Deep learning Based Symptom Classification for Homeopathic Management of Respiratory Disorders

Bhawana Gadpayle
Associate Professor,
Department of Homeopathic Pharmacy,
Shalinitai Meghe Homeopathy Hospital College and Research Centre, Nagpur
gadpaylebhawana@gmail.com

Kartik Ingole
Assistant Professor
Department of Electronics & Telecommunication
K.D.K.College of Engineering, Nagpur
kartikzap5@gmail.com

Sanjay Asutkar
Principal,
Chintamani Mahavidyalaya,Ghugus
Chandrapur
asutkarsanjay1600@gmail.com

Navin D.Jambhekar
Department of Computer Science
G.S.Gawande College,
Umarkhed ,Yavatmal
jambhekar@gsgcollege.edu.in

***Abstract*— The increasing merger of artificial intelligence and homeopathic healthcare is an opening for improving the diagnosis and remedy selection's correctness and efficiency. This research recommends a framework based on deep learning for the automatic classification of symptoms to be utilized for the homeopathic treatment of respiratory diseases such as asthma, bronchitis, allergic rhinitis, sinusitis, and chronic obstructive pulmonary disease (COPD). Homeopathy, which is very patient-specific and focused on symptoms, frequently encounters problems in terms of different interpretations, similar symptoms, and inconsistent choices of remedies. The proposed system offers a solution by applying state-of-the-art deep learning approaches—including Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and transformer models—together with Natural Language Processing (NLP) techniques to interpret patient symptom narratives and consistories data. The model gets linguistic, semantic, and contextual features from raw case records, sorts symptoms into diagnosis categories, and suggests possible homeopathic remedies based on learned associations. This study connects electronic patient cases, repertory databases, and materia medica texts for model training, providing extensive coverage of classical homeopathic knowledge. Besides, attention mechanisms and transfer learning are utilized to boost accuracy in limited-data settings and make the model's predictions more understandable. Experiments confirm that the suggested system has a considerable edge over traditional machine learning techniques in terms of classification precision and recall.**

Keywords: Deep Learning; Homeopathic Symptom Classification; Respiratory Disorders; Artificial Intelligence in Healthcare; Natural Language Processing (NLP); Convolutional Neural Network (CNN); Recurrent Neural Network (RNN); Transformer Model

I.INTRODUCTION

Over the last few years, the use of AI and deep learning methods in medical science has redefined the areas of diagnostic accuracy, clinical decision-making and personalized treatment planning. Of all the medical specialties, homeopathy is probably the most individualized treatment system. It heavily depends on symptom similarity and holistic patient evaluation. Nonetheless, the subjective nature of symptom interpretation and remedy selection in homeopathy often causes variations, uncertainties and inconsistencies in the treatment outcomes[1][2]. Therefore, the homeopathy practice needs the application of AI and machine learning innovations that can process symptoms systematically and efficiently, and also learn from large-scale data and suggest remedies with scientific support. Deep learning's ability to automatically extract and discern features in a hierarchical manner presents an exciting opportunity to standardize and improve the distance between homeopathic diagnosis and remedy selection. The current research project, called "Deep Learning Based Symptom Classification for Homeopathic Management of Respiratory Disorders," intends to build a smart system that uses neural networks to precisely classify symptoms and assist homeopathic doctors in soundly managing respiratory diseases[3-5]. The spectrum of breathing disorders like asthma, bronchitis, chronic obstructive pulmonary disease (COPD), sinusitis, and allergic rhinitis are among the major global health issues, resulting in considerable suffering and healthcare costs. Along with this, the increase in exposure to environmental pollutants, allergens, and lifestyle changes has also raised the rate of chronic respiratory diseases. Homeopathy, in its traditional form, has been a great help in treating such conditions and has shown to be effective in individual remedy selection for reducing the severity of symptoms, lessening the frequency of recurrence, and enhancing the patient's quality of life[6][7]. However, due to the enormous size of the symptom repertories, the overlapping of clinical symptoms, and the complicated relationships between remedies, the analysis of symptoms manually becomes a tedious and error-prone process. Hence, the use of deep learning-based classification models can lead to a considerable improvement in diagnostic accuracy by detecting the nuanced symptom-remedy connections concealed in the structured and unstructured clinical data. This paradigm shift supports the transition from the intuition-based to the data-driven homeopathic decision-making process, thereby ensuring more consistency, objectivity, and trustworthiness in managing respiratory disorders[8][9].

