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A SYSTEMATIC LITERATURE REVIEW OF MACHINE AND DEEP LEARNING-BASED DETECTION AND CLASSIFICATION METHODS FOR DISEASES RELATED TO THE RESPIRATORY SYSTEM

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ABSTRACT

Deep Learning (DL) is a sub field of Machine Learning (ML) that has considerable prospective in many areas of study like computer vision, image, and audio processing. A great number of studies using DL methods are published yearly. The emphasis of this study is on diseases related to the respiratory system detection and classification using audio files. This study outlines a systematic literature review that harmonizes the indication related to diseases related to the respiratory system detection and identification published during the years between 2015 and 2021. The goal is to collect, analyze, and epitomize the indication related to DL identification, classification and detection of diseases related to the respiratory system. The importance is that the review will aid professionals and specialists to comprehend how DL methods can be used in this respect and theoretically further backing more precise detection of diseases related to the respiratory system. 47 articles are analyzed in the current review. Most of the articles published emphasis on supervised learning with deep convolutional neural networks. Moreover, a great number of articles use data sets that are privately-prepared as opposed to open source data sets. The outcomes likewise show a shortage of tools, that is an obstruction in adjusting academic research in industrialized circumstances.

Keywords:—*Literature Review; Deep Learning; Respiratory System; Classification; Machine Learning; Detection; Audio*

1. INTRODUCTION

Respiratory diseases are the causes for an excess of 4 million deaths per year. After the heart diseases, they are the leading providers to the worldwide disease problem. The latest epidemic of corona virus has additionally put into open argument the significance of the availability and precise diagnosis of respiratory diseases [2].

Currently, computed tomography (CT) scans and chest X-ray are frequently employed to analyze individuals with respiratory problems. These images, nevertheless, are expensive and raise the danger of cancer due to radioactivity. Stethoscopes are likewise engaged to listen to the lungs of the individual, however it is not sufficient to make a dependable diagnosis. Using deep learning to diagnose individuals could lessen radioactivity dangers and reduce cost. It can make precise forecasts more manageable to the developed countries and isolated geographic sites—areas that do not have essential money for costly tools or a skilled workforce [3].

There is a motive to trust this might be imaginable. DL methods have been applied positively in numerous health settings, for example identifying heart diseases [5] and using medical images to discover signs of skin melanoma [6] or tuberculosis [7]. Whereas these have repeatedly been caused by the skills of computer vision, respiratory audio investigation is still in its initial steps, and obtainable modest articles demonstrate unlimited perspective [8]. Respiratory disease classification models still need additional investigation and consideration to grasp widespread usage in the medical situation.

The determination of this study is enhancing the area of respiratory diseases audio examination by producing and implementing a model that comprises experimentations with different DL models on a data base of respiratory audio.

Systematic Literature Reviews (SLRs) collect, categorize, and analyze up-to-date info from obtainable literature. A SLR is a kind of subordinate study that gathers and sums up the published literature in a specific field. The articles under review are contemplated as main articles [7].

The current study introduces a SLR on DL based identification and classification of diseases related to the respiratory system. This effort collects, examines, and sums up 47 studies related to deep and machine learning on diseases related to the respiratory system categorization. The goal of this article is assisting fresh investigators by providing them systematic visions from previous studies. Additionally, this SLR is likewise advantageous for specialists as it pinpoints the state-of-the-art tools, frameworks and methods in this field. Explicitly, this study make available the subsequent additions:

- Documentation of the DL diseases related to the respiratory system categorizing methods offered in the previous studies. This study shows an arrangement and categorizes standing literatures based on the categories of DL methods, learning natures, and employed tools to classify diseases related to the respiratory system.
- An expressive investigation of quantitative and structural data analysis of qualitative data to offer sense into DL methods and data sets. This study likewise gives a relative examination to look for the likenesses and variances in assessment of performance metrics and tools presented in the reviewed studies.
- Sense for specialists into the up-to-date progressions in tools, methods, and frameworks in the deep and machine learning based classification of respiratory system problems. Reporting of benchmark datasets and performance assessment metrics used to evaluate the performance of deep and machine learning approaches for respiratory system problems classification.

The rest of the study is organized as follows: Section II presents the background of several deep and machine learning methods in general. Section III discusses the research methodology used in this study. Section IV outlines the results of this study. Finally, Section V gives out a discussion and the conclusion.

2. BACKGROUND

2.1 Up-to-date Survey on Deep and machine Learning Theory and Constructions

Deep learning is a subfield of machine learning, which comes out in view in many traditional and new regions. Deep and machine learning has gained remarkable consideration from academics and specialists in recent years. In contrast with conventional methods, deep learning has produced investigational results that demonstrate amazing achievement in diverse areas for example natural language processing, robotics, biotechnology, image processing, translation, and speech recognition [2] [3] [4]. In deep learning construction, there are pretty few intermediate layers amongst the input and output layers. These intermediate layers permit deep learning models to choose up designs and do classifications. Deep learning is an overall answer that can relate to almost any area, if recent or old, and has confirmed effectiveness in answering practically any type of problems [4].

2.2 Types of Deep and Machine Learning Methods

Deep and machine learning methods can be categorized into four types: supervised, unsupervised, and semi-supervised reinforcement learning methods.

2.2.1 Supervised learning method:

It "makes use of labeled input and output datasets. Examples of supervised learning techniques are Convolutional Neural Network (CNN), Support Vector Machine (SVM), Logistic regression (LR), Random forest (RF), K-Nearest Neighbors (KNN)."

2.2.2 Unsupervised learning methods:

Machine learning and deep learning use untagged datasets in un-supervised learning methods. Clustering is an example of un-supervised learning. In un-supervised learning, a learning agent identifies and explores indeterminate associations between input data. It guarantees detection of very complex and nonlinear models with many allowed parameters. Un-supervised learning uses millions of parameters and unlabeled data. Generative adversarial networks use un-supervised learning.

2.2.3 Semi-supervised learning method:

This sort of learning happens when some of the records are labeled and others are not. It is a combination of supervised and un-supervised learning. Supervised learning role is to recognize important features from a dataset with known labels. Then un-supervised learning occurs when there is little information about the dataset and basically no information about the labels. This unsupervised learning helps you manipulate the data you just entered to recognize other attributes. For example, in the cat detection problem, eyes can

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recognize by supervised learning that are vital attributes in distinguishing cats from other objects. Un-supervised learning then recognizes other novel attributes, such as nose, eyebrows, and mouth, which are important for recognizing cat faces when eyes are unrecognizable. Un-supervised learning therefore increases the generalizability of semi-supervised learning models [5]. Semi-supervised learning techniques include RNNs, GANs, and deep reinforcement learning (DRL).

2.3 Convolutional Neural Network (CNN):

CNN is a kind of ANN that supports classification and detection of tasks. A CNN is like a multilayer modest neural network, except that it is different from other neural networks, the layers of a CNN are arranged on top of each other. CNNs work similarly to the processing of images by humans and have the ability of multidimensional images processing [11]. The standard CNN architecture consists of an attribute classifier and extractor. It can be additionally divided to three layer kinds: pool layers, convolutional layers, and a layer is fully connected. The layers are put in between the input and output layers. Input layers specify input arguments such as depth, width, and height. Even layers are for convolution tasks and odd layers are for pooling. A convolutional layer extracts and creates an attribute map, which is processed and biased by an activation function to yield the concluding result. The job of the pooling layer is to decrease the dimensionality of the result made by the previous convolutional layer. It is important since as dimensions grow exponentially, it becomes progressively difficult for the PC to handle them. Lastly, the outputs obtained by convolutional and pooling layers are fed as inputs to classification or fully connected layers [6]. A classification layer collects features and applies an activation function. Because this layer computation is intensive, alternatives like average pooling layers and global pooling layers are specified. This reduces the parameters and overall complexity of this layer. Figure 2 shows the structure of CNN. Example of CNN architectures:

- Visual Geometry Group (VGG16): it is a convolutional neural network model that was proposed as one of the most popular models submitted in the ILSVRC competition in 2014 by scientists K. Simonyan and A. Zisserman working at the University of Oxford in an article titled "Very Deep Convolutional Networks for Large-Scale Image Recognition". The model scored 92.7% of the top 5 tests in ImageNet. ImageNet is a dataset of more than 14 million images belonging to 1,000 categories. The reason for the existence of the VGG16 model, is that it improves on the AlexNet model in the way that large kernel-sized filters (11 and 5 in the first and second convolutional layer, respectively) are replaced by multiple 3×3 kernel-sized filters one by one [27].
- Residual Network (ResNet): It is a CNN that is 50 layers deep or more. ResNet is a "classic neural network used as a backbone for many computer vision jobs. The essential breakthrough with ResNet was it permits us to train extremely deep neural networks with 150+layers". Residual Network which uses the skip connections concept. The skip connection skips training in some layers and connects the output.
- MobileNet: It is Google's first convolutional neural network with a small size and a small amount of accounts, which is suitable for mobile devices. The reason why MobileNet is so lightweight is to replace the typical convolution with a Depth wise separable convolution, and use width multiplication to reduce the amount of parameters.
- InceptionV3: It is a convolutional neural network that helps in the process of analyzing and classifying images and discovering patterns. Google Inception Networks in terms of the origin of the word "Inception" it idiomatically means the beginning of something, the reason for the name comes from Christopher Nolan's movie Inception. The Google Inception network has had a clear impact on the development of classifiers within the Convolutional Neural Network. This network relies on stacking layers of folding one by one, in order to improve performance.
- Xception: It is a convolutional neural network that is 71 layers deep. It involves Depth Wise Separable Convolutions. Xception is also known as "extreme" version of the Inception model. This network was introduced by Francois Chollet who works at Google, Inc. «
- LeNet: In general, LeNet refers to LeNet-5 and is a simple convolutional neural

network. LeNet was the first CNN architecture that used back-propagation to practical applications and suddenly deep learning was not just a theory anymore. LeNet was used for handwritten digit recognition and was able to outperform all other existing methods with ease.

