Classification of Lungs Diseases Using Machine Learning Technique

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Abstract— The application of contemporary technologies is important to medical progress. To create accurate and specialised treatment choices for a range of ailments, extensive study performed in partnership with researchers, health care professionals, and patients is important. This study aims to identify the degree of accuracy that is acceptable in the medical sector by using deep learning on publicly available data. First, we extracted spectrogram features and labels from the annotated lung sound recordings to feed into our 2D Convolutional Neural Network (CNN) model. In this paper, we solve the problem of medical data scarcity by identifying pulmonary diseases from chest X-Ray pictures using small volume datasets with less than a thousand samples. Several studies have been conducted on the application of deep learning to identify lung disease have been published in the literature. The research goes into the history of deep learning and its applications in pulmonary imaging.

Deep learning algorithms are utilised to treat pneumonia, tuberculosis, lung cancer and other lung diseases. A review of various typical deep learning network topologies used in medical image processing is also provided. A taxonomy shows the links between previous work and categorises it based on characteristics that might help readers better understand the topic. Trend analysis, on the other hand, gives an overview of the research direction of the area of interest that has been emphasised in previous work.

Keywords—deep learning; lung disease detection, Machine learning, pneumonia detection using deep learning, lung cancer detection using deep learning, tuberculosis detection using deep learning

1. INTRODUCTION

Lung disorders, often called respiratory diseases, are diseases that affect the airways and other components of the lungs. Lung illnesses include pneumonia, lung cancer, tuberculosis, and Coronavirus disease 2019. The influence of illness on health is rapidly growing because of changes in the environment, climate change, lifestyle, and other factors.

According to the Forum of International Respiratory Societies, TB, lung cancer kills 1.4 to 1.6 million people each year, and pneumonia kills millions more. The COVID-19 epidemic wreaked havoc throughout the world, infecting millions of people and putting a burden on healthcare systems. The COVID-19 epidemic wreaked havoc throughout the world, infecting millions of people and putting a burden on healthcare systems. Lung diseases are unquestionably one of the world's leading causes of death and disability.

Early diagnosis is essential for increasing long-term survival rates and enhancing recovery chances. Lung disease has previously been detected via skin testing, blood tests, sputum sample tests, chest X-ray exams, and computed tomography (CT) scan tests. Deep learning has lately shown great potential when used to medical images for identifying illnesses, particularly lung disease. Lung diseases are a danger, especially in low- and middle-income countries, where millions of people live in poverty and are exposed to pollution. According to WHO estimates, million people die prematurely each year because of illnesses including tb, pneumonia caused by home air pollution. Deep learning is a subset of machine learning that works with algorithms based on the structure and function of the human brain. Recent advancements in machine learning, particularly deep learning, have made identifying, quantifying, and classifying patterns in medical pictures much easier. Deep learning's ability to learn features from data rather than hand-designed features based on domain-specific expertise enabled these improvements. Deep learning is quickly becoming the industry norm, leading in improved performance across a wide range of medical applications. Consequently, physicians will find it simpler to recognise and identify certain medical problems because of these advancements.

Lung sounds are the acoustic signals produced by breathing. An auscultatory approach was used by doctors to study lung sounds associated with various respiratory diseases. The auscultatory method has traditionally been the easiest technique to diagnose respiratory illnesses such as pneumonia, tb, covid and lung cancer. However, because of the intricacy of sound patterns and characteristics, it is a time-consuming manual operation that may result in various degrees of accuracy. There's a significant risk that data will be absent, resulting in outcomes that are underdiagnosed or misdiagnosed. Residents in one research were unable to detect 100% of wheezing sounds in a collection of pulmonary disease sounds, demonstrating that auscultation accuracy is not always precise and trustworthy.

Lung disease is the leading cause of serious illness and death worldwide. In the medical sector, early detection and treatment of disease are extremely important. Computer-assisted systems for lung illness detection are excellent techniques for assisting clinicians in making accurate diagnoses. As a result, the multimodal identification of lung sound using spectrograms is the subject of this work. An integrated network Multimodal Lung Disease Classification model was utilised using sophisticated pre-processing techniques to analyse the classification accuracy acceptable in the medical area, based on the classification of lung illnesses by deep convolutional neural networks. The study makes three major contributions.

