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Research Progress and Application of Artificial Intelligence in Medical Assisted Diagnosis and Disease Prediction

Siting Chen

School of software engineering, Guangzhou Southern University, Guangzhou, China
2814825881@qq.com

Abstract: With the rapid development of artificial intelligence(AI) and breakthroughs in computer deep learning and machine learning technologies, AI is gradually replacing traditional disease diagnosis. At the same time, medical institutions have also accumulated a large amount of case information, medical data, etc., providing powerful and rich databases for AI disease prediction and diagnosis, thus achieving more accurate prediction and diagnosis of AI. AI has been widely applied in the medical field and continues to make new progress in areas such as medical image analysis, biological signal analysis, and case analysis. This article reviews the research progress and related technologies of AI in medical assisted diagnosis and disease prediction in recent years, aiming to promote research in the field of artificial intelligence medicine. AI has made significant achievements in the fields of medical assisted diagnosis and disease prediction. Medical image and biological signal analysis have greatly improved the accuracy of disease diagnosis, but still face many challenges.

Keywords: Artificial Intelligence(AI), medical image analysis, medical image registration, medical image fusion, biological signal analysis

1. Introduction

Nowadays, artificial intelligence technology is entering a new era, and the introduction of deep learning technology greatly improves the ability of artificial intelligence to analyze data patterns, even comparable to humans. Given that deep learning algorithms are built on the basis of artificial neural networks that mimic the neural network of the human brain, and have the ability to learn highly complex nonlinear relationships [1]. Therefore, they are widely used in various tasks of processing medical data.

Medical image analysis is a branch of technology of artificial intelligence in the medical field. It mainly achieves image analysis through convolutional neural networks (CNN). CNN is suitable for performing image recognition tasks because it can maintain the local spatial relationships of images. And its ability to process two-dimensional (such as X-rays) and three-dimensional images (such as CT or MRI) is outstanding [2].

Biological signal analysis can help medical staff monitor the condition of patients and convey the patient's situation to them through signals. Biological signal analysis generally involves observing human body parts, tissues, gene structures, etc., and using different types of sensors to receive corresponding biological signals according to different needs, achieving high-precision medical monitoring [3].

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AI has important research significance in the fields of medical image analysis and biological signal analysis. Medical image analysis can accurately process various images and assist in the diagnosis of diseases. Biological signal analysis can achieve high-precision medical monitoring, allowing medical staff to timely grasp the condition. Thoroughly studying these technologies and cases can improve the quality of medical services and provide patients with a better medical experience.

This article will provide an in-depth introduction to the technologies and related cases currently used by artificial intelligence in medical image analysis and biological signal analysis, and discuss the challenges faced by medical image analysis and biological signal analysis by reviewing relevant studies and literature.

2. Medical Image Analysis Technology: Image Registration and Image Fusion

The primary applications of Convolutional Neural Networks (CNNs) encompass computer vision, medical image analysis, natural language processing and speech recognition, among other numerous fields.

The CNN architecture consists of several key components: the input layer receives raw image data and passes it to subsequent network layers such as convolutional layers and pooling layers. Convolutional layers extract local features from the image, while pooling layers reduce the size of the feature maps to decrease computational load. Fully connected layers perform global analysis and decision-making on the features extracted by the preceding convolutional and pooling layers, and the output layer produces the final classification or regression results [4].

Medical image analysis methods can be categorized into various types, including image detection (identifying the location of lesion areas or organs), image segmentation (a prerequisite step for lesion assessment and disease diagnosis, separating lesion areas or organs from the background in medical images), image registration (aligning two or more medical images into a coordinate system with matching content), and image fusion (integrating medical images obtained from different imaging techniques to obtain more comprehensive information) [5].

2.1. Medical Image Registration: Four Major Types Based on Modality

In most auxiliary medical diagnostic processes, capturing images such as CT (Computed Tomography), MRI (Magnetic Resonance Imaging), and PET (Positron Emission Tomography) is essential for diagnosis and treatment. However, these images may differ in terms of time, space, dimensions, and other aspects, potentially affecting subsequent analysis, diagnosis, and treatment.

Nevertheless, through image registration and image fusion, these images from different modalities can be aligned into the same spatial coordinate system, generating a comprehensive image that integrates multiple pieces of information. This facilitates doctors in gaining a more thorough understanding of the patient's condition. Image registration generally involves feature extraction from two or more images to obtain feature points, finding matching feature point pairs through similarity metrics, and then deriving image spatial coordinate transformation parameters based on these matched feature point pairs. Finally, image registration is performed using these coordinate transformation parameters [6, 7]. Image fusion is responsible for integrating and displaying the information from the registered images.

