COMPUTER-AIDED DIAGNOSIS AND DETECTION IN CHEST RADIOGRAPHY

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SUMMARY

Artificial intelligence (AI) is a computer science that deals with the ability of computers and robots to perform tasks that require some form of intelligence, such as learning, planning, object recognition, understanding foreign languages, etc. It is applied in various fields such as medicine, science, finance, entertainment, security.

Artificial intelligence is slowly but surely being integrated into the healthcare system, where it aims to improve patient outcomes, reduce costs, and increase efficiency. It has a special role in the field of radiology, where it should increase diagnostic and therapeutic accuracy.

Different types of artificial intelligence that have found application in radiology are machine learning, deep learning, and neural networks. Radiological imaging data is growing rapidly and increasing the need for the number of available trained radiologists. Artificial intelligence makes the radiologist's job easier by reducing the time needed for diagnosis, but also serves as a support for diagnosis and interpretation of findings. Artificial intelligence systems play a special role in chest radiography. Chest radiography uses a computer program for pattern recognition that detects suspicious features in the image and brings them to the attention of the radiologist in order to reduce false negative readings. Computer-aided diagnosis or CAD is the name of the mentioned computer program. CAD systems, known as computer-aided detection (CADe) and computer-aided diagnostics (CADx), are based on the principle of deep learning, i.e. convolutional neural network (CNN). The aim of this paper is to point out the role of CAD systems in the accuracy and acceleration of diagnostic decision-making by radiologists in radiography of thoracic organs.

Keywords: Computer-aided diagnosis, radiology, detection, chest radiography

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INTRODUCTION

With the development of technology in the last 10 to 15 years, medicine has also developed exponentially. We could not even imagine the healthcare system and medicine nowadays, without highly developed computer equipment. Since computer equipment and a large amount of information from various fields of medicine are everyday things, artificial intelligence has the potential to increase the efficiency of healthcare. The development of radiological equipment, although it leads to faster and better quality work, increases the amount of findings and information that radiologists need to interpret. Storing large number of data, stronger and faster computers, faster diagnosis, and deep and machine learning algorithms are some of the possibilities offered by artificial intelligence (1). The application of artificial intelligence in medicine could also create more time for doctor-patient interaction and make the patient a clinical point-of-care (POC). Artificial intelligence recognizes subtle changes that the human eye may miss. Recognizing lesions at an early stage can increase the accuracy of diagnosis.

The development of artificial neural networks has been traced throughout history since the mid-20th century. In the 1940s, Warren McCulloch and Walter Pitts published a scientific paper in which they proposed the use of a neural network as a way to imitate the human brain. In the 1950s, Minsky and Dean Edmunds produced a stochastic neural calculator that is recognized as the first neural network in history. A few years later, the first artificial intelligence programs were produced. In the late 1950s, Arthur Samuel accelerated the development of artificial intelligence by introducing the concept of machine learning. In the 1960s, research was conducted to identify the fundamental problems of artificial intelligence. Joseph Weizenbaum also developed an artificial intelligence program called ELIZA. ELIZA enabled humans to communicate with machines in English, thus demonstrating that a machine is able to communicate with humans on a superficial level without self-awareness or deep understanding of the person within the communication (2).

Today, the goal of artificial intelligence in medicine, especially in radiology, is to increase diagnostic and therapeutic accuracy. Artificial intelligence could tackle systemic problems in healthcare systems, such as long waiting times, diagnostic errors, inadequate access to specialist care in remote areas (rural areas, islands), a system of diagnostic criteria based on population (statistical) averages instead of individual health status, etc. (3).

The aim of this paper is to explain in more detail the concept of artificial intelligence in radiology, to define the different types of artificial intelligence implemented in radiology, and the mode of operation and benefits of artificial intelligence in radiology, especially in chest radiography. The second part of the paper discusses artificial intelligence systems derived from various radiological databases and their accuracy in interpreting findings. This document uses literature from scientific articles, books and research in clinical and non-clinical settings.

ARTIFICIAL INTELLIGENCE SYSTEMS

Artificial intelligence (AI) is a very basic term that encompasses general AI (or strong AI) and narrow AI (highly specialized or weak AI). Speculations in domain of science fiction, fall into the category of projections of general AI, not narrow AI, but they have greatly influenced the perception of most of the public about the status of the discipline's current progress, with symptomatic periods of enthusiasm and disillusionment with it (4).

