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A NOVEL CLASSIFICATION WITH DEEP CONVOLUTIONAL NEURAL NETWORKS ON PULMONARY NODULE

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Abstract. Medical images are an important part of a patient's health record, and they need data manipulation, processing, and handling by computers. As a result, medical data is a type of bigdata, and its analysis has become complex. Because manual disease diagnosis takes longer and produces less accurate results, it may result in incorrect treatment. Three DCNN architectures have been exploited and evaluated for tumor detection and classification. The sample image for the experimentation is chosen from Lung Image Database Consortium (LIDC) with Image Database Resource Initiative (IDRI) and Kaggle dataset which consists of normal and abnormal image. The experimental results of proposed DCNN classifier achieved best accuracy than the GoogleNet, AlexNet, Artificial neural network and support vector machine.

Keywords: *Lung cancer, DCNN, LIDC and GoogleNet, AlexNet.*

Rezumat. Imaginile medicale sunt o parte importantă a dosarului de sănătate al pacientului și necesită manipularea, procesarea și manipularea datelor de către computere. Drept urmare, datele medicale sunt un tip de *bigdata*, iar analiza lor a devenit complexă. Deoarece diagnosticarea manuală a bolii durează mult și produce rezultate mai puțin precise, aceasta poate duce la un tratament incorect. Trei arhitecturi DCNN au fost exploatate și evaluate pentru detectarea și clasificarea tumorilor. Imaginea eșantion pentru experimentare este aleasă din *Lung Image Database Consortium* (LIDC) cu *Image Database Resource Initiative* (IDRI) și setul de date Kaggle care constă dintr-o imagine normală și anormală. Rezultatele experimentale ale clasificatorului DCNN propus au obținut mai bună acuratețe decât GoogleNet, AlexNet, rețeaua neuronală artificială și mașina de suport vector.

Cuvinte cheie: *cancer pulmonar, DCNN, LIDC și GoogleNet, AlexNet.*

1. Introduction

The Lung tumor detection and classification is one of the most difficult tasks in medical image processing due to the wide variation in tumor density, size, and location, as well as the low contrast of the scanned image. Because it directly affects human mortality,

the accuracy of such a classification system should be high. When the volume of input is large, the existing classifier performs poorly. As a result, there is a need to develop an algorithm that provides greater accuracy in lung tumor detection and classification.
Tumors' unpredictable appearance makes detecting their presence, as well as determining shape and size, difficult tasks in medical image analysis. Medical images are prone to contrast and luminance issues, resulting in very low image quality and degraded image features. As a result, it is critical to develop an algorithm that combines image enhancement and segmentation to solve the segmentation problem.

2. Survey of the work

SVM classifier for predicting lung tumors. Image denoising was performed using variation-based denoising, followed by optimal thresholding and morphological-based segmentation. SVM classifier was used to classify lung tumors. Pixels within the very dense body and chest wall structures have a different density distribution than low-density pixels [1]. The region of interest is a lung nodule, and a labelling algorithm is used to extract the region. Correlation, homogeneity, energy, contrast, and area were extracted as texture and region features.

A hyper plane represents the largest separation or margin between the two classes in an SVM linear classifier used for tumor classification. When tested on a large image database, this classification algorithm performs less well [2].

Eigengene extraction via Independent Component Analysis (ICA) is one method for tumor classification feature extraction. A novel approach for tumor classification based on eigengene and SVM-based Classifier Committee Learning (CCL) algorithm. The algorithm must still investigate the design of an effective approach for optimal results [3].

SVM classifier for classifying cancer stages. Image features are extracted after preprocessing. Then, for classifying medical images, the support vector machine algorithm is used. When the input data became large, processing time was required, and it was suspected to be notoriously redundant [4].

By applying the kernel trick to maximum margin hyper planes, a nonlinear classifier was created. Kernel functions of various types were used, including polynomial, quadratic, and Multi-Layer Perceptron (MLP). SVM produces better classification results [5-7]. They combine generalization control with a method for dealing with the curse of dimensionality. The kernel mapping provides a unifying framework for the majority of the model architectures that are commonly used. When the number of images used in the testing process increases, the accuracy of image enhancement must improve [8-10].