- Dense Convolutional Network (DenseNet): This is a model focused on making deep learning networks even deeper while training more efficiently with short connections between layers. DenseNet is specifically designed to ameliorate the accuracy loss caused by vanishing gradients in high-level neural networks. Simply put, information vanishes before it reaches its destination due to the long path between the input and output layers. Long short-term memory networks (LSTM): it is a deep recurrent neural network architecture used for classification of time-series data. It is a variety of recurrent neural networks (RNNs) that are capable of learning long-term dependencies, especially in sequence prediction problems. This is a behavior required in complex problem domains like machine translation, speech recognition, and more. LSTMs are a complex area of deep learning.

Machine Learning (ML): Machine learning is a subfield of artificial intelligence and is broadly defined as the ability of machines to imitate intelligent human behavior. Artificial intelligence systems are used to perform complex tasks in a manner similar to human problem solving. Examples of machine learning algorithms:

- Support Vector Machine (SVM): it is a supervised machine learning algorithm which is used for classification and regression. Yet it is used in regression problems as well as it is best suitable for classification problems. The aim of the SVM algorithm is to find a hyperplane in an N-dimensional space that clearly categorizes the data points. The dimension of the hyperplane is subject to the number of attributes. If the number of input attributes is two, then the hyperplane is just a line. If the number of input attributes is three, then the hyperplane becomes a 2-D plane. It becomes difficult to imagine when the number of attributes surpasses three.
- Decision Trees (DTs): They are non-parametric supervised learning methods used for classification and regression. The goal is to create a model that forecasts the value of a class attribute by learning modest decision rules concluded from the data attributes.
- Logistic Regression (LR): It is an example of supervised machine learning. It is used to compute or forecast the probability of a binary (yes/no) event arising. For example, logistic regression could be applied in machine learning to predict if a person is likely to have heart problems or not.
- K-Nearest Neighbors (KNN): It is a non-parametric, supervised learning classifier that uses proximity to make predictions or classifications about the combinations of an individual data point.
- Random Forest (RF): It is a supervised machine learning algorithm that is used widely in classification and regression problems. It builds decision trees on different samples and takes their majority vote for classification and average in case of regression.
- Gradient Boosting (GB): This is a machine learning technique used especially in regression and classification tasks. It produces predictive models in the form of an ensemble of weak predictive models (usually decision trees).

3. METHODOLOGY

This Systematic Literature Review followed the recommendations offered by [10] [11]. These recommendations are widely acknowledged in the field and have been utilized by a number of papers [12] [13]. Figure 3 shows the review rules. This review is divided into three stages. The first stage shows the plan. This stage outlines the research questions that are conveyed based on the aims of the study. The second stage is divided into three portions: description of the search approach with the help of key-words, preparation of the inclusion and exclusion criteria for the paper collection, and extraction of the data of the carefully chosen attributes to answer the research questions. Lastly, the data is produced. In the third stage, the outcomes are conveyed by answering each research question. The next sections are connected with the stages and phases as drawn in Table 1.

3.1 Research Questions

The following research questions linked with the aims of the current study.

Q-1 what is the greatest state of the art in the area of machine and deep learning based detection and classification of respiratory system problems?

This question is additionally divided into the following sub questions:

Q-1-1 what are the methods/machine and deep learning models that have been used in the primary studies?

Motivation: This research question is answered by finding the machine and deep learning models used in each primary study, for example, the CNN, RNN, SVM, KNN, and RF. The summary of research methodology of machine and deep learning models described in the primary studies are recorded. The recording includes, for example, the number of layers and steps used during the pre-processing, training, and testing stages of each paper.

Q-1-2 which kinds of learning have been used?

Motivation: The aim of this research question to obtain the kinds of learning used by the methods. For example, un-supervised learning, supervised learning, semi- supervised and re-enforced learning. This is measured by mapping each machine and deep learning model on the taxonomy as shown in Figure 1.

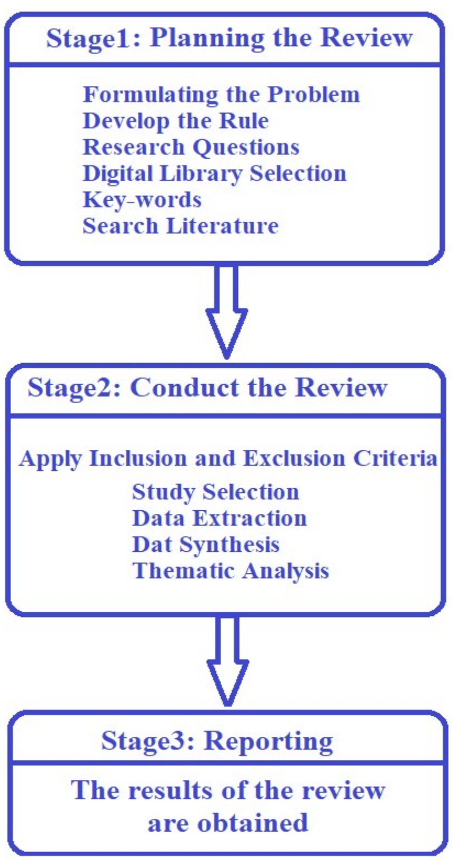

Figure 1: Review Rules.

Table 1: Steps Followed In Each Stage

Stages	The followed steps
Planning Stage	Formulating the Problem
	Developing Rules (Protocols)
	Establishing the Research Questions
	Selecting of the Online Digital Library
	Formulating of Query String
	Inclusion and Exclusion Criteria Definition
Carrying out the Review Stage	Selecting the Study
	Identifying the Attribute
	Extracting the Data
	Analyzing the Data
Reporting of the Review Stage	Reporting the Results

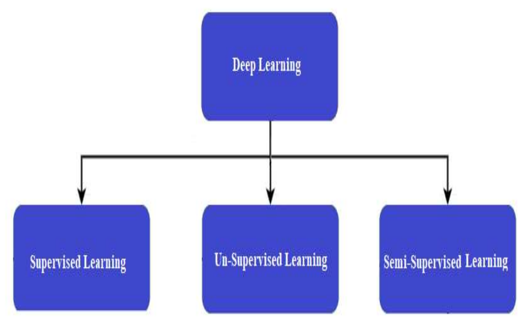

Figure 2: Taxonomy of Machine and Deep Learning Methods.

Q-1-3 what tools are available for machine and deep learning based detection and classification of respiratory system problems?

Motivation: Accessibility of tools is a vital fear for specialists. To answer this research question, the objective is to determine and report the tools established and used by primary studies. The answer to this research question comprises a list of tools obtainable and used in primary studies.

Q-2 what kind of datasets have been utilized for the evaluation in the primary studies linked to machine and deep learning based detection and classification of respiratory system problems?

Motivation: The answer to this research question includes recognizing the name and sorts of datasets employed for the training and testing of the machine and deep learning models described in the primary studies. The datasets are classified into three types: open-source, academic, and industrial. Datasets built in lab settings that are not connected with any organization or institute are considered academic. Open-source datasets are those that are publicly available, well acknowledged, and used in related studies. Datasets gotten from a particular

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organization that are not publicly obtainable and only used for the scope of a specific primary study are called industrial datasets. This research question is additionally divided into the following sub-questions.

Q-2-1 what are the features of the datasets?

Motivation: The objectives of this research question is to identify the features of the dataset, such as type of sample (images, audio, video, etc.); number and size of the dataset; and number of classes (number of diseases). The answer to this research question is by comparing and analyzing the studies as shown in a table listing dataset name, number of classes, type, and size.

