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An Improved Deep Transfer Learning Approach For Specific Lung Disease Classification

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ABSTRACT

In every region of the world, the prevalence of lung illness is quite significant. Lung conditions such as pneumonia, tuberculosis, fibrosis, and chronic obstructive pulmonary disease are examples of conditions that are included in this category. A respiratory disease must be identified as soon as possible in order to be of the utmost importance. As a result of this, a great number of computational models that make use of deep learning (DL) and image processing have been established. Within the scope of this research, an innovative deep learning transfer learning (TL) method for the classification of a specific lung ailment is investigated in great detail. The availability of image datasets such as computed tomography (CT) and X-ray scans has made it possible for us to easily obtain important medical information. Combining TL with convolutional neural networks (CNN) is the approach that this method takes. In this study, the utilisation of Kaggle datasets that are accessible to the general public and contain chest X-ray images and CT scans of the lungs is investigated. The value of data augmentation strategies and preprocessing stages in improving the performance of models is investigated in depth in this article. The purpose of this study is to evaluate three enhanced CNN architectures by placing them through a series of tests. These designs are modified VGG-16, improved VGG-19, and improved MobileNetV2. Based on the findings, it appears that the improved VGG-19 model exhibits superior recall, precision, and accuracy when compared to alternative designs on both the training dataset and the testing dataset. This method's improved accuracy in diagnosing instances of pneumonia and tuberculosis is further highlighted by comparing it to earlier research that has demonstrated its usefulness in assessing medical images. This comparison highlights the fact that this method is improved. In general, this work introduces a complete method for classifying lung disorders and gives useful insights that can be utilised in the course of future research in the fields of deep learning and medical imaging.

Keywords: Deep Learning, CNN, Transfer Learning, Lung Diseases, classification.

1. Introduction

Over the course of the last few years, there have been major developments in the field of medical imaging, which has led to an unparalleled time of improved accuracy and effectiveness in the diagnosis of illnesses. In light of the current circumstances, it is becoming increasingly vital to diagnose and categorise respiratory illnesses by employing procedures that are both inventive and imaginative [11]. This study presents a more advanced image retrieval system that makes use of convolutional neural networks (CNNs). This approach has the potential to change the overall understanding and diagnosis of lung illnesses [13]. X-rays and computed tomography (CT) scans of the lungs have been demonstrated to disclose a variety of signs of lung disorders, according to a number of study examinations. CT scans and X-rays are two imaging modalities that are frequently utilised and have the ability to successfully detect early indicators of lung illness. Several attempts have been made to make use of artificial intelligence in order to improve the speed at which the healthcare system analyses images [12]. Researchers are now learning more about deep CNN architectures for lung illness categorization in both X-ray and CT scans, because of the significant advancements made by DL techniques in identifying specific anomalies in medical images [14]. Using innovative data augmentation techniques and improving pre-trained CNN architectures, our method aims to solve issues like sparse annotations and different picture resolutions that are frequently present in medical imaging datasets. We seek to prove the superiority of the technique we propose in correctly identifying cases of TB and pneumonia by thorough testing and comparison analysis with current approaches [16].

Advanced characteristics may be automatically extracted from photos by DL algorithms, but this can make it challenging to comprehend the findings and identify the elements that are driving the classification [15]. Lung disease databases can occasionally be unbalanced, with an excessive number of instances of one condition relative to others. This may make it challenging for the algorithm to provide an appropriate classification for every condition. This study effort developed an

effective lung disease categorization model to address those problems [17][18].
The organisation of this work can be summarised as follows: In the second section, a comprehensive analysis of the existing literature in this topic is presented, along with an in-depth discussion of the various subject areas. Section 3 outlines the data description and the proposed methodology, detailing the implementation of three algorithms. Section 4 of the document presents the results and analysis of the proposed methodology. The conclusion section then summarizes the study's findings and discusses their implications.

