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Association of Artificial Intelligence Aided Chest X-ray in Chest Trauma: Review Article

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ABSTRACT

The most significant imaging technique for chest imaging has continued to be chest X-ray (CXR). In comparison to other imaging methods, which include computed tomography, chest X-ray is a cost-effective and easily available imaging method with a wide range of applications. It is distinguished by its short scan time and reduced dosage. A significant quantity of imaging sections and series are produced by thoracic computed topography (CT), that comprises twelve pairs of ribs with varying shapes. The process of sequentially evaluating all images, rib-by-rib and side-by-side, is both time-consuming and demanding. Chest computed topography has been found to have a misdiagnosis rate of 19.2 to 26.8% for any of the chest emergencies, some of that have the potential to result in severe consequences, regardless of the best human effort**.** Therefore, it is crucial to develop a machine learning identification system that assists radiologists in reducing the reading time, facilitating improved localization, and minimizing misdiagnosis. In radiology, artificial intelligence (AI) is utilized extensively. The deep learning algorithm of artificial intelligence shows excellent diagnostic precision and has the potential to enhance the speed and quality of image interpretation, as well as to increase the effectiveness of clinicians.

Keywords: CXR, CT, AI.

INTRODUCTION

The CXR is the most frequently applied plain film in the field of medical procedures. It is commonly utilized to diagnose diseases that can impact organs in the thoracic cavity**.** The chest X-ray operates on a straightforward principle. X-rays are absorbed by tissues of varying densities as they pass through the body. The tissues with the highest density, such as bone, absorb the most radiation, resulting in a white appearance. Conversely, the tissues with the lowest absorption, such as the air in the lung, appeared black. A gray image is produced when tissue density lies among these two extremes [(1)] **.**

However, chest X-ray has limitations in its sensitivity and scope, and its interpretation is difficult to determine as a result of the complex 3-D volume in a 2-dimensional image that is overlaid with a variety of tissues. The variance in density among pathological and healthy lung parenchyma can be subtle and difficult to identify, particularly in pneumothorax, as approximately forty percent of the parenchyma of lung is covered by the mediastinum and ribs. The clinical utility and efficacy of chest X-ray in case treatment are immediately influenced by the cognitive process and experience of the radiologist who interprets it. In addition to complicating matters, the growing need for imaging exams, especially in emergency knowledge, can be responsible for an increase in the number of mistakes [(2)]**.**

Artificial intelligence is currently making significant progress in the field of perception, which involves the interpretation of sensory information. This has enabled machines to more effectively illustrate and interpret complicated information. This has resulted in significant advancements in a variety of applications, as computer vision, natural language processing, and self-driving vehicles. These tasks were previously exclusively performed by humans [(1)].

The study aimed to establish the role of artificial intelligence for diagnosing chest emergencies (pleural effusion, lung contusion, and fractures) and guide individuated management.

Chest X-ray (CXR)

The beam is divergent and operates as a point source. In a posterior anterior (PA) CXR, the beam enters the thorax posteriorly, and the plate is positioned anterior to the case. This is the most optimal chest X-ray that can be obtained, as the case is typically standing. As the heart has an anterior structure, its size is minimally magnified. The beam enters anteriorly into the chest in an anterior-posterior film, with the plate positioned posterior to the case, who is typically semi-erect in bed. Due to the anterior site of heart, its size is enlarged, making it impossible to comment on its cardiothoracic ratio (Division of the maximum cardiac diameter by the maximum thoracic diameter) and the size. Posterior anterior films are accessible films of chest that are kept for cases that are seriously sick and are incapable to stand up [(3)]**.**

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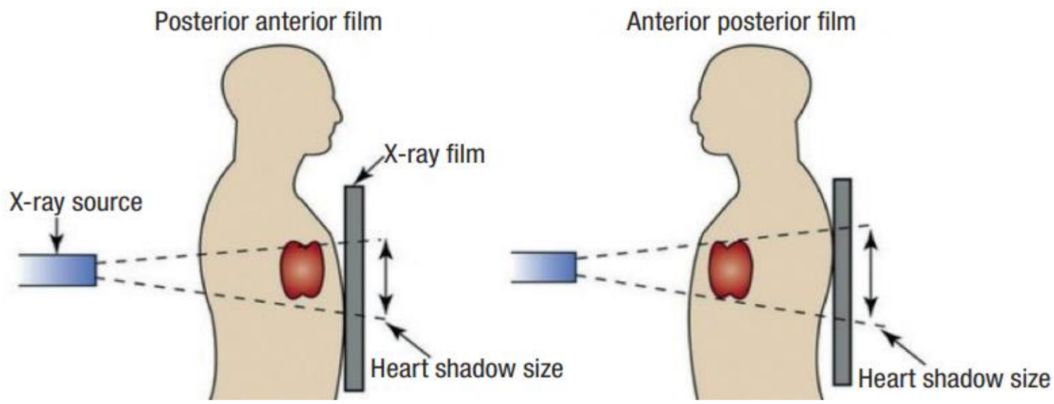

