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Article

Diagnosing Multiple Chest Diseases with Deep Learning: A Comprehensive Approach Using X-ray Images

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Abstract: Recent research indicates that healthcare is a critical component of our daily lives, and the medical industry is developing advanced techniques for detecting illnesses as technology continues to evolve. The rapid spread of infectious diseases has a significant impact on people's lives and has caused significant global problems. Unfortunately, the COVID-19 virus is one such disease that is often misdiagnosed as pneumonia or lung cancer. Deep learning technology has made remarkable advancements in identifying diseases from radiographic images such as CT scans, X-rays. Due to a shortage of resources for RT-PCR, early detection of illnesses is difficult. Therefore, chest X-rays can be used to detect severe disorders. This study focuses on the detection of diseases using X-ray image datasets for four conditions: COVID-19, lung cancer, Tuberculosis, and pneumonia. Various deep learning techniques, including VGG16, Densenet, Autoencoder, Resnet, and Convolutional Neural Networks (CNN) are used to identify these disorders. Ensemble learning is applied to diagnosing diseases.

Keywords: convolutional neural network; densenet; autoencoder; chest X-rays; deep learning; medical imaging

1. Introduction

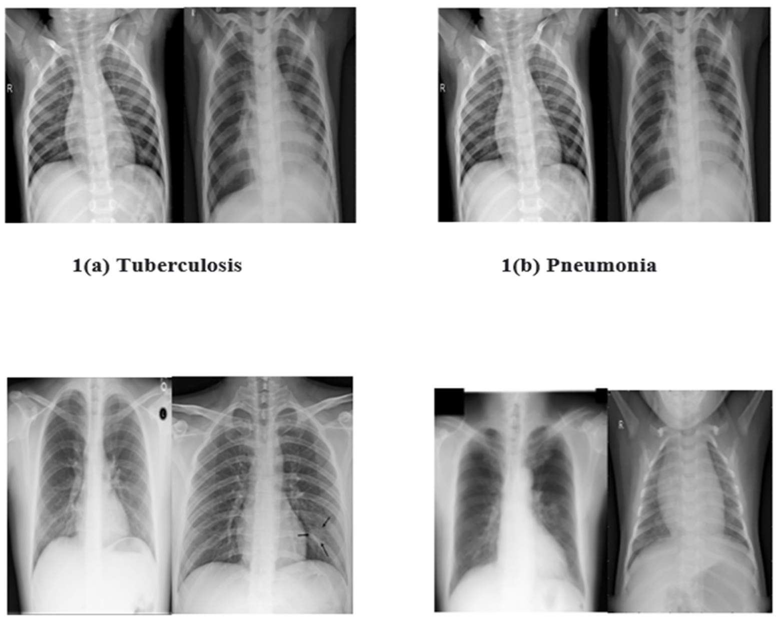
Currently, pulmonary ailments are the most frequently encountered illnesses. With the passage of time, these conditions can have severe consequences on an individual's well-being, and ignorance or failure to detect them early on can even result in death. There are numerous life-threatening respiratory diseases, including lung cancer, pneumonia, tuberculosis, and more recently, COVID-19, which can have a profound impact on an individual's health. Detecting these conditions early on can save a patient's life. In modern times, chest X-rays are crucial in identifying these types of ailments, and the application of machine learning and artificial intelligence is playing a vital role in the medical field.

According to 2022 statistics, one in every 16 individuals will develop lung cancer during their lifetime, and millions of cases are diagnosed annually. Lung cancer is the deadliest cancer compared to other types, but early detection through methods such as chest X-rays, CT scans, and lung cancer screenings can increase the chances of successful treatment with proper medication. Pneumonia is a hazardous respiratory ailment that affects infants, individuals over the age of 65, and those with weakened immune systems. Smoking and air pollution have contributed to 1.6 million deaths among adults aged 50 or older.

Tuberculosis is a contagious illness that can spread between individuals, and it can lead to serious lung issues and even death. Early identification of the disease can prevent others from contracting it. The COVID-19 virus is having a vital global impact and continues to spread through its various variants such as alpha, beta, gamma, and omicron. The WHO reports that COVID-19 has caused approximately 6.68 million estimated fatalities and 659 million documented cases, with 632 million individuals having recovered. By utilizing various pre-processing techniques and implementing a range of algorithms and models for detection, deep learning is playing a crucial role in accurately identifying diseases.

Deep learning can also be utilized to automate time-consuming tasks such as segmentation, classification, monitoring, and predicting treatment responses that radiologists typically perform. Thousands of chest X-ray images representing various diseases, such as COVID-19, Pneumonia, Lung Cancer, and TB, are taken into consideration, and before the model is completely saved, a particular deep learning algorithm is run on each disease. Once the model has been stored as an h5py type, each disease's deployment is sent through a flask. To identify the specific situation, certain CNN models like VGG-19, ResNet15, Dense, and Sequential are used. The performance of the models is enhanced by the use of ensemble learning. This report focuses on a dataset comprising one normal and three diseased cases that will be classified based on the X-ray images. When a chest X-ray image is uploaded, the result shows the likelihood that each disease will present itself in the form of a bar chart.

The figure below, Figure 1, describes the chest X-ray images that have been collected for the datasets used in this project. These are the samples showing one disease-affected X-ray and the other is a normal X-ray image of diseases like lung cancer, pneumonia, COVID-19, and tuberculosis.



1(a) Tuberculosis **1(b) Pneumonia**

1(c) Covid **1(d) Lung Cancer**

Figure 1. Sample chest X-ray images.

2. Literature Survey

This article focuses on using inexpensive and commonly available X-ray imaging to identify diseases early on. Three stages namely feature extraction, dimensionality reduction, and classification make up the proposed paradigm. Images of the chest are the input for this model, and the output is the image's classification into one of four groups: COVID-19, Normal, Pneumonia, or Lung Cancer. Three distinct convolutional neural network models were utilized to analyze chest X-ray radiographs to identify coronavirus-induced pneumonia in infected patients: InceptionV3, ResNet50, and Inception-ResNetV2 [1].

