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VIEWS ON DEEP LEARNING FOR MEDICAL IMAGE DIAGNOSIS

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ABSTRACT
Deep learning models are more often used in the medical field as a result of the rapid development of machine learning, graphics processing technologies, and accessibility of medical imaging data. The convolutional neural network (CNN)-based design, adopted by the medical imaging community to assist doctors in identifying the disease, has exacerbated this situation. This research uses a qualitative methodology. The information used in this study, which explores the ideas of deep learning and convolutional neural networks (CNN), taken from publications or papers on artificial intelligent (AI) Convolutional neural networks has been used in recent years for the analysis of medical image data. CNN's *development of its machine learning roots is traced in this study. We also provide a brief mathematical description of CNN as well as the pre-processing process required for medical images before inserting them into CNN. Using CNN in many medical domains, including classification, segmentation, detection, and localization, we evaluate relevant research in the field of medical imaging analysis. It can be concluded that CNN's deep learning view of medical imaging is very helpful for medical parties in their work.*

Keywords : *Deep Learning, Convolutional Neural Network, Medical Image, Segmentation, Classification.*

1. Introduction

Making computers smarter is the goal of artificial intelligence which is a branch of computer science (Zohuri & Moghaddam, 2020). Learning is one of the fundamental prerequisites for any cognitive behavior (Garcia-Pelegrin et al., 2022). Researchers today largely agree that intelligence cannot exist without learning. Therefore, deep learning is one of the main subfields of artificial intelligence studies and is truly one of the fastest growing areas of the discipline (Das et al., 2021).

From the very beginning, deep learning algorithms were created and used for medical dataset analysis (Charbuty & Abdulazeez, 2021). Some essential tools for intelligent data analysis are now provided by deep learning (Alsufyani et al., 2021). The digital revolution, especially in recent years, has made it very affordable and accessible to collect and store data (Turner & Pera, 2021). Large information systems are used to collect and share data in modern hospitals, which are equipped with other monitoring and data collection technologies (Yang et al., 2020). Today, deep learning technologies are highly adapted for the analysis of medical data, and a lot of work has been done in the field of medical diagnosis, especially for small and specialized diagnostic problems (Miah et al., 2021).

Medical records of specialized hospitals or their departments often contain information about an accurate diagnosis (Artzi et al., 2020). It is enough to enter the records of patients with a known correct diagnosis into the computer software to run the learning algorithm and everything necessary (Reddy Allugunti, 2022). Of course, this oversimplifies things, but in theory, information about previous successfully completed examples can automatically provide medical diagnostic expertise. The resulting classifiers can then be used to train medical students or non-specialist physicians to diagnose patients in specific diagnostic difficulties or to assist physicians when diagnosing new patients to improve diagnostic speed, accuracy, and/or reliability (Mitsui et al., 2020). Therefore the purpose of this paper is to provide an overview of the progress of intelligent data analysis in medicine from a deep learning perspective relating to medical diagnosis.

2. Literature Review

Not a few studies have been done for medical image processing using deep learning. Like the research done by Bhattacharya (Bhattacharya et al., 2021) that they first summarized recent research on deep learning applications for COVID-19 medical image processing. Then they provide an overview of deep learning and the latest developments in healthcare using this technology. Three use cases from China, Korea, and Canada were then granted to demonstrate the use of deep learning in COVID-19 medical image processing. Finally, they present a number of difficulties and problems with the implementation of deep learning for COVID-19 medical image processing, which is expected to motivate additional research on outbreak and crisis management, leading to smart and healthy cities.

Guo (Guo et al., 2019) In his research mentioned they first provided an algorithmic framework for the analysis of supervised multimodal images with cross-modality fusion at feature learning levels, classifier levels, and decision rates. This is motivated by the successful application of deep learning methods recently to medical image processing. Then, by utilizing multimodal data from MRI, computed tomography, and positron emission tomography, they built and practiced an image segmentation system based on deep convolutional neural networks to decompose soft tissue sarcoma lesions. Compared to networks trained with single modal images, networks trained with multimodal images perform better. Image merging performed inside a network (i.e., on a convolution or fully connected layer) is usually superior to image merging performed at tissue output for tumor segmentation tasks (i.e., voting). Their research offers empirical recommendations for the design and implementation of multimodal image analysis.

