Lung disease Detection Employing LungNet-7- a fine-tune CNN Model

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This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering

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APPROVAL

This Project titled "Lung disease Detection Employing LungNet-7- a fine-tune CNN Model", submitted by Easin Arafat, ID No: 191-15-2692 and Asif Ahmed Chayan, ID No: 191-15-2769 to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 04-02-2023.

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I hereby declare that, this project has been done by me under the supervision of **Naznin Sultana, Associate Professor, Department of CSE,** Daffodil International University. I also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.

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ABSTRACT

In current times, there has been a multifold growth in the prevalence of lung illness, which is responsible for millions of deaths yearly. It is now absolutely necessary to have a method of diagnosing lung illness that is rapid, accurate, and reasonably priced in order to address the epidemic. The purpose of this research was to offer a multiclass categorization of lung illness based on forward chest X-ray imaging by employing a finely tuned CNN model. The categorization is based on the four different disease classes that might affect the lungs. These disease classes include COVID-19, tuberculosis, pneumonia, and normal class. The dataset is a compilation of other people's work that was obtained through the open-source website Kaggle. Following the completion of the preprocessing step, all of 7135 X-ray pictures were loaded into the model so that it could perform categorization. At the outset, the dataset was run through five different pre-trained CNN models: VGG16, VGG19, Mobile Net, MobileNetV2, and InceptionV3. After that, a CNN model known as LungNet-7 was used for training purposes. The accuracy reached by the CNN was the greatest among them, coming up at 96.07%. The fundamental structure of the LungNet-7 model was used as the basis for the construction of the in order to further increase the classification accuracy. As part of the research, an ablation study was carried out to identify the various hyper-parameters. The suggested model attained an impressively high level of accuracy of 98.83% by using the Adam Optimizer. As part of the process of validating the performance of the architecture, multiple performance matrices were also constructed.

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CHAPTER 1
INTRODUCTION

1.1 Introduction

Corresponding to the World Health Organization (WHO), lung disease is the third biggest reason of fatality worldwide [1], accounting for an expected total of five million fatalities annually [2]. The lung is a key respirational organ that is not just susceptible to infection from its components but also from the outside environment. Different types of air pollution, microbiological infections, chemical ingestion, or even just plain old physical illness may all appear as lung diseases. COVID-19 has emerged as highest concerning forms of lung illness in recent years. COVID-19 may be identified by determining if a patient has an infection of the upper respiratory tract and lungs in addition to pneumonia and a cold-like symptoms. The city of Wuhan in China was the location where the sickness was initially investigated [3]. The infection caused by COVID-19 makes it harder to breathe because it reasons the air purses in the lungs to fill with fluid that has leaked from the blood vessels. Pneumonia and pneumothorax are two of the most frequent disorders that may affect the lungs. Pneumothorax is diagnosed when air is foun d to be present between the patient's lung and the chest wall. This results in the patient's lung being fully collapsed. Meanwhile, pneumonia is an acute respiratory infection in which pus or fluid fills the alveoli of the lungs [4]. This occurs as a result of an infection in the respiratory tract. A lung disease is present when there is abnormal growth in the lungs. If the growth is more than three centimeters in diameter, we refer to it as a mass. On the other hand, the growth is referred to as a nodule if its diameter is smaller than 3 centimeters. A malignant nodule, on the other hand, As well as spreading throughout the body, lung cancer is also caused by this disease. A benign nodule does not have the potential to become cancerous. The accumulation of fluid is referred to as effusion. An abnormally large quantity of fluid accumulates outside of the lung as well as inside the pleural layers [5]. Pulmonary fibrosis is a condition that develops when the lungs get damaged and scarred; as a result, the tissues become thick and rigid, making it difficult to breathe. The lung is harmed by tuberculosis because it causes the formation of a big hollow inside the lung and exacerbates bronchiectasis. A portion of the lung that has been injured by intraparenchymal hemorrhage is what is known as a pulmonary opacity. In X-ray imaging is a worldwide diagnostic method for illness analysis. When using an X-ray, it is possible to determine the interior physical structure of organs as well as bones [6]. X-rays are very helpful diagnostic tools that have been employed by medical professionals for many years to identify a variety of illnesses, including fractures, some malignancies, pneumonia, dental difficulties, and others. Under extreme conditions, computed tomography (CT) may be used to do a series of body scans, which are then combined to produce an X-ray image that is three-dimensional and is evaluated by a computer. On the other hand, in comparison, a standard X-ray is not only less complicated, but also less time-consuming, less costly, and less intrusive [7]. X-rays are not enough to offer a diagnosis in the vast majority of cases; CT scans are often necessary to confirm the diagnosis [8]. For disorders that progress quickly, several CT scans may be necessary; however, this is not only very expensive and time-consuming, but it also poses a possible health risk to the patient since both CT scans and radiation therapy involve radiation [9]. A chest-related AI system is in urgent need of development [10,11], as a result of this. The study uses deep learning to extract information from photographs about spatial rotation and shape to provide predictions about medical imaging. As a result of CNNs, we are able to identify characteristics and learn patterns that allow us to make predictions [12]. A range of fields have benefited from the integration of AI with machine learning and deep learning algorithms, including medicine [7], biometrics [13], agriculture [14], cloud computing [15], and renewable energy [16]. The use of AI technology in the medical field comes with a number of benefits. For instance, rural areas and third-world nations often lack qualified doctors who are able to provide the essential therapy [17]. Artificial intelligence technologies help these people acquire the necessary medical care by offering access to specialists online. In addition, the healthcare sector will reap considerable benefits from this line of study since medical experts will be able to use it to bolster their diagnosis; in addition, individuals who do not have any prior experience in the medical field will be able to run it. It is possible that even patients will benefit from the use of this technology [18,19]. Because there are only a few specialists, all of this is done to minimize their workload by focusing them only on X-rays that are predicted to be problematic. In addition to this, they drastically cut down on the amount of subjectivity that a doctor has to deal with, speed up the diagnostic process, and accurately pinpoint information that the human eye could miss [20]. In the course of our research, X-ray pictures of the chest were taken from a variety of different locations. The data sets came from many databases [21–36], including GitHub, Kaggle, and the NIH Clinical Center. In addition to the Controlled class, this archive has a variety of X-ray pictures related to lung diseases such as COVID-19, Effusion, Lung Opacity, Mass, Nodule, Pulmonary Fibrosis, Pneumonia, Pneumothorax, and Tuberculosis. Deep learning models make it possible to recognize the symptoms of the illness in a straightforward and expedient manner, which paves the way for a quicker and more precise diagnosis.