In technical and medical contexts, one always speaks in narrow AI, which is not a single “artificial intelligence” but a series of algorithms whose capabilities do not superimpose – an algorithm that has learned to recognize images cannot understand language, and if it has learned to classify intestinal lesions based on colonoscopy videos, it will not be able to classify respiratory diseases), therefore any further mention of “artificial intelligence” refers to an “artificial intelligence algorithm”. Narrow AI consists of symbolic AI and machine learning. Symbolic AI is considered obsolete. Machine learning consists of traditional machine learning and deep learning. Machine learning encompasses methods that use mathematical operations to process input data, resulting in predictions. Deep learning is a subtype of machine learning that learns directly from raw, unstructured data (e.g., language, images, video) that assumes a different model structure (in the form of neural networks) that is capable of “learning” independently and in layers – first building a rough view of the problem, and then fine-tuning and becoming more faithful to the real representation (5). Neural networks, the main structure within deep learning, basically search for the best set of model parameters that will describe a given phenomenon using an iterative optimization process. Deep learning is currently in the spotlight due to recent advances in vision systems based on convolutional neural networks, natural language processing (NLP), and generative (GAN) architectures, but classical machine learning methods are often sufficient for everyday challenges, which are, in fact, more robust and interpretable than neural networks. The main types of machine learning are: supervised, unsupervised, semi-supervised, reinforcement and deep learning. In supervised learning, the model uses data as input on which regions of interest are manually marked (in the case of medical data, they are marked by doctors, e.g. the location of a pneumothorax, a collapsed lung, on chest X-rays). Unsupervised learning takes unmarked data as input, while semi-supervised learning uses a combination of marked and unmarked data. Reinforcement learning uses a system of rewarding and punishing the model to take useful and unhelpful actions. It is useful to note that deep learning is also considered only a subset of machine learning (6). According to Zhang et al. (7), deep learning models are divided into discriminative models whose output is a class (they distinguish between features and perform classification), representative models whose output is a data representation (they extract features from data), and generative models whose output is a new data sample (they generate new and reconstruct from old data). Neural networks, the main structure within deep learning, are types of computer networks that build their systems similar to the architecture of the central nervous system for solving tasks and problems. When it comes to input data that are images, including medical images, convolutional neural networks are used. The emergence of convolutional neural networks has significantly increased the adaptability and robustness of computer vision systems (vision systems), which previously depended on rigid rule-based approaches to image processing and could not learn from raw data, but each application required prior extraction of image features or attributes (feature extraction). In addition to medical images obtained for diagnostic purposes, an interesting source of image data are recordings of entire surgical operations, most often collected for the purpose of educating residents and specialists. Operations usually have a strictly defined protocol that can be described in steps, therefore, research into the applications of neural networks has included the problem of recognizing individual phases of operations, such as a study published in 2020 in the journal Nature on the example of laparoscopic cholecystectomy (8).

It is useful to note that from the point of view of machine and deep learning algorithms, there are differences in the processing of static (e.g. X-ray) and dynamic images (e.g. a recording of a surgical operation). In the first case, it is a simple image type of data for which convolutional neural networks are used, and in the second, a time series type of data in which each image is linked to a specific moment in time (the links between previous and subsequent images must be maintained in order for the display to make sense), for which recursive neural networks are best suited (9). The basic difference between convolutional and recursive neural networks (RNN) is in their architecture - CNN uses feed-forward, and RNN uses a recursive (repetitive) approach in which the output of parts of the network is fed back into the network as an input, i.e. the network works in a loop (3). Important features of deep neural networks are activation functions, such as a rectified linear unit (ReLU). The general structure of a convolutional neural network consists of inputs (radiological image), convolutional layers, compression layers, one-dimensional fully coupled layers, and outputs -classification of the radiological image (Figure 1) (10).

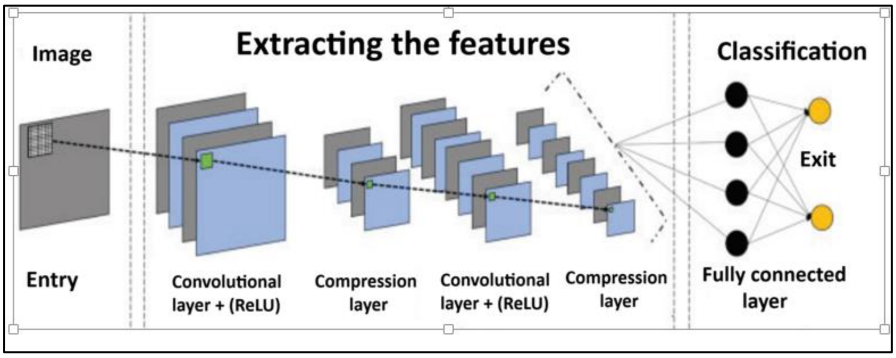

Figure 1. *Process of radiological image classification using deep neural networks technique (10).*

