WWW.IJRPR.COM

International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Artificial Intelligence a Diagnostic Tool for Respiratory Diseases

Vikas Kumar, Jyoti Pathania, Sidhanshu, Nikhil Sharma, Amit Kaundal, Shiv Kumar Kushawaha, Nishant Gautam

Laureate Institute of Pharmacy Kathog

ABSTRACT:

Coughing is a typical symptom of a variety of respiratory illnesses. When diagnosing a condition, the sound and kind of cough are important factors to consider. Respiratory illnesses endanger human lives and cause severe economic downturns, particularly in nations with inadequate treatment resources. In this study, we looked at the most recent proposed technology for reducing the burden of respiratory disorders. Artificial intelligence (AI) is a promising technology that assists in data analysis and result prediction, therefore insuring people's well-being. We demonstrated how AI algorithms can consistently detect and diagnose many illnesses such as pneumonia, pulmonary edema, asthma, tuberculosis (TB), COVID19, pertussis, and other respiratory disorders using the cough symptom. We also discovered various strategies for identifying respiratory illness using cough samples that yielded the best results. This paper discusses the most recent difficulties, answers, and possibilities in the detection and diagnosis of respiratory diseases, allowing practitioners and researchers to create improved procedures.

Keywords: artificial intelligence, respiratory diseases, asthma, cough sound detection, respiratory illness diagnosis Machine learning; Imaging; Lung; Respiratory; Pulmonary disease; Coronavirus disease 2019

1. Introduction:

Lung illnesses, often know as respiratory diseases, are pathological ailments that damage the organ and tissue that make gas exchange challenging in human that breath air. They consist of ailment affecting the trachea, bronchi, bronchioles, alveoli, pleurae, pleural cavity, nerves, and breathing muscles.(1) From minor, self-limiting conditions like the common cold, influenza, and pharyngitis to serious, life threatening condition like bacterial pneumonia , pulmonary embolism, TB, acute asthma, lung cancer and severe acute respiratory syndrome like COVID 19, there are many different respiratory illness. (2)

Respiratory disorders can be categorised in a variety of ways, such as by the organ or tissue affected, the kind and pattern of the accompanying signs and symptoms, or even by the underlying cause of the illness.(3)

Pulmonology is the study of respiratory illnesses. A pulmonologist, a chest medicine expert, a respiratory medicine specialist, a respirologist, or a thoracic medicine specialist is a medical professional who focus on respiratory diseases.

Air way blockage is a common feature of obstructive lung illness such as asthma, chronic bronchitis, bronchiectasis, and chronic obstructive pulmonary diseases COPD. Many obstructive lung illness are treated by avoiding their triggers controlling their symptoms with bronchodilators and in severe cases, supressing inflammation with corticosteroids. Smoking is a common contributor to COPD which includes emphysema and chronic bronchitis, and severe infection and cystic fibrosis are common contributors to bronchiectasis. Asthma exact root cause is yet unknown (4).

Any component of the respiratory system might get infected. Upper respiratory tract infection and lower respiratory tract infection are the usual categories.

1. The most common upper respiratory tract infection is the common cold. Upper respiratory tract infection also include conditions including sinusitis, tonsillitis, pharyngitis, and laryngitis that affect certain upper respiratory organs.
2. Pneumonia, an infection of the lungs typically brought on by bacteria, primarily streptococcus pneumoniae in western nations, is the most prevalent lower respiratory tract illness. Around the world, pneumonia is frequently brought on by tuberculosis TB.(5)