2. Literature Review

Despite the first CAD system for identifying lung diseases was introduced in the late 1980s, it was insufficient. This is a result of the countless insufficient computational resources available at the time to apply cutting-edge image processing algorithms. It takes longer to recognize lung diseases using simple image processing methods. Subsequent to the successful development of ANN and CNN, there have been significant and noticeable improvements in performance. There have been a number of studies [6–15] that have investigated several DL models for the purpose of diagnosing lung illnesses, including cancer of the lung.
VDS Net is a hybrid deep learning framework that was presented by Subrato et al. (2020). It is designed to improve lung disease diagnosis by combining a number of different methodologies. CNN is incorporated into the framework, together with VGG, data augmentation, and spatial transformer network (STN), in order to facilitate improvements in accuracy and efficiency. The VDSNet algorithm outperforms other approaches in terms of precision, recall, F0.5 score, and validation accuracy when it is tested on the chest X-ray dataset from the National Institutes of Health (NIH). When applied to the entire dataset, it obtains an amazing accuracy of 73%. VDSNet is able to maintain its competitive performance while simultaneously greatly lowering the amount of time required for training, despite the fact that it uses a sample dataset. This research presents a promising approach to simplify lung disease detection, benefiting both experts and doctors [9]. An automated technique for identifying patterns of interstitial lung disease in high-resolution CT scans is presented by Sunita et al. (2021). Their method offers greater performance without lung field segmentation, based on a reduced GoogLeNet backbone. Their approach beats current methods when tested on the MedGIFT database using five-fold cross-validation, potentially leading to effective ILD pattern screening and diagnosis [4]. An automated method for identifying various lung disorders in CT and X-ray images is proposed by Mona et al. (2023). They provide a new image enhancing approach and use pre-trained models for classification in addition to customized CNN architectures. High accuracy, sensitivity, and specificity are demonstrated in testing on publically accessible datasets, underscoring the usefulness of their method in enhancing lung disease identification using medical imaging [5].
Adem and Ismael (2023) propose a DL-based method for identifying lung diseases, focusing on COVID-19 detection from chest X-ray images. Utilizing MobileNet and DenseNet models, they achieve 96% accuracy and a 94% AUC value. Their study underscores the potential of DL in accurately identifying COVID-19 signs from chest Xray images, offering valuable insights into performance parameters such as precision, recall, and F1-Score [6]. Negar et al. (2023) use CT scans to look at early lung cancer diagnosis. For image analysis, they use pre-processing and segmentation methods in addition to CNN and ANN. They attain a promising 95% diagnostic accuracy by using machine learning techniques like SVM and RF. The significance of automated learning and sophisticated imaging in the identification of a variety of illnesses is brought into focus by this [7]. Matthew and Adam (2020) investigate the problem of restricted accessibility to health information by creating a method to identify lung problems from X-ray images of the chest utilising insignificant data sets. This method is used to diagnose lung conditions. They employ pre-trained deep CNNs (VGG16, ResNet-50, and InceptionV3) and TL, segmenting images before classification. Their study demonstrates competitive performance with existing frameworks, achieving comparable accuracy levels on the Montgomery dataset with fewer trainable parameters. Notably, their InceptionV3 model performs well on the Shenzhen dataset despite its computational efficiency. This research underscores the effectiveness of TL and streamlined architectures in overcoming medical data scarcity for pulmonary disease detection [8].
A novel image retrieval system using CNNs is presented by Atul et al. (2024) to improve the precision of lung disease diagnosis from medical pictures. With the help of carefully considered CNN architecture, pre-processing, and carefully chosen datasets, the system exhibits remarkable accuracy in differentiating between lung illnesses and healthy conditions. Using image retrieval algorithms makes it easier to obtain pertinent medical pictures quickly, which helps doctors diagnose patients and arrange treatments more accurately. This work demonstrates how cutting-edge DL methods may transform the detection of lung diseases and enhance patient outcomes [10].

3. Proposed Methodology

This section addresses the different algorithms that were employed, the datasets that were used, the preprocessing, and the techniques for data augmentation.

3.1. Materials

Datasets that have been produced and made available on the "Kaggle" site are all publicly accessible, and they have all been used in this research. Over 5,856 frontal chest X-ray pictures were included in the dataset that Paul Mooney made accessible to the public. A total of 1,583 of these portray individuals who do not have any abnormalities in their lungs, while 4,273 of these individuals have possible abnormalities and symptoms of influenza.

There are 662 frontal X-rays in the Scott Mader tuberculosis dataset. These photos were taken by medical professionals at the Guangdong Hospital in China. It has 326 images total including lung images of healthy individuals and another 336 images with tuberculosis infections.

The 907 lung CT-scan images in Mohamed Hany's cancer dataset include 215 images of individuals without cancer and 692 images of individuals with the disease.

Three different cancer image types are included in the dataset: squamous cell carcinoma, large cell carcinoma and adenocarcinoma. A few sample images from the CT-scan dataset are displayed in Figure 1.