Based on different modalities of registration, registration tasks primarily encompass four major categories [8]: Mono-modal registration occurs between images from the same medical imaging modality, such as CT-to-CT or MRI-to-MRI registration. Since the images are from the same modality, they usually have similar intensity mappings and anatomical representations. This type of registration is commonly used to confirm the effects of a treatment intervention or to track a patient's disease progression.

Multi-modal registration involves images from different imaging modalities, such as CT and MRI, or PET and MRI. The differences in intensity mappings and anatomical representations between images from different modalities render multi-modal registration more challenging.

Modal-to-model registration aligns actual patient image data to a predefined anatomical model or a patient-specific 3D model. This type of registration is particularly prevalent intra-operatively, often used to combine preoperative images with real-time surgical views to provide precise spatial localization, thereby reducing surgical risks.

Conversely, model-to-modal registration aligns anatomical models or 3D models to actual patient image data. It aids histomorphological studies by collecting and analyzing statistical data to understand the impact of diseases on anatomical structures.

2.2. Introduction to Some Methods of Medical Image Fusion

In the field of medical image fusion, various fusion methods exist. Some examples are pixel-based fusion methods, subspace methods, multi-scale methods, ensemble learning techniques, and methods for estimating both truth and performance level at the same time (STAPLE). In pixel-based fusion methods, simple arithmetic operations such as addition, subtraction, multiplication, and division can be directly performed on the pixel values of images to achieve fusion. However, this method may result in reduced image contrast.

Subspace methods, such as Principal Component Analysis (PCA), Independent Component Analysis (ICA), Non-negative Matrix Factorization (NMF), and Canonical Correlation Analysis (CCA), all extract and fuse image features in different ways. For example, PCA, a commonly used dimensionality reduction method, removes redundant information by finding the principal components of image data, thereby achieving image dimensionality reduction and fusion. In medical image fusion, PCA can be used to extract the main features of images and fuse the features of different images into a new space.

Multi-scale image analysis, also known as Multi-Resolution Analysis (MRA), achieves fusion by decomposing images into representations at different scales. This method captures detailed information in images and fuses it at different scales to obtain more comprehensive image information.

Ensemble learning techniques construct accurate predictors or classifiers by assembling multiple weak predictors or classifiers. In medical image fusion, ensemble learning can be used to fuse images from the same or different imaging modalities to obtain higher-quality fused images.

As a way to combine a lot of separate images, the Simultaneous Truth and Performance Level Estimation (STAPLE) algorithm uses the Expectation-Maximization (EM) algorithm. This algorithm can be used to evaluate the quality of different segmentation algorithms and calculate the final segmentation result by weighing the decisions of these algorithms.

2.3. Medical Image Registration and Image Fusion: Technological Challenges

In recent years, with the introduction of advanced technologies such as deep learning, the field of medical image registration and fusion has achieved certain developments; however, there is still room for further advancements in this area.

One of the main challenges in image registration and fusion lies in the limitations of medical imaging technologies. Each medical imaging modality (such as CT, MRI, PET, etc.) has its unique strengths and limitations. For instance, CT scans are particularly sensitive to bone structures but have poorer imaging effects on soft tissues, and this imaging modality involves radiation, which may pose a threat to patients' health with long-term exposure. MRI, on the other hand, excels in soft tissue imaging but can be interfered with by metal implants or motion artifacts in certain situations.

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Furthermore, the processes of image registration and fusion often involve complex computations and optimizations, which may result in longer processing times, especially when dealing with high-resolution images or multimodal data. Maintaining high quality in registration and fusion results while pursuing efficient computations is also a challenge. Some methods may be faster in speed but may compromise accuracy.

Despite the introduction of deep learning technologies improving the effectiveness of image registration and fusion, there are still certain deficiencies. For example, insufficient training data can lead to overfitting or underfitting of the model, thereby affecting the accuracy and precision of image registration and fusion [9].

3. Application of Biological Signal Analysis

Biological signal analysis plays a crucial role in the fields of medicine and biology. This advanced technology detects and diagnoses various diseases in a timely manner by studying and analyzing signals generated by biological systems such as EMG, fNIRS, SCR, ECG, etc. For example, EMG analysis can identify potential stroke risks. Combining fNIRS, SCR, and ECG analysis can help diagnose and treat functional dyspepsia (FD).