A two-stage CAD system for automatically detecting and classifying MRI brain tumors. The system classified brain tumor images as normal or abnormal. The abnormal MRI is then used to determine whether the tumor is benign or malignant [11-14]. K-means clustering is used for image segmentation, DWT is used for feature extraction, and PCA is used for feature reduction. The feature reduction method is used after feature extraction to select the relevant features. Classification was used to determine whether an image was normal or abnormal [6]. This system was tested for brain image classification, which had not previously been done for the other modalities. ANN is used to create a system for detecting and classifying brain cancer. The main issue in detecting the edge of a tumor is that the tumor appears very dark on the image. Histogram equalization was used to solve this problem [15-16]. Segmentation is the process of dividing an image into its constituent parts or objects.

Deep learning architecture for classifying medical images of anatomy objects in a modified CNN architecture with different convolutional and pooling layers used for feature learning in the modified CNN architecture [7]. The outcomes were compared to existing architectures such as LeNet, AlexNet, and GoogLeNet. a pulmonary CT image classification using a hybrid 3D-DCNN architecture. This CNN architecture was implemented with various layers, and the results were compared to 3D-AlexNet and 3D-GoogleNet.

3. Layout of Proposed Work

DCNN architecture 2 is made up of thirteen layers: seven convolutional layers, four pooling layers, a fully connected layer, and a SoftMax classifier. All convolutional layers have a filter size of 5 5 and pooling layers have a filter size of 2 2. In convolutional layers, the number of filters on feature maps is 64, 96, 128, 192, and 256, respectively. Similarly, DCNN architecture 3 has seven convolutional layers, four pooling layers, two fully connected layers, and a SoftMax classifier. In the first convolutional layer, 64 filters with 5 5 filter size are applied to 256 256 patch size input images. By applying 2 2 filters, the max pooling layer reduces the output size of the previous convolutional layer. The first pooling layer's output image size is 126126; this image is passed to the second and third convolutional layers, which apply 98 and 128 filters to the image, respectively. Following that, max pooling is used, resulting in an output image size of 5959. Initially, DCNN architecture 1 was implemented with a small number of layers, yielding good results up to a thousand images. Accuracy decreases as the number of images in the dataset grows. As a result, two additional DCNN architectures are implemented in this work that shows in Figure 1.

To improve accuracy, the number of convolutional and pooling layers is increased in this architecture compared to architecture 1. Approximately ten thousand images were tested with these classifiers and yielded better results. Similarly, the fourth and fifth convolutional layers with 128 and 192 filters are applied to the down sampled images with the third max pooling layer, yielding a 2525 feature map. The model progresses through the remaining layers until it reaches fully connected layers, where all neurons are connected to all neurons of the previous layer.

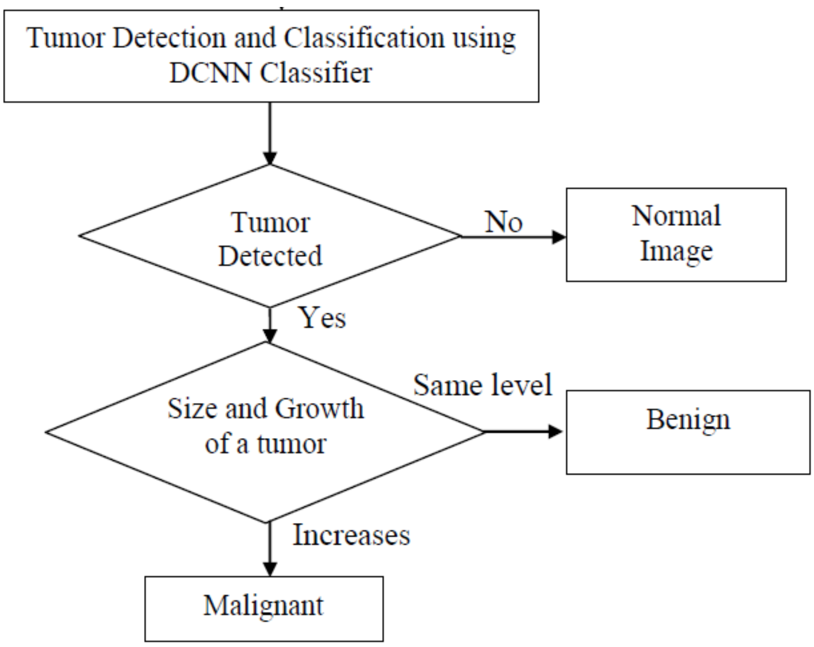

Figure 1. Proposed system flow.