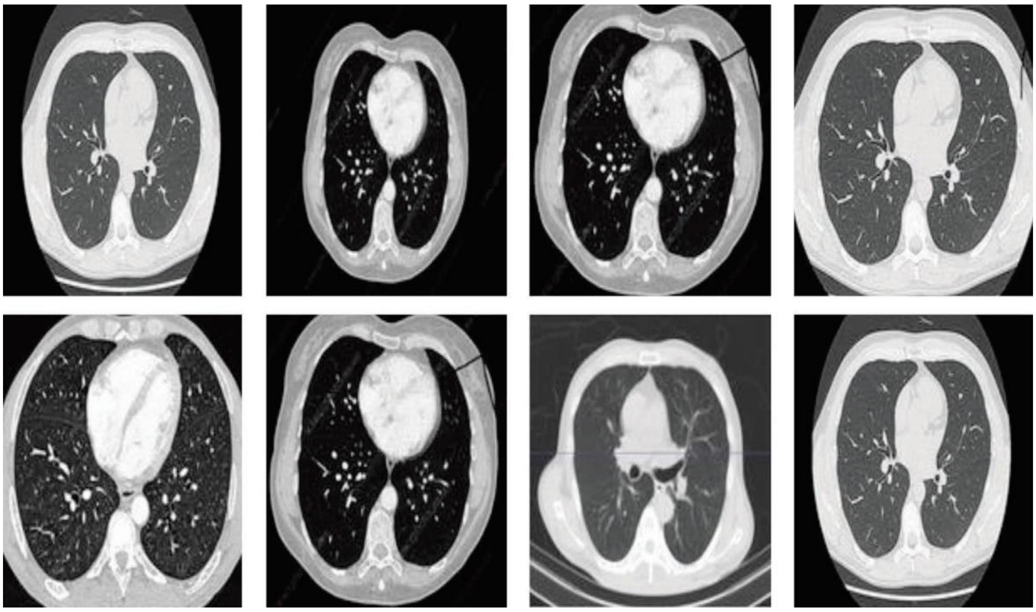


Figure 1. Chest-CT Scan Images

3.2. Preprocessing and Data Augmentation

There are variations in resolution among the images included in the datasets. Still, images must be a certain size according to the CNN models. This meant that every image in the dataset had its size changed to 224 × 224. Reduce the size of the input image to help the model execute images more quickly for the particular task at hand.

The process of data augmentation is an efficient way that can significantly increase the amount of training data that is available. During each training epoch, this method includes introducing tiny variations to the images that are being used. Adjusting the scale, rotation, shear, horizontal Eip, and zoom are some of the approaches that were utilised so that this operation could be completed. As a result of the CNN model's capacity to train on a greater quantity of data than what was initially available in the dataset, this method plays an essential part in the process of achieving high levels of accuracy. A single sample image can be used to generate a variety of distinct variants, which are displayed in Figure 2.

