A Survey of Convolutional Neural Network Architectures for Deep Learning via Health Images

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ABSTRACT

Convolutional Neural Network (CNN) designs can successfully classify, predict and cluster in many artificial intelligence applications. In the health sector, intensive studies continue for disease classification. When the literature in this field is examined, it is seen that the studies are concentrated on the health sector. Thanks to these studies, doctors can make an accurate diagnosis by examining radiological images more consistently. In addition, doctors can save time to do other patient work by using CNN. In this study, related current manuscripts in the health sector were examined. The contributions of these publications to the literature were explained and evaluated. Complementary and contradictory arguments of the presented perspectives were revealed. It has been stated that the current status of the studies carried out and in which direction the future studies should evolve and that they can make an important contribution to the literature. Suggestions have been made for the guidance for future studies.

KEYWORDS: *Deep learning, convolutional neural network, image processing, classification*

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I. INTRODUCTION

Today, deep learning algorithms are widely used. Different sectors such as agriculture, health and industry are using deep learning for their own purposes. Among the deep learning algorithms, the convolutional neural network algorithm (CNN) is the most preferred algorithm. CNN first was announced, surprisingly, in computer vision, for especially object recognition processes. In fact, CNN can be thought of as a mixture of computer and biological sciences, surprisingly which in the past were unlikely to come together. It is a subject that emerged with the joint work of computer science, which is electromechanical, and biology, which examines life science. Image processing, which takes place automatically in the human brain without the person being aware of it, can be performed artificially thanks to CNN. This process is very successful in image recognition.

In this study, firstly the necessity and usage areas of CNN are explained, then the CNN structure is explained. The next section describes common Convolutional Neral Networks. Under Section 5, designed CNN systems that can be used in the health sector, which have an important place in the literature, are introduced. In the last section, there are conclusions and recommendations.

Shared with virtual machines hosted on the hypervisor. Today, most of the cloud providers actively use virtualization technology [3]. Container technology is a technology that has been popular in recent years. Container technology can be used alongside virtualization technology as well as to run isolated applications on physical machines without virtualization.

II. CONVOLUTIONAL NEURAL NETWORK STRUCTURE

Convolutional neural networks (CNN) deep learning architecture is frequently used in the processing of medical image data. Recently, deep learning algorithms such as CNN have been used as a decision support system in various clinical tasks such as detection of breast cancer in mammograms, segmentation of liver metastases with computed tomography (CT), brain tumor segmentation with resonance (MR) imaging, classification of high-resolution chest CT images of interstitial lung patients. started to be used [Ref:26]. CNNs were first proposed by Fukushima in his article on “Neocognitron” based on the hierarchical receptive field model of the visual cortex proposed by Hubel and Wiesel [1].

In order for the designed system to produce correct results, CNN processes the image with various layers. These layers are;

Convolutional Layer: This layer is the main building block of CNN. It is responsible for detecting the properties of the Image. This layer applies filters to the image to extract low- and high-level features from the image. It is used to detect properties. A matrix is obtained by applying a filter. This matrix is called Feature Map. Indicates where the image is located in the feature represented by the filter. CNN can have more than one Convolutional layer. Each of the applied filters reveals a separate feature [2].

Non-Linearity Layer: Non-linearity is introduced to the system. Since one of the activation functions is used in this layer, it is called the Activation Layer. Previously, nonlinear functions such as sigmoid and tanh were used, but the Rectifier(ReLu) function has been used because it gives the best results for the speed of Neural Network training.

Pooling Layer: It reduces the number of weights and controls the fit. It controls the incompatibility within the network by reducing the parameters and the number of calculations in the network. The most commonly used poling process is Max Pooling. Apart from that, it is used in Average Pooling and L2-norm pooling [3].

Flattening Layer: The task of this layer is to prepare the data in the input of the FLC, which is the last and most important layer. It turns the matrix into a one-dimensional array.

Fully-Connected Layer: Some of the most well-known CNN architectures nowadays can be listed as follows:

LeNet, AlexNet, VGGNet, GoogLeNet, ResNet, ZFNet [4].