First, we used two approaches to pre-process the data: Firstly. Data Normalization and Data Augmentation helps in eliminating undesirable noise and correcting the peak values of a sound signal, the data was normalised. The publicly accessible data was insufficient for training purposes. As a result, we used advanced data augmentation techniques to produce some more data while keeping the categories intact. Second, we collected spectrograms from lung sound and utilised them as signal and image

processing characteristics and pictures. Finally, we developed an integrated model for high-performance lung disease categorization. We compared the outcomes of audio and spectrogram image-based approaches and discovered that the image-based technique is more cost-effective, efficient, and trustworthy. Much research on the application of deep learning to identify lung disease have been published in the literature. Only one survey research analysing the state-of-the-art on this issue has been published in the last five years, to our knowledge.

Machine learning techniques for predicting diagnostic information from X-ray pictures have been studied by several researchers. Now is a key time to address this problem, as the public has unrestricted access to computers and a large collection of papers. This method, with the rise of computer science for health and medical research initiatives, has the potential to lower medical costs. The implementation uses the NIH chest X-ray image dataset from the Kaggle repository, and the technique is entirely open source. Deep learning algorithms are utilised to treat various lung diseases like pneumonia, tuberculosis and also lung cancer.

There's also a look at some of the most common deep learning network topologies used in medical image processing. Their study, however, falls short in terms of taxonomic presentation and analysis of contemporary labour patterns. A taxonomy depicts the connections between prior work and categorises it according to qualities that may help readers better grasp the problem. A trend analysis, on the other hand, provides an overview of the research direction in the subject of interest based on previous work. A taxonomy of deep learning applications for lung illnesses, as well as a trend analysis, are included in this paper. The remaining problems are also discussed, as well as potential future methods. Image kinds, features, data augmentation, types of deep learning techniques, transfer learning, the ensemble of classifiers, and types of lung diseases are among the seven variables found in the reviewed studies. Other researchers might use the taxonomy to organise their research contributions and activities. The proposed future path might boost the number of deep learning-assisted lung disease detection apps while also increasing their efficiency.

2. LITERATURE SURVEY

The initial prototype was a big gadget having a microphone input for the stethoscope and audio out for headphones. However, this instrument recorded much too much ambient noise, which drowned out respiratory sounds. It was also too large to transport in a hospital setting.

The second prototype was a scaled-down version of the first, with two inputs: one for the stethoscope microphone signal and the other for recording. It also featured a headphone audio output. The gadget captured stereo audio, with one channel dedicated to respiratory sounds and the other to ambient noise. The gadget was designed to record audio as well as remove noise from the respiratory signal. However, we discovered that the noise in the respiratory signal was not equal to the noise signal from the second channel, resulting in a significant data loss on the signal when it was recovered owing to the low frequency Wilderness of respiratory audio signals. As a result, we opted against using the second one as well. Due to a shortage of computer resources at the time, sophisticated
image processing techniques could not be used. Basic image processing approaches for identifying lung disease take around the same amount of time. A state-of-the-art in chest X-ray categorization and analysis is used to highlight the relevance of AI.

In addition, the Chest X-ray database has been upgraded to allow for multi-classification of lung diseases. A system for predicting lung cancer, TB, covid and pneumonia includes two deep learning algorithms. To diagnose chest X-rays, they first utilised a customised version of Alex Net. In the upgraded Alex Net, SVM is also utilised for classification. The authors used the LIDC-IDRI and Chest X-ray datasets. A collection of chest X-rays is also used. According to DenseNet121 and VGG 16, the discovery of consolidation requires extensive investigation. This method is based on deep learning-based computer aided diagnostics. A deep learning-based CAD system is used to detect clinically significant lung nodules on chest X-ray images.

Additionally, given the large datasets available, it is expected that all pictures will be recognised and separated quickly. As a result, several techniques for detecting objects and segmenting instances are required. FCN and F-RCNN are two such effective methods. GBM is used to classify two datasets: LUNA16 and LIDC-IDRI, which are used to identify lung nodules. To detect and categorize lung diseases in big and fresh datasets, more study is needed, according to the findings. The performance of CAD and decision support systems improved dramatically after the successful development of GPU and CNN.