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DCNN consists of two important layers:
1. Input layer
2. Classification layer

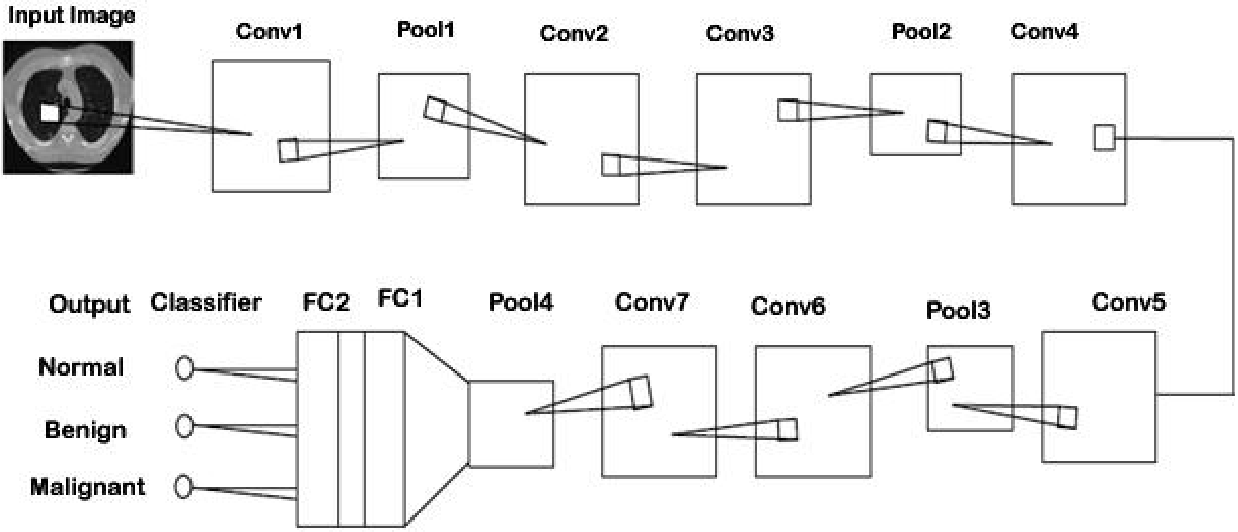

Figure 2. Proposed DCNN Architecture 3.

Finally, the SoftMax classifier is used to determine whether the images are normal, benign, or malignant. The accuracy of the second architecture is higher than that of the first. In addition, one fully connected layer with the same layer descriptions and hyperparameters is included in architecture 3 shows in Figure 2.

4. Results and Discussion

From the result, 85.02% accuracy rate obtained in the proposed architecture 3 which is higher than other two architectures. The second-best accuracy rate is 84.34% and the next better accuracy rate achieved by 83.53% of the proposed architecture 2. By considering of all three architectures, the architecture 3 used a greater number of convolutional and fully connected layers it leads to extract more features and resulted in received higher accuracy rate. Graphical representation of accuracy comparison is presented in the Figure 3.

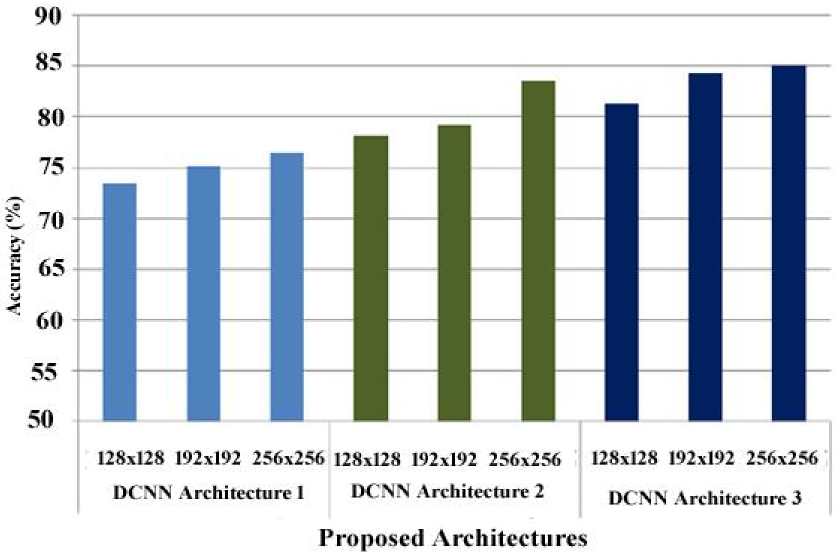

Figure 3. Accuracy of three proposed DCNN Architectures.

Precision is calculated for all three architectures using 9696, 128 128, 192192, and 256 256 patches, in that order. The results show that architecture 1 had a higher true positive prediction rate in 128 128 patches, but this rate gradually decreased as patch size increased. The architecture 2 received better results in 128 128 and 256 256 patches, but the true positive rate gradually increased in architecture 3, which also produced better results when compared to the other two architectures, as shown in Figure 4.

