



The Transformative Role of Radiology in Emergency Settings and Trauma Management: Leveraging Artificial Intelligence for Enhanced Diagnostic and Therapeutic Outcomes

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Abstract

Background: Radiology plays a crucial role in emergency settings and trauma cases, where timely and accurate imaging is essential for effective patient management. The integration of artificial intelligence (AI) is poised to enhance radiological practices, improving diagnostic accuracy and workflow efficiency.

Methods: This review examines the current landscape of AI applications in emergency radiology. A comprehensive literature search was conducted using reputable databases, focusing on studies published from 2018 to 2023 that explore AI's role in image acquisition, interpretation, and reporting within emergency settings.

Results: The findings indicate that AI technologies significantly improve patient outcomes by facilitating rapid diagnosis and treatment decisions. AI algorithms enhance image acquisition through automated patient positioning, optimizing radiation exposure, and improving image quality. Additionally, AI assists in prioritizing worklists, ensuring that critical cases receive prompt attention. The review highlights successful implementations of AI in detecting pathologies, such as intracranial hemorrhage and pulmonary embolism, showcasing improved diagnostic performance compared to traditional methods.

Conclusion: The adoption of AI in emergency radiology represents a paradigm shift, enhancing the efficiency and accuracy of imaging processes. However, challenges remain, including the need for robust validation, interpretability of AI models, and integration into existing workflows. Ongoing research is essential to maximize the potential of AI technologies in emergency radiology and ensure their safe and effective use.

Keywords: Emergency radiology, artificial intelligence, imaging, trauma cases, diagnostic accuracy.

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Introduction

In 2018, around 130 million evaluations were conducted in Emergency Departments, with the majority of patients requiring imaging studies [1]. Emergency radiologists are required to deliver precise and prompt reports that inform significant—occasionally crucial—decisions, all while contending with an ever-increasing workload and constrained time for image analysis. In this scenario, where timing and medical accuracy can profoundly influence outcomes, their performance is vital in-patient management, facilitating rapid identification and precise disease description [2,3].

Artificial intelligence (AI) may assist emergency radiologists in many duties, so serving as a significant asset in this challenging and high-pressure situation [4,5]. In emergency situations, AI may aid with patient placement, picture capture and reconstruction, worklist prioritizing, image interpretation via automated or assisted anomaly identification, and the generation of structured reports [2] (Figure 1).

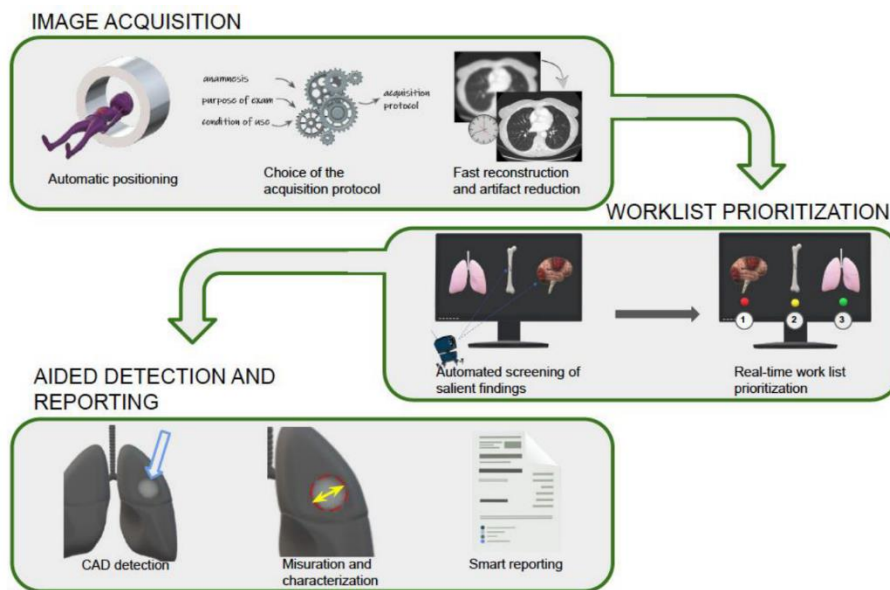


Figure 1. Illustrative elucidation of the roles that AI technologies may perform in emergency radiology.

