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Article

The Role of Imaging Techniques in the Diagnosis and Management of Respiratory Problems

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Abstract: Respiratory problems are a significant public health concern, with various conditions posing a threat to individuals' respiratory systems. These conditions can range from common illnesses such as pneumonia and bronchitis to more serious diseases like lung cancer and COVID-19. For respiratory disorders to be effectively treated and managed, early identification and precise diagnosis are essential. Traditional methods of diagnosing respiratory problems often involve the use of imaging techniques, such as X-ray images. However, manual interpretation of these images by radiologists can be time-consuming and subjective. According to the World Health Organization, respiratory diseases were responsible for over 4 million deaths worldwide in 2017 alone ("Global Burden of Disease" report). Effective treatment and management of respiratory disorders depend on early detection and precise diagnosis. Traditional methods of diagnosing respiratory problems often involve the use of imaging techniques, such as X-ray images. However, manual interpretation of these images by radiologists can be time-consuming and subjective.

Keywords: deep learning; respiratory problems; CNN-model; medical images

1. Introduction

Hospitals have implemented several high-quality instruments and techniques over time to increase the effectiveness of their services. Maintaining any quality improvement initiative requires careful selection of the appropriate instrument and adherence to the proper methodology. This also applies to healthcare organizations. Prioritizing the requirements that can have the biggest impact on the result is important for deep learning models. A model must be able to determine the best course of action for resolving an issue while striking the correct balance between the resources at hand and the desired outcome. Prioritizing requirements in deep learning models is a multi-faceted process that requires a nuanced understanding of the factors influencing model performance. Striking the correct balance between resource allocation and desired outcomes is essential for the successful deployment of deep learning models across various domains. This comprehensive exploration aims to shed light on the intricacies of this critical aspect of deep learning research and application. In summary, the application of deep learning and convolutional neural networks (CNNs) to respiratory problem diagnosis from medical images represents a significant achievement in the healthcare sector. Because of their special qualities, deep learning models CNNs in particular have shown to be remarkably successful at extracting complicated patterns and traits that are necessary for accurate diagnosis. Traditional approaches have been replaced by deep learning, ushering in a new era of efficiency, automation, and greater diagnostic accuracy. Dyspnea, or shortness of breath, is the second most significant sign of lung illness. This complicated sensation can manifest acutely, in the event of a severe asthma attack, or as a foreign body being inhaled into the trachea [1]. CNNs have demonstrated to be quite good at spotting minute characteristics that may suggest respiratory difficulties since they can automatically generate hierarchical representations from raw visual data. These models can adapt to complex patterns and variances in medical images thanks to their end-to-end learning process and ability to handle large and different datasets. The first step in creating an instance of the framework is selecting the optimal segmentation and classification models independently from the test data. If the inputs are different, we must introduce an adaption transformer. Otherwise, both models must accept the same input format. The input layer of the framework is positioned before the segmentation and classification models [2].

A fast and correct diagnosis is essential for efficient treatment of respiratory disorders, which represent a major worldwide health burden. Traditional diagnostic methods for respiratory problems, particularly those detected through X-ray imaging, often rely on manual interpretation and can be time-consuming. The purpose of the study is to investigate the automated diagnosis and classification of respiratory issues utilizing medical pictures with deep learning, more especially Convolutional Neural Networks (CNN). The primary question is whether a deep learning approach can enhance the efficiency and accuracy of diagnosing respiratory conditions from X-ray scans. Respiratory diseases, including pneumonia, tuberculosis, and various lung disorders, contribute significantly to global morbidity and mortality. The traditional process of analyzing X-ray images to detect respiratory problems requires skilled radiologists, leading to delays in diagnosis and potential misinterpretations. Recent advancements in deep learning and CNNs have shown promise in image recognition tasks, raising the possibility of automating the detection of respiratory issues from X-ray images. This study builds upon the intersection of medical imaging, deep learning, and respiratory health to address the limitations of current diagnostic practices. The results of using data mining techniques with their classifiers and extending the classifiers to predict any kind of heart disease were discussed. The research in the current publication identified several classifiers with good performance. Neural Networks (NN), Support Vector Machines (SVM), and other classifiers, algorithms, or approaches were applied in various research articles [3]. The same methods can be applied for respiratory problem identification. In general, the use of machine learning (ML) in the field of mental health has shown promise in several domains, including research, clinical administration, diagnosis, treatment, and support [4]. There is a great deal of room for the application of machine learning to other areas of psychology and mental health, since most of the studies that were found focused on the identification and diagnosis of mental health issues. Several features are retrieved from each image and supplied to the classifier [5].

The leading causes of death worldwide are infections related to the respiratory system, including bronchopneumonia, acute bronchitis, emphysema, and chronic obstructive pulmonary disorders (COPD). In practice, several pulmonary function tests are available, including spirometry, arterial blood gas testing, and auscultation. Auscultation is the primary method used for all patients; it is a cheap and non-intrusive screening technique [6]. In addition, spirometry which uses the Forced Oscillation Technique is employed based on the patient's needs (FOT). FOT assists in determining the respiratory impedance and measures air pressure and flow. Nonetheless, compared to spirometry or radiation imaging, the auscultation method is straightforward, patient-friendly, and simpler to collect data from. Generally, lung sound signals are divided into two categories: aberrant and normal. Breathing noises normally pass over the chest wall.

The primary goal is to create and verify a CNN, a deep learning model, for the automatic detection and categorization of respiratory issues from medical photographs. The objectives include utilizing a sizable dataset of tagged medical photos that represent a range of respiratory ailments, assessing the sensitivity, specificity, and overall accuracy of the generated model's performance, and comparing the deep learning model's diagnostic capabilities with traditional manual interpretation by radiologists.

Figure 1 explains how respiratory diseases are starting and how it is spreading completely. Respiratory disorders are, to put it simply, illnesses that affect the lungs and airways, making it difficult for a person to breathe correctly. The respiratory system, which includes the lungs, windpipe, nasal cavities, throat, and breathing muscles, can be affected by these disorders in different ways. Emphysema is one example of a respiratory disease that decreases by causing damage to the air sac walls, the surface area accessible for the exchange of carbon dioxide and oxygen in the lungs. Shortness of breath, coughing, and wheezing are possible side effects of this. Severe emphysema episodes can make breathing difficult, which lowers oxygen levels in the body and causes headaches and cognitive problems.

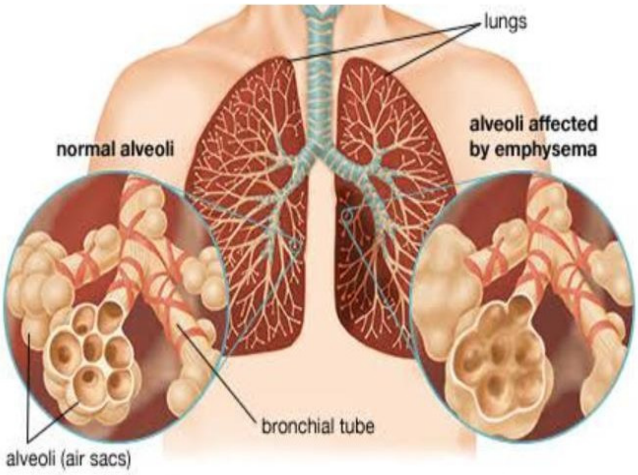

Figure 1. The Current State of Respiratory Diseases [1].

