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Oncology Advancement Technologies Focus in Tumor Diagnosis and Treatment

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Abstract

Through the integration of radiomic and pathomic signatures from the MRI (T2-weighted imaging, contrast-enhanced T1-weighted imaging, and diffusion-weighted imaging) image and H&E-stained whole-slide images, they developed a radio-pathomics integrated prediction system With progressively investigated belief systems and advances for possible utilizations of computerized reasoning (man-made intelligence) in oncology, we here depict a comprehensive and organized idea named wise oncology. Oncology, radiology, pathology, molecular biology, multi-omics, and computer science are all included in the definition of intelligent oncology, which aims to promote cancer prevention, screening, early diagnosis, and precise treatment. The rapid advancement of AI technologies like natural language processing, machine/deep learning, computer vision, and robotic process automation has made it easier to advance intelligent oncology. We are optimistic that intelligent oncology will play a pivotal role for the future of basic, translational, and clinical oncology despite the fact that the concept and applications of intelligent oncology are still in their infancy and face numerous obstacles.

Keywords: Artificial intelligence • Oncology • Cancer prevention • Cancer screening • Diagnosis

Introduction

Man-made brainpower (man-made intelligence) alludes to the utilization of a PC, robot or other machine to lead human-like canny behavior. Progressively progressed simulated intelligence advances have shown extraordinary applications in clinical practices, and artificial intelligence has in practically no time turned into a vital piece of healthcare. There are no questions that these clinical applications will significantly affect the future medical services. The idea of intelligent oncology has emerged as a result of the increasing use of AI technologies in clinical oncology and the constant discussion of important scientific issues. We characterize it as a between disciplinary mix of clinical oncology, radiology, pathology, sub-atomic science, multi-omics with computer based intelligence. Preclinical and clinical medicine, public health, and computer science are all parts of intelligent oncology. In particular, shrewd oncology is planned to utilize center artificial intelligence procedures, for example, nature language handling, machine/profound learning, PC vision, biometric recognizable proof, and mechanical cycle robotization, to lay out the brilliantly biological chain during the time spent malignant growth care. In the end, smart oncology will make cancer prevention and screening, early diagnosis and treatment, prognosis, and risk stratification more accurate and effective.

Literature Review

In oncology, intelligent oncology's primary focus is on the development, improvement, and application of AI technologies in tumor screening, diagnosis, treatment, and prognosis prediction, which may assist clinicians in meeting clinical needs. This is in contrast to precision medicine and personalized medicine. Intelligent oncology does not include statistical analysis, omics analysis, or clinical trials with more medical attributes in precision medicine and personalized medicine.

ML can be divided into supervised learning and unsupervised learning. The main difference between them is whether the training dataset contains the target label or not. ML is a type of algorithms that enable machines to have learning, predicting, and cognizing ability. In supervised learning, data-label pairs are used to train an ideal model, and the model is then used to predict possible labels or values for unknown data. Classification and regression are the usual tasks that are suitable for supervised machine learning algorithms. Naive Bayes, logistic regression, k-nearest neighbors (KNN), decision tree (DT), support vector machines (SVM), and random forest (RF) are just some of the supervised learning tools used in intelligent oncology. In unsupervised learning algorithms, the input data do not have corresponding labels, so an optimization model must be computed based on the similarity between training samples. Essentially a statistical tool, unsupervised learning is a learning method for clustering unlabeled original data by calculating potential structures or features. In oncology, a variety of unsupervised learning techniques, such as principal component analysis (PCA), singular value decomposition (SVD), k-means, mean-shift, hierarchical clustering, DBSCAN, are utilized for cancer screening, prognosis analysis, key-marker extraction, feature dimension reduction, and gene representation clustering.

Discussion

DL is a part of ML in light of the muti-layer brain network structure. Contrasted with ordinary ML models, DL calculations can deal with tremendous datasets and remove likely high level semantic elements through multi-facet nonlinear transformations. Albeit these semantic highlights are difficult to comprehend and decipher, they empower exceptionally precise execution of the objective undertaking, making machine savvy. Because DL is a useful tool for precisely resolving tasks related to tumors, it makes intelligent oncology research broadly applicable in the clinical setting. Backbone modes in DL techniques that guarantee applications' fundamental performance include convolutional neural networks (CNN), recurrent neural networks (RNN), long short-term memory (LSTM), fully convolutional networks (FCN), and generative adversarial networks (GAN). Graph convolutional networks (GCN), attention, muti-head attention, transformer, vsion-transformer (ViT), auto-encoder (AE), variational auto-encoder (VAE), deepclustering, and others have recently been proposed and utilized in intelligent oncology research. Contrastive learning techniques have also been extensively utilized in intelligent oncology tasks to reduce the high cost of medical

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data annotation and maximize raw data. The contrastive learning algorithm is a useful self-supervised tool for automatically learning latent information from non-annotation data, particularly in hard-to-annotate research fields like digital pathology, single cell omics, and spatial transcriptomics, among others [1].

