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Automated differential diagnostics of respiratory diseases using an electronic stethoscope

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Abstract

Introduction: The outbreak of the coronavirus infection, which has escalated into a pandemic, has worsened the already unfavourable situation with respiratory system diseases in Ukraine. The burden on doctors has significantly increased, necessitating the exploration of simplified and expedited methods for conducting routine respiratory examinations. The research aims to describe a model for creating an automated differential diagnosis of respiratory noise using an electronic stethoscope, combining medical and clinical information about the types of respiratory noise characterizing the normal or pathological state of the respiratory system with a means of its information and technical processing.
Material and methods: The research methods were analysis of theoretical information about the types of respiratory noise, analysis of technical information for choosing an information technology tool for processing biological signals; synthesis of the results; modelling.
Results: The research resulted in a model of automated differential diagnosis based on the principle of auscultation, which includes the process of extracting the sound of air movement inside and outside the lungs and the classification of the extracted sounds. Automation of this process concerned only the classification of the extracted sounds since the principle of extraction itself was the same for both mechanical and automatic implementations.
Conclusions: The automatic classification process was intended to reduce the time of the procedure and reduce the influence of the human factor, eliminating the possibility of medical error. To implement the process, a deep machine learning method was used, the array of information for which was to be a created phonotheque of acoustic signals of the respiratory system, which would include all types of respiratory noise concerning normal or pathological processes in the body.

Keywords: auscultation process; deep machine learning method; acoustic signals; pulmonology; lung sounds.

Introduction

Since 2020, the healthcare situation in Ukraine has been complicated by the COVID-19 outbreak.[1] The danger of the disease and the complications it provokes for the human respiratory system, along with the high rate of disease spread, has become a challenge not only for doctors but also for medical engineering specialists in the field of pulmonology. Auscultation with a stethoscope has been and remains the primary link in the diagnosis of the respiratory system. Scientists and engineers created an electronic stethoscope with the function of recording respiratory sounds, which made it possible to automate the auscultation process and thus increase its speed, accuracy, and reliability. The reliability and adaptability of electronic stethoscopes in real-world conditions depend on various factors, such as the quality of the device, the expertise of the user, and the specific patient and condition being assessed. Several studies have evaluated the performance of electronic stethoscopes in different clinical settings. For example, compared the performance of an electronic stethoscope with a traditional acoustic stethoscope and found that the electronic stethoscope provided comparable or even better sound quality and diagnostic performance in most cases.[2] Another study evaluated the performance of an electronic stethoscope in a pediatric emergency department and found that it was reliable and effective in detecting abnormal heart and lung sounds in children.[3] However, it is important to note that the reliability and adaptability of electronic stethoscopes can vary depending on the specific device and its features, as well as the training and experience of the user. It is always recommended to use

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electronic stethoscopes in conjunction with clinical judgment and other diagnostic tools for accurate assessment and diagnosis.

The process, which involves two stages - extracting the sound of air movement inside and outside the lungs and classifying the extracted sounds - can benefit from automation. This will not only mitigate the risk of subjective sound perception errors at the initial stage but also facilitate accurate sound classification at the second stage, leveraging the extensive sound library of recordings archived within the software. Automated systems in auscultation can save a significant amount of time compared to traditional methods performed by medical professionals. With traditional auscultation, healthcare providers need to manually listen to and interpret respiratory sounds using a stethoscope. This process can be time-consuming, especially when multiple patients need to be examined. On the other hand, automated systems in auscultation utilize digital stethoscopes and advanced technologies such as artificial intelligence (AI) to analyze respiratory sounds. These systems can quickly record, store, and analyze sounds, providing healthcare providers with immediate feedback and analysis. AI algorithms can help detect abnormal sounds or patterns, potentially aiding in the early detection and diagnosis of respiratory conditions. By reducing the time needed for auscultation, automated systems can improve workflow efficiency and allow medical professionals to focus on other aspects of patient care. However, it's important to note that automated systems should not replace the expertise and clinical judgment of healthcare providers. They should be used as supportive tools to enhance the accuracy and efficiency of auscultation.

Automated differential diagnostics of respiratory diseases is essential in practice, but at the same time, many problems stand in the way of its rapid implementation in the healthcare sector of Ukraine. The practical problem is to provide the automation process with a database on which the developed software will rely to identify the most accurate match of the test sample with the data of the created database. This requires the creation of appropriate software, logistics, and communication between doctors and scientists, on the one hand, and medical device engineers and software development specialists, on the other. A legal problem arises from the need to use a patient's personal medical information in the process of creating a large-scale respiratory noise library. For this purpose, regulatory documents must be developed that will certify the patient's consent to the use of his or her medical information. The philosophical problem lies in the view of the automation process as a replacement of the accumulated knowledge and experience of many doctors with a single system that will "eliminate" them from the process of diagnosing respiratory system diseases. The solution to this problem can only be provided by time, which will show the effectiveness or ineffectiveness of the automation of diagnostic processes.