The focus of this article is on detecting diseases in their early stages using X-ray images, which are readily accessible and affordable. The authors propose a three-phase model for this purpose, comprising feature extraction, dimensionality reduction, and classification. To perform feature extraction, they employ a combination of Xception and InceptionResnetV2 ensembles, which are then fed into a sparse encoder to reduce dimensionality. A feed-forward neural network processes the resulting feature vector to perform classification. The authors built a single CNN model that could recognize different diseases by concatenating many pre-trained networks [2].

The authors addressed 11 different pre-trained convolutional neural network models and tested them on an image dataset containing normal as well as three types of diseased cases. The study found that DenseNet169, ResNet50V2, and DenseNet169, VGG16 models performed the best in detecting COVID-19, viral pneumonia, and pneumonia images, respectively. To achieve optimal classification performance of pulmonary illnesses in X-ray images, several reliable and selective deep learning models were utilized. The researchers also acknowledged the need for securing COVID-19 patient data and plan to incorporate security and privacy measures in the next version of their deep learning system for the transfer of medical images through common communication networks [3].

The author proposed creating and assessing a profound learning architecture for the multi-class classification of different chest illnesses. Among the afflictions were TB, pneumonia, lung mistiness, lung cancer, COVID-19 and Normal. The collection comprised 3,615 CXR pictures of COVID-19 and 20,000 X-ray pictures of lung cancer from different open sources. 5,856 CXR photographs of pneumonia and 6,012 CXR pictures of lung opacity from the RSNA (Radiological Society of North America) were also included. The model's execution was essentially enhanced and its capacity to recognize a wide extend of sicknesses was enlarged much appreciated to the outfit of VGG19 + CNN utilized within the think about. VGG19 + CNN had a 96.48 accuracy, 97.56% precision, 93.75% recall, 99.82% AUC, and 95.62 F1 score based on the information [4].

The author discussed data that has to be divided up into many categories. The categories comprised COVID and Normal as a two-class classification, COVID, Normal, and Pneumonia as a three-class classification, and COVID, Normal, Non-COVID Viral Pneumonia, and Non-COVID as a four-class classification. The model's outcomes were examined and approved by a clinician, and the suggested model is supported by data. The proposed model's accuracy rates for the two-class classification, the three-class classification, and the four-class classification were 99.1%, 94.2%, and 91.2%, respectively [5].

To increase accuracy, a block-based STM-RENet via CNN with channel boosting was utilised to find Covid-19 in chest x-rays. As an extra method to provide the algorithm more information from two sources of data, channel boosting was used. F-score (0.98 for both STM-RENet and CB-STM-RENet), MCC, and channel boosting (97.98% for STM-RENet and 98.53% for CB-STM-RENet) were used to assess the model's performance. STM-RENet and CB-STM-RENet have MCC values of 0.96 and 0.97, respectively [6].

The author addressed about the tested with numerous lightweight models by training them on a chest X-ray images dataset from pediatric patients aged one to five years in order to find a compromise between accuracy and performance on low-complexity platforms [7].

According to the report, two of the most significant datasets for identifying pneumonia are the Chest X-rays 14. The experimental findings demonstrate that logistic regression outperforms classifiers with accuracy, specificity, sensitivity of 96.63%,97.57%,93.68%. Yet, out of all the classifiers examined, naive bayes analysis has the highest overall accuracy [8].

The extensive dataset that was employed in the study provides evidence that deep models outperform shallow systems. The best results were obtained by AlexNet, which had a loss of 0.153 and an overall accuracy rating of 94.7%. The model obtained, 0.94 recall, 0.94 F1 score, and 66 specificity, 0.94 precision [9].

The model was demonstrated to be generalizable to new dataset on which it is a step in the right direction towards creating a reliable computer-aided diagnostic tool. Unfortunately, it was discovered that building a deep neural network from scratch takes a lot of effort and computation to perform at its best [10].

The main aim of this investigation is to identify the diseases, notably pneumonia, COVID-19, and tuberculosis, that can be predicted from chest x-rays. Using pre-trained CNN models like VGG19, Resnet50V2, and Densenet201, they created a fully automated sickness classification system to accomplish this [11].

The author talks about the chest X-ray images that can be used to identify COVID-19 using deep learning algorithms. The images were 299 by 299 by 3 pixels in size and were retrieved in PNG format. The popular and reliable CNN technique can accurately diagnose COVID-19 from digital photos. ResNet50, one of the CNN models examined, performed with the best test accuracy, scoring around 86% [12].

The study is constrained by the scant availability of COVID-19 X-ray images of regularly updated public dataset. The model immediately recognizes chest X-ray pictures rather than employing a feature extraction method, giving medical personnel an effective tool for establishing diagnosis. An expert radiologist evaluates the heatmaps the model produces [13].

Transfer learning was used, which entails taking models that have been trained on substantial datasets and modifying them in various ways to address the current issue. A high accuracy rate of 99.5% from the categorization accuracy calculation may be useful in clinical practice. Deep learning models might be enhanced by future study [14].

This article examines a number of CNN-related topics, such as training, data augmentation methods that go beyond lung X-ray pictures, and preprocessing settings that can be adjusted to certain systems [15].

Utilizing Chest Radiographs for Disease Identification

Chest radiography could be a common demonstrative imaging test utilized in medical hone, and can be utilized within the recognizable proof of infections such as penetration, atelectasis, cardiac hypertrophy, emission, protuberances, knobs, pneumonia, and pneumothorax [16]. Later large-scale datasets have empowered ponders utilizing profound learning for robotized chest radiograph conclusion. A later ponder displayed a CNN prepared and tried on ab-normal and ordinary radiographs, yielding an AUC of 0.98, affectability of 94.6%, and specificity of 93.4%. Despite this victory, profound convolutional neural systems can be prepared to recognize irregular chest X-rays to prioritize ponders for a quick survey and announcement. Past strategies have as it were been able to distinguish one or several illnesses from the chest radiograph. In any case, profound learning strategies can examine the appearance of different sorts of suspected diseases at the same time and directly from the chest radiograph. Profound learning strategies have appeared more precision within the classification of different sorts of suspected diseases from chest radiographs as compared to conventional computer-aided conclusion procedures [17]. Analysts require numerous chest radiographs for the preparation, approval, testing, and execution of comparisons of CAD frameworks. Moreover, the sweeping statement of the systems prepared with constrained datasets is deficient. To advance move forward the classification capacity of profound learning methods, a more agent dataset ought to be made based on existing datasets. Chest radiographs carry additional prognostic data past conventional symptomatic findings. Actualizing modern models like CXR-Lung-Risk into the EMR or PACS seems to increment the demonstrative esteem of chest radiographs [18].