Natural language processing, or NLP, is one of the most important subfields of artificial intelligence because it enables computers to comprehend human speech from text, audio, and video. NLP is useful for oncology research and clinical applications. There are three primary strides in NLP calculations, getting, changing and producing. Ordinarily, NLP applications typically perform undertakings utilizing two groups of approaches: statistical and symbolic A set of rules that are either manually created or learned automatically by modeling various linguistic phenomena make up symbolic approaches. Language phenomena are typically learned using ML algorithms in statistical approaches. Multi-layer network-based NLP algorithms have become commonplace models as a result of the widespread use of DL. ULMFiT, bidirectional encoder representations from transformer (BERT), Transformer-XL, Google PaLM, and GPT-3, among others, are among the numerous successful NLP models. By automatically generating standard medical records, NLP can boost doctors' efficiency in clinical treatment. In disease research, NLP apparatuses can naturally remove key data from non-organized text information. It is able to process free text documentation, such as oncological clinical notes and reports in pathology and radiology reports [2].

Cloud computing and telemedicine telemedicine aims to improve a patient's health by enabling two-way, real-time interactive communications between the patient and a practitioner or physician at a remote location. Large-scale medical images like computed tomography (CT), magnetic resonance imaging (MRI), positron emission tomography (PET-CT), endoscopy, and pathological whole slide images can be transmitted in real time using 5th generation (5G) technology. This is the foundation for remote diagnosis, surgery, and education. Telemedicine can create augmented reality (AR) scenes for remote surgery by combining virtual reality (VR) scenes with real-world scenes. Distributed computing is the on-request accessibility of PC framework assets, particularly information capacity (distributed storage) and registering power. Cloud computing is an excellent option because AI needs a lot of computing power. Through the sharing of distributed computing assets, it gives center establishment to the heartiness and flexibility of shrewd oncology applications [3].

Development of intelligent oncology also depends on developing oncology- and computer-science-specific skills and encouraging interdisciplinary integration and innovation in the training of the next generation of physician-scientists. Undergraduate programs like intelligent medicine have been established by institutions of higher education all over the world. Additionally, in a variety of contexts, AI technologies have been utilized in medical training tutoring. In addition, talent training includes continuing medical education, e-learning, self-learning, mentorship programs, and more. For instance, randomized clinical trials have demonstrated superior performance outcomes and skill transfer for AI-based surgical simulation training. Meanwhile, interdisciplinary collaborations focusing on intelligent oncology have been a mainstream direction in oncology-specialized institutions. ML can be used to extract data from epidemiological studies that combine multi-omics and molecular cancer biology to create models for primary cancer prevention. Precision prevention platforms could be established by incorporating relevant cancer control programs. These AI platforms include some of the most important preventative measures, like keeping track of healthy choices and activities. Man-made intelligence advances are additionally assuming progressively significant parts in disease screening, in which high-risk populaces are examined by radiological or obsessive techniques to early catch indications of malignant growth. At least four types of cancer clearly benefit from screening. These diseases incorporate bosom, lung, colorectal and cervical tumors. For breast cancer colorectal cancer and cervical cytology, AI-assisted methods have been used. In other cancers, retrospective studies have looked into the value of using DL-based algorithms for screening. Future optimization of the methods might make screening more effective [4].