ARTIFICIAL INTELLIGENCE IN RADIOLOGY

The primary driver of AI in radiology is the desire for greater efficiency and effectiveness in clinical care. Radiological imaging data is growing rapidly and increasing the need for trained radiologists. These factors have contributed to a dramatic increase in the workload of radiology. An integrated AI component within the imaging workflow would increase efficiency, reduce errors, and achieve goals with minimal manual input by providing trained radiologists with pre-rendered images and identified features. Almost all image-based radiology tasks depend on the quantification and evaluation of radiographic features from images. These features may be important to the clinical task, such as the detection, characterization, or monitoring of disease (11).

In radiological image analysis, artificial intelligence systems are commonly used to target lesions in an image. For example, deep learning methods are used to classify lung nodules on a CT image and classify them as benign or malignant. A large amount of data with appropriate labels is required for efficient classification. In lung nodule classification, CT images of lung nodules and their labels as benign or malignant are used for training. After training the neural network, it can be implemented in decision support systems to detect lesions in radiological images.

SEGMENTATION

Segmentation of organs or anatomical structures is a fundamental technique in radiological image processing. It most often uses parameters such as organ volume and shape. Classification depends on good segmentation of the organ, or lesion of interest. The segmentation system most often receives the entire image directly and displays the segmentation result. The training data for the segmentation system consists of radiological images containing the organ or structure of interest and the final segmentation result. The segmentation results are usually obtained by previously performed manual segmentation methods. Since the entire image is input to the segmentation system, the system must capture the entire spatial connectivity in the image for more efficient segmentation. Segmentation can be performed using a classifier, a convolutional network to calculate the probability of the organ or anatomical structure. In this approach, the segmentation process is divided into two steps. The first step creates a probability map of the organ or anatomical structure using a convolutional network and image layers. The second step uses map building refinement where the image content and the probability maps of the structures are used and merged. One previous study used a convolutional network classifier to segment the liver on CT images. A layer of images collected from the entire CT images was used as input for the convolutional network. A convolutional network calculated the probability of the liver from the image layers. By calculating the probability of the presence of the liver in the images, a 3D map of the liver probability was obtained. The results reveal that the approach is efficient and accurate for estimating liver volume under operational conditions. The high correlation between automatic and manual interpretation indicates that the method may be good enough for possible implementation in a system (12-14).

CHEST RADIOGRAPHY

In chest radiography, a computer program for pattern recognition is used to detect suspicious features in the image and bring them to the attention of the radiologist in order to reduce false negative readings. Computer-aided diagnosis which consists of CADe and CADx systems is the name of the aforementioned computer program. CADe are systems designed to locate lesions on medical imaging. CADx systems perform actions such as characterization of lesions (the difference between benign and malignant tumors). The radiologist reviews the image, then activates the CAD systems and re-evaluates the areas marked by the CAD before making a final decision. Numerous studies have shown that radiographic abnormalities are not always detected on the images, despite their presence. This problem is solved by selectively using strategies such as double readings, which contribute to increasing cancer detection rates. The goal of CAD systems is to reduce and prevent false negative findings due to observational errors. The advantage of using computers is also a reduced workload for the radiologist. CAD algorithms are designed to search for the same features that the radiologist searches for during the case review, CAD systems are mostly divided into image processing, region of interest extraction, region of interest feature extraction, and disease classification by features (15, 16).

Chest radiography has an important clinical value in the diagnosis of diseases, as it is one of the most common examinations in medical practice. The development of AI combined with the accumulation of a large amount of radiological images opens up new possibilities for building CAD systems. The overlapping of tissue structures on chest radiographs increases the complexity of interpretation. Lesion detection is challenging when the contrast between the surrounding tissue and the lesion is low or when the lesion is covered by, for example, ribs or large blood vessels. Therefore, there will be a certain degree of missed detection of pulmonary diseases on chest radiographs. A CAD system can help physicians detect missed suspicious lesions, thereby improving the accuracy of their detection.