The incorporation of AI would help not just radiologists and emergency room workers but also individuals and the whole healthcare system, enhancing the quality of treatment, improving working settings and conditions, and optimizing healthcare expenditures [2]. This narrative review presents a summary of AI approaches in emergency radiology to inform radiologists of advancements in this domain.

1. Fundamental Terminology of Artificial Intelligence

Artificial Intelligence (AI) is a broad phrase denoting a machine's capacity to demonstrate human-like characteristics, including thinking, learning, and problem-solving. Although human analytical and cognitive faculties are essential, robots possess an unparalleled advantage: the capacity to process vast quantities of data in a very short period [6]. AI-driven instruments for image analysis provide the foundation of the radiomics paradigm, which is equivalent to quantitative imaging, signifying the interpretation of biological images as data sets rather than simply visuals [7].

Machine learning (ML) is fundamental to AI, focusing on the creation and optimization of algorithms that exhibit human-like learning capabilities for data analysis, distinguished by performance, resilience, and speed that can only be attained by machines. Diverse machine learning methodologies utilize an extensive array of candidate maps to deduce forecasts of a quantity of concern (or elevated parameters) that meet specific criteria, based on an initial amount: these candidate maps embody various theoretical hypotheses for delineating the relationship between specified inputs and desired outputs [8]. The validity of the hypothesis fundamentally relies on the divergence between the predicted outcome and the empirical facts.

The machine learning model is anticipated to diminish the approximation's uncertainty by being exposed to many data samples [9].

There are four primary machine learning methodologies: semi-supervised learning, supervised learning, unsupervised learning, as well as reinforcement learning. These approaches vary in the extent of data preprocessing necessary, the algorithmic techniques employed to elucidate data relationships, and the specific problems they address. The first three are predominantly utilized in radiology and can be tailored to various clinical tasks [10].

Supervised learning is the most fundamental kind of machine learning, suitable for broad categorization problems; for instance, in pneumonia screening, determining if a chest X-ray is normal or abnormal. In this kind of machine learning, the algorithm's learning phase necessitates a dataset in which every entry (independent parameter) is associated with the description of the matching output (or class). In classification tasks, each variable is categorized into discrete labels, but in linear regression activities, labeling is represented by a constant variable, such as an outcome like disease-free survival. During the training process, the techniques learn to deduce the connections among the data based on a mapping assumption (a model), continuously refining their performance as they encounter more samples. Subsequently, during evaluation, the model categorizes fresh unlabeled targets into one of the established class labels. The algorithm's overall performance is assessed by comparing the actual labels with the proposed labels [11].

In unsupervised learning techniques, the training dataset lacks labels, requiring the computer to identify any underlying structure to deduce correlations among the data, or at least within a subset of the data. Unsupervised learning can be employed to tackle various issues associated with data mining, including clustering tasks that seek to partition the dataset into categories according to particular feature attributes, and association tasks that aim to identify relationships within the dataset [8,9].

Semi-supervised learning occupies a position between unsupervised as well as supervised learning: this methodology predominantly utilizes unlabeled data while incorporating a limited quantity of labeled data; thus, this form of machine learning mitigates the challenge of insufficient data availability by exploiting the vast amount of accessible yet unannotated data (such as undiagnosed images) to develop precise classifiers.

Numerous models exist for deducing potential correlations among data, each characterized by distinct designs for presenting information, evaluation, and the reduction of loss functions, which delineate the approximation to the desired performance [8,9]. When we see various machine learning methodologies, such as supervised learning, as distinct tactics for identifying significant patterns in data, each model may be viewed as a unique strategy. Models used in supervised learning include logistic regression, decision trees, and assistance vector machines. Each model delineates a distinct framework for data deception, which may be converted into computer code for automated computing [11].