Automation in healthcare offers several advantages and disadvantages, particularly in terms of improving diagnostic accuracy and reducing medical errors. Automated systems can analyze large amounts of data and detect patterns that may be difficult for humans to identify. This can aid in the early detection and accurate diagnosis by medical professionals to make more accurate diagnoses. Automated devices and systems can continuously monitor patients, providing real-time data on vital signs and alerting healthcare professionals to any concerning changes. Automation can streamline administrative tasks, such as appointment scheduling, billing, and insurance claims processing, reducing errors and saving time. Automation can enhance the patient experience by reducing wait times, increasing appointment availability, and improving communication between patients and healthcare providers. By automating certain tasks, healthcare facilities can potentially reduce costs associated with manual labour and improve overall efficiency. Automation removes some of the personal interactions between patients and healthcare professionals, potentially leading to a more impersonal experience. Automation relies on technology, and technical issues can arise, leading to system malfunctions or errors. As automation increases, there is a concern that certain healthcare jobs may become obsolete, leading to job displacement for some healthcare professionals.[4]

The study by D.V. Panaskin et al. noted the technical support issues that limited the use of artificial intelligence (AI) in the diagnostic process for some time but were resolved with the advent of deep learning technology in healthcare.[5] M.F. Babakov et al. described how sensors should be constructed to record the acoustic noise of the breathing process.[6] In this work, they showed the possibility of connecting several stethoscopes to an acoustic signal recording unit, which would allow recording the sounds of several subjects simultaneously or recording the sounds of one subject at several points in the chest. The monograph by I.Y. Dediv et al. considered the issue of creating software for processing respiratory sounds in computer auscultation diagnostic systems.[7] The research described in detail the construction of a mathematical model of respiratory noise and the improvement of statistical methods for processing these noises. The research aims to develop software in the MATLAB (Matrix Laboratory) environment for an automated procedure for assessing the state of the respiratory system. I.S. Ponomarenko compared the legal regulation of personal data protection in the healthcare sector of Ukraine with international experience.[8] He proposed to bring the legislative acts on the protection of patients' personal information in line with the EU (European Union) Regulation developed in 2018. O.E. Radutnyy conducted a comprehensive study of the immediate prospects for the development and implementation of AI, robotics, and digital human in all areas of life, including healthcare.[9] The benefits of their use and the risks associated with them were described. It is noted that in the short term, the complete replacement of human labour with AI is not considered for both practical and ethical reasons.

All the above works contained exclusively technical information on the construction of mathematical models of a particular diagnostic program. The research aims to describe the construction of the process of automating the differential diagnosis of respiratory noise by synthesizing medical information about the types of respiratory noise in various types of respiratory system diseases with the means of its information and technical processing. The novelty of the research lies in the development of a model for automated differential diagnosis of respiratory noise using an electronic stethoscope. Given the challenging situation with respiratory system diseases, including the recent outbreak of the coronavirus pandemic, there is a growing need for simplified and faster methods of conducting routine respiratory examinations.

Material and Methods

To achieve the research aim, the following methods were used: analysis of medical information on anatomy and pulmonology, analysis of technical information for the selection and justification of an information technology tool for processing biological signals, synthesis of data obtained as a result of the previous methods, and modelling. Through the analysis of medical literature, the features of the respiratory system, diagnosed by auscultation, were investigated, and respiratory noises were classified by their types concerning the normal or pathological state of the respiratory system, as well as their belonging to a particular syndrome in case of detection of a pathological condition. The materials used included theoretical works on anatomy containing information on the peculiarities of the structure of the lungs, chest, and other organ systems involved in the formation of acoustic vibrations when air enters their cavities; scientific works on pulmonology about diseases of the respiratory system and methods of their acoustic diagnosis; description of the auscultation process using an electronic stethoscope, its technical characteristics and advantages.

After analyzing technical information, a suitable technological tool for processing biological signals, namely the deep machine learning method, was selected and justified. This method was utilized to develop an algorithm for recognizing respiratory diseases based on the sound signals of respiratory noise. Specifically, the algorithm employed biological sounds of air movement in and outside the lungs, obtained from an electronic stethoscope and converted into the appropriate format. The utilization of analyzing technical information stems from its capability to nonlinearly process extensive datasets and identify common features between the object of inspection and the control samples present in the dataset. The algorithm encompasses pattern recognition and classification, aligning with the mechanism of the auscultation process. In selecting the technology for processing acoustic signals, research conducted by American scientists in the field of AI technologies, including the deep machine learning method, was considered.

The preliminary algorithm validation was conducted using lung sound recordings obtained from the R.A.L.E. Lung Sounds Depository[10]. The R.A.L.E. repository is a recognized and comprehensive collection of lung sound recordings, representing a wide array of pulmonary conditions. These recordings have been rigorously curated and are commonly used in the academic and clinical communities to study lung auscultation. Both normal breathing sounds as well as sounds of various respiratory pathologies, including asthma, pneumonia and chronic obstructive pulmonary disease (COPD) were used during the study. Audio data was acquired containing normal and abnormal respiratory sounds at multiple chest locations. The recordings were used to validate the differential analysis algorithm's ability to detect pathological respiratory noise events before testing on real patient data.

By synthesizing the results obtained using the previous methods, a classification of respiratory sounds by their types was formed. This classification was developed as a basis for creating a data set in the form of a phonotheque of lung sounds, differentiated by their belonging to a particular syndrome, each of which includes several diseases related to the respiratory system. Based on the sound library, using the method of deep machine learning, information technology specialists can create software to automate the process of quickly comparing a control sample with an array of recordings from this sound library.

Using the modelling method, the final model of automated differential diagnosis of respiratory noise using an electronic stethoscope was developed. This process involved synthesizing the results obtained from analyzing both medical and technical information. The modelling method encompassed several key steps. First, the available medical information regarding the types of respiratory noise characterizing normal and pathological states of the respiratory system was analyzed. This information served as a basis for understanding the diagnostic criteria for different respiratory conditions. Simultaneously, technical information related to the electronic stethoscope and its capabilities for capturing and recording respiratory sounds was examined. This included studying the technical specifications, signal processing capabilities, and the appropriate format for storing and analyzing the acquired data. Through this comprehensive approach, the final model of automated differential diagnosis of respiratory noise using an electronic stethoscope was successfully developed. The model combined medical knowledge with technical advancements, providing a streamlined and efficient method for diagnosing respiratory diseases. Based on the data obtained in the study, recommendations were made regarding the sources of filling the phonotheque with recordings of respiratory sounds, and their choice was substantiated.

