

Case Report,

Chest Examination With Wireless Technology In A Patient With Fibrotic Disease: A Pilot Case Report

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Abstract:

Physicians use auscultation as a standard method of thoracic examination: it is simple, reliable, non-invasive, and widely accepted. Artificial intelligence (AI) is the new frontier of thoracic examination as it makes it possible to integrate all available data (clinical, instrumental, laboratory, functional), allowing for objective assessments, precise diagnoses, and even the phenotypical characterization of lung diseases. Increasing the sensitivity and specificity of examinations helps provide tailored diagnostic and therapeutic indications, which also take into account the patient's clinical history and comorbidities.

Several clinical studies, mainly conducted in children, have shown a good concordance between traditional and AI-assisted auscultation in detecting fibrotic diseases. On the other hand, the use of AI for the diagnosis of obstructive pulmonary disease is still debated as it gave inconsistent results when detecting certain types of lung noises, such as wet and dry crackles. Therefore, the application of AI in clinical practice needs further investigation.

In the case we present, data integration allowed us to make the right diagnosis, avoid invasive procedures, and reduce the costs for the national health system; we show that integrating technologies can improve the diagnosis of restrictive lung disease. Randomized controlled trials will be needed to confirm the conclusions of this preliminary work.

Key words: Artificial intelligence (AI), thoracic objective examination 3.0, obstructive and restrictive lung diseases, chest CT, crackles.

Introduction:

Lung sounds have been used to understand the health of the respiratory system since ancient times. The introduction of the Laennec's stethoscope in the nineteenth century set a milestone in the diagnosis of lung diseases; nowadays, we are witnessing a revolution in respiratory assessment thanks to the introduction of more sensitive and specific methods and computerized spirometry [1, 2]. In the last decade, we have improved our understanding of lung sounds, even though we still lack a comprehensive model of thoracic and pulmonary acoustics.

Traditional stethoscopes have limitations, especially in detecting the crackles that characterize restrictive respiratory diseases. Today, mobile applications can help physicians by recording, storing, playing, and analyzing respiratory sounds, complementing the chest examination. Simulation studies have shown that mobile apps have high accuracy, sensitivity, and specificity in the detection of fine crackles, while they do not perform as well in detecting coarse crackles. It has also been shown that a mobile app can help assess lung sounds in patients [3]. Some studies have tried to describe the audiological

characteristics of wheezing and crackles in adults and children using digital stethoscopes [4]. It has been shown that digital stethoscopes can analyze and display data in new ways, work in real-time, classify lung sounds following the conventional categories, and differentiate single sounds when multiple sounds are present simultaneously [5]. Electronic stethoscopes offer several advantages over analog stethoscopes as they can reduce background noise, amplify, store, and transmit sounds. However, clinicians may find it difficult to switch to a digital stethoscope because of the different acoustics [6].

Lung auscultation has a key role in the diagnosis of respiratory diseases. Standardized nomenclature and computational analysis of the sounds have improved the technique, however, auscultation lacks reproducibility as it relies on the clinician's judgment [7]. AI can overcome this limitation and help diagnose lung diseases. ANN

and k-nn are the most used machine learning algorithms for the analysis of lung sounds. Kandasamy et al. showed that ANN classified different breath sounds with 100% and 94.02% accuracy during training and testing, respectively, proving that ANN is efficient at processing and classifying complex non-linear data [8]. Another study concluded that AI could detect fine and coarse crackles in respiratory sounds recorded by different digital stethoscopes, although there were some device-dependent differences [9]. Grzywalski T et al. integrated the thoracic examination of children with an AI diagnostic algorithm, improving both the sensitivity and specificity of the examination, reaching values close to 100% diagnostic specificity and sensitivity [10]. It will be essential to perform independent validations of the AI tools that enter medical care to ensure quality control [7].

Table 1: Comparison between the first spirometry from September 2022 and the complete spirometry from February 2023

FEV1%	FVC%	FEV1/FVC	PEF	FEF ₂₅₋₇₅ %	RV	TLC%	RV/TLC%
71%	86%	89%	61%	35%	/	/	/
66%	79%	82%	67%	39%	124%	93%	135%

In 2023, the patient still shows signs of an obstructive condition with a further reduction of the lung volumes and air trapping also due to poor therapeutic adherence.

FEV1%: Percentage of predicted value of FEV1

FVC%: Percentage of predicted value of FVC

FEV1: Maximum Expiratory Volume at first second

FVC: Forced vital capacity

TLC: total lung capacity

RV: Residual volume

RV/TLC: ratio of total lung capacity to residual volume expressed as a percentage of the predicted value

FEF_{25-75%}: forced expiratory flow between 25 and 75% of FVC

Table 2: Laboratory exams carried out in January 2023.