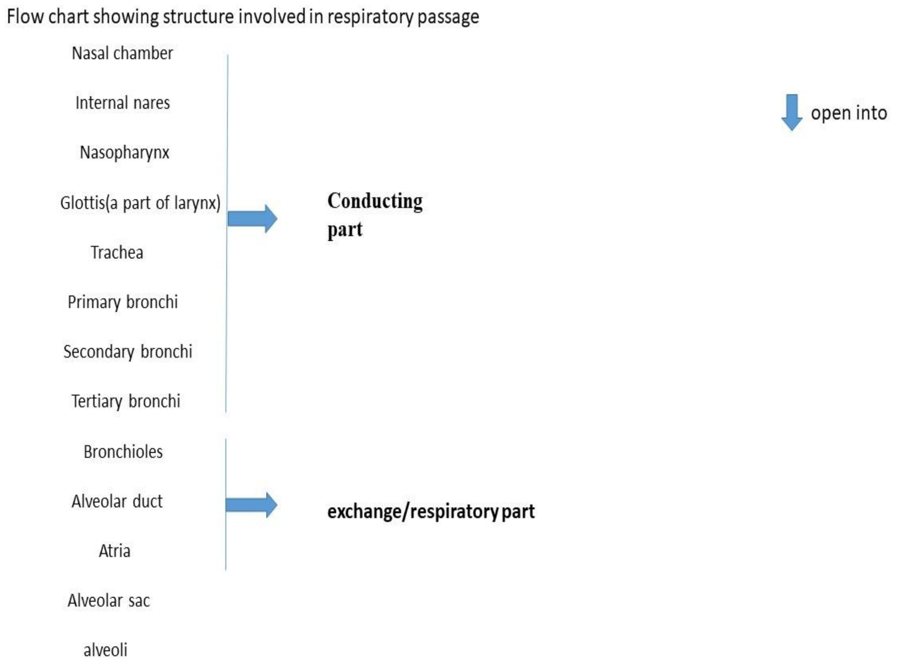


Figure 1: flow chart of structure involved in respiratory diseases

Pneumonia: Inflammation of the lungs caused by bacterial or viral infection, in which the air sacs fill with pus and may solidify. Inflammation of the lungs can affect both (double pneumonia) or simply one (single pneumonia).

Pulmonary infarction: Pulmonary infarction (PI) is the loss of lung tissue caused by a lack of blood flow. Symptoms include chest discomfort and bloody coughing. It is frequently caused by another health problem, such as a pulmonary embolism (PE). It has the potential to be deadly. Smoking and being young are also risk factors for PI.

Tuberculosis: A particular illness caused by infection with the tubercle bacteria Mycobacterium tuberculosis, which can damage practically any tissue or organ in the body; the most common location is in the lungs.

Asthma: A respiratory disorder characterised by spasms in the bronchi of the lungs that make breathing difficult. It is generally associated with an allergic response or another type of hypersensitivity.

Bronchitis: Bronchitis is an inflammation of the airways between the nose and the lungs, including the windpipe or trachea and the bigger air tubes of the lung (bronchi) that draw air in from the trachea. Bronchitis can be either acute (short-term) or chronic (long-term).

Pertussis: The bacteria Bordetella pertussis causes pertussis, often known as whooping cough, which is a highly infectious respiratory ailment. In 2018, there were about 151 000 cases of pertussis worldwide. Pertussis is easily transmitted from person to person, mostly by droplets produced by coughing or sneezing. The condition is especially hazardous in babies, where it is a leading cause of illness and death.

COVID 19: An acute human disease caused by a coronavirus, characterised mostly by fever and cough and capable of escalating to severe symptoms and, in rare cases, death, particularly in the elderly and those with underlying health issues. It was discovered in China in 2019 and became pandemic in 2020.

2. Epidemiology:

The prevalence of harmful environmental occupational and behavioural inhalational exposers is a major factor in why chronic respiratory disorders are among the most prevalent non communicable diseases in the world (6). Chronic respiratory illness in addition to asthma and COPD include interstitial lung diseases pulmonary a condition called and pneumoconiosis including silicosis and asbestosis. Regrettably chronic respiratory disorder have gotten substantially less public attention and research money than other diseases type including cardiovascular, cancer, stroke, diabetes, and Alzheimer diseases (7). The global impact of disorder injuries and risk factor study GBD 2017 is used by Joan Soriano and colleagues in the lancet respiratory medicine to assess the prevalence and associate health impact of chronic respiratory disorders (8, 9).

They discovered that in 2017 there were be about 545 million people worldwide who had a chronic respiratory condition, a rise of 398 % since 1990. Asthma 36%prevelance worldwide and COPD 39% globally where the most common chronic respiratory disorders. A total of 112.3 million DALYs an increase of 13.3% since 1990, where caused by chronic respiratory disorder in 2017, accounting for 3.99 million deaths and 1470 DALYs per 100,000 people. Sub Saharan Africa had the lowest facility rate associate with chronic respiratory diseases, while south Asia had the highest. (10)

3. Sign and symptoms:

people who are having breathing difficulties frequently exhibit symptoms of respiratory distress, which having to work harder to breath or not getting enough oxygen. The symptom listed below may suggested that someone is having to work harder to breath and may not be getting enough oxygen. To know how to react it is crucial to get familiar with the symptom of respiratory distress. To get a diagnosis always visit a doctor.

