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Performance of VGG-16 Convolutional Neural Network Model Based Lung Cancer Classification on Computed Tomography

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Abstract— *The robust nodule detection challenge in lung cancer identification has become difficult due to the variability of lung nodules and the complexity of the surrounding environment. Early detection of lung nodules is crucial for lung cancer survival and is an effective strategy to reduce patient mortality. The proposed method for identifying lung nodules from CT images utilizes VGG-16 convolutional neural networks, eliminating the need for manual feature extraction, as per previous feedback. The network is fed with raw lung CT images from publicly available LIDC-IDRI dataset. The VGG-16 convolutional neural network successfully classified lung CT images into benign and malignant categories, achieving 86% accuracy and reducing false positive rates.*

Keywords— VGG-16, Lung Cancer, Computed Tomography, Classification

I. INTRODUCTION

Identifying lung cancer through CT images is crucial for minimizing patient death rates, and screening for pulmonary nodules is a vital step in this process. Therefore, an effective mechanism should be implemented to detect and diagnose this disease at an early stage in order to save the lives of many individuals affected by lung cancer. Early detection and diagnosis can significantly increase the survival rate of numerous patients. Later after disease identification, by providing proper diagnosis can reduce the death rate of patients. So, in order to avail a suitable and instantaneous outcome the importantly, applying recent techniques of machine leaning in the medical image processing field by enhancing the amount of duplication for the methods use can increase the accuracy of the classification. Therefore, proper timely detection and identification in the prior stage will definitely improve the level of survival and can decrease the death rate. The medical images taken in most of the earlier studies comprise of computed tomography (CT), magnetic resonance, and mammography images. Specialist doctors in this field analyse these images to detect and determine the stages of lung cancer using appropriate techniques. Various laboratory and clinical procedures are employed, including chemical treatments to inhibit the growth or replication of malignant cells, targeted therapy, and radiotherapy All these procedures adopted to identify and detect the cancer diseases are lengthy, costlier and more painful for the patients. Thus, to overcome all these problems suitable machine learning techniques for processing these medical images were used which comprise of CT scan images. CT scan images are preferred compared to other images because CT images are less noisy as compared to MRI and X-Ray reports.

II. LITERATURE REVIEW

Disha Sharma and Gagandeep Jindal [2] proposed an automated system for detecting lung tumours using Computed Tomography (CT) images. Techniques such as binary image slicing, erosion, and the Wiener filter were applied to extract the region of interest from the CT scans. The system demonstrated a sensitivity of 90% with a false positive rate of 0.05 per image. Additionally, it was capable of detecting lung nodules as small as 3 mm in diameter, facilitating early-stage diagnosis and improving patient survival rates. Farzad Vasheghani Farahani et al. [3] proposed a system for the early detection of lung nodules using CT images. In their approach, the lungs are first segmented through a combination of region growing and thresholding techniques. Subsequently, features such as circularity, eccentricity, and compactness are extracted from the CT scans. During the classification stage, these features are used as input for individual classifiers—including K-Nearest Neighbors (KNN), Support Vector Machine (SVM), and Multi-Layer Perceptron (MLP)—as well as for an ensemble system. Each classifier makes an independent prediction, and the final decision is determined using majority voting. Jin, Zhang, and Jin [5] developed a model that utilizes a Convolutional Neural Network (CNN) as a classifier to detect lung nodules. The model attained an accuracy of 84.6%, a sensitivity of 82.5%, and a specificity of 86.7%. Hence quality of diagnosis increases from the large dataset. Ryota Shimizu et al. [6] proposed a deep neural network-based system for detecting lung malignancy using urine samples to identify specific substances. The model achieves an accuracy of 90% in detecting the presence of malignancy; however, it does not classify the type or nature of the cancer.

Po-Whei Huang et al. [7] developed a system that classifies malignant and benign tumors from CT images using a Support Vector Classifier. The classification is based on a set of fractal features derived from the fractional Brownian motion model. The system achieved an accuracy of 83.11% and an ROC area of 0.8437. Vaishali C. Patil [8] proposed a system for lung tumor recognition using CT images. To detect the malignancy of the disease, a computer-aided design (CAD) system was employed. Image processing techniques were applied to remove noise from the CT images. Following segmentation, various classifiers, including Artificial Neural Networks and Support Vector Machines, were used to identify different stages of lung cancer, aiming to improve efficiency and reduce the error rate. Ailton Felix et al. [9] developed a 3D CAD system to extract texture and 3D margin sharpness features from the LIDC dataset. This system classifies small pulmonary nodules with diameters ranging from 3 to 10 mm. For this task, they employed three machine learning algorithms: Random Forest, Multilayer Perceptron, and K-Nearest Neighbor. Sri Widodo et al. [11] proposed a Principal Component Analysis (PCA) method for the automatic classification of pulmonary nodules and arteries in chest CT scan images. The study consists of three steps: the first step involves lung organ segmentation using the Active Appearance Model, the second step performs nodule segmentation using a morphological method, and the third step classifies the pulmonary nodules and arteries using the PCA technique. Experimental results indicate that the classification system achieved an accuracy of 90%. Ravindranath K [12] proposed a system for the early detection of lung malignancy, including the identification of uncertain tumors. The nodule is classified according to various stages of the disease. The detection process involves image pre-processing and segmentation, which enhances accuracy through the use of statistical classifiers, SVM, and fuzzy logic. Variations in intensity levels are used to distinguish between normal and abnormal tumors at an early stage. The identified tumor is then classified using neural network classifiers to differentiate between normal and abnormal lung malignancy.