Fig. (1): Because the heart is an anterior structure in the thorax, the heart size is minimally magnified in a posterior anterior film in comparison to an anterior posterior film [3].

The silhouette signs: The silhouette sign, which is a term used to describe the air-soft tissue interface, is a distinct indication of the structures of thorax in a typical chest X-ray. Pathology may be affected in the absence of an easily identifiable air-soft tissue interface. The location at which the well-defined interface is removed may act as an indicator of the pathology's most probable location [3]

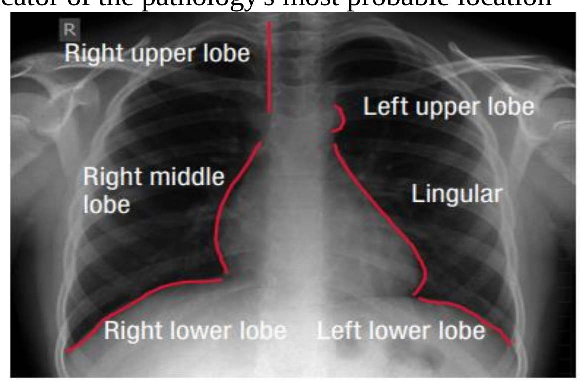

Figure (2): The probable location of pathology may be determined by the location of the silhouette sign's loss (red) [3].

Lungs: Comparing right and left lungs is crucial for identifying opacification, lung borders, and lung volumes. Opacification can be unilateral or bilateral, and lung borders may be weakened, suggesting underlying conditions. Lung volumes should be visualized, with more than 7 ribs indicating inadequate inspiration or hyper expansion [3]. **Mediastinum:** The mediastinum is the central chest compartment between the lungs, often difficult to identify due to its soft tissue structure. It may be drawn towards or away from the impacted side and may be widened due to conditions [4].

Heart: The heart is a soft density structure that ought to fill less than half of the cardiothoracic ratio. Cardiomegaly can be presumed if the ratio exceeds fifty percent; however, this conclusion shouldn't be made from an anterior posterior film. For excluding any potential underlying pathology, the borders of the right and left hearts must be traced [4].

Hemidiaphragms: The contours of the right hemidiaphragm must be clearly established, and it must be superior to the left. An increased hemidiaphragm can be an outcome of hepatomegaly, phrenic nerve palsy, or lung or lobar collapse [5].

Bones: Confirm the absence of fractures, inconsistencies in density, or metastases that are found. In the event of rib fractures happen, assess lung fields for absent pneumothorax. Review areas for pathology, including lung fibrosis, lung apices, Pancoast's tumor, costophrenic angle, fluid, and soft tissues [3].

Artificial Intelligence in Radiology

Introduction

Artificial intelligence is progressively being applied to a variety of uses in health care, such as remote case monitoring, discovering medications, imaging and medical diagnostics, risk treatment, virtual assistants, wearables, and hospital management. Artificial intelligence has been shown to be advantageous in numerous domains that utilize components of big data, including the analysis of RNA and DNA sequencing data [6].

Artificial intelligence in medical imaging

The main driver for the development of artificial intelligence in medical imaging was the goal to enhance the effectiveness and efficacy of clinical care. Health-care providers have been compensated to increase productivity to make up for the decrease in imaging reimbursements, as the volume of radiological imaging data continues to increase at a disproportionate rate in comparison to the number of trained readers. The demands of radiologists have experienced a significant rise as a result of these factors. In particular situations, research indicates that an average radiologist is needed to interpret one image every three to four seconds during an eight-hour weekday to satisfy workload requirements. AI is rapidly evolving in radiology, driven by data and computational power growth. There are 2 main artificial intelligence procedures: handcrafted features defined in mathematical equations and machine learning models. These features are utilized for clinical decision-making but rely on expert identification and may not be optimal for different imaging modalities [7].