This study aims to identify and categorize lung disease hooked on covid19, normal, pneumonia, and tuberculosis at an early stage, thereby reducing the danger of death by supplementary experts in more effective as well as efficient medication. It is crucial to remove noise and artefacts to accomplish excellent execution from a CNN model. Furthermore, the similarity in the middle of impenetrable lung tissue and disease regions might lead to poor interpretation capabilities. By balancing brightness and contrast levels of raw images, it can improve the visibility of diseases lesions. A completely automatic and reliable deep learning model, namely finetuned and hyper-tuned VGG16 established on transfer learning and ablation study, is proposed in this research to classify lung disease in chest x-ray images.

1.2 Problem Statement

As was explained previously, when it comes to lung disease, time is a crucial component in protecting lives. Many nations lack the technology and human resources necessary for patients to receive prompt lung disease monitoring, diagnosis, and treatment services. Numerous tactics and approaches for detection and diagnosis have been proposed by researchers; nevertheless, these systems frequently provide false positive and false negative results. By improving models and image preprocessing methods for early diagnosis and detection, this study aims to reduce radiologists' workload and misdiagnosis rates. The development of a quick and inexpensive method could save lives in underdeveloped, rising, and even advanced countries. It is described how to get good accuracy of brain tumor using best image preprocessing techniques and models.

1.3 Research Objectives

- To investigate research gaps of the existing deep learning based systems to correctly classify different categories of lung disease in their classes.
- To apply a straightforward deep learning based approach for improving the accuracy for separating them in their class.

1.4 Research Questions

- How can we investigate the gaps of the existing deep learning based systems that can correctly classify different categories of lung disease?
- How can we develop a deep learning based approach for improving the accuracy of differentiating different kinds of lung disease correctly in their class?