Research conducted by Liu (Liu et al., 2018) that to provide a thorough introduction to the processing and analysis of MRI images using deep learning. First, a brief overview of MRI imaging modalities and deep learning is provided. Introduction to the following widespread deep learning architecture. The discussion turned to MRI image deep learning applications, including image recognition, registration, segmentation, and classification. The advantages and disadvantages of a number of widely used tools are then explored, and a number of deep learning techniques are provided for use with MRI scanning. Final thoughts: Future advances and trends in deep learning for MRI images are discussed, along with an objective evaluation of deep learning in MRI applications.

Minaee (Minaee et al., 2022) In his research, he said they offer a thorough analysis of this latest literature, which includes a variety of breakthrough initiatives in semantic and instance segmentation, including convolution pixel labeling networks, encoder-decoder architectures, multiscale and pyramid-based methods, repetitive networks, visual attention models, and generative models in aversive settings. They studied the connections, benefits, and weaknesses of various DL-based segmentation models, looked at the most popular datasets, evaluated the results, and talked about future research paths.

Mittal (Mittal et al., 2019) in their research that they proposed a deep learning-based method for image segmentation of brain tumors. The idea of Stationary Wavelet Transform (SWT) and Novel Growing Convolution Neural Network are included in the suggested methodology (GCNN). The main purpose of this work is to make traditional methods more accurate. In this work, a comparison of the Support Vector Machine (SVM) and the Convolution Neural Network (CNN) was performed. Experimental findings suggest that, in terms of accuracy, PSNR, MSE, and other performance metrics, the proposed technique outperforms SVM and CNN.

Research conducted by (Ma et al., 2020) that on the Internet of Medical Things (IoMT) platform, the Heterogeneous Modified Artifical Neural Network (HMANN) has been suggested for early detection, segmentation, and diagnosis of chronic renal failure. The recommended HMANN is also categorized as a Multilayer Perceptron (MLP) with Backpropagation (BP) algorithm and Support Vector Machine (SVM). The regions of interest of the kidneys are segmented in the ultrasound image, which is used as the basis for the operation of the recommended algorithm. The recommended HMANN approach to kidney segmentation provides high accuracy while greatly lowering the time to decompose contours.

3. Research Methods

Through a literature review, this study uses a qualitative methodology. The information used in this study, which explores the ideas of deep learning and convolutional neural networks (CNN), is taken from publications or papers on artificial intelligence (AI).

4. Results and Discussions

Deep Learning

When neural networks with many layers of interconnected artificial neurons are used to study patterns in data samples, this process is known as deep learning (Dargan et al., 2019). Similar to biological neurons, artificial neurons receive some inputs, perform direct calculations, and output something (Escamilla-García et al., 2020). This direct calculation takes the form of an activation function followed by a linear function of the input (usually non-linear) (Rao & Reimherr, 2021). Fixed linear units (ReLU) and their variants, sigmoid transformations, and various non-linear activation functions often used as examples (Bawa & Kumar, 2019).

Deep learning was first developed by Walter Pitts and Warren McCulloch (1943). Due to the creation of models of backpropagation (1960), convolutional neural networks (CNN) (1979), long short-term memory (LSTM) (1997), ImageNet (2009), and AlexNet, their work has been followed by substantial breakthroughs (2011)(Krizhevsky et al., 2017). In essence, deep learning is a new iteration of artificial neural networks in which we stack layer after layer of synthetic neurons (Hohman et al., 2020). We can begin to describe an arbitrarily complicated pattern using the output from the terminal level, which is built on top of the output from the previous layer (Ni et al., 2019).