Breathing rate, Colour change, Grunting, Nose flaring, retractions, sweating, wheezing, body position

If you see someone with these symptoms, call 911. If the person is in a healthcare facility, immediately notify a health care professional. You may also want to consider taking a first aid or CPR class so you are prepared for medical emergencies.

Knowing respiratory infection symptoms is critical in assisting clinicians and technology developers in developing efficient and effective methods for identifying illness type. The subsections that follow provide several respiratory illnesses and their associated symptoms, as well as a comparison of them. (11-24)

Serial number	Diseases	Symptoms
1	Pneumonia	Fever, breathlessness, rib tightness, wheezing, running nose, diarrhea, vomiting, heart problem
2	Pulmonary diseases	Dry or bloody cough, breathlessness, chest tightness, heart problem
3	Tuberculosis	Fever, dry or bloody cough, impairment of lung function, change weight, night sweat
4	Asthma	Fever, breathlessness, chest tightness, wheezing, impairment of lung function, hyperventilation of the lung, change weight, dizziness, depression
5	Bronchitis	Dry or bloody cough, impairment of lung function, phlegm, heart problem
6	Pertussis	Fever, dry or bloody cough, whooping cough, red lip, cyanosis
7	Covid 19	Sore throat, chest tightness, impairment of lung function, nausea, heart problem, red lip face, dizziness, fever

Figure 2: sign and symptom

4. Pathogenesis:

All smokers have inflammation in their lungs, particularly their tiny airways. In COPD, the natural defensive reaction to inhaled toxins is magnified, resulting in tissue death, impairment of defence systems that prevent such destruction, and disruption of healing processes. In general, airway inflammation and structural abnormalities worsen with disease severity and continue even after smoking cessation. Aside from inflammation, two more mechanisms play a role in the pathophysiology of COPD: an imbalance between proteases and ant proteases in the lungs and an imbalance between oxidants and antioxidants (oxidative stress). (25)

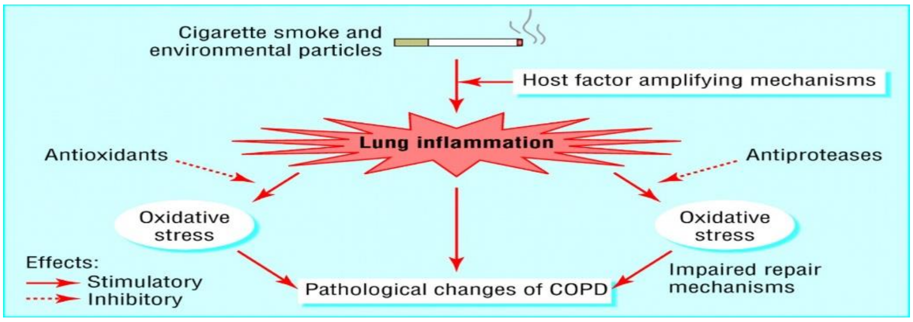


Figure 3: lung inflammation

Protease and anti-protease incompatibility: An imbalance emerges from increased protease synthesis (or activity) and decreased antiprotease production (or inactivation). Tobacco smoke, as well as inflammation, cause oxidative stress, which primes various inflammatory cells to release a cocktail of proteases and inactivates several antiproteases through oxidation. Proteases generated by neutrophils (including the serine proteases elastase, cathepsin G, and protease 3) and macrophages (cysteine proteases and cathepsins E, A, L, and S), as well as matrix metalloproteases (MMP-8, MMP-9, and MMP-12), are the key players. One antitrypsin, a secretory leucoprotease inhibitor, and tissue inhibitors of metalloproteases are the primary antiproteases implicated in the aetiology of emphysema. (26)