Although several approaches may be relevant to the same job, some ones exhibit superior efficacy in certain contexts. Artificial neural networks are frequently employed to tackle biomedical imaging challenges among many models. In contrast to statistical approaches such as logistic regression, artificial neural networks embody a learning paradigm modeled after the functioning of natural neural networks in the human brain [12].

In recent years, the accessibility of extensive datasets and accelerated computational speed has facilitated the advancement of sophisticated neural networks, specifically Convolutional Neural Networks (CNNs), which have propelled the deep learning (DL) paradigm. DL tools are particularly adept at uncovering complex patterns in large imaging datasets, surpassing the features that can be visually evaluated by radiologists. The depth of a deep learning model pertains to the number of layers it comprises, with each layer signifying a heightened level of abstraction, rendering it difficult to ascribe meaning to the computations executed by the neural network. This issue underlies the so-called "black box phenomenon," which constitutes a principal challenge in the interaction among artificial intelligence and humans. In

summary, deep learning algorithms have shown exceptional performance in the recognition of images and are leading the AI-driven transformation in radiology [13,14].

2. Artificial Intelligence in Image Acquisition

Computed tomography (CT) is the primary modality in emergency radiology because to its extensive availability and rapid collection techniques; yet it is constrained by prolonged exposure to ionizing radiation, despite technical advancements allowing substantial dose to decrease over time. CT scan collection algorithms focus on enhancing diagnostic efficacy by tackling three primary concerns: obtaining high-quality images; minimizing acquisition durations; and decreasing radiation exposure in accordance with the ALARA (as low as possible attainable) concept. The manual placement and focusing of the patient is a labor-intensive and radiotechnologist-dependent task, crucial for obtaining high-quality diagnostic pictures and minimizing radiation exposure.

The "papillon filter," a pre-patient attenuator that obstructs low-energy X-rays aimed at the periphery of the examined body region, necessitates precise patient positioning at the isocenter to enhance the concentration of the X-ray beam [15]. This leads to diminished radiation exposure and improved, more focused images with fewer artifacts (such as beam hardening). Numerous studies have assessed the viability and efficacy of autopositioning software, which employs anatomical references and scout data to pinpoint essential surface landmarks and establish initial and final positions through a three-step process: determining the patient's position and the various body parts; locating the isocenter; and creating an avatar utilizing a statistical model tailored to the camera data.

Booji and Saltybaeva assessed the precision of automated patient placement with a 3D camera directed by an AI-driven system, which was trained on a collection of photos from other patients, enabling it to identify the patient's surface [16,17]. Both investigations demonstrated substantial improvements in patient centering relative to manual placement, exhibiting reduced standard deviations from the optimal isocenter of the patients. Recent research by Gang et al. used automated positioning, revealing a 16% reduction in the dose given to patients and a 28%-time savings [18].

The appropriate selection of the CT research protocol is vital for minimizing patient radiation exposure and limiting the loss of critical information, which may lead to diagnostic mistakes or treatment delays. The selection of the CT protocol is at the discretion of the radiologist, consuming time that could be allocated to reporting; thus, there is a necessity for an AI-driven system that can amalgamate the patient's medical history with the examination's objectives and usage conditions to recommend the optimal protocol option.

The existing literature on the topic is few. MyExam Companion is a newly launched data-driven CT scan automation tool that utilizes decision trees derived from an extensive training dataset of patient characteristics and corresponding scan procedures across diverse clinical institutions. This automated methodology accommodates site-specific and regional preferences, alleviating technological complexity and minimizing operator error, potentially leading to enhanced uniformity in image quality [19]. This AI-driven technique may enhance procedural consistency, reducing variability among radiologists, who sometimes choose procedures based on individual preferences and local knowledge rather than data-driven methodologies.

The decrease in dosage is a well-debated topic, and a significant application of AI lies in enhancing CT collection techniques [20]. Conventional reconstruction methods, utilizing filtered back projection algorithms, yield high image quality but result in significant radiation exposure [21,22]. In contrast, contemporary Iterative Reconstruction (IR) algorithms can reduce dose administration while preserving diagnostically acceptable image quality, albeit with increased reconstruction times [23-25]. The rapid processing and extensive parallelism have facilitated the creation of AI-driven reconstruction methods, namely those based on deep learning, which may reduce radiation dosage while preserving superior picture quality compared to conventional filtered back estimates and iterative reconstruction techniques [26].

