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A Review of Various CNN Models and Applications in Healthcare

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Abstract: *Medical image analysis is an essential component of contemporary healthcare systems. The spectrum of medical imaging modalities includes X-rays, ultrasound, magnetic resonance imaging, and more. The probable disease process has been illuminated through the use of computer-aided diagnostic tools (CAD), but analysis and diagnosis based on a single image are typically difficult. Artificial intelligence (AI) applications possess considerable potential to optimize and enhance routine medical procedures, including but not limited to diagnosis, treatment, prevention, progression, and personalized care. With medical imaging, machine learning—the cornerstone of the current artificial intelligence (AI) revolution—offers new opportunities for clinical practice. Algorithms for machine learning (ML) recognize recurring patterns in these videos or images and use that information to accurately identify unfamiliar images. Deep learning approaches have attracted a lot of attention recently as a means of solving a variety of issues, particularly in the disciplines of medical imaging. This chapter is a comprehensive compilation of CNN in context of medical image analysis and approaches to utilize it in varied applications. An extensive and elaborate study of the models applied for the detection and classification of different diseases. The study demonstrates how CNNs may automate feature extraction, making it possible to identify symptoms and patterns in medical images that are essential for a precise diagnosis.*

Keywords*:* Convolutional Neural Network, Medical Imaging, Diseases Detection and classification

I. INTRODUCTION

Medical imaging techniques such as ultrasound images and videos-ray images, Wireless Capsule Endoscopy (WCE) Images, CT Images, MRI, Endoscopy images, Mammograms are being widely used for the timely identification and diagnosis of some serious disease. These images are analyzed and diagnosed by the human experts like radiologists and physicians in the hospitals, which might be sometimes less accurate or might not be the most promising way, as the analysis of the vast amount of these medical image data become difficult for biomedical research, diagnosis, and treatment planning and follow-up. [22]. The use of Computer-Aided Diagnosis is being proved more beneficial and fast alternative approach for detecting the features of the medical images, classifying the images into benign or malignant and diagnosing the disease from the medical images. Since machine learning and deep learning are emerging as the efficient models for finding out patterns from numbers, we can leverage the same ability of these models to look for a specific symptom or feature in the medical image which can help the doctors have a better idea for various diseases. CNN use filter optimization to automatically learn feature engineering, has become widely employed in image analysis during the last decade. Using the CNN, researchers have developed automated systems for the analysis of the medical images and classifying these images into normal or abnormal images. Although there are several deep learning models available to learn the image features, the most successful models are the CNN models [19]. After the development of various techniques to efficiently train the CNN model for image analysis, the use of CNN resulted in promising outcome. Using the convolutional layers along with the transfer learning, CNN can perform segmentation, detection, classification and disease prediction on the available medical image dataset [30]. This study aims to review the applications of various CNN model modifications utilizing various multi-layer combinations in the detection and classification of medical image analysis. Overview of CNN and various CNN models.

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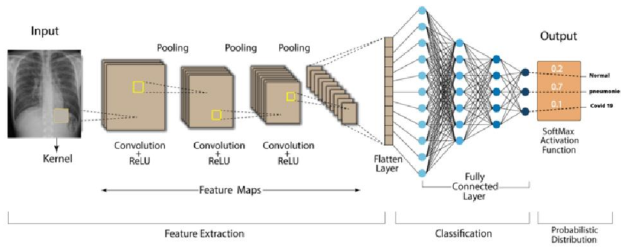
Convolutional neural networks are feed-forward neural networks that use convolution computing [31], consisting of a collection of various neural layers, for bringing out the required functionality based on the data provided. CNN is inspired by the exploration of human brain [31]. Neurons are the basic functioning unit in the CNN, similar to neurons in the human brain.

Multiple neurons are connected to each neuron, combining the results to produce a single outcome. These multiple neurons make a layer of the network, CNN kernels represent different receptors that can respond to different features, activation functions replicate the notion that only neural electric signals that exceed a certain threshold can be transmitted to the next neuron, and biological neurons are analogous to artificial neurons [18]. The entire CNN system is trained using loss functions and optimizers to understand what we anticipate. [18].



