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Deep learning for Lung Infection Segmentation and prediction of COVID-19 from CT Images

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Abstract:

The timely and precise detection of lung diseases, such as pneumonia, cancer, and COVID-19, a common and possibly fatal respiratory infection, is extremely difficult. The goal of this project is to create a dependable and effective pneumonia detection system by utilizing developments in machine learning (ML) techniques. A convolutional neural network (CNN) model is trained to distinguish between lung images that are healthy and those that have pneumonia by analyzing chest CT images. A wide variety of chest CT pictures gathered from several sources make up the dataset used for training and validation. The suggested methodology shows encouraging outcomes, detecting pneumonia with good sensitivity and accuracy. Long-term damage to the lungs and other organs is another potential COVID-19 risk. The COVID-19 virus is primarily spread by droplets released when an infected person coughs, sneezes, or exhales. These drops swiftly land on floors or other objects because they are too heavy to float in midair. As everyone knows, in early 2020, the corona virus illness 2019 (COVID-19) began to spread around the world. resulting in an existential health problem for the entire world. Therefore, there is a lot of opportunity to enhance the conventional healthcare approach to COVID-19 by automating the detection of lung infections from computed tomography (CT) images. However, there are a number of difficulties in separating infected areas from CT slices, such as the wide range of infection traits and the weak contrast between normal tissues and infections. Furthermore, it is impractical to gather a lot of data in a short amount of time, which prevents a deep model from being trained. Our suggested method will examine the lung's CT scan to identify the infected area and the proportion of the lung that is impacted. The system will determine the severity of the inflection and assist patients in taking necessary action.

***Index Terms* – Machine learning, Convolutional neural network, Lung Infection, pneumonia, Covid-19, CT Images**

I. INTRODUCTION

Medical imaging analysis is currently becoming more and more common in the field of medicine, particularly in non-invasive treatment and clinical examination. For a thorough diagnosis, the collected restorative images—such as computer tomography (CT), x-rays, ultrasound imaging, and so forth—are used. CT is a crucial filtering technique that makes use of the intriguing domains for image capture among medical imaging techniques. According to a study, lung cancer is a major cause of the 1.61 million fatalities that occur there each year. According to a different study, early detection of cancer increases the likelihood of survival. Lung cancer is the second most common disease worldwide, ranking second in men and tenth in women. One of the most deadly and deadly illnesses in the world is lung cancer. Nonetheless, a life can be saved by prompt diagnosis and treatment.

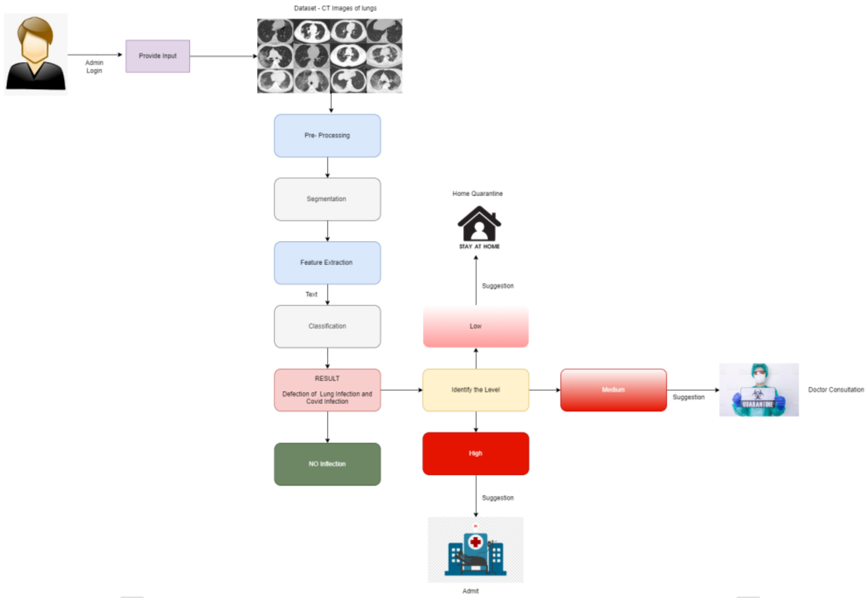
Despite being the most effective imaging method in the medical sector, clinicians find it challenging to decipher and detect cancer from CT scan data. As a result, computer-aided diagnostics can assist physicians correctly identify malignant cells. The combined number of deaths from prostate, colon, and breast cancer is less than the number of deaths from lung cancer. Considering the current state of affairs, where we are battling a condition like corona, which heavily involves the lungs.

