

Classification of Lung Diseases using Deep Learning Techniques: A Comparative Study of Classification Algorithms

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Abstract— The significant health impact of lung diseases hampers the life of an individual and his/her family. It is crucial to ensure that everyone lives a healthy life, hence early detection of lung diseases is encouraged at an early stage. As several lung illnesses reduce the life span of people, they are not able to live a healthy life. There are errors in many detection algorithms, so a better algorithm is required to detect such diseases. In this paper, we have discussed lung diseases and how to recognize them. The two primary techniques for identifying lung illness are therefore image processing and deep learning. Deep learning is increasingly emphasized as the preferable method with convolutional neural networks. We further discussed various machine learning algorithms and compared their results with the newly designed algorithm of a convolutional neural network with an autoencoder. There are several approaches described in the literature for classifying medical images. This paper aims to develop a useful tool that will assist medical practitioners in quickly determining if a patient has a lung disease or is at risk of contracting one; by analyzing lung images and examining disease development risk factors with the use of an autoencoder.

Keywords— Machine Learning, Deep Learning, Lung Disease, Convolutional Neural Network, Image Recognition, Disease Grading

I. INTRODUCTION

Understanding lung disorders and their classification has become one of science's most fascinating current topics. The size of medical image databases is expanding quickly due to the documentation of hospital-acquired diseases and the various ways that pathologies, hospitals, and diagnostic centers use medical pictures for different purposes. Even though this problem has been the focus of in-depth research, this topic is still challenging and puzzling [1].

There are several approaches described in the literature for classifying medical images. The main issue with traditional methods is the semantic gap between the high-level semantic information that people perceive and the low-level visual information that imaging technologies gather [2]. Additionally, they increase the reliability of predictions for timely and early disease diagnosis utilizing medical imaging. A growing number of factors are having a detrimental effect on health, including changes in the environment, climate, lifestyle, and other factors [3]. Considering this, this study aims to develop a useful tool that will aid physicians in quickly determining whether a patient has a disease or is at risk of contracting one by evaluating disease development risk variables using machine learning (ML) techniques. This project will be

created by analyzing and classifying the various lung-related X-rays for lung disease prediction [4]. The approach to lung disease prediction is open source, and the implementation makes use of the customized NIH thorax X-ray dataset and datasets of other lung-related diseases taken from the Kaggle and GitHub repositories [5]. Treatments and detection for lung conditions including pneumonia, tuberculosis (TB), and COVID-19 (COV19) are done using ML and deep learning (DL) frameworks and algorithms [6].

ML is making healthcare more intelligent. Hence, doctors and administrators may now make timely, knowledgeable choices regarding patient care and operational programmes that have an impact on millions of lives because of this new abundance of ML-derived insight [7]. Although it has shown promising results in the prediction of lung illness, several issues must be resolved before these algorithms can be used in clinical settings. For ML algorithms to reach great accuracy and sensitivity, they need a lot of high-quality data. After studying and analyzing various ML algorithms, the best algorithms were selected for lung disease prediction, some of those models include DenseNet201, EfficientNetB0, Inception ResNet50V2, VGG-16, VGG-19, AlexNet, autoencoder, etc [8].

Initial processing done for the present experiment aims to improve the image's look by eliminating it [9] to us are able to evaluate it better. Preparation enables removal of undesired deformities or improvement of critical components that are essential to the app's operation. When it comes to medical databases, finding a high-quality image dataset or removing noise from it can be very tedious. Fortunately, we now have access to a variety of technologies and methods that help computer systems handle data compression issues more effectively. One of them is an autoencoder. To put it simply, autoencoders are used to reduce data noise. Autoencoders compress input (i/p) data, encode it and then recreate it as output, allowing you to reduce dimensionality and focus only on areas with genuine value. Since, autoencoders are not used much as can be seen from previous literature studies, hence this project tried to reduce that semantic gap and high-quality data problems with the newly designed algorithm of autoencoder with the help of CNN and catering to problems of high-quality data.

Also, this project employing autoencoders with CNN performs well and may be useful for lung disease diagnosis in the real world. Since the autoencoder is implemented with CNN to improve its result hence the working and architecture of the autoencoder are also explained in the

methodology section.