CHAPTER 2
LITERATURE REVIEW

2.1 Related works

Recently, there has been a growing interest in the ability of algorithms for machine learning, specifically deep learning, to detect irregularities in X-ray images. In some studies, conducted on the topic, artificial intelligence has been shown to improve diagnostic accuracy in the field of medical research. Using artificial intelligence and deep neural networks, previous researchers have been able to treat lung-related conditions such as asthma and COPD using artificial intelligence and deep neural networks. A deep learning model is used to classify chest X-rays and CT scans to diagnose COVID-19, pneumonia, and lung cancer based on chest X-rays and CT scans in [37]. Four different architectures are being evaluated, including a combination of VGG19 and CNN, ResNet152V2 with CNN, GRU, and Bi-GRU. Based on VGG19 + CNN, the model had an accuracy of 98.05 percent. In the paper [38], the authors describe a hybrid deep learning framework called VGG Data STN, which integrates CNN, VDSNet, and a spatial transformer network (STN). As well as enriching the data, the authors used data augmentation. Also included in the study are Capsule Networks, Hybrid CNN + VGG, Vanilla Grays, Vanilla RGBs, and a Capsule Network. Using the VDSNet model that has been proposed, 73% of the validation is accurate. Researchers developed an accurate strategy for identifying COVID-19, pneumonia, and the normal class [39] using the CNN classification approach in combination with histogram-oriented gradient (HOG) feature-extraction techniques. A publicly available X-ray dataset was used to train and validate the proposed CNN model. Verifying the model's accuracy was accomplished through cross-validation and metric confusion. According to [40], the UCMobN model can be used to classify chest X-rays for a variety of lung disorders and make forecasts. In order to create the model, MobileNetV2 is modified. Among the 10 lung illnesses included in the dataset are Atelectasis, Consolidation, Edema, Effusion, Emphysema, Fibrosis, and Infiltration. Mass is also a condition to be considered. A CNN-based model is described in the article [41] for detecting pleural effusions automatically. The paper contains this model. X-ray images of individuals with pleuraleffusion and healthy individuals were used in the study. An accuracy of 95% was found when the CNN model was used to categorize the data during this investigation. Decompose, Transfer, and Compose (DeTraC) is a deepCNN method used by the authors of [42] to handle picture datasets that contain abnormalities. This methodology uses a variety of CNN models, including AlexNet, VGG19, ResNet, Google Net, and Squeeze Net, to categorize data with an accuracy of 97.53%. Using three different deepCNN models that utilize augmented synthetic data, the authors suggest a technique for diagnosing 14 chest-related illnesses [43]. A DenseNet121 model, an Inception-ResNetV2, and a ResNet152V2 model are all used. Multiclass classification was used to find and identify anomalies in X-rays using the recommended models. Based on the X-ray dataset, the researchers in the article [44] classified individuals according to whether they had COVID-19 infection using the Mask R-CNN method. Five-fold cross-validation was used to train the Mask R-CNN for 100 iterations. [45] proposes an architecture for the COVID-aid model based on the design of DarkCovidNet for COVID-19 and pneumonia detection. Six maximum-pooling layers are included in this model and 19 convolutional layers. Based on the particular features described in [46], the authors present a CNN-based classifier for the diagnosis of pneumonia. In this study, X-ray images are analyzed using VGG16, VGG19, NasNetMobile, ResNet152V2, and InceptionResNetV2 models. An article [47] uses DenseNet201, ResNet50V2, and InceptionV3 CNN models to identify COVID-19 patients using chest X-ray images. In order to provide self-contained predictions, the models are first taught independently. A class value is then predicted by combining the models via weighted average assembly. As inputs, the article [48] constructs an automated CNN model that can be used to classify COVID-19 into four severity categories: COVID-19 (Mild), COVID-19 (Moderate), and COVID-19 (Severe).

2.2 Scope of the Problem

As was explained previously, when it comes to lung disease, time is a crucial component in protecting lives. Many nations lack the technology and human resources necessary for patients to receive prompt lung disease monitoring, diagnosis, and treatment services. Numerous tactics and approaches for detection and diagnosis have been proposed by researchers; nevertheless, these systems frequently provide false positive and false negative results. By improving models and image preprocessing methods for early lung disease diagnosis and detection, this study aims to reduce radiologists' workload and misdiagnosis rates. The development of a quick and inexpensive method could save lives in underdeveloped, rising, and even advanced countries. It is described how to get good accuracy of lung disease using best image preprocessing techniques and models.

2.3 Challenges

There are some researches challenges focused on this study which are following:

- **Data Collection:** In medical imaging real medical data is important but in our study we face some difficulties to collect real medical data. For this reason we took datasets from online open source platform kaggle. Therefore, it was very arduous work to accumulate the image data from the lung disease's field.

- **Raw Image Processing**: There is a lot of noise and artefacts in lung disease chest X-ray dataset images, so this study focuses on improving the model's accuracy through image processing techniques. Because images are usually filled with noise and artefacts, image processing is the first step in training a deep-learning model.

- **Select deep learning Approach**: Several researchers use different deep learning techniques to complete the tasks effortlessly. So, the selection of optimum deep learning technique which can correctly classify different categories of lung disease.