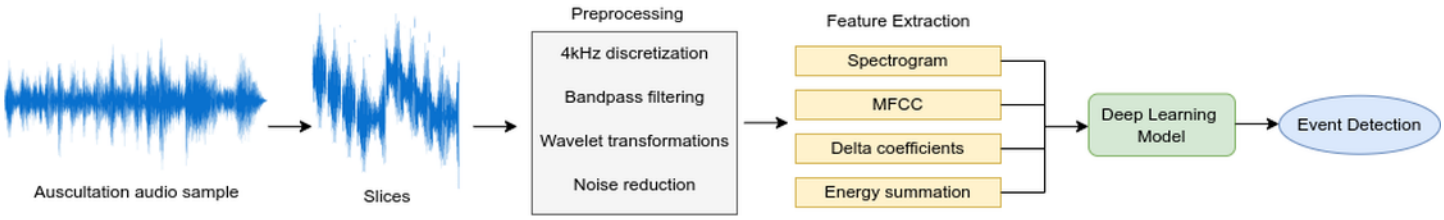


Figure 1. Auscultation signal processing pipeline.

Results

To study the ability of differential analysis to recognize respiratory noise from lung sounds, audio signals were obtained from electronic stethoscope recordings. The recordings were auscultatory sounds from patients suffering from asthma, pneumonia, chronic obstructive pulmonary disease, and heart failure, as well as control sounds from healthy patients. Each signal first underwent a pre-processing procedure to ensure the quality of the analysis and then went through a feature extraction procedure to obtain clean data ready for further analysis (**Figure 1**).

As with any other electronically recorded biological signal, lung sound recordings are disturbed by acoustic noise caused by ambient noise, background conversations, electronic interference, or any displacement of the stethoscope. Therefore, in this study, audio recordings were pre-processed. Its stages included the removal of extraneous noise, wavelet transform, and normalization. Wavelet transform is widely used to analyse non-stationary signals. Its basic idea is to use the mother wavelet to transform and decompose the signal into various functions. The Dobeshi family of wavelets was used to smooth the shape of the original signal. After that, the amplitude coefficients of the processed signal were normalized using standardization techniques to improve the propagation of gradients by the differential analysis algorithm.

To validate the differential analysis algorithm for respiratory sound classification, preliminary testing was conducted on lung sound data obtained from the R.A.L.E. Lung Sounds Depository[10]. The normal breathing sounds as well as sounds mimicking asthma, pneumonia, and COPD pathologies were used.

Lung sounds were recorded using a single-channel electronic stethoscope placed in the upper, middle, or lower left/right half of the chest, as well as a multichannel electronic stethoscope fixed in specific areas of the chest. The duration of the audio stream ranged from 20 seconds to 3 minutes and necessarily contained several respiratory cycles. All signals were resampled at a sampling rate of 4 kHz to eliminate high-frequency noise that does not contain useful information during breathing. The method of expert judgment was used to register and label lung sounds by class. At the stage of data pre-processing, the signal was divided into parts, each of which should either contain an event of respiratory noise or contain only pure respiratory cycles. Segmentation was performed in 15-second segments.

The audio signals were pre-processed as described in the methods section. Each recording was divided into 15-second segments, with the segments manually labeled by an expert as either containing a respiratory noise event or normal breathing sounds.

A total of 150 segments (75 normal and 75 with noise events) were used for initial algorithm validation. The segments were input to the differential analysis algorithm, which generated a probability output predicting whether the segment contained a noise event. The algorithm output was compared to the expert labels using sensitivity and specificity metrics.

On this preliminary dataset, the algorithm achieved a sensitivity of 0.82 and a specificity of 0.74 for respiratory noise detection. 82% of segments containing labeled noise events were correctly identified by the algorithm (true positives). Meanwhile, 74% of normal breathing segments were correctly classified as not having noise (true negatives).

The idea of the differential analysis algorithm is based on a spatial and sequential representation of the audio signal. As a spatial element, the spectral representation of the signal obtained by the fast Fourier transform and the mel-cepstral coefficients were used to obtain additional information about the frequency response of the respiratory cycle. In addition, as an additional source of information, the energies of the frequency bands from 0 to 2 kHz were calculated to improve the understanding of the change in amplitude characteristics in the frequency range and over time. Since the analysis of a pure frequency representation cannot fully characterize the signal, the idea of applying differential analysis of frequency pattern sequences helps to obtain complete information, in particular, regarding the beginning and end of respiratory noise events.

The algorithm for automated differential analysis of respiratory noise consists of several parts: spatial processing of the selected signal characteristics as convolutional layers, the kernels of which summarize the information of frequency change patterns, and sequential processing of the characteristics obtained from the convolutional layers, which forms a representation of the recurrent change of patterns in time. The resulting representation is transferred to the linear layer of the algorithm, which forms the dependencies of the frequency and time parts into a probabilistic output characterizing the presence of a respiratory noise event in the signal or its absence (**Figure 2**).