To explore the potential for early detection and improved efficiency in diagnosing respiratory problems through automated deep learning algorithms. This research holds importance in multiple aspects. First, it addresses the vital necessity of a quick and precise diagnosis of respiratory issues, potentially leading to earlier intervention and improved patient outcomes. Secondly, by leveraging deep learning and CNN, the study demonstrates the potential for automation in healthcare diagnostics to advance the rapidly expanding field of medical image analysis. Lastly, the study provides insight into the comparative effectiveness of deep learning models versus traditional diagnostic methods, contributing valuable knowledge to the broader medical imaging and respiratory health literature. Overall, this research has the potential to revolutionize the way respiratory problems are diagnosed and managed, offering a more timely and accurate approach to patient care.

The article [7] explores the application of deep learning in detecting neurological disorders such as Alzheimer's disease, Parkinson's disease, and schizophrenia using magnetic resonance images. This data facilitates the deep learning model's accuracy management for respiratory issues. One method for studying the nervous system and brain is neuroimaging. It involves creating images of the structure and activity of the brain using imaging technologies including electroencephalography (EEG) and magnetic resonance imaging (MRI). The journal Anniversary Review of Biomedical Data Science published a paper [7] addressing the developments in informatics and computation for repeatable data analysis in neuroimaging. They emphasized the application of numerous methods for data processing and visualization and talked about how crucial it is to guarantee the repeatability and integrity of neuroimaging data [8].

1.1. How Does CNN Aid with Respiratory Disease Detection?

Convolutional Neural Networks can aid in respiratory disease detection through the analysis of medical imaging such as X-rays and CT scans. These networks can spot anomalies and trends in the pictures that could point to the existence of respiratory conditions like pneumonia, lung cancer, or tuberculosis. CNNs can be trained on a large dataset of labeled medical images to learn the intricate features and characteristics associated with different respiratory conditions. Through this training, CNN can then analyze new, unseen images to provide predictions and assist medical professionals in the detection and diagnosis of respiratory diseases.

Furthermore, CNNs can aid in automating the process of screening and analyzing medical imaging, potentially reducing the time and workload for healthcare providers. However, CNNs can be useful tools, but it is crucial to remember that they cannot replace a medical professional's experience. The final diagnosis and treatment decisions should always be made by qualified healthcare professionals.

CNNs (Convolutional Neural Networks) can be trained to detect various respiratory diseases by analyzing medical imaging data such as X-rays and CT scans. These powerful deep-learning models can identify patterns and anomalies within the images that may indicate the presence of different respiratory conditions. Lung cancer, pneumonia, tuberculosis, chronic obstructive pulmonary disease (COPD), and other respiratory conditions are among the conditions that CNNs can assist in identifying. A significant alteration to our architecture is the inclusion of numerous feature channels in the up-sampling phase. This enables the network to transmit context information to layers with higher resolution. This results in a U-shaped design as the expanding path is roughly symmetrical to the contracting path [9]. Applications of deep learning and reinforcement learning to biological data have been achieved with success. These include analyzing gene expression data for customized treatment, predicting protein folding for drug discovery, and studying EEG signals for brain-computer interfaces. The paper reviews the current status of this field's research and identifies some of the obstacles that still need to be [10]. A list of current open-source libraries and frameworks that can be used to harness the power of these techniques, along with a comparison of their relative and performance; and a list of publicly accessible data repositories that provide data for method development. In the conclusion, a few unresolved concerns are noted and some hypothetical future viewpoints are sketched out [11]. A significant part of the pipeline for computer-aided medical image analysis is the automatic segmentation of medical pictures. The use of CNN to image segmentation for MRI diagnosis, disease detection, therapy, and treatment response is presented in this study [12].

Using a large and varied collection of tagged medical photos depicting various respiratory disorders, a CNN is trained. Because the model considers both short- and long-term memory, it can accurately represent the intricate and frequently erratic character of oil pricing. The model's performance on historical data on oil prices is presented in the paper, demonstrating its efficacy as a tool for price prediction [13]. The network can learn to recognize specific features and signatures associated with each condition. This enables CNN to subsequently analyze new, unseen images and provide predictions regarding the presence of respiratory diseases. It is imperative to acknowledge that although CNNs are potent instruments that facilitate the identification of respiratory ailments, they do not supplant the proficiency of medical experts. The final diagnosis and treatment decisions must always be made by qualified medical practitioners. Convolutional neural networks (CNNs) are used in the deep learning approach to attain an accuracy of 84.2% in MCI to AD conversion prediction and 96.0% in feature selection [14].

1.2. How Do Features Become Learned by CNNs

The purpose of Convolutional Neural Networks (CNNs) is to effectively process and analyze visual information, including pictures and videos. Their proficiency in identifying spatial patterns and feature hierarchies in images enables them to perform tasks like object identification, image segmentation, and image classification. The following are CNN's main goals:

1. Feature Learning: From the raw pixel values in images, CNNs automatically discover hierarchical representations of features. The network can now recognize intricate patterns and textures as a result.
2. Translation Invariance: CNNs are made to identify patterns in images regardless of where they are located. Convolutional operations are used to accomplish this, enabling the network to identify characteristics regardless of where they are in the input.
3. CNNs employ parameter sharing, which lowers the number of parameters and improves the network's capacity to generalize to new data by using shared weights across different input regions.
4. Effective Feature Extraction: By using successive layers of convolution, pooling, and non-linear activation functions, CNNs can extract high-level features from raw data, contributing to their effectiveness in visual recognition tasks.

Overall, the purpose of CNNs is to learn and understand the intricate details of visual data in a way that is robust, efficient, and generalizable, making them invaluable in the field of computer vision.
CNNs learn features through a process called convolution, wherein filters or kernels are applied to the input images to detect various visual patterns and structures. The subsequent steps are involved in this process:

1. Convolution: In the convolution process, distinct regions of the input image are subjected to regularly applied filters. By emphasizing patterns, like edges, textures, or forms, these filters function as feature detectors. Feature maps emphasizing the identified patterns are produced by the filters as they are applied to the input image.
2. Non-linear Activation: Once convolution is complete, non-linearity is usually added to the network by applying a non-linear activation function (like ReLU). This facilitates CNN's discovery of intricate links and patterns in the data.
3. Pooling: Following non-linear activation, the feature maps are down-sampled and their spatial dimensions are decreased using pooling layers. For example, max pooling reduces computing complexity while maintaining crucial information by choosing the maximum value from regions.
4. Parameter Sharing: CNNs apply the same set of weights to several input components by using parameter sharing. As a result, the network has fewer parameters and is better able to identify patterns and features wherever they may be in the input.