Autoimmune test	Results	Blood test	Results
ANA	Negative	GOT	23 U/l
P-ANCA	Negative	Glycemia	214 mg/dl
ENA	Negative	Antiphospholipid antibodies	Negative
C-ANCA	Negative	Serum creatinine	1.01 mg/dl
Rheumatoid factor	9 UI/mL	Azotemia	60 mg/dl
Calciuria	290 mg/24h	Coagulation	Negative
Anti-CCP	Negative	D-Dimer	Negative
Lysozyme	16 mcg/ml	LAC	Negative
ACE	<1 U/l	Glycated hemoglobin	8.8%
CRP	2 mg/dl	Leukocyte count	230 Eosinophils
ESR	30 mm/h	GPT	30 U/l

ANA: antinuclear antibodies

ANCA: antineutrophil cytoplasmic antibodies

ENA: extractable nuclear antigen

Anti-CCP: anti-cyclic citrullinated peptides

ACE: Angiotensin-converting enzyme

CRP: C-reactive protein
ESR: Erythrocyte sedimentation rate
GOT: glutamic-oxaloacetic transaminase
LAC: lupus anticoagulant
GPT: glutamate pyruvate transaminase

Case Presentation:

A Caucasian female presented to the clinic for nocturnal dyspnea and cough, wheezing, and moderate exertional dyspnea. She was taking inhaled corticosteroids, a once-daily long-acting beta-2 agonist (LABA), a long-acting muscarinic antagonist (LAMA), and montelukast, but the therapy had not given any clinical benefits. The patient was allergic to non-steroidal anti-inflammatory drugs type II (NSAIDs), different antibiotics (cephalosporins, penicillin, sulfonamides, pyrimidoids), salicylates, and barbiturates. She reported nasal polyposis, never smoked, had insulin-independent diabetes mellitus (for which she was taking metformin twice daily), obesity (BMI: 31), systemic hypertension, hypercholesterolemia, and hypertriglyceridemia. She underwent coronary stent placement two years before and was on clopidogrel therapy. She had been diagnosed with asthmatic chronic bronchitis (ACOS) and atopy, but she had never performed a bronchodilator reversibility test. She showed the results of a sleep cardiorespiratory monitoring that recorded an apnea hypopnea index (AHI) of 6.7 that, according to the pneumologist who previously assessed it, was not indicative of obstructive sleep apnea (OSA). Despite the high AHI and the evidence of supine-related OSA (supine AHI/non-supine AHI > 3:1), the patient was not under any treatment.

She presented three previous chest computed tomography (CT) scans: the first from 2018 showed a nodule of 1.4 cm in diameter with light borders, a rounded nodule of 8 mm with light borders at the apical-medial segment of the left lower lobe, a small fibrotic thickening, and an intra-mediastinal lymph node of 3 cm in diameter. The second scan from 2021 showed nodular formations of 2-3 mm in the apical segment of the left lower lobe and parenchymal thickening with air bronchogram in the medial segment of the middle lobe; there were thickenings at the base of the lungs and a 3 cm medial iliac lymphadenopathy. The third scan from February 2023 showed calcified centrilobular nodules and a calcified medial iliac lymphadenopathy with areas of air trapping and bilateral bronchiectasis.

Table 1 compares the results of the spirometry tests the patient carried out in September 2022 and February 2023. Table 2 shows the results of the blood test done in January 2023.

When the patient presented to the clinic, we auscultated the lungs with a digital stethoscope, the Eko Core stethoscope (Image 1), and detected diffuse velcro crackles over the entire area and signs of airway obstruction on forced expiration (moans and hisses). The lung sounds were recorded, assessed, and compared with the chest CT findings. The patient was then diagnosed with bronchial asthma with hypereosinophilia and nasal polyposis associated with bilateral bronchiectasis and reduced lung volumes, stage II pulmonary sarcoidosis (diffuse pulmonary lymphadenopathy and nodules with calcifications) with renal involvement, mild OSA with higher frequency in supine position associated with obesity, and uncontrolled type 2 diabetes mellitus. Positional therapy was prescribed for the OSA and the patient was referred for evaluation of diabetes and renal assessment.

Discussion:

Auscultation is a standard method to hear lung sounds and it is widely used as it is simple, reproducible, and non-invasive. Auscultation can be either direct or indirect: during direct auscultation, the physician listens to the lungs with her ear, whereas during indirect auscultation she uses a stethoscope. Since the introduction of the acoustic stethoscope, indirect auscultation has gradually replaced the direct method [11].

Discerning normal and abnormal respiratory sounds (such as crackles, wheezes, and hisses) is crucial for an accurate and early diagnosis, which can prevent chronic respiratory diseases. For instance, an early diagnosis of hypersensitivity pneumonitis prevents pulmonary fibrosis, reversing a poor prognosis.