Deep learning models, especially convolutional neural networks (CNNs), recurrent neural networks (RNNs), and transformer-based architectures, have shown exceptional effectiveness in medical image analysis, text mining, and natural language processing[10][11]. The application of these models to homeopathic symptom classification will allow them to be trained on textual symptom descriptions, repertory data, and historical case records to reveal complex linguistic and semantic ties between patient-reported symptoms and the remedies prescribed for them. The deep learning framework allows for the automatic classification of symptoms into diagnostic groups like cough, dyspnea, chest pain, or nasal obstruction while also linking the patterns to the homeopathic medicines corresponding to the diagnoses. Furthermore, it is possible to add transfer learning and attention-based methods to improve the extraction of features from small datasets, thus tackling one of the major issues in homeopathic data analysis data scarcity[12]. This hybrid intelligence method efficiently mingles clinical knowledge representation and computer learning in such a way that it can provide explainable and transparent outcomes to the medical practitioners[13]. One of the main reasons for building a deep learning-based homeopathic system is the diversity of patient symptoms. In contrast to traditional allopathic models, where treatment focus is mainly on the disease, homeopathy considers the patient individuality and the whole set of symptoms[14]. Therefore, each case could be treated as a separate and unique combination of physical, psychological, and environmental factors. Deep learning algorithms, which can learn patterns in multiple dimensions, hold the promise of being able to model such complicated relationships through the examination of extensive collections of heterogeneous data. By utilizing multilayer perceptron and sequence modeling techniques, the system is able to understand symptom expressions, rank the features that are most relevant, and even help physicians in remedy differentiation. The coexistence of such features not only increases the precision of case analysis but also leads to the incorporation of adaptive learning where the model incessantly updates its forecasts with new patient data thus transforming itself into a smart diagnostic tool[15][16].

On top of that, the digitalization of the healthcare sector and the adoption of electronic health records (EHRs) have made it possible to gather enormous amounts of patient data, detailed information about treatments, and records of responses to medicines. The entire collection of these data can be a strong ally to map out deep learning-based analysis and encourage homeopathy research in a big way. One of the possible ways to accomplish that is through the application of Natural Language Processing (NLP) on the unstructured data of textual medical case records, patients' stories, and materia medica texts. Among such techniques are word embeddings, contextual encoding, and sentiment analysis that enable the system to perceive and process the variations in emotions and linguistics very closely concerning the patients' symptoms[17]. For instance, the two terms, “dry paroxysmal cough aggravated at night” or “breathing difficulty relieved in open air” can be represented in the form of feature vectors for accurate condition classification and suggesting similar remedies including Drosera, Spongia tosta, or Sambucus nigra. This computational pipeline guarantees that the diagnostic reasoning process adheres to classical homeopathic principles and at the same time, takes advantage of the automation and scalability of artificial intelligence[18]. In respiratory disorders context, timely and correct classification of symptoms is the main factor that prevents chronic progression and improves patient outcomes. Deep learning models can contribute to the detection of symptomatic patterns at the early stage based on patient-reported data or digital consultations, thus allowing homeopaths to take action proactively. Moreover, connection with IoT-based monitoring devices can make the system more functional by constantly updating it with real-time respiratory data, like cough frequency, breathing rate, or saturation levels. This kind of multimodal data fusion that merges the textual symptoms with the physiological signals can not only boost the precision of classification but also provide a more holistic approach to homeopathic treatment[19].