- **Accuracy Improvement:** Another challenging issue is to improve the accuracy of the deep learning model. Also another challenging issue is to selecting the optimum model.

CHAPTER 3

MATERIALS AND METHODS

3.1 Working Process

There are four different stages to accomplish the entire work. These are the following:

- Original datasets
- Image Pre-processing
- Model selection
- Result analysis

The total working process starting from image collection to result in the analysis is presented in figure 1 and explains elaborately in the following sections.

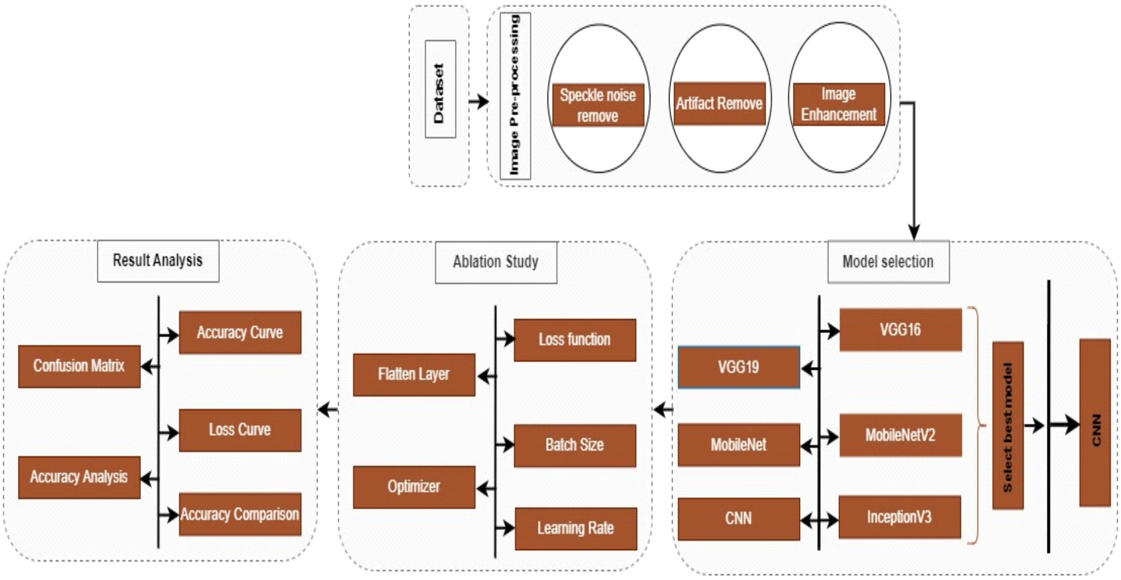

Figure.3.1.1 An overview of the entire classification process

3.2 Dataset Preparation

For the purposes of this study, the dataset contains a total of 7135 photos for analysis. In all, the dataset contains four different classes: covid19, normal, pneumonia, and TB. There are 4273 pictures in the pneumonia class, 1583 pictures in the normal class, 700 pictures in the tuberculosis class, and 556 pictures in the covid19 class. All of the photos in the databases have varying pixel sizes in their grayscale representations. The dataset was obtained via the use of the Kaggle website. As can be seen in Table 1, the dataset is broken down into its component parts as follows:

Table3.2.1 Description of the dataset utilized in this research

Name	**Description**
Images	7135
Color Gradings	Grayscale
Data Formats	PNG
Covid-19	556
Normal’s	1583
Pneumonia’s	4273
Turberculosis	700