3. Methodology

To develop a methodology for detecting diseases using chest X-ray images, we follow these steps as in Figure 2:

1) **Data Collection:** Collect a large dataset of chest X-ray images annotated for the presence of various diseases, such as pneumonia or tuberculosis. Make sure the dataset is diverse, representative, and balanced to avoid biases in the model.
2) **Data Preprocessing:** By scaling the images to a uniform size, standardizing the pixel values, and dividing the dataset into validation, training, and test sets, the data is made ready for deep learning. To expand the training dataset and enhance the model's robustness, think about using data augmentation techniques like random rotation and flipping.
3) **Model Selection:** Choose a suitable pre-trained deep learning model, such as VGG16 or VGG19, or design a custom CNN architecture for the disease detection task. Consider using transfer learning to fine-tune a pre-trained model on the medical images dataset to reduce the amount of training data required.
4) **Model Training:** Use a suitable loss function, such as binary cross-entropy or categorical cross-entropy for multi-class classification, along with an optimization technique, such as stochastic gradient descent (SGD) or Adam, to train the chosen model on the training dataset. To avoid overfitting, monitor the model's performance on the validation dataset and employ strategies like early halting and learning rate scheduling.
5) **Model Evaluation:** Use metrics like accuracy, precision, recall, and F1 score to gauge the model's performance on the validation dataset and determine its propensity to detect illnesses in chest X-ray pictures. Visually evaluate the instances that the model is incorrectly classifying to look for any trends or biases.
6) **Model Fine-Tuning:** Adjust the model's hyperparameters, such as the learning rate and the number of layers, or train more layers of the network to make it more precise. To methodically explore the hyperparameter space and identify the optimal model configuration, think about employing methods like grid search or random search.
7) **Model Testing:** Use the test dataset to run the final model and metrics like accuracy, precision, recall, and F1 score to assess its performance. Compare the model's performance to that of other cutting-edge techniques, and then talk about the findings in terms of the model's advantages and disadvantages.
8) **Deployment:** Deploy the final model in a clinical setting and use it for real-world predictions, making sure to use it in conjunction with clinical interpretation and confirmation by trained

medical professionals. Consider integrating the model into a user-friendly interface, such as a web application or mobile app, to make it accessible to healthcare professionals and patients.

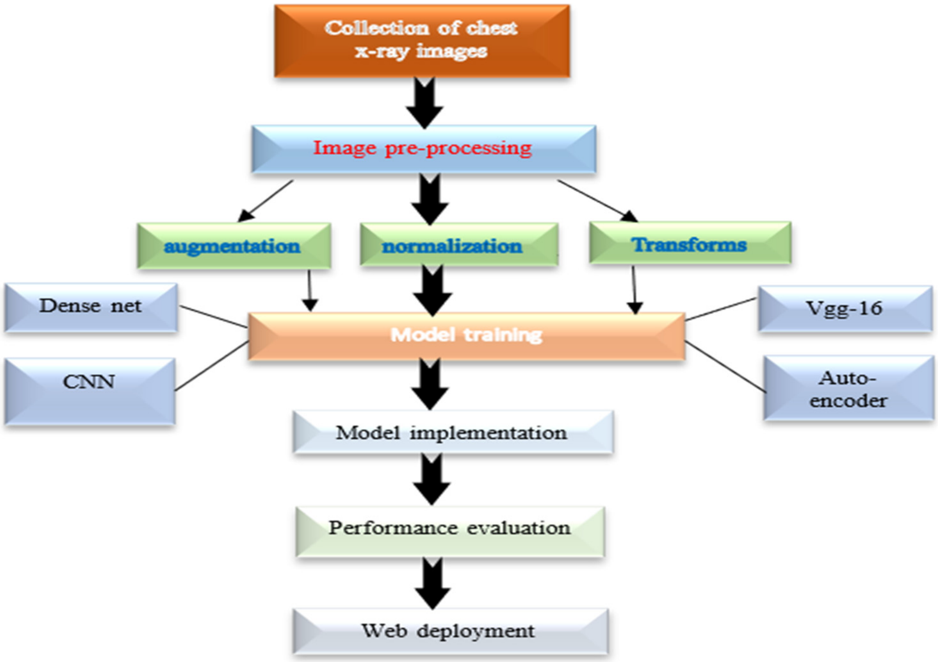


Figure 2. Model Architecture.

3.1. CNN Architecture

Figure 3 describes the CNN architecture for disease detection in chest X-ray images involves three main layers: convolutional, pooling, and fully connected layers. CNNs are a type of neural network that works well with data arranged in a grid-like structure. The convolutional layer is the core component of the CNN and performs most of the computational tasks. The pooling layer, on the other hand, reduces the spatial dimension of the feature maps and helps to decrease the computational load. Lastly, the fully connected layer is connected to both the preceding and the current layers.

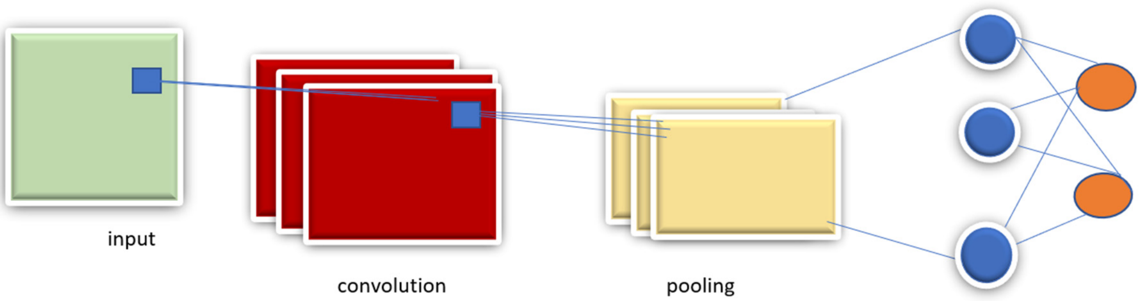


Figure 3. CNN model.