CNN Model Architecture

Variations of CNN Models

XCovNet: It is the optimization of the Xception model which can be also referred as “Extreme Inception”, where the inception model selects the combination of convolutional and pooling layers independently and compute the convolutions of different filter sizes. Convolution, Depth-wise Separable Convolution, and Fully Connected Layer blocks are the three blocks that make up the optimized XcovNet [21]. ResNet50, which is considered to be the baseline for comparing several research results with its pretrained ImageNet Dataset[16], a similar architecture with some modifications- DenseNet used for visual image recognition with a fewer parameters[11].It concatenates the attributes along with the combining the previous layer output to the future layer by densely connecting all the layers[11]. A regional CNN called SSD-Single Shot Detector is a single network that predicts object category scores and boundary offsets by applying simple detection filters to the output feature maps of a base network. numerous default bounding box features are applied to each spatial site to detect the item of diverse shapes, and detection filters are used to feature maps at numerous spatial locations for object detection of varying sizes [17]. One of GoogleNet's network topologies is the Inception module, which stakes all of the outputs and has convolutions of varying sizes for the same input [20]. The network depth increased as a result of the addition of the additional level, or "inception module," to GoogleNet [20]. An further network architecture, VGG-16, consists of a max pooling layer with stride 2 after the first 4 convolutional layers, each with 64 and 124 filters of size 3×3. A max pooling layer with stride 2 is then used, followed by three further convolutional layers of size using 256 feature maps. The max pooling layer of stride 1 comes after two sets of convolutional layers with 512 filters, eight to thirteen. A SoftMax output layer comes after the completely connected hidden layers in positions 14 and 15 [29].

Different modifications of CNN Models

CNN Model	Technique Used	Use Case
XCovNet	Optimized version of Xception with Convolution, Depth-wise Separable Convolution, and Fully linked layer blocks.	Classification of COVID-19, viral pneumonia, and healthy images using lung ultrasound images
DenseNet	Similar architecture to ResNet but with dense connections between layers, reducing parameters.	Visual image recognition

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CNN Model	Technique Used	Use Case
SSD (Single Shot Detector)	Regional CNN that applies small detection filters to feature maps for object detection.	Object detection of various sizes and shapes in images.
GoogleNet	Incorporates Inception modules with different convolution sizes for the same input, increasing network depth.	General image recognition tasks.
VGG-16	Consists of multiple convolutional layers with varying filter sizes followed by max pooling layers.	Image classification tasks, particularly in healthcare.
Modified DenseNet-121	Adapted architecture for improved prediction accuracy, achieving 95% recall for COVID-19 detection.	Predicting COVID-19 using CT images.
Mask R-CNN	Framework for predicting and classifying wound images, providing average precision of 0.71.	Classification of wounds in patients with peripheral artery disease (PAD).
AlexNet	Fine-tuned for classifying wound patches, combining features with a multi-layer perceptron.	Classifying various types of wounds.

This table summarizes the several CNN models discussed in the study, highlighting their distinguishing characteristics and applications in healthcare, particularly medical image processing.

A deep neural network called XCovNet, based on Google's Xception model was created to recognize COVID-19 in ultrasound pictures, consisting of depth-wise separable convolutions for the Inception module and 10 depth-wise separable convolution layers in addition to two standard convolutional layers. The model first employs depth-wise spatial convolution and subsequently point-wise convolution to link the output channels of POCUS images. Batch normalization improves training efficiency by preventing local minima and promoting faster convergence. After the sixth separable convolution layer, dropout layers (0.2 ratio) are added to reduce overfitting. The final module includes a categorical cross-entropy loss function for multi-class classification and a fully linked layer [21]. [32] Proposed system processes brain MRI images in a number of phases, including reducing the noise like thresholding and refractive error correction. The MRI images are then analyzed, enhanced, and scaled for model input followed by implementing a pre-trained VGG-16 convolutional layer, and dividing images into two categories: "yes" and "no." VGG-16, a better version of VGGNet, performs better on classification tasks. DenseNet – a modification of Resnet, concatenates (.) previous and future layer outputs consisting of 5 convolution and pooling layers, **3** transition layers, 1 classification layer and 2 dense blocks to predict COVID- 19 [11]. [25] utilized fine-tuned AlexNet architecture for the patch classification from wound images with the use of DCNN and AlexNet.