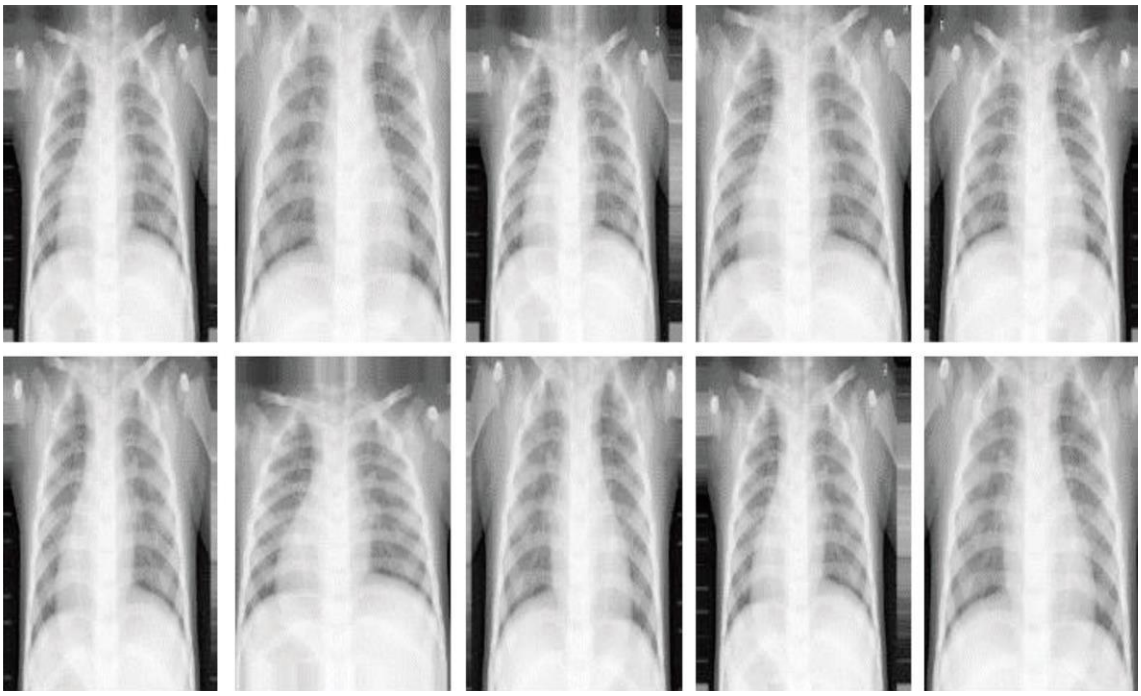


Figure 2. Variations of a Chest X-ray Image

3.3. CNN and TL Approaches

CNN is an example of a deep learning neural network (NN) that is extremely effective for image processing. Convolutional neural networks (CNNs) are designed to process images by utilising many convolutional layers (CL), with each layer employing a convolutional filter to extract useful information from the image. It is necessary to process the output of each CL with a non-linear stimulus function, such as the ReLU [11], in order to guarantee that the network as a whole is non-linear. Utilising the result of the ultimate CL, that was previously processed by the layer or layers that are entirely connected, as shown in Figure 3,

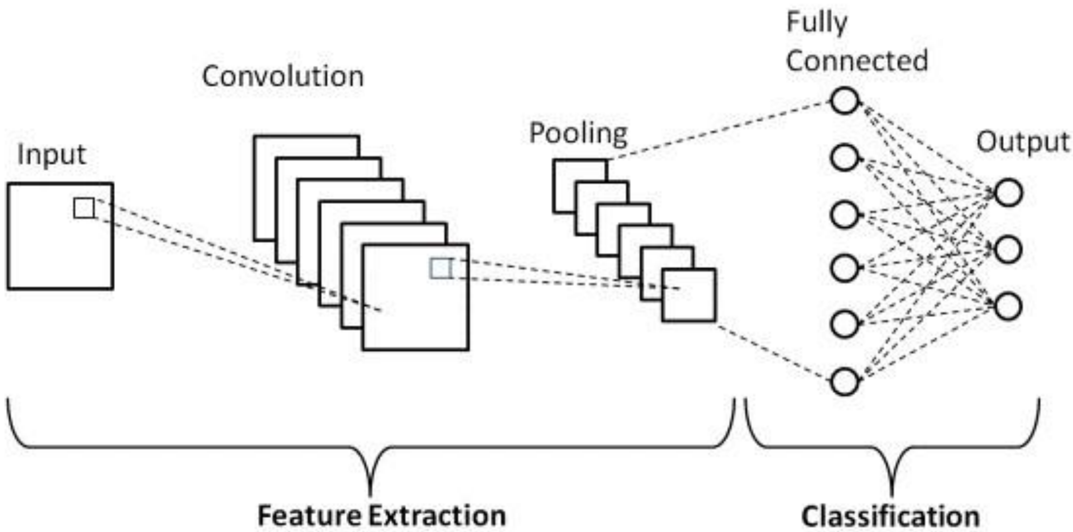


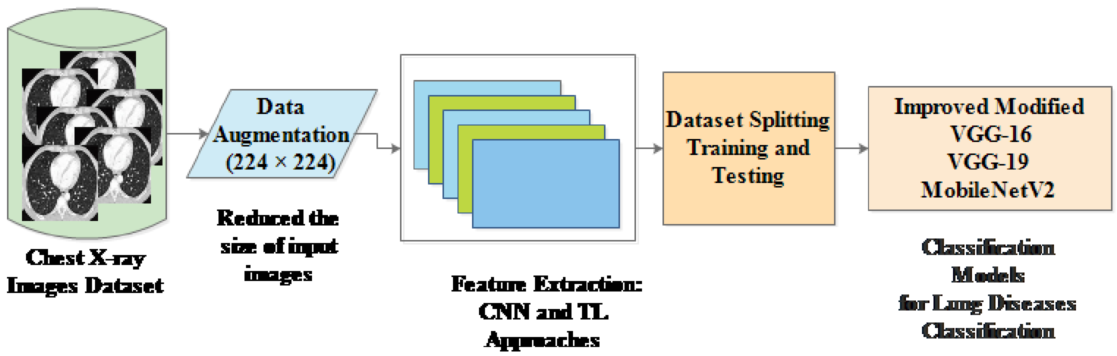
Figure 3. CNN Framework.