This paper contains a total of 6 sections, where Section I contains an introduction, and Section II provides a brief idea about related work. Section III gives us the dataset description, and Section IV gives us an overview of the methodology being used, whereas Section V explains the working architecture and Section VI shows the result of all the algorithms that are being used. Section VII contains a conclusion and related work.

II. LITERATURE REVIEW

We have studied several research papers and surveyed them accordingly. The observations from some of those papers are mentioned below.

J Liu et al. [10] suggested 39D Mel Frequency Cepstral Coefficients (MFCC) were utilized to extract characteristics from audio samples, resulting in a structured dataset. 90% selectivity and 85% uniqueness were both attained by the suggested model. A two-layer CNN architecture was put forward by J Amoh et al. located cough occurrences in audio data. The researchers recorded the thorax voices of 14 subjects—7 of each sex—using a wearable chest-fitted sensor, producing a collection of 627 samples. Each sample (cough or non-cough) is of a 64-ms window on which a 128-bin STFT is utilized in order to obtain 6416 spectral segments for input into the two-layered CNN for binary classification, i.e., cough or non-cough. In order to train CNNs, Wang et al. [10] investigated the best techniques for converting auditory inputs into visual images. R. Xaviero et al. [11] selected a logistic regression classifier with a feature set of three cough signal-retrieved spectrum components. A dataset of sound signals from 1980 was examined by the authors, who discovered a sensitivity of 90.31%, a specificity of 98.14%, and an F- score of 88.70%. (Coughing: 980; not coughing: 1000).

J Amoh et al. [12] investigated and chose to learn discriminative features from data rather than manually creating features from cough audio signals in order to distinguish cough audio signals from non-cough audio signals. The sensitivity and specificity of the recommended models by the authors (2dCNN) were 87.7% and 92.7%, respectively.

The authors used five distinct strategies: the original spectrum. Sundararajan et al. proposed a support vector machine for the diagnosis of pneumoconiosis by using several textural signals for unconnected portions of the lung and focusing on a particular category of lung diseases [13]. A recent comprehensive evaluation and meta-analysis of the diagnostic efficacy of existing DL methods for determining whether someone has lung cancer was carried out by Forte et al. [14]. For the identification of lung cancer, the combined sensitivity and specificity of DL methods were 93% and 68%, correspondingly.

According to Hashemi et al. [15], their goal is to increase the effectiveness of the system for diagnosing lung cancer through the use of a region-growing segmentation technique for CT scan lung images. Prior to segmentation, the picture was first pre-processed to remove noise using linear filtering and contrast enhancement techniques. After that, a fuzzy inference method was introduced for recognizing cancer and distinguishing between malignant, benign, and advanced lung nodules. Class analysis is frequently used to fit a probabilistic model to a dataset with several variables, such as allergy or asthma symptoms.

As a result, a number of recent studies have constructed,

verified, and used latent class analysis based on AI and ML for the classification of asthma, proving its suitability for modeling data from symptomatic or asymptomatic asthma patients. Several AI methods that have been developed in the past for CXR applications might be used in the study of COVID lung-infection. The use of AI applications to distinguish between COVID and non-COVID lung infections using CXR and CT has been detailed in a number of studies. Here, several peer-reviewed-prints are referenced [16].

These investigations categorized COVID images vs. non-COVID images rather than grading the severity of lung disease. Unfortunately, the specificity of COVID vs. non-COVID picture categorization for AI-based diagnosis is poor [17]. A reverse-transcription polymerase chain reaction test must be performed on an oropharyngeal swab to make a specific diagnosis. On the other hand, deep-learning AI is well suited to assessing the severity of lung illness.

No studies have employed DL AI to mark the severity of the sickness on the CXR of COVID lung infection, as far as researchers are aware. In a human, artificial neural networks (ANN) can detect lung cancer [18].

A few of the symptoms used to identify lung cancer are yellow fingers, anxiety, chronic illness, exhaustion, allergies, asthma, crouping, less capacity of lung, difficulty swallowing, and thorax discomfort. Together with other bits of the person's information, they served as input variables for our ANN [19].