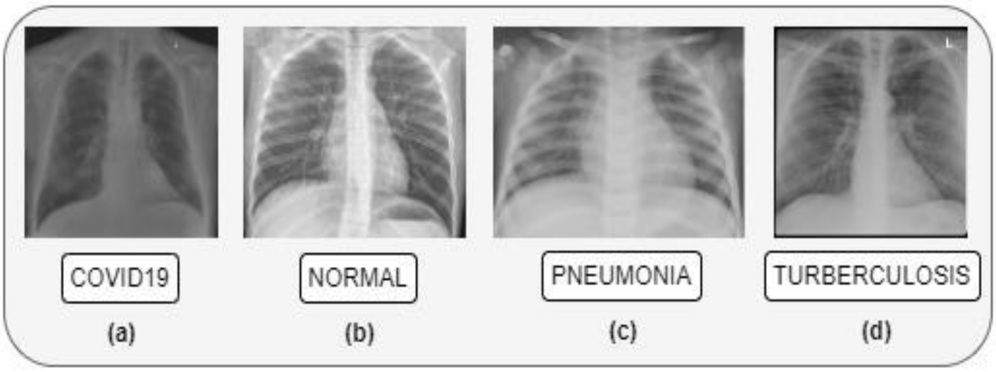

Figure.3.2.2 Example images the datasets

3.3 Image Pre-processing

Because the pictures in the lung disease chest X-ray dataset include a lot of noise and artifacts, the primary objective of this work is to improve the accuracy of the model via the application of image processing. Image processing is the initial stage in training a deep learning model since images are often full of noise and artifacts, which need to be removed before the model can be trained. In order to clean up this picture and get rid of the artifacts, a morphological closure was performed to it. Before that, a median filter was used to get rid of the noise.

3.3.1 Image resizing

Through the process of resizing, we can reduce the size of an image without losing quality. When an image's dimensions are changed, it often results in a loss in quality and an increase in file size [33]. With smaller images, our transfer learning models can train more quickly. If the dimension of the input image is doubled, our network will have to learn from eight times as many pixels, which takes more time. In our dataset there are many large and small combined images. We resized our dataset's images into 224 X 224 [34] from 512 X 512 pixels to get the perfect shape of images.

3.3.2 Median Filter

Median filters are a kind of nonlinear filter that are straightforward and cut down on noise. This is a well-known order-statistic filter that is particularly effective in removing Gaussian noise, as well as random noise and noise with a salt-and-pepper pattern. Image 3 depicts what this step looks like in its physical form.

Figure 3.3.2.1 Output of the median filter

3.3.3 Morphological Opening

The operation that has to be completed should determine the appropriate kernel size for the filter. This research makes advantage of the cv2.getStructuringElement work to produce a rectangular kernel in order to accomplish the task of artifact removal from a picture. The results of this phase are shown in picture which may be seen here.

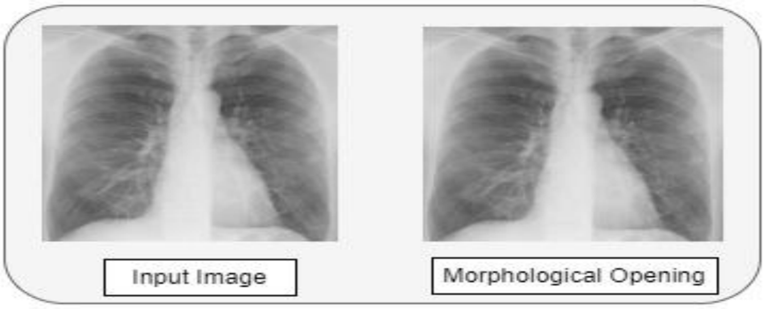

Figure 3.3.3.1 Output of the morphological opening

3.3.4. CLAHE

Clahe's method is used in order to do the calculation necessary to determine the total contrast. In comparison to adaptive histogram equalization, Clahe is a more complex and advanced algorithm. Clahe was developed with the intention of improving the superiority of complex structures in medical imaging [24]. The improvement of medical picture readability may be accomplished by increasing the local contrast [25]. The results of this phase are shown in picture 5.

Figure 3.3.4.1 Output of the Clahe

3.4 Verification

3.4.1. MSE

The pixels in the two images that are being compared have a cumulative squared error, as stated by MSE. Values that are quite near to 0 indicate an exceptional picture quality. Pictures that are free of noise have a value of 0. If the number is more than 0.5, it implies that the quality has decreased.

$$MSE = \frac{1}{AB}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}(O(m,n) - P(m,n))^2$$

3.4.2. PSNR

Before attempting to compute PSNR, it is necessary to first calculate MSE. The ratio of the highest strength of a signal to the power of the corrupting noise that is impacting the quality of a picture is called the signal-to-noise ratio (SNR). The PSNR is then determined by using the following formula:

$$PSNR = 10\log_{10}\left(\frac{Q^2}{MSE}\right)$$

3.4.3. SSIM

The standard statistical image measure (SSIM) reveals that preprocessing methods degrade picture quality. A result of 0 implies that there is no structural resemblance, whereas a score of 1 suggests that there is "perfect structural similarity" [26].

$$SSIM(x,y) = \frac{\left(2\mu_x\mu_y + c_1\right)\left(2\sigma_{xy} + c_2\right)}{(\mu_x^2 + \mu_x^2 + c_1)(\sigma_x^2 + \sigma_x^2 + c_2)}$$

3.4.4. RMSI

RMSE is used to determine the quality of a picture by making a comparison among the initial and the pre-processed image. A good picture with minimal mistakes are indicated by an RMSE value that is close to 0.