3.2. VGG-16

The VGG16 architecture is comprised of 16 layers, consisting of 13 convolutional layers, 3 fully connected layers, and 5 max pooling layers. To improve its accuracy, the model is trained on large amounts of data and employs techniques like data augmentation, dropout, and batch normalization. The initial layers of the VGG16 architecture identify basic features like edges and textures, while the subsequent layers employ these features to recognize more intricate shapes and patterns. The last layers of the model generate the image classification outcomes. Due to its high accuracy and excellent generalization performance. In a variety of computer vision tasks, including object detection, semantic segmentation, and image classification, VGG16 is frequently utilized. By changing the fully linked layers, it can also be modified for particular applications.

3.3. Auto-Encoder

Figure 4 specifies an autoencoder which is a specific architecture of neural network used for unsupervised learning in deep learning. Its primary aim is to obtain a compressed representation of the input data, which is called the "encoding". The autoencoder comprises two main parts: the encoder and the decoder. The encoder accepts the input data and maps it to a lower-dimensional representation, which is the encoding. The decoder then receives the encoding and transforms it back to the original data, which is known as the reconstructed data. The fundamental goal of an autoencoder is to minimize the distinction between the input data and the reconstructed data. The encoding can be used for various purposes, such as data compression, dimensionality reduction, and anomaly detection. Training an autoencoder on a vast dataset can enable it to recognize patterns and regularities in the data, and thus produce a more efficient representation of the input data. Moreover, an autoencoder can be used as a pre-training step for other deep learning models, such as supervised learning models. This pre-training can enhance the performance of the downstream model by providing a better initial representation of the input data.

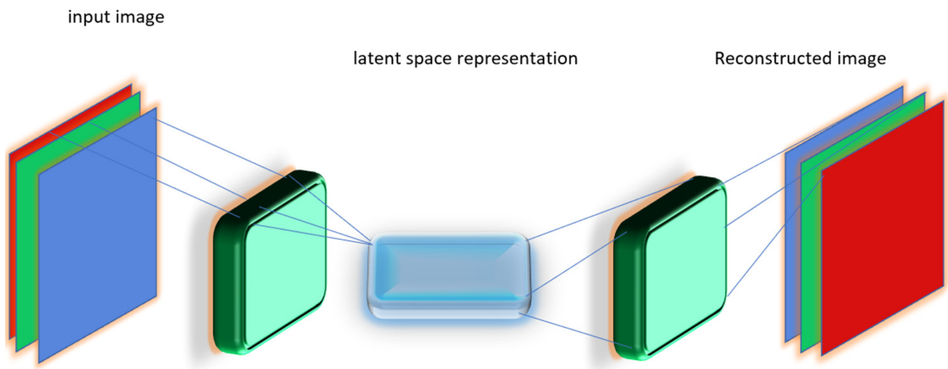


Figure 4. Autoencoder.

3.4. Dense-Net

A dense layer is a type of layer widely used in deep learning models that are made up of a group of neurons, with each neuron linked to all neurons in the previous layer. This differs from other types of layers, such as convolutional layers, in which the neurons are only linked to a local region of the prior layer. Typically, the dense layer is employed in the final stages of a deep learning model to generate output predictions. The dense layer receives activations from the previous layer, which may have been processed by several convolutional and pooling layers, and utilizes them to make a prediction. To produce the output, the dense layer employs a set of weights and biases to execute a linear combination of the activations. The dense layer is a crucial element in many deep learning models since it enables the model to utilize the knowledge learned by the prior layers to make a final prediction as shown in Figure 5 Depending on the specific task's requirements, the dense layer can also be changed to produce a different number of output neurons.

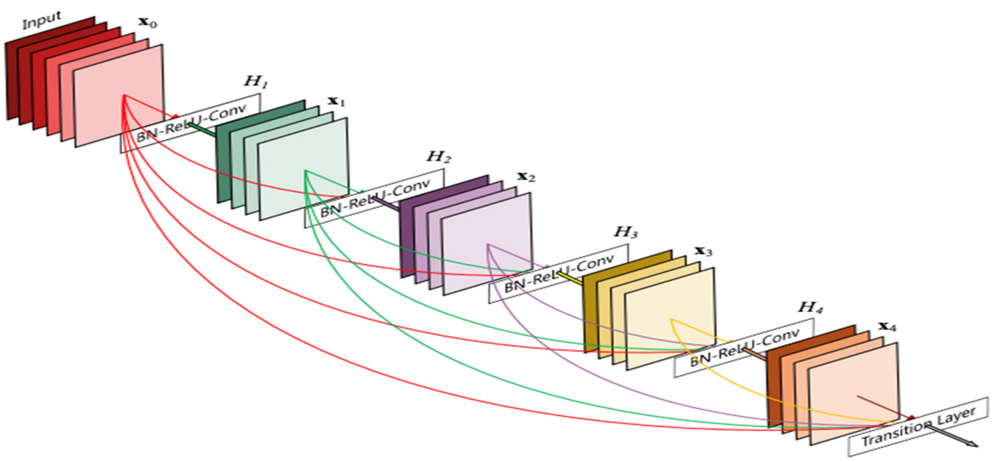


Figure 5. Densenet.

4. Proposed System

In this setup, as shown in Figure 6, sets of chest X-ray images for pneumonia, lung cancer, tuberculosis, and COVID-19 are collected separately from different sources on the internet, with a total of 5600 images. Various models are utilized for detecting each disease. Initially, image data is preprocessed using different augmentation and normalization techniques, along with image data generators. Subsequently, a convolutional neural network model is employed for each disease detection. For pneumonia detection, models such as VGG16, sequential models, and CNN are used. For COVID-19 detection, Densenet, sequential models, and CNN are utilized. For tuberculosis detection, the China chest X-ray dataset and Montgomery dataset are combined into a single folder, with the dataset normalized via batch normalization. An autoencoder model is then applied to the images, followed by training of the data to detect whether the chest X-ray report indicates tuberculosis or is normal.