The "survey lung cancer" artificial neural network was developed, trained, and validated using a data set. Using ImageNet transfer learning and training on a dataset of 10848 chest X-rays, Hwang et al. [20] achieved an accuracy of 90.3% and an AUC of 0.964. Lakhani and Sundaram [21] used pre-trained versions of Google's Neural Network and Amazon's AlexNet to classify pulmonary TB, and they discovered that the pre-trained models were more precise. Lopes and Valiati [22] used feature extractors trained on the GoogLeNet, ResNet, and VggNet architectures together with the SVM classifier to categorize TB. Their AUC varied between 0.900 and 0.912.

The first autoencoders (AEs) were created around the end of the 1980s (Bourlard & Kamp, 1988), but it wasn't until recently (Goodfellow et al., 2016) [23] that their deep variations were applied in practical contexts. In this respect, the objective of deep autoencoders (DAE) is to learn, using a set of weight parameters, an encoding (also known as hidden-features or feature-vector) for a set of (perhaps raucous) initial data that is both compact and intelligible. In order to estimate (decode) the input data, linked weights are frequently used (Goodfellow et al., 2016).

In a wide range of applications, autoencoders and CNNs are now two of the most used algorithms. In order to detect myocardial infarction, Sugimoto et al. [24] analyse electrocardiogram (ECG) data using a CNN. ECG data was seriously out of balance, and it's probable that the minority class, which contains abnormal ECG data, wasn't taught effectively. To solve this facade, the writers advised using the conv autoencoder as follows: If normal ECG data is provided, each lead's convolutional autoencoder (CAE) model is created, producing rebuilt input ECG data. Otherwise, distortion is outputted in the waveform.

CNN model was created by Antonio VAA et al. [25] using a variety of autoencoders that served as the brain network's foundation. To get characteristics, researchers

additionally display their sparsely deeply autoencoder. They both employ SoftMax as a classifier and the Adam optimisation approach. As a consequence, a sparse autoencoder with picture input has a classification accuracy of 98.9%.

III. DATASET DESCRIPTION

There are 7135 chest X-ray pictures in total, which are divided into three sections, train, val, and test these folders further contain subfolders COV19, normal, pneumonia, and tuberculosis [26].

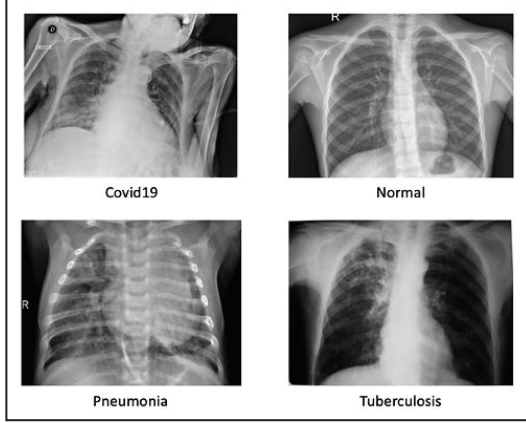


Fig. 1. Description about the Dataset [26]

This dataset is based on chest X-ray pictures where it is divided into 4 categories:

1. COV19
2. Normal
3. Pneumonia
4. Tuberculosis

IV. METHODOLOGY

In the work we have followed 5 steps for determining the In the paper, we have followed 8 steps for determining the lung disease prediction using DL techniques on medical images that have been obtained from Kaggle [26]:

1. **Image Acquisition:** Collected the customized NIH dataset from various Kaggle and GitHub repositories.
2. **Image Selection:** Images were then selected and divided the dataset into 3 subfolders (train, test, val).
3. **Exploratory Analysis (EDA):** Visualized the lung images to check their quality and pixel distribution.
4. **Image preprocessing:** Used autoencoders to denoise the image, and used functions like `cv2.cvtColor()` for changing the color of all lung images from RGB to grayscale, `image.resize()` used for resizing the image into 224x224 pixels, `imread()` for loading images of chest X-rays into the dataset, etc.
5. **Applying Models:** Applied 11 DL models like VGG16, EfficientNetB7, VGG19, etc. using transfer learning techniques.
6. **Autoencoder:** Used autoencoder model with CNN to denoise the chest X-ray images, improving their quality, and performing feature extraction, and dimensionality reduction.
7. **CNN (Adam Optimizer):** Out of all optimizers used for various DL models, it was seen that the Adam optimizer gave the best validation accuracy

hence, it was used.

