An overview of neural networks for medical image recognition

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Abstract. Medical image recognition plays a crucial role in computer diagnostics and has been greatly enhanced by the advancements in deep learning techniques, particularly neural networks. This article provides a comprehensive review of the application of neural networks in medical image recognition, highlighting their advantages and disadvantages. Neural networks, inspired by the functioning of the human brain, consist of interconnected artificial neurons organized in layers. Through the learning process, neural networks can analyze and classify medical images, enabling accurate diagnosis and treatment. The article explores the fundamental components of neural networks, including neurons, weights, and activation functions, and explains the training process using algorithms like backpropagation. It also discusses various types of neural networks commonly used in image recognition tasks, such as Convolutional Neural Networks (CNN) for processing images and Recurrent Neural Networks (RNN) for analyzing sequential data. By examining research examples from different medical fields, this review demonstrates the effectiveness of neural networks in medical image recognition and their potential to revolutionize healthcare by improving diagnostic accuracy and patient outcomes.

1 Introduction

Biomedical image analysis is a crucial and relevant topic, especially in the context of computer diagnostics [1]. With the advancements in machine learning, particularly deep learning, neural networks are becoming increasingly popular for automatic analysis and classification of medical images. This opens up new possibilities for accurate diagnosis and effective treatment of various diseases. The high speed and accuracy with which neural networks can process massive amounts of data make them an integral part of biomedical research and practical applications.

This article examines the fundamental components of neural networks, including neurons, weights, and activation functions, and explains the training process using algorithms like backpropagation. Various types of neural networks widely used in image recognition tasks are discussed. The advantages and disadvantages of using neural networks in medical image

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recognition are also considered, along with examples of recent research that demonstrate the effectiveness of neural networks in various medical fields, from cancer diagnosis to the detection of rare genetic disorders. Our goal is to provide a comprehensive overview of the applicability of neural networks in medicine and explore their potential for improving healthcare and quality of life for patients.

2 Basic principles of building neural networks

Neural networks (NN) are machine learning algorithms that mimic the brain's functioning. They are composed of interconnected artificial neurons, which process and transmit information. Each neuron receives input data, performs a non-linear operation on them, and passes the result to the next neuron. These neurons are organized in layers, and the data is passed from the input layer to the output layer, going through intermediate layers called hidden layers. Neural networks are capable of learning from existing data, adjusting their parameters and weights to optimally perform a given task, such as pattern recognition, classification, or prediction. [2, 3]

Neurons are the basic building blocks of neural networks. They receive input data, multiply it by weights, and pass the result to the activation function. Each neuron typically has its activation value, which determines the signal to be passed to the next neuron.

Weights are numerical values that connect neurons to each other. Each connection has its weight, which determines the importance of that connection to the output. Weights influence the contribution of each neuron to the overall network output and can be adjusted during the learning process.

Activation functions determine the output signal of a neuron based on the input received from previous neurons. They introduce non-linearity into neural networks and allow modeling complex relationships between data. Different activation functions have different properties, such as sigmoid, hyperbolic tangent, ReLu, and others.

Neural networks learn by adjusting weights based on available data. This is done by feeding input data into the network, calculating the error between the predicted and actual results, and adjusting the weights to minimize this error. Training can be performed using various algorithms, such as backpropagation or gradient descent.

The process of transmitting data from the input layer through hidden layers to the output layer is called forward propagation. Input data is multiplied by weights and passes through activation functions to obtain the network's output data.

Backpropagation is used to update the neuron weights based on the obtained error. The error is propagated from the output layer to the input layer, and the weights are adjusted according to the error gradient. This process is repeated until optimal training results are achieved.

These key components interact in neural networks, allowing the modeling of complex data and performing various machine learning tasks.

3 Application of neural networks in medical image recognition

Various types of neural networks are widely used in image recognition tasks [2, 4-6]. Some of them include:

Convolutional Neural Networks (CNN): This is one of the most common types of networks for image recognition. They excel at processing images due to specialized convolutional and pooling layers, allowing them to learn local hierarchical features.

Convolutional neural networks have historically been the most successful of all types of neural networks. They are used widely for image recognition, object detection/localization,

and even text processing. The performance of these networks has recently exceeded that of humans in the problem of image classification. Convolutional neural networks provide a very good example of the fact that architectural design choices in a neural network should be performed with semantic insight about the data domain at hand. In the particular of the convolutional neural network, this insight was obtained by observing the biological workings of a cat's visual cortex, and heavily using the spatial relationships among pixels. This fact also provides some evidence that a further understanding of neuroscience might also be helpful for the development of methods in artificial intelligence.

