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DEEP NEURAL NETWORK FOR MEDICAL IMAGING: A SYSTEMATIC REVIEW

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ABSTRACT

Deep learning is a branch of machine learning that extracts complex features from data. Deep learning has emerged as an effective alternative to traditional machine learning methods in the field of medical imaging. Convolutional neural networks (CNNs) have excelled in medical image classification tasks. Most medical imaging applications of DL use supervised learning or a mix of both. Neural networks have evolved over time, with convolutional, pooling, fully connected, activation, normalization, dropout, and up sampling layers being common layers. Convolutional neural networks (CNNs) have become a prominent solution approach in illness detection due to the disparities between virus-infected and uninfected individuals. Deep learning has proven effective in addressing common challenges in medical imaging, such as disease detection, prognosis, automatic tumor detection, and image reconstruction. CNN has particularly excelled in image classification tasks, such as pneumonia identification from X-rays.

I. INTRODUCTION

Machine learning (ML) is an artificial intelligence (AI) technique that utilizes data to teach itself how to classify objects or predict uncertain outcomes. ML encompasses various tasks such as regression, classification, detection, segmentation, and more [13]. It learns from data to make informed decisions and automate processes. Deep learning is a specialized branch of machine learning that automatically extracts complex features from input data to understand the underlying relationships between different datasets. It offers distinct advantages over traditional machine learning methods by leveraging its ability to capture intricate patterns and structures. In the field of medical imaging, deep learning has shown great success in tackling challenging tasks like disease classification and tumor segmentation, where identifying relevant image features manually can be arduous and impractical [19]. There is a massive amount of healthcare data that needs to be predicted as mentioned in [25] which requires security [26] in terms of computing for better patient care as the whole data is stored on cloud [30]. There are lot of companies using high computational power specifically GPU and FPGA [31] for working on analyzing patients data.

II. TYPES

Unsupervised learning enables the model to identify key characteristics and classes without matching data, in contrast to supervised learning, which trains the model using a matched pair of data. Due to the possibility that unsupervised learning might lead to the model discovering patterns that do not correspond with clinical interpretation, most medical imaging applications of DL have employed supervised learning or a mix of both [1].

III. HISTORY

The McCulloch and Pitts M-P neuron model, which was developed in 1943, was the first neural network. Later, Hebb's learning rule and Rosenblatt's perceptron were developed. The absence of learning rules for the multilayer perceptron hampered progress, but the emergence of the neo cognitron in 1980 and the backpropagation algorithm in 1985 enabled the development of the LeNet and, finally, the ground-breaking AlexNet in 2012 [3]. Since that time, neural networks have advanced in a number of ways, including deepening, strengthening the convolutional layer, shifting tasks to detection, and including additional functional modules. There is a lot of healthcare data being generated by hardware devices [27,28] and a lot of software devices [29] which collect the data and process it for better care.

IV. STRUCTURE AND FUNCTION

Convolutional, pooling, fully connected, activation, normalization, dropout, and up sampling layers are the many kinds of layers often employed in modern deep neural networks. The fundamental building block of CNNs, convolutional layers are composed of trainable filters that travel over the input pictures or feature maps to produce feature maps. Network computing is made easier by pooling layers, which lower the spatial size of the feature maps. Each neuron from the preceding layer is linked to the current layer via fully connected layers [22]. To inject non-linearity into the network, activation layers use an activation function. To make training easier and prevent overfitting, dropout and normalization layers are utilized. The picture size is increased, and intricate characteristics of an item are recreated using up sampling layers. Convolutional neural networks (CNNs) with high discriminating power and high processing capacity have emerged as a prominent solution approach in the illness detection process because of the major disparities between virus-infected and uninfected individuals [19].

V. APPLICATION

Deep learning has emerged as a highly effective alternative for addressing common challenges in the field of medical imaging. Tasks such as classification, regression, segmentation, as well as image synthesis and denoising, are commonly employed using deep learning techniques. These applications have proven valuable in tackling medical imaging issues such as disease detection and prognosis, automatic tumor detection, and image reconstruction [11].