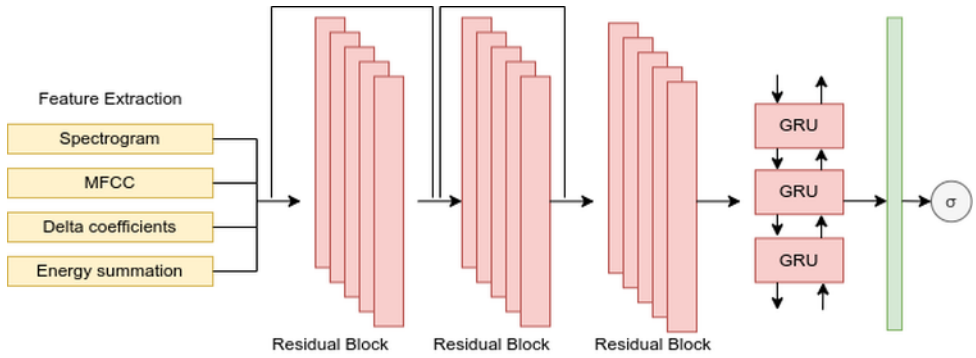


Figure 2. Algorithm for automated differential analysis of respiratory noise.

The convolutional layers of the algorithm are built on the principle of residual blocks so that the input of each subsequent block is the sum of the representation obtained by the previous block with the input set of characteristics, thus regulating the passage of gradients through each stage of the algorithms and guaranteeing the presence of root characteristics of the signal at each stage. The Gated Recurrent Unit approach is used as recurrent layers, which is similar in methodology to long short-term memory, but has fewer parameters since it does not have an output gate. This layer allows for better performance on data sets with lower repetition rates. The output of the algorithm is the probability of an event based on the initial characteristics. To analyse the quality of the algorithm were obtained the basis for classifying the initial respiratory noise events into positive, false positive, and false negative. The classification was performed by applying the Jaccard index of the received respiratory noise events with the previously correct ones obtained by the method of expert assessments:

$$J(A,B) = \frac{|A \cap B|}{|A \cup B|} \qquad \text{Eq. 1}$$

Hence, if the Jaccard index for a segment is > 0.5, the event is assessed as a true positive, for values > 0 and < 0.5 the event is assessed as a false negative, and for an index of = 0 as a false positive. Automation of any process is based on the same algorithm of actions that was used for its mechanical or manual implementation. Auscultation as a diagnostic process consists of two stages: the first is the extraction of the sound of air movement in the lungs, and the second is its classification concerning a particular normal or pathological process of the respiratory system. The quality of the result in the first stage is ensured by the sensitivity of the stethoscope membrane, and in the second stage by the knowledge and experience of the doctor performing the procedure. The automation of this method was aimed at improving the quality of the second stage, reducing the procedure time and reducing the possibility of medical errors. This process is a symbiosis of clinical information and technical methods for its fast and accurate processing. The task of studying clinical information is to create a voluminous data set that will contain pre-processed recordings of respiratory sounds characterizing normal and all possible pathological conditions of the respiratory system. Technical methods should perform the task of finding a match between the diagnostic object and the generated data set. The algorithm for automating the process of diagnosing respiratory sounds considered in this study included: the formation of a theoretical base of clinical data, based on which an array of information in the form of a phonotheque of respiratory sounds can be developed, a description of the features of using the deep machine learning method as a tool for finding correlations in an array of information, and a synthesis of the results obtained.

When forming the theoretical basis of clinical information, it is necessary to rely on data on the peculiarities of the anatomical structure of the respiratory system organs involved in the formation of sounds, clinical information on the types of pulmonary diseases, and methods of their acoustic diagnosis; characteristics of the electronic stethoscope as a tool for automating the auscultation process. The main feature of the respiratory system structure stems from the function it performs, namely respiration and gas exchange. Thus, all organs of this system are cavities through which air enters and leaves the body. The movement of air in each of them causes acoustic vibrations, which can be used to determine the presence or absence of pathological processes in the respiratory system. According to these sounds, the following types of breathing are distinguished: vesicular breathing, bronchial breathing, and adverse respiratory sounds.

The mechanism of formation of normal vesicular breathing is caused by vibrational oscillations of the elastic alveolar walls and is audible as a soft noise heard throughout the inhalation and in the initial third of the exhalation. The loudness of this sound is inversely proportional to the thickness of the chest, so in children and people with an asthenic body type, it will be enhanced, and in people with obesity or muscle gain during exercise or other factors – weakened. In addition to the peculiarities of the chest structure, increased and decreased vesicular respiration may indicate the presence of pathologies in the respiratory system. Pathologic weakening of vesicular respiration is characterized by a shortened inhalation and an almost inaudible exhalation sound caused by impaired upper airway patency, accumulation of air or fluid in the pleural cavity,

decreased depth of respiratory excursions, and decreased elasticity of the lung tissue. The presence of this type of breathing may indicate the following pathological processes of the respiratory system: pulmonary emphysema, pneumonia, diffuse or large-focal pneumosclerosis, lung tumour, foreign body obstruction in the airways, technical damage to the ribs, chest contusion, or intercostal muscle injury.

Pathologically increased vesicular breathing is heard on inhalation and exhalation. Amplification and prolongation of the sound in the exhalation phase can be caused by the narrowing of the lumen of small bronchi due to oedema of their mucous membrane or bronchospasm. Additionally, there is a special type of increased vesicular breathing – rigid breathing. It is characterized by higher frequency, sharpness, and coarseness of sound in terms of acoustic properties. These features are since the sound of turbulent airflow colliding with uneven and rough bronchial walls is added to the usual noise of alveolar wall vibrations. With rigid breathing, the duration of exhalation becomes equal to or even longer than the duration of inhalation. Listening to this type of breathing may indicate bronchitis or focal pneumonia.