II. APPLICATION OF CNN IN HEALTHCARE

A. COVID-19

The authors of [21] developed a novel optimized xception CNN Model: XCovNet, used for the classification of COVID-19,viral pneumonia, and healthy labelled images using the Lung ultrasound images. Paper [23] used a variation of CNN Model with 5 convolutional connector blocks, to increase the accuracy of the system using fusion to classify COVID-19, bacterial pneumonia, and healthy images or videos. A modified CNN architecture based on the DenseNet-121, used to predict COVID-19 using the CT images achieving 95 recall [11].

B. Lung Diseases

By first segmenting the lung tissue and then using a modified U-Net to identify the nodule candidate in the CT images, the 3D CNN can detect and classify the lung unmarked nodules. These nodule candidates are then sent to the 3D CNN

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to determine the likelihood of lung cancer [2]. A CNN algorithm for identifying five features of abnormal lung condition, by analysing the short ultrasound videos of in vivo swine models. Inception V3 was used on the simulated M-mode images to detect weather there is an absence of lung sliding and some of the features were identified using Single Shot Detection framework [17]. The output of a CNN model trained with Endobronchial ultrasound images(EBUS) using ImageNet was transferred to the CaffeNet for classifying the lung lesions, which was further optimized by the EBUS training data. The features were extracted using 7 fully connected layers. Support Vector Machine was used for classifying benign and malignant images. The classification using the features obtained by the transfer learning with CNN obtained better performance [9]. In order to classify the bigger patches of Whole Slide lung images (WSIs), a unique method for identifying and labeling lung cancer-affected areas was developed in [15]. This method used a pixel-level image segmentation technique with a bespoke Fully Convolutional Neural Networks (FCNN). In biomedical images, FCNN was able to learn area-based human labeling, which is similar to drawing a line around a region that has a dispersed number of tiny malignant tissues but occasionally does not correlate to a texture or a bounded item as a whole. [15].

C. Liver Disease

A liver abnormality detection framework using the DenseNet CNN for training and region growing segmentation use for preprocessing was developed for detecting liver abnormalities. CT image dataset was used for training the model and the results were verified with the real time data from a government general hospital[24]. By examining the CT scan images of the 3D segmented liver from the LiTS17 dataset and passing them through a light CNN with eight layers and a single convolution layer, the study uses deep learning classification, the extracted features, and a support vector machine classifier to determine whether liver tumors are benign or malignant [3]. The study in [8], used the residual convolutional neural networks for the liver extraction(LERCN) using the low density CT images(LDCT). The study shows the comparative results for clinical and publicly available MICCAI datasets, using the LERCN based on back propagation gradient descent[8]. The authors in[7], proposed an approach combining two CNN models for the segmentation of the liver lesions from the CT images. The approach first segments the regions containing lesions by applying RetinaNet detection network, while the next step involve the segmentation of the lesions obtained from the first step by using U-Net[7]. The proposed architecture in [4], is inspired by a semantic pixel-wise classification of road scenes, and modified to be used for the liver CT segmentation. The proposed architecture was bad on the SegNet, consisting of encoder decoder layers for pixel-based semantic segmentation[4].

D. Gastric Cancer

Several CNN designs, including AlexNet, VGG, DenseNet, ResNet, Inception and Deeplab, are used to identify gastric cancer in endoscopy from pathological images. Depending on the needs, each architecture has a different number of convolutional and fully connected layers. [33]. A CNN model for the identification of protruding lesions and classification of the same into different categories, including masses and tumor, according to the Capsule Endoscopy structured Terminology. The trained dataset of Wireless Capsule Endoscopy(WCE) Image was fed in the single shot multiBox detector (SSD) consisting of 16 or more layers through Caffe deep learning framework[26].