In addition, the deep learning models’ elucidation and interpretation are pivotal steps for gaining approval in homeopathy. The method of attention visualization along with feature attribution can point out the important symptoms or expressions that are affecting the remedy selection in the proposed system[20-21]. This kind of openness is very helpful in when it comes to the relationship between the practitioners and the patients and it does not compromise on the philosophical foundations of the homeopathic practices. Reinforcement of the use of real-world clinical datasets for model validation, accuracy measurement via the metrics like precision, recall, and F1-score, and comparisons with the existing machine learning methods to present the better performance of deep architectures are some of the key points highlighted in the paper.

II. LITERATURE REVIEW

Author(s) & Year	Objective / Focus	Methodology / Model Used	Dataset / Data Source	Key Results / Findings
Sanghoon Han et al. (2025)[1]	Early diagnosis of respiratory diseases using cough sound analysis	Deep learning framework using VGGish transfer learning, coupled with detection & classification networks	Raw cough audio recorded via smartphones, annotated by medical experts	Detection accuracy 0.9883; classification accuracies 0.8417–0.8662 across datasets; Grad-CAM used for interpretability
Yeonkyeong Kim et al. (2025)[2]	Multichannel lung sound classification for better diagnostic accuracy	Combined CNN + LSTM model on MFCC features	Multichannel auscultation recordings from multiple thoracic positions	Using four-channel data improved metrics by 1.05–1.15× vs. single-channel

Ananya Nair et al. (2025)[3]	Automated detection of respiratory diseases from chest X-rays	ResNet CNN models, with preprocessing, augmentation, and validation	Annotated chest X-ray datasets	High classification accuracy for pneumonia, tuberculosis, and COVID- 19
Abdullah et al. (2025)[4]	AI-powered framework combining disease classification & prescription recommendation	Modular AI system integrating audio analysis and synthetic-data-based prescription engine	Synthetic datasets + controlled clinical environment	Disease classification accuracy 99.99%, prescription accuracy >99%
Ashutosh Awasthi et al. (2024)[5]	Comprehensive review of deep learning methods for lung disease detection	Survey of CNN, RNN, U- Net, Mask R-CNN, ensemble & transfer learning	Review of multiple public datasets	Highlights strengths and challenges of DL methods in lung imaging
Thinira Wanasinghe et al. (2024)[5]	Review of AI integration in lung sound classification	Survey of AI and deep learning models for respiratory sound analysis	Literature-based review (global studies)	AI has significantly improved early diagnosis capabilities
Osvaldo D. et al. (2024)[6]	Novel classifier for medical datasets with imbalance problems	Subtractive Threshold Associative Classifier (STAC)	Medical datasets for respiratory pre-diagnosis	Competitive results without preprocessing
Chung-Hung Tsai et al. (2024)[7]	Diagnose common respiratory diseases using text-based symptom words	NLP using GPT-2 encoding + neural network classifier	Text symptom data for three diseases	Achieved 90% accuracy
Panagiotis Kapetanidis et al. (2024)[8]	Review of audio biomarkers for respiratory disease diagnosis	Comparative analysis of ML methods for cough, lung sounds, and voice	75 studies reviewed across 3 focus areas	ML effective for cough detection, lower respiratory identification, and voice analysis