$$RMSE = \sqrt{\sum_{J=1}^{N}(d_{fi} - \frac{d_d)^2}{N}}$$

Table.3.4.4.1 MSE, PSNR, SSIM, RMSE value for 5 images

Image	**MSE**	**PSNR**	**SSIM**	**RMSE**
Image-1	12.88	38.35	0.95	0.12
Image-2	14.23	36.79	0.95	0.13
Image-3	15.49	44.36	0.96	0.11
Image-4	14.38	36.36	0.94	0.12
Image-5	14.35	39.28	0.96	0.11

3.5 Proposed Model

As was said earlier, this study investigated a total of five models in order to find the most effective transfer learning model to solve the classification problem. One of the models' focuses was on locating the optimal network in terms of accuracy. Model of Transferable Learning: There are a total of five pre-trained networks, which include InceptionV3, MobileNetV2, MobileNet VGG16, and VGG19. These networks are trained on training data and tested on testing data respectively.

3.5.1 VGG 16

The VGG-16 model is widely considered to be among the most successful examples of transfer learning approaches. Simonyan and Zisserman [28] presented the Deep Convolutional Neural Network model that is known as VGG16. The model received a top 5 test accuracy score of 92.7% in the ImageNet dataset [29]. According to research on the effectiveness of transfer learning [30], a pre-trained VGG16 achieved a much higher accuracy than a fully trained network did. With the increased depth provided by the VGG model, the kernel may be able to learn a greater variety of complex features.

3.5.2 VGG 19

In the VGG19 model, which is a variation of the VGG model, there are a total of 19 layers. The VGG19 model comes to a close with three more FC levels, bringing the total number of layers to 19. Each of these layers has 4096, 4096, and 1000 neurons respectively. In addition to that, there are five Maxpool layers and a Softmax layer that are provided. The activation of ReLU is a feature that is present in layers that are convolutional in nature.

3.5.3 InceptionV3

By making modifications to prior iterations of the Inception design, the recently developed InceptionV3 architecture hopes to minimize the required amount of processing power. Regularizing the data, lowering the dimension, factorizing the convolutions, and parallelizing the calculations are some of the ways that the computational cost may be reduced. The InceptionV3 model includes a label smoothing factorized 77 convolutional layers as well as an auxiliary classifier for the purpose of transmitting label information down the network. InceptionV3 cuts down on the amount of time required for training by using smaller convolutions instead of bigger ones.

3.5.4 MobileNet

MobileNet implements depth-wise discrete convolutions. When compared to a network with conventional convolutions of the same depth, the number of parameters in this network is drastically reduced. As a direct consequence of this, portable versions of deep neural networks have been developed. Two different methods are used in order to produce a depth-separable convolution. The first method is called the convolution at the point of interest, while the second method is called the in-depth convolution. MobileNet, which is a CNN class that Google freely licenses, is an excellent place to begin training our ultra-short and ultra-fast classifiers since it has a large amount of training data.

3.5.5 MobileNetV2

MobileNetV2 is the name that's been proposed by the Google community. It has two distinct types of blocks, and each of those blocks may be stacked to a total of three layers. Every block is comprised of 11 convolutional layers, with 32 filters distributed over the first, third, and second layers respectively. It is very necessary to have longitudinal bottlenecks between layers in order to avoid non-linearity from corrupting a significant amount of data. The two blocks have different strides, with block 1 having a stride of one and block 2 having a stride of two. There is a discrepancy in the strides of the two blocks.

3.6 Proposed best model

The LungNet-7 contains three convolutional layers, and inside each convolutional layer is one max pool layer. The model has three convolutional kernels that are each three times three. In the first block of the convolutional kernel, the dropout value is set to 0.5, and in the second block of the convolutional kernel, the dropout value is set to 32. As the activation function for the topmost layer, the choice that was made was "Relu," and it was followed by "SoftMax." The categorical crossentropy was utilized as a loss function, and the batch size used was 32. The optimizer used was Adam. There is a learning rate of 0.001 per hour.