8. **Prediction:** For the prediction and classification of lung diseases, the best accuracy, and validation accuracy of any model are two parameters that were taken into consideration by training them on different epochs and optimizers.

The first step we followed was data acquisition; we took data that consisted of chest X-ray images from Kaggle and GitHub, then worked on data pre-processing following different techniques to improve the image quality. Next, we did some EDA, i.e., exploratory data analysis, then defined models for classification and trained them using different epochs and parameters. At last, we can predict any image and see which class it belongs to.

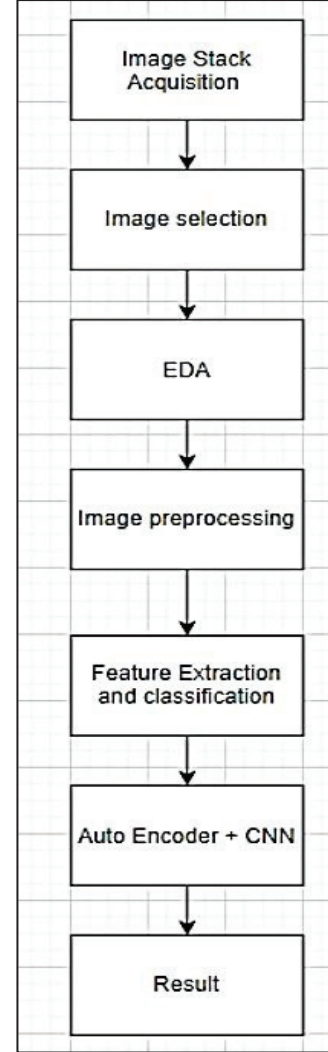


Fig. 2. Methodology

V. ALGORITHM USED

A. VGG16

The most notable feature of VGG16 is that it used the padding and max pool layers from a 2x2 filter with stride 2 along with stride 1 and prioritized the convolution layers of both. This was done rather than using numerous hyper-parameters. The convolution and max pool layer arrangements remain the same throughout the entire design. Its final features are a SoftMax and two FCs (completely connected layers). VGG16's 16 weighted layers are represented by the number 16 in the acronym [27]. The structure as VGG16 is given in Figure 3.

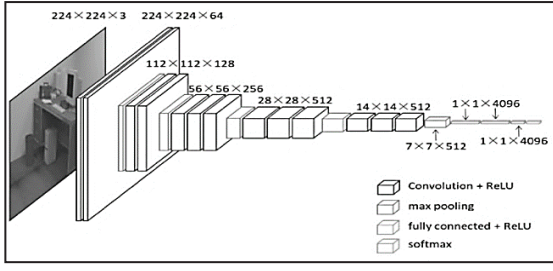


Fig. 3. The Architecture of VGG16 [28]

A 224 X 224 RGB picture is an input for VGG. The picture from the training set is utilized as the input for the VGG convolution network after being calculated as the mean RGB value for all image data.

B. VGG19

A variant of the VGG model known as VGG19 contains 19 layers in total, 16 of which are convolutional, 3 of which are completely connected, 5 of which are MaxPool layers, and 1 layer is SoftMax. Among them are VGG11, VGG16, and different versions of VGG. In all, VGG19 has 19.6 billion FLOPs.

The architecture of VGG19 is given in Figure 4. The network was fed with RGB picture as fixed size ($224 * 224$), demonstrating that the dimensions of the matrix were rectangular ($224, 224, 3$).

The only pre-processing that was done was to take each pixel's mean RGB value over the whole training set and eliminate it. It used kernel as a stride size=1 pixel and a size of ($3 * 3$) to cover the whole visual idea [29].

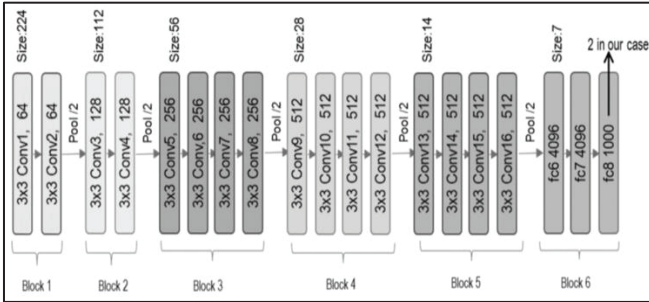


Fig. 4. The Architecture of VGG19 [30]

The picture's dimensions were preserved by using spatially buffering. Stride2 was utilised to carry out max-pooling across a $2*2$ pixels screen. Early versions of the mathematical framework used tanh or sigmoid functions, but they eventually proved to be the most suitable option. The nonlinear nature is used to enhance identification for processed.