III. REVIEWED STUDIES

In the study of Uçar and Uçar [6], lung nodules were detected using convolutional neural network with the help of chest x-rays. Today, x-ray images are used to detect the differences in the lungs. Diagnosis with X-ray images significantly reduces the disease diagnosis process. However, X-ray images must be properly examined by doctors. In this study, the authors aimed to increase the accuracy of convolutional deep learning by using different filters. In this study, royalty-free publicly available chest X-rays were used. The total number of images is 247. In the study, after the introduction, related works are explained. In the third part, dataset and analysis methods are explained and in the last part, the results are shown and a comparison is made between this method and other different methods.

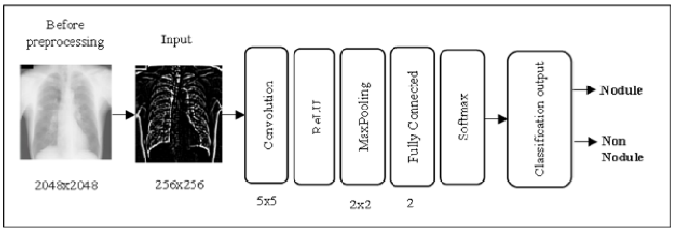

Figure 1 Architecture of the intended method [6]

As seen in Figure 1, LoG filter normalization was performed and the input data was created to increase the accuracy of the convolutional neural network, as it was first targeted. Then versions of the AlexNet and GoogLeNet models were used to test the accuracy of the results. According to a Classic CNN application, 7 layers are used in this model as in Figure 1. 70% of the input data was used for training and 30% for testing. The system was run on MATLAB. According to the results, in the 4 models used, LoG Filtered model produced 82.43%, Deep Conventional Neural Network 72.97%, GoogLeNet 68.92% and AlexNet 64.86% accuracy nodule and non-nodule values. [6].

In the study of Arı and Hanbay [Ref:10], a Regional Convolutional Neural Networks (RCNN) based system was developed that helps experts by detecting the presence and location of the tumor with magnetic resonance images. According to the working principle of the system, the following operations were carried out respectively: a) Preprocessing was applied to the data obtained from the sources. The noise in the image is removed by the histogram stretching process. b) Tumors were labeled manually in the training set. c) 4 RCNNs were designed. In each design, access filter, pooling filter, pooling operator, activation function, Euclidean function are used. d) Tumors have been detected in the designed RCNNs. If 80% of the tumor is detected in that area in the test images, that area is marked as a tumorous area. e) The developed system was evaluated according to accuracy, sensitivity, specificity, false positive rate and false negative criteria. 360 MR images obtained from Benchmark, Rembredant and Harvard datasets were used. Coding and testing was done in MATLAB 2016 environment. In the system, 252 MR images were used for training and 108 images were used for testing. [7].

Table 1 Average Accuracy Performance Rates of Designed RCNNs [7]

	RCNN1	RCNN2	RCNN3	RCNN4
Average accuracy performance rate	97.34%	98.15%	96.58%	98.66%

When the results obtained were compared with the designed RCNNs, RCCN4 gave the most accurate result. Table1 shows the results. The performance of RCNN4 was compared with similar studies and it was found to be higher than them [7].

In the study by Rajee and Mythili [8], an algorithm was designed to predict the gender of a human using a dental dental x-ray image (DXI). The system can detect gender with an accuracy rate of 98.27% after classification. In the architecture of the system, preprocessing was done for DXI first. Then, segmentation and gender classification were made, respectively. In the preprocessing, the image is free of noise using Gaussian, speckle and impulse filters. Next, DXI is segmented using the gradient-based recursive thresholding segmentation. In the last step, classification was made on the DXI image using the ResNet50 deep convolutional neural network (DCNN) classification algorithm. In the designed system, 600 training data and 400 test data were used. After the system was designed, it was compared with similar methods. It has been seen that the proposed system gives better results. It has been concluded that the system designed with these results will help dentists to determine gender using the tooth of a dead person [8]. The architecture of the proposed system is shown in Figure 2.

