AN EXPLORATION OF DEEP LEARNING FOR MEDICAL IMAGE ANALYSIS

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ABSTRACT

The Methodology of capturing pictures of inner organs for medical reasons, like diagnosing or identifying diseases is called medical imaging. The primary goal of Imaging data analysis in medicine is to enhance the effectiveness of medical research and medicament decisions. Deep learning and Machine learning has revolutionized Clinical image analysis, by delivering exceptional output in works like feature extraction, categorization and differentiation. The development of deep convolutional neural networks and the availability of advanced technological resources are key factors driving this progress. Deep learning methods excel at identifying hidden patterns in images, aiding medical professionals in making accurate diagnoses. These methods have proven to be the most effective for computer-assisted diagnosis, disease classification, organ segmentation, and cancer detection. Numerous deep learning techniques have been described for analyzing medical pictures for diverse diagnostic reasons. In this study, we examine research utilizing the latest advancements in DL techniques for healthcare image processing. We start survey by reviewing convolutional neural network-based medical imaging research projects. Second, we go over widely used pre trained models and generic adversarial networks that help boost the efficiency of convolutional networks. Finally, we collect performance data from Deep learning techniques that objective is detecting COVID-19 and analysis the maturity of children's bones to enable direct evaluation.

KEYWORDS: *CNN, GAN, ALEXANET, GOOGLENET*

1. INTRODUCTION

CAD, or computer-aided diagnosis, has become the most significant areas of medical imaging research. In CAD, the imaging data from previous samples of patients is frequently examined using machine learning methods [1]. The created model helps medical professionals make swift judgments. The most popular imaging techniques utilized in computer-assisted tomography and X-ray applications (CT), positron emission tomography, and ultrasonography and photoemission tomography (PET). The only goal is the understanding of medical image processing would be enhanced of the data presented in [2]. The subsequent are the primary classifications of image analysis in medicine: improvement, segmentation, localization, detection, classification, and registration [3]. Previously, clinical images were processed through basic techniques like region growth, thresholding, and Outline detection [4]. However, the increasing size and complexity of medical imaging data have driven the development of machine learning approaches for analyzing these images. Despite this progress, these methods depend on handcrafted features, requiring significant manual effort in algorithm design. These limitations of traditional machine learning approaches have led to the rise of artificial neural networks (ANNs). The availability of large datasets and advanced computational power has further enabled the advancement of ANNs [5]. Consequently, the advent of deep learning techniques, such as convolutional neural networks, has expanded the possibilities for automating medical image processing.

A kind of artificial network(NN) designed to handle pixel values is the convolutional neural network (CNN). CNN uses linear mathematical ideas to identify patterns inside a picture, which increases the scalability of image categorization. Modern CNN designs like DenseNet, ResNet, and Inception develop a novel and creative ways to assemble Convolutional layers arranged in a fashion that improves training efficiency, in contrast to older CNN architectures that only included Convolutional layers placed one above the other [6].

We provide review of recent developments in deep learning approaches for medical image interpretation in this work. he paper is structured in the following manner: First, survey articles pertaining to the analysis of medical images are talked about. Next, strategies for enhancing CNN performance and CNN models used in radiology are discussed. The results of models designed to identify COVID-19 and forecast a child's bone age are then examined. Lastly, the conclusion is presented.

2.1 RELATED WORKS

This module contains survey papers on deep learning-based methods for clinical image analysis. It covers four deep learning frameworks: Autoencoders, FCN, Deep Belief Networks, and CNN are utilized for image analysis, according to Hu et al. [9]. Additionally, they assembled current studies on the detection and diagnosis of cancer. The focus of Liu et al.'s study [10] was deep learning for clinical image segmentation. Firstly, he describes DL framework that use for segment medical pictures. Next, cutting-edge segmentation designs were investigated, including generative adversarial networks (GAN), FCN, and U-Net.Shin et al. [29] employed CNN models like —AlexNet, CifarNet, and GoogLeNet—to address two clinical diagnostic challenges: identifying diffuse parenchymal lung disease and classifying lymph nodes. They also analyzed How transfer learning improved each model's ability to perform. Kazeminia et al. [30] explored an in-depth review of the current methods, examining the advantages and disadvantages of using GANs for medical applications, and highlighted potential directions for future research.

2.2 Deep Learning (DL) in Medical Image Interpretation

The primary objective of clinical image analysis is to pinpoint the affected areas within the anatomy, enabling doctors to gain deeper insights into the progression of lesions. Four main phases are involved in medical image analysis: (1) preprocessing the image (2) segmentation (3) classification (4) feature extraction [14]. Data preprocessing is the process of improving image information for subsequent processing or removing undesired distortions from photos. Segmentation is the technique of isolating specific areas, such as tumors and organs, for further analysis. Feature extraction involves obtaining specific information from these areas of interest (ROIs) to facilitate their recognition. Classification aids in ROI categorization based on retrieved attributes.