Several deep learning models for identifying lung cancer and other lung diseases like pneumonia, tuberculosis and covid have been proposed in several research. The study focuses on identifying thoracic diseases. A 3D deep CNN with multi scale prediction methods is given to detect lung nodules from segmented images. Multiscale prediction methods are employed for small nodules since the work in cannot discriminate between disease kinds. A fully CNN is proposed to minimise the number of false positives while identifying lung nodules. To reduce the possibilities of making a wrong diagnosis, this approach can only look at the type of CT scan pictures.

The FP rate is reduced by using a quicker R–CNN to detect affected lung nodules. A quicker R–CNN produces promising results for object detection. A mix of deep CNN architecture and dual path network is utilised for detecting and retrieving nodule characteristics. A multi-patches arrangement with a Frangi filter was used to increase the sensitivity of identifying pulmonary nodules from lung X-ray images. This section explains how to perform a deep learning-based survey of recent lung disease detection. First, a suitable database of articles was identified as a primary source of information. A multi-patches arrangement with a Frangi filter is used to increase the efficacy of identifying pulmonary nodules from lung X-ray images. A sub-subject of image classification is medical image classification. Many image classification techniques may be applied to it. Many image enhancements approaches, for example, are used to improve the discriminable features for classification. However, because CNN is end-to-end image classification solution, it will learn the feature on its own. As a result, there will be no study of the literature on how to pick and improve characteristics in medical images. The evaluation focuses mostly on the use of conventional techniques as well as

CNN-based transfer learning. Also, on the capsule network on medical image related article, to see what elements in those models are critical to the outcome, as well as the gaps in their work.

3. FLOW DIAGRAM

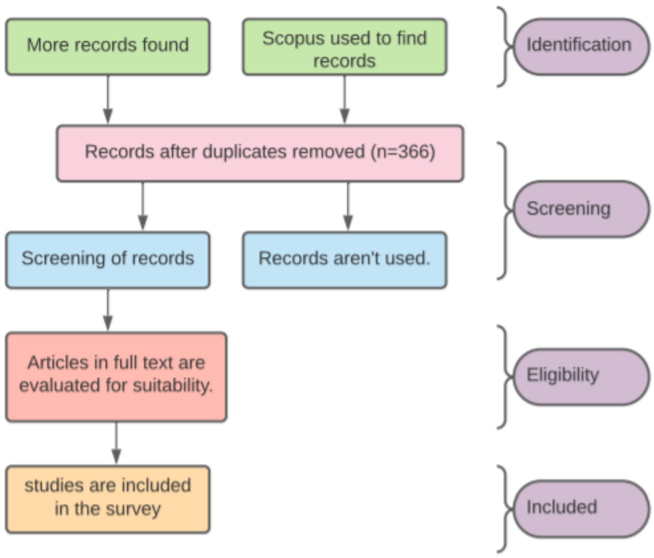


Fig1. Flow diagram of the methodology used to conduct this survey

First, an appropriate database of publications was chosen as a primary source of reference. Scopus was chosen since it is one of the largest databases of peer-reviewed scientific publications. Several important publications that are indexed by Google Scholar but not Scopus are included based on the number of citations they have gotten. Due to the disease's recent emergence, several preprint publications on covid are also included.

Only publications published are included in this study to guarantee that it only includes state-of-the-art research. However, there are a few older yet important pieces included as well. To find all potential deep learning aided lung disease detection papers, relevant keywords were utilised in the search.

Second, screening was used to pick just the relevant works. Only the title and abstract were evaluated during the screening. The primary selection criteria were that this survey was solely interested in work, and that deep learning techniques were used to diagnose the disorders in question.
Articles that were deemed irrelevant were omitted. Only 98 articles were shortlisted based on the screening process. Finally, the eligibility check was performed on all the items that were examined.
The full-text examination of the articles was done instead, using the same criteria as in the screening step. This survey comprised all 98 screened items that cleared this step. This indicates that deep learning-based lung disease diagnosis is

still a very active field. Figure 1 depicts the number of studies that were identified, reviewed, and evaluated. This survey is open to anybody who meets the criteria.