Park et al. evaluated the efficacy of a deep learning reconstruction technique, "True Fidelity" (TFI), in comparison to an iterative reconstruction (IR) system, "ASIR-V," focusing on picture quality [27]. The

algorithms operated at an 80–100% mixing ratio (ASIR-V) and low/medium/high intensity (TFI) to rebuild raw data pictures of the liver, arteries, and muscle from a 256-slice CT scan. The pictures were then confirmed by two seasoned radiologists and assessed based on quantitative (area of interest as well as noise) as well as qualitative (tissue inhomogeneity) criteria. The conclusive research revealed that the DL algorithm produced better balanced pictures regarding noise and sharpness than the conventional IR system.

Pediatric radiology departments might greatly benefit from AI-driven dose reduction solutions. Curtise et al. conducted a comprehensive analysis of several applications of deep learning reconstruction methods in pediatric patients, concluding that DL-assisted image restorations may provide radiologists superior picture quality and a general dose reduction of 30–80% [28].

Deep learning-based systems are also relevant in various radiological settings: McLeavy et al. documented their interactions with the sophisticated Intelligent Clear-IQ Engine-AiCE method in an emergency department, emphasizing the necessity of obtaining low-dose CT scans, particularly for radiosensitive populations, such as women of childbearing age and children [29]. They demonstrated that the implementation of this algorithm resulted in a mean dose-length product of only 0.8 mSv absorbed by patients during an arterial/venous phase abdominal scan.

The optimization of CT acquisition protocols has been examined utilizing phantoms. For instance, Greffier et al. analyzed the impact of varying degrees of DL-based rebuilding on reduced doses and objective as well as subjective image quality, in comparison to the typical IR software typically integrated into CT machines, within a chest imaging context, employing an anthropomorphic simulation [30]. Two radiologists independently assessed the subjective picture quality based on many attributes, including image noise, image softening, vessels-to-fat contrast, boundary recognition, and others. Utilizing a "smoother" filter setting yielded a low-noise picture at the same infrared dose, enhancing the detectability of modeled chest lesions, but with higher image smoothing. AI technologies may enhance artifact reduction techniques by substituting the object with an estimate derived from the surrounding areas [31].

3. Prioritization of Worklist

The automatic announcement of critical results represents a compelling application of AI in emergency radiology. As the requirement for imaging examinations increases, the delayed transmission of important results to the referring physician may lead to postponed clinical intervention, thereby jeopardizing treatment outcomes, particularly in cases necessitating immediate action [32]. The priority designated by the first-line emergency physician often dictates the sequence of required imaging examinations; however, this prioritization is not always suitable for the identified abnormalities. AI-driven models can pre-determine essential outcomes and facilitate real-time worklist prioritization, thereby decreasing report turnaround times and enhancing clinical pathways. For instance, Davis et al. exhibited a notable reduction in report turnaround time, from 67 to 59 minutes, and in length of stay, from 471 to 425 minutes [33].

Kao et al. assessed the efficacy of Computer-Aided Detection (CAD), integrated with image storage and communication technologies and the radiological information system, for the proactive identification of anomalous chest X-rays and prioritizing them for the radiologist's review. The specificity and sensitivity of CAD were 0.790 and 0.697, accordingly, and its implementation reduced the turnaround time for aberrant X-rays by 44 percent, demonstrating the efficacy of CAD systems for first assessment of the most crucial studies [34]. Annarumma et al. developed and evaluated a machine learning solution using convolutional neural networks to facilitate automated triage of adult chest X-rays based on the urgency of imaging results, achieving a potential decrease in reporting delay for urgent studies from 11.2 to 2.7 days [5].

