Study on Application of AI Medical Image Analysis

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Abstract

The integration of artificial intelligence (AI) into medical imaging has guided in an era of transformation in healthcare. This literature review explores the latest innovations and applications of AI in the field, highlighting its profound impact on medical diagnosis and patient care. The innovation segment explores cutting-edge developments in AI, such as deep learning algorithms, convolutional neural networks, and generative adversarial networks, which have significantly improved the accuracy and efficiency of medical image analysis. These innovations have enabled rapid and accurate detection of abnormalities, from identifying tumors during radiological examinations to detecting early signs of eye disease in retinal images. The article also highlights various applications of AI in medical imaging, including radiology, pathology, cardiology, and more. AI-based diagnostic tools not only speed up the interpretation of complex images but also improve early detection of disease, ultimately delivering better outcomes for patients. Additionally, AI-based image processing facilitates personalized treatment plans, thereby optimizing healthcare delivery. This literature review highlights the paradigm shift that AI has brought to medical imaging, highlighting its role in revolutionizing diagnosis and patient care. By combining cutting-edge AI techniques and their practical applications, it is clear that AI will continue shaping the future of healthcare in profound and positive ways.

Keywords: artificial intelligence, medical imaging, review, diagnostics, segmentation, classification

Introduction:

Advancements in medical imaging and artificial intelligence (AI) have ushered in a new era of possibilities in the field of healthcare. The fusion of these two domains has revolutionized various aspects of medical practice, ranging from early disease detection and accurate diagnosis to personalized treatment planning and improved patient outcomes.

Medical imaging techniques such as computed tomography (CT), magnetic resonance imaging (MRI), and positron emission tomography (PET) play a pivotal role in providing clinicians with detailed and comprehensive visual information about the human body. These imaging modalities generate vast amounts of data that require efficient analysis and interpretation, and this is where AI steps in.

AI, particularly deep learning algorithms, has demonstrated remarkable capabilities in extracting valuable insights from medical images [1]. Deep learning models, trained on large datasets, are capable of recognizing complex patterns and features that may not be readily discernible to the human eye [2,3]. These algorithms can even provide a new perspective about what image features should be valued to support decisions [4]. One of the key advantages of AI in medical imaging is its ability to enhance the accuracy and efficiency of disease diagnosis [1,5]. Through this process, AI can assist healthcare professionals in detecting abnormalities, identifying specific structures, and predicting disease outcomes [5,6].

By leveraging machine learning algorithms, AI systems can analyze medical images with speed and precision, aiding in the identification of early-stage diseases that may be difficult to detect through traditional methods. This early detection is crucial as it can lead to timely interventions, potentially saving lives and improving treatment outcomes [1,2,3].

Furthermore, AI has opened up new possibilities in image segmentation and quantification. By employing sophisticated algorithms, AI can accurately delineate structures of interest within medical images, such as tumors, blood vessels, or cells [7,8,9]. This segmentation capability is invaluable in treatment planning, as it enables clinicians to precisely target areas for intervention, optimize surgical procedures, and deliver targeted therapies [10].

The integration of AI and medical imaging has also facilitated the development of personalized medicine. Through the analysis of medical images and patient data, AI algorithms can generate patient-specific insights, enabling tailored treatment plans that consider individual variations in anatomy, physiology, and disease characteristics. This personalized approach to healthcare enhances treatment efficacy and minimizes the risk of adverse effects, leading to improved patient outcomes and quality of life [1,11,12].

Additionally, AI has paved the way for advancements in image-guided interventions and surgical procedures. By combining preoperative imaging data with real-time imaging during surgery, AI algorithms can provide surgeons with augmented visualization, navigation assistance, and decision support. These tools enhance surgical precision, reduce procedural risks, and enable minimally invasive techniques, ultimately improving patient safety and surgical outcomes [13].

Recently several cutting-edge articles have been published covering a wide variety of topics within the scope of medical imaging and AI. Many of these outstanding advancements are directed to cancer, a major cause of severe disease and mortality. The main contributions and fields will be addressed in the next sections.

Recent trends in AI research

It is well-established that automated analytical systems have begun to emerge as a database system capable of scanning medical images with computers and configuring big data . With the development of back-propagation deep-learning artificial intelligence (AI) architectures, medical imaging has begun to be applied and it has been reported that accurate diagnosis is possible. The most efficient model for image analysis is the 'Convolutional Neural Network' (CNN), a key block in the configuration of deep networks. CNN involves developing various optimization algorithms such as LeNet, AlexNet, ZF Net, GoogleNet, VGGNet and ResNet. CNN is a powerful feature extractor with a deep layer that can extract features from images.1,2) Deep learning algorithms, especially using the AI methods that make up the deep-learning architecture

The need for AI in medical imaging

Finding non-invasive and quantitative assessment techniques for early detection of Alzheimer's disease [AD] is fundamentally important for early treatment. Tumor detection, classification, and quantitative assessment in positron emission tomography (PET) imaging are important for early diagnosis and treatment planning. A number of techniques have been proposed for segmenting medical image data through quantitative assessment. However, some quantitative methods of evaluating medical images are inaccurate and require considerable computation time to analyze large amounts of data. Analytical methods using AI algorithms can improve diagnostic accuracy and save time.

