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Multi Class Classification of Lung Disease Through Customized VGG-19 From Chest X-Rays

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Abstract: Several global epidemic lung diseases, including COVID-19, tuberculosis (TB), and pneumonia, have increased in large numbers, resulting in the loss of millions of lives. Identifying these diseases accurately poses a challenge for medical specialists, primarily due to minute differences in Chest X-Ray images (CXR). This study proposes a computer-aided method for identifying lung diseases based on CXR images to support healthcare professionals. CXR is a widely used diagnostic tool in the healthcare sector, providing both rapid and precise diagnoses. Algorithms like deep learning have demonstrated exceptional capabilities in detecting and classifying lung diseases, streamlining the diagnostic process and saving valuable time for medical practitioners. This research introduces a customized VGG-19developed architecture for multiclass classification of Covid, Normal, Pneumonia, and tuberculosis (TB). A total of 5928 CXR images, sourced from various open-access websites (Covid 1626, Normal 1802, Pneumonia 1800, tuberculosis 700) were used, various pre-processing techniques like resizing, Gaussian filter for noise removal and CLACHE for image enhancement is used and data augmentation for increasing the size of dataset. Based on experimental data, our suggested model performed good with an accuracy of 93.33%.

Keywords: *Covid, Normal, Pneumonia, Tuberculosis, Deep Learning, VGG19, Transfer Learning*

1. Introduction

Respiratory diseases stand among the leading global causes of mortality [1], some of the diseases are pneumonia, pneumothorax, tuberculosis and recently covid-19. Pneumonia is a severe respiratory infection that results in fluid or pus filling the lung's alveoliand Pneumothorax, on the other hand, damages the patient's chest wall and lung air escapes, causing the lung to totally collapse.[2].A chronic cough, unintended weight loss from a decreased appetite, chills, fever, and night sweats are some of the symptoms of tuberculosis, which is caused by an airborne bacterial infection in the lungs.[3]. Timely assessment and diagnosis play an essential role in mitigating the fatal impact of pulmonary diseases and enhancing the quality of life for affected persons. In contemporary medical imaging, chest X-rays (CXR) and computed tomography (CT) scans are invaluable tools allowing doctors to visualize internal structures non-invasively [4]. Computer-Aided Detection (CAD) systems in medicine do extremely well in processing complex clinical data, offering assistance to clinicians for gaining insights and improving diagnostic accuracy. These intelligent systems, incorporating deep learning and artificial intelligence (AI) methodologies that is instrumental in diagnosing a spectrum of diseases and medical disorders [5]. Deep learning has shown amazing potential across numerous fields especially in the medical area. Without the need for human interaction, many diseases, such as COVID-19, pneumonia, lung cancer, and tuberculosis can reliably diagnose and classify using deep learning algorithms. Compared to standard machine learning, deep learning is more successful as the network size increases deeper data representation which is possible with larger networks. Consequently, the model automatically collects attributes and generates more accurate results. Compared to conventional machine learning techniques, deep learning algorithms yield higher accuracy since the models employ a combination of non-linear functions instead of linear ones. [6]. A unique customized VGG-19 deep learning model was proposed by us to automatically classify lung illnesses from chest x-ray images.

The primary contributions of this study are as follows.

- We have developed customized VGG-19 model for lung disease classification from the input chest X-Ray images.
- The dataset of chest X-rays was acquired from Kaggle and GitHub.
- Gaussian filter is used to denoise images
- CLACHE is used for Image enhancement
- Data augmentation is done on fly to enhance the dataset
- In order to assess performance, a confusion matrix and

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classification report is created in order to calculate precision, recall, and accuracy. Finally, ROC curves are projected.

This paper's remaining sections are arranged as follows: The background information and research-related works on deep learning-based lung disease classification are presented in Section 2. Dataset, pre-processing, Gaussian filter, image enhancement and proposed model is present in section 3, section 4 addressed the experimental results and performance measures and at last Section 5 provides the conclusion.

2. Related Work

Sreeja et al. [7] implemented deep learning-based approach that can classify COVID-19 in a patient's chest x-ray. They used a histogram of oriented gradients (HOG) with a CNN model. The performance of the suggested model was examined and compared with other statistical techniques. The suggested model yielded 92.95% accuracy, 85.00% recall, and 91.50% precision.

