clinical usage is hampered by interpretability challenges, dataset bias, low generalisability, regulatory concerns, infrastructure constraints, and insufficient integration with PACS, RIS and electronic health records.

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AI is becoming a significant part of radiological CDSS, not a replacement for radiologists. Future directions should include explainable AI, multimodal integration, external validation, federated learning, and prospective clinical trials. The future of radiology is collaborative intelligence, where AI aids radiologists, boosting diagnostic confidence and helping to deliver faster, safer, and more patient-centred healthcare.

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