One of the most valuable capabilities of the activation layer is its capacity to calculate any nonlinear function. It is the CL that is responsible for transmitting the feature map to the activation layer process [12]. The representation created by earlier kernels is spatially reduced using pooling layers following convolution. As a result, less computation is required because there are fewer parameters. These layers are used to extract dominant features that are positionally and rotationally invariant. Max pooling and average pooling are the pooling layers

that are most frequently used. Both methods reduce the dimensions and computational expense [13].
Training a CNN model from scratch is extremely time-consuming and computationally expensive [29]. The standard method of training CNN algorithms entails making use of datasets. This is done in order to train the algorithms. Information that is up to date is being utilised by TL. In classification problems where there are not enough training examples, pre-trained samples of TL are used. Pretrained models can be used in TL in two different ways. In the first technique, features are extracted from the data and the data is then classified utilizing a pre-trained CNN model. The last fully connected layer is then altered based on how many classes are present in the data set. In the alternative method, a set of preset techniques is used to retrain all or a subset of the CNN model's layers. Consequently, an altered architectural design is used in the new classification task.

3.4. Architectures with Improved Proposed

Through the use of a deep learning technique known as Improved, it is possible to modify a neural network (NN) that has been trained in the past so that it is suitable for a new dataset or task. After a supervised convolutional neural network (CNN) has finished its training, it is essential to either fine-tune or retrain particular layers by making use of a new dataset. This happens after the model has finished its training and is ready to go. The fundamental idea behind improvement is that the model that has been trained has amassed a considerable and diverse collection of generic features. This is the primary principle underlying improvement. This is the foundation around which the improvement notion is built. By making modifications to the top layers on a new dataset, the model can be modified to perform a different task in a more effective manner. This is accomplished while maintaining the weights for the bottom layers, which are responsible for capturing the critical features. This allows the model to take advantage of shorter training times and fewer samples. When it comes to adapting current models to new tasks, a more advanced technique can be quite beneficial. This is especially true in situations when the dataset is limited or when there are time constraints during the training process. It is essential to select the pre-trained model and the fresh dataset with careful consideration, in addition to making adjustments to the hyperparameters, in order to get the highest potential level of performance outcomes. Within the scope of this investigation, three superior models are utilised to categorise lung illnesses. Modified VGG-16, VGG-19, and MobileNetV2 are the models that have been suggested for further refinement. There is a possibility that the succeeding sections will provide additional analysis of the models that have been offered.



3.4.1. Improved modified VGG-16 model

Among the CNN architectures, VGG-16 is one of them. By increasing the depth of the VGG model, it is possible to improve the kernels' capacity to comprehend more complex properties. The performance of a trained VGG-16 network was shown to be superior to that of a fully trained network throughout the course of research on the practicability of transition learning. A total of more than one million photos from the ImageNet collection were utilised in the training of this network. It is possible for the sixteen-layer network to identify photos that belong to a variety of categories. Regular RGB images with dimensions of 224 by 224 pixels are sent into the initial CL. In order to reduce the size of the receptive field and make adjustments to the image, a collection of specialist kernels is utilised. Additionally, the input channels are modified by a 1x1 convolutional filter that is a part of one of the pairings. Adjustments are made to the spatial padding of the CL, and the stride of the convolution is reset to one pixel, It is necessary to perform certain actions in order to preserve the spatial resolution once the convolution process has been completed. In addition to the CL, there are five layers that have the greatest pooling capabilities that are utilised in order to accomplish the goal of spatial pooling. The pooling methods are carried out on frames that have a dimension of 2x2 pixels and are moved by a stride level of 2. There are three items arranged in a vertical stack stacked. As seen in Figure 6, the structure of VGG-16 is depicted.

During the course of this research, a modified version of the VGG-16 model was employed in order to solve the problem of underfitting and overfitting that occurs during training. One of the mechanisms that has been implemented in this improved VGG-16 network is one that is more advanced. A single large convolutional kernel was replaced with two consecutive tiny convolutional kernels for the purpose of feature extraction in the VGG16 convolutional network. This allowed the original architecture of the network to be preserved. Facilitating the acceleration of training while maintaining the network depth can be accomplished by streamlining the settings and maintaining the VGG16 perceptual effects. It was 224 pixels wide and 224 pixels tall when the image was submitted. There were five blocks hidden within the layer that was concealed. When it came to reducing the size of the image, the pooling layers were really helpful, while the flattened layer was an essential component in reducing the dimensions of the map of features. A total of fifty epochs were spent training the VGG-16 model before it was subjected to fine-tuning. Implementing improvements to the baseline model beginning with the eleventh layer resulted in a reduction in the rate at which the model learned new information. After the process of fine-tuning was finished, the model went through a total of fifty consecutive training epochs.