C. MobileNetV3

MobileNetV3 is a family of efficient CNNs designed for mobile devices that includes two versions: MobileNetV3- Large and MobileNetV3-Small. MobileNetV3-Large is a state-of-the-art DL model that achieves high accuracy while maintaining a small model size and low latency, making it suitable for deployment on mobile and embedded devices. The model was introduced in a research paper by Google in 2019 [31]. The structure for the MobileNetV3 has been given in Figure 5.

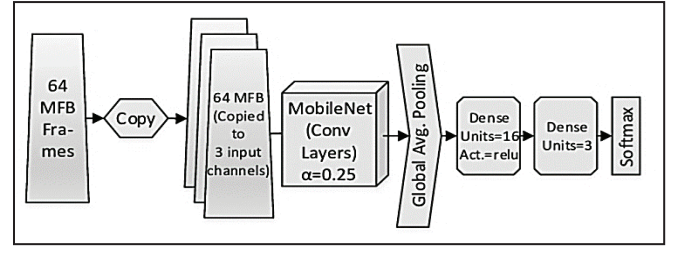


Fig. 5. The Architecture of MobileNetV3-Large [32]

D. DenseNet

Any network which employs DenseNet design has a feed-back connection between each tier. The feature maps of all tiers before it serve as distinct feeds for the various layers plus the levels below, whereas each cell's individual pattern mappings are employed as outputs [33]. Structure for DenseNet is given in Figure 6.

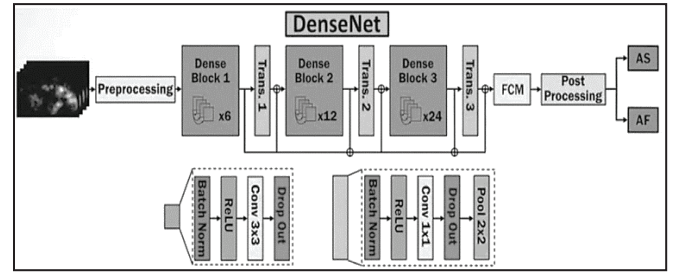


Fig. 6. The Architecture of DenseNet [34]

E. EfficientNetB7

All dimension, length, and quality variables are uniformly scaled utilising a combined factor during the CNN construction and scalability technique EfficientNetB7.

Sizing technique makes utilise an array of preset, fixed values for these elements as opposed to present practise, which adjusts these. The sizing approach makes use of a number of predetermined variables so as to equalise the network's length, depth, and resolution evenly [35]. Figure 7 shows the EfficientNetB7 design.

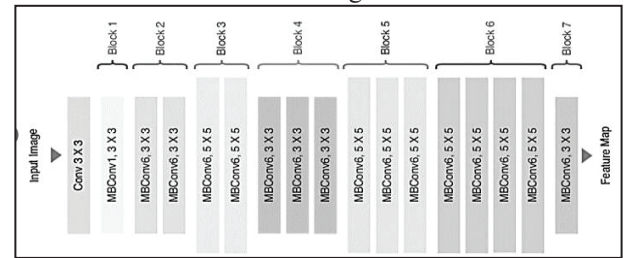


Fig. 7. The Architecture of EfficientNetB7 [36]

F. Autoencoder

An ANN Algorithm referred to as an autoencoder (AE) is utilized to create an appropriate classification for unidentified input. An AE learns two major functions: a decoding utility that reconstructs the incoming data from either the encoding image and an embedding function that modulates the input data. The structure of the autoencoder is given in Figure 8.