Bronchial breath is heard during the inhalation phase and full exhalation in the areas above the larynx and trachea. The sound of bronchial breath differs from the previous types of breathing in timbre, volume, and increased duration of the exhalation phase. This type of breathing over other areas indicates pathological changes in the lungs, which may be a compaction of the lung tissue and the formation of a cavity in the lung. Lung tissue compaction is a conductor of high-frequency noise from the lungs to the large bronchus and is acoustically audible as loud bronchial breathing, which is an indicator for diagnosing pneumonia. The formation of a cavity in the lung that communicates with the large bronchus causes acoustic vibrations that resemble the sound of blowing air into an empty vessel and are called amphoric breathing. This breath is heard during the inhalation and exhalation phases and indicates the presence of a drained empyema, drained abscess, and cavitary tuberculosis. By type of sound, adverse respiratory noises are divided into wheezing, crepitation, and pleural friction noise. Wheezing is the most common adverse respiratory noise and occurs as a result of impaired airway patency caused by sputum. They are heard on inhalation and exhalation, formed in the bronchi, trachea, and lung cavities. The sound of wheezing depends on the amount, viscosity, and localization of the secretion in the bronchi. According to the amount of sputum, dry and wet rales are distinguished, and according to the area of listening – local and diffuse. Dry wheezing occurs due to narrowing of the bronchial lumen caused by: swelling of the bronchial mucosa, spasm of the bronchial smooth muscles, and accumulation of sputum in the bronchial lumen.

Under the acoustic classification, there are high (whistling) and low (humming, buzzing) types. Both types of dry wheezing occur in the presence of an accumulation of heavy sputum, in the case of high wheezing it is localized in the small bronchi, in the case of low wheezing – in the trachea and large bronchi. The presence of dry rales is a characteristic feature of bronchial asthma, total bronchitis, and focal lung damage in tuberculosis or tumour. Wet wheezing is formed in the lumen of the bronchi, in which liquid secretion accumulates. They differ from dry wheezes in their heterogeneity and variability, and their sound can be heard more clearly when you inhale. According to the calibre of the bronchi, wet rales can be small vesicles, medium vesicles, and large vesicles. Listening to wet rales helps in the diagnosis of pulmonary oedema and congestive heart failure. Crepitations occur due to the simultaneous dissolution of many alveoli filled with exudate. Listened to at inspiratory height, it makes it possible to diagnose partial pneumonia in the initial stages, compression atelectasis, and pulmonary infarction. Pleural friction noise is formed on the pleural sheets when fibrin is deposited. It is heard on inhalation and exhalation. Acoustically, pleural friction noise is an intermittent quiet, loud, or "scratching" sound that increases with stethoscope pressure and does not change with coughing. Due to the clarity of listening and specificity of sound, pleural friction noise is a characteristic feature of dry fibrinous pleural effusion and dehydration.[11]

The main task of differential diagnostics of respiratory diseases is to identify diseases of the respiratory system that have similar clinical symptoms and atypical clinical courses. To solve this problem were reviewed the main syndromes of respiratory system disorders, were diseases associated with these syndromes, their clinical features, and methods of acoustic diagnosis. There are 5 main syndromes of the respiratory system: pulmonary infiltrate syndrome, bronchial obstruction syndrome, choking syndrome, pulmonary dissemination syndrome, and pleural effusion syndrome.[11] Pulmonary infiltrate syndrome is characterized by an increase in volume and compaction of the lung tissue as a result of the accumulation of cellular elements and biological fluid in it. This syndrome occurs in the following diseases: pulmonary tuberculosis; pneumonia; central and peripheral lung cancer; extra bronchial benign tumours (osteochondroma, hematoma, adenoma, etc.); pulmonary infarction; parasitic lung diseases (echinococcosis, hookworm); eosinophilic infiltrate; lung segment atelectasis; lung damage caused by physical, chemical, radiation and other environmental factors (Mendelssohn's syndrome, gasoline pneumonitis); filled bronchial cysts. Acoustic diagnostics of these diseases is carried out by listening to the sounds of respiratory noises, which are manifested by wet rales of different calibre, and crepitation.[12]

The main symptom of bronchial obstruction syndrome is expiratory or mixed dyspnoea, which is caused by a narrowing of the bronchial lumen and, accordingly, a decrease in airflow in the bronchial tree. Diseases of the respiratory system accompanied by this syndrome are divided into 3 groups chronic diseases with permanent respiratory disorders (bronchial

tuberculosis, chronic obstructive pulmonary disease, cystic fibrosis), chronic diseases with paroxysmal respiratory disorders (bronchial asthma, tracheobronchial dyskinesia, byssinosis, goitre, bronchopulmonary aspergillosis bronchial and mediastinal tumours, Churg-Strauss syndrome, helminthiasis), acute pathologies (Quincke's oedema, anaphylactic shock, bronchiolitis, Mendelssohn's syndrome, foreign bodies in the respiratory tract, pulmonary embolism, acute left ventricular failure, β-blocker overdose, poisoning with chemical organophosphorus compounds). It is auscultated by rigid breathing, dry rales, and wheezing exhalation.[12]