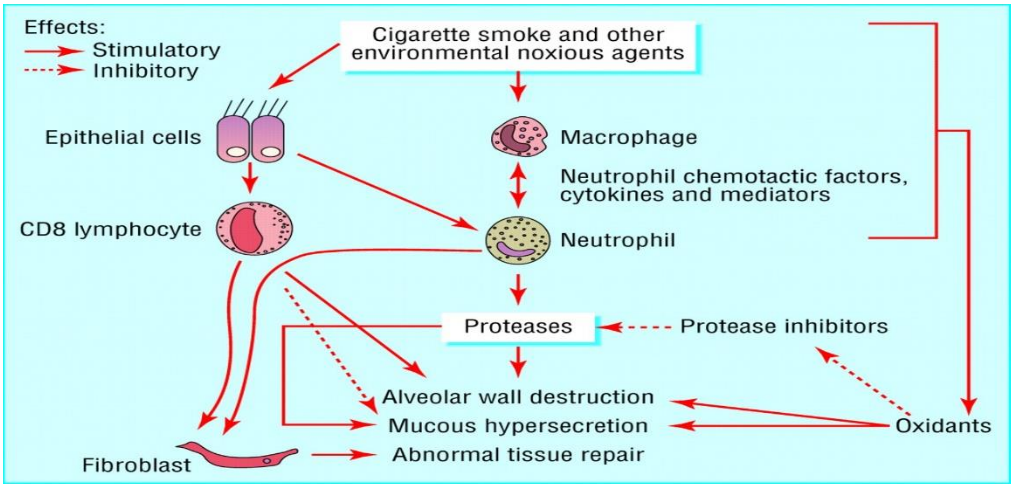


Figure 4: Protease and antiprotease imbalance

Role of viral respiratory infections in asthma: The most frequent cause of wheezing disorders and asthma flare up in both children and adult is viral respiratory tract infection (27).Acute bronchiolitis, croup, and recurrent wheezing symptom in young children can result from viral respiratory infections. Infants and young children who sneeze with viral illness, notably respiratory syncytial virus (RSV) and human rhinovirus (RV), are at the risk of developing asthma later in life. Many viruses have been linked to wheezing episodes, including respiratory syncytial virus (RSV), human rhinovirus (HRV), metapneumovirus, parainfluenza, and cor onavirus. Wheezing episodes associated with respiratory infections decrease with age in most children, but for some people, wheezing episodes in childhood can signal the onset of asthma. In individuals with pre-existing asthma, respiratory virus infections can have serious consequences; viral respiratory infections cause roughly 80% of asthma exacerbations. (28–32) In both children and adults, there is a link between viral respiratory infections and asthma exacerbations. It is unclear if respiratory infections influence disease development or illness severity (33). In this Review, we look at the significance of viral respiratory infections in the development of asthma and how they contribute to asthma exacerbations. Infections in childhood can cause wheeze or protect against the development of allergic illness.

