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"Putting Together Surgical Prioritie: The Fusion of Immunology and Robotics"

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ABSTRACT-:

Artificial machines using learning and Neural networks offer faster and more accurate solutions to the problems faced by oncologists. The use of artificial intelligence is likely to grow exponentially. However, the primary responsibility for concerns about the patient population, social inequalities, and wisdom reports regarding the disease and its natural course will rest with the physician. Artificial Intelligence (AI) is likely to bridge the gap between knowledge acquisition and knowledge acquisition. Its meaning is explained. This method has been shown to outperform most classification and regression methods to date and is able to learn data representations best suited to the tasks held and presented, becoming better for the respective process. This article attempts to convince radiologists about the role of AI and their goal to achieve more. The paper discusses a number of oncology topics, with a focus on radiation oncology as this is the arena where AI-based research has been conducted. AI has improved patient survival and result definition by precisely characterizing several aspects of healthcare, including prognostic tests, diagnosis, and screening modalities. AI-based techniques are now being used in radiation oncology for a number of protocols and procedures, including radiation delivery, segmentation, and planning. AI's benefits for the health industry as a whole might soon result in more advanced, individualized medicine.

Keywords; Convolutional neural networks, radiation oncology, artificial intelligence, machine learning, deep learning, and planning

Introduction-

Over the past 50 years, radiation oncology has quickly moved from clinical and hypothesis-based medicine to technological and evidence-based research. Every attempt has been made to identify the best course of action, necessary dosages, delivery schedule, anticipated results, and potential for improvement. With the advent of 3D computer planning, we now possess a variety of clinical and patient-related data that may be usefully evaluated to guide future patient care and optimize additional treatments. There has been a legitimate reliance on medical data, which is now more accurately analyzed and transformed into practical knowledge. It appears that machine learning and artificial intelligence are closing the gap between data collection and insightful cancer interpretation. These methods have demonstrated exceptional skills, surpassing the majority of classification and regression techniques available today. They can also automatically choose the best data representation for the job at hand and display it in a way that improves correlation and comprehension. This article aims to simplify for researchers and clinicians the concept of artificial intelligence (AI) and its various applications in the field of oncology, including what has been accomplished thus far, what more can be done in this area, and how machine learning, deep learning, and convolutional neural networks (CNNs) are used.

Use of AI in Oncology and Radiation Oncology

(A) Role in Screening:

Assessment has long been a multiple risk. activity. Classification methods to identify patients with inexpensive, easy-to-interpret methods that can detect cancer at an early stage. The main problem with these methods is that they use only some of the patient's characteristics for risk stratification. For example, mammography to detect breast cancer in patients used only people under the age of 40 as an inclusion criterion. There is conflicting information regarding its benefits in women, and data show no benefit in reducing patient mortality (1). Similar problems arise in the diagnosis of lung cancer (2), prostate cancer (3) and ovarian cancer (4). According to research, screening has a positive effect, but the disadvantage of these tests is that a large number of patients need to be screened to detect some types of cancer that provide less benefit and cause less impact on the body. the population is less. Artificial intelligence can go a long way in reducing the number of groups that need to be analyzed. Analyzing the patient's characteristics and including more factors than the classical risk stratification method helps divide the population into low-risk and high-risk groups, and the analysis can be designed accordingly. For example, the age, family history, menstrual cycle, smoking history, body mass index, etc. of patients diagnosed with breast cancer. They may be at risk depending on factors. A similar approach has achieved results in the United Kingdom, where the risk of future heart attack can be determined simply by analyzing patient data through machine learning, thus replacing all existing models (5). intelligence. Thanks to information, cancer diagnosis should be faster, more accurate, more cost-effective and more effective.

(B) Role in diagnosis; It is important for radiology..