The physical manifestation of choking syndrome is a painful feeling of lack of air. The causes of this syndrome can include impaired upper respiratory tract patency, pulmonary oedema, bronchial obstruction, accelerated reduction of the respiratory part of the lung, respiratory rhythm disorders, and diaphragmatic diseases. Diseases accompanied by choking syndrome include laryngospasm, whooping cough, allergic laryngeal oedema, diphtheria croup, pharyngeal abscess, croup stenosing laryngitis, tracheal tumours, tracheobronchial dyskinesia, bronchial asthma, carcinoid tumours, bronchopulmonary aspergillosis, Churg-Strauss syndrome, bronchial cancer, benign bronchial tumour, Mendelssohn's syndrome, β-blocker overdose, poisoning with chemical organophosphorus compounds, toxic pulmonary oedema, cardiogenic pulmonary oedema, nephrogenic pulmonary oedema, pneumonia, spontaneous pneumothorax, exudative pleurisy, acute respiratory distress syndrome, pulmonary embolism, diaphragmatic fibrillation, Erb-Goldflam syndrome, hyperventilation syndrome, organic lesions of the central and peripheral nervous system. Auscultation is characterized by dry rales, in some cases dry wheezing. Pulmonary dissemination syndrome is characterized by many focal opacities and a reticular change in the pulmonary pattern, which are detected on X-ray examination. The diseases accompanied by this syndrome include Idiopathic fibrosing alveolitis, exogenous toxic alveolitis, exogenous allergic alveolitis, sarcoidosis, disseminated pulmonary tuberculosis, histiocytosis, pneumoconiosis, bronchoalveolar cancer, metastatic lung lesions, disseminated pulmonary tuberculosis, pulmonary lymphangioleiomyomatosis, alveolar proteinosis, idiopathic hemosiderosis, bronchopulmonary amyloidosis, Wegener's granulomatosis, Goodpasture syndrome, Churg-Strauss syndrome, vasculitis, interstitial pneumonitis, cardiogenic pneumosclerosis. Auscultation reveals weakened vesicular breathing, gentle crepitation at the height of deep inspiration, and an additional sound called "squeaking" that occurs in certain cases of pneumofibrosis.[10]

The main characteristic of pleural effusion syndrome is the accumulation of biological fluid in the pleural cavity, provoked by inflammatory processes in the adjacent organs or deterioration of the ratio between hydrostatic pressure in the capillaries and colloidal-osmotic pressure of the blood plasma. The presence of pleural effusion syndrome indicates the following diseases liver cirrhosis, congestive heart failure, nephrotic syndrome, glomerulonephritis, peritoneal dialysis, myxoedema, mesothelioma, pleural empyema, tuberculosis, aspergillosis, candidiasis, blastomycosis, dysentery, echinococcosis, pancreatitis, subdiaphragmatic abscess, intrahepatic abscess, diaphragmatic hernia, oesophageal perforation, drug allergy, collagenous, systemic vasculitis, rheumatoid arthritis, systemic lupus erythematosus, Sjogren's syndrome, Mediterranean fever, sarcoidosis, uraemia, pulmonary embolism, hemothorax, chylothorax. Auscultation above the upper border of the pleural effusion reveals a stiff or bronchial breath, and pleural friction noise occurs mostly in fibrinous pleural effusion.[13]

Mechanical and technical characteristics of the electronic stethoscope play an important role in the automation process. An improved mechanical characteristic is the presence of a sensitive membrane, which contributes to a clear and clean recording of respiratory sounds with a minimum amount of acoustic interference in the form of extraneous sounds. The main advantage of the electronic stethoscope was its technical characteristic, such as the ability to record respiratory sounds in electronic format.[14] The obtained recordings can be used to attach them to the medical history, especially for patients with chronic diseases of the respiratory system, as it becomes possible to observe changes in respiratory noise and draw conclusions about the effectiveness of treatment. Also, these recordings can be used as a database for the formation of a respiratory sound library as a clinical basis for automating the auscultation process.

The choice of a technical tool for digital signal processing was based on the correspondence between the bioinformatics method and the type of biosignals to be recognized by this method. Given the natural variability and diversity of respiratory noise, classical methods of computer analysis were excluded due to the linearity of data processing, which is due to the formality of the model of the information-matching algorithm. It was decided to use the deep machine learning method, as it allows for the nonlinear processing of large amounts of information, and its effectiveness has already been proven in solving the problem of speech signal recognition.[15] In this case, the process for automating the differential diagnosis of respiratory noise should be based on training the program to compare the obtained sample of respiratory noise with control samples from the phonotheque of recordings of all available respiratory sounds. The result of the diagnosis using such a program should be the classification of the sample by the type of noise corresponding to the state of the normal or pathological respiratory system, and in case of detection of pathological noise, the program should also display the symptom accompanying their presence. The process of creating a model for detecting respiratory pathologies should consist of several main stages: preparation of historical data, including samples of healthy breathing signals and samples of possible pathologies to be detected, and their preliminary

processing; development and implementation of a deep learning model, determination of the most efficient architecture; verification of respiratory pathology recognition metrics; gradual introduction of the model into real-world conditions.

Creating a high-quality, diverse set of respiratory noise data and ensuring a clear annotation system for all breath samples is the most complex and comprehensive process that requires clear interaction between doctors and scientists, and the collection of such sensitive data faces possible problems of personal information protection and anonymity, which significantly slows down progress in this area and encourages artificial enrichment of existing data or the use of open sources of information. A prerequisite for the successful application of deep learning algorithms is the availability of a rich and large-scale data set that covers many possible output signals regarding the presence or absence of pathology. The presence of many instances of each class or their combination significantly increases the chances of a differential model reproducing and learning the necessary dependencies of signal characteristics. Signal pre-processing may include resampling, sound cleaning from extraneous noise, filtering of certain frequency bands characteristic of certain types of noise, and normalization. In addition to the raw signal, its derived characteristics, such as spectrograms, fine-frequency cepstral coefficients, wavelet transforms, frequency band activity indicators, and time characteristics, are also widely used. A cleaned and prepared signal is a much better and more stable source of input data for a deep-learning model. Depending on the type of input signal, different architectures of deep learning models can be applied. To process a complex signal that contains both a time and spectral component, complex architectures are used, consisting of convolutional neural networks to process the characteristics of the selected spectrum, and recurrent neural networks that can track time dependencies, such as the limits of noise manifestation in the sample.