Globally, COVID-19 has had a profound effect on people and healthcare systems. In addition to reverse transcription-polymerase chain reaction testing, computed tomography images can be a useful tool. A convolutional neural network was used in this study to screen for COVID-19. We looked at how well various pre-trained models performed on CT testing and found that the models' testing capacity is increased by using larger, out-of-field datasets. This implies that CT pictures can also benefit from a priori

knowledge of the models gained from out-of-field training. The suggested transfer learning strategy outperforms the existing strategies discussed in the literature. We think our method has so far produced identification performance that is at the cutting edge of the field. Experiments using randomly selected training datasets show that our model performs satisfactorily. We looked into the pertinent visual features of the CT scans that the model uses; these could help medical professionals with manual screening.

II. PROPOSED SYSTEM

A CT picture can be submitted using the admin module of our suggested system. In order to provide us with the ideal result, the system will further analyze the uploaded image and carry out a number of tasks, such as pre-processing, segmentation, feature extraction, classification, etc. The system will notify him and offer suggestions, such as the need for emergency care or a simple home quarantine. There is currently no system in place that analyzes CT images, provides an alarm based on the results, and allows for the taking of appropriate action.



Description of the Module

Step 1: The administrator can upload the lung CT image.

Step 2: The system will process those CT images by performing operations such pre-processing, segmentation, feature extraction, and classification.

Step 3: The system will finally display its output. i.e. Lung is infected or not.

Output: Depending on the degree of the infection, the system will indicate whether the user is infected with Lung Cancer, COVID-19 and, if so, what actions are required.

III. METHODS USED IN PROPOSED SYSTEM

The goal of the current study is to create a system that includes three main activities. First, a web-based application will be developed that will allow radiologists to upload CT scan images of patients with lung infection due to cancer, covid 19 etc., Additionally, radiologists will be able to enter the patients' symptoms to ascertain the stage of the disease. Second, the system will segment and pre-process the images. The CT scan by using the watershed method and supplying the convolutional neural network with the resulting images to find lung infection . This technique offers a quicker and more precise way to measure nodules, which eventually results in enhanced staging of lung infection by taking the patient's symptoms into account.

The Phase Pre Processing

In contemporary medicine, computed tomography (CT) scans constitute a vital diagnostic and therapeutic planning tool. They frequently entail exposing the patient to ionizing radiation, though, which may be harmful to the lungs or other organs. Therefore, pre-processing techniques are employed to provide high-quality photos while minimizing radiation exposure. Filtering is a popular pre-processing method for CT images that involves eliminating undesirable features and noise from the pictures. The Gaussian filter is a popular filtering method used in CT image pre-processing. A smoothing filter called the Gaussian filter is used to

eliminate noise and other high-frequency information from an image. It creates a bell-shaped curve by convolutionally transforming the image using a Gaussian kernel, a mathematical function. The amount of smoothing that is applied to the image depends on the curve's width; bigger curves result in greater smoothing. Because it reduces noise while maintaining edges, Gaussian filtering is especially helpful for CT scans. This is so because the Gaussian filter is a low-pass filter, meaning that low-frequency information is preserved while high-frequency information is reduced.
Low-frequency information in CT scans represents the lung tissue's underlying architecture, whereas high-frequency information represents noise and other undesired aspects. Pre-processing produces a more precise and clear image of the lung tissue, which is

essential for efficient diagnosis and treatment planning. Filtering techniques enhance the clarity of the CT scan image and assist physicians in making more precise diagnosis and treatment decisions by removing noise and higher frequency data.