AI-driven software has been created for emergency abdominal imaging, as demonstrated in a study by Winkel et al., where the designed CNN-based algorithm autonomously identified acute pathological abdominal outcomes with high diagnostic accuracy, facilitating the categorization of abdominal CT scanning in acute scenarios within the radiology workflow [35]. Emergency results in neuroradiology have been extensively researched, leading to the development of several machine-learning algorithms for the

automated identification of brain bleeding, mass effect, and hydrocephalus in unenhanced CT scans, as well as for the integration into clinical workflows [36-38]. Arbabshirani and his colleagues achieved notable outcomes with a machine learning system trained on 37,074 head CT images, enhancing worklist priority and decreasing the time required for diagnosing cerebral bleeding [39].

4. Intelligent Reporting

Standardized radiological documentation is crucial for guaranteeing completeness and comparability, minimizing ambiguity, and enhancing communication with other doctors [40]. Owing to technical challenges and insufficient engagement with existing reporting structures, the utilization of structured reports remains uncommon in clinical practice [41]. Natural language processing, sometimes referred to as text mining, is an AI-driven operation that integrates linguistics, statistics, and deep learning models to analyze unstructured text; this process yields a structured format for each component, according to a specified arrangement and terminology.

The initial phase of natural language processing involves feature extraction, encompassing segmentation, sentence splitting, and tokenization [42]. The objective is not to produce a mere quantitative report akin to a blood analysis model, but to generate a comprehensive report that integrates quantitative metrics with radiologist observations. The procedure of dividing radiological reports into their constituent elements is known as "segmentation." The phrases "sentence splitting" and "tokenization" characterize this process [43]. The objective of the semantic analysis is to provide each distinct concept as an individual item in an organized way. The principal natural language processing technologies employed for these tasks are pattern matching and language analysis; the latter, being more complex, can identify quoted concepts within the text and elucidate their interrelations, while the former entails the matching of letter sequences. NegEx is a pattern-matching tool that identifies negational keywords around a specified notion, such as "no" or "absent."

The aforementioned steps established the properties of natural language processing. To resolve this problem, we must now get data from these features. Machine learning and deep learning may be capable of processing textual characteristics [44,45]. Machine learning traditionally required the use of labeled data for training to establish a correlation between extracted characteristics and a predefined class; in this context, the classifier's efficacy is significantly contingent upon the training dataset [46]. Recurrent neural networks are deep learning models used to analyze natural language processing features, since they effectively manage sequential data, making them suitable for NLP, where sentences consist of word sequences. The primary uses of natural language processing include the identification and categorization of outcomes, the automated generation of diagnostic recommendations, and the monitoring and identification of cases for prospective research projects [43]. The incorporation of these AI systems into RIS/PACS frameworks is crucial for the extensive dissemination of AI-driven structured reports [47].

5. Obstacles and Viewpoints

Radiomics signifies a pivotal advancement in radiology; yet several issues related to the development and use of AI-based technologies in clinical practice have to be resolved [48]. Artificial intelligence needs a collaborative interdisciplinary team, substantial quantities of high-quality data, and a stringent procedure. The initial limitations frustrated researchers' lofty expectations, resulting in the term "winter of artificial intelligence," a phase characterized by diminished funding and interest in AI research; however, recent methodological advancements have revitalized the significant potential of AI in biomedical imaging, especially in emergency contexts, where a shift from subjective evaluations to data-driven decision-making is essential [49].

The advancement of AI-driven tools necessitates multidisciplinary expertise that a solitary radiologist cannot oversee, posing a challenge for small teams and research institutions lacking the financial means to employ non-medical professionals solely for research or support functions. The abundance of extensive data is the principal limitation on the advancement of machine learning models, which require substantial datasets for training, validation, and testing. Recently, the increasing prevalence of open-source image

databases has partially mitigated this issue, fostering collaborative research among various institutions and promoting the standardization of acquisition protocols [50].

The issue of data quality poses a significant challenge to the advancement of AI-based solutions, stemming from the variability in image capture procedures, producers, and post-processing algorithms used in clinical practice. High-quality pictures are required and may be obtained using the same apparatus, ensuring a high signal-to-noise ratio. Poor data quality results in worse model quality. Various techniques have been established for data harmonization, which may substantially influence the repeatability of radiomic characteristics [51-54].