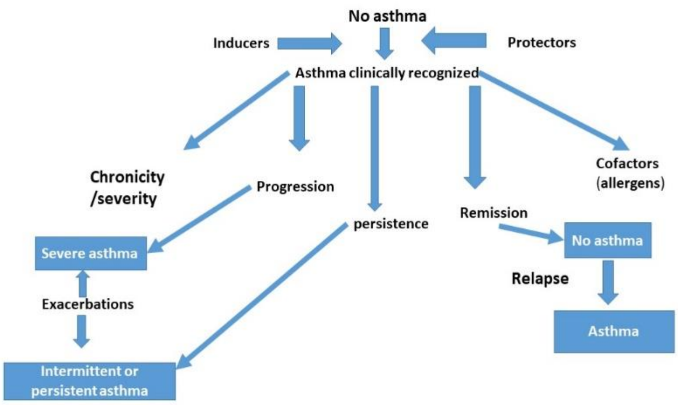


Figure 5: Role of viral respiratory infections in asthma

Human respiratory pathogens associate with respiratory diseases or asthma

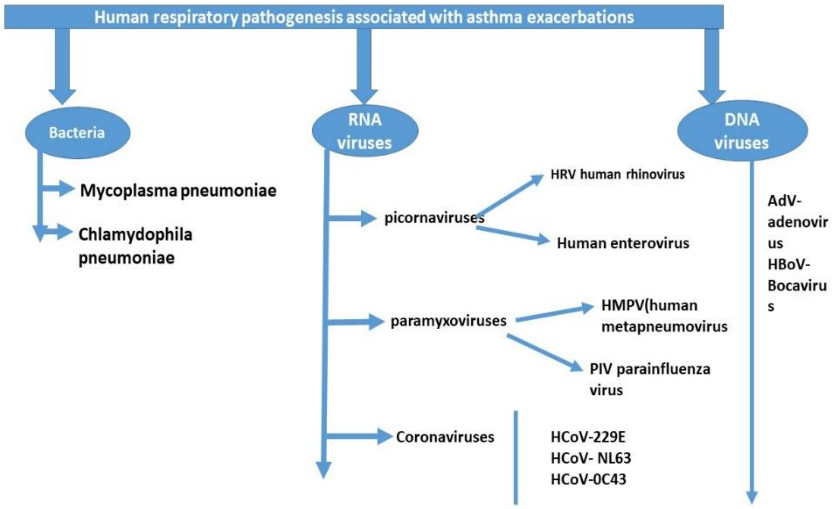


Figure 6: Respiratory pathogens

Artificial intelligence: AI and machine learning, a type of AI, are rapidly being employed in medicine. AI excels at well-defined tasks like image identification, such as identifying skin biopsy lesions, assessing the severity of diabetic retinopathy, and detecting brain tumours. This article provides an overview of the use of artificial intelligence (AI) in medicine, specifically in respiratory medicine, where it is used to evaluate lung cancer images, diagnose fibrotic lung disease, and is more recently being developed to aid in the interpretation of pulmonary function tests and the diagnosis of a variety of obstructive and restrictive lung diseases. Artificial intelligence (AI), machine learning, and deep learning are concepts that are sometimes used interchangeably but are really hierarchical. AI is the umbrella notion that simulates human intellect It encompasses tasks like as reasoning, learning, language processing, and the presentation of knowledge or information using computer systems (i.e., the use of a computer to mimic intelligent activity with little human interaction).

Machine learning also allows for the examination of data kinds previously inaccessible to computer analysis, such as image and auditory data. The influence of feature engineering, the transformation or integration of distinct data points into new information, on final classification accuracy is an overlooked part of classic machine learning methodologies (34). Deep learning is a subset of machine learning that has lately gained prominence as the quantity of data available to researchers has increased rapidly. Rather of depending on the intuition and knowledge of the researcher to pick and design characteristics, these techniques allow the algorithm to automatically uncover the exact features and transformations necessary for the job in the raw data (35). Deep learning is being utilised to achieve significant breakthroughs in image (36, 37) and voice recognition, (38-40) to predict the activity of new therapeutic compounds, 8 and to predict the impact of non-coding DNA mutations on gene expression and illness.

Role of artificial intelligence (AI) in health care system

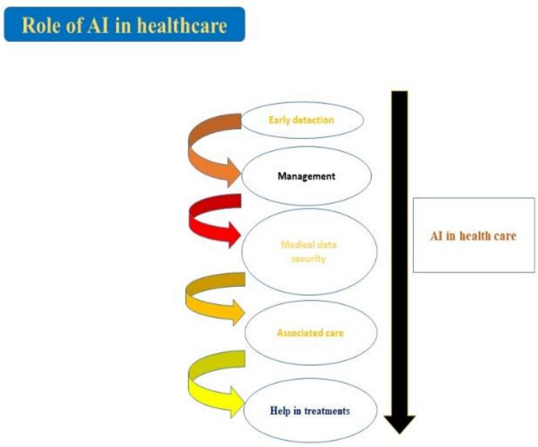


Figure 7: Role of AI in health care

Represented diagram how to work artificial intelligence and application in respiratory diseases

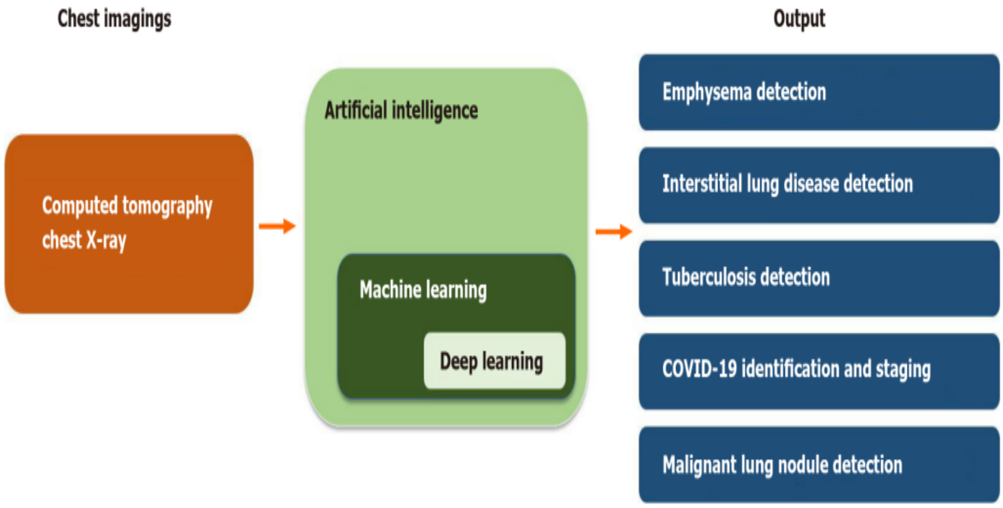
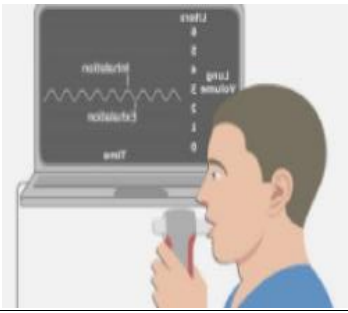