Artificial intelligence (AI) algorithms, particularly deep learning, convolutional neural networks, and variational autoencoders, show great promise in identifying precise and subtle changes in images. see Traditionally in radiology, doctors are qualified to evaluate medical images to identify, diagnose and monitor diseases. Artificial intelligence methods can detect complex patterns in image data, enabling quantitative and qualitative evaluation of radiographs in a short time. For most individuals, accurate and early diagnosis facilitates early treatment to reduce morbidity, mortality, and complications associated with treatment or disease. For example, it is recommended that women between the ages of 50 and 70 have a mammogram every three years for breast cancer screening (6). The high frequency of mammograms yielding negative results is a major problem when interpreted by radiologists (7). This causes approximately 50% of healthy people to undergo further surgery to remove the cancer (8). Interpretation with the help of artificial intelligence is 30 times faster and more accurate than humans (9). Leizhen (10) and colleagues proposed a combined technique with differential wavelet (DWT) for fat detection at X-ray power. Test results show that the sensitivity of the algorithm is 97.3% and the number of false alarms per image is 3.92. This number is very low compared to the false positive results of traditional screening, which was 49% after 10 mammograms in one study (11). These negative tests not only lead to increased medical expenses but also increase the patient's stress and anxiety level. (12) The use of artificial intelligence in technology can show many abnormal results to radiologists performing suspicious scans for the first time. This has the potential to shorten time, aid in early diagnosis at the time of mammography, and reduce the need for unnecessary biopsies and concerns of misdiagnosis (13). Techniques similar to those described above are used to evaluate eye images, skin lesions, electrocardiograms, x-rays, and cross-sectional images such as CT or MRI. The use of artificial intelligence can also help with complex images where the characteristics of the lesion may not be clear, such as classifying lung nodules as benign or malignant (14).

C. . Role in prediction..

Cancers are a special group of diseases that are associated with the risk of micrometastasis, increasing the risk locally or throughout the body. Cancer management strategies have long used multiple risk factors to determine future metastatic potential. For example, postoperative histopathological features such as grade, size, local infiltration status, and number of lymph nodes; It has been used as a marker of recurrence of postoperative pain. In other fields, such as prostate cancer, the use of nomograms is widespread and will be one of the earliest methods to determine the risk of locoregional and metastatic recurrence based on familiarity with the similar nature layer (15 , 16). In addition to this measurement, many genetic, molecular markers and features have been demonstrated in the tumor (17, 18). However, risk assessment tools are still evolving, as demonstrated by recent results from TailorX (19) and their limited use among medical professionals. Breast cancer (20) Moreover, risk assessment and treatment tools only use a number of features such as: stage, histopathological features, understanding the risks of local and repetitive procedures, and finally determining the indications for adjuvant treatment. Artificial intelligence not only uses historical parameters such as tumor stage, histopathological features, genetic structure, but also takes into account different characteristics of the patient such as age, gender, male characteristics, performance, and geographical inequality. diseases to create predictive analytics to guide treatment (21). Algorithms developed by AI can predict future risk or potential metastasis in the local area by analyzing meaningful data. Many studies have been conducted in this field (22,23). A comprehensive risk assessment will help tailor treatment to the individual and may be followed by further assessment to ensure it is effective and cost-effective.

D. Artificial Intelligence in Radiation Oncology

In Radiation Therapy The medical work of the patient involves many aspects. Steps such as positioning and immobilization of the patient, planning the CT scan, segmentation of tumors and organs at risk, radiation planning and determination of the required dose, time and time distribution, optimizing the beam coverage for tissue location as optimal dose and protection, followed by the actual radiation treatment and final as post-treatment. Artificial Intelligence (AI) systems are especially necessary to make these tasks easier and more efficient. Machine learning has been proposed for automatic organ classification, error prevention, or treatment planning (24, 25)

1. Image acquisition

Images are important for electronic planning. CT scans are always the easiest images to prepare because dose algorithms always require electron density values. However, the hope of correcting the decrease in electron density values that occurs with CT scans is the reason why we cannot switch between CT scanning and PET CT preparation for MRI or PET MRI as planned; Since MRI has better tissue coverage. and multiplanar image capture capability. For example, when treating diseases of the brain, MRI, although better than the standard for detecting tumors, can only be used if its analysis is done in preparation for a CT scan to better understand the tumor. As a solution, continuous efforts are being made in the form of atlas-based methods, sparse coding-based methods, learning-based methods to create CT scans using MRI data, also called synthetic CT scans (sCT). Among the many ways to convert MRI data to sCT, Deep Embedding Convolutional Neural Network (DECNN) is an AI-based method that has been proven to be more efficient, consume less time again, and produce higher resolution images and fewer artifacts. (26). Therefore, in the future, the use of artificial intelligence may be the first method to eliminate the need to prepare CT scans; because synthetic CT scans will be rapidly generated by MRI along with reliable electron density data for design planning. Synthetic CT scans will also have a good effect on segmentation, and fusion errors will be reduced as the resulting sCT will be easier and combined with MRI, which forms the basis of synthetic CT. Its use is more prominent in MRI-only prostate radiation therapy (27 , 28), where evidence-based deconvolution algorithms are used to generate sCT and maps from raw MRI images.