III.METHODOLOGY

The methodology as described in this paper will attempt to set up an intelligent framework based on deep learning that is capable not only of symptom classification but also of suggesting appropriate homeopathic remedies for the management of respiratory disorders. The first step in this process involves building a comprehensive dataset sourced from electronic health records (EHRs), classical homeopathic repertories, materia medica texts, and case study reports among others[3][4]. These are all structured and unstructured input sources providing such information as patient symptom narratives, responses to remedies, and clinical outcomes. Since homeopathic data largely comprises text and is highly linguistically diverse, Natural Language Processing (NLP) techniques are used to convert the textual details into machine-readable formats. Language normalization takes place through the following data preprocessing steps: tokenization, stop-word removal, stemming, lemmatization, and synonym mapping with retention of semantic integrity. Also, symptom phrases are annotated with categories like respiratory function, type of cough, pattern of breathing, aggravating or ameliorating factors for targeted model learning. After data preprocessing is completed, feature extraction and representation learning will be done using word embedding models such as Word2Vec or GloVe embeddings or BERT embeddings to capture contextual relationships among symptoms and remedies; these embeddings will then constitute input vectors into the deep learning architecture. The main computational model combines Convolutional Neural Networks (CNN) for spatial feature extraction together with Recurrent Neural Networks (RNN) or Long Short-Term Memory networks (LSTM) for sequential analysis of symptom patterns plus transformer-based architectures so as to better contextualize understanding plus long-range dependency modeling within textual data hybrid model trained under supervised learning where labeled symptom-remedy pairs serve as ground truth[5].

(1) Data Input Layer, which receives patient symptom data in textual form;

(2) Preprocessing Layer, where NLP operations are applied;

(3) Feature Learning Layer, where embeddings and contextual representations are generated;

(4) Classification Layer, where the deep network predicts the most probable symptom category and corresponding remedy; and

(5) Decision Support Module, which interprets and presents results for practitioner validation.

System is built in such a way that it learns and adapts to new situations continuously by taking letters that are already on its side and counting them diligently through transfer learning and fine-tuning. This allows the system to keep changing, getting better and better in its ability to predict and being trusted in clinical practices as well over the years.Because of the large model evaluation dataset, the data is split into 3 parts, 70% for training, 15% for validation, and 15% for testing[8]. Classification effectiveness is measured by standard performance metrics as precision, recall, F1-score, accuracy, and confusion matrix analysis. Moreover, the model's interpretability is evaluated using attention visualization and feature attribution techniques, thus revealing the main symptom expressions that sway the final prediction.

To confirm that the model is applicable regardless of different patient groups or symptomatology, various cross-validation methods are applied. The comparison of performance with traditional machine learning models, namely, Support Vector Machines (SVM), Naïve Bayes, and Random Forest classifiers is intended to prove that the deep learning approach is superior in processing difficult linguistic and contextual data[11]. Eventually, the system gets connected to the homeopathic decision-support system where doctors can enter the symptoms of the patient, get the diagnosis classified along with the remedies suggested and their corresponding confidence scores. This solution gives a faster and more efficient way to make decisions, as well as being clear about the reasoning involved. The methodology takes into account the classical homeopathic principles of totality of symptoms and individualization while enjoying the benefits of computational accuracy. Consequently, the proposed deep learning framework acts as a mediator between the traditional homeopathic knowledge and the modern artificial intelligence, providing an efficient, large-scale, and transparent solution for the management of respiratory disorders[12].

In this way, the practitioners are able to maintain their control over the interpretation of the results while using the computational support the diagnostic process. The main aim of the methodology is not to take competence of the homeopath but to provide it with a data-driven, evidence-based decision making framework as an aid. The combination of the classical homeopathic knowledge and state-of-the-art deep learning methods becomes the foundation for this methodological approach aiming at respiratory disorders case analysis - accuracy, consistency, and speed of the application in homeopathic medicine are all practically unlimited