A significant challenge is to the interpretability of outcomes from AI-based models, particularly with the "black box" phenomena. Accuracy and interpretability may not align: for instance, "decision tree" models possess high interpretability due to the ease of comprehending the algorithm's inner workings and attributing precise meanings to its operations; nonetheless, they may lack accuracy in complicated tasks. Conversely, deep CNNs demonstrate superior efficacy in image analysis, but with less interpretability. A comprehensive grasp of prediction methodologies is a valid issue for doctors, particularly in emergency rooms where erroneous decisions may result in catastrophic outcomes [55-57].

Model validation is essential for confirming its applicability since the training dataset serves as a sample that may not accurately reflect the whole population. Without validation, it would be unsurprising to see a decline or even a failure in the model's performance in a real-world context. Validation is a critical phase that must be appropriately positioned within the radiomics process, and the selection of the appropriate validation method (such as sample selection, k-fold cross-validation, bootstrap) is contingent upon several aspects, including the model type and the amount and quality of data [8,9].

Medical imaging studies are encountering an influx of publications introducing novel AI-driven diagnostic and prediction tools, claiming exceptional performance. Limited research has concentrated on assessing the applicability of these frameworks and the tangible advantages they would offer to clinical practice in real-world contexts [58-60]; the outcomes can be unexpectedly unsatisfactory when these models are evaluated across diverse patient cohorts or institutions. In emergency situations, suboptimal outcomes produced by some software should caution radiologists against over-reliance on these technologies.

The underperformance of AI-based tools in real-world scenarios may alleviate emergency radiologists' concerns regarding the potential threat of AI to their profession [61]; however, upon further examination and clarification of AI, it is widely acknowledged that the role of the radiologist is unlikely to face significant jeopardy from AI, at least in the foreseeable future. Human decision-makers engage in various responsibilities beyond image interpretation, including selecting suitable diagnostic examinations, analyzing complex cases necessitating multimodal integration, collaborating with colleagues, interpreting results within the clinical context, communicating with patients, and performing interventional procedures. The prevailing expectation is that AI will not supplant radiologists; however, "radiologists who utilize AI will supersede those who do not," as AI can enhance routine tasks undertaken by radiologists and improve diagnostic accuracy. In the next years, the position of the radiologist is expected to be redefined, necessitating beneficial collaboration among various professional responsibilities; this approach is essential for successfully addressing the aforementioned difficulties.

Emergency departments serve as a critical testing ground for evaluating the relevance and advantages of AI-powered solutions. In emergency situations, artificial intelligence systems may assist radiologists in lengthy and repeated activities, therefore diminishing diagnostic mistakes in environments characterized by high workload, expectations, and error risk [62]. The effective integration of AI may possibly liberate resources for allocation to other tasks, such as patient communication, which have been excessively compromised owing to heightened workload [63]. Numerous studies indicate that the primary advantages of existing commercial software are elevated sensitivity and negative predictive value, particularly in the detection of pulmonary embolism; this software could be effectively incorporated in the pre-screening phase, with the responsibility of confirming the diagnosis assigned to the expert radiologist [64].

The utilization of AI in medicine addresses diagnostic and therapeutic challenges; however, AI must not be regarded solely as a tool, but rather as a principal entity within a complex socio-technical system. Consequently, a question emerges regarding the reliability of AI, defined as a characteristic of a socio-technical system that meets specific criteria from legal, ethical, and technical perspectives [65].

6. Conclusions

The integration of artificial intelligence (AI) in emergency radiology is not merely an enhancement of existing practices; it signifies a transformative shift in how radiological services are delivered in high-pressure environments. As emergency departments face increasing patient volumes and complexity, the need for rapid and accurate diagnostic tools becomes paramount. AI technologies, through their ability to analyze vast datasets and improve imaging techniques, provide essential support to radiologists, ultimately leading to better patient outcomes.