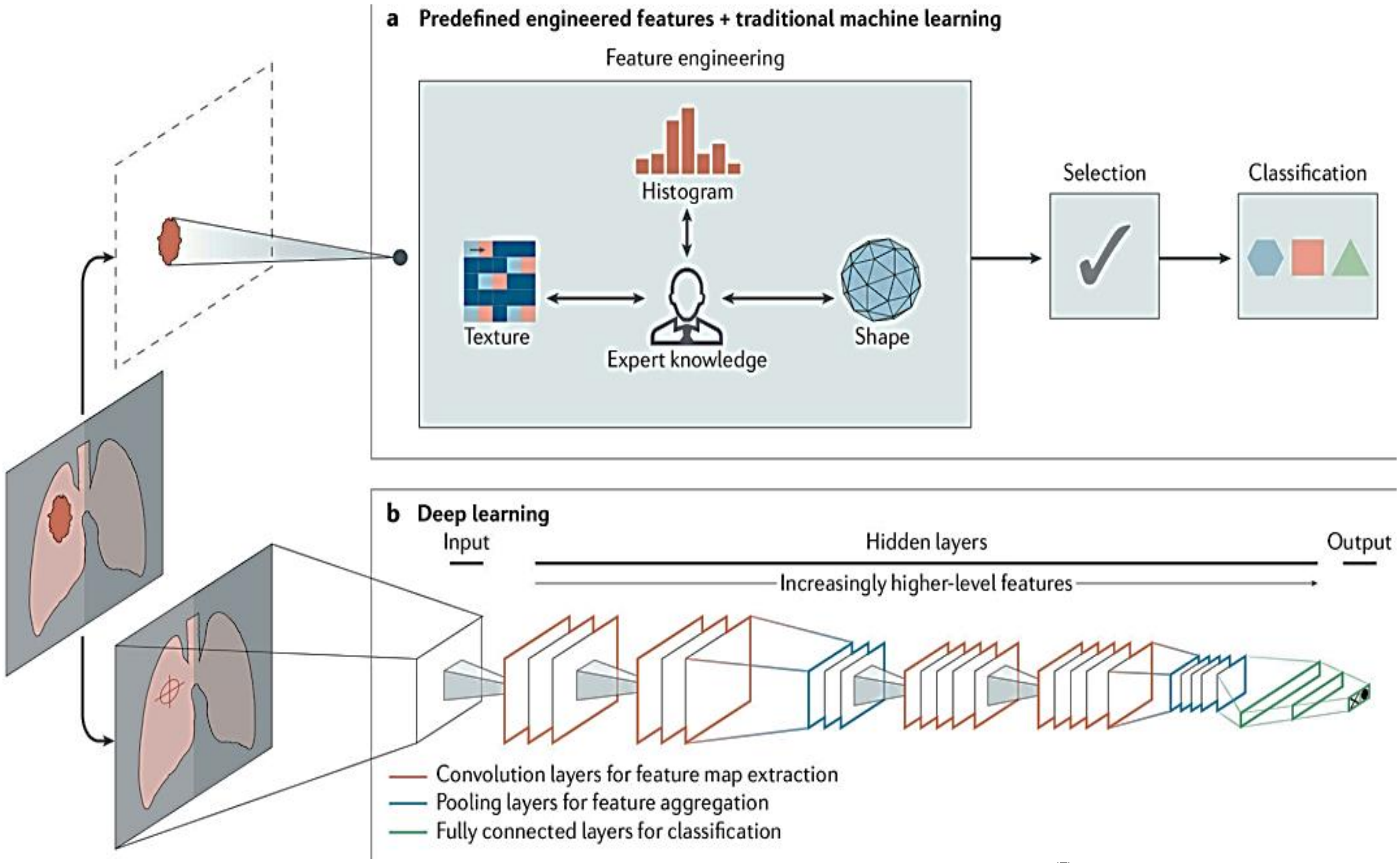

Figure (3): Artificial intelligence methods in medical imaging [7].