Q-2-2 what metrics are used in performance evaluation of the studies of machine and deep learning based methods for the detection and classification of comparative analysis?

Motivation: The aim of this research question is to examine the performance of a machine and deep learning models based on its capability to do the classification precisely. To answer this question, the evaluation data of each model was extracted for all datasets. Different studies use different measures for the performance evaluation provisional on the dataset, machine and deep learning method applied. Performance measurements may include accuracy, precision, recall, F1-score, sensitivity, confusion matrix, etc. The answer to this research question is a comparative analysis as shown in a table providing the name of the machine, deep learning model, dataset, and best accuracy achieved using that dataset.

3.2 Selecting Digital Libraries

The search was done using the broad databases shown in Table 2. The search was done on five digital databases: Google Scholar, ACM, IEEE, Springer, and PubMed. Key-words, titles, abstracts were used, and (in the case of Google Scholar) full texts to recognize the relevant primary studies. These libraries delivered virtually complete sets of significant studies. For the completion of the search process, a manual search was similarly led by looking for relevant journals and recognizing papers from references of primary and secondary studies.

Table 2: URL and Digital Libraries

Name	URL
Springer	https://springer.com
ACM	https://dl.acm.org
Google Scholar	https://scholar.google.com
PubMed	https://pubmed.ncbi.nlm.nih.gov
IEEE Explorer	https://ieeexplore.ieee.org

3.3 Formulating the Enquiry String

By using the key-words recognized in Table 3, query strings were conveyed. Key-words were recognized based on the research questions. Alternative words and alternate terms and spellings were utilized to do the advanced search. Inquiry strings were employed to do the advanced searches on the digital databases. The Boolean operator OR was used for alternate key-words, and the operator AND was used for connecting key-words and expressions. Multiple versions of enquiry strings were established and done on various databases in order to find as numerous pertinent studies as possible.

Table 3: Shows the Main Enquiry Strings Used To Search the Digital Databases.

Digital Library	Key-Words Searched
Springer Link	"Machine Learning" AND "Deep Learning" AND "Respiratory System" AND Classification
ACM	[Publication Title: machine, deep learning] AND [Abstract: bacteria*] AND [Abstract: classification identification] AND [Publication Date: (01/01/2015 to 12/31/2021)]
Google Scholar	("Machine Learning" OR "Deep Learning" AND "Respiratory System") AND (Classification OR Detection) AND Audio AND Image
PubMed	((Deep Learning) AND (Machine Learning) AND ("Respiratory System" [Title/Abstract])) AND (Classification[Title/Abstract])
IEEE Explore	("Document Title": Deep Learning) AND ("Document Title": Machine Learning) AND ("Document Title": Respiratory System Classification)

3.4 Inclusion and Exclusion Criteria

A SLR excludes and includes articles from a pool of articles with the support of precise criteria. So as to choose pertinent articles, a modest however straightforward exclusion and inclusion criteria were conveyed. During the first stage of selecting articles based on their titles. During the next stage, article abstracts are studied. Lastly, only full articles were studied, and any article that was not in alliance with the criteria of inclusion were excluded from the pool of articles. The criteria of exclusion and inclusion are as follows:

3.4.1 Criteria of inclusion

I1: Published in the year between 2015 and 2021

I2: Language of the article is English only

I3: Complete article is available
I4: Article was Peer reviewed
I5: Article discusses DL approaches to classify and detect Respiratory System Diseases

3.4.2 Criteria of Exclusion

E1: Published before 2015
E2: Written in a language other than English
E3: A version other than the most recent version (if multiple versions are available)
E4: Non-peer reviewed (e.g., presentations or books) E5: Duplicate article
E6: Discusses classification of other than Respiratory System Diseases

3.5 Managing the SLR

This division outlines the selection of articles, synthesis procedure and data extraction,

3.5.1 Primary studies selection:

The search through five digital libraries online gathered a total of 535 papers. In the first round, the abstracts and titles of all the papers were analyzed. As a result, 80 papers were selected (I2, E2, I5, and E6). In the next round, all duplicated papers (i.e., papers showing up more than one time) were deleted (E5). Moreover, any non-peer reviewed papers like lecture notes, books, presentations, editorials, and magazines were removed (I4, E4). Full text papers that are not obtainable were excluded also (I3, E3). A physical search was likewise led by looking into related journals and recognizing papers from the references of primary and secondary studies. Consequently, a total of 47 papers were currently in the study pool. Figure 5 shows the process of selection of a study.

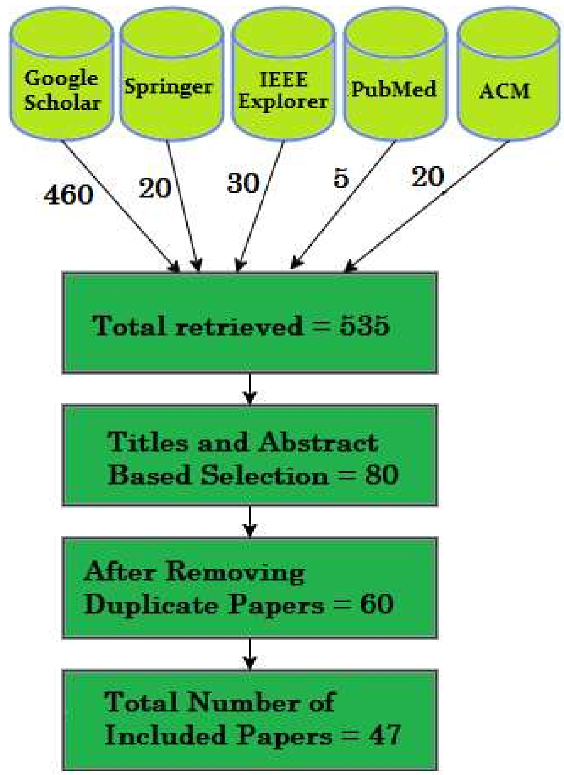

Figure 3: Process of Study Selection.

3.5.2 Data synthesis and extraction:

The designated features were pulled out from the primary articles and deposited in an Excels file for the examination. The quantifiable data were too extracted, for example number of datasets, number of labels, size, and accuracy, the qualitative data include type of dataset, the learning type, and steps followed to create the DL model. Data synthesis is a method to make a summary of reported indications from primary articles to answer the questions of research. Table 4 shows the data features extracted from every primary study and maps those features on each research question respectively. To synthesize qualitative data, a descriptive analysis was performed, and to synthesize quantitative data, a thematic examination was done.

4. RESULTS

This section shows the results and answers of the research questions discussed in section 3.1.

Q-1. What is the most state of the art in the field of machine and deep learning based detection and classification of Respiratory System Diseases?

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Table 4: Data Features Mapping On Research Questions

Data Attributes	Possible Values	Research Question
Deep Learning Model	e.g. RNN, CNN, DBN, AE	Q-1-1
Machine Learning Model	e.g. SVM, RF, DT, GB, KNN	Q-1-1
Type of Learning	Supervised, Unsupervised, Re-enforcement, Semi-Supervised	Q-1-2
Tool	Tool Name	Q-1-3
Tool Language	e.g. MATLAB, Python etc.	Q-1-3
Tool Availability	Available, Not available	Q-1-3
Name of Dataset	e.g. ICBHI 2017	Q-2
Dataset Type	Academic, Open source, Industrial	Q-2
No. of Classes	e.g. 2, 3,5	Q-2-1
Type of data sample	e.g. Audio	Q-2-1
Highest Accuracy Achieved	Value in percentage	Q-2-2
Evaluation Metrics	F1 score, precision, Recall, sensitivity, etc.	Q-2-2

To recognize DL approaches most state of the art used for Respiratory System Diseases detection and classification, the data is shown in Table 4 that was pulled out and used for all sub questions answering.

Q-1-1 what DL and ML architectures/models have the primary studies utilized?

These studies were categorized by “thematic analysis” that includes recognizing different arrangements. 68% of these studies use diverse CNN architectures. Table 5 displays the primary studies and the models/architectures used in each study. Figure 2 illustrates the DL and ML models distribution. Further classification of the studies were done based on different models of CNN (LetNet, ResNet, AlexNet, InceptionNet, MobileNet, Xception, and VGG16) and Machine learning models (SVM, KNN, RF, GB, LR). The distribution of architectures within CNNs are shown in Figure 4. A good number of primary studies incorporated architecture of VGG since it is very deep architecture and has the capabilities to attain better performances. The succeeding sections discourse the summaries of the research for each architecture category.

4.1 Deep Learning Based models:

Deep learning methods include Convolution Neural Network, Long Short-Term Memory (LSTM), VGG16, VGG19, ResNet, AlexNet, Inception, and DenseNet121.

