

Diagnosis of Lungs X-ray Using Image Processing

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Abstract- The abstract of the document discusses the use of convolutional neural networks (CNN) and support vector machines (SVM) to detect Covid-19 patients based on X-ray chest images. The study focuses on using the ResNet-50 model to extract features from the images and classify them using SVM. The results show high sensitivity and overall performance values for Covid-19 detection. The study suggests that this method can be beneficial for radiology specialists and help reduce false detection rates. These methods offer potential solutions for the early and accurate diagnosis of COVID-19 patients using X-ray imaging.

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Keywords- covid-19, convolutional neural network, SVM, prediction, feature extraction, deep learning.

I. INTRODUCTION

The most prevalent and serious medical conditions in the world are chest disorders. Every day, a large number of people pass away from chest illnesses, primarily from COVID-19, pneumonia, lung cancer, and tuberculosis (TB). If chest disorders are not identified in their early stages, they can be fatal. The World Health Organization (WHO) states that chest disorders have a very high fatality rate and can be fatal in a number of circumstances. The World Health Organization estimates that 3 million people die from COPD (chronic obstructive lung disease) each year, affecting 65 million people globally. The death rate from pneumonia is concerning; in 2017, 808,694 children under the age of five died from it. Approximately 10 million individuals (3.2 million women, 5.6 million men, and 1.2 million children) contracted TB, resulting in 1.4 million fatalities. Similarly, lung cancer claims the lives of almost 1.6 million people each year.

Discusses the importance of detecting and isolating Covid-19 patients at an early stage to control the spread of the disease. It mentions that reverse transcription polymerase chain reaction (RT-PCR) tests are commonly used for detection but have limitations in terms of sensitivity and time consumption. The study aims to develop alternative methods using chest Xray images and convolutional neural networks (CNN) with support vector machines (SVM) for Covid-19 detection. The dataset used in the study consists of X-ray images of Covid-19, Normal, and Viral Pneumonia cases. The study focuses on using the ResNet-50 model for feature extraction and SVM for classification. The results show high sensitivity and overall performance values for Covid-19 detection. The study suggests that this method can be beneficial for radiology specialists and help reduce false detection rates.

1.1 Flowchart and Methodology



1.2 Literature Survey

The literature survey in the given context focuses on the use of machine learning for computer-aided COVID-19 identification from CT and X-ray images. The study evaluates the accuracy, sensitivity, specificity, positive predictive value (PPV), and negative predictive value (NPV) of the suggested method in comparison to other previous studies. The study makes use of a number of classification techniques, including Bag of Tree, k-NN, SVM, and K-ELM. According to the findings, the suggested strategy has a high success rate and requires little time to apply, making it a viable tool for COVID-19 early detection and treatment. The study also emphasizes the value of early identification and the ability of traditional learning techniques to yield effective outcomes on par with those of deep learning techniques.[1]

The field of lung cancer detection has already produced works such as automatic back propagation-based image segmentation, gray coefficient mass estimation approach, and lung cancer detection and classification by learning and multi nominal detection. But the publication doesn't offer a thorough review of the literature or a synopsis of these earlier studies conclusions. [6]

The effectiveness and interpretability of transfer learning for COVID-19 detection in chest X-ray (CXR) images using pretrained deep convolutional neural networks (CNNs). The use of well-known CNN architectures, including VGG16,



DenseNet201, ResNet50, and EfficientNetB3, for the classification of viral pneumonia, COVID-19, and healthy CXR pictures is included in the survey. The study uses criteria like accuracy, sensitivity, and specificity to assess how well these models perform. Furthermore, in order to comprehend the features utilized for predictions, the study investigates the interpretability of the models utilizing Local Interpretable Model-Agnostic Explanations (LIME). The findings demonstrate that whereas VGG16 had trouble learning lung properties, DenseNet201 fared well in terms of accuracy and sensitivity. The research highlights the significance of comprehension in medical applications and proposes that LIME explanations can enhance the models' reliability and applicability.[13]

It states that COVID-19 is a worldwide health emergency and that early clinical intervention and efficient screening are essential to containing the virus. The gold standard for COVID-19 detection is the Reverse Transcription Polymerase Chain Response (RT-PCR) assay, which is laborious, manual, and complex. Chest X-ray (CXR) pictures are one type of radiographic imaging that can be utilized to screen suspected instances early. Convolutional Neural Networks (CNN), one type of deep learning technique, demonstrate promise in image analysis and classification applications. Utilizing pre-trained models such as Inception V3, transfer learning can enhance CNN performance on smaller datasets. The use of data augmentation methods to expand the training dataset is also mentioned in the document. According to the study, this computer-aided diagnostic tool can greatly increase the efficiency and precision of diagnosing COVID-19 patients, which is essential during a pandemic. [12]