The additional advantage of deep learning is that it minimizes the necessity for manual preprocessing procedures. In particular, to extract predefined features, it is frequently necessary for specialists to perform precise segmentation of diseased tissues**.** Investigations additionally showed that deep learning methods are comparable to the performance of radiologists in the identification and segmentation of ultrasound and magnetic resonance imaging tasks, respectively [8].

In categorization of lymph node metastases using PET-CT, deep learning demonstrated greater sensitivities but decreased specificities compared to radiologists. As these techniques are iteratively refined and modified for particular applications, it is predicted that an improved understanding of the sensitivity-specificity trade-off will result. Deep learning additionally allows for quicker development times by relying solely on curated data and the corresponding metadata rather than domain expertise. Conversely, conventional predefined feature systems have demonstrated a plateauing performance during the past few decades and, as a result, don't typically satisfy the stringent standards for clinical effectiveness. Consequently, only a small number of them have been translated into the clinic. It is believed that high-performance deep learning techniques may exceed the threshold for clinical utility very soon, allowing for their rapid translation into the clinic [9].

AI challenges in medical imaging

The 1st stage of the development of automated solutions depend on deep learning will involve handling the most frequent clinical problems in the presence of adequate data. These problems could be related to conditions in which expertise of human is in elevated need or data is exceedingly complicated for human consumers. For example, the reading of lung screening computed topography, mammograms, and images from virtual colonoscopy. A 2nd wave of attempts is likely to address more complex problems, as multiparametric magnetic resonance imaging. As is the case with any narrow intelligence, the inability of current AI tools to resolve more than one task is a common trait. A comprehensive AI system capable of identifying numerous abnormalities throughout the human body has not yet been created. Data remains the most essential and critical component of artificial intelligence systems that are learning [7]**.**

Discussions are currently ongoing regarding the legal right of regulatory entities to examine artificial intelligence frameworks for the mathematical reasoning in a result, from a regulatory perspective. New artificial intelligence methods, as deep learning, have opaque inner workings, as previously noted, despite the fact that explicitly programming mathematical models allows for such questioning. It is impossible to comprehend the stimulation sequence of a neural network by sifting through the hundreds of thousands of nodes and their respective correlated connections. Complex decision-making is facilitated by an elevated network depth and node count, which also presents a significantly more difficult system to take apart and investigate. Nevertheless, numerous effective and safe US Food and Drug Administration (FDA)-accepted medications have unidentified mechanisms of action [(7)].

Despite their uncertain working mechanisms, the Food and Drug Administration has accepted high-performance software solutions for artificial intelligence algorithms. The shift to deep learning introduces new regulatory challenges and necessitates revised submission guidelines. It is essential for understanding the implications of lifelong learning in adaptive systems. Artificial intelligence-specific benchmarking and periodic testing must be adjusted accordingly. Compliant storage systems may assist in the preservation of privacy, and ethical concerns might come up when case data is utilized for artificial intelligence training. Systems that facilitate numerous entities to jointly train AI models without the necessity of sharing input data sets are the subject of research [(10)].

Future perspectives

Medical imaging has remained an essential part of health care from the earliest days of imaging of X-ray in the 1890s to the most current advances in computed topography, magnetic resonance imaging, and PET scanning. The discrimination of minute variances in densities of tissue is made possible by recent improvements in imaging hardware, which are characterized by their quality, sensitivity, and resolution. At times, these variances are challenging to identify, even by conventional artificial intelligence techniques employed in clinical settings and by a trained eye. Therefore, these techniques aren't fully comparable to the sophistication of imaging instruments; however, they provide a further motivation to pursue this paradigm shift toward more potent artificial intelligence tools [(7)].

In addition, deep learning algorithms are scalable as more data is generated each day and as continuing investigation efforts continue, compared to traditional techniques that rely on predefined features. A decrease in the number of routine tasks that exhaust effort and time as well as an improvement in precision are all benefits of these advancements. To accurately evaluate the effect of artificial intelligence on case outcomes, it is essential to align study methodologies [(11)].

In addition to the undeniable significance of generalizability and reproducibility, the utilization of standard imaging protocols, agreed-upon benchmarking data sets, reporting formats and performance metrics will level the experimentation field and facilitate the use of unbiased indicators. It is additionally crucial to recognize that artificial intelligence is very different from human intelligence in numerous respects; excelling in one task doesn't essentially imply excellence in others. Consequently, the potential of emerging artificial intelligence methodologies must not be overstated. The narrow artificial intelligence category encompasses the majority of state-of-the-art advancements in the field of artificial intelligence. This category is characterized by artificial intelligence that is trained for a single task and a single task only, with only a small number of artificial intelligences exceeding human intelligence. Although these advancements are highly effective in the bottom-up interpretation of sensory perceptual information, they are unable to make correlations in the same manner as the human brain and they also lack greater-level and top-down knowledge of contexts [(7)].