E. Brain Disease

By using the VGG-16 CNN architecture to create convolutional feature maps and then classifying them to identify potential tumor regions, the work in [32] created an efficient method for detecting brain cancers from MRI images. By combining Deep CNN (DCNN) with transfer learning, overfitting can be avoided [13]. For the classification of normal and abnormal MR pictures with various neurological illnesses, a pre-trained VGG-16 model with transfer learning is modified by changing the final few layers to suit the new MRI data [13]. The work in [28] used a pre-trained CNN model GoogleNet to extract the properties of MRI images due to the significance of brain tumor classification. Transfer learning was then used to further categorize these features into three classes: pituitary, meningioma, and glioma [28]. The MRI image collection is classified using SoftMax, Support Vector Machine, and K-Nearest Neighbor [28]. A fully automated system for brain tumor segmentation, by combining handcrafted feature-based methods [10][1] with the

CNN [14]. Along with the MRIs, the SVM employed the features that were derived using the manual method as prior knowledge for the new three-path CNN design [14]. Another approach classifying the multistage brain tumors from MRI images using VGG-19 was proposed by [27], which further uses data expansion to deal with the problem of inadequate data [31]. The CNN model and genetic algorithm are combined in the glioma classifier to use MRI to categorize various glioma grades. [5].

F. Breast Cancer

Diagnosing and screening for the breast cancer is done through the Mammography imaging method. Pre-detected breast masses in mammography can be classified as benign or malignant using the AlexNet and Google Net algorithms. Oxford Net's CNN architecture can be used to classify the hard-to-identify microcalcification pixels to address the issue of significant class imbalance between those pixels and other breast tissue [31].

G. Clinical Wounds

The use of mask R-CNN framework for the prediction and classification of wound images of the patients with PAD (peripheral artery disease), including the wounds in patients with PAD as well as general trauma represents a significant role for addressing the challenges of PAD and chronic wounds by giving average precision of 0.71[12]. A study developed a deep neural network-based multi-modal classifier to categorize wounds, including diabetic, pressure, surgical, and venous ulcers, using both wound images and the locations that correspond to them. To get the tagging wound locations, a body map was made, and databases were made especially for this use. The study greatly increased classification accuracy by merging location-based and image-based classifier outputs. [6]. The use of patch classifiers with fine-tuned ALexNet for classifying the wound patches, and extracted features were combined using a multi-layer perceptron to form an image-wise ensemble classifier which categories the wounds in multiple types [25].

The review suggests that there are multiple variations of the CNN models which can be used for several application for the analysis of the medical images. Table 1 gives a summary of different variations of CNN models and their applications in healthcare.

Applications of CNN Models in healthcare

CNN Model	Application	Reference
VGG	Gastric Cancer, Brain Disease	[33,32,13,27]
DenseNet	COVID-19, Liver Disease, Gastric Cancer	[11, 24, 33]
AlexNet	Gastric Cancer, Clinical Wounds	[31, 33, 25]
Transfer learning	Brain Disease,Lung Diseases	[13, 9, 28]
SSD(Single Shot Detection)	Gastric Cancer, Lung Diseases	[17, 26]
CaffeNet	Gastric Cancer	[9, 26]
U-Net	Lung Diseases, Liver Disease	[7, 2]
ImageNet	Lung Diseases	[9]

III. CONCLUSION

The study highlights how CNNs are revolutionizing healthcare by demonstrating their efficacy, adaptability, and capacity to solve current issues in medical image processing, by emphasizing the numerous CNN architectures, including DenseNet, AlexNet, and XCovNet, being effectively used to treat a range of illnesses, including liver disorders, COVID-19, and stomach cancer thereby providing the future research directions and decision support to the researchers.

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