A large database is essential for successful training of the system, and today there are large and publicly available databases of chest X-ray images. They differ in the number of different conditions that the images contain, and in the way the images are annotated (e.g., some are intended only for training systems that recognize pneumonia, while others are intended for training systems that recognize a wide range of different conditions). Most of the systems that are popular today are trained on one of these databases (16).The most significant and largest of these databases are: ChestX-ray14 (17), CheXpert (18), MIMIC-CXR (19), PadChest (20).

In order to make it easier for the model to draw conclusions from X-ray images, they are improved using various methods before being passed through the model, i.e., their information content is somehow enhanced. Some of these methods (21, 22), often used in the works, are: improving the quality of the images (increasing the contrast means increasing the difference between the lighter and darker parts of the image, thus making the entire image and some smaller objects on it clearer and more visible. Reducing the "noise" in the image is also carried out, during which the amount of data that is not useful information is reduced, while preserving this useful information as much as possible. Various techniques for manipulating the black and white spectrum are used to make the edges of objects in the image appear clearer. The images are also passed through various filters designed specifically to maximize the quality of such images); segmentation (segmentation identifies parts of the image that represent certain objects, for example the heart and lungs. This allows, for example, atelectasis or pulmonary nodules to be searched only in parts of the image where they can appear, which are the lung fields). Segmentation can improve analysis and facilitate diagnosis by allowing the radiologist to focus on specific parts of the image; bone suppression (since bones cover a large part of the surface in which objects need to be recognized, it is useful to eliminate them from the image by various methods. In many cases, the presence of bones can interfere with the visualization of soft tissues or other anatomical structures. Shadow suppression techniques, such as specific contrast adjustments or the use of different imaging modalities (e.g., using MRI instead of CT), can help reduce the impact of bones on image quality.

The functionality of the CAD system is divided into the following sections: image processing, Region of Interest (ROI) extraction, description of morphological features and classification of diseases. CAD systems first process input images to improve quality and clarity, thereby facilitating further analysis. This process may include techniques such as filtering, significant contrast enhancement, and noise removal. After image processing, the systems identify areas of interest that require further analysis. This may include the detection of lung nodules, changes in parenchymal structure, or abnormalities in the mediastinum. CAD systems collect data on the morphological features of identified pathological conditions. These features may include size, shape, density, and other relevant characteristics that help in assessing the nature of the lesion. Based on the extracted features, CAD systems can classify selected regions according to the probability of being pathological or according to specific diseases. It is important to emphasize that the CAD system primarily helps in identifying various pathological conditions of the lungs, pleura, mediastinum, heart, and spine. The CAD system focuses on detecting abnormalities such as: reduced air permeability, emphysematous changes, nodular lesions, consolidation changes, fibrous changes, mass changes, shadows of the lateral f.c. sinuses, X-ray signs of pneumothorax, hilar prominence, mediastinal width, cardiomegaly in heart disease, raised peritoneal membranes, X-ray signs of pneumoperitoneum, detection of X-ray signs of scoliosis. On X-rays, pathological conditions are presented as shadows and increased translucency, and due to the two-dimensional nature of the image, different phenomena often overlap. In addition, there is significant variability between patients. The simultaneous presence of different pathological conditions is common, all of which makes diagnosis and classification of conditions challenging. Today, numerous models are being developed and tested to assist physicians in diagnosis and provide them with a certain level of certainty. More specifically, these deep learning models should not be seen only as a method that would bring a final diagnosis, but can provide significant assistance in diagnosis, for example, by marking a place on the image that could be pneumonia, and then physicians could focus on that part and be more confident that they did not miss something (23).

Pneumonia, as one of the most common pathological conditions of the chest and a frequent reason for chest X-ray, is one of the reasons for the development of CAD models. They typically present as opacities on X-rays, and similar opacities can be produced by a number of other conditions, such as lung cancer and excess fluid (24), and therefore diagnosis can sometimes be a major problem. Pneumonias are classified into four types based on their radiological appearance: lobar, lobular, bronchopneumonia, and interstitial pneumonia. They often coexist with other pathological conditions and show significant variability between patients. Also, the radiological appearance of pneumonia usually lags behind the clinical appearance by several days, which further delays diagnosis (25), and late diagnosis delays the initiation of effective treatment. Given the difficulties and uncertainties in diagnosis, there are also large differences in the diagnoses of different radiologists (26-28). The introduction of an automated diagnostic model would eliminate such variability and enable a certain level of standardization. CAD models in use predict whether or not pneumonia is present on an X-ray. Those images that have annotated pneumonia as present (from one of the databases) are marked as positive, and all others as negative. In addition to predicting whether there is pneumonia in the video, the model also indicates which parts of the video are suspicious for pneumonia, i.e. from which parts of the recording came the most information for predicting that pneumonia is present (29). CAD seems to focus most of its attention on recognizing pathological conditions of the lung parenchyma, while in mediastinal diseases it recognizes only cardiomegaly.