5.1 Medical image classification:

The deep neural network, a cutting-edge machine learning technique, has demonstrated significant potential in various categorization problems. Among these, the convolutional neural network (CNN) has particularly excelled in numerous image classification tasks. For example, when it comes to analyzing X-rays, CNN has emerged as the most effective approach for pneumonia identification, a condition responsible for approximately 50,000 deaths in the US annually [17]. However, accurately detecting pneumonia from chest X-rays typically relies on skilled radiologists, which can pose challenges in terms of availability and cost, particularly in certain regions. Convolutional neural networks in particular, which are a subset of deep neural networks, have shown outstanding performance in a range of image classification tasks, including the categorization of medical images. The transfer learning system developed by Kermany et al. and CheXNet are only two instances of CNNs being successfully used for medical image categorization [11]. CheXNet was able to categorize chest X-rays better than the average performance of four radiologists, while Kermany et al. 's system was able to classify optical coherence tomography (OCT) pictures better than the average performance of six human specialists. Data augmentation, transfer learning, and capsule networks may all improve the performance of CNN-based algorithms for image classification on short datasets. In several research, these techniques have shown encouraging outcomes [10]. There are use cases developed by certain authors in the areas of radiology [23], orthopedics [24] and many more.

In the categorization of medical images, conventional techniques like SVM, ORB, and SIFT have been frequently used. Feature extraction in medical picture classification tasks is another common use for CNN-based deep neural networks, and transfer learning with CNNs is especially helpful when data is scarce [20]. Due to its capacity to preserve the spatial connections between items in an image, capsule networks are often used to classify medical images. Numerous studies have shown that CapsNet can categorize brain tumors and breast tissue samples with good prediction accuracy. On big datasets of CXRs, OCT pictures, and other medical imaging datasets, CNNs have been applied to provide state-of-the-art outcomes [6].

5.2 Application of DNN in medical image segmentation:

Deep learning networks have helped with a number of applications, including computer vision, object identification, picture segmentation, and image recognition and classification. Data collection is the initial stage of a deep learning system [12]. The gathered data is next examined and prepped so that it may be made accessible in the format required by the following block. A further division of the preprocessed data into training, validation, and testing datasets is made. The model is trained using a deep neural network. The trained model is put to the test and assessed. The analysis of the whole planned system is completed in the end.

This deep learning model's fundamental structure (shown in Figure 1) is used in a number of medical applications, including image segmentation [11]. The items in a picture are split during image segmentation. Identification of regions of interest (RoI) in medical images, such as tumors and lesions, is the goal of segmentation. Due to the existence of various artifacts, inhomogeneity in intensity, and other factors, medical pictures are often complex in nature, making automated segmentation of these images a challenging process. In literature, many deep learning models have been put out. The selection of a specific deep learning model is based on several variables, including the body part to be segmented, the imaging modalities used, and the kind of sickness, since different body parts and diseases have distinct needs.

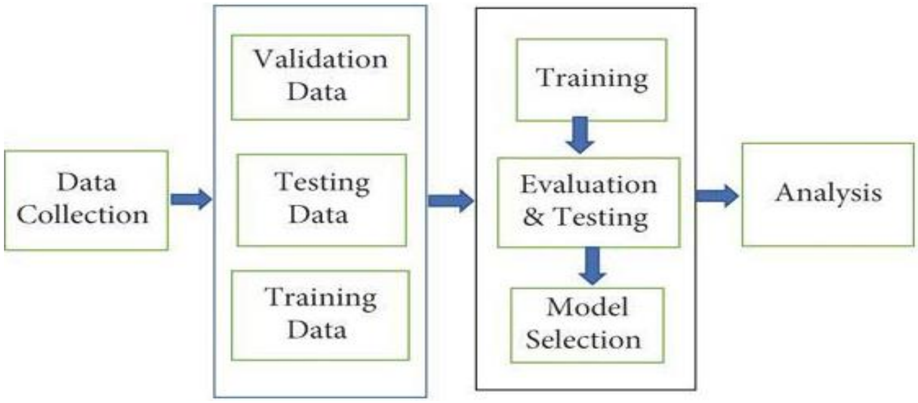

Figure 1: Basic layout of typical deep learning-based system.