Figure 8: Work and application of artificial intelligence

Traditional approach to diagnosis airway diseases:

Technique	**Image**	**Description**	**Drawback**
Spirometry (41)		Spirometry is the most often used pulmonary function test. It evaluates lung function, namely the volume of air that can be breathed and exhaled, as well as the rate at which this can be done.	For a brief period following the test, the patient experiences dizziness and shortness of breath.
Body plethysmography (42)		Body plethysmography is a pulmonary (lung-related) function test that determines how much air is in your lungs when you take a deep breath. It also regulates how much air remains in your lungs after you have exhaled as much as possible.	Technically difficult and time-consuming

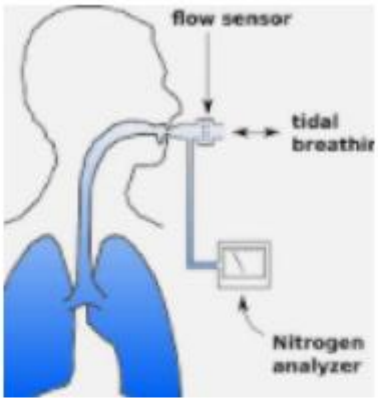
Impulse oscillometry (43)		The impulse oscillation system (IOS) is a novel approach for assessing airway resistance and reactance. It's a type of forced oscillation in which oscillating sound waves of varying frequencies, generally between 5 and 20 Hz, are sent down the bronchial tree.	The test impulse is strong, causing a modest alteration in the lung mechanism.
Washout tests (44)		Nitrogen washout (also known as Fowler's technique) is a breathing test that analyses anatomic dead space in the lungs as well as other parameters linked to airway closure throughout the breathing cycle.	It takes a long time and fails to estimate the lung sections that are poorly ventilated.

Table 1: Traditional approach to diagnosis airway diseases

Classification of current cough based detection and diagnostic methods

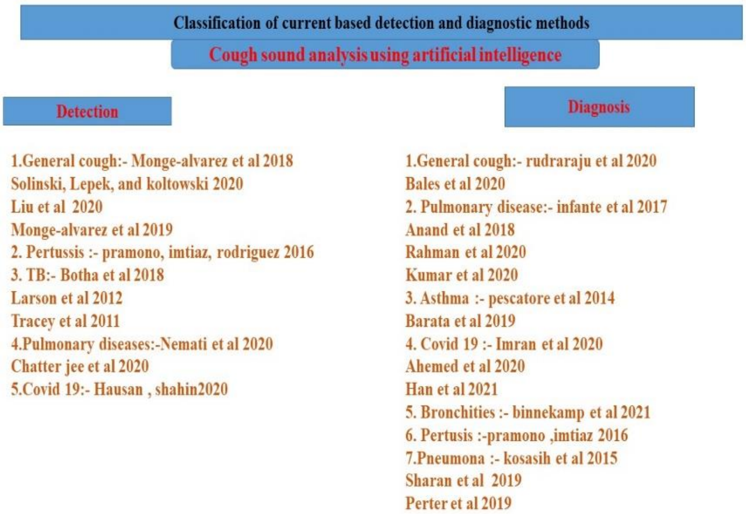


Figure 9: Classification

Cough sound detection approaches: Human sounds include regular breathing, speaking, coughing, whooping, wheezing, snoring, sneezing, and crackling.

Detecting cough sounds may be difficult and pose numerous problems for inexperienced physicians using instruments; thus, advanced automated system monitoring tools are required.

The created tool should concentrate on improving the prediction algorithm's ability to recognise the specified sound despite a noisy backdrop.

In these works, many AI-based approaches and deep learning models were presented to identify cough and discriminate RD from each other in recording devices.