The architectural approach to building a model for automating differential diagnosis is to detect noise events and, accordingly, analyse possible pathologies among breath samples taken with an electronic stethoscope. To do this, each sample is divided into time frames within which one or more classes of events can be detected. To do this, the pre-processed and cleaned sample is fed to the input convolutional layers of the deep learning model, which finds, organizes, and summarizes the spectral characteristics of the signal to update the weights of the convolutional layer kernels in such a way as to memorize the dependencies of the manifestation of different classes of pathologies. The output of the convolutional layers is fed to the recurrent layers of the neural network, where the obtained characteristics are analysed for consistency and the probability that a particular class is present in a particular frame is formed. Based on the obtained probability map, an output probability map is generated, indicating possible respiratory noise on the sample.

To evaluate the model's performance on historical data were used sensitivity and specificity metrics that determine the number of correctly classified pathological noises among all noises in the audio, and the ratio of misidentified noises to the number of frames that do not contain any noise. The analysis of such metrics makes it possible to evaluate the accuracy and redundancy of the results and the readiness of the model to make predictions on new real-world data. Introducing a model that works with sensitive medical data into the production environment should be done gradually and always under the supervision of development specialists and practitioners. The first stage of launching such a model can be a "shadow mode" – when the model and the doctor work with the same input signals and the model does not have access to the information entered by the doctor. At this stage, the model's probability results are compared with the doctor's original map for critical differences, online metrics are calculated, and the model's readiness to work as an assistant is analysed. The second stage must necessarily be the assistance stage, where the results of the model analysis must be shown to the doctor and considered or reviewed by a human.

The model for automating the differential diagnosis of respiratory noise was built based on two elements: the clinical classification of respiratory noise and the symptoms they are accompanied by, as well as a technical tool that will allow for accurate comparison and classification of the test sample with the available control samples. The clinical classification, formed from the theoretical information obtained in the study, was divided according to the relation of respiratory noise to the normal or pathological state of the respiratory system, and pathological noise was, in turn, distributed according to the syndromes they accompany. Noises characterizing the normal state of the respiratory system: normal vesicular respiration, normal decreased vesicular respiration, normal increased vesicular respiration, and bronchial respiration. Noises characterizing pathological changes in the respiratory system and beyond pathologically weakened vesicular respiration, pathologically increased vesicular respiration, rigid breathing, pathological bronchial respiration, wheezing (dry and wet), crepitation, pleural friction noise.

Classification of the main syndromes and types of breath sounds in them: pulmonary infiltration syndrome – wet rales, crepitation; bronchial obstruction syndrome – harsh breathing, dry rales; suffocation syndrome – dry rales, abnormally increased vesicular breathing; pulmonary dissemination syndrome – abnormally decreased vesicular breathing, crepitation; pleural effusion syndrome – harsh breathing, abnormal bronchial breathing, pleural friction noise. Since vesicular and bronchial breathing has the same acoustic sound for both normal and pathological conditions, the deep learning method will be able to distinguish between them using additional sounds that accompany different pathological syndromes.

The material embodiment of the constructed model of automated differential diagnosis of respiratory noise can be the creation of a sound library containing samples of all sounds of the respiratory system distributed according to the above classification. It is recommended to use materials of respiratory noise recordings from an electronic stethoscope obtained from family doctors, paediatricians, employees of pulmonology departments, researchers of research centres for the study of respiratory system problems, or any other clinical practice entities that have these materials and can provide them with the prior consent of patients. The technical embodiment of the deep machine learning method can be the development of software based on it by bioinformatics and medical engineering specialists.

Discussion

The results obtained in the research can be analysed in terms of their practical significance for clinical diagnostics. The process of automating routine processes in the healthcare industry can reduce the time of their execution, avoid medical errors and relieve doctors, especially during medical examinations and large-scale routine checks associated with seasonal or spontaneous epidemic outbreaks. The possibility of automating medical processes became real after the joint efforts of medical and technical specialists, and this cooperation contributed to the creation of such fields of science as medical engineering, bioinformatics, and biophysics.[16-20]

The development of AI technology provided an additional impetus to bring the healthcare process to a new level. Prospects for the development of this technology have been explored in the works of Ukrainian and international scientists. For example, the work of S.K. Ramazanov et al. on the use of AI in medicine focused on the role of AI in working with visual diagnostic objects, such as computed tomography, magnetic resonance imaging, electrocardiogram recordings, X-rays and other images, but did not provide information on the use of this technology in the process of diagnosing acoustic biological signals.[21]

H.Y. Chang et al. in their research on the role of AI in pathology investigated the use of deep learning in pattern recognition based on clinical, radiological, and genomic data.[22] In this study, an in-depth study of the history of the development of AI technology and the use of its capabilities in the diagnosis of pathological processes was conducted, but the diagnostic capabilities in the recognition of acoustic signals were not fully disclosed. L. Shi et al. proposed a technical solution to the problem of creating an algorithm for recognizing lung sounds.[23] For this purpose, the transfer learning method was chosen. It was interesting to consider this method as an alternative to the deep machine learning method, but both methods can only prove their real efficiency and advantages through practical implementation. In the study on machine learning by O. Koteluk et al. an overview of various models of machine learning processes and algorithm training was conducted.[24] The article by Polish scientists was useful because it explored the use of machine learning in creating automation models for such healthcare industries as radiology, pharmacology, and the pathology of infectious diseases.