Through repetitive application of these steps across multiple layers, CNNs gradually learn and refine hierarchies of features within the input data. This allows them to automatically extract meaningful representations of the visual information, resulting in their extreme effectiveness for tasks like segmentation, object detection, and image classification. Multiple neural networks are used in this approach as decision-makers, and their predictions are combined using a fuzzy weighted voting scheme. When the method is compared to other cutting-edge techniques, it performs better on a dataset of ADL activities carried out by people with Parkinson's disease [15].

1.3. Benefits of Medical Image Processing by CNN

The advantages of medical image processing have shown to be a significant area of expertise for Convolutional Neural Networks (CNN), a potent implementation of deep learning techniques. This article examines the main advantages of CNNs and how they help this industry: CNN image processing for all Enhanced Precision: With their capability to automatically learn and track features from images, CNNs provide paralleled accuracy in performing critical activities techniques including detection, segmentation, and classification are used in medical image analysis. This has crucial implications for healthcare professionals in making precise diagnoses. Typically, the dropout DNN is only used during the classification problem's training phase. Still, this results in an average production. It is enabled during the test step of the prediction that needs the precision value [16]. A method used in computer vision and image processing called super-resolution (SR) shown in Figure 2 seeks to increase an image's resolution. Several network architectures have been created to enhance the super-resolution architectures' performance. All architectures have their advantages and are designed to tackle different super-resolution difficulties like increasing training efficiency, decreasing computing complexity, or improving image quality.

Identification & Categorization of Anomalies: Leveraging CNNs enables accurate identification and classification of specific health conditions or abnormalities displayed within imaging outputs like X-rays, CT scans, or MRIs correctly [17]. The effort aids in the detection of diseases including tumors, lung afflictions, and bone fractures along with identifying early signs of diseases which are invaluable insights for medicine practitioners. Strong candidates are also those with a large quantity of medical picture datasets, such as those in the fields of radiology, pathology, and cardiology. DL can analyze photos, identify anomalies, and point out areas that need improvement, which will increase the accuracy of all these advancements [18]. Traditional machine learning is helpful in situations where features are observable and resources and datasets are limited. When feature engineering is a challenging task and resource availability is not a restriction, deep learning (DL) can be helpful [19]. DNN has several different hyperparameters, each with its architecture, which contribute to its problems. When evolutionary algorithms are utilized to determine the ideal or nearly ideal hyperparameters for the DNN, these are regarded as a problem.

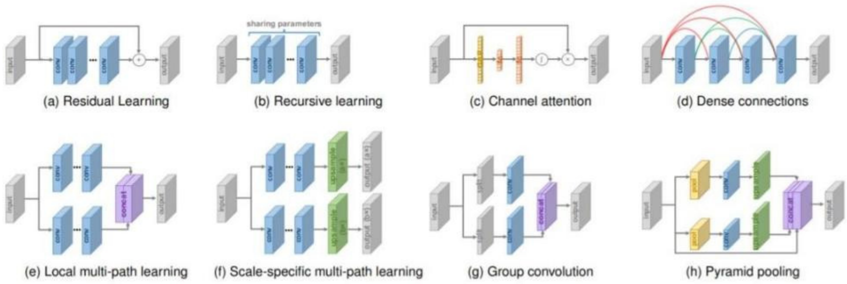

Figure 2. Various network designs in super-resolution architecture.

Large-Scale Feature Extraction Efficiency: By gaining insights from medical imagery without manual intervention NBCNNs can conduct efficient feature extraction tasks efficiently thereby significantly reducing dependency on expert knowledge.

Uniform Learning across Diverse Data Sets: As networks adept at managing varied types of medical imagery data including different resolutions modalities, and image quality levels, CNN demonstrates versatility by adapting well across various tasks involved in Medical Image Analysis.

Knowledge Sharing & Transfer Learning Applications: Pre-existing Customized versions (pre-trained models) of these networks initially learned on extensive datasets like ImageNet can be fine-tuned towards helping the process related to Medicinal Imaging. Invariably, this allows one to leverage prior domain-non-specific experiences while using a relatively reduced medicinal dataset yielding good output performance. This advantage proves very useful, especially during emergencies that demand prompt pronouncement/interventions. Decision Supplementing Inputs- Convolution Medical imaging processing extends help providing superfluous insights/information to the radiologists/doctors assisting them towards making their diagnoses. Mixing human proficiency with CNN's Analytic capability is instrumental in augmenting accuracy and minimizing diagnostic error chances

Daily Learning leading to enhancement -Moreover, as more medical imagery data gets processed by these network models, they invariably learn continually which helps improve/sophisticate their performance. The COVID-19 pandemic has also made extensive use of deep learning, particularly for infection detection. In the modern world, stopping the spread of COVID-19 is a crucial and developing issue [20].

Convolutional Neural Networks play a pivotal role in effective Medical Image Analysis and Processing. They offer accurate, efficient real-time image analysis. This coupled with feature extraction ability, and abnormality classification skillset, alongside handling diverse datasets thus efficiently aids doctors/healthcare professionals in the diagnosis/decision-making process. The importance of pulmonary auscultation as a non-invasive technique to track lung health and diagnose conditions like pneumonia, asthma, and chronic obstructive pulmonary disease (COPD) is covered in the study. It also emphasizes how conventional manual stethoscopes have limitations when it comes to correctly identifying respiratory conditions and how electronic stethoscopes may be able to interpret lung sounds more effectively. The study's methodology, which makes use of deep learning algorithms and wavelet smoothing, tries to overcome these drawbacks and enhance lung sound classification and disease identification. To stop respiratory disorders from getting worse, the paper highlights the significance of early detection as well as the potential benefits of deep learning models for enhancing clinical decision-making.

2. Methods

Artificial neural networks are used in deep learning, a subset of machine learning, to learn from and make judgments based on massive volumes of data. Its capacity to automatically extract features from raw data and produce precise predictions or classifications has drawn a lot of interest in recent years. Deep learning has demonstrated significant potential in medical image processing, particularly in tasks like picture segmentation, classification, and detection. To support disease diagnosis, treatment planning, and disease monitoring, medical image processing entails the analysis and interpretation of medical pictures. Conventional image processing methods frequently necessitate the laborious and subjective process of manually extracting and selecting features. Conversely, deep learning can automatically extract pertinent information from the photos itself, producing findings that are more reliable and accurate. The capacity of deep learning to handle big and complicated datasets is one of its main advantages in medical image processing. Deep learning algorithms may be taught on enormous volumes of images to identify patterns and relationships that could be difficult for human experts to see, thanks to the growing availability of medical imaging data. This may result in more precise and effective diagnoses in medical contexts. Medical images can be segmented using deep learning algorithms into several regions of interest, such as tumors, organs, or anomalies. This can support both treatment planning and quantitative analysis. Classification of diseases: Medical images can be classified into several illness categories, such as cancer, pneumonia, or Alzheimer's disease, using deep learning models that have been trained. Early diagnosis and detection may benefit from this. All things considered, deep learning holds the potential to completely transform the medical image processing industry by offering precise and automated methods for evaluating and interpreting medical pictures. However, to fully reap the rewards of deep learning in healthcare, issues including interpretability, data scarcity, and regulatory constraints must be resolved. Deep learning in medical image processing refers to the analysis and interpretation of medical images, such as MRIs, CT scans, and X-rays, using sophisticated machine learning algorithms. In this case, deep learning is being used to help medical practitioners with disease diagnosis, treatment planning, and disease progression tracking. Enhanced Accuracy: With the use of deep learning algorithms, medical images can be examined for patterns and abnormalities with a high degree of accuracy, which may result in more accurate diagnoses. Deep learning algorithms can help improve patient outcomes by assisting in the early diagnosis of problems like tumors, aneurysms, and other abnormalities by evaluating vast quantities of medical pictures. Radiologists and other medical practitioners can save time and effort by using deep learning models to automate the process of processing medical pictures and then analyze and report the results. Deep learning can aid in the creation of individualized treatment plans that cater to the requirements of each patient by analyzing patient data and medical imagery.