3.4.2. Improved VGG-19 model

The VGG-19 model, which has been fine-tuned, is a CNN architecture that has been adjusted to perform better on a given task by modifying the parameters of the pre-trained VGG-19 model on a particular dataset. With 19 layers, including max-pooling and CL with tiny 3x3 filters, VGG-19 is a DL architecture recognized for its simplicity and depth. The VGG-19 model is improved by first initializing it with weights that have already been pre-trained on a sizable dataset such as ImageNet and then retraining it on a lighter, taskspecific dataset. During this process, the model retains the knowledge it gained from the old dataset while picking up additional features relevant to the new dataset. The optimized VGG-19 model is frequently applied to computer visual tasks such as object recognition, picture segmentation, and image classification. Because of its deep architecture and capacity to recognize complex patterns in images, the model has proven to perform well in these applications.

3.4.3. Improved MobileNetV2 model

A representation of the MobileNetV2 architecture that has been adjusted for a particular job or dataset is the improved MobileNetV2 model. A lightweight CNN architecture called MobileNetV2 was created with embedded and mobile vision functions in mind. Its depth-wise separable convolutions, which lower the computational burden and model size while preserving high precision, are its defining feature. A pre-trained MobileNetV2 model is improved by retraining it on a smaller, task-specific dataset after it has already been trained on a larger dataset, such as ImageNet. During this procedure, the model can modify its acquired representations to more effectively fit the intended task or dataset. When computing resources are restricted or a model that can operate effectively on mobile devices or at the edge is required, the improved MobileNetV2 model proves to be very helpful. The application of this technology has been widely utilised in a variety of computer vision applications, including semantic segmentation, object identification, and image classification, amongst others. Because it is able to establish a balance between efficiency and production, it has garnered a substantial amount of popularity in recent years. This method can be used to train the whole model across 60 epochs. A modest learning rate is provided via improving, which was applied to the underlying model starting at the 85th layer. The model was fine-tuned and then trained for 50 training epochs.

3.5. Performance Metrics

The Recall, precision, accuracy, F1_score, and ROC curve are among the performance measures that have been used to assess the effectiveness of DL systems. The equations below can be used to calculate these performance metrics.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$$

$$\text{Precision} = \frac{TP}{TP+FP}$$

$$\text{F1\_score} = \frac{2TP}{2TP+FP+FN}$$

$$\text{Recall} = \frac{TP}{TP+FN}$$

4. Discussion and Experimental Results

Before the suggested concepts were put to the test, the dataset was created and produced. TensorFlow and Python were extremely important tools to have at your disposal during the entire process of designing and training the models on Google Collaboratory. For the purpose of carrying out the categorization, the Adam optimisation method was utilised. A categorical cross entropy loss function was utilised in the inquiry, and a batch size of 32 was selected as the appropriate size for the batch. The effectiveness of the model was assessed on the basis of the enhancements that were implemented. It is usual practise to make use of visualisations such as precision plots and loss displays in order to monitor the development of a model's training capabilities. It is possible to evaluate the performance of the model on both datasets by looking at a plot that displays various lines. Two lines are used to illustrate the degree of accuracy achieved by the training and validation processes. When a loss plot is created, it displays the amount of loss that the model has experienced. This is accomplished by using both the training dataset and the validation dataset. The loss metric is a method that may be utilised to assess the accuracy of the model in determining the actual labels that are present in the dataset. When one examines the plot in great detail, one could see that there are a few lines that are similar to the plot itself. Both the training losses and the validation losses are displayed here in the form of lines showing their performance. At this point, the precision and degradation plot of the upgraded architectures that have been recommended are exhibited. in Figure 4-6.