1. Iyawa et al. (45) presented a system for detecting cough sounds in noisy environments by using MFCC that specify time frequency time frequency decomposition and filter application. It has a sensitivity and specificity of about 90%.

2. Kanemitsu et al. (46) proposed a method for detecting cough in spectral sound events by combining only three spectral variables with LR to classify sound segments as cough or not cough. The specificity is 98.14% and the sensitivity is 90.31%.

3. Khomsay et al. (47) used an ANN model for preliminary classification and an HMM for final classification to distinguish between coughs and other types of noises.

Furthermore, Kosasih et al. (48) suggested a cough detection approach that involves transmitting the cough sound to a mobile phone that has an AI model to analyse the cough.

To choose the best performance classifying strategy, the approach employed many classifiers such as LR, ANN, SVM, and RF.

Finally, Kumar (49) describes a cough detection method for microphones that use HMMS to represent the time changing characteristic of the cough approach for categorised coughs.

Monge-Alvarez et al. (50) developed a cough detection system that used SVM for classification to extract the cough sound from a noisy background.

Cough diagnosis approaches: This section is organised as follows to introduce numerous cough-based diagnosis techniques.

1. This section discusses generic cough diagnosing techniques.

2. Go through the pneumonia diagnosing strategy.

3. Introduce methods for diagnosing asthma and pulmonary disorders.

4. Provide a COVID 19 diagnosing strategy.

1. Morrell et al.51 general cough diagnosis approach Classifier for logistic regression LR

Multiplex, ligation-dependent probe amplification by Nemati et al. (52) Polymerase chain reaction (MLPA) PCR detection of bronchitis sound. Convolutional neural networks are used by Monge Alvarez et al.

2. Pneumonia: Pneumonia is an acute infection of the lower respiratory tract. ALRI affects almost 1.6 million children.

Chest radiography may be used to detect illness. Clinical evaluation imaging during a physical examination oxygen saturation testing cross-wavelength transformation of lung ultrasound CWT

3. Asthma: a disease that causes serious damage to the human lungs.

4. COVID-19: Several studies proposed automated COVID 19 diagnosis utilising x-ray, CT scan, clinical data, vital signs, and cough samples. (53-57)

Deep transfer learning based multi class classifier (DTL-MC) Classical machine learning based multi class classifier (CMC-MC) Deep transfer learning based binary class classifier (DTC-BC) Svanes et al.

Public health function and associate type of artificial intelligence: Our nation's top concern is public health; in this review article, we discuss the public health functions associated with artificial intelligence that are useful in diagnosing respiratory diseases. (59-62)

The table describes the many forms of AI used in health research in LMICs. The majority of AI-powered health therapies employed machine learning, signal processing, or both. Machine Learning was frequently examined in conjunction with other AI technologies, most commonly signal processing, in studies.

	Type of AI	Example
Diagnosis	Machine learning, natural language processing, and signal processing are all examples of expert systems.	To identify TB patients, researchers used machine learning and signal processing technologies on digital chest radiographs.18 instances of drug-resistant tuberculosis

Risk assessment for mortality and morbidity	Data mining; machine learning; signal processing	Researchers utilised machine learning algorithms to administrative records from a big tertiary care hospital in Thailand to evaluate the risk of dengue fever severity.
Prediction and monitoring of disease outbreaks	Data mining, machine learning, natural language processing, and signal processing are all examples of data mining.	Remote sensing data and machine learning techniques were utilised to define and forecast Zika virus transmission patterns worldwide.
Policy and planning for health	Machine learning; expert planning	Machine learning algorithms were used to predict duration of stay among health-care employees in underprivileged regions using administrative data from South Africa.
AI=artificial intelligence. *Many types AI were implemented together.		

Table 2: Public health function and associate type of artificial intelligence

Recommendation for AI-driven health application development in low and medium income outcomes

Machine learning classification algorithms were also utilised to predict the health consequences of non-infectious diseases. For example, research have focused on assessing anaemia risk in children using standardised household survey data, identifying children at high risk of skipping vaccination sessions, and diagnosing high-risk deliveries using cardiotocography data. (65) A Brazilian research sought to analyse the behavioural risk categorisation of sexually active teens. (66)These instruments' stated accuracy ranged from moderate (about 65%) to high (almost 99%).