A wide spectrum of illnesses that impact the lungs, airways, and other breathing-related structures are referred to as respiratory diseases. The following information pertains to common respiratory diseases:

Asthma: Asthma is a long-term illness marked by airway inflammation and constriction, which can cause symptoms like coughing, chest tightness, and wheezing. Exercise, other stimulation, or allergens frequently cause it to flare up.

Emphysema and chronic bronchitis are two of the progressive lung disorders that are included in the category of chronic obstructive pulmonary disease (COPD), which is characterized by restricted lung airflow. Sputum output, a persistent cough, and dyspnea are among the symptoms.

An infection that causes inflammation in one or both lungs' air sacs is known as pneumonia. It may result in symptoms like chills, fever, coughing, and breathing difficulties. Fungus, viruses, or bacteria can cause pneumonia.

Mycobacterium tuberculosis is the bacterial agent that causes tuberculosis (TB). Pulmonary TB is the main type that affects the lungs, causing symptoms including exhaustion, coughing, and chest pain in addition to weight loss. Extrapulmonary TB is another area of the body that can be affected by TB.

Blood clots that enter the lungs and obstruct blood flow are known as pulmonary emboli. Chest pain, blood in the cough, and abrupt dyspnea are possible symptoms.

Idiopathic Pulmonary Fibrosis (IPF): IPF is a form of interstitial lung disease in which the lung tissue gradually scars. This results in symptoms like exhaustion, shortness of breath, and a persistent cough.

There are differences in these respiratory disorders' etiology, symptoms, and methods of treatment. The prognosis of many illnesses can be greatly affected by early discovery, appropriate management, and lifestyle modifications. Please feel free to inquire for more information if you have any questions regarding any of these illnesses or any other respiratory-related issues.

Dataset Selection for DL Model

Researchers and developers can use several publicly available datasets for respiratory issue identification to build models and conduct analyses. Here are a few datasets that are frequently used in this field:

A sizable publicly accessible collection of chest X-ray pictures with radiologist annotations and structured reports is called MIMIC-CXR (Multiparameter Intelligent Monitoring in Intensive Care—Chest X-ray Database). It can be utilized for several purposes, including the identification of respiratory disorders.

The dataset known as Chest X-ray 14 consists of 112,120 frontal-view chest X-ray pictures that show 14 common thoracic diseases, such as emphysema, pneumonia, and other respiratory disorders. It can be used to train deep-learning models for the identification of respiratory illnesses.

The Radiological Society of North America (RSNA) is hosting the RSNA Pneumonia Detection Challenge. This collection includes chest X-ray pictures annotated for pneumonia, a serious respiratory illness. This dataset was a component of an algorithmic competition to diagnose pneumonia.

The Lung Image Database Consortium (LIDC) is a collection of annotated thoracic CT scans that include lesions linked to respiratory conditions like lung cancer and pulmonary nodules. It can be applied to the development of nodule detection and classification algorithms.

COVID-19 Image Data Collection: Different institutions and organizations have made available several COVID-19-related datasets of chest X-ray and CT images since the pandemic's outbreak. AI models for COVID-19 identification and characterization can be researched and developed using these datasets.

It is necessary to read the specific terms of use and any associated ethical issues before utilizing any of these datasets for study or development. Furthermore, while working with medical picture datasets, maintaining patient privacy and data security is essential.

Detecting respiratory diseases using convolutional neural networks (CNNs) involves using an image collection to train a model representing different respiratory conditions. Here are the steps to build a CNN model for this task: Data Collection: Gather a large dataset of chest X-ray or CT scan images that cover a variety of respiratory diseases such as pneumonia, bronchitis, tuberculosis, lung cancer, etc. Ensure that the images are labeled with the corresponding diagnosis [21].

Preprocessing the data includes scaling the photographs to a consistent size, normalizing the pixel values, and adding to the dataset using methods like flipping, rotating, and zooming to add more variety to the training set. Model Architecture: Design a CNN architecture suitable for image classification tasks. Multiple convolutional layers, pooling layers, and fully linked layers for classification could be the conventional design for this task. Training: Divide the dataset into sets for validation and training. Utilizing methods such as Adam optimizer or stochastic gradient descent, train the CNN model on the training set. To avoid overfitting, keep an eye on the model's performance on the validation set. Evaluation: Use a different test set to gauge the trained model's performance in identifying respiratory illnesses. To assess the model's efficacy, compute measures like accuracy, precision, recall, and F1 score. Interpretation: To see which areas of the image are crucial for the model's predictions, apply methods like class activation maps or gradient-weighted class activation mapping (Grad- CAM). This can aid in comprehending the decision-making process used by CNN. Deployment: After the model has been trained and assessed, put it to use in a real-world scenario where it can identify respiratory disorders by analyzing fresh chest CT or X-ray pictures. By following these steps and utilizing a well-designed CNN architecture, can effectively detect respiratory diseases from medical images with high accuracy and reliability. Figure 3 emphasizes that creating or improving a dataset from learned information entails using the insights, patterns, and representations that a trained model has learned. These strategies for applying gained knowledge help to build new datasets or improve ones that already exist, which helps with activities like model training, assessment, and deployment in various applications.

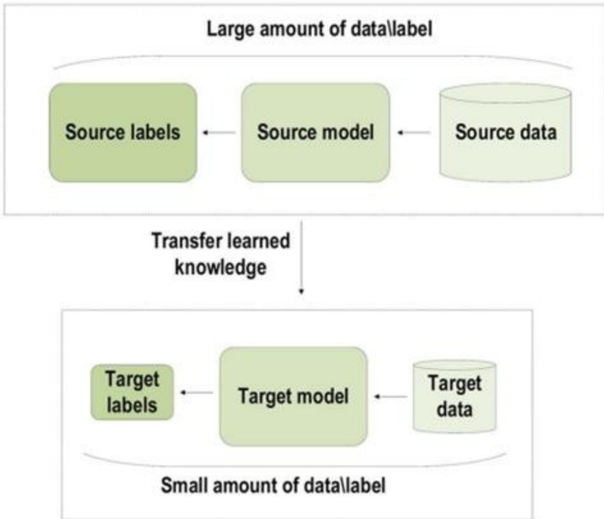

Figure 3. Extraction of dataset from learned knowledge.