Lung sounds give valuable information about the physiological and pathological condition of the lungs and airways. Indeed, the first step of non-invasive diagnoses of respiratory disease involves auscultation and comparison with the medical

history. However, the detection of abnormal lung sounds depends on the skills and expertise of the physician. To overcome these limitations, different digital methods have been proposed. Electronic stethoscopes automate the detection of lung sounds by processing the signal with time-frequency analysis or time-varying autoregressive modeling [12].

A Korean clinical study tested the accuracy of deep learning convolutional neural network for the analysis of lung sounds. The predictive model accurately detected abnormal sounds and was also able to classify them into three categories, namely crackles, wheezes, and rhonchi. The model proved to be more precise than human evaluation [13]. Similar results were obtained in a pediatric study where abnormal sounds were categorized into crackles, rattles, and buzzes with such a high accuracy that it was considered suitable for the initial screenings and follow-ups of patients with respiratory diseases [14].

In another pediatric clinical study, breath sound recordings were collected in a clinical setting that was full of other baby noises, cries, voices, and movements. The AI algorithm analyzed 93.3% of the recordings, reaching an accuracy comparable to the one of experienced pediatric pulmonologists [15]. Cardiologists compared the results of personal heart auscultation and echocardiogram with the recordings of an EKO Core stethoscope and found that the categorization was comparable and showed moderate reliability [16]. Another study demonstrated how lung auscultation with a new-generation wireless stethoscope is possible in hospitalized patients with SARS-CoV-2 pneumonia and allows the assessment of velcro crackles, which indicate a poor prognosis if widespread and audible [17]. Finally, Horimasu et al. compared how a machine-learning-based algorithm they developed and X-rays performed in the diagnosis of interstitial lung diseases (ILDs). The researchers concluded that quantifying fine crackles using an electronic stethoscope and their algorithm was more sensitive than X-rays in determining the presence of ILDs. Their study demonstrated that the quantification of fine crackles can predict the high-resolution computed tomography (HRCT) results and help the diagnosis of ILDs [18].

In the clinical case we present, our approach, which integrated data from function tests, instruments, and AI, allowed us to make the right

diagnosis. Our diagnosis was complicated because, despite the radiological evidence of calcified central-lobular nodules and mediastinal lymph nodes, the laboratory tests and the spirometry results initially suggested a different diagnosis by showing low angiotensin-converting enzyme (ACE) levels and the absence of a restrictive ventilatory defect.

Conclusion:

Researchers have started to introduce AI in thoracic examinations, but there are still doubts about its use in the diagnosis of obstructive pulmonary diseases, while different clinical trials have already confirmed its high potential in the detection of fibrotic diseases. Mobile apps integrated with a digital stethoscope can improve the sensitivity and specificity of the thoracic examination, and machine learning can generate algorithms that improve the diagnostic efficiency of lung diseases.

In this clinical case, the integrated approach allowed us to make the right diagnosis, while saving costs for the national health system and avoiding invasive procedures such as bronchoscopy, which is still the gold standard for the histological diagnosis of lung sarcoidosis. We have shown that integrated technology can strengthen the diagnostic capacity of restrictive lung diseases.

The specialist maintains a crucial role in recognizing lung pathologies and preventing potential progressions; moreover, integrating data from instruments, chest CT, and thoracic examination is still the cornerstone of the diagnosis of respiratory diseases in clinical practice. Today, mobile apps make it possible to integrate data, store physiological and pathological noises, and listen to them with specific filters that improve their quality, allowing the physician to better differentiate the lung sounds. The real strength of the objective thoracic examination is the integration of all available data (clinical, instrumental, laboratory, functional) to achieve precision in the diagnosis and to characterize the phenotype of lung diseases. A precise diagnosis is key to personalized medicine and tailored therapeutic indications that also take into account the medical history and the comorbidities of the patient.

Electronic auscultation allows for storing pathological and physiological lung sounds that

can be then compared to other types of examinations, such as chest high-resolution CT scans. However, data in the literature do not always agree on the use of digital devices to detect certain types of sounds, such as wet and dry crackles; therefore, the application of electronic stethoscopes in clinical use needs to be further investigated. Moreover, we still need to pinpoint the limitations of the technology and find the right way to integrate its use into clinical practice. The applications of integrated technology and AI are wide-ranging as they allow the assessment of heart, lung, and bowel sounds. Electronic auscultation can also be useful to teach medical students how to discern different lung sounds since it allows them to download files or generate QR codes that can be listened to on smartphones or tablets.

In this clinical case, the use of an electronic stethoscope allowed us to diagnose an interstitial lung disease with percentages of specificity and sensitivity that are in line with the ones reported in the literature (80 and 90%, respectively). However, randomized controlled clinical trials are needed to confirm the results of this pilot study.