4. DATASET

The data is collected from various open-source citations and publications. Kaggle and Scopus repositories have the maximum contribution. The data is divided into three folders (train, test, and Val) with subfolders for each image category. There are 5,863 X-Ray pictures in .jpeg format and two categories in this collection. To analyse chest x-ray pictures, all chest radiographs were first checked for quality control, with any scans that were low quality or illegible being removed. After that, the diagnoses for the photos were assessed by two experts before being approved for use in the AI system. A third expert examined the assessment set to make sure there were no grading mistakes. When the number of training samples increases, model-based approaches substantially improve their predictions. When there is just a limited quantity of data, various modifications must be done to the current dataset to synthetically expand the training set. To supplement the training dataset, we used three methods. The first method included cropping a 224x224 pixel fixed-size window from a 256x256 pixel picture at random. The second approach included horizontally flipping the picture, which allowed information regarding reflection invariance to be captured. Finally, to capture colour and illumination variance, the third technique used randomly produced lighting.

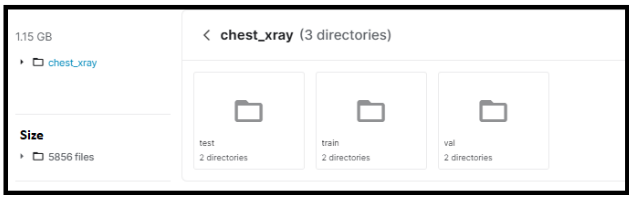


Fig2. Dataset

V. METHODOLOGY

The Kaggle and Scopus repository just become home to a big quantity of X-ray data. This dataset was created using a novel deep learning technique that included CNN, VGG, data augmentation, and a spatial transformer network. This paper refers to this unique hybrid technique as hybrid VDSNet. This study examines a lung disease dataset using the new VDSNet algorithm to anticipate lung sickness in individuals. This is accomplished by performing a binary classification using the dataset's input properties, with the outcome being sickness detection represented by Yes or No. Because this dataset is both complicated and large, data processing is challenging. Furthermore, there is a lot of noise, and there isn't enough information to forecast disease accurately. Data processing is difficult since this dataset is both sophisticated and big. Furthermore, there is a lot of noise, and there isn't enough data to correctly predict illness.

As a result, processing this dataset is a difficult task. In this study, patients' X-ray pictures were used to classify them using the CNN deep learning approach. The capsule network also known as Caps Net, is one of the most powerful algorithms, with both generative and deterministic capabilities. However, this network has been found to be more image-sensitive than basic CNN architectures. Caps Net can cram many convolutional layers inside a capsule.

They are then subjected to nonlinearity. As CNN models have become increasingly popular in medical applications, Caps Net has become increasingly involved in medical-related research, such as brain tumour segmentation and classification. As a result, the paper's primary contribution is the creation of VDSNet, a novel algorithm that can detect lung disease in X-ray pictures with better accuracy than previous techniques.

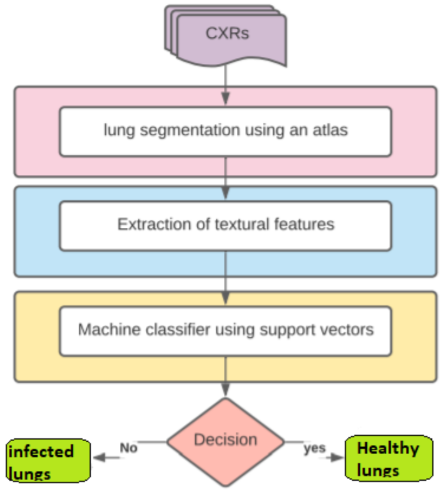


Fig3. Overview of the screening system developed for lung infection/disease detection

This method is a multistage processing system based on a multistage framework established by researchers, which first segments images before attempting to predict illness using CXRs by combining texture and form data. When doing a lung evaluation, the algorithm uses the same logic as radiologists, which entails comparing the right and left lung functions. The form characteristics are concerned with
incorporating the essential geometrical aspects, whereas the texture features are concerned with describing the areas of the inner lungs. Segmentation, feature extraction, and classification are the three steps of the method.

The first uses a partial Radon transform and the Bhattacharyya shape similarity measure for content-based image retrieval. Create a patient anatomic model of lung shape using SIFT-flow. Finally, the lungs' boundaries are eliminated using a graph cut optimization approach. The intensity histogram, gradient magnitude, a histogram of directed gradients, and other features are used to derive the textural properties of segmented lungs. Finally, the data is classified using a Support Vector Machine Model.

5. Result and Discussion

The paper's first contribution is a taxonomy of current work on lung disease detection using deep learning, which is presented in this section. The taxonomy's purpose is to summarise and clarify the major topics and areas of focus in the preceding work. To be included in the taxonomy, seven qualities were chosen. These qualities were chosen because they were prevalent in all the previous papers reviewed. The taxonomy includes seven attributes: image types, features, data augmentation, types of deep learning approaches, transfer learning, the ensemble of classifiers, and types of lung illnesses.