AI research field

The deep-learning technology, known as the AI method, dramatically improves diagnostic performance by automatically extracting features of complex and precise medical images and comparing their differences.3,4) Image analysis by AI algorithm is superior to the traditional image analysis method. Automatically classifying skin lesions using images is a challenging task because the skin lesion shapes differ a lot, but they have successfully categorized skin cancer successfully.5) When evaluating diabetic retinal fundus photographs, deep-learning using Inception-v3 architecture enabled diagnosis of diabetic retinopathy with high sensitivity and specificity.6) Early detection of pulmonary nodules on a chest by computed tomography (CT) scan was performed using the Lung Image Database Consortium (LIDC) and the Image Database Resource Initiative (IDID) database for the diagnosis of lung cancer, and extracted successfully using the network back propagation algorithm.7) CNN (Convolutional Neural Network)-type deep learning model, trained for large mammography lesions, is superior in performance to existing CAD system.8) An automated detection system has been successfully established by studying the feasibility of a deep learning approach for detecting cartilage lesions in the knee joint with MR images.9) PET images with low spatial resolution overestimated the volume due to the partial volume effect, but the optimal volume was extracted using the Artificial neural networks (ANN) algorithm.10) Through the development of AI algorithms, the diagnostic performance of various medical images has been improved, and it is expected to be continuously introduced into medical image diagnosis systems because it has a higher diagnostic performance index than any other quantitative analysis methods so far

Application of AI Medical Image Analysis

AI in Brain Imaging

In brain research using AI, many studies have been conducted in the field of Alzheimer's disease classification, anatomical segmentation of brain regions, and tumor detection. Alzheimer's disease (AD)/mild cognitive impairment (MCI)/HC classification was successfully performed by using the Gaussian Restricted Boltzmann Machine (RBM) to find feature expressions in volume patches of MRI and PET images.26) The 3-D convolution neural network in AD classification is superior to other algorithm classifiers.27,28) It automatically segments the magnetic resonance (MR) images of the human brain using CNN.29) Segmentation of striatum segmentation was performed using deep CNN, and the results were compared with those of FreeSurfer.30) In the brain area, manual segments are time-consuming with individual differences occurring, while automatic segmentation has significant difficulties in performing in complex structures. Twenty-five deep-layers called the 'voxelwise residual network' (VoxResNet) were developed and successfully segmented automatically.31) To demonstrate end-to-end nonlinear mapping from MR images to CT images, a 3-D fully convolutional neural network (FCN) was employed and verified in a real pelvic CT/MRI data set.32) Input and output improved performance by using twovolume CNNs, and excellent performance was observed by evaluating the input and output forms in the MRI and PET images of the Neuroimaging Initiative (ADNI) database

AI in Chest Imaging

By introducing the multiple-instance learning (MIL) framework, a de-convolutional neural network is constructed to generate the heat map of suspicious regions.34) A unique set of radiologic datasets of publicly available chest X-rays and their reports were used to find and report 17 unique patterns by applying CNN algorithms.35) It has been reported that the presence of interstitial patterns have been found by applying a segmentation-based label propagation method to a dataset of interstitial lung disease,36) and it has been reported that lung texture patterns are classified using CNN.37) A method for classifying frontal and lateral chest Xray images using deep-learning methods and automating metadata annotations has been reported.38) A new method of using a three-dimensional (3-D) CNN for false positive reduction in automatic pulmonary nodule detection in a Volumetric Computed Tomography (CT) scan has been proposed. 3-D CNN is able to enter more spatial information and extract more representative features through a hierarchical architecture, trained with 3-D samples. The proposed algorithm has achieved high CPM (Competition Metric) scores, has been extensively tested in the LUNA16 Challenge, and can be applied to 3-D PET images.

AI in Breast Imaging

Since most mammograms are 2-D and the number of data is large, AI images can be successfully analyzed using deep-learning in natural images. The discovery of breast cancer is the detection and classification of tumor lesions, the detection and classification of micro-calcifications, and risk-scoring work, which can be effectively analyzed by CNN or RBM methods. For the measurement of breast density, CNNs for feature extraction were used,39) and a modified region proposal CNN (R-CNN) has been used for localization. It has been reported that U-net is used for segmentation breast and fibro-glandular tissue (FGT) in MRI in a dataset and accurate breast density calculation results are observed.40) It has been reported that a short-term risk assessment model has been developed by achieving a predictive accuracy of 71.4% by calculating the risk score by implementing the mammographic X-ray image as a risk prediction module MLP (multiple layer perception) classifier.