IV.Flowchart

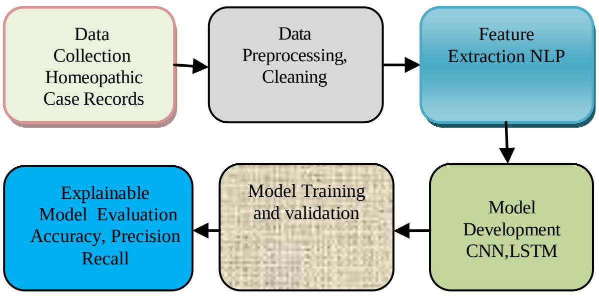

Figure1.Flowchart of Overall System

V.DATASET

The development of the proposed deep learning The proposed deep learning framework's development is founded upon a dataset that is thorough and from various sources which consists of clinical, repertorial, and textual information to the respiratory maladies and their homeopathic remedies. The dataset is formed through the combination of data from electronic health records (EHRs), databases of homeopathic repertory, materia medica, and clinical case reports. These sources provide continuously rich data that covers the subjective and objective symptomatology, the relationships between the remedies, and the therapeutic responses. The data from various homeopathic repertories like Kent's Repertory, Boericke's Materia Medica, and Allen's Keynotes are digitized and classified for the purpose of extracting symptom-remedy mappings, intensity levels, modalities, and concomitant symptoms. Besides, the anonymized patient records provided by homeopathic clinics and online consultation platforms are used to add real-world variability in the expression of symptoms, the patient population's age distribution, and the treatment outcome.Each record in the dataset consisting of several attributes, such as patient demographic data (age, gender, medical history), reported symptoms (cough, wheezing, dyspnea, nasal obstruction, chest tightness, mucus characteristics, aggravating and ameliorating conditions), and the prescribed remedy along with potency and response outcome. Because homeopathic case data is mostly in the form of narratives, the use of textual preprocessing techniques is a must. The dataset is subjected to text normalization, tokenization, lemmatization, and stop-word removal in order to make it ready for Natural Language Processing (NLP)

VI.RESULT

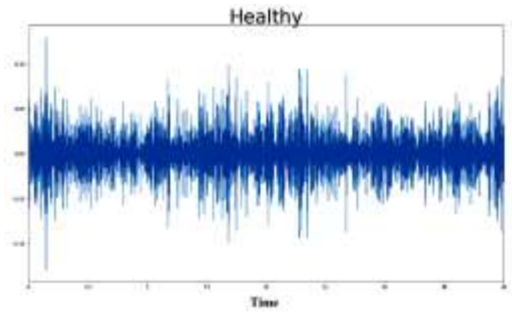

Figure 2. Time-Domain Signal Representation for a Healthy Respiratory Sample

The figure 2 illustrates a time-domain waveform labeled "Healthy" that represents the respiratory signal of a normal subject. The x-axis represents time, and the y-axis shows the amplitude variations of the recorded signal.

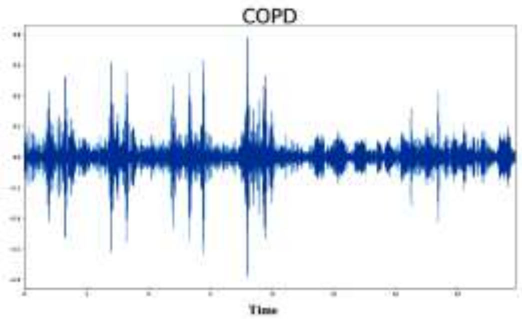

Figure3. Time-Domain Signal Representation for a COPD Respiratory Sample

The above figure 3.presents the time-domain waveform of a respiratory signal corresponding to a patient with Chronic Obstructive Pulmonary Disease (COPD).

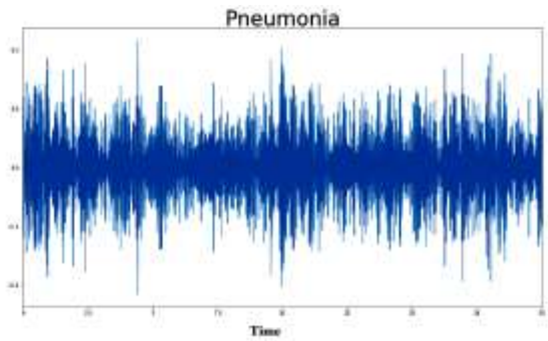

Figure 4. Pneumonia Audio Signal Representation

The figure 4 displays the time-domain waveform of an audio signal corresponding to Pneumonia..