The process of diagnosing respiratory issues is complex and includes imaging, laboratory testing, clinical assessment, and specialist procedures. The accurate identification and management of respiratory diseases are facilitated by the combination of various diagnostic approaches. The clinical appearance and presumed underlying illness guide the choice of diagnostic instruments. Figure 4 shows how this process happens with the help of image processing techniques and the learning process.

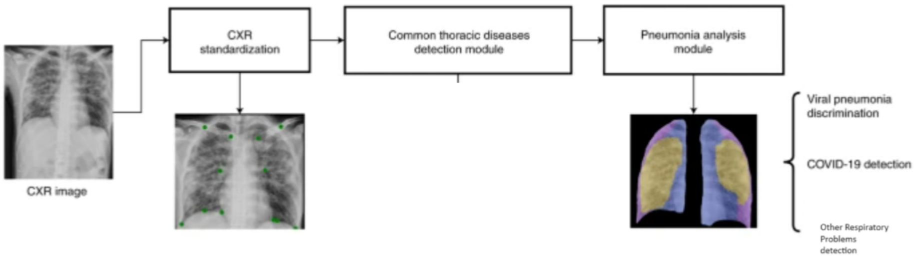

Figure 4. Diagnosis of Respiratory Problems.

The system has a pipeline with three modules: one for common thoracic disease identification, one for pneumonia analysis, and one for CXR standardization. The respiratory problems detection, severity assessment, and viral pneumonia categorization are included in the pneumonia analysis module. The identification of respiratory problems using X-ray images is a well-studied and useful use of convolutional neural networks (CNNs) in machine learning. Large datasets of labeled chest X-ray images are collected, with annotations indicating the presence or absence of specific respiratory conditions such as pneumonia, tuberculosis, or other pulmonary abnormalities. The X-ray images are preprocessed to enhance clarity, remove noise, and normalize the data for training. This may involve resizing, histogram equalization, and noise reduction. A CNN model architecture is designed, typically involving multiple convolutional, pooling, and fully connected layers. Transfer learning can also be utilized by leveraging pre-trained models like VGG, ResNet, or Inception. There are training and validation sets inside the provided dataset. After that, the validation set is used to assess the CNN model's performance and make sure it performs well when applied to fresh data. To maximize the model's performance and avoid overfitting, parameters including learning rate, batch size, number of layers, and architecture are adjusted. Additional test datasets are used to evaluate the trained model to determine its accuracy, sensitivity, specificity, and other pertinent metrics. To improve the resilience of the model, ensemble approaches and uncertainty quantification techniques might be used. When the model performs well enough, radiologists can use it to help them identify respiratory issues from X-ray pictures by integrating it into healthcare systems or using it as part of a diagnostic tool. It is important to note that while CNNs can be powerful tools for diagnosing respiratory problems in X-ray images, they should be utilized as supportive tools for healthcare professionals rather than as standalone diagnostic solutions. Additionally, model interpretability and transparency are crucial considerations in deploying AI in medical settings to ensure trust and understanding by the end-users. Analyzing the results of a respiratory disease detection system based on deep learning involves evaluating the performance of the model using various metrics and visualizations. Here is a step-by-step guide on how to conduct result analysis:

In data Splitting divide the dataset into training, validation, and test sets. Ensure that the distribution of classes is representative in each set. Train your deep learning model on the training set. Monitor the training progress by observing loss curves and accuracy metrics on the validation set. Performance Metrics evaluate your model using standard performance metrics such as:

Accuracy: The model's overall correctness.

Precision: The capacity to recognize positive cases with accuracy. Sensitivity (Recall): Capability to Record All Positive Examples. F1 Score: Equilibrium recall and precision.

Specificity: The capacity to recognize negative cases with accuracy.

To see true positives, true negatives, false positives, and false negatives, use confusion matrices.

AUC-ROC and the ROC Curve. Utilize a Receiver Operating Characteristic (ROC) curve to examine how sensitivity and specificity are traded off. Find the Area Under the ROC Curve (AUC-ROC) to obtain a thorough performance measure. AUC-PR with the Precision-Recall Curve: To evaluate the precision-recall trade-off, plot the precision-recall curve. Determine the imbalanced dataset's Area Under the Precision Recall curve (AUC-PR). Confidence Intervals, if applicable, calculate confidence intervals for performance metrics to quantify uncertainty in your results. Visualizing Misclassifications, examine misclassified examples to understand the model's weaknesses. This can provide insights into potential improvements. Heatmaps and Grad-CAM: Create heatmaps or Grad-CAM (Gradient-weighted Class Activation Mapping) to show the regions of the pictures that the model considers important while making decisions. Threshold Analysis: Evaluate the impact of adjusting classification thresholds on performance metrics. This is especially crucial when working with unbalanced datasets. Metrics Specific to a Domain: Consider domain-specific metrics depending on the respiratory disease you are detecting. For instance, if it's pneumonia, metrics like sensitivity to specific pneumonia characteristics might be relevant. Ex- Ternal Validation: If possible, validate your model on an external dataset to assess generalization performance. Interpretable Models: If applicable, use interpretable models or techniques to provide explanations for model predictions. Documentation: Document your findings, including strengths, limitations, and potential areas for im- improvement. Remember to interpret the results in the context of the specific requirements and constraints of the medical application. Continuous refinement and validation are crucial for deploying models in real-world healthcare settings. The accuracy of several deep learning models is probably shown in Figure 5. Depending on the architecture, dataset, and evaluation metrics employed, evaluating the accuracy of different deep learning models can vary significantly, especially when it comes to tasks like image super-resolution. Different models or experimental circumstances are most likely represented by the x-axis, and accuracy measures like mean squared error or classification accuracy are most likely represented by the y-axis. A distinct model or a model variation may be represented by each line or data point on the display. The amount of data utilized for training has a big impact on how well deep learning (DL) models perform. More training data generally leads to better performance of deep learning models, allowing them to learn stronger and more broadly applicable features. The performance of deep learning (DL) models in response to the volume of data utilized for training is probably shown in Figure 6. Understanding how model performance scales with dataset size is a vital component in machine learning and deep learning research, and this kind of graphic may be essential for doing so.

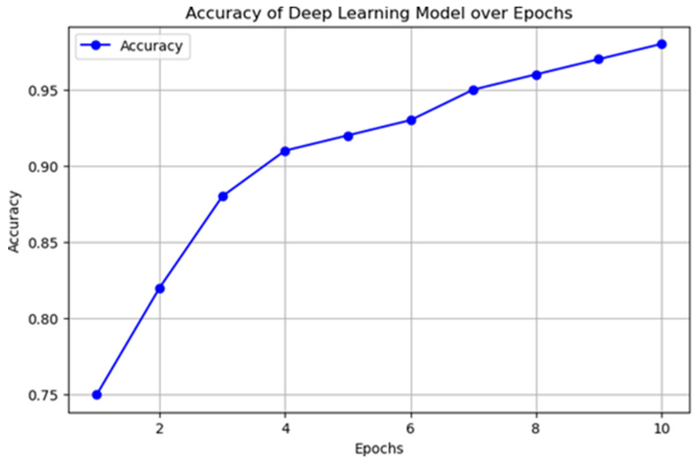

Figure 5. The plot shows the accuracy of the deep learning models.