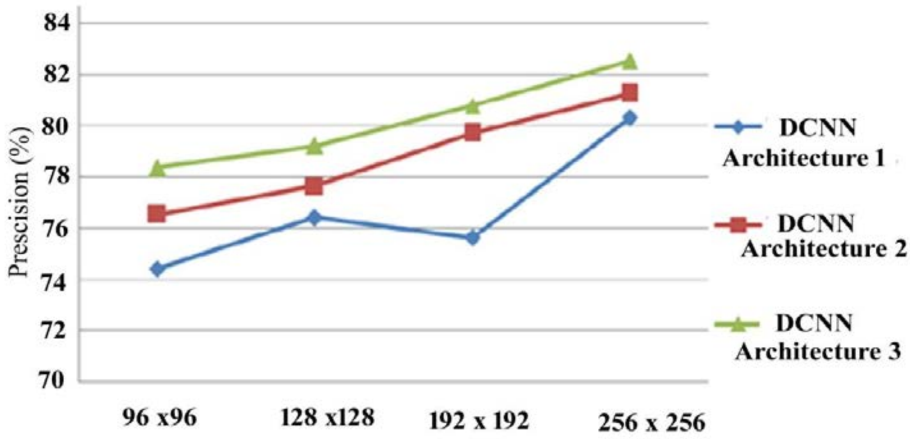

Figure 4. Precision Comparison for proposed architectures.

The results show that the GoogleNet achieved higher precision of 82.43%, recall of 83.55% and Specificity of 84.77% compared to AlexNet architecture, but the proposed architecture is obtained higher precision, recall and specificity than the GoogleNet architecture shown in Figure 5.

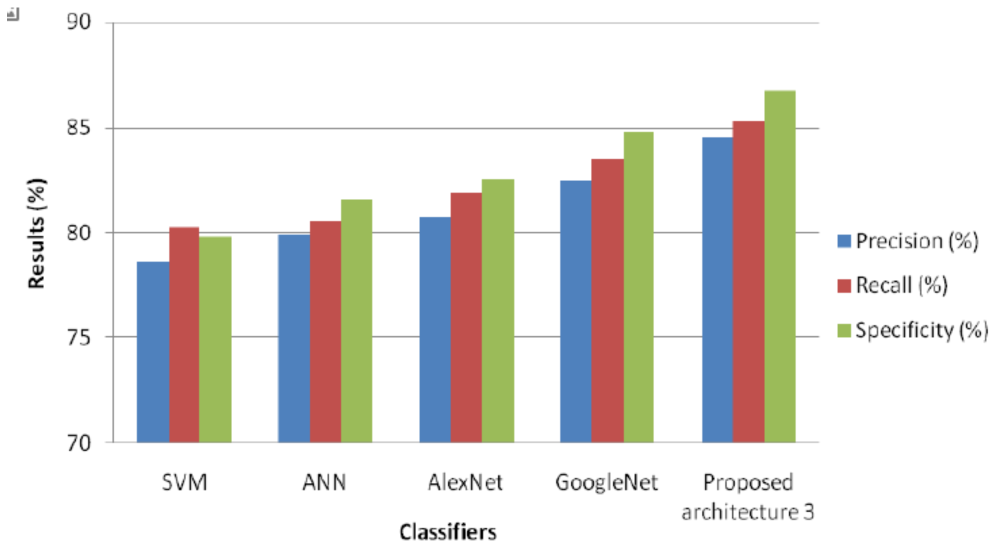

Figure 5. Performance of proposed DCNN architecture with existing algorithm.

5. Conclusions

Deep learning-based algorithms are currently emerging in the field of medical image classification. Deep learning-based DCNN architectures for CT lung image detection and classification were presented in this section. The layers of deep learning architecture were discussed in detail, along with the proposed three types of DCNN architectures. This section describes the hyperparameters used in the proposed architectures, as well as the input and output feature sizes. The proposed DCNN architectures take a CT lung image as input and classify it as normal, benign, or malignant. The experimental results show that the proposed architecture 3 outperforms other existing architectures in terms of accuracy, precision, recall, and specificity for CT lung image classification. In the future, the proposed HPSO algorithm can be tweaked to produce higher accuracy with a shorter execution time. HPSO parameters such as the number of iterations and particles can be optimized to produce better image quality

Conflicts of Interest. The authors declare no conflict of interest.

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