A lung cancer detection system based on neural networks and image processing methods. Through the analysis of chest X-ray pictures, the method seeks to identify lung cancer early on. The methodology which includes image acquisition, preprocessing, enhancement, feature extraction, lung region extraction, and neural network analysis is described in the study.[4]

Image processing methods for the detection of lung cancer in CT scans. It draws attention to how deadly lung cancer is and how crucial early detection is to raising survival rates. The report states that when it comes to identifying and diagnosing lung cancer, CT scans are superior to standard chest x-rays. Additionally, it goes over the various phases of lung cancer and how important precise segmentation and feature extraction are in determining each stage. Using MATLAB, the study focuses on feature extraction, segmentation, and image enhancement. There is mention of a number of methods, including watershed segmentation, auto-enhancement, thresholding, and Gabor filter. The paper highlights the need for more precise findings as well as the promise of image processing methods for the identification of lung cancer.[7]

Early-stage lung cancer candidate tumors are detected by the method. Patient-provided helical X-ray CT lung pictures serve as the system's input data. The technology analyzes blood artery anatomy and diagnoses lung cancer using image processing techniques and medical knowledge. Using data from 20 patients, the algorithm's efficacy is assessed; in 8 cases of abnormal individuals, the tumor was successfully detected.[9]

The division of chest radiography The article highlights the several image processing and analysis techniques that have been put forth for chest radiographs, with an emphasis on lung field and rib cage segmentation. While clustering techniques have been employed in certain ways, region-based characteristics computed as wavelets have been used in others. Additionally highlights the value of computer-aided diagnostic (CAD) systems and the affordability, ease of use, and minimal radiation exposure of chest radiographs.[18]

II. TECHNIQUE:

- **Data Collection:** The first step in using ResNet50 MATLAB(CNN) model is to gather large dataset of images. These images includes healthy plants as well as those infected with various diseases. It is crucial to have a diverse and well labeled dataset to train and test the CNN effectively.
- **Preprocessing:** Before inputting images into a CNN, preprocessing steps are commonly applied. This could involve resizing images to a uniform resolution, standardizing pixel values, and augmenting the dataset with variations such as rotation, flips, and brightness adjustments. These steps aid the CNN in learning invariant features and enhancing its ability to generalize.
- **ResNet50 Model:** ResNet50 is a deep neural network with 50 layers, renowned for tasks like image classification. It employs skip connections to address the vanishing gradient problem, aiding in training very deep networks. By learning residual functions, ResNet50 achieves top-tier performance on standard datasets and facilitates transfer learning. Pre-trained on ImageNet, it's easily adaptable to various computer vision tasks.
- **Training:** The CNN is trained using labeled dataset. During training the network learns to associate image features with disease labels. This process involves feeding forward an image, calculating the error between the predicted and acutal label, then using backpropogation to adjust the networks parameters to minimize the error.
- Validation and Testing: Validation methods assess a model's resilience, with external validation using fresh data and internal validation using training data. Both split datasets into training and testing sets, with many studies using a train-and-test split or k-fold cross-validation. Seven out of sixteen studies employed an independent dataset for external validation.
- **Confusion Matrix:** A confusion matrix is a table that summarizes the performance of a classification model. It displays the counts of true positive, true negative, false



Volume: 08 Issue: 04 | April - 2024

SJIF Rating: 8.448

ISSN: 2582-3930

positive, and false negative predictions. Each row represents the actual class, while each column represents the predicted class. The diagonal elements of the matrix represent correct predictions, while off-diagonal elements represent errors. The matrix provides insights into the model's accuracy, precision, recall, and F1 score, aiding in evaluating its performance.

• **Deep Dream Image Generation:** Deep dream image generation is a technique that utilizes deep neural networks to enhance and manipulate images in an artistic and surreal manner. It involves amplifying and emphasizing patterns and features within an image by iteratively modifying the image based on its response to various layers of a pretrained neural network. Deep dream images often exhibit dream-like hallucinatory qualities, revealing intricate and abstract visual patterns within the original image.

III. CONCLUSION:

An overview of the literature on AI systems for COVID-19 detection on CT and chest X-rays is provided in this review. In terms of automated COVID-19 diagnosis by both modalities utilizing deep-learning techniques, the research that are being presented show favorable findings. AI has a lot of potential as a diagnostic tool, butits applicability in clinical practice is limited because to asignificant risk of bias resulting from small datasets, a lack of external validation, and an appropriate clinical comparator. So, to improve the chances of new AI systems being implemented in areas where patients stand to gain the most, future research should incorporate appropriate clinical comparison and external validation.

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