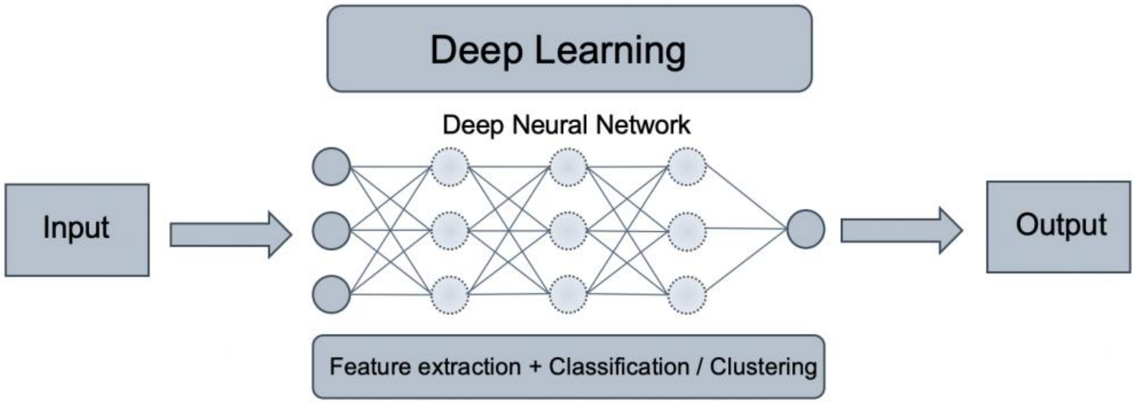

Fig. 1. How Deep Learning Works

In Figure 1 the neural network approach is mainly used in deep learning. Due to the fact that they operate at many levels or layers, this is what gave them the name "deep neural network". Traditional neural networks, for example, offer only two or three layers. When this happens, the inner network has more than 150 layers.

Convolutional Neural Network (CNN)

Deep learning techniques such as Convolutional Neural Network (CNN) can be used to find and identify objects in digital images (Boonsirisumpun et al., 2018). Since CNN is a development of the backpropagation approach and does not require large computations throughout the process, CNN is considered the best model for addressing the problem of object identification and object recognition (S. Singh et al., 2021). The CNN network feature is generated by convoluting the output of the kernel layer with the layer below it, so that the kernel in the first hidden layer executes the convolution on the input image. While early hidden layers typically capture shapes, curves, or edges as a feature, deeper hidden layers generally capture more abstract and intricate information (Nandhini et al., 2021). Traditional approaches to automating image classification involve complex rule-based algorithms or the creation of human features (Chau et al., 2020), which takes time, has limited ability to generalize, and requires subject expertise.

For all types of imaging modalities, pre-processing the image dataset before feeding CNN or other classifiers is essential. Before a medical image is provided as input to a deep neural network model, a number of preprocessing techniques are suggested, including (1) artifact removal, (2) normalization, (3) wedge time correction, (4) image registration, and (5) refractive field correction. While procedures 1 through 5 all help in getting reliable results, STC and image registration are essential when dealing with 3D medical images (especially MR and CT images). The most popular preprocessing operations across modalities are artifact removal and normalization (S. P. Singh et al., 2020). Medical imaging is increasingly multimodal, using the same patient images taken using multiple modalities to reveal various organ properties. Multiple photographs of the same patient and place can also be taken in different orientations under certain circumstances. In this case, it is required to visually compare the photos in order to match them (Maes et al., 1997). Automatic alignment or registration of images to templates can also be used to find sites of recurrent abnormalities. In addition to making it easier to manually assess photos and spot lesions or other anomalies, image alignment also makes it easier to train 3D CNN on these images (Tsai & Huang, 2019).