Reference:

- [1] Kevat AC, Kalirajah A, Roseby R. Digital stethoscopes compared to standard auscultation for detecting abnormal paediatric breath sounds. *Eur J Pediatr.* 2017 Jul;176(7):989-992. doi: 10.1007/s00431-017-2929-5
- [2] Ohshimo S, Sadamori T, Tanigawa K. Innovation in Analysis of Respiratory Sounds. *Ann Intern Med.* 2016 May 3;164(9):638-9. doi: 10.7326/L15-0350.
- [3] Pasterkamp H, Kraman SS, Wodicka GR. Respiratory sounds. Advances beyond the stethoscope. *Am J Respir Crit Care Med.* 1997 Sep;156(3 Pt 1):974-87. doi: 10.1164/ajrccm.156.3.9701115.
- [4] Böhme, H. R. 1974. Attempt at physical characterization of the passive sound behavior in the lung in a model. *Z. Gesamte Inn. Med.* 29:401–406.
- [5] Kevat A, Kalirajah A, Roseby R. Artificial intelligence accuracy in detecting pathological breath sounds in children using digital stethoscopes. *Respir Res.* 2020 Sep 29;21(1):253. doi: 10.1186/s12931-020-01523-09.
- [6] Challen R, Denny J, Pitt M, et al. Artificial intelligence, bias and clinical safety. *BMJ Qual Saf.* 2019;28(3):231–7.
- [7] Grzywalski T, Piecuch M, Szajek M, et al. Practical implementation of artificial intelligence algorithms in pulmonary auscultation examination. *Eur J Pediatr.* 2019 Jun;178(6):883-890. doi: 10.1007/s00431-019-03363-2.
- [8] Ye P, Li Q, Jian W, et al. Regularity and mechanism of fake crackle noise in an electronic stethoscope. *Front Physiol.* 2022 Dec 12; 13:1079468. doi: 10.3389/fphys.2022.1079468. PMID: 36579022.
- [9] Bertrand Z F, Segall K D, Sánchez D I, et al. La auscultación pulmonar en el siglo 21 [Lung auscultation in the 21st century]. *Rev Chil Pediatr.* 2020 Aug;91(4):500-506. Spanish. doi: 10.32641/rchped. v91i4.1465.
- [10] Andrès E, Gass R, Charloux A, et al. Respiratory sound analysis in the era of evidence-based medicine and the world of medicine 2.0. *J Med Life.* 2018 Apr-Jun;11(2):89-106. PMID: 30140315.
- [11] Palaniappan R, Sundaraj K, Sundaraj S. Artificial intelligence techniques used in respiratory sound analysis--a systematic review. *Biomed Tech (Berl).* 2014 Feb;59(1):7-18. doi: 10.1515/bmt-2013-0074.
- [12] Olvera-Montes N, Reyes B, Charleston-Villalobos S, et al. Detection of Respiratory Crackle Sounds via an Android Smartphone-based System. *Annu Int Conf IEEE Eng Med Biol Soc.* 2018 Jul;2018:1620-1623. doi: 10.1109/EMBC.2018.8512672.
- [13] Kim Y, Hyon Y, Jung SS, Lee S, et al. Respiratory sound classification for crackles, wheezes, and rhonchi in the clinical field using deep learning. *Sci Rep.* 2021 Aug 25;11(1):17186. doi: 10.1038/s41598-021-96724-7.
- [14] Kim Y, Hyon Y, Lee S, et al. The coming era of a new auscultation system for analyzing respiratory sounds. *BMC Pulm Med.* 2022 Mar 31;22(1):119. doi: 10.1186/s12890-022-01896-1.

- [15] Zhang J, Wang HS, Zhou HY, et al. Real-World Verification of Artificial Intelligence Algorithm-Assisted Auscultation of Breath Sounds in Children. *Front Pediatr.* 2021 Mar 23; 9:627337. doi: 10.3389/fped.2021.627337.
- [16] Behere S, Baffa JM, Penfil S, et al. Real-World Evaluation of the Eko Electronic Teleauscultation System. *Pediatr Cardiol.* 2019 Jan;40(1):154-160. doi: 10.1007/s00246-018-1972-y.
- [17] Zhang P, Wang B, Liu Y, et al. Lung Auscultation of Hospitalized Patients with SARS-CoV-2 Pneumonia via a Wireless Stethoscope. *Int J Med Sci.* 2021 Jan 28;18(6):1415-1422. doi: 10.7150/ijms.54987.
- [18] Horimasu Y, Ohshimo S, Yamaguchi K, et al. A machine-learning based approach to quantify fine crackles in the diagnosis of interstitial pneumonia: A proof-of-concept study. *Medicine (Baltimore).* 2021 Feb 19;100(7):e24738. doi: 10.1097/MD.00000000000024738.



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