4.1.1 Convolutional Neural Networks

A proposed work [37] uses machine learning techniques to identify lung diseases. Fuzzy logic and deep learning techniques based on convolutional neural networks (CNN) for improved performance/accuracy. The CNN includes several hidden layers that help in diagnosing pulmonary diseases accurately and also has improved accuracy. These hidden layers are very effective in performing convolution and subsampling with the goal of extracting low to high feature levels from the input data. The combination of CNN and fuzzy logic outperforms the others. The proposed work aims to identify lung disease and use a combination of machine and deep learning algorithms to prevent further lung infections in future patients.

A sign of recent advances in the field of image classification, using Convolutional Neural Networks (CNNs) to classify images with high accuracy. In this paper (Saraiva, et al., 2020), they propose, train and test a method for classifying breath sounds using CNN. For this purpose, a visual representation of each audio sample was created. This allows you to identify resources for classification using the same techniques used to classify images with high accuracy. To do this, we used a technique known as Mel-Frequency Cepstrum Coefficients (MFCC). For each audio file in the dataset, we used MFCC to extract resources. That is, we have an image representation of each audio sample. The method proposed in this article achieved over 74% results in classifying breath sounds used in the four classes available in the database used (normal, crackle, wheeze, both).

This study [45] aims to propose a feature engineering process to extract features dedicated to depth separable convolutional neural networks (DS-CNN) for accurate and efficient classification of lung sounds. They extracted a total of three features of the reduced DS-CNN model. Short-time Fourier transform (STFT) function, Mel-frequency cepstrum coefficient (MFCC) function, and a combination of these two functions. We found that the DS-CNN model trained with either the STFT or MFCC functions achieved accuracies of 82.27% and 73.02%, respectively, and the fusion of both functions achieved a higher accuracy of 85.74%. Moreover, their method achieves 16x faster inference speed on edge devices and only 0.45% lower accuracy than RespireNet. This result suggests that the fusion of STFT and MFCC capabilities with DS-CNN can be a model design for lightweight edge devices to achieve accurate AI-assisted disease detection.

In the study [51] Autodetector performance was analyzed using: (1) synthetic fine and coarse crackles randomly inserted into basal breath sounds recorded from healthy subjects with different signal-to-noise ratios, and (2) true bed from patients with interstitial diffuse pneumonia. In the simulated scenarios, we found fine crackle accuracy between 84. 86% and 89. 16%. In simulated scenarios, detecting coarse crackling turned out to be a more difficult task.

In this study [53], the authors experimented with a smartphone-based time-frequency threshold dependent (TFTD) algorithm for breath sound detection and classification. The TFTD algorithm uses spectral temporal analysis of recorded lung sounds to compute important and distinct features of each breath sound. This improves the qualitative measurement and quantitative indexing of various breath sounds. Several algorithms have been developed that run only on desktop computers to detect and analyze specific lung sounds such as wheezing. However, few attempts have been made to perform such analyzes on portable devices such as mobile phones due to the computational complexity and high power consumption involved. Our experimental results show that new smartphones with increased computational power can offer comparable performance in analyzing respiratory signals. Additionally, these phones serve as useful tools for measuring and detecting early signs of lung disease, especially in home and ambulatory care settings where conventional specialized medical equipment may not be accessible.

4.1.2 Long Short-Term Memory (LSTM)

In research [61], features originally extracted from short-term Fourier transform (STFT) spectrograms via convolutional neural networks (CNN) are given as input to a long short-term memory (LSTM) network. The data typically store and classify four types of lung sounds, including crackling, wheezing, and both crackling and wheezing. The model was trained and tested on the ICBHI 2017 breath sounds database and achieved state-of-the-art results using three different data splitting strategies. That is, 47.37% sensitivity, 82.46% specificity, 64.92% score, and 73.69% accuracy for formula 60. /40 fold, sensitivity 52.78%, specificity 84.26%, score 68.52%, precision 76.39% (10-way cross-validation between patients), sensitivity 60.29%, precision 74, 57% with leave-one-out cross-validation.

In this article [62], research is conducted to investigate the ability of deep learning to detect lung disease from electronically recorded lung sounds. The selected dataset included a total of 103 patients derived from locally recorded stethoscope lung sounds obtained at King Abdullah University Hospital, Jordan University of Science and Technology. Additionally, 110 patient data from Int. Conf. on Biomedical Health Informatics Public Challenge Database. First, all signals were checked at a sampling frequency of 4 kHz and divided into 5 second segments. Next, several preprocessing steps were performed to ensure a smoother and less noisy signal. These steps include wavelet smoothing, displacement artifact removal, and z-score normalization. The deep learning network architecture consisted of two phases. Convolutional neural networks and bidirectional long short-term memory units. Model training was evaluated based on a 10-fold k-fold cross-validation scheme using multiple performance metrics including Cohen's kappa, accuracy, sensitivity, specificity, precision, and his F1 score. The developed algorithm achieved the highest average accuracy of 99.62% with 98.85% accuracy in classifying patients based on lung disease type using CNN + BDLSTM. Furthermore, an overall agreement of 98.26% was achieved between the predictions in the training scheme and the original classes. This study paves the way for implementing Deep learning models in clinical practice to help physicians make decisions related to lung disease detection.

4.1.3 VGG16

In the study [36], they have developed and implemented the first application of deep learning CNN models in the medical field to detect diseases of the chest or lungs from chest X-rays. They are trying to develop an application that identifies abnormalities in the human chest and lungs from affected areas in images and detects them. The design of deep complex neural networks (CNNs) as modern image recognition solutions is currently of great interest. Here we collect some images of infected lungs and some images of normal lungs and try to train the system on all these images. After the model is trained, we give it a sample chest X-ray as input and check this image for any abnormalities. To solve the above problem, we developed a deep learning model to detect human breast abnormalities using CNN algorithm. By running various experiments with the proposed model, they achieved a classification accuracy of 95.0% when applied to the test data set. If this application is fully designed, this model could be used for COVID-19 patients, so they could check the current lung status of patients infected with COVID-19 and reduce the number of physical examinations in this pandemic situation.

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In this article [49], the ICBHI 2017 database with different sampling frequencies, noise, and background noise was used for lung sound classification. Lung sound signals were first converted to spectrogram images using the time-frequency method. The short-time Fourier transform (STFT) method was considered as the time-frequency transform. We classified lung sounds using two deep learning-based approaches. In the first approach, a pretrained deep convolutional neural network (CNN) model was used for feature extraction and a support vector machine (SVM) classifier was used for lung sound classification. In the second approach, a pretrained deep CNN model was improved using spectrogram images for lung noise classification (transfer learning). The accuracy of the proposed method was tested using 10-fold cross-validation. The accuracies of the first and second proposed methods were 65.5% and 63.09%, respectively. They then compared the obtained accuracy with some existing results and found that the obtained score was superior to the others.

In [60], CNN was pre-trained on 595,506 radiographs from two centers to identify common chest findings (such as opacity and exudate) and analyzed 8,072 radiographs annotated by multiple physicians. It was trained using different transfer learning approaches in ARDS on radiographs. The best-performing CNN was tested on internal and external cohort chest radiographs, including a subset reviewed by her six physicians, including a chest radiologist and a critical care physician. Chest radiograph data were obtained from his four US hospitals.

4.1.4 VGG19

The authors of [54] defined lung breath sounds as an important indicator of respiratory health and respiratory disease. Human breath sounds are directly related to air movement, lung tNo. changes, and the location of secretions in the lungs. For example, wheezing is a common indication that a patient has an obstructive airway disease such as asthma or chronic obstructive pulmonary disease (COPD). Lung breath sounds can be recorded using a digital stethoscope or other recording technology. With this digital data, CNN's Deep Learning technology can be used to automatically diagnose respiratory diseases such as asthma, pneumonia, and bronchiolitis.

In this project [57], pulmonary problems are classified primarily based on time, frequency, and photographic skills extracted from auscultation datasets, using in-depth knowledge of methods. The rule set used is a convolutional neural network using Mel-frequency cepstrum coefficient feature extraction.

In this article [58], they proposed and evaluated a deep convolutional neural network developed for breast disease classification. The proposed model consists of convolutional layers, ReLU activations, pooling layers, and fully connected layers. A final fully connected layer consisting of 15 output units. Each output unit predicts her 1 probability out of 15 diseases. Thoracic, consisting of 15 classes named "atelectasis, cardiomegaly, pleural effusion, infiltration, mass, nodule, pneumonia, pneumothorax, consolidation, edema, emphysema, fibrosis, pleural thickening, hernia, and no findings". A publicly available dataset called X-Ray 14. This model. Surprisingly, this model gives good results in multi-class classification. An average accuracy of 89.76% is attained for the classification of various diseases. A comparative analysis demonstrates the efficiency of the suggested method. The suggested method is well-suited for the classification of multi-class medical images of various thoracic diseases.