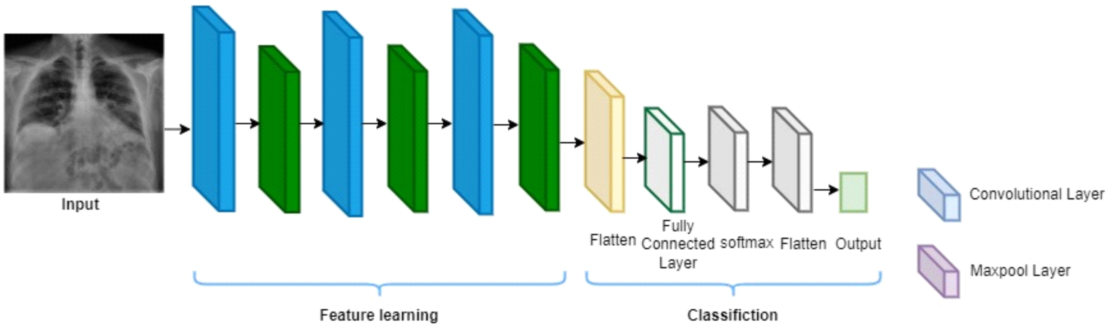

Figure.3.6.1 Basic Structure of LungNet-7 architecture with parameters

3.7 Ablation Study

When working with CNN-based applications, it is common practice to carry out ablation research in order to evaluate the stability and performance of the model after removing or modifying a number of layers or hyper parameters. In this research, the generation of resilient and finely tuned networks is accomplished by the use of hyper parameter ablation. There are five different case studies that have been tested with using the lung disease x-ray preprocessed dataset in this work.

CHAPTER 4

EXPERIMENTAL RESULTS AND DISCUSSION

4.1 Results and Discussion

The mathematical formulas for these performance metrics are as follows:

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

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

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

$$\text{F1 – score} = 2\ (\frac{Precision\ X\ Recall}{Precision+Recall})$$

$$\text{FPR} = \frac{FP}{FP+TN}$$

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

4.2. Model accuracy

The results of the five transfer learning models' training accuracy, test accuracy, and validation accuracy, as well as their train, test, and validation loss, are summarized in Table x. According to table 3, the most accurate model is the VGG-16. This is clear from the data presented there.

Table 4.2.1 Accuracy table of models

Model	**Train_Accuracy**	**Train_Loss**	**Val_Accuracy**	**Val_loss**	**Test_Accuracy**	**Test_loss**
VGG19	95.56	0.24	94.66	0.23	95.24	0.24
VGG16	96.46	0.19	95.85	0.13	95.16	0.19
Mobile Net	95.43	0.18	94.23	0.28	94.24	0.33
Mobile Net V2	95.76	0.25	94.63	0.32	94.59	0.39
Inception V3	76.86	0.421	76.21	0.392	76.21	0.384
CNN	96.98	0.21	96.07	0.22	96.07	0.23

4.3 Result of ablation study:

Reliable design changes may increase categorization accuracy. Five ablation experiments change LungNet-7 parts using improved CNN architecture.

Case Study 1: Changing Flatten Layer

Table 4.3.1 Altering flatten layers

Configuration No.	Flatten layer types	Epochs x training times	Test_accuracy (%)	Findings
1	**Flatten**	**97 x 6s**	**96.83%**	**Highest accuracy**
2	Global Max pooling	60 x 4s	95.24%	Accuracy_dropped
3	Global Average pooling	54 x 5s	96.03%	Accuracydropped

Case Study 2: Changing the batch size

Table 4.3.2 Altering the batch sizes

Configuration No.	Batch size	Epochs x training times	Test accuracy (%)	Finding
1	16	97 x 5s	96.83%	Modest accuracy
2	**32**	**43 x 4s**	**96.93%**	**Highest accuracy**
3	64	82 x 5s	93.65%	Modest accuracy
4	128	27 x 5s	92.06%	Modest accuracy

Case Study 3: Changing Loss Function

Table 4.3.3 Altering losses functions

Configuration No.	Loss Functions	Epochs x training times	Test_accuracy (%)	Findings
1	Binary Crossentropys	Error	Error	Error
2	**Categorical Crossentropys**	**97 x 5s**	**96.93%**	**Highest accuracy**
3	Mean Squared Errors	96 x 5s	96.82%	Accuracy dropped
4	Mean absolute errors	12 x 4s	68.25%	Accuracy dropped
5	Mean squared logarithmic error	45 x 5s	96.83%	Accuracy dropped

Case Study 4: Changing Optimizer

Table 4.3.4 Altering optimizers

Configuration No.	Optimizers	Epochs x training times	Test_accuracy (%)	Findings
1	**Adam**	**97 x 5s**	**98.41%**	**Highest accuracy**
2	Nadam	44 x 5s	96.93%	Previous dropped
3	SGD	91 x 6s	83.13%	Accuracy dropped
4	Adamax	89 x 6s	91.51%	Accuracy dropped

Case Study 5: Changing Learning Rate

Table 4.3.5 Altering learning rates

Configuration No.	Learning rates	Epochs x training times	Test accuracy (%)	Findings
1	0.01	92 x 55s	98.41	Accuracy dropped
2	**0.001**	**97 x 5s**	**98.83%**	**Highest accuracy**
3	0.0001	68 x 57s	98.28	Accuracy improved

4.4 Performance Analysis of Best Model:

Table provides a brief overview of LungNet-7's final setup.