2. Tumors and organs at risk Segmentation::

Shaping organs at risk (OARs) and target areas is an important part of prepared radiation oncology However, this process is time-consuming and there are significant inter-observer differences depending on the skill level of the assessor (29). Automated shaping software has been shown to speed up this process and improve agreement between inspectors. Many commercial products are available, but they are not widely used in medicine (30). Recently, much effort has been devoted to learning new techniques to identify patterns in different imaging modalities (CT, PET, and MRI). Methods include cognitive techniques such as atlas-based contours, machine learning, statistical models, and shape-like models; regional trends such as changing maps and watersheds; or a combination of knowledge-based and domain-based approaches (31). Recently, machine learning methods and deep learning, especially deep learning using artificial intelligence, have become popular in many fields. In a recent study, Tim Lustberg (32) attempted to compare manual shaping, automatic segmentation, and deep learning. Deep learning contours for lungs and spine outperform atlas-based contours. Deep learning is better off in the future but needs further development. An average of 79% time savings were achieved with the help of deep learning compared to manual methods for similar tasks. Kuo Man and colleagues (33) proposed a new method based on deep dilated convolutional neural networks (DDCNN) for fast and consistent automatic segmentation of targets and hazards, determination of body volume. They developed a novel multi-scale convolutional architecture to extract various features such as text and borders and full pixel-level segmentation, which are crucial for true automatic segmentation. A total of 218 patients were selected for training and an additional 60 patients were used for validation. When Dice similarity coefficient (DSC) was used to measure the segmentation accuracy, the average DSC value of DDCNN was 87.7% for CTV, 93.4% for bladder, 92.1% for left femoral head, 92.3% for right femoral head, 65.3% and 61.8% for colon. This rate is 61.8%, which is better than the previous rate. Additionally, segmentation testing time for all CTVs, bladder, left and right femoral head, bowel, and colon was 45 seconds per patient; This is as fast as the time it takes to traditionally draw patterns. However, since there are still uncertainties about the structures shown in the study, such as the optic chiasm and mandibular gland, not all organs can be classified accurately and uniformly (34). Thanks to ongoing research, we can expect that in the future, AI-based methods (such as neural networks) will be able to create contours for patients faster and more regularly (such as where the target volume and organs are at risk) play an important role. It's much better than what we can do now.

3. Image registration

Image registration is the process of spatially aligning two or more image datasets of the same scene taken at different times and from different views. It uses a variable number to apply to the image while giving more space to the reference image. There are many ways to register on the market. The two main recording methods used in radiation therapy are the dynamic technique and the rigid technique. In their research on medical record systems, Viergever et al. reviewed the developments that occurred between 1998 and 2016 [35]. They stated that deep learning for image registration is likely to be revolutionary, making the recording process simpler and more user-friendly, and suggested that using Deep learning techniques to perform image registration is an important part of the entire process. A missing piece. Clinical imaging. Yang et al. (36) and Miao et al. (37) use DL and CNN-based methods, respectively, which are faster than registration and energy model

4. **Radiation planning:** Electrical planning is a complex process that involves the use of computer-based optimization. Determination of dosimetry targets before actual delivery of radiation. The current process is labor intensive and time consuming and involves some degree of "hit and try" operation. Artificial intelligence can be used to complete the planning process better and faster. Different beam alignments and beam timings, as well as the complex dynamics of collimator motion, can be optimized for algorithmic scale and efficiency. McIntosh et al (38) pioneered the use of voxel-based dose estimation and dose simulation methods in the planning process of head and neck surgery. Dose testing along with multiple patient selection reports and machine learning help create new, all-in-one electronic radiation treatment plans. The artificial intelligence-based system reached full accuracy in a short time. This concept is especially useful in planning radiation therapy (ART) where time is a critical constraint (39). ART methods can be used in current situations as long as they are fast and accurate. In this case, deep learning for automatic segmentation and image registration will be faster than standard methods and can reduce the electronic planning process. Currently, machine learning or information planning is used; This means using software tools to estimate the dose histogram (DVH) of vital organs associated with the tumor. This tool helps complete the recovery plan in less time. Obtaining and personalizing the patient's medication limit during preparation is another area of artificial intelligence application (40). Artificial intelligence has the ability to effectively create algorithms that can include not only knowledge of drug packaging restrictions but also many patient-related factors such as age, gender, race, and makeup to help doctors make better decisions at the time. dosing time The balance in the preparation of radiation is difficult to evaluate clinically (41). As a next step, knowledge planning will be used to test knowledge change planning; Here, in addition to electronic information instructions, all information about the patient (treatment, dosimetry, tumor biology) will help modify radiation therapy. brings it down to a personal level, thus reducing toxicity as cancer develops. Medical use and use will become a reality in the future (42). The future of AI is bright and has great potential to predict which patients will actually benefit from radiation. PORTOS is the first of many future radiogenomic tests that will help identify tumor radiosensitivity as predictive biomarkers. (43).