4.1.5 Inception

To compare the classification performance of their custom-designed, BOA-optimized CNNs with other available CNNs, three typical commercial CNN models, including AlexNet, VGG-16, and Inception-V1, were used with back view gray snapshot. The Inception-V1 module consists of three convolution layers (1_1 convolution, 3_3 convolution, and 5_5 convolution) and a MaxPooling layer where the 1_1 convolution is used to provide a reduction from the computationally expensive 3_3 and 5_5 convolutions. Configured. They also tried using a pre-trained CNN with _ne tuning. For pre-trained AlexNet with _ne tuning and VGG-16, the last three layers of the pre-trained CNN into three new layers: a fully connected layer, a softmax layer, and a classification output layer. A new layer is trained using snapshots of the 3D lung airway tree and corresponding labels [20].

In this study [52], they applied Fourier analysis to visually examine abnormal breath sounds. They performed spectral analysis using a combination of artificial noise addition (ANA) and various deep convolutional neural networks (CNN) to classify seven abnormal breath sounds, both continuous (CAS) and discrete (DAS). The proposed framework contains adaptive mechanisms to add similar types of noise to unhealthy breath sounds. ANA provides a sufficient range of sound signatures that can be identified more accurately than breath sounds without ANA. The results obtained using the proposed framework are superior to previous techniques as they considered seven different classes of abnormal breath sounds simultaneously.

4.1.6 AlexNet

Since attention mechanisms are widely used [50] to handle sequence problems, this paper proposes a CNN attention classification model and introduces a new data preprocessing method with better effects than previous experimental results. As a complex information system, large-scale networks have complex system characteristics and generally cannot implement overall survival strategies and integrated management. For example, the backbone of the Internet does not respect global policy. The reason is that there is no global control. Simple network survivability structures therefore do not apply to open and complex systems. Large-scale network survivability primarily looks at the system as a whole and provides survivability for critical services. Theories and methods of large-scale network survivability should be examined and proposed based on the essential characteristics of large-scale networks as open complex systems.

In the experiments performed, they used functions from the Librosa machine learning library such as MFCC, Mel-Spectrogram, Chroma, Chroma (Constant-Q) and Chroma CENS. The presented system can also interpret the severity of the identified disease, such as mild, moderate, or acute. Research results support the success of the proposed deep learning approach. The classification accuracy of the system improved to an ICBHI score of 93%. Additionally, in the experiments performed, we applied 10-fold K-fold cross-validation to optimize the performance of the presented deep learning approach.

4.1.7 Resnet

In this study [43], they gift the development and promise of exploring ML for respiration circumstance screening. AI-powered auscultation through respiration sounds amassed with the aid of using digital stethoscopes and microphones has superb flexibility and scalability: the screening may be performed remotely, and the effects may be introduced to customers with the aid of smartphones, expediting clinical analysis outdoors the hospital. To facilitate the improvement of automated respiration circumstance screening systems, they summarize extra than 10 publicly to be had audio databases overlaying diverse respiration situations and speak numerous consultant capabilities in addition to structure designing procedures for respiration sound modeling. Those trendy strategies have proven favorable overall performance in a few contexts; however, there are nonetheless many open troubles which might have had to be solved earlier than deploying the advanced fashions to the public. Specially, they factor out that small-records learning, interpretable capabilities, uncertainty-conscious fashions, and privacy-maintenance prediction are really well worth exploring in destiny paintings to deal with the unsolved challenges.

The study in [43] proposed automatic detection of pneumonia from chest X-rays using a Deep Siamese-based neural network. Many methods have been devoted recently, but these rely only on transfer learning approaches or traditional craftsmanship to classify pneumonia diseases. Viral and bacterial pneumonia infections are distinguished by analyzing the amount of white matter distributed in her two parts on a chest x-ray. Deep Siamese networks use the symmetric structure of two input images to compute or classify problems. Each chest X-ray is divided into two segments and sent to the network, where symmetrical structures and the amount of infection spread over these two areas are compared. Use the Kaggle dataset to train and validate a model that automatically detects different types of pneumonia. This proposed model will help doctors easily identify the pneumonia problem from her X-ray images. The model outperforms the state-of-the-art on all performance metrics with reduced bias and improved generalization.

4.1.8 DenseNet121

This article [55] proposes a new classification method to distinguish between normal and incidental lung sounds. First, we use a dual-channel electronic stethoscope to improve noise-exposed lung sounds in a real-world setting using an active noise control (ANC) approach. Next, we use Hidden Markov Models (HMMs) to characterize normal or accidental lung sounds. It applies a maximum likelihood approach to compute the acoustic probability for each respiratory phase. Third, deep neural networks (DNNs) estimate the posterior probabilities of HMMs for each observation rather than traditional Gaussian Mixture Models (GMMs). The DNN's acoustic input features also consist of Mel-frequency cepstrum coefficients (MFCCs) extracted from each frame of lung sound samples. To evaluate the proposed DNN-HMM framework for lung sound classification, the detection rate between the proposed method and the conventional GMM-HMM approach is compared. The results show that the proposed classification method can significantly improve the classification performance.

This paper [64] presents an effective method to professionally diagnose lung diseases using deep learning. It focuses on creating systems to help radiologists detect lung disease. This is especially beneficial in rural areas where radiologists are not readily available. Their system connects radiology labs and radiologists, who can use our models to make faster and better diagnoses.

4.2 Machine Learning Models

Machine learning methods include: SVM,

KNN, Gaussian Bays, Random forest.

4.2.1 Gaussian Bayes (GB)

This study [29] made a comparison between k-nearest neighbor (K-NN), and Gaussian Bayes (GB), support vector machine (SVM) procedures for classification of respiratory disease using text and speech data. Record of patient information and their 17930 lung sounds from 1630 subjects using an electronic stethoscope and its software. K-NN, GB and SVM procedures were run on six data sets for classifying patients. (1) illness or health with text data, (2) illness or health with voice MFCC function, (3) illness or health with text data and voice MFCC function, (4) 12 diseases with text data, (5) for 12 diseases with voice MFCC function, (6) for 12 diseases with text data and voice MFCC function. The SVM accuracy outcomes was %75, for KNN %66; for GB %58 respectively. For the 12-class classification of lung disease, the most accurate algorithm was SVM using text data. When classifying on audio data, k-NN was the top accurate. SVM was top accurate with speech and text data. When classifying health and illness across text, speech, and combined data, GB is consistently the most accurate with very high accuracy, followed closely by k-NN. From this, we can conclude that SVM and k-NN are best suited for classifying datasets into more than two classes when there are many features but a limited number of samples. However, when it comes to dividing into two classes, GB is the best (Murat, et al., 2020).

In this paper [44], a robust categorization approach for lung sounds (that is, wheezing or Polyphonic) are suggested features are pulled out. First, they use the “Discrete Wavelet Transform (DWT)”. Second, “the Linear Prediction Cepstrum Coefficients (LPCC) are then LPCC delta and delta-delta are calculated. Variance and kurtosis of extracted LPCC, delta LPCC and delta-delta LPCC are extracted as lung features sound”. Classification of lung sounds employed SVM. Training and test data were randomly selected from 42 subjects by cross-validation. Number of test and training topics is 21. The achieved detection rate is 95.24%. In the meantime, the new classification algorithm runs Polyphonic and wheezing pulmonary sounds and received the highest recognition rate.

4.2.2 Support Vector Machine (SVM)

This method in [30] is very important in systems involving machine learning and classification steps. As a result, scientists are constantly working to improve their processes. However, data on methodology performance is just as valuable as methodology development. Data are used to show the results of the modeling process, but it is important to consider proper data labeling, acquisition techniques, and quantity. Acquiring data in certain fields, especially medical fields, can be expensive and time-consuming. Therefore, data enrichment using classical and synthetic methods has gained popularity recently. Their research uses synthetic data augmentation, which is newer, more efficient, and has the desired effect. The aim of our study is to use data augmentation to divide the lung sound data collection into four groups. Obtain and standardize the wavelet scattering transform of each cycle of lung sounds, split the transformed data into test and training, and augment and classify the training data. In the extension phase, we used ELM-AE, then ELM-W-AE, and added six wavelet functions (Gaussian, Morlet, Mexican, Shannon, Meyer, Ggw). SVM and EBT classifiers improved the performance of ELM-W-AE by 4% and 3% compared to the original structure [2].

The proposed method [61] uses Mel-frequency cepstrum coefficients (MFCC) as features extracted from respiratory sounds. The extracted features are identified using a Support Vector Machine Classifier (SVM). Classifier performance is analyzed using the confusion matrix technique. The proposed method reported an average classification accuracy of 90.77%. A performance analysis of the SVM classifier using the confusion matrix revealed that normal, airway obstruction, and parenchymal pathology were classified with classification accuracies of 94.11%, 92.31%, and 88.00%, respectively. The analysis shows that the proposed method shows promising results in distinguishing between normal airway obstruction and parenchymal pathology.