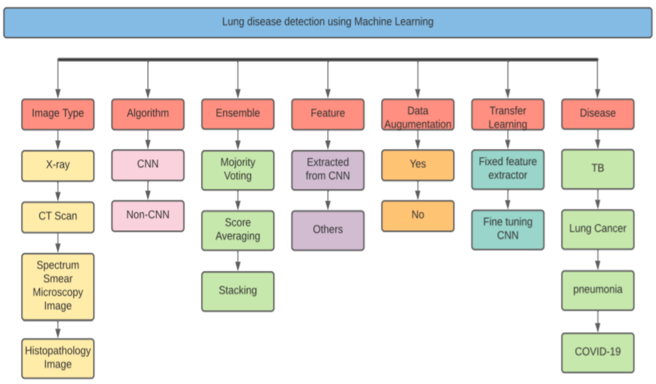


Fig4. Taxonomy of lung disease detection

Image Type
Chest X-rays, CT scans, sputum smear microscopy pictures, and histopathology photographs were all used to train the model in the research evaluated. Other imaging techniques worth mentioning include positron emission tomography and magnetic resonance imaging studies.

CT Scans
X-rays do not provide as much detail as CT scan pictures. A CT scan is a form of radiography that uses computer processing to produce sectional pictures at different depth planes from images obtained from different angles around the patient's body. The picture slices may be examined separately or layered to display the tissues, organs, skeleton, and any anomalies in a 3D representation of the patient.

Sputum Smear Microscopy Images
Sputum is a viscous fluid that collects in the lungs and the airways leading to them. To do a sputum smear examination, a very thin coating of sputum sample is applied to a glass slide.

Chest X-rays
An X-ray is a diagnostic test that helps doctors diagnose and treat medical problems. It is the most often utilised diagnostic procedure. medical An X-ray of the chest produces pictures of the blood vessels, lungs, airways, heart, spine, and chest bones. Previously, medical X-ray pictures were exposed to photographic films that had to be processed before being inspected. Digital X-rays are utilised to solve this problem.

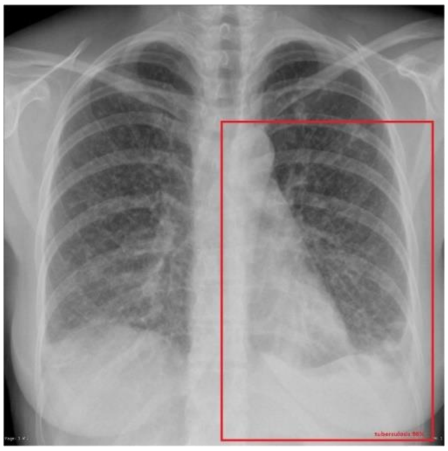


Fig5. Tuberculosis infected lungs X-ray

Fig6. Pneumonia infected Lungs X-ray

Fig7. Lung Cancer infected lung X-ray

Fig8. Covid infected Lungs X-ray

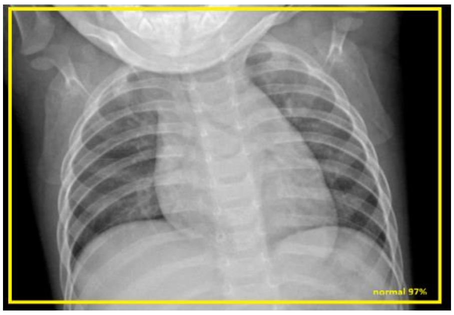


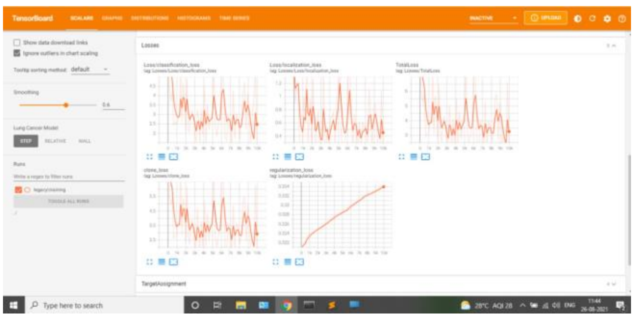
Fig9. Healthy (normal Lungs)

Histopathology Images
The microscopic study of a biopsy or surgical specimen on glass slides to detect the symptoms of a disease is known as histopathology. The slices are coloured with one or more stains to help see the various components of the tissue.