Recurrent Neural Networks (RNN): RNNs are suitable for analyzing sequential data such as text or time series. In the context of image recognition, RNNs can be used to process a sequence of image regions or generate image captions.

Deep Neural Networks (DNN): These are networks with a large number of layers. Deep neural networks can be used for recognizing high-level features in images. They can consist of convolutional layers, pooling layers, and fully connected layers.

Transform coding (Transformers): Transformers were initially developed for processing sequential data, but they can also be applied to image recognition tasks. They have the ability to model interactions between different parts of an image and can be effective in tasks such as image segmentation or text generation.

These are just a few examples of the types of networks used in image recognition. Depending on the specific task and data, different architectures and combinations of layers can be employed to achieve optimal results.

Traditional architectures for solving computer vision problems and the degree of success they enjoyed have been heavily reliant on hand-crafted features. However, of late, deep learning techniques have offered a compelling alternative – that of automatically learning problem-specific features. With this new paradigm, every problem in computer vision is now being re-examined from a deep learning perspective. Therefore, it has become important to understand what kind of deep networks are suitable for a given problem. We specifically consider one form of deep networks widely used in computer vision – convolutional neural networks (CNNs).

4 Examples of Using Neural Networks for Disease Diagnosis

Neural networks have a wide range of applications in the diagnosis and prediction of various diseases.

Cancer diagnosis: Neural networks can be used to analyze medical images, such as MRI scans or X-rays, to detect and classify cancerous tumors. They can assist doctors in early cancer detection and decision-making in diagnosis [9, 11, 12].

Prediction of heart diseases: Neural networks can analyze data on symptoms, patient medical histories, and test results to predict the risk of heart diseases such as myocardial infarction or arrhythmia. This can help doctors determine patient susceptibility to certain conditions and develop a treatment plan [7, 13].

Diagnosis of neurodegenerative diseases: Neural networks can be used to analyze neurodiagnostic data, such as results from electroencephalograms (EEGs) or neuroimaging, to diagnose and classify neurodegenerative diseases like Alzheimer's disease or Parkinson's disease [10].

Prediction of treatment outcomes: Neural networks can analyze patient historical data and treatment results to predict the effectiveness of certain treatment methods. This can help determine the most effective treatment strategies for individual patients and improve treatment outcomes [13].

These are just a few examples of the use of neural networks in disease diagnosis and prediction. They demonstrate the potential of neural networks in medicine and their ability to assist doctors with more accurate diagnosis and treatment decision-making.

Fast and robust detection, segmentation and tracking of anatomical structures or pathologies support the entire clinical workflow enabling real-time guidance, quantification, and processing in the operating room. Most state-of-the-art solutions for parsing medical images are based on <u>machine learning methods</u>. While this enables the effective use of large annotated image databases, such techniques typically suffer from inherent limitations related to the efficiency in scanning high-dimensional <u>parametric spaces</u> and the learning of representative features for modeling the object appearance.

In [5] context was presented Marginal Space <u>Deep Learning</u>, a novel framework for <u>volumetric</u> image parsing which exploits both the strengths of efficient object <u>parametrization</u> in hierarchical marginal spaces and the representational power of state-of-the-art deep learning architectures.

The system learns classifiers in clustered, high-probability regions of the parameter space capturing the appearance of the object under the considered pose transformations and shape variations, gradually increasing the dimensionality of the exploration space from translation (3D), translation-orientation (6D) to incorporating also the anisotropic scaling (9D) and shape variability (ND). During runtime the system uses the learned classifiers to exhaustively scan these spaces to select the most probable transformation parameters. As this implies a significant computational effort in the order of billions of scanning hypotheses were proposed cascaded sparse adaptive neural networks, learning to focus the data sampling patterns of the networks on sparse, context-rich parts of the input, thereby considerably reducing the runtime and increasing the robustness of the system. Although this method greatly improves the performance of a modern system, it has a significant limitation: the learning of the appearance model and the parameter scanning are completely decoupled as independent algorithmic steps. To address this was made a step toward human-like intelligent parsing, presenting an extension of the system that models the object appearance and the parameter search as a unified behavioral task for an artificial agent. As opposed to exhaustively scanning the parameter space, the system uses reinforcement learning to discover optimal navigation paths guiding the search to the optimal location. The initial effectiveness of this approach has been confirmed in detecting arbitrary landmarks in ultrasound, magnetic resonance, and computed tomography data, with significant improvement compared to the current state-of-the-art techniques.