4.2.3 K-Nearest Neighbor (K-NN)

The authors of [41] developed and verified different classification models to attain a clinical DSS to help detect abnormalities in respiratory with patients who have systemic sclerosis. The parameters of oscillometric respiration alone can only attain modest diagnostic accuracy of (AUC=0.78) in the CGvsPSNS scenario. Using the ML classifier, we were able to improve accuracy and achieve better accuracy (AUC≥0.90) in these circumstances, which denotes early stages of disease. For CGvsPSAS, high diagnostic accuracy could be achieved with oscillometric parameters alone (AUC=0.94). Still, the ML algorithm may offer a slight improvement (AUC=0.96). The established system could also assist in simplifying the use of oscillometry in the detection of airway changes in with systemic sclerosis patients. In particular, embracing the selection feature identified the top important parameters of oscillation and simplified their investigation.

This article [56] compares three ML methodologies for classification of lung sounds. The first of his two approaches is based on a series of hand-crafted feature extractions trained using three various classifiers" (support vector machines, k-nearest neighbors and Gaussian mixture models), while the third approach is based on convolutional neural Based on network design". (CNN). In the first approach, from the audio file he extracted 12 MFCC coefficients and calculated 6 MFCC statistics. They also investigated standardization with "zero mean and unit variance to improve accuracy". In the second method, "local binary pattern (LBP) features are extracted from visual representations of audio files (spectrograms)". Facial attributes are standardized by bleaching. The data set utilized in that study involves seven labels: fine crackle, normal crackle, polyphonic gasping, monophonic gasping, screeching, and wheezing. They also experimentally verified a spectrogram data set augmentation technique to improve the final accuracy of the CNN. The results show that CNN outperforms handcrafted feature-based classifiers.

4.2.4 Artificial Neural Networks

This paper [46] describes a method for analyzing signals of lung sound with "the wavelet packet transform (WPT) and a classification method using an ANN". Signals of lung sound were subdivided into frequency sub-bands with WPT and a statistical suite of functions taken out from sub-bands to show the wavelet coefficient distribution. ANN was trained for classifying lung sounds into one of the following labels: Normal, wheezing or crackling. The classifier was implanted in a micro-controller, providing an automatic moveable device that aids in respiratory function assessment research and diagnostics.

The aim of this study [47] is to demonstrate the efficiency of ML methods in breath noise investigation. Feature vectors are directly collected from sound breath and supervised ML methods are used to recognize whether feature vectors are associated with patients suffering from lung disease. Furthermore, the proposed method can characterize pulmonary disease in: "asthma, bronchiectasis, bronchiolitis, chronic obstructive pulmonary disease, pneumonia, and lower or upper respiratory tract infections". A retrospective investigational examination of his 920 recording sessions in 126 patients demonstrated the efficiency of the suggested technique. Investigational examination showed that lung disease can be detected using ML methods. After examining several supervised ML procedures, neural network models yielded the most interesting performance. The F-value was 0.983 for lung disease detection and 0.93 for lung disease characterization, enhancing the performance of the state-of-the-art.

4.2.5 Random Forest

This study [40] uses the enhanced computing and storage abilities of modern smart-phones to identify symptoms of breath sounds using ML procedures. K Nearest Neighbors (K-NN), Random Forests (RF), and Support Vector Machines (SVM). The excellent performance of these classifiers on mobile phones demonstrates that smartphones are an alternative tool for detecting and distinguishing symptoms of the respiratory system in real time situations. In addition, clinical data objectives delivered by ML processes can help doctors examine and treat patients during outpatient care when specialized medical equipment is not readily available.

In a study [63], they proposed a "fresh automatic classification method based on a deep learning algorithm for breath sounds to help diagnose respiratory diseases". The suggested procedure consists of two phases. The first, "generate a spectrogram by applying a short-time Fourier transform to the breath sound data". Then classify the resulting spectrograms into normal and abnormal (three classes: they use an enhanced convolutional RNN to generate crackle, wheeze, and both breath sounds. Classifying breath sounds with the suggested model yields these outcomes: "specificity, 0.82; sensitivity, 0.62; mean score, 0.72; harmonic score, 0.71. Moreover, the proposed method provides better accuracy compared to other methods". »

Table 5: Used Models/Methods In Each Study.

Reference	LR	AlexNet	LeNet	DenseNet	VGG	Inception	SVM	KNN	GB	LSTM	RF	Res-Net	ANN
[19]												X	
[20]		X			X	X							

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[21]							X						
[22]												X	
[23]							X						
[24]							X						
[25]							X	X					
[26]								X					
[27]								X					
[28]						X							
[29]							X	X	X				
[30]							X						
[31]			X										
[32]					X								
[33]								X					
[34]			X										
[35]										X			
[36]					X								
[37]		X											
[38]		X											
[39]										X			
[40]							X	X			X		
[41]								X			X		
[42]												X	
[43]												X	
[44]							X		X				
[45]					X								
[46]	X						X	X					X
[47]												X	X
[48]					X		X						
[49]							X						
[50]		X											
[51]				X									
[52]		X	X		X	X						X	
[53]					X								
[54]				X									
[55]				X	X								
[56]							X	X					
[57]					X								
[58]					X								
[59]		X											
[60]					X								

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[61]							X						
[62]										X			
[63]											X		
[64]				X									
[65]										X			

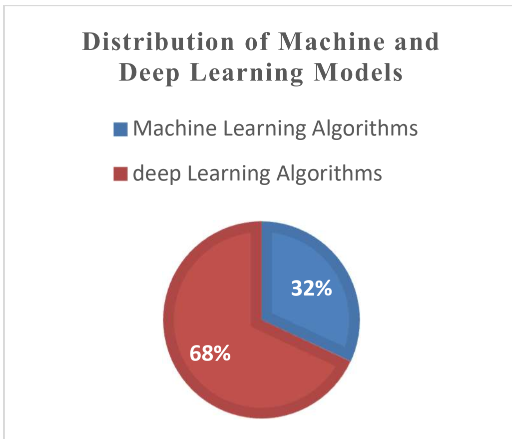

Figure 4: Distribution of machine and Deep Learning Models.

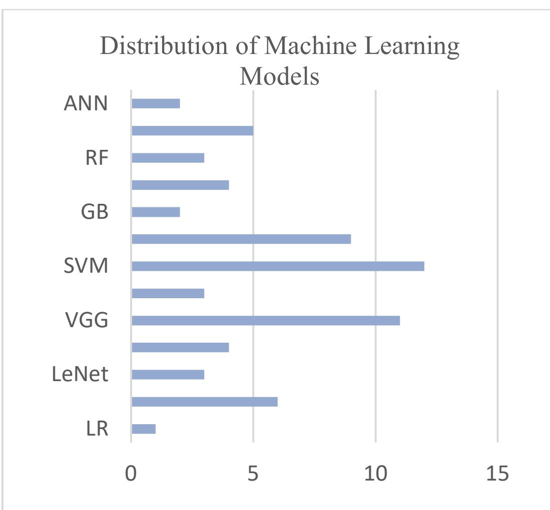

Figure 5: Distribution of Machine and Deep Learning Models.

Q 1.2 Which types of learning have been applied?

The research question is answered by doing a map of each type of deep learning model on the taxonomy in Figure 2.

In [25] [29], the authors employed un-labelled data, which means the proposed method is of type un-supervised learning. The proposed classifiers are using un-supervised learning. The classifiers detect two types: healthy or not healthy.

The authors in [35] [39] make use of semi-supervised learning to train the LSTM model which is an RNN-based model. The author in [35] proposes an RNN model called LSTM to recognize Respiratory System Diseases. Meanwhile the authors use the LSTM model as a semi-supervised one, we classify it in the learning of semi-supervised.

The authors in [20]-[24] [28] [36]-[37] [44] [51] [55] use different models to detect if the patient has repository disease or not (Normal, Diseased). The dataset was interpreted hereafter as supervised learning. In [19] [26] [31] [33] [38] [41] [46] [48] [53] [61], the authors differentiated between three types of repository disease (wheezes, crackles and stridor) using the supervised learning technique. The study [27] [30] [34] [42]-[43] [45] [49]-[50] [54] [57] [59] [63] [65] use a labelled dataset to classify repository disease (Normal, crackles, wheezes, both). The authors in [40] used supervised learning by labelling the dataset into five classes (wheeze, stridor, cough, throat clearing, and other sounds) manually. The authors in [62] classified repository disease into six classes (Pneumonia, Normal, COPD, Asthma, heart failure, BRON) using labelled open-source dataset. In [32] [47] [56], the authors used supervised learning as they categorized the dataset into seven labels: (mono-phonic wheeze, Normal, stridor, squawk, polyphonic wheeze, coarse crackle, fine crackle). The authors in [64], employed a labelled dataset for recognizing repository disease into 14 labels (Cardiomegaly, Atelectasis, Consolidation, Effusion, Edema, Emphysema, Fibrosis, Infiltration, Pleural Thickening, Mass, Hernia, Module, pneumothorax, Pneumonia). In [58] [60], the authors utilized a labelled data to examine the categorization accuracies of a few deep learning models on 15 labels of repository disease (Cardiomegaly, Atelectasis, Effusion, Nodule, Mass, Pneumothorax, Infiltration, Pneumonia, Consolidation, Emphysema, Edema, Fibrosis, Pleural Hernia, Thickening, and No Finding).