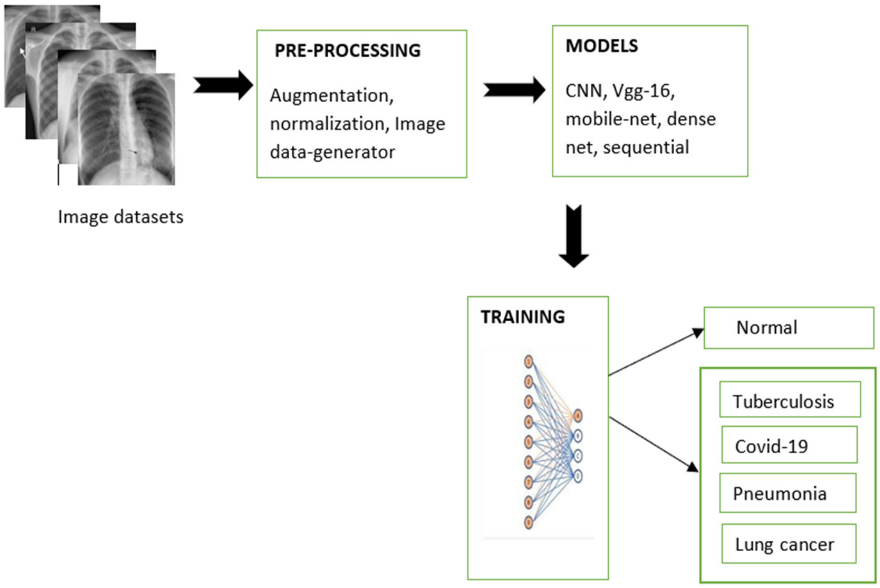


Figure 6. Proposed model.

For lung cancer, chest X-ray images are compiled from various resources on the internet and Kaggle datasets, containing images of both lung cancer patients and normal individuals. In the first step, image data is augmented and normalized during the pre-processing stage. Then, the training data is divided into batches using a data loader. Subsequently, an Artificial Neural Network (ANN) model is applied to the data, followed by training of the model. Finally, the accuracy and loss of the model are visualized, and the entire system is implemented using PyTorch in Google Colaboratory.

The project’s front end is depicted in Figure 7, highlighting the home page where users can explore descriptions of different chest diseases. Additionally, hyperlinks are provided for disease detection.

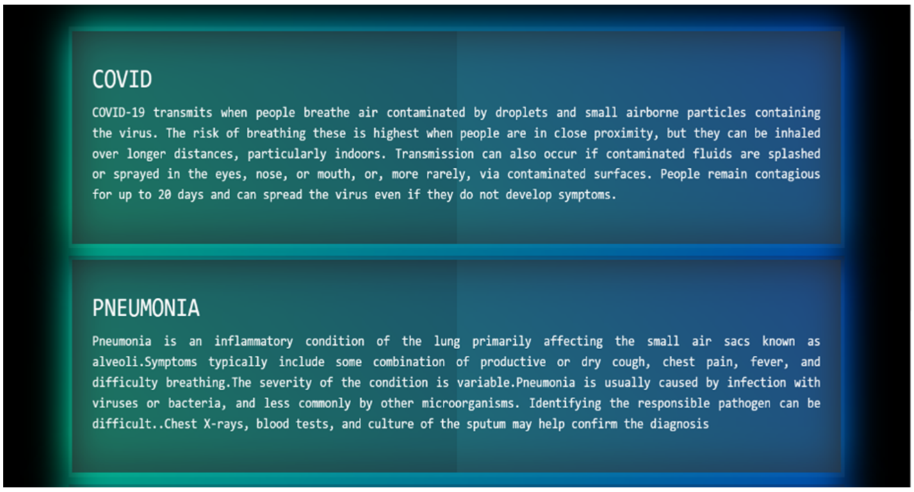


Figure 7. Home Page.

A web page has been created to enable users to upload chest X-ray images, as shown in Figure 8. The system utilizes these images for the detection of specific diseases through analysis of the X-ray images.

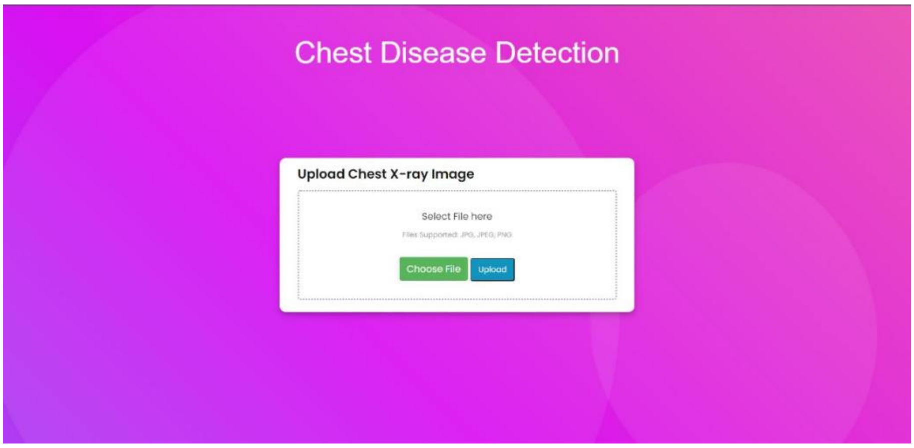


Figure 8. Image upload page.

The uploaded image undergoes the steps outlined in our proposed model, and the outcomes are presented in the figures below. Each image features a graph illustrating the accuracy of the specific disease.

Figure 9 describes the result for Pneumonia-affected cases,
Figure 10 describes the result for COVID-19-affected cases,
Figure 11 describes the result for Lung cancer-affected cases, and
Figure 12 describes the result for Tuberculosis-affected cases.
In each graph, higher values indicate a higher likelihood of the corresponding disease being identified.

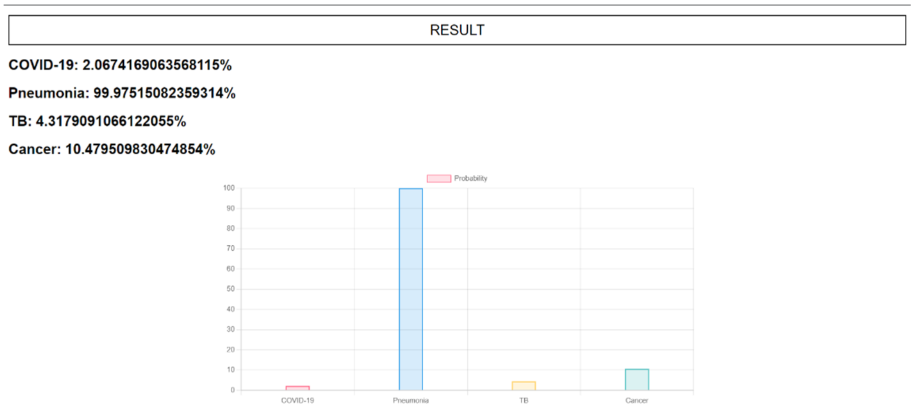


Figure 9. Results Page—Pneumonia affected.