As with every advanced development in science and technology, AI and machine learning as a field of study have received both significant support and criticism regarding the scientific and ethical aspects and data protection issues.[25-27] Criticism was caused by the complexity of technical support for controlling big data, which is the basis for the application of AI technology. Studies have been conducted on this issue. The issue of disadvantages and hidden threats of the introduction of AI in the medical industry was addressed by B. Chin-Yee and R. Upshur.[28] They conducted a useful study and identified three problems in the use of big data by AI in medicine. The use of big data as a basic basis for AI technology was considered by most researchers as an advantage of this technology. In their work, the researchers considered three other aspects that may cause inconvenience and affect the adequacy and reliability of the results obtained. The first problem is the theoretical overload of big data, the second is the limitation of algorithms that affect the reliability and correctness of interpretation, and the third is that the amount of human experience in units of information will exceed the amount of big data. The result of this work was not a solution to the issues raised, but a critical dialogue initiated by the authors to ensure a more reliable assessment of big data and AI technologies in the approach to patient care. In support of the dialogue initiated by the scientists were can propose the creation of a program to monitor compliance with the information "hygiene" of big data, involving both information technology specialists and clinical staff in its development. As far as this study is concerned, none of the three reasons will affect the results of automated differential diagnosis, since the array of clinical information has a clear classification and is limited to one type of information – acoustic signals.

M.H. Arnold's work examined the reasons for ethical criticism of AI and machine learning in medicine.[29] The author named the ontological and epistemological problems of doctors and patients that manifest themselves in the presence of AI as a third independent participant during a medical appointment, which violates the autonomy of both the doctor and the patient. The next reason for ethical criticism is the lack of clearly defined legal relations between AI and the user. To solve these problems, the researcher proposes to actively involve practising clinicians to create a comfortable environment for the use of AI, where each healthcare provider will perform its functions, based on their recommendations. This will allow, on the one hand, to relieve doctors by transferring some of their responsibilities AI, and, on the other hand, to retain the authority of judgment in building the treatment process. As for the legal relations linking AI and the patient, such practice can currently be regulated by

the aspect of legal precedent, and with the expansion of the scope of application of this technology, it can be built on the principle that applies to standard medical practice, considering the peculiarities of the subjectivity of AI in the field of healthcare.[30-33] However, it is worth noting that it makes no sense to consider AI as a full-fledged subject of healthcare activity at the moment since as such, it will not be responsible for medical errors. As far as this study is concerned, the use of the deep machine learning method in the process of automating the differential diagnosis of respiratory sounds will avoid the problems raised by the author, as it will not limit the role of the doctor in the diagnostic process and will not have legal problems with its use.

The issue of personal information protection in the use of AI technology began to be raised following the intensity of the introduction of this technology in the medical field of a particular country. It was useful to get acquainted with the world's experience in solving this problem and compare it with Ukrainian developments in this area. Thus, the work of D. De Araujo Dourado and F.M.A. Aith on the regulation of AI for healthcare in Brazil considered the possibility of building a system for regulating the protection of personal information in the use of AI based on the current law on personal data protection.[34] Amendments to the law relating to AI technology should take into account the necessary instrumentalization and automation of transparency in the use of such technology in the healthcare sector, as well as decide on the limitations of the "black box" system used in some algorithms. Thus, the authors see the solution to this problem as accepting a compromise between transparency and accuracy of the automated system of AI algorithms.

The study by C. Wang et al. on the Chinese regulation of privacy protection in the use of AI for healthcare, a comparative study of the legal norms of China, the United States, and the European Union on the protection of medical data collected and used as information for AI was conducted.[35] Based on the results of the comparison, the authors proposed to strike a balance between privacy protection and the development of new technologies, as well as to establish additional rules for the protection of medical information and introduce clearer accountability mechanisms. The peculiarities of the legal norms of information protection in the European Union were described by R. Beckersa et al.[36] The article examines the new European Medical Device Regulation. This regulation also applies to the development of medical systems based on AI technology and is a process of continuous monitoring of the technical performance of these systems and compliance with the protection of medical information used in them.

Regarding developments in the field of personal data protection by Ukrainian information technology specialists, there is a successful experience in the implementation of the Ministry of Digital Transformation's project to create the Diia application. Thus, the information protection tools used in the project can also be implemented to protect data used for AI and machine learning technologies in the healthcare sector. It is important to note that previous works that have drawn attention to the disadvantages and threats of AI and machine learning were not intended to deny or diminish the effectiveness of the introduction of these technologies in the healthcare sector. On the contrary, the results of the studies have formed a platform for considering and resolving issues related to the prediction and settlement of all negative factors that may be manifested in the uncontrolled use of technologies.

Conclusions

This study develops a model for automating the differential diagnosis of respiratory noise via a stethoscope, merging biomedical information about types of respiratory noise with deep machine learning techniques. The physical manifestation of this model is an electronic respiratory noise library, with recommendations provided on its content sources. The results serve practical roles in reducing the time required for automated auscultation, avoiding medical errors, and relieving doctors during routine checks.

The preliminary validation on a small dataset of lung sound recordings provided by R.A.L.E. Repository indicates reasonable performance of the differential analysis algorithm. Further extensive testing and refinement of the algorithm will be needed before clinical implementation. However, these initial results provide early support that the proposed technique can automatically detect respiratory noise events.

The application of AI and machine learning in healthcare shows promise in automating diagnosis, treatment, and prevention, yet also presents challenges that need conscious addressing for effective, safe utilization. With a recent surge in respiratory system diseases, deep machine learning offers new directions in diagnosis and treatment. The model's future research potential lies in recognizing and classifying biological objects within large data volumes, particularly in the context of X-ray recognition for diagnosing respiratory diseases.

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