To recap, 91% of the models use supervised learning and consequently utilized labeled datasets. Moreover, 4% of the models use semi-supervised learning. The lasting 5% of models use un-supervised learning. Figure 8 shows the learning methods distribution for repository disease identification by two types of learning methods.

Q-1-3 what tools are existing for the classification of machines and deep learning of Respiratory System Diseases?

Tools improvement has vital effects for specialists. Developing automatic machines and deep learning tools permits academic research to help specialists. Likewise, it helps naive researchers to adjust to machine and deep learning approaches by avoiding the technology obstruction. Table 6 outlines the available tools in the area of repository disease classification and detection in machine and deep learning. Figure 9 shows the tool names used in implementing the machine and deep learning algorithms

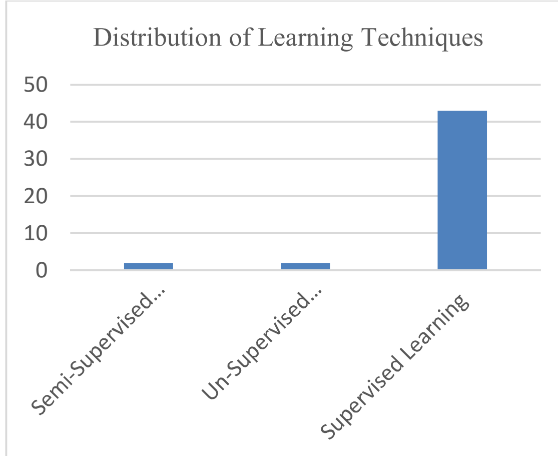

Figure 6: Distribution of Learning Techniques.

Table 6: List of Available Tools in Respiratory System Diseases Detection and Classification

Reference	Dataset Provider	Data Type	Size of the Dataset	Programming Language Used
[48]	Kaggle	images	5,528	PyTorch,
[26]	Private	Audio	51	Matlab
[31]	-	Audio	15328	-
[32]	-	Audio	2141	PyTorch
[30]	ICBHI 2017	Audio	6898	Matlab
[51]	Private	audio	274	Matlab
[47]	-	Audio	920	Matlab
[23]	Private	Audio	81	R
[27]	Private	Audio	73	Python
[50]	ICBHI 2017	Audio	6898	R
[53]	Private	Audio	81	Android Development
[40]	Private	Audio	163	R
[56]	Private	audio	74	python
[49]	ICBHI 2017	Audio	6898	Matlab
[34]	ICBHI 2017	Audio	6898	Python
[41]	Private	Audio	246	Python
[20]	Private	Audio	280	PyTorch
[22]	Private	Audio	241	Python
[62]	ICBHI 2017	Audio	1483	Matlab
[38]	Kaggle	Audio	14,145	PyTorch
[35]	Private	Audio	920	Matlab
[24]	Private	Audio	31	Python
[39]	Private	Audio	224	Matlab
[19]	Kaggle	images	6800	-
[28]	Automatic	Audio	128	Python

[45]	-	Audio	11170	-
[55]	Private	audio	353	Matlab
[60]	CheXpert and MIMIC-CXR	Images	595,506	python
[44]	Private	Audio	42	Matlab
[29]	Private	Audio	12	Python
[29]	Private	Text	12	Python
[64]	NIH	images	112,120	Python
[63]	ICBHI 2017	Audio	6898	python
[61]	RALE database	Audio	68	Python
[65]	ICBHI 2017	Audio	6898	Python
[36]	Kaggle	images	1000	PyTorch
[25]	Private	Audio	11	PyTorch
[57]	ICBHI 2017	Audio	6898	R
[37]	Kaggle	Audio	241	R
[37]	Kaggle	images	1000	R
[42]	ICBHI 2017	Audio	6898	Matlab
[33]	-	Audio	1152	Python
[58]	Kaggle	images	5,606	R
[59]	ICBHI 2017	Audio	6898	python
[46]	Private	Audio	92	Matlab
[21]	Private	Audio	13	Matlab
[54]	ICBHI 2017	Audio	6898	R
[43]	ICBHI 2017	Audio	6898	R
[52]	Private	audio	70	Python

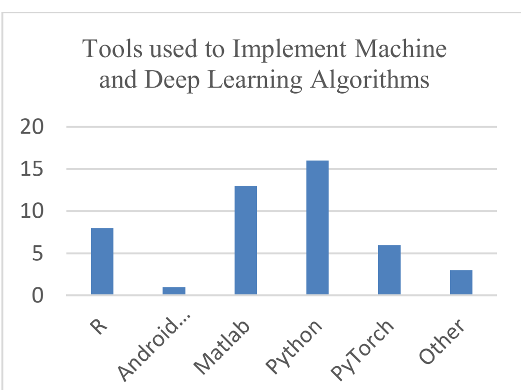

Figure 7: Tools used to implement Machine and Deep Learning algorithms.

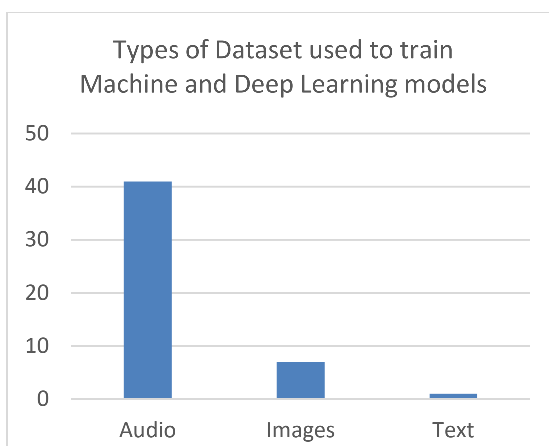

Figure 8: Types of Dataset used to train Machine and Deep Learning models

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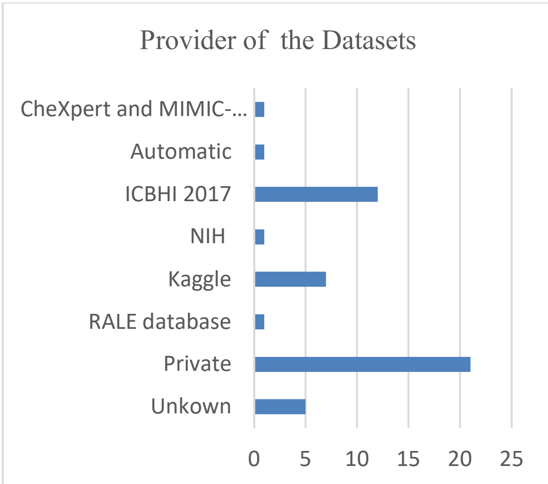

Figure 9: Provider of the Datasets.

Q-2 What sort of data sets have been utilized for evaluating the primary studies linked to ML and DL classification and detection of Respiratory System Diseases?

Table 7 also shows dataset provider, size of the dataset, and types of the dataset (Audio, Images, Text). Figure 10 shows the types of Dataset used to train Machine and Deep Learning models. 84% of the datasets are of type Audio, 14% of type Images and 2% text type. Figure 11 shows the dataset provider. 42% of the dataset is Private and is not open source. 21% of the datasets use “ICBHI 2017” which is open source. 14% of the datasets are from Kaggle where it is open source while 10% of the dataset are unknown.

Q-2-1 what are the characteristics of the data sets?

Table 7: Open-Source Data Sets Stated and Applied In the Primary Studies

Dataset	Type	Size	Classes
Kaggle	Audio	14,145	3
Kaggle	images	1000	2
NIH	images	112,120	14
CheXpert and MIMIC-CXR	Images	595,506	15
RALE database	Audio	68	3
ICBHI 2017	Audio	6898	4

Figure 10 shows the types of Dataset used to train Machine and Deep Learning models. «

Q-2-2 What performance evaluation metrics do the studies use to evaluate the performance of machine and deep learning based techniques for the detection and classification of Respiratory System Diseases?