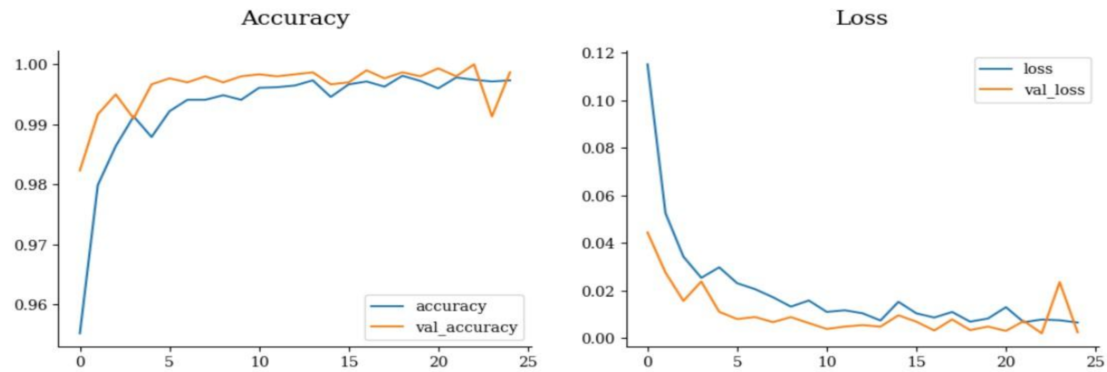


Figure 4. Accuracy plot and Loss plot of Suggested Improved VGG-16

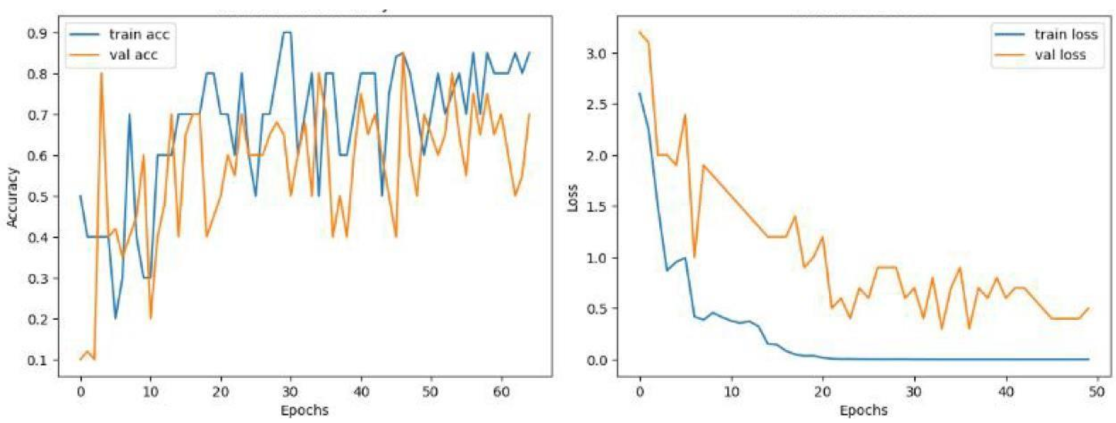


Figure 5. Accuracy plot and Loss plot of Suggested Improved VGG-19

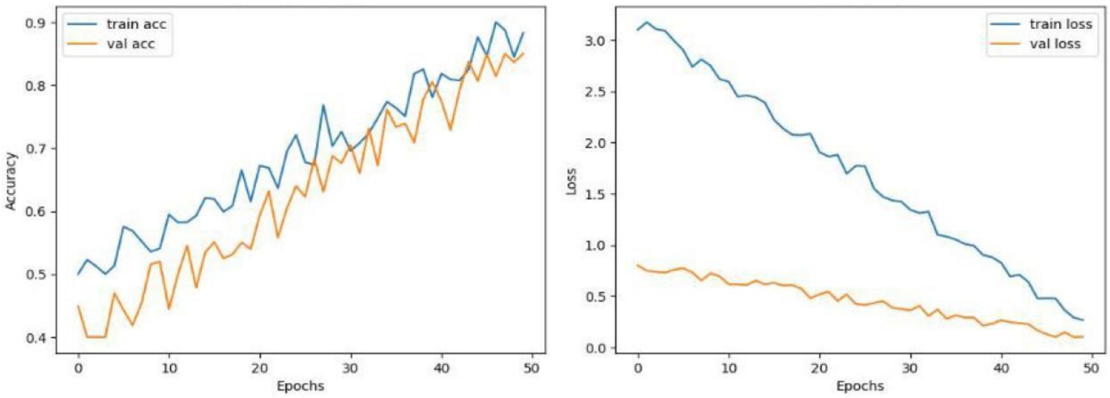


Figure 6. Accuracy plot and Loss plot of suggested Improved MobileNetV2

Table 1 represents the performance metrics of the recommended improved architectures on the training dataset while Table 2 shows the performance on the testing dataset. Let's analyze each table:

4.1. Improved Modified VGG-16

Training Dataset: The model demonstrates high recall (0.962) and precision (0.978) indicating that it effectively identifies and classifies instances of each class. The accuracy is good (0.978) suggesting that most forecasts were accurate. Since the F1-score, which takes into account both precision and recall, is 0.970, it can be concluded that there is a satisfactory equilibrium between the two.