Shamrat et al. [8]. Implemented system design called LungNet22, whose model structure is comparable with VGG16, the study used chest X-ray pictures to attempt to categorize ten distinct lung illnesses. The study compared with eight deep learning models for the classification of lung diseases. VGG16 was found to have the best classification effectiveness, with a 92.95% classification rate. Subsequently, VGG16 and Adam optimizer were used, and LungNet22 achieved a greater accuracy of 98.89%.

Yimer et.al. [9] Developed transfer learning techniques to train xception model for accurately classify of various lung diseases using CXR images. With an impressive accuracy of 97.30%, sensitivity of 97.20%, and specificity of 99.40%, xception outperformed other methods and proved to be the most effective in this task.

Kim et al. [10] used a novel method to categorize lung conditions using CXR pictures. In order to extract pertinent characteristics for disease categorization, their method involved supplying raw CXR images directly to deep learning model that is Efficient Net v2-M in a single step, end-to-end learning process. They tested their suggested method on the American NIH dataset using three categoriesi.e. Normal, pneumonia, and pneumothorax. Loss is 0.6933, accuracy is 82.15%, sensitivity is 81.40%, and specificity is 91.65% were the validation metrics. The results were encouraging. The testing accuracy was 63.60% for each of the four separate classes (pneumothorax, tuberculosis, pneumonia, and normal), with corresponding specificities and sensitivities of 82.20%, 81.40%, and 94.48%. Using chest X-rays, this technique provides a promising method for automatically classifying lung illnesses

Pan et al.'s [11] assessed and examined the best CNN for abnormality identification in chest images. The CNN algorithms DenseNet and MobileNetV2 were used to predict the occurrence of 14 different pathological abnormalities and to classify chest X-rays as normal or abnormal. In the study, MobileNetV2 performed better than DenseNet, with AUC values of 0.893 and 0.900, respectively.

Perumal et al. [12]the researchers put forth an innovative approach for COVID-19 detection utilizing CXR and CT images, incorporating Haralick features and transfer learning. The utilization of transfer learning technology offers a rapid alternative that can assist in the diagnostic process, potentially curbing the spread of the virus. The main goal of this study is to present a simpler model that radiologists can use to help detect COVID-19 early. The proposed model achieves impressive results, with a 91% accuracy rate, 90% retrieval rate, and 93% accuracy rate using VGG-16 and transfer learning, surpassing other models currently available during this pandemic.

3. Dataset and Methodology

In this study, the authors have compiled a dataset from open source websites like Kaggle and GitHub and a multi class deep learning classification algorithm was developed for identifying the most prevalent chest disorders in chest x-rays. The different x-ray scans in this image dataset are separated into four categories: covid, normal, pneumonia, and tuberculosis. The dataset is split into Train and Test data with a proportion of 80:20. The classification of category wise images was displayed in Table 1

All the Chest X - Ray images are collected of Posterior Anterior (PA) view which is considered the standard and preferred posture for chest X-ray (CXR) classification. The PA view provides a clearer visualization of the anatomy of the chest, including the heart, lungs, ribs, and diaphragm. This allows for a more accurate assessment of the structures within the chest cavity. The PA view allows for more consistent imaging when compared to the AP view. Consistency is important for monitoring changes over time and for comparing images in longitudinal studies moreover The PA view is a standard and widely accepted approach in radiology. Standardization facilitates communication among healthcare professionals and ensures that images are acquired and interpreted in a uniform manner.

Table:1 Chest X-ray dataset overall Statistics

Number of Chest X-ray Samples	5928
Number of Covid X-ray Samples	1626
Number of Pneumonia X-ray Samples	1802
Number of Normal X-ray Samples	1800
Number of Tuberculosis X-ray Samples	700

Total Test Samples (20%)	1225
Total Train Samples (80%)	4703

3.1 Data Pre-processing

Data pre-processing in image processing involves a series of steps and techniques applied to raw images before they are fed into a machine learning model. The goal is to enhance the quality, extract relevant information, and prepare the data for effective interpretation by model. Some of the data pre-processing steps performed in this work are resizing, Normalization, Noise reduction, contrast enhancement and data augmentation. All the images in this work are resized to 224 x 224.