When we investigate the results of models with and without transfer learning in lung disease classification tasks using segmented images, we show that transfer-learning models perform well even when data resources are restricted. We compare the performance of our models to published results across several datasets in this area. The algorithm InceptionV3, which was trained on segmented images, received the greatest scores in most of the findings. Furthermore, it had very high scores in the disease classifications and had a better probability of being properly diagnosed.

Although the scores of the healthy class are lower than those of the ill class, the real cost is lower since misclassifying a sick patient as healthy is always worse. The model based on InceptionV3 fared the best as compared to VGG16 algorithms. We discovered that the InceptionV3-based model performed the best, therefore due to space restrictions, we only display its performance
results.

The vanilla CNN has the lowest performance because to the early stop-ping checkpoint paradigm since it overfills too early and clogs. The capsule network outperforms the vanilla CNN despite its sluggish convergence. VDSNet has the best performance, however it converges slowly due to a lack of data on the properties of large images. The capsule network outperforms the vanilla CNN, although it has a slower convergence rate. Include extra data in the full dataset to speed up convergence times. The VDSNet paradigm of early pausing leads the vanilla CNN to stop and overfill, as we discovered.



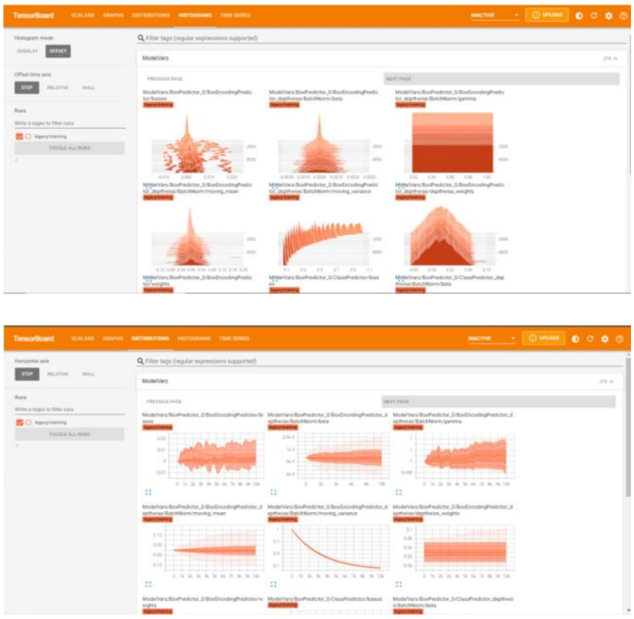


Fig10. Output Images

6. CONCLUSIONS

We created a transfer learning-based lung disease classification pipeline and tested it on small lung imaging datasets. It was put to the test in terms of identifying non-segmented and segmented chest X-Ray images. In our best-performing design, we used the U-net segmentation network and the InceptionV3 deep model classifier. Current models were compared to the frameworks we created.

As time goes on, more studies on lung disease detection using deep learning will be released. There was, however, no detailed evaluation of the current level of research and application. This research looks at how deep learning may be used to identify lung diseases, with an emphasis on tuberculosis, pneumonia, lung cancer and coronavirus. This research considered many articles on the issue. A taxonomy of state-of-the-art deep learning assisted lung sickness detection was established based on the survey of the works assessed to synthesise and arrange the key ideas and emphasis of the existing work on lung disease detection using deep learning. Analyses of the trend in current research on this topic, based on the taxonomy's recognised traits, are also presented. Recent research on this topic is also presented, based on the recognized characteristics of the taxonomy. We developed a lung disease classification pipeline using transfer learning and applied it to small datasets of lung pictures. We tested its accuracy in classifying non-segmented and segmented chest X-ray pictures. We employed the U-net segmentation network and the InceptionV3 deep model decoder in us architecture. Our framework was compared to other models. We proved that models pre-trained using the transfer learning technique, as well as basic classifiers such as shallow neural networks, may compete well with sophisticated systems. Both CNN and transfer learning are frequently utilised, according to a study of task allocation. Aside from the ensemble feature, the trend of the research revealed that all the recognised traits in the taxonomy grew linearly with time.