Rui Xu et al. [13] introduced a deep Convolutional Neural Network (CNN)-based system for lung segmentation in CT scans, targeting both mild and severe lung diseases. Detecting lung diseases with complex opacities in the region of interest (ROI) is challenging for radiologists. To address this, a Deep-CNN model was developed for lung segmentation. In this approach, complex opacities are treated as a texture-based problem, where each pixel is classified as either inside or outside the ROI. The system uses a CNN model to solve this problem. It was tested on 42 CT images with severe lung disease and 7 CT images with mild lung cancer, which included six types of opacities. The model's Jaccard index outperforms those of commonly used lung segmentation methods. In this research various classifiers are used such as Naive Bayes classifier, decision trees, SVM, k-nearest neighbors, logistic regression. In lung sound data, both Decision Tree and SVM classifiers provide high accuracy in decision-making and results. It is assumed that as the input data increases, the accuracy also improves. Pratiksha Hattikatti [15] proposed a Convolutional Neural Network (CNN) to analyze the lung texture patterns associated with diseases in CT images. The term 'interstitial lung disease' encompasses a variety of lung-related diseases, and characterizing lung tissue is a key component of a CAD system for diagnosing these conditions. The CNN achieved an accuracy of 94% with high sensitivity, while the same data processed through an SVM classifier resulted in an accuracy of only 86%. This indicates that CNN provides more accurate results for detecting interstitial lung diseases. Pouria Moradi [17] introduced a 3D Convolutional Neural Network aimed at reducing the false positive rate and enhancing sensitivity in lung cancer detection. The primary goal of this research was to improve classification accuracy. The researcher achieved an accuracy of 91.23% with an average of 3.99 false positives per scan by combining different classifiers in the method. Sakif Rahman *et.al*, proposed a lung cancer identification and prognosis method using deep neural network (DNN) which reduce the time complexity and increase accuracy.

III. METHODOLOGY USED

A. VGG-16 Network Model

The proposed lung cancer identification system, utilizing the VGG-16 model, is primarily divided into two parts. In the first part, preprocessing is applied to the images before they are fed into the system. Next, the nodules are identified and used for training, ultimately allowing the system to classify the CT input images as either malignant or benign for lung cancer detection. Figure 2 depicts the algorithm of VGG-16 based lung cancer classification.

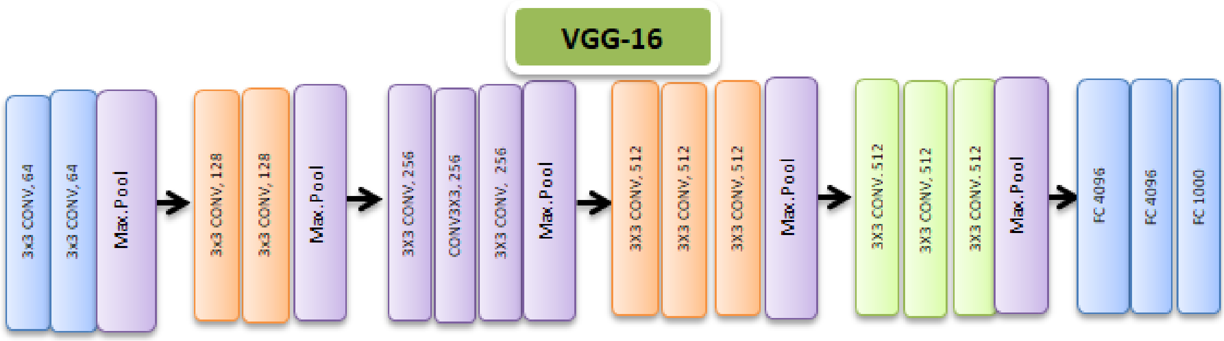

Figure 1: VGG-16 Network Model

Algorithm

1. **Acquire the images of lung cancer containing both diseased and non-diseased images and also, using existing dataset and augmentation technique.**
2. **Preprocess all the images for resize the images based on the algorithm /technique used**
3. **Assign the class labels to the images that are benign and malignant.**
4. **Categorize the images among training and testing dataset selecting from all the class labels.**
5. **Train the VGG16 network model with the help of training images**
6. **Test the VGG16 network model with the help of testing images**
7. **Calculate the various performance measure parameters**
8. **Validate the performance of the proposed model and compare the results with the other state-of-the-art approaches.**

Figure.2 Algorithm VGG-16 Based Lung Cancer Classification

The proposed VGG16 architecture, as illustrated in Figure 1, consists of the following layers: thirteen convolutional layers, five max-pooling layers, and one fully connected layer. As shown in Figure, the network starts with a convolutional layer where the first layer takes an input image with a size of 224 × 224 pixels. The second convolutional layer features 32 feature maps with a 3 × 3 convolution kernel. The max-pooling layers use a 2 × 2 kernel size with a stride of 2 pixels, and the fully connected layer outputs a 1024-dimensional vector. After applying this architecture, some images were identified with cancerous nodules, while others were classifiedasnon-cancerous.