Artificial Intelligence Aided Chest X-Ray in Chest Emergencies

Introduction

AI techniques are increasingly being used in medical imaging, particularly in emergency settings, for CXR examinations. These examinations provide crucial information on lung parenchyma, pleural disorders and cardiovascular circulation, but their accuracy and speed are crucial for treatment and patient outcomes [(12)].

It is possible to identify artificial intelligence as a technology that mimics human cognitive processes, including problem-solving, learning and reasoning. Artificial intelligence-powered evaluation has the potential to make a significant improvement to the field of conventional radiology by decreasing the variability in image interpretation and increasing the precision of diagnosis, as diagnoses are mainly qualitative in this field [(13)].

The system promotes the human cognitive process of "learning by examples" in supervised learning, the most basic form of ML. This type of machine learning is appropriate for extremely general categorization tasks that necessitate the labeling of new elements in accordance with predefined categories [(7)].

Artificial neural networks are a learning paradigm inspired by the biological network of human brain. They operate based on their structure and computational properties, with each node representing a cell that processes input information. The computation of each unit is impacted by its weight and interconnections, shaping the network and achieving global functions like image recognition. Convolutional neural networks (CNNs) are ideal for recognition tasks and image analysis.

Deep learning (DL) uses these networks to notice intricate patterns in data. DL models capture full image context and learn local feature associations, leading to improved performance in radiological tasks like interpreting radiographic examinations [14].

Worklist Prioritization

One of the most exciting uses of artificial intelligence in emergency radiology is the automatic notification of important discoveries. The delay in communicating critical data to the managing physician may affect the effectiveness of treatment and prolong critical care, especially in essential scenarios, due to a higher demand for imaging investigations**.** The sequence in which the imaging examinations are documented is determined by the priority established by the emergency physician that 1st examines the case; unfortunately, the precedence is occasionally not in accordance with the abnormalities noticed. Artificial intelligence-based models have the potential to optimize therapeutic pathways, decrease the report response times for significant results, and identify and highlight emergency chest X-ray outcomes in real time. The time needed to make the diagnosis was significantly reduced by a notification system advanced by GE Medical System and Zebra Medical Vision for the assessment of pneumothorax on chest X-ray. The HealthPNX prioritization software was utilized by 3 experienced radiologists to assess 588 chest X-ray images. The average diagnosis time was 8.05 minutes, compared to 68.98 minutes without the software. The radiograph was evaluated in only 22.1 seconds, and a notification was sent [15]**.**

Pneumothorax

Pneumothorax is defined as a pathological disease where the pleural cavity becomes completely filled with air, thus impairing ventilation and oxygenation. It may appear spontaneously or as a consequence of infections, medical interventions, or trauma. Pneumothorax is a significant mortality and morbidity factor because of the extensive range of underlying causes and clinical scenarios. Certain forms show a severe progressive hemodynamic compromise, which may result in cardiovascular collapse and respiratory failure when left unmanaged. ChestX-ray enables the objective quantification and timely diagnosis of pneumothorax, and that's essential for the selection of the most successful treatment approach. Artificial intelligence has the potential to enhance the sensitivity of pneumothorax detection and provide quantification through volume segmentation, especially in low-resource settings in which experienced radiologists may be limited. The variability of pneumothorax appearances on chest X-ray makes automated pneumothorax identification a difficult technological challenge. Nevertheless, the rapid advancement of deep learning and the availability of extensive CXR datasets have prompted the progression of a variety of artificial intelligence solutions in recent decades. A massive chest X-ray database was published, which included image-level labels for 8 chest conditions, one of which involves pneumothorax. The dataset was subjected to a multilabel deep convolutional neural networks model, which showed an accuracy of 0.0816 for pneumothorax identification. The average false positive rate was only 0.2317 [16].