Table 4.4.1 Configuration of best models

Configuration	Value
Image sizes	224 x 224
Epochs	92
Optimization Functions	Adam
Learning rates	0.001
Batch-sizes	32
Activation-functions	Softmax
Dropout	0.5
Momentum	0.9
Accuracy	98.83

4.5 Statistical Evaluation:

Table 5.1.1 Performance Analysis and Statistical Analysis

Accuracy	FPR (%)	FNR (%)	FDR (%)	KC (%)	MCC (%)	MAE	RMSE	Precession	Recall	Specifity	F1 Score
98.83	1.55	2.41	2.56	99.04	88.39	2.11	5.57	96.22	97.39	96.56	96.33

CHAPTER 5

IMPACT ON SOCIETY, ENVIRONMENT AND ETHICAL ASPECTS

5.1 Impact on Society

This project will play an important role in the society. Every year countless people die from lung related problems and many more suffer from it. The main goal of our project is to get more success in less time, with less data loss. In the case of medical data, image quality, brightness, noise is very high, we have pre-processed our database well. As a result, the rate of disease detection has increased and the success rate has increased. As a result of early detection of the disease, the patients can take the treatment of this disease at the right time. As a result, the number of deaths from this disease can be reduced to a large extent and no one will suffer as a result of proper diagnosis. Through correct diagnosis of diseases, a positive perception of technology will be created among the people of the society and the use of new technology and technology in the diagnosis of diseases in the country will increase a lot.

5.2 Impact on Environment

The success of our research will bring good to our surroundings and environment. X-rays that patients undergo to diagnose lung problems are printed in a type of plastic that does not decompose easily and is limited in the recycling process. Billions of X-rays are reported every year which are very harmful to the environment. Which remains around us for thousands of years. But hard copy of x-ray report will not be a prerequisite for diagnosis through our model.Through online copy will be able to identify the disease accurately. This will reduce the amount of plastic used every year. Plastics that remain a problem in the environment. Reducing the use of these plastics will have a positive impact on our environment.

5.3 Ethical Aspects

Due to poor image quality of medical data, there are many times wrong errors in disease detection. Misdiagnosis and wrong treatment can lead to unintended death of a person. So it is our moral responsibility to diagnose the disease correctly and at the right time. So that the disease can be detected at the right time and the right treatment can be given.

CHAPTER 6

CONCLUTION AND FUTURE WORK

6.1 Conclusion

For the principle of training, deep learning algorithms for illness detection in medical imaging need very large datasets that have been annotated. One of the most common tasks in a radiology specialism is the manual annotation of pictures. The unreasonably high costs involved are a barrier to progress in the field of artificial intelligence applied to medical imaging (time and expertise). Transfer learning strategies are now being researched as a potential means of training competitive classifiers with the least amount of money spent on annotations. The method of transfer learning enables models to make advantage of the knowledge they have obtained from working with enormous datasets in order to identify and categorize new data. This paper offers a method for categorizing lung disease chest x-ray pictures more correctly using a transfer learning model. This would result in a reduction in the number of deaths caused by lung disease. Several different preprocessing methods are used in order to clear the picture of speckle noise and artifacts for the purpose of this investigation. Using the dataset consisting of lung illness chest x-rays, we conducted research on five different transfer learning models. After that, a hyperparameter ablation study is performed on the transfer learning model that had the greatest performance overall so that the best possible outcomes may be achieved. The suggested model was able to reach the best level of accuracy as a result of careful hyperparameter optimization.

6.2 Limitations and Future Work

The performance of transfer learning models for multiclass classification was much better than that of conventional classifiers in this experiment. Even if the study has a critical problem in the form of the loss of a considerable quantity of real medical data, the dataset used for the recommended architecture is not big enough. This is the case despite the fact that the research has another major flaw. It is possible that in the not too distant future, bigger quantities of medical photos that have not been evaluated may be deployed in combination with real-time medical data in order to test how effectively the suggested model performs. On the other hand, the results of the vast majority of the tests indicate that the model that was presented

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