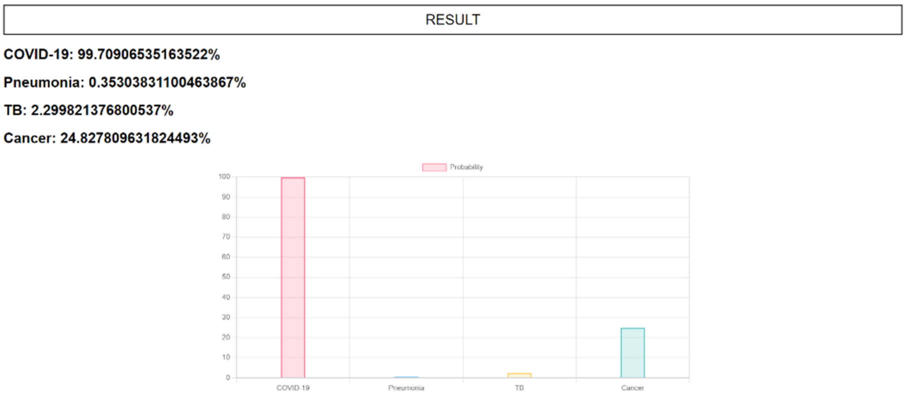


Figure 10. Covid affected.

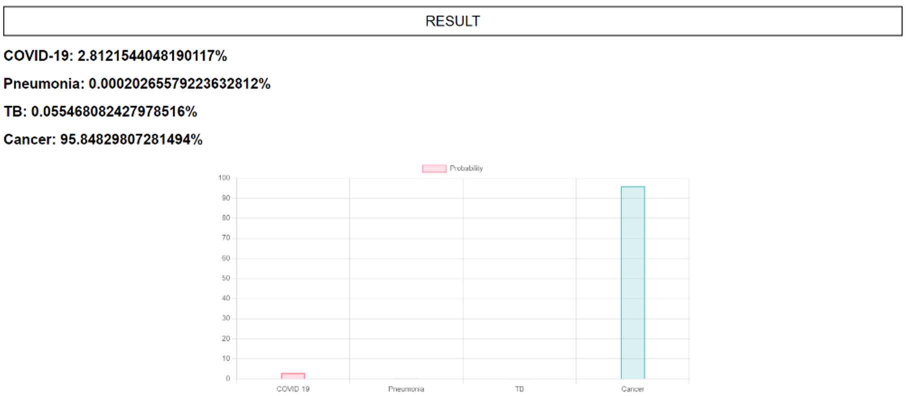


Figure 11. Lung cancer affected.

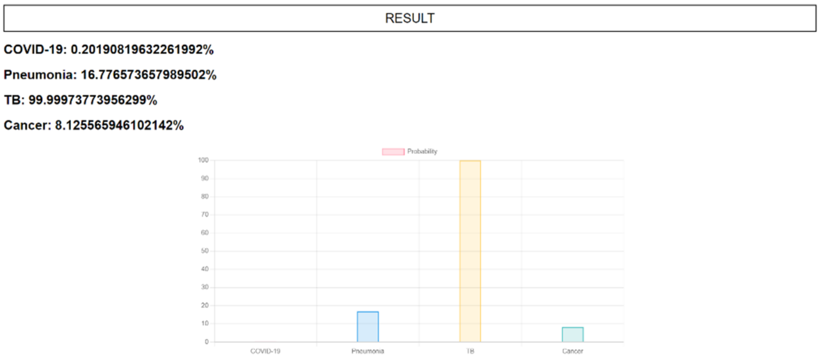


Figure 12. Tuberculosis affected.

5. Results and Discussion

5.1. Existing Methods

In this work, four architectures—VGG19 + CNN, ResNet152V2, ResNet152V2 + GRU, and ResNet152V2 + Bi-GRU models—were provided in relation to the various accuracy and loss for diseases including pneumonia, COVID-19 lung cancer, and normal.

The performance of each model for each disease is presented in Table 1 as follows:

Table 1. Existing Methods Performance.

Models	Loss	Accuracy	F1-Score	Recall
VGG19+CNN	0.3280	98.05	98.24	98.05
ResNet152V2	0.1693	95.31	95.31	95.31
ResNet152V2+GRU	0.1350	96.09	96.09	96.09
ResNet152V2+Bi-GRU	0.2554	93.36	93.26	93.16

5.2. Proposed Methods

This paper involves Deep Learning models such as CNN and ANN models for the detection of diseases. For each disease Detection for pneumonia, VVG-16 performed well with an accuracy of 95%. For lung cancer, the ANN model acquired an accuracy of 99% for the Tuberculosis auto-encoder model acquired an accuracy of 92%, and for covid-19 Neural-Net+ Conv-Net acquired an accuracy of 96% as shown in Table 2.

Table 2. Performance of each model for each Disease.

Disease	Model	Accuracy	Loss
Pneumonia	VGG-16	0.95	0.1521
Lung cancer	ANN	0.99	0.14
Tuberculosis	Auto-Encoder	0.92	0.2012
Covid-19	NeuralNet+ ConvNet	0.96	0.1216

5.3. Sample Results

The sample results, denoting the accuracy and loss graphs for training and validation, are illustrated in the following figures:

Figure 13 displays the accuracy and loss graph for COVID-19. Figure 14 showcases the accuracy and loss graph for Lung Cancer. Figure 15 represents the model accuracy and model loss for Tuberculosis disease. Figure 16 exhibits the accuracy and loss graph for Pneumonia.