The Society for Imaging Informatics in Medicine organized a pneumothorax segmentation competition in 2019. The winning team obtained a Dice score of 0.8679 by utilizing a deep neural network ensemble and massive data augmentation and pre-processing. In an additional investigation, the researchers achieved a mean pixel-wise accuracy (MPA) of 0.93 ± 0.13 and a dice similarity coefficient of 0.92 ± 0.14 by utilizing a fully convolutional network algorithm that was trained on a large dataset with pixel-level labels. These results were achieved with a diagnostic accuracy of 93.45% and high segmentation accuracy [17]**.**

Several researchers have suggested pneumothorax identification algorithms that are dependent on ResNet artificial neural networks illustrated an area under the curve of 0.96 for a ResNet-50 model[18].

Pneumonia

Considering the progress made in the diagnosis and treatment of pneumonia, it remains a significant risk to health. The heterogeneity of pneumonia's epidemiology, symptoms and signs, diagnostic test appearance, and clinical course is a result of the fact that a variety of agents may cause it. Regarding the World Health Organization, pediatric pneumonia is a persistent global healthcare problem that is responsible for fourteen percent of all pediatric pneumonia among kids under the age of five. The 1st imaging test performed to diagnose pneumonia is the chest X-ray. Furthermore, the accurate interpretation of chest X-ray enables the differentiation among the bacterial and viral etiology of pneumonia, which is beneficial for case treatment. This is especially crucial in developing nations, where pneumonia is responsible for a significant portion of pediatric mortality and morbidity, despite the fact that they have restricted access to other diagnostic tests. It is predictable that artificial intelligence investigators have shown considerable interest in the diagnosis of pneumonia through X-ray of chest, especially within pediatrics, and have suggested a wide diversity of models. The multilabel CXR 8 project, that was previously reported, showed an average false positive probability of 0.0691 and an accuracy of 0.75 in the identification of pneumonia [19].

Similarly, A customized VGG16 model achieved a diagnostic accuracy of 96.2% and a classification accuracy of 93.6% in the differentiation of viral and bacterial pneumonia. It additionally utilized a novel approach to enhance the transparency of the inner workings and behavior of deep learning by visualizing the algorithm region of interest on chest X-ray [20].

In one study [21], the possible function of artificial intelligence within directing treatment approaches and refining diagnosis can be seen by an ensemble convolutional neural networks model that demonstrated an AUC of 0.983 to identify pneumonia on chest X-ray and demonstrated a predictive value in distinguishing patients, which have been enhancing from cases that worsened over 7 days of monitoring (p-value = 0.001).

Coronavirus Disease 2019

The outbreak of the coronavirus disease 2019 pandemic initiated a worldwide competition for the development of precise and dependable diagnostic tools. Chest X-ray was one of the 1st tools to be extensively utilized to screen cases for coronavirus disease 2019 pneumonia due to its high prognostic value, economical price, and widespread availability. Nevertheless, the indistinct radiological characteristics of chest X-ray, such as consolidation and diffuse elevated opacities, may make it difficult to interpret in a COVID-19 condition [22].

The potential of artificial intelligence to help radiologists in the differentiation of COVID-19-positive cases on CXR was shown. One of the 1ry challenges in the advancement of artificial intelligence-driven illness identification models was the initial lack of wide datasets. Furthermore, the computational requirements and memory constraints necessitate a significant amount of time for the training of convolutional neural networks. Transfer learning provides an alternative progress technique that may solve this problem by utilizing pre-trained models. The CXR-based detection and identification of coronavirus disease 2019 was advanced with benchmark accuracies of ninety nine percent, applying pre-trained networks that include InceptionV3, VGGNet, InceptionResNetV2, ResNet, and others [23].

The STM-RENet architecture, which is a unique convolutional neural network architecture, was developed to interpret radiographic patterns from X-ray pictures[24]. A novel convolutional block known as STM was proposed, which is capable of doing region-based operations apart from one another as well as together. Additionally, the learning capacity of STM-RENet has been improved through the development of a new CB-STM-RENet. This new CB-STM-RENet was able to successfully screen the X-ray images by applying channel boosting and learned textural differences. On 3 datasets, the proposed model demonstrated a significantly greater identification rate (97%) and accuracy (96.53%) than typical convolutional neural networks, with a particular focus on the CoV-NonCoV-15k dataset.