AI-driven tools have demonstrated their potential in various facets of emergency radiology, including image acquisition, interpretation, and reporting. Automated systems can aid in patient positioning and image reconstruction, resulting in higher quality images while minimizing radiation exposure. Furthermore, AI algorithms can prioritize worklists, ensuring that critical findings are flagged and addressed promptly. This capability is particularly crucial in emergency settings, where delays in diagnosis can have dire consequences.

The evidence supporting the efficacy of AI in detecting specific pathologies, such as intracranial hemorrhage and pulmonary embolism, underscores its role in enhancing diagnostic accuracy. Studies have shown that AI can match or even exceed the performance of human radiologists in certain scenarios, demonstrating its utility as a valuable adjunct in clinical practice. However, the implementation of AI is not without challenges. Issues such as data quality, algorithm interpretability, and the need for comprehensive validation studies must be carefully addressed to ensure the safe and effective integration of AI technologies into routine workflows.

Future research should focus on refining AI algorithms, enhancing their ability to generalize across diverse populations and clinical scenarios. Collaboration between radiologists, data scientists, and healthcare providers will be essential in developing robust AI systems that are user-friendly and clinically applicable. Ultimately, the successful incorporation of AI into emergency radiology promises to optimize patient care, improve operational efficiency, and redefine the role of radiologists in the evolving healthcare landscape. Embracing these advancements will pave the way for more precise, rapid, and individualized healthcare delivery in emergency settings.

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الدور التحويلي لعلم الأشعة في البيئات الطارئة وإدارة الإصابات: تسخير الذكاء الاصطناعي لتحسين التشخيص والعلاج

الملخص

الخلفية:

يلعب علم الأشعة دورًا حيويًا في البيئات الطارئة وحالات الإصابات، حيث يُعد التصوير الطبي الدقيق والسريع أمرًا ضروريًا لإدارة المرضى بفعالية. ومن المتوقع أن يُسهم الذكاء الاصطناعي (AI) في تعزيز ممارسات الأشعة، مما يحسن دقة التشخيص وكفاءة سير العمل.

المنهجية:

تستعرض هذه المراجعة التطورات الحديثة في تطبيقات الذكاء الاصطناعي في علم الأشعة الطارئ. تم إجراء بحث شامل في قواعد بيانات موثوقة، مع التركيز على الدراسات المنشورة بين عامي 2018 و2023 والتي تستكشف دور الذكاء الاصطناعي في اكتساب الصور، تفسيرها، وإعداد التقارير في البيئات الطارئة.

النتائج:

تشير النتائج إلى أن تقنيات الذكاء الاصطناعي تعزز بشكل كبير نتائج المرضى من خلال تسريع التشخيص واتخاذ قرارات العلاج. وتُظهر الخوارزميات الذكية تحسينات في اكتساب الصور عبر تحديد موضع المريض تلقائيًا، تقليل التعرض للإشعاع، وتحسين جودة الصور. إدارة قوائم العمل عن طريق تحديد الأولويات للحالات الحرجة لضمان حصولها على الرعاية الفورية. الكشف المبكر عن الأمراض مثل النزيف داخل الجمجمة والانصمام الرئوي، حيث أظهرت الدراسات أن الذكاء الاصطناعي يتفوق على الطرق التقليدية من حيث الأداء التشخيصي.

الاستنتاج:

يمثل اعتماد الذكاء الاصطناعي في الأشعة الطارئة نقلة نوعية من شأنها تعزيز كفاءة ودقة عمليات التصوير الطبي. ومع ذلك، لا تزال هناك تحديات مثل الحاجة إلى تحقق سريري قوي، وضمان تفسير واضح لنماذج الذكاء الاصطناعي، ودمجها بسلاسة في سير العمل القائم. يتطلب الاستغلال الأمثل لهذه التقنيات أبحاثًا مستمرة لضمان استخدامها الآمن والفعال في بيئات الطوارئ.

الكلمات المفتاحية: الأشعة الطارئة، الذكاء الاصطناعي، التصوير الطبي، حالات الإصابات، دقة التشخيص.