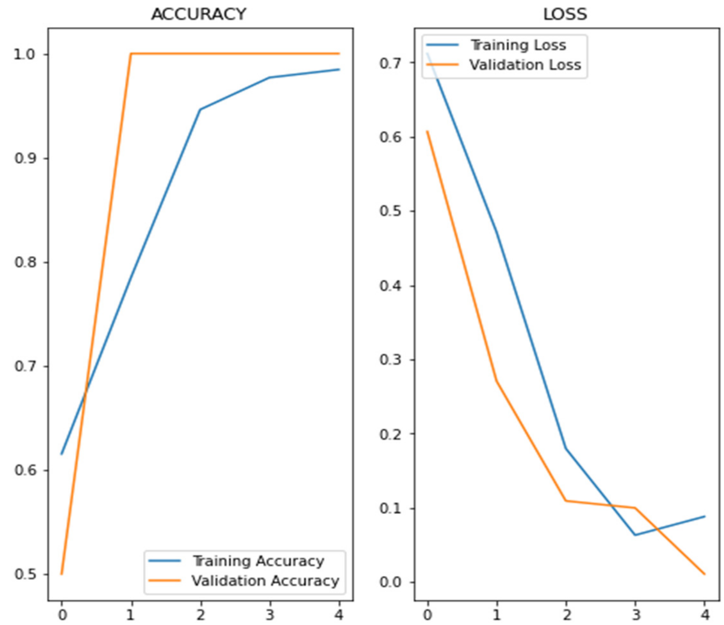


Figure 13. COVID-19.

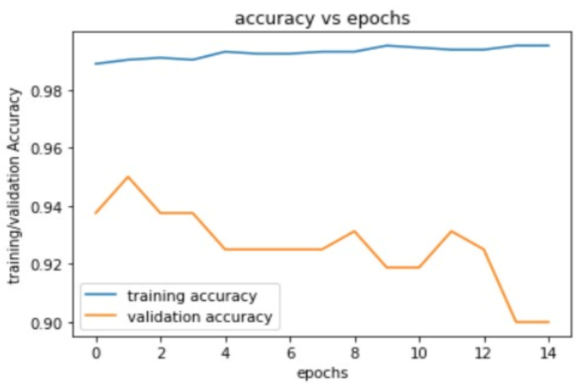


Figure 14. Lung Cancer.

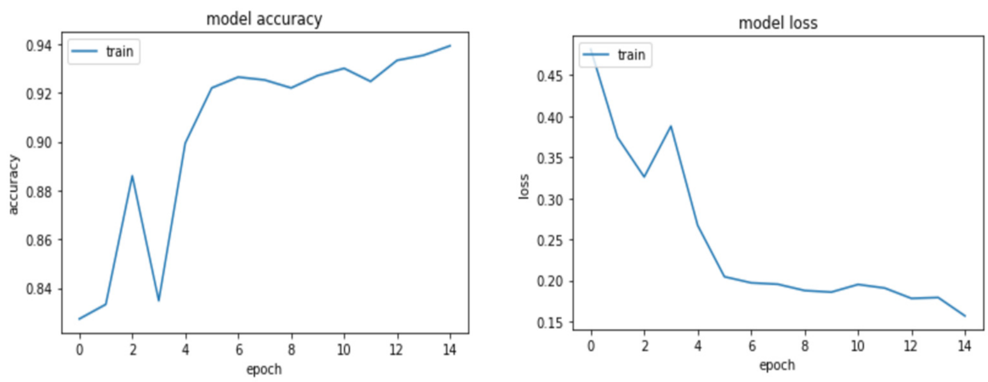


Figure 15. Tuberculosis.

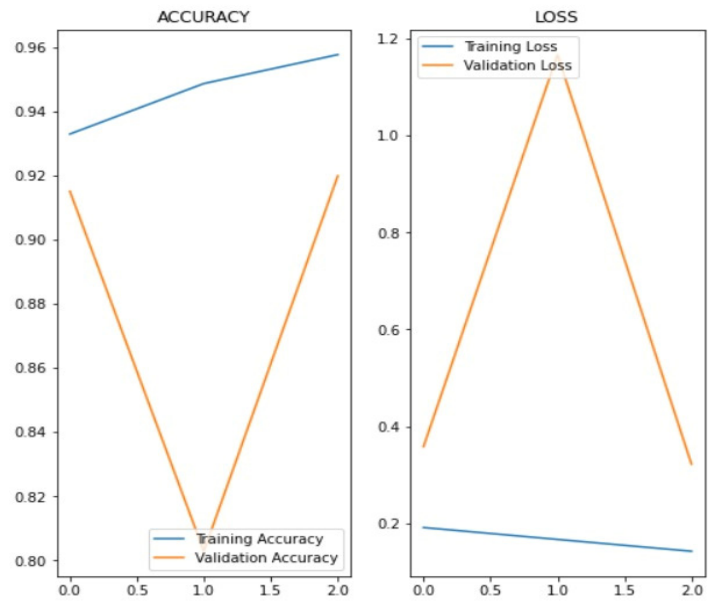


Figure 16. Pneumonia.

5.4. Comparison Results

Figure 17 presents a comparison between the existing system and the proposed system in terms of accuracy for the diseases Pneumonia, Lung Cancer, and COVID-19.

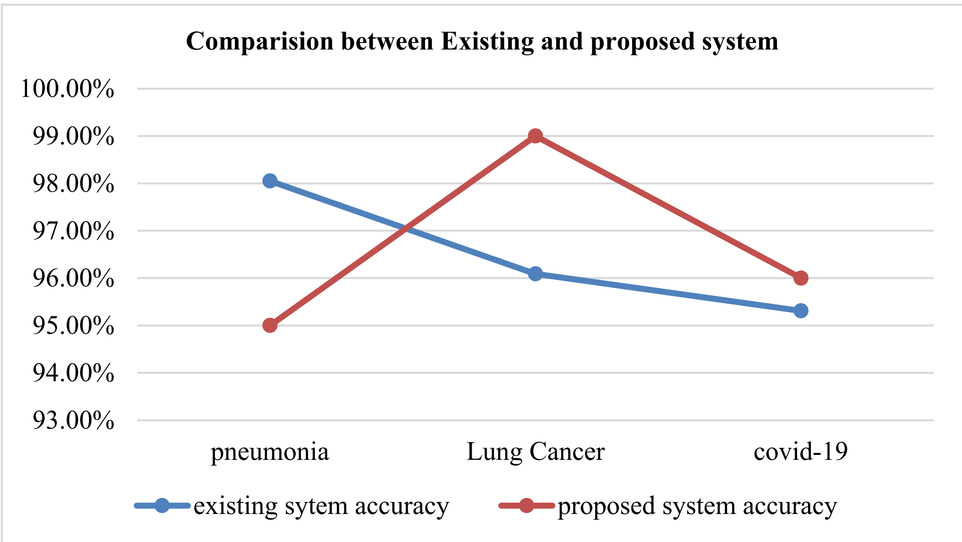


Figure 17. Comparison graph.