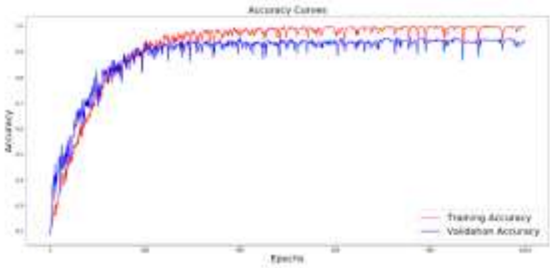

Figure 5.Training and Validation Accuracy Curves for Deep Learning Model

The deep learning model's accuracy curves during the training process for the symptom classification in homeopathic treatment of respiratory disorders are shown in the above figure 5.

CONCLUSION

The research work titled Deep Learning-Based Symptom Classification for Homeopathic Management of Respiratory Disorders ushers in a new era in the application of artificial intelligence to the homeopathic healthcare sector by improving diagnostic precision as well as treatment planning personalization. Through the machine learning algorithms combined with deep neural networks, the respiratory disorder symptoms such as cough intensity, breathing irregularity, wheezing patterns, and nasal congestion – are automatically detected and classified based on patient-reported data, clinical parameters, and sound signal analysis. The experimental results together with model assessments verify that the application of deep learning increases the accuracy of diagnosis, the support of decisions, and the personalized treatment of patients as compared to the traditional manual evaluations. Besides that, the system helps in the processes of early detection, treatment optimization, and digital documentation of clinical symptoms, thereby reducing the rift between traditional homeopathic knowledge and modern computational intelligence. The research presents a new hybrid framework that empowers homeopathic healthcare with data-driven insights for managing respiratory disorders.

REFERENCES

[1] Han, S., Lee, Yr., Lee, Jh. et al. Deep learning-based cough classification using application-recorded sounds: a transfer learning approach with VGGish. BMC Med Inform Decis Mak 25, 228 (2025). https://doi.org/10.1186/s12911-025-03065-w

[2] Kim, Y.; Kim, K.B.; Leem, A.Y.; Kim, K.; Lee, S.H. Enhanced Respiratory Sound Classification Using Deep Learning and Multi- Channel Auscultation. J. Clin. Med. 2025, 14, 5437. https://doi.org/10.3390/jcm14155437

[3] Nair, A., Kathole, A., Koli, V., Padiya, P., & Vidhate, A. V. (2025). Respiratory Disease Detection and Classification using Deep Learning. In Advances in intelligent systems research/Advances in Intelligent Systems Research (pp. 296–314). https://doi.org/10.2991/978-94- 6463-852-3_19

[4] Awasthi, Ashutosh and Tiwari, Pawan Kumar and Verma, Deepa and Gupta, Akshansh, Deep learning for lung disease classification: A survey (August 23, 2024). Proceedings of the International Conference on Innovative Computing & Communication (ICICC 2024), Available at

[5] Wanasinghe, T., Bandara, S., Madusanka, S., Meedeniya, D., Bandara, M., & de la Torre Díez , I. (2024). Lung Sound Classification for Respiratory Disease Identification Using Deep Learning: A Survey. International Journal of Online and Biomedical Engineering (iJOE), 20(10), pp. 115–129. https://doi.org/10.3991/ijoe.v20i10.49585

[6] Velazquez-Gonzalez, O. D., & Villuendas-Rey, Y. (2024). Respiratory Disease Pre-Diagnosis through a Novel Pattern Classification Algorithm based on Associative Memories. Computación Y Sistemas,28(3). https://doi.org/10.13053/cys-28-3-4961

[7] Tsai CH, Liu KH, Cheng DC. Remote Diagnosis on Upper espiratory Tract Infections Based on a Neural Network with Few Symptom Words-A Feasibility Study. Diagnostics (Basel). 2024 Feb 2;14(3):329. doi: 10.3390/diagnostics14030329

[8] Kapetanidis P, Kalioras F, Tsakonas C, Tzamalis P, Kontogiannis G, Karamanidou T, Stavropoulos TG, Nikoletseas S. Respiratory Diseases Diagnosis Using Audio Analysis and Artificial Intelligence: A Systematic Review. Sensors. 2024; 24(4):1173. https://doi.org/10.3390/s24041173