In radiology, AI-based technologies have been integrated into daily practices in recent years, and methods range from convolutional neural networks to VAE. VAE is a powerful generative model that has been improved from AE. Intelligent oncology has some of the best examples showing successful applications of ML/DL-based algorithms for fast and accurate diagnosis of cancers using radiological and pathological images. In radiology, AI-based technologies have been integrated into daily practices, and methods range from convolutional It also has an encoder and decoder network, like AE. The initial high-dimension input is converted into the latent low-dimensional code by the encoder network. The data is recovered from the code by the decoder network, likely with ever-increasing output layers. In contrast to AE, VAE samples recover vectors from a multi-Gaussian distribution and maps the input data into that distribution. They are able to produce diverse samples in addition to extracting the discrimination representation for use in VAE applications. Enterprises have been supported for licensees for significant programming. For instance, the National Medical Products Administration (NMPA) has granted approval to at least eleven different pieces of software for diagnosing lung nodules in China. Lung nodules can be automatically classified as benign or malignant using these products. In addition, multi-task algorithms for automatically fast-tracking tumor lesions and classifying corresponding histological subtypes50 have been developed for lung cancer. At the same time, digital pathology has accelerated the development of clinical pathology, resulting in diagnosis that is more effective, cost-effective, and accurate. Digital pathology, in contrast to conventional pathology, stores images that are viewable on a computer monitor or mobile device. A few disease types have been helped by these innovations. For example, recently developed AI algorithms can automatically diagnose a large number of cervical cytological slides, both neoplastic and non-neoplastic [5].

A Harvard University research team developed an algorithm called "tumor origin assessment via deep learning" (TOAD) based on a DL method that can be used to distinguish between the origin of the primary tumor using conventionally obtained histological sections. In addition, TOAD can be used as an adjunctive tool to distinguish between cases of cancer of unknown primary (CUP) and complex metastatic tumors. It can also be used in conjunction with or in place of extensive or adjunctive diagnostic tests to reduce the incidence of CUP. Utilizing ML/DL-based algorithms to predict the therapeutic response of cancer is one of the major research directions in intelligent oncology. AI algorithms based on DL are more self-adaptive than traditional Cox-based prediction methods and can be used with non-linear representation. They also have a better predict performance and can be used to predict a cancer prognosis. Major AI-based cancer prognostic prediction studies published in leading medical journals are listed. These studies include research on lung, breast, colorectal, liver, prostate, and other types of cancer also include major cancer treatments like radiation therapy, targeted therapy, neo-adjuvant therapy, and immunotherapy. Four papers published in the Lancet investigated outcome prediction based on deep network models for conventional treatment, neo-adjuvant chemo-radiotherapy, immunotherapy, and treatment evaluation in colorectal cancer. Utilized entire slide picture of stained to build model in light of CNN and lingering organizations which can foresee the microsatellite soundness condition of colorectal disease and hence the result of immunotherapy. It was able to predict treatment and microsatellite instability (MSI) with AUCs of 0.931 and 0.865, respectively. Deep neural network models based on the entire H&E-stained slide image were developed proposed a muti-module method for rectal cancer neo-adjuvant chemo-radiotherapy outcome prediction [6].

There are three fundamental calculations in RAPIDS, visual math flexible organization, and SVM is used to extract features from whole slide images (WSIs), and an elastic network is used to evaluate the radiomics-derived features. The SVM, which was trained to predict pathological complete response (pCR) of neo-adjuvant chemo-radiotherapy in locally advanced rectal cancer, would combine all two types of omics features. In the validation setting of the retrospective study, RAPIDS received a prediction result with an AUC of 0.872. It also had in a prospective validation study. Although image data are the most frequently used type of data for predicting cancer treatment outcomes, clinical text and other types of data can also add value. A DL model and trained using radiology text report data. They estimated non-small cell lung cancer outcomes based on response evaluation criteria in solid tumors (RECIST) using the model. The test shows that the AI method can accurately predict outcomes for non-small cell lung cancer (NSCLC).

Conclusion

Applications of AI technologies in cancer one of the most important parts of intelligent oncology is combining AI and oncology for clinical applications. AI technologies have multiple applications in clinical oncology, including cancer prevention, screening, early diagnosis, prognosis prediction, drug discovery and development, clinical trials, protein structure prediction, surgery, radiotherapy, nursing and rehabilitation, and generalization stages for many studies. We will demonstrate these applications with examples and new developments. Savvy oncology contains a huge amount of large information and prescient examination in clinical dynamic cycles, hence the information security techniques and morals guideline of computer based intelligence innovations in the oncology setting, explicitly whether information driven choices could risk dehumanizing patients are of extraordinary concerns,25 in spite of that these issues are not well defined for oncology. The risk of violating a person's privacy is also high because there are a lot of personal data there. The content of intelligent oncology also includes data security strategies and ethical laws for relevant AI technologies because healthcare providers are responsible for protecting patient data.

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Conflict of Interest

None.

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