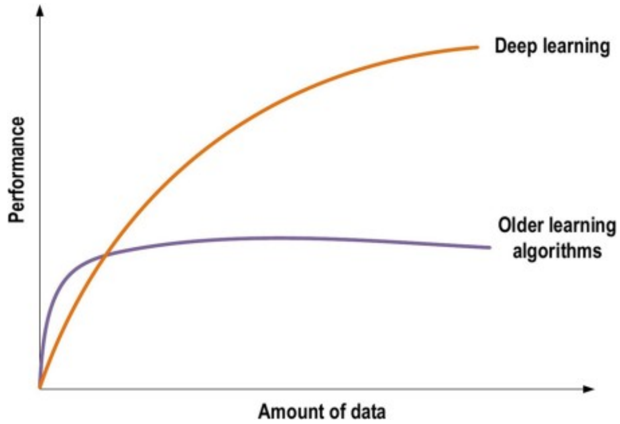

Figure 6. The performance of DL regarding the amount of data.

It is noteworthy that the decision between deep learning and conventional models is contingent upon various parameters, including but not limited to the dataset's size, task complexity, processing capacity, interpretability demands, and the accessibility of labeled data. In certain situations, classical models might still be appropriate, particularly for jobs involving smaller datasets or when interpretability is a crucial factor. The representativeness and quality of the training data have a major impact on a model's efficacy as well.

3. The Advantage of Deep Learning Models in Image Diagnosis over Other Models

Compared to standard models, deep learning models frequently show performance improvements in image diagnosis, particularly in applications where complex patterns and hierarchical representations are essential. In the domain of picture diagnostics, deep learning models have the following significant advantages over standard models. Convolution operations are used by CNN in at least one layer in place of basic matrix multiplication. It mainly appears in unstructured datasets (like pictures and video) [22]. 2D-CNN uses 2D-convolutional kernels to predict a single slice's segmentation maps [23]. The application of ensemble learning to medical diagnostics is covered in the study. A machine learning method called ensemble learning mixes several models to increase prediction accuracy [24]. To diagnose medical disorders using patient data, the research provides a classification model that makes use of ensemble learning. The model's accuracy in diagnosing a range of medical disorders was quite good.

1. Hierarchical Feature Learning:

Deep Learning: Deep neural networks can automatically learn hierarchical representations of features from raw data. Each layer extracts increasingly abstract features, allowing the model to capture complex patterns. Deep learning techniques like Convolutional Neural Networks (CNNs) are frequently applied to image processing and recognition applications. Overfitting, interpretability, and the requirement for a lot of data are issues with deep learning [25]. Deep learning has applications in computer vision, natural language processing, image and audio recognition, and autonomous systems.

Traditional Models: Traditional machine learning models may require handcrafted feature engineering, making them less adept at automatically learning hierarchical representations.

2. End-to-End Learning:

Deep Learning: Deep models can learn end-to-end mappings from raw input to output, eliminating the need to manually extract intermediate features. To avoid problems and enhance overall patient outcomes, it also emphasizes the significance of early identification and appropriate care of nail psoriasis [26]. This can be made as an end-to-end learning.

Traditional Models: In traditional models, feature extraction and classification are often separate steps, requiring domain expertise to design effective feature sets. In the paper, the authors discuss the challenges and limitations of deep learning models in imbalanced datasets and propose several techniques for addressing this issue [27].

3. Capacity to Handle Large Datasets:

Deep Learning: Deep models can benefit from large datasets, as their capacity to learn parameters scales with data volume. Due to its potential to affect both the speed and accuracy of data processing as well as the dependability of the outcomes, this is a crucial factor for companies and organizations handling enormous amounts of information.

Traditional Models: Some traditional models may struggle with large datasets due to limitations in model complexity and computational requirements [28].

4. Transfer Learning:

Deep Learning: Pre-trained models on large datasets can be fine-tuned for specific tasks, allowing for effective transfer learning and improved performance, especially when labeled data is limited.

Traditional Models: Transfer learning is less common and often requires extensive domain knowledge for effective implementation.

5. Non-Linearity and Complex Decision Boundaries:

Deep Learning: Neural networks can model non-linear relationships and capture complex decision boundaries, making them suitable for tasks with intricate patterns.

Traditional Models: Linear models may struggle with capturing complex relationships in data.

6. Adaptability to Varied Input Modalities:

Deep Learning: Deep models can handle various input modalities (e.g., images, text, time series) and learn relevant representations for different types of data.

Traditional Models: Traditional models may require significant modifications to handle different input modalities effectively.

7. Reduced Dependency on Handcrafted Features:

Deep Learning: Deep models can automatically learn features from raw data, re- ducing the reliance on handcrafted features and domain-specific knowledge.

Traditional Models: Handcrafting features can be challenging and time-consuming, and the effectiveness depends on domain expertise.

8. Robustness to Noisy Data:

Deep Learning: Deep models can often handle noisy data and still learn meaningful representations, making them robust in real-world scenarios.

Traditional Models: Some traditional models may be sensitive to noise and may require extensive preprocessing.

A robust diagnostic tool was created by the authors by combining deep learning algorithms, feature extraction, and image segmentation techniques. As a result of their findings, which demonstrated that the suggested approach could detect COVID-19 instances with high accuracy, the field is set to advance [29].

Automating the process of examining many medical photos for respiratory issues is possible by utilizing deep learning. This improves efficiency and permits quicker diagnosis by lowering the time and effort needed for analysis. By recognizing small signals or trends that may be difficult for human observers to notice, deep learning models can help with the early diagnosis of respiratory issues. Improved patient outcomes and prompt therapies may result from this early diagnosis [30]. By examining a patient's medical imaging data and recognizing certain signs of respiratory issues, deep learning algorithms can aid in the creation of individualized treatment plans. This may result in individualized treatment programs based on personal traits. Large-scale medical imaging databases can be analyzed using deep learning to find new information about respiratory disorders. This can help in the creation of novel diagnostic instruments, therapeutic approaches, and comprehension of the mechanisms underlying disease. Healthcare systems can benefit from the integration of deep learning models, which can help physicians comprehend medical imaging data, offer decision assistance, and increase the diagnostic precision of respiratory problem identification [31]. All things considered, using deep learning to identify respiratory issues has the potential to boost patient care, increase diagnostic precision, and progress respiratory medicine research.

4. Discussion of the Implications of the Results

Prompt Identification and Assessment:

Enhanced Results for Patients: Early detection enables prompt intervention and therapy, which may stop respiratory disorders from worsening and enhance patient outcomes. Lower Healthcare Costs: When respiratory disorders are diagnosed early, treatment options might be simpler and less expensive than when they are diagnosed at an advanced stage. The program demonstrated a high degree of accuracy in identifying several kinds of artifacts, such as muscular activity and ECG signals, after it was trained on a dataset of recordings tainted by artifacts. According to the study's findings, neural network-based methods can be useful for eliminating artifacts from brain signal data and enhancing the precision of later analysis [32].