5. **Method of sending electronic messages.** It is difficult to monitor the difference between different fractions during normal firing, and near-effective control has become the basis of radical hypofractionated firepower. Assessment of the patient's position and immobilization attempts to provide skills to reduce uncertainty regarding movement. Ogunmolu et al. (44, 45) developed a maskless soft generator for H&N radios. Position-based visualization of a radiotransparent soft robot is used to control flexion/extension of the mannequin head. The Kinect RGB-D camera is used to measure head position, measure perception error and desired position, and control the pneumatic system that controls the pressure in the inflatable airbag (IAB). Their results showed that the system was able to control head movement within 2 mm

relative to the reference orbit. Problems related to tumor detection are also solved with the help of artificial intelligence. A limitation of tumor tracking is that there is always a lag time of several microseconds between penetration and final fixation; In one study, it was estimated to be approximately 0.09 seconds (46). This can usually be corrected using gambling software, which has a predictive accuracy of approximately 80% (47). Cancer technology can be improved by combining various patient data, especially respiratory patterns, and predicting the next respiratory cycle (48). Parker et al. (49) proposed a new intra-fraction and inter-fraction data change estimator called intra-fraction and inter-fraction fuzzy deep learning (IIFDL); Here FDL is equipped with breathing data and breathing data to accurately predict movement and reduce time. To obtain more accurate results. They also found that IIFDL had an average calculation time of 1.54 ms for the difference between two variables; which is less than current models. By taking into account the reduction in movement and the delay time between the initiation signal and transmission, a reduction in treatment can be achieved with greater confidence in fire radiation oncology.

6. Discussion-We tried to collect the main points of oncology and radiation oncology and intelligent will soon (Table 1). The purpose of this article is not to cover all of the various AI-related technologies, but rather to provide readers with an understanding of the many aspects of oncology that are or may be affected by AI. As the example above shows, it can impact almost all areas of oncology, making the much disease- and patient-related data we already have useful to guide doctors. AI can also reduce the time and energy doctors and nurses need to complete certain tasks. There is great potential for AI to be used to improve many aspects of the patient care process in the future. In the future, artificial intelligence can be used to enhance self-healing, develop appropriate diagnosis, treatment and follow-up plans, monitor health and patient safety, and thus reveal new medical information that can directly impact quality care. . There are other areas in oncology, such as the development of guidelines and optimal treatment follow-up data, the need for and frequency of additional biochemical tests or diagnostics. Many government agencies and non-governmental organizations can use AI to solve public needs, such as preventing diseases and helping build medical facilities and oncology clinics. Using large amounts of population data information, AI can determine which areas need to invest in medical equipment or personnel. However, with new technology comes new issues and problems. One must be careful when making decisions based on information produced by intelligence because the main purpose of intelligence is the evaluation of information and in the absence of information, computer learning is always limited. There are even reports of intelligence-based control. The mechanism of deceptive deception in facial recognition, even in the form of deception, has been well researched and documented (50). The difference in technology between developed and developing countries is also a factor that can lead to wrong decisions (51). Information from developing countries cannot be easily added to developing countries without being expected to make mistakes. Therefore, fairness in the representation of data and keeping in mind different areas of disease, population and healthcare seems to be the way to go. The authors believe that the current focus is on obtaining and accessing more patient-related information, particularly from developing countries, that can be used to provide important and actionable information for the use of medicine. Finally, it should not be forgotten that the doctor relies not only on data but also on his experience and judgment. Its main goal is to make the patient's life better by following his expectations, needs and resources, which are sometimes more important than quick and accurate treatment. . important asset. Control decision making in radiation oncology. It has the potential to impact every step of the process, from screening, diagnosis, risk stratification, treatment planning, follow-up, and influencing decision making. However, it should not be seen as a one-size-fits-all solution or a magic formula that solves all problems. Honesty in data collection should be an important step to ensure that developing countries do not have to use technologies for which they are not ready. Finally, the process that creates the necessary intelligence needs to be clearly defined before making decisions based solely on its algorithms and inferences.

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