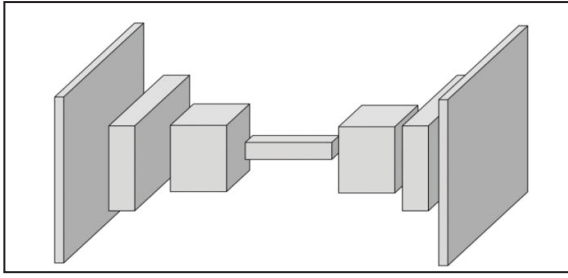


Fig. 8. Structure of Autoencoder [37]

VI. RESULTS

For lung diseases classification, we trained 10 different models in total: InceptionResNetV2, EfficientNetB0, ResNet50V2, DenseNet201, MobileNet, MobileNetV3Large, VGG16, VGG19, InceptionV3, and EfficientNetB7. Using transfer learning, where models are directly called using Keras and Tensorflow, all models were typically trained. We employed transfer learning models that had already been trained on the Image-Net dataset before being trained on our dataset to achieve better results. Image pre-processing was done using the Image Data Generator of the Keras library.

Table I below has discussed the implementation of the model with the following parameters. The default image size is (224,224). The result is obtained with 15 epochs using the Adam optimizer. The following parameters were taken are shown in below Table I:

TABLE I. PARAMETERS

S.No.	Parameters	Values
1.	Target Size	(224, 224)
2.	Target Dimension	(224, 224, 3)
3.	Batch Size	64
4.	Validation Fraction	10% of the data
5.	Optimizer	Adam
6.	No. of classes	4
7.	No. of epochs	15

The accuracy and validation accuracy of various ML algorithms is shown in Table II:

TABLE II. RESULT OF VARIOUS ML ALGORITHMS

S.No.	Algorithm	Accuracy	Validation Accuracy
1.	Autoencoder	0.9955	0.9361
2.	EfficientNetB0	0.9998	0.8610
3.	ResNetV250	0.9998	0.7425
4.	DenseNet201	0.9989	0.7773
5.	MobileNet	0.9998	0.7757
6.	VGG16	0.9997	0.8910
7.	VGG19	0.9996	0.9100
8.	InceptionV3	1	0.7820
9.	EfficientNetB7	1	0.7662
10.	MobileNetV3Large	1	0.5829
11.	InceptionResNetV2	0.9997	0.7725

The above table II clearly explains that the autoencoder with CNN has produced a validation accuracy of 0.9408 which is greater than other ML algorithms like EfficientNetB0, ResNet50V2, DenseNet201, MobileNet, etc. As a result, CNN and Autoencoder were the best tools for diagnosing pulmonary illnesses.

VII. CONCLUSION AND RELATED WORK

The prediction of is to primarily lung disease using DL algorithms is to find a way to make both the patients and the doctors aware of the symptoms, causes, and effects of lung disease. Herein, the categories into which lung disease is divided are just four, but there are 'n' number of categorizations when we get into the medical field of this disease. Within this segment, the categorization is limited because the dataset present is not vast enough to meet every classification need. In the future, we will try to gather data where the classification is more than four, and the algorithms that are used are hybrid. The novelty of working in this sector is that we have tried to incorporate the latest algorithms, like autoencoders, which are in high demand in the sector of DL. The ongoing implementation of ChatGPT has shown a vast usage of autoencoders. The accuracy obtained while dealing with autoencoders is 99.55%, and the val- accuracy acquired is 94.08 %.

In the future, the work can be obtained by using a large image dataset, a comparison should be drawn on various algorithms that are used in DL, and a combination of hybridized models should be incorporated for the final decision-making. The authors can study more on how to combine different types of autoencoders with transformers As well as offering a fresh framework to determine respiratory illness. New model will have the features of both an autoencoder as well a transformer, and we can use different optimizers to find the best results so that both the medical field, as well as those who are studying medicine, will have benefits of the same.

The use of Autoencoders is trying to shape the world for the better use of AI. ChatGPT is trying to shape the domain of user and server interaction at the fastest possible microseconds. Therefore, the use of Autoencoder has an encoder and decoder that takes an encoded part and gives a decoded part. The benefits of using Autoencoder is that it tries to eliminate and get rid of the complexities present. It also helps in reducing the dimensions and helps in dimensionality reduction. Auto encoders constitute a flexible but efficient technique having a wide range of uses in computer-vision. Algorithms may utilise decreasing dimensionality to gather relevant facts and dynamically understand complicated characteristics using data provided.

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