An important prerequisite for building a heart model [7] is the fast and reliable analysis of the anatomy of the cardiovascular system based on image data. This involves detecting, segmenting, and tracking anatomical structures or pathologies in the human heart and vascular system. Current solutions to these problems are based on machine learning and require large databases of annotated images for effective training. However, in practice, these methods often suffer from inherent limitations related to the efficiency of scanning multidimensional parametric spaces and learning representative functions for describing image content.

For image analysis in the system presented in [5], the structure of marginal space learning is described, including the original version of the system based on manually crafted feature functions, as well as the modernized structure based on state-of-the-art technology of automatic learning of functions using deep learning. To overcome the limitations of these exhaustive search-based methods, the concept of intelligent image analysis is presented in [5]. This approach, based on deep reinforcement learning and the theory of scale space, enables efficient analysis of high-resolution volumetric data in real-time mode. Several experiments have been conducted to analyze the effectiveness of these methods in solving various tasks using large datasets. The analysis and classification of lung diseases using chest X-ray images is a crucial step in the procedure for diagnosing pneumonia, especially in critical periods such as the COVID-19 pandemic, which is a type of pneumonia. Therefore, for the classification of lung diseases, an automatic method with high classification accuracy is necessary due to the increasing number of cases. Classification based on Convolutional Neural Networks (CNN) has gained popularity in recent years due to its speed and accuracy in solving image classification tasks. In [8], an implementation of CNN-based classification models using transfer learning was proposed to detect pneumonia and compare the results to determine the best model based on certain parameters. As this field is rapidly expanding with multiple models available, it was appropriate to focus on the best-performing architectures in terms of layer architecture, length, and type, as well as evaluation parameters for classification tasks. An analysis of existing traditional methods and deep learning architectures used for segmentation as a whole is also necessary. The performance is then evaluated, and an analysis based on accuracy and loss function of the implemented models is conducted. A critical assessment of the results is carried out to highlight any important issues requiring improvement.

5 Advantages and Limitations of Neural Networks in Medical Image Recognition

Neural networks have several advantages compared to traditional methods of image recognition [14, 15]:

Automatic feature extraction: Neural networks are capable of automatically extracting and identifying important features in images without the need for manual feature engineering. They learn from the images and determine by themselves which features are most significant for object classification or recognition.

Flexibility: Neural networks can be trained to recognize different types of objects or classify them into multiple categories. They can process different types of data, including images, videos, and sound.

Recognition of complex patterns: Neural networks can successfully recognize and classify objects with a high degree of complexity and variability. They can identify objects even when they appear from different viewpoints, under different lighting conditions, or against different backgrounds.

Comparable or superior accuracy: Neural networks, especially convolutional neural networks (CNNs), demonstrate high performance in image recognition, surpassing traditional methods in terms of classification or object recognition accuracy.

Training on large amounts of data: Neural networks can be trained on large volumes of data, allowing them to obtain more accurate and generalized models for image recognition. The more data available for training, the better the performance of the neural networks.

However, neural networks also have limitations and drawbacks when applied to medical images:

Required amount of annotated data: Neural networks require a large amount of annotated data for training. This is particularly challenging in the case of medical images, where data can be limited, and the annotation process can be costly and require specialized medical expertise.

Availability and quality of data: Data quality and accessibility can be challenging in medical applications. Many medical data are confidential and have limited access, which can restrict the availability of sufficient data to train neural networks.

Generalizability and decision justification: Neural networks can struggle to generalize to new data that differs from the training data. If a neural network is trained on data that differs from the real clinical context, it may provide inaccurate results. Additionally, neural networks often operate as "black boxes," meaning they do not always provide explanation or justification for their decisions, which can be problematic in clinical practice.

Poor interpretability: Neural networks can be complex and difficult to interpret. This can be problematic in medical applications where it is important to understand which features the model identifies as significant or how it reaches conclusions.