Testing Dataset: The model maintains high recall (0.958) and precision (0.967) on the testing dataset with a slightly lower accuracy of 0.956. However, the F1-score remains high at 0.980 indicating robust performance.

4.2. Improved VGG-19

Training Dataset: This architecture exhibits even better performance metrics compared to the modified VGG-16. It achieves exceptionally high recall (0.982), precision (0.989) and accuracy (0.979) indicating superior classification capability. The F1-score is also very good at 0.988 reflecting strong overall performance.

Testing Dataset: The refined VGG-19 model exhibits a slight drop in recall (0.822) and accuracy (0.822) when compared to the training dataset but it still performs well. However, it maintains a high accuracy (0.973) and a respectable F1-score of 0.841 indicating satisfactory performance.

4.3. Improved MobileNetV2

Training Dataset: This architecture demonstrates a decent performance with recall, precision and accuracy of 0.911, 0.910 and 0.910 respectively. The F1-score is 0.910 suggesting a balanced performance in terms of precision and recall.

Testing Dataset: The model performance remains consistent on the testing dataset with recall, precision and accuracy of 0.870, 0.870 and 0.910 respectively. The F1-score of 0.900 indicating overall performance is good.
Overall, the improved VGG-19 model emerges as the top performer among the recommended architectures obtaining the highest scores across most metrics on both the training and testing datasets.

Table 1. The performance of the model on the training dataset.

Models	Recall	Precision	Accuracy	F1-score	Training loss
Improved Modified VGG-16	0.962	0.978	0.978	0.970	0.202
Improved VGG-19	0.982	0.989	0.979	0.988	0.179
Improved MobileNetV2	0.911	0.910	0.910	0.910	0.311

Table 2. The performance of the model on the testing dataset.

Models	Recall	Precision	Accuracy	F1-score	Training loss
Improved Modified VGG-16	0.958	0.967	0.956	0.980	0.212
Improved VGG-19	0.822	0.822	0.973	0.841	0.178
Improved MobileNetV2	0.870	0.870	0.910	0.900	0.310

Table 3. Comparison with Previous Works

Reference	Dataset	Model	Accuracy
[1]	Annotated dataset-87	CNN	93
[2]	Planar data	CNN	74
[3]	Annotated dataset-1000 images	MLP	93
Our proposed Method	Pneumonia and tuberculosis	CNN	97

Table 3 indicates the comparison of different model performances on various datasets including the proposed method measured by accuracy. Lee et al. (2022) achieved an accuracy of 93% using a CNN on an annotated dataset of 87 samples while Tomassini et al. (2022) attained a lower accuracy of 74% with a CNN on planar data. Desai et al. (2022) utilized an MLP on an annotated dataset with 1000 images achieving an accuracy of 93%. In contrast, our proposed method employing a CNN model on a dataset concerning pneumonia and tuberculosis cases showcases superior performance with an accuracy of 97%. When compared to previous studies, it is clear that the method that has been developed is quite effective in accurately categorising instances of tuberculosis and pneumonia.

Conclusion

This work concludes by presenting a thorough deep TL strategy that makes use of TL and CNN for the categorization of certain lung diseases. This work has empirically shown the efficacy of improved CNN architectures such as Improved modified VGG-16, Improved VGG-19 and Improved MobileNetV2 using publicly accessible datasets like X-ray and CT scans. Our findings demonstrate that the Improved VGG-19 model is better in correctly classifying the insets of pneumonia and TB exhibiting remarkable precision accuracy and recall on the train and test datasets. Furthermore, a comparison with earlier studies highlights the progress made in medical image analysis using this suggested approach. In the future the studies might look at new methods of data augmentation like how to combine clinical and imaging data for better diagnosis and how to further optimize model architectures for better performance. Furthermore, it would be beneficial to carry out trials and validations of the suggested methodology in actual clinical settings as this would promote its acceptance as a useful instrument for lung disease diagnosis and treatment. This work adds to the continuing attempts to use DL methods for medical image interpretation which might have a big future influence on patient care and healthcare outcomes.

Complaints with Ethical Standard: Not Required

Data Availability Statement:
Name: Chest CT-Scan Images Dataset,
Repository –Kaggle

WEB LINK:-
https://www.kaggle.com/datasets/mohamedhanyyy/chest-ctscan-images

Conflicts of Interest: The authors declare no conflicts of interest.
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Ethical Conducted: Not Required

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