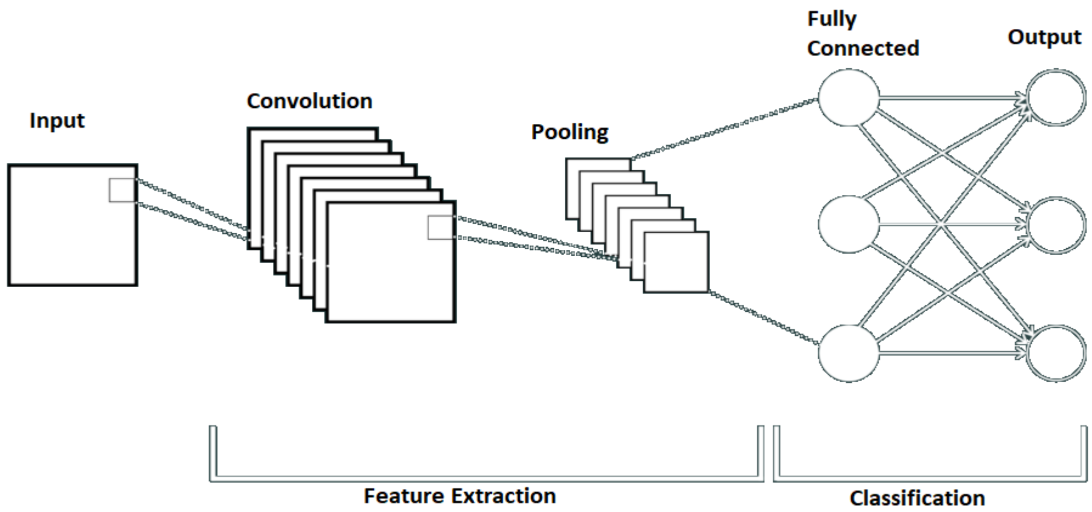

Fig. 2. CNN Architecture

In Figure 2 the first layer in CNN is the convolutional layer. This layer performs a number of convolution operations to the image after receiving it as input. In other words, the convolutional layer receives an input image tensor, processes it through a predetermined number of convolutional filters (kernels), adds bias, and then outputs the result with a non-linear activation function, often ReLU.

Segmentation

For several years, machine learning and artificial intelligence algorithms have facilitated radiologists in the segmentation of medical images, such as leukoplakia lesions. Segmentation not only helps to focus on specific areas in the medical picture, but also helps radiologists in quantitative assessment, and plan further treatment. Several researchers have contributed to the use of CNN in medical image segmentation.

Lesion segmentation is perhaps the most challenging task in medical imaging because lesions are rather small in the vast majority of cases. Furthermore, there are many variations in its size in various scans that can cause imbalances in the training sample. The CNN architecture has been introduced for automatic segmentation of leukopakia lesions. The network provides a convolution map in which the tissue believes that the lesion is located. DeepMedic is implemented on data sets where the patient has leukoplakia and has also been shown to work well for classification and detection problems in the oral cavity images to detect leukoplakia.

Classification

Disease classification using deep learning technology on medical images has gained a lot of traction in recent years. For neuroimaging, the main focus of deep learning is detecting diseases from anatomical images. Several studies have focused on detecting dementia and its variants from different imaging modalities. Leukoplakia disease is the most common form of abnormalities in the oral cavity, usually associated with the similarity of color, area area and anatomical contours in the oral cavity. Timely diagnosis of leukoplakia plays an important role in preventing the development of the disease.

5. Conclusion

Deep learning in medical diagnosis shows that from simple and easy-to-use algorithms, systems, and methodologies have emerged that enable sophisticated data analysis. In the future, intelligent data analysis will play a more important role due to the large amount of information generated and stored by modern technology. Today's Deep learning algorithms provide tools that can significantly help medical practitioners to reveal interesting relationships in medical image data. For all types of imaging modalities, pre-processing the image dataset before feeding CNN or other classifiers is essential. Segmentation as one of image processing has a very significant influence in classifying medical images related to certain types of diseases. It can be concluded that CNN's deep learning view of medical imaging is very helpful for medical parties in their work.

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