3.1.1 Gaussian Smoothing (Gaussian Filter)

Gaussian blur, also known as Gaussian smoothing, occurs when an image is filtered using a Gaussian function, a common technique in graphics software to reduce visual noise. This process yields a smoothly blurred appearance, similar to viewing images through a clear screen, distinct from the bokeh effect of an out-of-focus lens or regular lighting shadows, Gaussian smoothing in computer vision is often used initially to enhance visual structures across various scales. Figure 1 illustrates the results of applying the Gaussian Filter. The mathematical expression for Gaussian Smoothing, denoted by Eq.1, utilizes pixel coordinates (x, y) and the standard deviation 'σ' [13].

$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \quad (1)$$

Original Image After Applying Gaussian smoothing

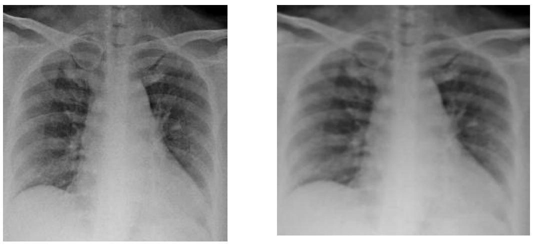

Fig 1 the result of applying the gaussian filter

3.1.2 Image enhancement (CLACHE)

Contrast Limited Adaptive Histogram Equalization (CLAHE) enhances image contrast, presenting a refined version of Adaptive Histogram Equalization (AHE). Renowned for its efficacy in amplifying the contrast of low-contrast images, CLAHE significantly contributes to strengthening both local contrast in medical imaging and overall image usability. Unlike global methods, CLAHE focuses on augmenting local difference, addressing their inherent limitations. The judicious selection of hyper parameters, notably the tile size and clip limit, profoundly influences CLAHE's effectiveness. In this study, a clip limit of 2.0 and a tile grid size of (8,8) were employed. Histogram analysis reveals that CLAHE-processed images exhibit markedly higher contrast compared to their original counterparts.

Original Image After Applying CLACHE

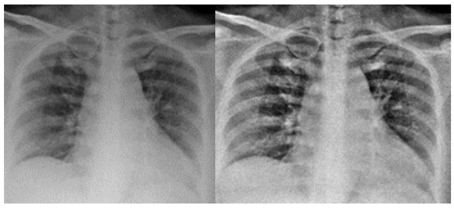

Fig. 2 The result of applying the CLACHE

3.1.3 Image Augmentation

To enhance the variety and robustness of our training dataset, we employed data augmentation on fly technique during the image preprocessing phase. The ImageDataGenerator from the Keras library was utilized to apply various transformations to the original images. These transformations include random shearing, zooming, and horizontal flipping. The rescaling parameter was set to normalize pixel values to the range [0, 1]. The augmented images were then generated on-the-fly and used to train our model. This approach not only increases the effective size of our dataset but also helps the model generalize better to variations in the input data.

3.2 Proposed Model

VGG-19 represents a pretrained Convolutional Neural Network (CNN) has a depth of 19 layers, with 3 completely connected layers and 16 convolution layers. In our model, VGG-19 is integrated to achieve optimal performance and accuracy. The initial layer of the model serves as the input layer, accepting RGB images with dimensions of 224 x 224 x 3 pixels. Convolution, Max Pooling, Fully Connected, and Softmax layers are the next layers in the sequence. Convolution layers play a crucial role in extracting features from images without pixel-related distractions. The feature map obtained from the convolution layer is then directed to the pooling layer, where identical features are merged, resulting in a reduced feature map size. The application of the ReLU kernel adjusts image resolution, promoting enhanced learning and classification of X-ray images. The output is subsequently forwarded to the fully connected layer, preceded by the Softmax function to adjust probability ranges

The Convolutional Neural Network Algorithm is a deep learning algorithm that processes images, assigning weights and biases to objects for effective differentiation. CNNs capture spatial and temporal dependencies in images through relevant filters, preserving essential features. VGG19 serves as the foundational model for feature extraction. Additionally, beyond the base models flatten layer, two dense layers, and two dropout layers are incorporated to further enhance the model.