Performance Evaluation Techniques for detecting and classifying respiratory disease include well-known metrics. Metrics such as F1 Score, Accuracy, Recall, Precision, Sensitivity, Specificity, and Confusion Matrix are often used to compare the performance of newly proposed methods with existing methods. In addition to these metrics, we also use criteria such as computational complexity, cost, dataset size, and amount of preprocessing activity to evaluate the performance of machine and deep learning classifiers and extracted features. Deep learning models are inherently complex. For example, the number of layers in CNN can increase the overall computational cost and complexity.

$$Accuracy=(TP+TN)/(TP+FP+TN+FN) \quad (1)$$
$$Precision=TP/(TP+FP) \quad (2)$$
$$Recall/Sensitivity=TP/(TP+FN) \quad (3)$$
$$Specificity=TN/(TN+FN) \quad (4)$$
$$F1\ Score=(2*Sensitivity*Precision)\ /\ (Sensitivity+Precision) \quad (5)$$

Equations 1–5 can calculate accuracy, precision, sensitivity, and F1-score. Here 'TP' stands for 'true positive', or the correct identification of Respiratory System Diseases presence. 'TN' stands for 'true negative', indicating correct identification of absent Respiratory System Diseases. 'FP' represents 'false positive', or the false presence of Respiratory System Diseases as absent, whereas 'FN' stands for 'false negative', or the incorrect identification of absent Respiratory System Diseases as present. Accuracy is the sum of correct identifications (both present and absent) divided by total samples. Accuracy is the percentage of correctly identified positive instances out of all positive instances. Sensitivity is the percentage of correctly identified positive instances out of all positive instances. Specificity is computed as the correctly identified negative instances for all negative instances. The receiver operating curve (ROC) represents the true positive and true negative rates, also called precision recall. The F1 score is a statistical measure calculated as the geometric mean of specificity and sensitivity. The confusion matrix represents the proportion of misclassified respiratory diseases. The rows of the confusion matrix represent the actual classes and the columns represent the predicted classes. The metrics used in the studies included in this review are shown in Table 8.

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Table 8: Evaluation Metrics Used In Primary Studies

Reference	Best Methods	Highest Accuracy	Precision	Recall/ Sensitivity	Specificity	Confusion Matrix	F1-Score	AUC/ROC
[19]	ResNet	70.00%						x
[20]	VGG-16	88.60%				x		x
[21]	SVM	%94.15						
[22]	ResNet	%64.50	x	x	x	x	x	
[23]	SVM	%65.50		x	x		x	
[24]	SVM	%86.50	x	x			x	x
[25]	KNN	91.70%						
[26]	k-NN	96.00%	x	x		x		
[27]	k-NN	93.20%						
[28]	Inception	83.78%	x	x		x	x	
[29]	SVM	75.00%	x	x	x			
[30]	SVM	72.69%	x	x	x	x	x	
[31]	SVM	80.00%	x	x	x			
[32]	VGG	95.56%	x	x		x	x	
[33]	VGG	87.41%						
[34]	LeNet	71.15%	x	x	x	x	x	
[35]	BDLSTM	98.61%	x	x	x			
[36]	VGG16	95.00%						
[37]	AlexNet	80.00%						
[38]	AlexNet	53.00%		x	x		x	x
[39]	LSTM	84.00%		x	x			x
[40]	RF	91.80%	x	x			x	
[41]	RF	97.00%						x
[42]	ResNet	74.00%	x	x	x	x	x	
[43]	ResNet	80.00%						
[44]	SVM	95.24%						
[45]	VGG	85.74%	x	x	x	x	x	
[46]	ANN	99.26%						
[47]	ANN	92.23%		x	x		x	
[48]	Resnet	88.00%				x		x
[49]	SVM	65.50%	x	x	x	x	x	
[50]	Alexnet	68.80%						
[51]	DenseNet	87.36%		x	x			x
[52]	VGG	94.00%	x	x			x	
[53]	VGG	80.00%						
[54]	DenseNet121	84.00%						
[55]	DenseNet121	95.59%						
[56]	KNN	95.10%		x	x	x		
[57]	Vgg19	95.00%				x		x
[58]	VGG19	89.77%	x	x			x	
[59]	AlexNet	93.00%		x	x			x
[60]	Vgg16	92.00%		x	x			x
[61]	SVM	90.77%						
[62]	BDLSTM	91.00%	x	x	x		x	
[63]	RF	72.00%		x	x			

[64]	DenseNet121	84.30%						
[65]	LSTM	76.39%	x	x	x	x	x	

5. DISCUSSION

This Systematic Literature Review, has reviewed a total of 47 primary studies. This section discusses the results and their effects.

Most of the reviewed work focuses on supervised learning techniques. Few papers discuss unsupervised learning methods. Further contributions on unsupervised and semi-supervised learning methods are needed. Overall, 91% of undergraduate research focuses on supervised learning, 4% on unsupervised learning, and only 5% on semi-supervised learning methods. In short, semi-supervised learning is a potential area to further explore respiratory disease detection and classification. This implication is important for researchers who need to contribute in the field of machine- and deep-learning-based identification and classification of respiratory diseases. Among supervised learning, most research has focused on CNN and its various architectures. About 55% of the algorithms rely on the CNN architecture. The distribution of different CNN architectures is as follows:

VGG (17%), AlexNet (9%), ResNet (9%), DenseNet (6%), LSTM (6%), LeNet (4%), Inception (4%) %). VGG is dominant compared to other CNN architectures. It is necessary to investigate how specific CNN architectures are chosen depending on the type and size of the dataset. Such research will enable new researchers and practitioners to choose the best deep learning model according to the size and nature of their data. His 45% of the studies reviewed use machine learning algorithms. They are distributed as follows:

SVM (19%), KNN (13%), RF (4%), GB (4%), ANN (3%), LR (2%). The most commonly used machine learning algorithm is SVM.

Tool development plays an important role in applying academic research to industrial practice. Lack of tools can be a major obstacle in translating academic research into industrial practice. Very few tools are publicly available. Most of the primary research was not developed end-to-end.

Datasets are the fundamental entities that determine the performance of machine learning and deep learning methods. We found that 43% of primary studies used private datasets. Therefore, most data samples were created in a laboratory setting. 45% of the primary studies used open source datasets, but only 12% used unknown datasets. Data sets created in laboratory settings under certain conditions always have inherent biases that threaten the validity of results. Future research should incorporate more open source datasets for academic research to solve real-world problems. Additionally, a large number of benchmark open source datasets should be readily available to researchers so that they can compare the performance of different methods. Therefore, the creation and updating of open source datasets also requires the attention of researchers.

Many studies have undergone data augmentation to increase dataset size and reduce sample bias. Images are enhanced in many ways. For example, in [24] [29] [38] the authors performed jitter and horizontal and vertical flips. Yet, there is little discussion about the cost of scaling or comparing the performance of deep learning models with and without scaling. It would be interesting to conduct such experimental studies and compare costs and accuracy.

Primary study performance evaluation was conducted using known metrics such as precision, recall, AUC/ROC, and F1 score. Accuracy, Precision, F1-Score, Confusion Matrix, and Recall were most commonly used to assess performance.

This study may benefit researchers and practitioners by providing a bird's-eye view and an in-depth analysis of existing research in the area of machine- and deep-learning-based respiratory disease identification and classification. Researchers can benefit from classifying existing research on deep learning model taxonomies. This research helps identify where primary research is lacking, allowing researchers to make targeted contributions in those areas. The study also benefits practitioners by reviewing recent developments in academic research, enabling them to adopt these developments in industry with confidence and evidence.

6. CONCLUSION AND FUTURE DIRECTIONS

The study analyzed 47 research papers to identify trends in the most commonly used machine learning and deep learning techniques, commonly used datasets, and tool availability. In this study, we presented a taxonomy of deep learning methods and mapped existing primary research to identify gaps in the literature. In addition, thematic and descriptive analysis of qualitative and quantitative data were conducted to answer research questions and provide insights into deep learning approaches. This study

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reports a benchmark dataset used in machine learning and deep learning approaches for respiratory disease classification. The study also presents a comparative analysis to find similarities and differences in the performance measures used in the primary studies. The results show that most articles focus on supervised learning methods. Among supervised learning, most articles focus on his CNN. Few people have used unsupervised learning techniques. Tool development plays an important role in applying academic research to industrial practice, but the number of publicly available tools is limited. The results also show that the majority of major studies use academic datasets. Furthermore, accuracy, precision, F1 score, confusion matrix, and recall were the most commonly used metrics to assess performance. This study is beneficial to researchers as it helps them identify areas in which they can contribute. »

Semi-supervised and unsupervised learning methods need to be further considered in future contributions. More future research should include more open source datasets for academic research to solve real life problems. Furthermore, we need a stand- alone tool that works without limitations that is technical and thus can be used by novices and specialists.

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