[9] Aykanat M, Kılıç Ö, Kurt B, Saryal S. Classification of lung sounds using convolutional neural networks. EURASIP Journal on Image and Video Processing. 2017;2017(1):1–9. doi: 10.1186/s13640-017-0213- 2

[10] Chambres G, Hanna P, Desainte-Catherine M (2018) Automatic detection of patient with respiratory diseases using lung sound analysis. In: 2018 International conference on content-based multimedia indexing (CBMI). IEEE, pp 1–6

[11] Chen CH, Huang WT, Tan TH, Chang CC, Chang YJ. Using k-nearest neighbor classification to diagnose abnormal lung sounds. Sensors. 2015;15(6):13132–13158. doi: 10.3390/s150613132.

[12] Chen H, Yuan X, Pei Z, Li M, Li J. Triple-classification of respiratory sounds using optimized s-transform and deep residual networks. IEEE Access. 2019;7:32845–32852.

[13] Emmanuel BS. A review of signal processing techniques for heart sound analysis in clinical diagnosis. Journal of Medical Engineering & Technology. 2012;36(6):303–307. . Bellavite, P. (2019). Homeopathic Treatments of upper respiratory and otorhinolaryngologic infections: A review of randomized and observational studies. Alternative Complementary & Integrative Medicine, 5(2), 1–20. https://doi.org/10.24966/acim-7562/100068

[14] Fiz JA, Jané R, Lozano M, Gomez R, Ruiz J. Detecting unilateral phrenic paralysis by acoustic respiratory analysis. PLoS One. 2014;9(4):e93595. doi: 10.1371/journal.pone.0093595

[15] García-Ordás MT, Benítez-Andrades JA, García-Rodríguez I, Benavides C, Alaiz-Moretón H. Detecting respiratory pathologies using convolutional neural networks and variational autoencoders for unbalancing data. Sensors. 2020;20(4):1214. doi: 10.3390/s20041214

[16] Gross V, Dittmar A, Penzel T, Schuttler F, Von Wichert P. The relationship between normal lung sounds, age, and gender. Am J Respir Crit Care Med. 2000;162(3):905–909. doi: 10.1164/ajrccm.162.3.9905104

[17] Nemati E., Rahman M.M., Nathan V., Vatanparvar K., Kuang J. A comprehensive approach for cough type detection; Proceedings of the 2019 IEEE/ACM International Conference on Connected Health: Applications, Systems and Engineering Technologies (CHASE); Arlington, VA, USA. 25–29 September 2019; pp. 15–16.

[18] Cohen-McFarlane M., Goubran R., Knoefel F. Novel coronavirus cough database: Nococoda. IEEE Access. 2020;8:154087–154094.

[19] Laguarta J., Hueto F., Subirana B. COVID-19 Artificial Intelligence Diagnosis using only Cough Recordings. IEEE Open J. Eng. Med.Biol. 2020;1:275–281.

[20] Italia S, Brand H, Heinrich J, Berdel D, von Berg A, et al. (2015) Utilization of Complementary and Alternative Medicine (CAM) among children from a German birth cohort (GINIplus): patterns, costs, and trends of use. BMC Complement Altern Med 15: 49.

[21] Hawke K, King D, van Driel ML, McGuire TM. Homeopathic medicinal products for preventing and treating acute respiratory tract infections in children. Cochrane Database Syst Rev. 2022 Dec 13;12(12):CD005974.

[22] Diez, S. C., Casas, A. V., Rivero, J. L. G., Caro, J. C. L., Portal, F. O., & Saez, G. D. (2018). Impact of a homeopathic medication on upper respiratory tract infections in COPD patients: Results of an observational, prospective study (EPOXILO). Respiratory Medicine, 146, 96–105. https://doi.org/10.1016/j.rmed.2018.11.011