Segmentation

Pixel or voxel separation is the first step in the second stage of image segmentation, which is accomplished by obtaining the pixel array and related metadata from the DICOM file. The radiodensity of the scanned tissue is then measured using the Hausfield units that are produced from the extracted pixel array. Hounsfield units are essential for picture segmentation, particularly when it comes to lung segmentation, as they aid in distinguishing lung tissue from other thoracic cavity components. Hounsfield units must be calculated in order to prepare the internal, external, and watershed markers needed for marker-controlled segmentation. These markers and the Sobel gradient are used in the marker-controlled segmentation approach to segment images and extract lung segments. Resizing and resampling are crucial steps in the image segmentation process. Resampling entails modifying the voxel size and spacing to take into account variations in acquisition settings across various CT scans, whereas resizing entails modifying the image's dimensions to meet the intended output size. To further hone the segmentation findings, the watershed segmentation approach is frequently used. This method first identifies regions of interest using gradient information and Hounsfield units, and then it separates these regions using a marker-based watershed transformation. In order to produce precise and reliable results, the image segmentation process entails pixel or voxel separation, Hounsfield unit computation, marker-controlled segmentation utilizing Sobel gradient and watershed segmentation, as well as resizing and resampling.

The Phase of Feature Extraction

The statistical results suggested DenseNet-169 as the best model for the feature extraction step, despite the fact that the features were extracted using various variations of pre-trained CNN models. Thus, the explanation of the DenseNet-169 model architecture and its role in feature extraction is the focus of this step.

The Phase of Classification

Following feature extraction, many classifiers were employed for the classification challenge, including Random Forest, Support Vector Machine, and others. However, it was discovered that using Support Vector Machine as the problem's classifier produced the greatest results. In order to achieve better results, the best suggested model combined features from DenseNet-169 with an SVM classifier. The following is a description of the SVM kernel and parameters:

Assume that a collection of training data, such as (x1,y1), (x2,y2),..(xn,yn), needs to be divided into two sets of classes, with yi ε (0,1) representing the label class and xi ε Fd representing the feature vector. A support vector machine that is used for binary classification can separate the data points of one class from the other by identifying the optimal hyperplane for the training data that is shown above, i.e., the one with the largest margin between the classes. The kernel and parameter choices have a significant impact on SVM performance. The Gaussian "radial basis function" kernel (rbf) was employed. The RBF kernel's gamma and C parameters have a significant impact on SVM performance. The gamma parameter, whose smaller value indicates "far" and whose higher value indicates "close," is intuitively used to determine the degree of influence that a single training example should have. Thus, the inverse of the radius of the influence of the samples chosen by the model as support vectors is displayed by the gamma parameter. However, the misclassification of training samples is compensated for by the C parameter. While a high C attempts to correctly categorize all training samples by granting the model an exemption to choose additional samples as support vectors, a low C offers a smooth surface.

IV. Acknowledgment

We will provide a method for uploading CT images as part of this project. In order to provide us with the ideal result, the system will further analyze the uploaded image and carry out a number of tasks, such as pre-processing, segmentation, feature extraction, classification, etc. The system will notify him and offer suggestions, such as the need for emergency care or a simple home quarantine. There is currently no system in place that analyzes CT images, provides an alarm based on the results, and allows for the taking of appropriate action.

References

[1] Y. Xu, A. Hosny, R. Zeleznik, C. Parmar, T. Coroller, I. Franco, H.J. Aerts Deep learning predicts lung cancer treatment response from serial medical imaging

[2] M.I. Faisal, S. Bashir, Z.S. Khan, F.H. Khan An evaluation of machine learning classifiers and ensembles for early stage prediction of lung cancer

[3] N. Coudray, P.S. Ocampo, T. Sakellaropoulos, N. Narula, M. Snuderl, D. Fenyö, …, A. Tsirigos Classification and mutation prediction from non–small cell lung cancer histopathology images using deep learning

[4] G. D. Rubin, L. B. Haramati et al., “The role of chest imaging in patient management during the COVID-19 pandemic: A multinational consensus statement from the fleischner society,” Radiology, p. 201365.

[5] C. Huang, Y. Wang et al., “Clinical features of patients infected with 2019 novel coronavirus in Wuhan, China,” The Lancet, vol. 395, no. 10223, pp. 497–506.

[6] V. Vanitha; R Srinidhi; R Darshana; S K M Nivetha, COVID-19 Detection using CT-Scan, 022 IEEE 3rd Global Conference.

[7] Tao Ai , Zhenlu Yang , Hongyan Hou , Chenao Zhan , Chong Chen , Wenzhi Lv 1, Qian Tao , Ziyong Sun , Liming Xia “Correlation of chest CT and rt-pcr testing in coronavirusdisease2019(COVID-19)inChina:Areportof1014cases,” Radiology, vol. 2019, p. 200642.