2.3 Convolutional Neural Network

CNN is a supervised DL system used for distinguishing between different types of data. It operates by taking pictures as input and applying filters to transform picture pixels into structures. This structure typically comprises three layers: the convolutional layer, the sharing layer, and the completely linked layer. In a convolutional network, the initial layer is the convolutional layer, succeeded by further convolutional or pooling layers, ultimately culminating in the fully connected layer.

3. OVERVIEW OF THE WORKS

An overview of several studies utilizing CNN models and deep networks is given in the Works Overview. Using MRI pictures, Badza and Barjaktarovic's study [15] classified brain cancers. By using 10-fold cross-validation to analyze 3064 MRI images, they were able to reach an accuracy of 95.56% using a basic CNN model with two convolutional blocks. Using an effective CNN architecture, Rachapudi and Lavanya set out to classify colorectal cancer histopathology pictures in a second investigation. With a dropout layer [16] to avoid overfitting, their model comprised five convolutional blocks and produced an error rate of 22.7%.

An image segmentation framework in deep learning comprises an encoder and a decoder. The encoder discerns features from the image employing filters, while the decoder produces the ultimate output, often a segmentation mask delineating the object's outline. A fully convolutional network (FCN) serves as an encoder-decoder model, substituting dense layers with 1x1 convolutions to mimic fully connected layers. For the segmentation of multimodal brain tumor images, Sun et al. introduced a 3D FCNN-based model featuring four pathways within the encoder to capture multiscale image characteristics. These four sets of feature maps are subsequently amalgamated and supplied to the decoder for further processing. Using Dice, the model successfully segmented the BraTS2019 brain tumor segmentation challenge dataset through experimental validation.

By applying 3D convolutions to process 3D MRI images, V-Net improves on U-Net [24]. A V-Net-based system was presented by Guan et al. with the purpose of differentiating between 3D MRI brain scans and brain malignancies. To reduce unnecessary data and increase segmentation accuracy, the attention guide filter (AG) and squeeze and excite (SE) modules were added to the V-Net architecture of this system [25]. Using the BraTS2020 dataset, the model achieved dice metrics of 0.68 for the total tumor region, 0.85 for the core tumor region, and 0.70 for the enhanced tumor region. CNN models are commonly used for image classification due to their ability to achieve high accuracy with a low error rate. Yet, to extend the hidden correlations recognized within the training data to broader contexts, extensive datasets are indispensable. Here, we have investigated two techniques that may improve CNN's performance: global adversarial network (GAN) and transfer learning.

Table 1: Outline of used models

References	Model Used	Results	Approach	Accuracy
[23]	GoogleNet	Classification of Alzhemier's	MRI	97.15%
[24]	AlexaNet	Classification of Lung nodule	CT & X ray	99.6%
[25]	ResNet 50	Classification of Breast Tumor	Mammogram	85.71%
[26]	VGG19	Classification of Thyroid nodule	Cytology images	93.05%
[27]	R-CNN + VGG 16	Segmentation of Brain tumor	MRI	77.60%
[28]	ResNet 50 and Mask R CNN	WBC diagnosis	Cytological images	85.3%

4. TRANSFER LEARNING

Table 1 offers an overview of the works pertaining to transfer learning. Because of its quick training time and straightforward construction, LeNet[29] is a popular CNN model. The max-pooling layer is incorporated into deep neural network models in order to gather the much pertinent information from a particular area. But, in clinical image analysis, where excellence often falls short, lower-intensity pixels might contain crucial data. Hazarika et al. incorporated minimum pooling layer into the modified LeNet to classify Alzheimer's disease (AD). This updated variation, combining min-pooling and max-pooling layers, swapped out every max-pooling layer. In an investigational learning utilizing 2000 head scans, the novel LeNet model achieved an 80% accuracy in AD classification, although the enhanced LeNet model achieved 96.64% accuracy. Meanwhile, Hosny et al. introduced a modified version of the AlexNet model for skin image classification, successfully categorizing skin lesions into seven categories. The final three levels of the model were changed to new layers made especially for the classification of skin lesions in order to modify it for this job [18].