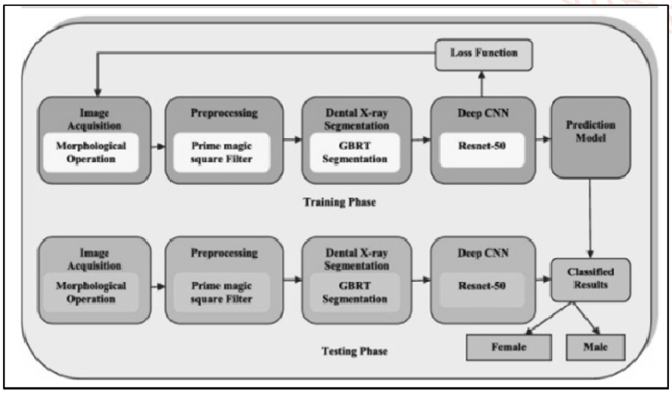

Figure 2 Architecture of the proposed system [8]

In the study by Jeyaraj and Nadar [9], a Deep Learning (DL) algorithm was developed for automated, computer-assisted oral cancer diagnosis using hyperspectral images of patients. In the developed system, the seven-way cross-validation technique was applied to the data given to the input layer of the CNN. Then, the first stage training was conducted with convoluational pooling and maximum pooling. The data were then classified by applying SVM classification, DBN and deep regression techniques. In the implementation of the algorithm, 500 image sets were used. The system has classified malignant and benign tumors. The proposed design achieved 91.4% accuracy. The system has also classified malignant tumor and precancerous tumor. The success rate in this is 91.56%.

The developed system achieved an accuracy of 94.5 compared to the other basic classifier system. With the Deep CNN training suggested in this study, it was possible to classify the tumor as benign or malignant without the need for expert knowledge. The structure related to the system is shown in Figure 3 [9].

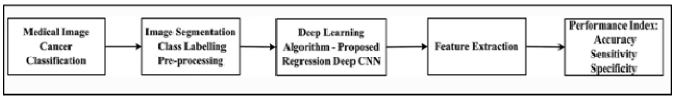

Figure 3 Architectural structure of the designed system [9]

According to Basaran et al. In his study [10], AlexNet, VGG16, VGG19, GoogLeNet, ResNet18, ResNet50, ResNet101 architectures were studied in the designed system. Experimental studies of the system were done with MATLAB R2019a software. First, the images were evaluated by 3 experts and labeled. Disease classification was made using 598 middle ear otoscope images. 70% of the images are reserved for training and 30% for testing. Training is completed in 1152 iterations. Stochastic gradient descent algorithm was used for optimization. Classification was made using 7 different CNN algorithms. The highest accuracy rate was achieved with the VGG16 algorithm. The accuracy rates of the algorithms are shown in Table 2.

Table 2 Accuracy Rates of CNN Architectures [10]

CNN Architectures	Accuracy Rates (%)
AlexNet	96.6480
VGG16	94.9721
VGG19	97.2067
GoogLeNet	94.9721
ResNet18	93.8547
ResNet50	92.1788
ResNet101	92.1788

As a result, it has been revealed that the diagnosis of chronic otitis media can be made successfully using CNN algorithms. The highest success rate was 97, 2067%. [10].

IV. CONCLUSION

In this study, important manuscripts published in health related to CNN were examined. It has been seen that there are a lot of deep learning-based studies for the automatic detection of diseased regions from health images. Generally, it was seen that 2/3 of the data was reserved for training and 1/3 for testing. It has been seen that the number of data sets should be higher for better training. The data were brought into ready-to-use form and optimized. Diseased areas were determined manually by experts on the image. Popular CNN architectures were used in the designed systems. The results were evaluated and it was seen that successful classification could be made. It has been shown that using the methods suggested in Health images can help doctors diagnose diseases and reduce their workload. It has been understood that the systems to be designed in the future can be more successful and can diagnose without experts.

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