Transfer learning is a technique that leverages previously acquired knowledge from a Convolution Neural Network (CNN) to train a model in identifying various characteristics such as weights and features. This method applies the learned knowledge to tackle similar problems by transferring it to a new dataset, where features are extracted and processed for classification. An essential feature of transfer learning involves freezing all layers except the last three, comprising the fully connected, SoftMax, and classification layers, which are then fine-tuned to recognize new categories or features. The primary objective is to attain precise outcomes from the pre-trained models. For successful transfer learning, together with test data, impartial and identical training data is essential. This approach significantly reduces training time while enhancing the model's performance. The hierarchical network structure of transfer learning yields high-level feature maps, reducing computational complexity and improving the model's generalization capabilities. Visualization techniques aid in image prediction and generating a confusion matrix, while an ROC Curve is utilized to illustrate accuracy and error percentages.

4. Experimental Results

4.1 Confusion Matrix

In this proposed work, we conduct multiple classifications with four types of categorizations, resulting in the generation of a confusion matrix. Performance assessment for the designed model is then carried out based on these values. The model achieved an accuracy of 93.33%

As seen in Figure 3, the TP values for the Covid X-ray photos are 291, identified Normal images are 381, pneumonia images are 329, and tuberculosis images are 136. To generate the accuracy, the values of TN/TP/FP/FN are used.

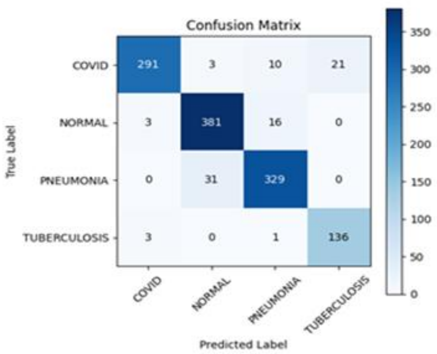

Fig 5 Confusion Matrix for the proposed VGG-19 Model

4.2 Classification Report

The primary classification metrics are represented for each class in the classification report. This provides an in-depth analysis of the behavior of the classifier.

Classification Report:

	precision	recall	f1-score	support
COVID	0.98	0.90	0.94	325
NORMAL	0.92	0.95	0.93	400
PNEUMONIA	0.92	0.91	0.92	360
TUBERCULOSIS	0.87	0.97	0.92	140
accuracy			0.93	1225
macro avg	0.92	0.93	0.93	1225
weighted avg	0.93	0.93	0.93	1225

Fig 6 Classification Report for the proposed VGG-19 Model.

4.3 Prediction (Accuracy vs. Loss Graphs)

To assess the algorithm's performance on both the training and test data and evaluate the model's fitness, Accuracy and Loss percentages are utilized. This involves employing graphs to analyse the output after receiving data as input. The layers within the model significantly influence its performance. To identify hyperparameters, the data is trained in epochs. The validation of this model is conducted over 10 epochs, with graphs plotting Valid/Train Accuracy and Valid/Test Loss. In Fig 7, Accuracy is on the Y-axis and the Number of Epochs is on the X-axis. The accuracy of the pretrained VGG-19 model is examined for 0 to 10 epochs gradual increase in accuracy is observed, reaching after a certain number of epochs. Conversely, resulting in an accuracy of approximately 0.93 for this period.

In Figure 7, the Number of training epochs is shown on the X-axis, and the accuracy is represented on the Y-axis in the epoch vs accuracy graph. When examining the training data, there is a rise in the accuracy while increasing the epochs. The model was trained over 10 epochs and we observed the accuracy between 0.93 – 0.94this showcase the model good performance despite being implemented on a small dataset. Consequently, this model has attained a commendable prediction rate through training on chest X-ray images. Where as in epoch vs loss graph the loss has continuously decreased over increase in epoch at certain point it has been constant. Thus, the model shows promising results.

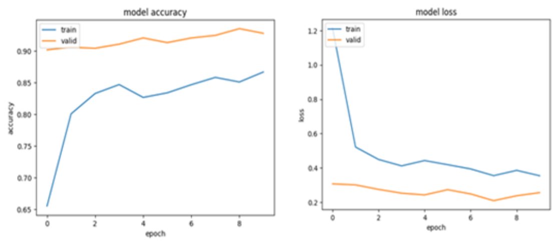

Fig 7 Epoch vs Accuracy& Epoch vs Loss Graphs of proposed model.