3.1. Stroke Prediction Utilizing Real-Time EMG Biological Signal Analysis

Nowadays, stroke has become a major threat to the health of adults and the elderly, which can not only lead to serious physical disabilities, but also trigger a series of socio-economic problems. Its high mortality and disability rates make timely and accurate diagnosis and treatment particularly important. In traditional stroke prediction and diagnosis methods, such as CT and MRI, they are effective but limited by high costs and delayed diagnoses, which restricts their widespread application.With the development of artificial intelligence, it has become possible to achieve early prediction of stroke by analyzing biological signals and real-time monitoring.

The system gets EMG (electromyography) signals from the thighs and calves in real time [10]. These signals are then processed to get important information about walking, balance, and muscle activity.These features not only contain basic information such as the intensity and frequency of muscle activity, but may also imply complex patterns associated with stroke risk.

As a sophisticated diagnostic tool, EMG tells us a lot about how muscles and the nervous system work by recording electrical activity in certain muscles or checking the speed at which nerve signals travel through the body.The comprehensive study of EMG on stroke indicates that there may be subtle changes in the patient's body balance, gait, and motor function before and after stroke [11, 12]. By utilizing EMG biological signal data to conduct in-depth analysis of these imbalances and gait disorders, we can identify biological signal features closely related to stroke risk, and input these biological signal feature information into an AI based stroke prediction system to achieve high-precision prediction.

3.2. Accurate diagnosis and treatment of functional dyspepsia through analysis of brain body biological signals

Functional dyspepsia (FD) is a common functional gastrointestinal disease characterized by chronic digestive symptoms, but no obvious structural abnormalities can be found in the patient's body. Traditional medicine generally combines various methods such as observation, inquiry, abdominal examination, and pulse diagnosis when diagnosing functional gastrointestinal diseases, but the objectivity of diagnosis still faces challenges. Nowadays, the application of artificial intelligence technology in the medical field is becoming increasingly widespread, and its powerful data processing and analysis capabilities provide new possibilities for objective and accurate diagnosis of

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diseases. By integrating brain body biological signals, objective and standardized diagnostic methods are provided for functional dyspepsia, improving the accuracy and efficiency of diagnosis.

Dysdigestion is a condition closely related to the gastrointestinal and duodenal regions, characterized by common symptoms such as upper abdominal pain or burning sensation, postprandial fullness or early satiety. There are significant differences in the activity of the prefrontal cortex, somatosensory cortex, insula, anterior cingulate cortex, amygdala, and hippocampus in FD patients compared to healthy individuals. These brain regions play important roles in emotion regulation, cognitive control, pain perception, and visceral sensation. In addition, the autonomic nervous system, including the sympathetic and parasympathetic nervous systems, plays an important role in regulating gastrointestinal function. The imbalance of sympathetic vagus and autonomic responses is also linked to changes in how the gastrointestinal tract works and how it feels. By collecting and combining various biological signals such as fNIRS, SCR, ECG, With Pulse Wave, we have a more comprehensive understanding of FD. By combining artificial intelligence with biological signals, the brain and body biological signals are combined with AI algorithms to accurately assess the patient's pain level and provide more precise pain treatment. Using machine learning to identify key clinical symptoms in FD, providing more targeted information for disease diagnosis and treatment [14].

With the development and popularization of sensor technology, it may become possible to collect data through sensors outside of clinical environments. By constantly capturing information on lifestyle factors, drug reactions, and dietary habits in daily life, subtle pattern changes can be detected early, allowing for timely intervention and prevention.

4. Conclusion

The research progress and application of artificial intelligence in medically assisted diagnosis and disease prediction have achieved significant results. Artificial intelligence algorithms, especially convolutional neural network (CNN), significantly improve the accuracy and efficiency of medical image analysis, and can detect cancer, stroke, diabetes and other diseases at an early stage.

Through techniques such as image registration and fusion, artificial intelligence integrates multimodal medical images to provide a comprehensive understanding of the patient's condition. AI used for biological signal analysis has also become a powerful tool for tracking and predicting diseases in real time, which makes diagnosis more accurate and treatment more effective.

Despite these advances, there are still challenges in terms of data privacy, algorithm transparency, and ethical considerations. At the same time, the dataset available for medical imaging tasks is very limited, and the number of samples and patients in public databases is limited. Insufficient training data leads to overfitting or underfitting of the model, which in turn affects the accuracy and precision of image registration and fusion, limiting the further development and application of this technology. In addition, due to the complexity of data structures, the cost of deep learning models is very high. Sometimes high-end GPUs and multiple computers are required, which leads to increased costs for consumers. Future research should focus on addressing these challenges while continuing to explore and innovate the application of artificial intelligence to promote the development of medical diagnosis and disease prediction.

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