The remaining challenges, as well as the future direction of lung disease detection using deep learning, were recognised, and debated after that. Four challenges with lung illness detection using deep learning were discovered: data asymmetry, handling of high image sizes, limited accessible datasets, and substantial correlation of errors when utilising ensemble techniques. Making datasets available to the public, using cloud computing, adding more features, and employing the ensemble are four viable methods for lung disease detection using deep learning to
overcome the identified challenges. Knowing how deep learning was employed in lung disease diagnosis is essential for keeping future research on track and enhancing the effectiveness of illness detection systems.

Because of the relevance of medical image classification and the unique issue of medical image-small datasets, this research opted to investigate and assess how to apply CNN-based classification to a tiny chest X-ray dataset. The following conclusion was reached because of the trials. Of the three approaches, CNN-based transfer learning is the most effective. The capsule network outperforms the ORB
and SVM classifiers in terms of accuracy. In general, CNN-based approaches are superior to older methods because they can automatically and effectively learn and pick characteristics.

VGG16 transfer learning with one retrained ConvLayer produces the best results, which are somewhat better than the state-of-the-art result. The specified feature may learn from the new dataset using the unfrozen ConvLayer. As a result, the specific feature is a critical component in improving accuracy; a model's strength of expression and overfitting must be balanced. A network that is too basic cannot learn enough from the data and hence cannot achieve high accuracy. An extremely complicated network, on the other hand, is difficult to train and soon overfits. As a result, accuracy remains a problem.

Only a network model with the appropriate size and other effective overfit prevention measures, such as a reasonable dropout rate and sufficient data augmentation, can produce the best outcomes. However, due to time constraints, further study is required. Training a fine-tuned deep neural network with unfrozen ConvLayers tends to overfit in. Other more powerful CNN models, such as ResNetv2 and an ensemble of several CNN models, have not been tested, although they may enhance the findings. The best results are obtained using VGG16 transfer learning with one retrained ConvLayer, which are somewhat better than the state-of-the-art result. Using the unfrozen ConvLayer, the given feature may learn from the fresh dataset. As a result, the unique feature is an important part of enhancing accuracy; the intensity of expression and overfitting of a model must be balanced. A network that is too simple will not be able to learn enough from the data to attain high accuracy.

A complex network, on the other hand, is difficult to train and quickly becomes overfit. As a result, accuracy continues to be an issue. The accuracy of five standard deep learning models is evaluated in this study when they are used to diagnose clinical data on a dataset consisting of X-ray pictures of the lungs with different diseases like pneumonia, tb, coronavirus, lung cancer and normal lungs. We focus on Mobile Net's network structure because of its superior performance. The findings showed that all five network structures can identify pneumonia, tb, covid and lung cancer, and Mobile Net's accuracy is greater than other network structures.

Furthermore, the use of artificial intelligence technology in the medical sector is insufficient, and the dataset in this field's kinds should be enhanced. As the number of cases of lung diseases rises, the amount of picture data grows, so does the network structure. The performance of CNN-based pneumonia diagnostic algorithms improves, so will the performance of CNN-based diagnosis algorithms. Based on a review of the works evaluated, a taxonomy of state-of-the-art deep learning aided lung illness detection was created to summarise and organise the major ideas and emphasis of the existing work on lung disease detection using deep learning. Analyses of the trend in recent studies
on this issue, based on the taxonomy's discovered features, are also provided. According to the distribution of works, both CNN and transfer learning are widely used. Except for the ensemble characteristic, all the detected qualities in the taxonomy saw a linear growth throughout the years, according to the trend of the surveyed work. Following that, the remaining difficulties and future directions of lung illness detection utilizing deep learning were evaluated and discussed. Four problems with big data lung illness diagnosis were identified such as data imbalance, handling of large picture sizes, limited accessible datasets, and high bit error correlation when utilising ensemble approaches. To address the highlighted difficulties, four potential works for lung disease diagnosis using deep learning are proposed by making datasets available to the public, applying cloud computing, using more features, and using the ensemble.

To conclude, examining how deep learning was used in lung disease diagnosis is critical to ensuring future research stays on track, therefore increasing the efficacy of disease detection systems. Other researchers might utilise the given taxonomy to arrange their research contributions and activities. The recommended future path might enhance efficiency and increase the number of deep learning-aided lung disease detection applications.

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