Personalized Treatment Plans: Optimal Healthcare Delivery: By minimizing the need for trial-and-error methods and maximizing the utilization of healthcare resources, personalized treatment plans can result in more successful treatments [33].

Enhanced Patient Happiness: By attending to each patient's specific needs, customized therapy based on individual evaluations might improve patient happiness.

Resource Optimization: Simplified Processes in Healthcare: Medical personnel can more efficiently manage their time and resources thanks to improved healthcare workflows that are facilitated by efficient triage and diagnostic procedures.

Improved Resource Allocation: By allocating resources optimally according to the severity of respiratory diseases, vital resources are directed to the areas where they are most required. A method discussed suggested method attained an accuracy of 98.5%, making it a helpful tool for quick and accurate COVID-19 diagnosis, according to the study, which was done on a sample of 531 patients [34]. The utilization of CNN-based diagnostics in telemedicine solutions enhances accessibility to healthcare services, particularly in underserved or distant areas. This leads to improved remote monitoring and telemedicine services.

Improved Continuity of Care: Proactive interventions and fewer hospital admissions are made possible by early detection of changes in respiratory conditions made possible by continuous monitoring via remote solutions. In diagnosing respiratory diagnosis instances, the study's findings demonstrated the excellent accuracy, precision, and recall of the suggested model [35].

Progress in Research: Quicker Discovery: The analysis of medical images by CNNs provides valuable insights into the pathophysiology of respiratory disorders, which could expedite research and development. Knowledge-Based Treatment Plans: Research based on data is useful in creating more focused and educated treatment plans. Impact on Public Health: Planning for Public Health Effectively Planning and activities related to public health are informed by precise prevalence data that come from extensive installations of CNN-based systems.

Preventive Measures: To address respiratory health issues, epidemiological research can provide insights that can inform the creation of preventive measures and health policies.

Difficulties and Moral Issues:

Algorithmic Fairness: To guarantee that the advantages of respiratory problem diagnosis are dispersed throughout varied patient populations, biases in CNN models must be addressed.

Patient Privacy Protections: Strong privacy controls must be put in place to safeguard private medical image data and foster patient trust.

In conclusion, using CNNs to detect respiratory issues has broad ramifications that affect patient care, healthcare systems, research, and public health initiatives. Although these technologies have many advantages, using them responsibly and ethically in the healthcare industry requires navigating obstacles and moral dilemmas. summary of the illness's epidemic and the difficulties it poses [35].

5. Conclusions

Convolutional neural networks (CNNs) and deep learning applied to respiratory problem identification from medical images, in summary, mark a major advancement in the healthcare industry. Deep learning models, and CNNs in particular, have proven to be exceptionally effective at extracting complex patterns and characteristics that are essential for precise diagnosis because of their unique capabilities. Deep learning has brought about a new era of efficiency, automation, and increased diagnostic accuracy, replacing traditional methods. Because CNNs can automatically build hierarchical representations from unprocessed picture data, they have shown to be very good at identifying minute details that may indicate respiratory problems. These models' ability to handle big and varied datasets and end-to-end learning methodology enables them to adjust to intricate patterns and variances in medical images. Deep learning models are made even more useful by the idea of transfer learning, which enables pre-trained networks to be adjusted for respiratory ailments. This not only makes use of information gleaned from large datasets but also makes efficient use of the few labeled medical images available a problem that is frequently encountered in the field of healthcare. The reduced dependence on manual feature engineering, coupled with the adaptability to different imaging modalities, enhances the scalability and applicability of CNNs in respiratory diagnostics. The non-linear nature of these models enables them to capture intricate relationships in the data, contributing to their robustness and effectiveness, even in the presence of noise. The application of CNNs and deep learning to respiratory problem identification not only improves diagnosis accuracy but also has the potential to completely transform patient care as we move into a future in which technological breakthroughs will continue to disrupt the healthcare industry. The current state of this field's research and development promises greater innovation and refinement, which will eventually lead to earlier and more accurate diagnoses, increasing patient outcomes and the overall quality of healthcare.

The study concludes by providing a thorough analysis of the use of deep learning models to distinguish lung illnesses from lung sounds. The study's conclusions highlight the created algorithm's high accuracy and precision and highlight its potential for usage in clinical settings. The potential of deep learning models to improve respiratory disease diagnosis and assist medical professionals in making more precise medical decisions based on lung sounds is highlighted in the paper. To enhance the deep learning model's performance and clinical scenario applicability, the team intends to grow the dataset and further refine it in subsequent work.

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The authors declare no conflicts of interest.

Data Availability Statement

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References

1. B. David V. and J. Hansen-Flaschen. "Respiratory disease". *Encyclopedia Britanni- ca*, 22 Feb. 2024, Accessed 2 March 2024.
2. A. Elaanba, M. Ridouani, L. Hassouni. A Stacked Generalization Chest-X-ray-Based Framework for Mispositioned Medical Tubes and Catheters Detection. *Biomedical Signal Processing and Control*, Volume 79, Part 1, 2023, 104111, ISSN 1746-8094.
3. S.N. Khan, N.M. Nawi, A. Shahzad, A. Ullah, M.F. Mushtaq, J. Mir, M. Aamir. Comparative Analysis for Heart Disease Prediction. *JOIV International Journal on Informatics Visualization* November 2017.
4. A.B.R. Shatte, D.M. Hutchinson, S.J. Teague (2019) Machine learning in mental health: A scoping review of methods and applications. *Psychol. Med.* 49:1–23.
5. N.A. Mathew, R.S. Vivek, P.R. Anurenjan. (2018) Early diagnosis of Alzheimer's disease from MRI images using pnn. In *Proceedings of the 2018 international CET conference on control, communication, and computing (IC4)*, 161–164.
6. M. Mahmud, S. Vassanelli. (2019) Open-source tools for Processing and Analysis of In Vitro Extracellular Neuronal Signals. In *In Vitro Neuronal Networks: From Culturing Methods to Neuro-Technological Applications*, Chiappalone, M., Pasquale, V., Frega, M. (Eds.); Cham, Switzerland: Springer, pp. 233–250.
7. M.B.T. Noor, N.Z. Zenia, M.S. Kaiser, S.A. Mamun, M. Mahmud. Application of deep learning in detecting neurological disorders from magnetic resonance images: A survey on the detection of Alzheimer's disease, *Parkinson's Disease and Schizophrenia*, Cham, Switzerland: Springer Open (2020) 7:11.
8. R.A. Poldrack, K.J. Gorgolewski, G. Varoquaux (2019). Computational and informatics advances for reproducible data analysis in neuroimaging. *Annu. Rev. Biomed. Data Sci.* 2:119–138.