In Figure 7, the Number of training epochs is shown on the X-axis, and the accuracy is represented on the Y-axis in the epoch vs accuracy graph. When examining the training data, there is a rise in the accuracy while increasing the epochs. The model was trained over 10 epochs and we observed the accuracy between 0.93 – 0.94 this showcase the model good performance despite being implemented on a small dataset. Consequently, this model has attained a commendable prediction rate through training on chest X-ray images. Where as in epoch vs loss graph the loss has continuously decreased over increase in epoch at certain point it has been constant. Thus, the model shows promising results.

4.4 Receiver Operating Characteristics (ROC)

ROC Curve is graphical visualization for evaluating performance measures through input data analysis with True Positive Rate (TPR) and False Positive Rate (FPR),where TPR represents accurate forecasts and FPR represents inaccurate predictions, are the metrics it depends on. The optimal cut point, a marginal line on the graph that divides the data into accurate and inaccurate groups, is present. Following the computation of true and false positives, linear regression is used to find the slope and y-intercept. The Area Under the Curve (AUC) is calculated using the Trapezoidal method to determine the measurement of the ROC plot. Figure 8 plots TPR on the y-axis and provides an explanation of FPR on the x-axis. The resulting AUC is shown, showing that some classes have met a predetermined cutoff point.

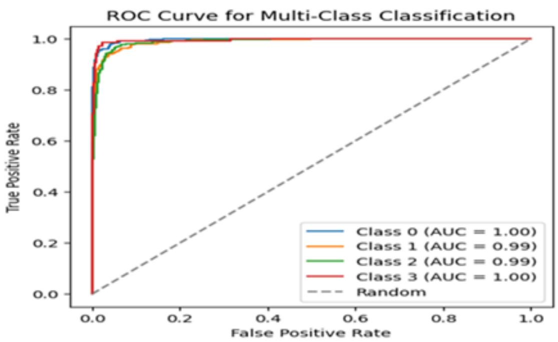

Fig 8 ROC Curve of VGG19 model

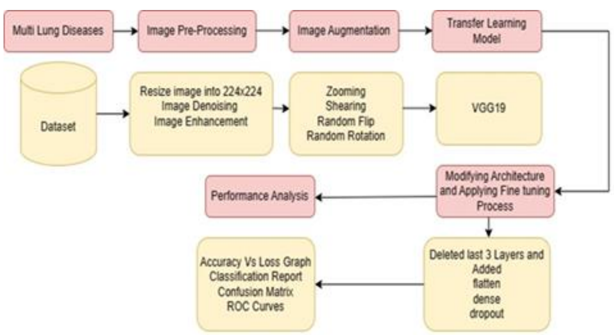

Fig 4: Proposed Architecture of Customized VGG-19 Model

4.5 Performance Metrics

The multi-lung disease classification model's results were evaluated using various parameters with accuracy (ACC), Recall, Precision, and F1-score.

$$Precision = \frac{sumofalltruepositives\ (Tp)}{SumofallTruePositives(TP) + AllFalsePositives\ (FP)} \quad (2)$$

$$Accuracy = \frac{No.ofimagescorrectlyclassified}{Totalnoofimages} \quad (3)$$

$$Recall = \frac{sumofalltruepositives\ (Tp)}{sumofalltruepositives(Tp) + AllFalseNegatives\ (FN)} \quad (4)$$

$$F1\ Score = \frac{2 * Precision * Recall}{Precision + Relcall} \quad (5)$$

5. Conclusion

In this work, a deep learning model consists of multi-classification for identifying tuberculosis, pneumonia, normal, and covid in chest x-ray images was developed and evaluated. The model is trained and tested using customized VGG-19, The performance measures are what define the accuracy, which comes out to be roughly 93.33%. Testing on more data may yield better accuracy. This was our initial effort to combine the four lung diseases into one model of classification. Ongoing research aims to improve accuracy in the future while increasing the dataset and improving the model with some attention mechanisms.

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