Table 2: GAN based models

References	Model Used	Approach	Metrics
[10]	GAN and LeNet (Capsule network)	Classification of Prostate image	89.20%
[11]	GAN and AlexNet	Identification of Parkinson's disease	89.23%

[12]	GAN and ResNet50	Classification of Brain tumor	96.25%
[13]	3D U-Net and VGG16	Segmentation of Brain tumor	90.1%
[14]	U-Net	Segmentation of Breast tumor	88.41%
[15]	DeepLapV2 and FCN	Segmentation of Left ventricle	88.0%
[17]	U-Net and FCN	Segmentation of Whole heart	86.32%

[31] employed VGG16 and AleNet to mine 1000 structures per model, aiming to classify brain tumors from MRI scans. These extracted features underwent evaluation to identify the most effective ones using the RFE technique. Ultimately, the SVM classifier utilized 200 selected characteristics, achieving an accuracy of 96.77%.

[32] introduced a Res Net-based SVM model for pneumonia identification from X-ray images. The model leveraged ResNet to extract features from chest X-rays, followed by an SVM classifier for pneumonia detection founded on these features. Additionally, a boosting technique was employed for selecting relevant features. After training on 5,863 X-rays, the model obtained 98.13% accuracy.

5. Generative Adversarial Network

Generative Adversarial Networks (GANs), a form of neural network tailored for unsupervised learning, were first introduced by Goodfellow et al. GANs comprise two competing neural networks: the discriminator, which discerns between real training data and the data generated by the generator, and the generator, which creates new data samples that replicate the training data. Table 2 lists the many GAN-based techniques that have been applied to medical picture analysis. Cirillo et al. used MRI scans from the BraTS2020 dataset to develop a 3D GAN for brain tumor segmentation. The generator effectively segmented the tumor region using U-Net architecture. In order to produce an appropriate segmentation mask, the generator's segmentation output and a 3D MRI image were fed into the GAN discriminator, Segmenting the entire tumor, the core, and the improved dice scores of 87.20%, 81.14%, and 78.67%. Upon examination of 100 CT scans of the lungs, the suggested model yielded an average dice score of 0.683. In order to improve classifier accuracy, GAN can also be castoff for data augmentation [23], which entails generating believable instances to supplement a dataset. Additionally, GANs have been used [16] to produce realistic representations of skin cancer. In this instance, the discriminator sought to discern amid the old data and the data generated by the generator, while the generator produced excellent training data. An additional GAN framework was created by Ahmad et al. to judge the precision of skin cancer classification. The latent noise vector was first obtained by training a variational auto encoder network, and the generator subsequently formed skin graze samples based on this useful noise vector [29].

Table 3: DL based networks for Covid-19

Ref	Standard Used (Model)	Techniques	Total Sample (Pneumonia)	Covid-19	Measures
[19]	GAN and VGG 16	X ray	0	403	Accuracy 95% recall 90%
[20]	VGG 19	X ray	0	2049	Accuracy 98.36%
[21]	VGG16	CT	23652	80800	Accuracy93.57%,precision 89.40%
[22]	VGG19	Ultrasound	277	399	Accuracy 100%

6. Discussion

To facilitate comparison, we have gathered research findings on COVID-19 detection and the prediction of adolescent bone age. COVID-Net is an publically access. project bring out in March 2020 to help medical authorities in combating COVID-19 using machine learning. In this effort, Wang et al.[9] developed COVID-Net, a profound CNN model designed to recognize COVID-19 from chest X-rays. To enhance feature efficiency while maintaining computational efficiency, the COVID-Net prototype incorporates projection-expansion-projection-extension (PEPX) blocks, consisting of four 1x1 convolutions [8]. The model's performance was confirmed using 13,975 X-ray images from the COVIDx dataset.. Experimental results demonstrated that the prototype could detect COVID-19 with a precision of 98.9% and a recall of 91.0%. The COVIDx dataset, derived from publicly accessible sources, now comprises 30,882 X-ray scans from 17,026 patients.. Table 3 illustrates the deep learning techniques employed for COVID-19 finding. Research indicates that various factors, such as the specific CNN model used, dataset size, modality type, data amplification techniques, and selected features for processing, influence classification accuracy.

7. CONCLUSION

We have offered a comprehensive overview of the latest deep learning-based medical imaging techniques published between 2019 and 2022. Developments in deep learning designs hold the promise of enhancing indicative accuracy in medicinal imaging. However, to outdo old-fashioned machine learning models, deep learning requires a huge size of records. In exercise, procurement of such wide-ranging datasets of medical images can be quite challenging. Transfer learning through pre-trained models may assist in resolving this issue. It is evident that pre-trained models are frequently modified to improve their suitability for a certain task. Another trend is utilizing GAN to increase segmentation accuracy since it can replicate the distribution of input data and generate high-quality medical images. GAN-based methods have shown effective in balancing differences between segmentation masks produced by the model and real-world data. Additionally, the validity of the classification model will be improved by GAN's ability to synthesize data to address problems like an uneven distribution of data or a dearth of medical images.

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