9. O. Ronneberger, P. Fischer, and T. Brox. U-Net: Convolutional Networks for Biomedical Image Segmentation Springer International Publishing Switzerland 2015, N. Navab et al. (Eds.): MICCAI 2015, Part III, LNCS 9351, pp. 234–241, 2015.
10. M. Mahmud, M.S. Kaiser, A. Hussain, S. Vassanelli (2018). Applications of deep learning and reinforcement learning to biological data. *IEEE Trans. Neural Netw Learn. Syst.* 29(6):2063–2079.
11. M. Mahmud, M.S. Kaiser, T.M. McGinnity, A. Hussain (2020). Deep learning in mining biological data. *CoRR* arXiv:abs/2003.00108, 1–36.
12. H.M. Ali, M.S. Kaiser, M. Mahmud (2019). Application of convolutional neural network in segmenting brain regions from mri data. In *Proceedings of the International Conference on Brain Informatics*, pp. 136–146. Springer.
13. Orojo O, Tepper J, McGinnity TM, Mahmud M (2019) A Multi-recurrent Network for Crude Oil Price Prediction. In *Proceedings of the 2019 IEEE Symposium Series on Computational Intelligence (SSCI)*, pp. 2953–2958.
14. A.D. Arya, S.S. Verma, P. Chakarabarti, T. Chakrabarti, A.A. Elngar, A.M. Kamali, M. Nami. A systematic review on machine learning and deep learning techniques in the effective diagnosis of Alzheimer's disease, *Brain Informatics* (2023) 10:17.
15. S.W. Yahaya, A. Lotfi, M. Mahmud (2019). A consensus novelty detection ensemble approach for anomaly detection in activities of daily living. *Appl. Soft Comput.* 83:105613.
16. R. Wongsathan, W. Puangmanee. "DNN and RNN Models derived by PSO for Predicting COVID-19 and R t under Control Measure". *International Journal of Computer Information Systems & Industrial Management Applications* 15 (2023).
17. D. Liu, W. Ding, Z.S. Dong, W. Pedrycz. Optimizing deep neural networks to predict the effect of social distancing on COVID-19 spread. Comput Ind Eng. 2022 Apr;166:107970. doi: 10.1016/j.cie.2022.107970. Epub 2022 Jan 29. PMID: 36568699; PMCID: PMC9757984.
18. Y. Kumar and M. Mahajan. "*Recent advancement of machine learning and deep learning in the field of healthcare system, From the book Computational Intelligence for Machine Learning and Healthcare Informatics"*, Berlin, Germany: De Gruyter, 2020.
19. R.B. Hegde, V. Kudva, K. Prasad, B.M. Singh, S. Guruvare. "*Chapter 11 Applications of Conventional Machine Learning and Deep Learning for Automation of Diagnosis: Case Study*", Machine Learning for Sustainable Development, edited by Kamal Kant Hiran, Deepak Khazanchi, Ajay Kumar Vyas and Sanjeevikumar Padmanaban, Berlin, Boston: De Gruyter, 2021, pp. 175-198.
20. S. Lilly Sheeba, L. Gethsia Judin. March 2022, "*Detection of Lung Cancer from CT Images Using Image Processing*", Lecture Notes in Networks and Systems, Cham, Switerlnad: Springer, vol. 418, pp. 686–695.
21. A. Sivakumar, S. Lilly Sheeba, M. Suganthy, B. Gunasundari, S. Sivamurugan, G. Sajiv, April 2023. "A Robust and Novel Hybrid Deep Learning based Lung Nodule Identification on CT Scan Images", In *Proceedings of the in the International Conference of Artificial Intelligence and Knowledge Discovery in Concurrent Engineering (ICECONF)*, pp. 326-331, IEEEXplore.
22. M. Fabietti, M. Mahmud, A. Lotfi, A. Averna, D. Gugganmos, R. Nudo, M. Chiappalone (2020). Neural network-based artifact detection in local field potentials recorded from chronically implanted neural probes. In *Proceedings of the 2020 International Joint Conference on Neural Networks (IJCNN)*, pp. 1–8.
23. M.B.T. Noor, N.Z. Zenia, M.S. Kaiser, M. Mahmud, S. Al Mamun (2019). Detecting neuro-degenerative disease from mri: A brief review on a deep learning perspective. In *Proceedings of the International Conference on Brain Informatics*, pp. 115–125.
24. P. Lohumi, S. Garg, T. P. Singh, and M. Gopal, "Ensemble Learning Classification for Medical Diagnosis," In *Proceedings of the 2020 5th International Conference on Computing, Communication and Security (ICCCS)*, Patna, India, 2020, pp. 1-5, doi: 10.1109/ICCCS49678.2020.9277277.
25. L. Alzubaidi, J. Zhang, A.J. Humaidi, A. Al-Dujaili, Y. Duan, O. Al-Shamma, J. Santamaría (2021). Review of deep learning: Concepts, CNN architectures, challenges, applications, future directions. *Journal of Big Data*, 8(1), 1-74.
26. Y. Oram, A.D. Akkaya. Treatment of nail psoriasis: common concepts and new trends. *Dermatology Research and Practice* 2013, 10.1155/2013/180496.
27. J.M. Johnson, T.M. Khoshgoftaar. Survey on deep learning with class imbalance, *J. Big Data* 6 (2019) 27.
28. C.R. Stewart, L. Algu, R. Kamran, C.F. Leveille, K. Abid, C. Rae, S.R. Lipner, The im- pact of nail psoriasis and treatment on quality of life: A systematic review. *Skin Appendage Disord.* 7 (2021) 83–89.
29. G.D. Rubin, C.J. Ryerson, L.B. Haramati, N. Sverzellati, J.P. Kanne, S. Raoof, N. Schluger, A. Volpi, J.-J. Yim, I.B. Martin, The role of chest imaging in patient management during the covid-19 pandemic: a multinational consensus statement from the Fleischner society. *Radiology* 296 (2020) 172–180.
30. N. Gianchandani, A. Jaiswal, D. Singh, V. Kumar, M. Kaur, Rapid COVID-19 diagnosis using ensemble deep transfer learning models from chest radiographic images. *J. Ambient Intell. Hum. Comput.* (2020) 1–13.
31. A.M. Sebdani, A. Mostafavi, Medical image processing and deep learning to diagnose COVID-19 with ct images, In *Proceedings of the 2021 5th International Conference on Pattern Recognition and Image Analysis (IPRIA)*, IEEE, 2021, pp. 1–6.

32. N. Gianchandani, A. Jaiswal, D. Singh, V. Kumar, M. Kaur, Rapid COVID-19 diagnosis using ensemble deep transfer learning models from chest radiographic images. *J. Ambient Intell. Hum. Comput.* (2020) 1–13.

33. M.A. Elaziz, K.M. Hosny, A. Salah, M.M. Darwish, S. Lu, A.T. Sahlol, New machine learning method for image-based diagnosis of COVID-19. *PLoS ONE* 15 (2020), e0235187.
34. C.-C. Lai, T.-P. Shih, W.-C. Ko, H.-J. Tang, P.-R. Hsueh, Severe acute respiratory syn- drome coronavirus 2 (SARS-CoV-2) and coronavirus disease-2019 (COVID-19): the epidemic and the challenges. *Int. J. Antimicrob. Agents* 55 (2020) 105924.
35. M.D. Hope, C.A. Raptis, T.S. Henry. Chest Computed Tomography for Detection of Coronavirus Disease 2019 (COVID-19): Don't Rush the Science. *Annals of Internal Medicine* 2020.