Machine learning and data mining approaches are also being used by researchers to improve road safety in LMICs. In one study, researchers utilised online street data and machine learning to determine the prevalence of helmet wear. (67) Another research employed a big government dataset of road injuries and data mining techniques to forecast the severity of road injuries. (68)

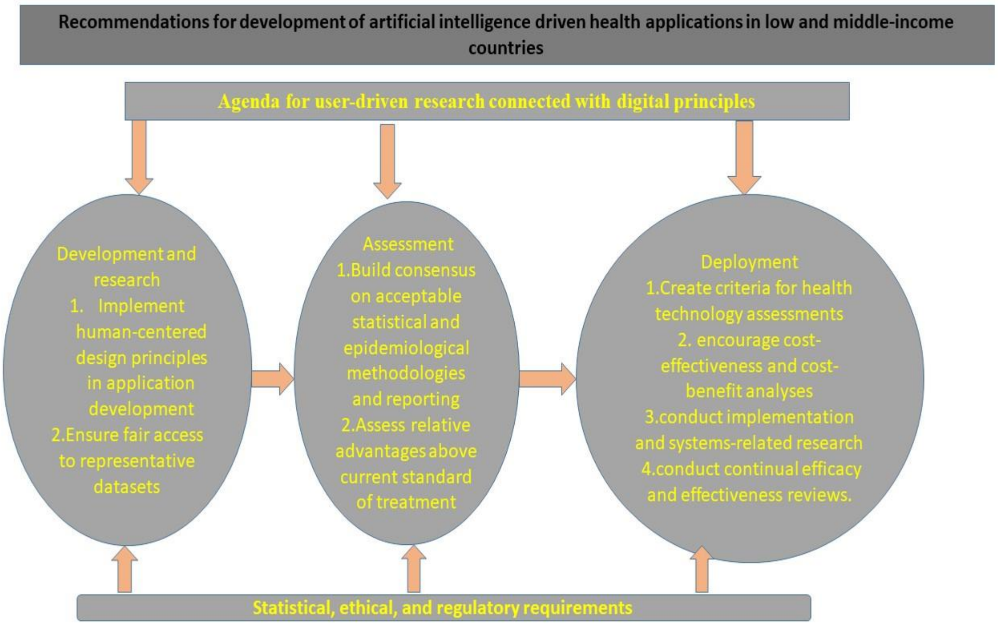


Figure 10: AI driven health application in low and middle income outcomes

Limitations and conclusions

Firstly, pertinent articles may have been released before to 2010. However, the subject of AI, particularly in global health, is quickly developing, thus any papers that were excluded because they were written before 2010 are probably not accurate depictions of the state of the field now. Additionally, the only articles featured in our Review were written in English. Considering the global importance of AI research, removing publications written in languages other than English may be a restriction. Publication bias is another possible drawback, as it is with all reviews. There are two likely places where this bias in AI research comes from. First, research with null outcomes have a lower publication rate. Therefore, it's possible that less AI-driven health treatments have produced statistically meaningful results of our review of the literature. Additionally, it was anticipated that investments in AI and health will total

$17 billion in 2018. These investments are increasingly being led by so-called large tech giants like Google and Baidu Ventures and controlled by private equity firms. Some AI developers might not place a high importance on releasing the results in academic journals because many interventions are created in the private sector for commercial application. In order to solve health challenges in LMICs, AI is already being developed. Numerous AI-driven health therapies are being used in current research to address a variety of health concerns. The scope and encouraging outcomes of these approaches highlight the pressing need for the international community to take action and develop guidelines to aid in the deployment of successful solutions. This notion is especially important in light of the rapid adoption of AI-driven health interventions that are being implemented widely as part of the response to the SARS-CoV-2 epidemic. In many instances, this roll-out is being done without sufficient justification or suitable protections. According to our suggestions, the global health community will need to act quickly to: establish global systems for assessing and reporting the efficacy and effectiveness incorporating aspects of human-centered design into the development process, such as starting from a needs-based rather than a tool-based approach, of AI-driven treatments in global health; Make sure that everyone has quick and fair access to representative datasets; create a research agenda that addresses system-related and implementation-related issues regarding the use of new AI-driven interventions; and create and put into practise international regulatory, economic, and ethical standards and guidelines that protect the interests of LMICs.

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26. The pictures of a mid-saggital slice of lung removed from a patient with COPD and of the early changes of centrilobular emphysema and of panacinar emphysema are reproduced with permission from Hogg JC. Lancet 2004;364: 709-21. The pictures of normal small airway and of emphysematous airway are reproduced with permission from W MacNee and D Lamb.\

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