Rib Fractures

Some cases show an evident symptom of compound injuries, while fractures of rib are a frequent and severe injury in chest trauma cases. Complex and aggravated cases represent a greater threat to cases. As a result, it is crucial to promptly diagnose and manage these conditions. Furthermore, the rate of missed diagnoses for rib fractures is significant. Localized pain, abnormal respiration, and skin bruising are among the clinical symptoms that cases with fractures of rib experience. The severity of trauma may be predicted by the number of fracture of rib, the type and locations of fracture, which may additionally be utilized for predicting mortality rates and complications [25].

Chest X-rays and computed tomography are the primary imaging techniques used to diagnose and categorize rib fractures. An X-ray (or DR) is typically obtained to diagnose trauma cases initially, as it is both convenient and cost-effective, according to the imaging modality selection criteria developed by the American College of Radiologists. The most frequently utilized imaging modalities for the identification of rib fractures are plain X-ray and computed topography. Plain X-rays are more convenient and rapid than computed topography scans; however, their identification rate is relatively low, with over fifty percent of rib fractures being missed [26].

Pleural Effusion

Pleural effusion is a medical condition that is defined by the pathological accumulation of fluid among both pleural leaflets. It is typically utilized as a general term for describing any abnormal deposition of fluid in the pleural cavity, as the majority of effusions are diagnosed using CXR, which is unable to differentiate among various types of fluids. In the past few years, the world of diagnostic imaging has been increasingly interested in the potential of artificial intelligence and has begun to experiment with its applications in an extensive variety of settings [27].

Zhou *et al.* developed and validated a deep learning system for the semi-quantitative evaluation and identification of pleural effusion, pneumothorax and cardiomegaly. Two datasets were included: one for segmentation and one for identification. The 1st dataset, which was utilized for identification, was composed of 2838 chest X-ray from 2638 cases that contained results positive for pneumothorax, pleural effusion and cardiomegaly. The 2ed dataset, which was utilized for segmentation, has been derived from 2 publicly available datasets and contained 704 chest X-ray. Semiquantitative indexes have been determined as a result of precise identification and segmentation. Pleural effusion, cardiomegaly, and pneumothorax were detected with excellent accuracy through the identification of models. Furthermore, the researchers maintained that semiquantitative assessment might enhance the objective accuracy of quantitative measurements, decrease the work of radiologists, and act as a viable alternative for use in clinical diagnosis [(28)].

Limits and Future Perspective

Artificial Intelligence applications for thoracic diseases have demonstrated promising results in according to improving the current prognostic prediction and clinical systems reasoning. Regarding a research that compared the opinions of thoracic computer scientists and radiologists [(29)], 15.6 percent of the computer scientists believed that the position of radiologist would become obsolete within the next ten to twenty years. However, the stakeholders' opinion is that this scenario is not probable, regardless of the significant importance placed on the training and education of radiologists in artificial intelligence.

The development of artificial intelligence algorithms was significantly influenced by the utilization of open datasets; however, the lack of standardized and clearly defined standards resulted in the development of defective datasets. This must be resolved to enhance the efficacy of artificial intelligence models through the use of high-quality training. Consequently, it is crucial for understanding the datasets' limits to optimize their utilization. An additional critical component could be the integration of artificial intelligence education into the postgraduate programs for radiology residents. The primary motivation for artificial intelligence-augmented radiological precision education is the potential to enhance performance through personalized learning. The integration of artificial intelligence might potentially free up resources that were overburdened by a higher workload and might be assigned to other tasks, including case communication [(30)].

Ethical considerations: All the procedures of the research were approved by the Ethics Committee of Diagnostic Radiology Department, Faculty of Medicine, Suez Canal University. Administrative consents required were taken.

CONCLUSION

MilvueSuite software smart urgence had a good accuracy and a very high sensitivity in detecting chest emergency findings including thoracic bone fractures, pleural effusions and contusions. AI significantly improve the sensitivity of expert radiologist in detecting different lung pathologies in emergency chest x ray and significantly decrease the time needed for reading however it a had a lower positive predictive values which should be re-checked by manual reading through AI aided reading AI aided reading chest x ray in emergency had a better diagnostic performance than un aided reading in everywhere , because of the higher sensitivity , lower consumed time and the non-effect on the specificity. qXR alone should not be used alone in the interpretation of the emergency chest X ray because of the unreliable PPVs.

DECLARATIONS

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- **Availability of data and material:** Available.
- **Conflicts of interest:** No conflicts of interest.
- **Competing interests:** None.

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