5.5. Conclusions and Future Scope

In conclusion, a promising method for the early detection and diagnosis of diseases like pneumonia and tuberculosis is the deep learning model for disease detection utilizing chest X-ray pictures. The model can learn and extract information from X-ray pictures using convolutional neural networks (CNNs), which can be used to categorize an image as healthy or diseased. This study underscores the value of additional research in this field and shows the promise of deep learning models in medical imaging. These models could help medical professionals make more accurate diagnoses in the future by increasing their accuracy and resilience enhancing patient outcomes as a result. Future research should concentrate on increasing accuracy. Although the current model can only identify a few diseases, it can be expanded to identify additional diseases. X-rays of the chest are only one sort of medical imaging. To develop a multi-modal diagnosis model, you can consider integrating chest X-rays with other types of imaging, like CT and MRI scans.

Author Contributions
Conceptualization, N.Y. and G.P.; methodology, J.k. and N.Y.; software, S.E.k.; validation, S.E.k.; formal analysis, G.P.; investigation, J.k.; resources, G.P.; data curation, J.k.; writing—original draft preparation, N.Y. and G.P.; writing—review and editing, N.Y. and J.k.; visualization, S.E.k.; supervision, N.Y.; project administration, N.Y. All authors have read and agreed to the published version of the manuscript.

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Conflict of Interest Statement
The authors declare no conflicts of interest.

Data Availability Statement
The datasets analyzed during the current study are available in the Kaggle repository.

References

1. Gayathri, J.L., Abraham, B., Sujarani, M.S., & Nair, M.S. (2022). A computer-aided diagnosis system for the classification of COVID-19 and non-COVID-19 pneumonia on chest X-ray images by integrating CNN with sparse autoencoder and feed-forward neural network. *Computers in Biology and Medicine*, *141*, 105134.
2. Karar, M.E., Hemdan, E.E.D., & Shouman, M.A. (2021). Cascaded deep learning classifiers for computer-aided diagnosis of COVID-19 and pneumonia diseases in X-ray scans. *Complex & Intelligent Systems*, *7*(1), 235-247.
3. Basu, S., Mitra, S., & Saha, N. (2020, December). Deep learning for screening covid-19 using chest X-ray images. In *2020 IEEE Symposium Series on Computational Intelligence (SSCI)* (pp. 2521-2527). IEEE.
4. Ayan, E., & Ünver, H. M. (2019, April). Diagnosis of pneumonia from chest X-ray images using deep learning. In *2019 Scientific Meeting on Electrical-Electronics & Biomedical Engineering and Computer Science (EBBT)* (pp. 1-5). IEEE.
5. Feng, Y., Yang, X., Qiu, D., Zhang, H., Wei, D., & Liu, J. (2022). PCXRNet: Pneumonia Diagnosis From Chest X-Ray Images Using Condense Attention Block and Multiconvolution Attention Block. *IEEE Journal of Biomedical and Health Informatics*, *26*(4), 1484-1495.
6. Hussain Khan, S., Sohail, A., & Khan, A. (2020). COVID-19 Detection in Chest X-ray Images using a New Channel Boosted CNN. *arXiv e-prints*, arXiv-2012.
7. Cococi, A., Felea, I., Armanda, D., & Dogaru, R. (2020, October). Pneumonia detection on chest X-ray images using convolutional neural networks designed for resource-constrained environments. In *2020 International Conference on e-Health and Bioengineering (EHB)* (pp. 1-4). IEEE.
8. Khan, W., Zaki, N., & Ali, L. (2021). Intelligent pneumonia identification from chest x-rays: A systematic literature review. *IEEE Access*, 9, 51747-51771.
9. Abirami, P., Darshan, K. M., Kirubha, S. A., Latha, S., & Muthu, P. (2021). Smart access development for classifying lung disease with chest x-ray images using deep learning. *Materials Today: Proceedings*, *47*, 76-79.
10. Ikechukwu, A. V., Murali, S., Deepu, R., & Shivamurthy, R. C. (2021). ResNet-50 vs VGG-19 vs training from scratch: a comparative analysis of the segmentation and classification of Pneumonia from chest X-ray images. *Global Transitions Proceedings*, *2*(2), 375-381.
11. Mangeri, L., OS, G. P., Puppala, N., & Kanmani, P. (2021). Chest Diseases Prediction from X-ray Images using CNN Models: A Study. *International Journal of Advanced Computer Science and Applications*, *12*(10).
12. Cannata, S., Paviglianiti, A., Pasero, E., Cirrincione, G., & Cirrincione, M. (2022). Deep Learning Algorithms for Automatic COVID-19 Detection on Chest X-Ray Images. *IEEE Access*, *10*, 119905-119913.
13. Ozturk, T., Talo, M., Yildirim, E. A., Baloglu, U. B., Yildirim, O., & Acharya, U. R. (2020).Automated detection of COVID-19 cases using deep neural networks with X-ray images. *Computers in Biology and Medicine*, 121, 103792.
14. Karhan, Z., & Fuat, A. K. A. L. (2020, November). Covid-19 classification using deep learning in chest X-ray images. In *Proceedings of the 2020 Medical Technologies Congress (TIPTEKNO)* (pp. 1-4). IEEE.
15. Bharati, S., Podder, P., & Mondal, M. R. H. (2020). Hybrid deep learning for detecting lung diseases from X-ray images. *Informatics in Medicine Unlocked*, 20, 100391.
16. Computer-aided detection in chest radiography based on artificial intelligence: a survey. (n.d.) Available at: biomedical-engineering-online.biomedcentral.com (Accessed on date: 13 January 2024).
17. Automated abnormality classification of chest radiographs using deep convolutional neural networks. (n.d.) Available at: www.nature.com/articles/s41746-020-0273-z (Accessed on date: 13 January 2024).
18. Deep learning to estimate lung disease mortality from chest radiographs. (n.d.) Available at: www.nature.com/articles/s41467-023-37758-5 (Accessed on date: 13 January 2024).