B. Training VGG-16 Network Model

Back-propagation algorithms are employed to train the VGG-16 model using CT images of size 224x224x3. The process is divided into two phases: the training phase and the testing phase. In the training phase, CT images are used to train the network to classify the lungs as either cancerous or non-cancerous. During the testing phase, an unseen image is input to the system for classification as either cancerous or non-cancerous. To reduce feature loss, the images are both trained and tested in DICOM format while adjusting the network parameters. The accuracy of the proposed network can be evaluated using suitable assessment techniques.

VI. RESULTS AND DISCUSSIONS

The dataset used in this research is from the LIDC-IDRI, which is the Lung Image Database Consortium collection. It contains diagnostic and lung cancer screening thoracic CT scans with annotated lesions. During the initial blinded-read phase, each radiologist independently examined each CT scan and categorized the lesions into one of three groups: 'nodule ≥ 3 mm,' 'nodule < 3 mm,' and 'non-nodule ≥ 3 mm. The inputs are the image files that are in DICOM format, it is important to note that in order to preserve the original values of the DICOM images as much as possible; no scaling.

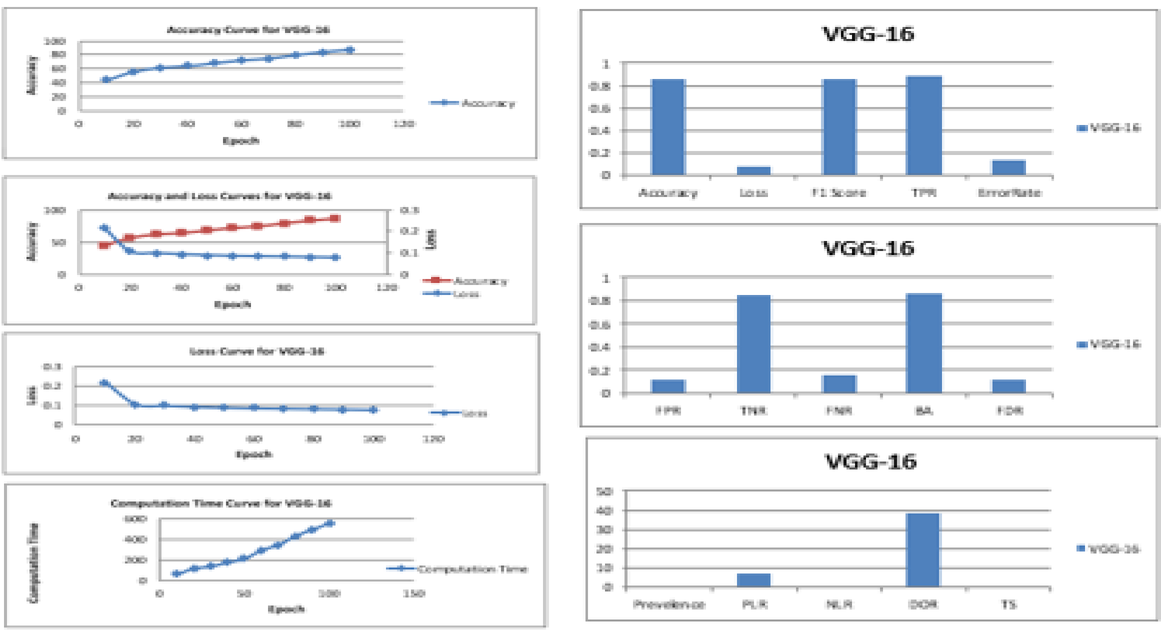

Figure-3 Results of Classification

The result of classification depicted in figure-3. The large dimension images cannot be fed directly into Convolutional neural network architecture because of the limit on the computation power. Hence it is preprocessed to reduce the size of the input data and thus segmenting the images into equal size and format. Also, dataset used was of size 15 GB but a subset of the images around 2.5GB were used for training and testing usage.[5][6]. In our research, lung nodule classification was implemented using MATLAB 2018b, with the dataset for training and testing sourced from LIDC-IDRI to better understand lung cancer. The image samples are fed into the network model, which is capable of detecting and identifying cancerous (malignant) and non-cancerous images. The results show that as the training progresses, classification accuracy increases with the computation time, leading to a reduction in the loss percentage, as depicted in the output graphs. The accuracy obtained was also compared with results from previous research [19][20].

V. CONCLUSION

In this research, VGG-16 Convolutional Neural Networks were employed to classify lung CT images as either cancerous or non-cancerous. Preprocessing was performed on the CT images before feeding them into the network model to ensure they were uniform in size and format. The dataset used in this study is from the LIDC dataset. As a result, an accuracy of 86% was achieved with relatively low false positive rates. While VGG-16 excels in identifying a wide range of objects in images, it faces challenges when dealing with less diverse or more subtle classification tasks.

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