AI in Cardiac Imaging

Cardiac artificial research fields include left ventricle segmentation, slice classification, image quality assessment, automated calcium scoring and coronary centerline tracking, and super-resolution. 2-D and 3-D CNN techniques are mainly used for classification, and deep-learning techniques such as U-net segmentation algorithm are used for segmentation. The high-resolution 3-D volume in the 2-D image stack has been reconstructed using a novel image super-resolution (SR) approach.42) The image quality is superior to the SR method because the CNN model is computationally efficient, but SR-CNN is advantageous in image segmentation and motion tracking.43) Using multistream CNN (3 views), it has been reported that low-dose chest CT can be identified with high accuracy by deep learning when the region of interest is considered as a coronary artery calcification candidate over 130 HU.44) Coronary calcium in gated cardiac CT angiography (CCTA) was detected using 3-D CNN and multi-stream 2-D CNN.

AI in Musculo-skeletal Imaging

Musculo-skeletal images are analyzed by deep-learning algorithms for segmentation and identification of bone, joint, and associated soft tissue abnormalities. 3-D CNN architecture has been developed to automatically perform supervised segmentation of vertebral bodies (VBs) from 3-D magnetic resonance (MR) spine images, and a 'Dice' similarity coefficient of 93.4% has been reached.23) Automatic spine recognition, including spine location identification and multiple image naming, requires large amounts of image data and is difficult to recognize due to the variety of spine shapes and postures. By using a deep-learning architecture called Transformed Deep Convolution Network (TDCN), the posture of the spine was automatically corrected to process the image.46) A CNN regression has a limitation in that its computation time is long and the capture range is small for implementing an intensity-based 2-D/3-D registration technology. It is reported that highly accurate real-time 2-D/3-D registration is possible, even in a greatly enlarged capture range.47) Several deep-learning methods have been developed for automatically evaluating the age of skeletal bones using X-ray imaging and their performance has been verified by showing an average discrepancy of about 0.8 years

References:

1. Farooq A, Anwar S, Awais M, Alnowami M. Artificial intelligence based smart diagnosis of alzheimer's disease and mild cognitive impairment. 2016;1-4.
2. Vieira S, Pinaya WHL, Mechelli A. Using deep learning to investigate the neuroimaging correlates of psychiatric and neurological disorders: Methods and applications. Neuroscience & Biobehavioral Reviews. 2016;74:58-75.
3. LeCun Y, Bengio Y, Hinton G. Deep learning. Nature. 2015; 521:436.
4. Zeiler MD, Fergus R. Visualizing and understanding convolutional networks. 2014;818-833.
5. Esteva A, Kuprel B, Novoa RA, et al. Dermatologist-level classification of skin cancer with deep neural networks. Nature. 2016;542:115.
6. Gulshan V, Peng L, Coram M, et al.Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs. JAMA. 2016;316:2402-2410.
7. Golan R, Jacob C, Denzinger J. Lung nodule detection in CT images using deep convolutional neural networks. 2016;243-250.
8. Kooi T, Litjens G, Van Ginneken B, et al. Large scale deep learning for computer aided detection of mammographic lesions. Med Image Anal. 2016;35:303-312.
9. Liu F, Zhou Z, Samsonov A, et al. Deep learning approach for evaluating knee MR images: Achieving high diagnostic performance for cartilage lesion detection. Radiology. 2016;289:160-169.
10. Sharif MS, Abbod M, Amira A, Zaidi H. Artificial neural network-based system for PET volume segmentation. Journal of Biomedical Imaging. 2010:4.
11. Illán I, Górriz JM, Ramírez J, et al. 18F-FDG PET imaging analysis for computer aided Alzheimer's diagnosis. Inf Sci. 2011;181:903-916.
12. Bien N, Rajpurkar P, Ball RL, et al. Deep-learning-assisted diagnosis for knee magnetic resonance imaging: Development and retrospective validation of MRNet. PLoS Medicine. 2016;15:e1002699.
13. Taylor AG, Mielke C, Mongan J. Automated detection of moderate and large pneumothorax on frontal chest X-rays using deep convolutional neural networks: A retrospective study. PLoS Medicine. 2016;15:e1002697.
14. Woods RP, Grafton ST, Holmes CJ, Cherry SR, Mazziotta JC. Automated image registration: I. general methods and intrasubject, intramodality validation. J Comput Assist Tomogr. 1998;22:139-152.