Lack of standardization: There is a lack of widely accepted standards and protocols for applying neural networks to analyze medical images. This can hinder the use and implementation of neural networks in clinical practice.

All of these factors highlight that the application of neural networks to medical images requires a careful approach, taking into account the limitations and ensuring thorough validation and quality assurance of the algorithms.

6 Future Directions for the Development of Neural Networks for Medical Image Recognition

Current and future trends in the development of neural networks for medical image recognition include the following aspects [14, 15]:

Increasing accessibility and volume of medical data: With the emergence of a large volume of data in the field of medicine, there is an opportunity to train and develop more accurate and reliable neural network models for the analysis of medical images.

Improving the accuracy and reliability of models: With the development of new neural network architectures and learning algorithms, improvements in the accuracy and reliability of models for medical image recognition are expected. For example, deep convolutional neural networks (CNN) and recurrent neural networks (RNN) can be applied to improve the quality of classification and object recognition in medical images.

Integration with other types of data: In the future, the integration of medical images with other types of data, such as electronic medical records (EMR) and genetic data, is expected. This will allow for the development of more comprehensive and complex neural network models.

There are several possible improvements and innovations that could potentially impact the development of this field:

Advanced deep learning architectures: Researchers are continuously working on developing new and improved deep learning architectures that can better analyze and interpret medical images. This could involve the use of advanced CNN or RNN models, as well as the integration of other techniques such as attention mechanisms or reinforcement learning.

Transfer learning and pre-training: Transfer learning, where models are pre-trained on large datasets and fine-tuned on specific medical image datasets, has shown promising results in improving the accuracy and robustness of medical image recognition models. Further advancements in transfer learning techniques could lead to more efficient training and improved performance in various medical imaging tasks.

Explainable AI and interpretable models: As medical image recognition systems become more sophisticated, there is a growing need for models that can provide explanations for their predictions. Developing interpretable models that can justify their decision-making process and provide insights into relevant image features can increase trust and adoption of these systems in clinical practice.

Integration of multimodal data: Combining medical images with other sources of patient data, such as electronic health records or genomics, can provide a more comprehensive understanding of a patient's condition. Integrating multimodal data using advanced fusion techniques, such as fusion deep learning, can enable more accurate diagnosis, personalized treatment planning, and prognosis prediction.

Telemedicine and remote diagnosis: The advancement of telemedicine allows medical professionals to provide remote diagnosis and treatment using medical imaging. Incorporating AI-powered medical image recognition technologies into telemedicine platforms can improve accessibility to healthcare in remote or underserved areas and enable faster and more accurate diagnoses [16].

Edge computing and real-time applications: Neural networks for medical image recognition are often computationally intensive. However, advancements in edge computing, where processing is done locally on devices or at the network edge, can enable real-time analysis of medical images without relying on high-bandwidth connections or cloud computing. This can be particularly useful in emergency situations or resource-limited settings.

These improvements and innovations have the potential to reshape the field of medical image recognition by enhancing accuracy, interpretability, accessibility, and real-time capabilities, ultimately leading to better patient care and outcomes.

7 Conclusion

The use of neural networks for medical image recognition is a powerful tool that can significantly improve the accuracy and speed of diagnosis and treatment outcomes. From early tumor detection to automatic analysis of X-ray images, neural networks show potential for transforming medical practice. However, there are some challenges to consider, such as the lack of annotated data and ethical concerns. Further research and development of neural network training methods will help overcome these obstacles and improve results in medical diagnostics. Overall, neural networks have enormous potential for improving healthcare and reducing diagnosis time.

The achievements of deep learning are significant, but there are still many problems with its application in healthcare. The main problem of applying CNN in the medical field has been the scarcity of data. There are already several methods to reduce the required size of the training data set, such as Transfer learning, Contrastive learning [17], or labor-intensive data augmentation methods. Despite recent achievements, actual implementation is limited due to the "black box" behavior of the neural network, as it does not explain its decision-making. Explainability is heavily limited, although several works, such as GradCAM or deep Taylor decomposition, have started the trend of research into the explainability of deep neural networks. A completely new research direction in neural networks has been initiated, called "Graph Neural Networks"[18]. Another research direction based on geometric deep learning [19] is Group Neural Networks. The invention of new neural networks that are rotationally and translationally equivariant can be a turning point in the segmentation and classification of anatomical structures in medical visualization.

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