The goal of CAD model detection would naturally be to recognize all conditions that can be recognized on chest x-rays. There are several models that aim for this goal. One of them is Wang et al. (30) which proved to be efficient in the detection of cardiomegaly and pneumothorax, and worse in the detection of smaller objects, such as, for example, would belong to the labels "mass" and "nodule". Rajpurkar et al. the model for recognizing pneumonia goes even further, so that model is adapted to recognize other pathological conditions as well. The model was effective in recognizing pneumonia, fibrosis and edema (28). Irvin et al. (17) compared the performance of the model and three radiologists. The model performed best in predicting pleural effusion and worst in predicting atelectasis. Compared to individual radiologists, the model performed better in detecting cardiomegaly, edema, and pleural effusion, but not better than the majority vote of the three radiologists. Yuan et al. (30) used the AUC maximization method (DAM – Deep AUC Maximization) to build their model and won the Stanford competition for the best model for predicting five conditions (cardiomegaly, edema, consolidation, atelectasis, pleural effusion).

CONCLUSION

CAD systems represents a significant advance in the field of medical radiology, especially in the analysis of chest radiographs. This technology uses artificial intelligence (AI) and machine learning algorithms to help radiologists recognize and analyze pathological changes in images. CAD system focuses on specific changes in the lung parenchyma, such as emphysematous changes, nodular lesions and consolidations, and on the analysis of the condition of the mediastinum and pleura. Although CAD systems can significantly improve diagnostic results, there is a limitation in its ability to completely replace the human intuition and experience of radiologists. Clinical practice still requires human judgment. In the future, further development of CAD systems technology and integration of more advanced algorithms are expected to further improve the accuracy and efficiency of diagnostic procedures.

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RAČUNALNO POTPOMOGNUTA DIJAGNOSTIKA I DETEKCIJA U RADIOGRAFIJI PRSNOG KOŠA

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SAŽETAK

Umjetna inteligencija (AI) je računalna znanost koja se bavi sposobnošću računala i robota da obavljaju zadatke koji zahtijevaju neki oblik inteligencije, kao što su učenje, planiranje, prepoznavanje predmeta, razumijevanje stranih jezika itd. Primjenjuje se u raznim područjima kao što su medicina, znanost, financije, zabava, sigurnost.

Umjetna inteligencija se polako, ali sigurno integrira u zdravstveni sustav, gdje ima za cilj poboljšati ishode pacijenata, smanjiti troškove i povećati učinkovitost. Posebnu ulogu ima u području radiologije, gdje bi trebala povećati dijagnostičku i terapijsku točnost.

Različite vrste umjetne inteligencije koje su našle primjenu u radiologiji su strojno učenje, duboko učenje i neuronske mreže. Podaci o radiološkom snimanju brzo rastu i povećavaju potrebu za brojem dostupnih obučenih radiologa. Umjetna inteligencija olakšava posao radiologu skraćujući vrijeme potrebno za dijagnozu, ali služi i kao podrška za dijagnozu i tumačenje nalaza. Sustavi umjetne inteligencije igraju posebnu ulogu u radiografiji prsnog koša. Radiografija prsnog koša koristi računalni program za prepoznavanje uzoraka koji otkriva sumnjive značajke na slici i skreće pozornost radiologa kako bi se smanjila lažno negativna očitanja. Računalno potpomognuta dijagnoza ili CAD naziv je spomenutog računalnog programa. CAD sustavi, poznati kao računalno potpomognuta detekcija (CADe) i računalno potpomognuta dijagnostika (CADx), temelje se na principu dubokog učenja, odnosno konvolucijske neuronske mreže (CNN). Cilj ovog rada je ukazati na ulogu CAD sustava u točnosti i ubrzanju dijagnostičkog odlučivanja radiologa u radiografiji torakalnih organa.

Ključne riječi: Računalno potpomognuta dijagnostika, radiologija, detekcija, radiografija prsnog koša

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