For the purpose of separating the myocardium from the left and right ventricle cavities in cardiac MR images, has proposed a completely automated framework based on 2D and 3D CNN. To partition brain tissues in MR images, the authors in created a deep CNN with layers that performed convolution, pooling, normalization, and other functions [20].

Two cascaded FCN were used by Christ et al. to segment the liver, and the lesions inside the ROI were segmented after that. A dense 3D conditional random field was used to create the final segmentation [4]. The authors constructed a 3D FCN from a 3D CNN with fixed field of view and produced a score map for the whole volume of CT images at once [7]. To segmenting pulmonary nodules in chest CT images, the authors used the developed network. The authors concluded that using FCN increased network performance and sped up output score production. For the purpose of segmenting the liver in CT scans, authors used FCN [4]. For segmenting pneumothorax in chest X-ray pictures, writers suggested a completely convolution spatial and channel squeeze ad excitation module [2].

On 2D CXRs images, Gordienko et al. reported using a U-Net based CNN for lung segmentation and bone shadow exclusion approaches [6]. The SDRes U -Net model, created by Zhang et al. in [21] integrated the dilated and separable convolution into the residual U-Net architecture. The network was used to separate out brain tumors that were visible in MR scans. The usage of Multi-ResUNet architecture for segmentation was suggested by the authors in [8]. The authors came to the conclusion that using the Multi-ResUNet model yields better outcomes in less training epochs than the traditional U-Net model. On CT imaging, the authors of segmented pneumothorax. The effectiveness of the U-Net model and PSPNet were compared by the authors. To autonomously segment the heart in the short-axis DT-CMR images, Ferreira used the U-Net model [5]. More specifically, the authors created an FCN network for segmenting 3D MRI volumes and used a VNet-based network to segment prostate in MRI images [15].

A recurrent fully convolutional network (RFCN) was created to identify and segment bodily organs. The proposed approach guarantees completely automated heart segmentation in cardiac MR images [14]. The RFCN design, according to the authors, shortens the segmentation pipeline, speeds up computing, and supports real-time applications. For the segmentation of the liver in CT and MR images, Mulay et al. introduced layered edge detection and Mask R-CNN network [16]. To create the drawing of the abdomen region, the input photos were first preprocessed using image enhancement. For the edge map, the network improves the input pictures. The authors used Mask R-CNN to segregate liver from the edge maps as a last step. To partition the region of pneumothorax from chest radiographs, scientists created a CheXLocNet based on Mask R-CNN [18].

A recurrent neural network using multidimensional LSTM was proposed by the authors [14]. The calculations were organized pyramidally by the authors. The PyraMiD-LSTM architecture was used by the authors to segment MR pictures of the brain in pixel-by-pixel fashion after they demonstrated that it could parallelize for 3D data.

VI. LIMITATIONS

There are limitations to using DL techniques in medical imaging, such as the reliance on the amount and quality of training data, which may result in overfitting. Data sharing is difficult due to the expense of data collection, the difficulty of acquiring ground truth data, and privacy issues. In certain circumstances, it may be preferable to understand and justify the completed analysis, however the "black box" nature of DL models may make this difficult. In certain cases, machine learning techniques like SVM and random forest may be more appropriate, particularly if the data is well-structured and there is a clear knowledge of the best features.

VII. CONCLUSION

Machine learning (ML) is an AI technique that uses data to classify objects or predict uncertain outcomes. Deep learning, a specialized branch of ML, extracts complex features from input data to understand underlying relationships between datasets. It offers advantages over traditional methods by capturing intricate patterns and structures. In medical imaging, deep learning has shown success in tackling challenging tasks like disease classification and tumor segmentation. Unsupervised learning identifies key characteristics and classes without matching data, while supervised learning trains the model using a matched pair of data. Most medical imaging applications of DL use supervised learning or a mix of both. Neural networks have evolved over time, with convolutional, pooling, fully connected, activation, normalization, dropout, and up sampling layers being common layers. Convolutional neural networks (CNNs) have become a prominent solution approach in illness detection due to the disparities between virus-infected and uninfected individuals. Deep learning has proven effective in addressing common challenges in medical imaging, such as disease detection, prognosis, automatic tumor detection, and image reconstruction. CNN has particularly excelled in image classification tasks, such as pneumonia identification from X-rays.

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