Classification of lungs disease with Electrical impedance tomography

Barbara STEFANIAK[1], Amelia KOSIOR-ROMANOWSKA[1], Paweł TCHÓRZEWSKI[1], Dariusz WÓJCIK[1,2], Tomasz RYMARCZYK[1,2], Paweł OLSZEWSKI[12]

[1] R&D Center Netrix S.A. Lublin, Poland
[2] WSEI University, Lublin, Poland

ABSTRACT

The article discusses research on a wearable medical diagnostic system using electrical impedance tomography. This system aims to diagnose long-term respiratory diseases. It seeks to reduce the number of tests needed for accurate diagnoses, thus saving time. The article compares two classification models for distinguishing between diseased and healthy individuals.

Keywords: electrical impedance tomography; chronic obstructive pulmonary disease; acute respiratory distress syndrome; pneumothorax; pneumonia; bronchospasm; pulmonary hypertension

Introduction [4]

Respiratory diseases are a growing problem in society, with common examples including chronic obstructive pulmonary disease (COPD), acute respiratory distress syndrome (ARDS), pneumothorax (PTX), pneumonia (PNA), bronchospasm, and pulmonary hypertension (PHTN). In medicine, various tests help diagnose respiratory diseases like spirometry, chest computed tomography, lung ultrasonography [6]. A solution will be presented that allows for an approximate diagnosis in just a few minutes.

The future of medical diagnostics relies on devices that enable long-term patient monitoring, which allows for the detection of pathological conditions. The Lung Electrical Tomography System (LETS) is responding to the demand of the medical market. It is a mobile electrical impedance tomography system in three spatial dimensions for area monitoring. The system consists of the vest (Figure 1), the measuring device and the analytics engine LETSWEB.

METHOD

The Vest has 32 electrodes dedicated to electrical impedance tomography, arranged on two planes with 16 on each one. Current injections are opposite and occur only between electrodes on the same level. Voltages are measured between adjacent electrodes. This configuration results in a data frame containing 448 independent voltages. Another component of the LETS, the analytics engine LETSWEB, is responsible for aggregating, processing and inferring from collected medical data.

Figure 1: Developed vest with 102 textile electrodes.

Numerical models were constructed to include a broad range of both diseased and healthy cases (example healthy and ARDS models correspond to Figure 2). Next, material parameters for the human body were identified. Several stages of disease progression were considered, with three stages for ARDS and four for the remaining conditions. To prepare the dataset, simulations of electrical impedance tomography measurements were performed using the finite element method.

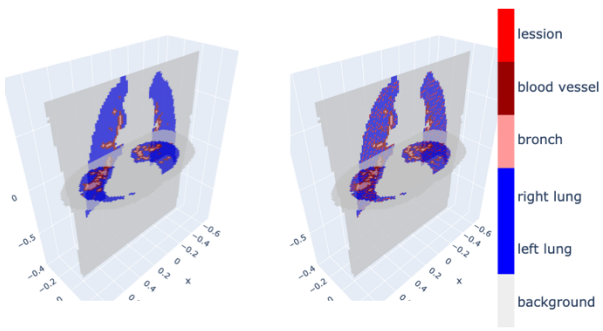

Figure 2: Model of healthy lungs and lungs with ARDS disease.

The models consist of at most seven components: 1 – torso without lungs, 2 - left lung without bronchi and blood vessels around the bronchi, 3 - right lung without bronchi and surrounding blood vessels, 4 - bronchi, 5 - blood vessels surrounding the bronchi, 6 - region with lesions corresponding to the disease, and 7 – area showcasing a secondary lesion (specifically utilized for pneumonia). The values in Tables 1 and 2 present normalized material parameters for all considered disease cases.

Table 1: Coefficients material parameters normalised (Part 1)[1]

Condition	1	2	3	4
Healthy patient	1.0	0.2410	0.2410	$2.2\cdot10^{-10}$
COPD	1.0	0.2410	0.2410	$2.2\cdot10^{-10}$
ARDS	1.0	0.2410	0.2410	$2.2\cdot10^{-10}$
PTX	1.0	0.2627	0.2410	$2.2\cdot10^{-10}$
PNA	1.0	0.2410	0.2410	$2.2\cdot10^{-10}$
Bronchial spasm	1.0	0.2410	0.2410	(1)
PHTN	1.0	0.2410	0.2410	$2.2\cdot10^{-10}$

Table 2: Coefficients material parameters normalised (Part 2)[1]

Condition	5	6	7
Healthy patient	1.4370	–	–
COPD	1.4370	(3)	–
ARDS	1.4370	5.8115	–
PTX	1.4370	$2.2\cdot10^{-10}$	–
PNA	1.4370	0.0035	0.0070
Bronchial spasm	1.4370	–	–
PHTN	(2)	–	–

$$\frac{\sigma_{\text{bronchi}}}{\sigma_{\text{ref}}}\alpha + (1-\alpha)\frac{\sigma_{\text{air}}}{\sigma_{\text{ref}}} \quad (1)$$

$$\frac{\sigma_{\text{blood vessel wall}}}{\sigma_{\text{ref}}}\alpha + (1-\alpha)\frac{\sigma_{\text{blood}}}{\sigma_{\text{ref}}} \quad (2)$$

$$\frac{\sigma_{\text{lung}}}{\sigma_{\text{ref}}}\alpha + (1-\alpha) \quad (3)$$

Where $\sigma_{\text{air}} = 10^{-10}$, $\sigma_{\text{blood}} = 0.6625$, $\sigma_{\text{bronchi}} = 0.5576$, $\sigma_{\text{blood vessel wall}} = 0.2320$, $\sigma_{\text{ref}} = 0.4610$, $\sigma_{\text{lung}} = 0.1111$. All values are expressed in units of S/m. The equation 1,2 and 3 have variable α which is value from set {0.1, 0.3, 0.5, 0.7}. The variable α is accountable for the degree or advancement of the disease state. The parameter α defines the degree to which the bronchi reduce their lumen during bronchial spasm, expressed as a percentage. In PHTN, it describes the degree to which blood vessels constrict, and in COPD, it represents the extent of fluid accumulation at the lung boundaries.

To distinguish between individuals with respiratory diseases and healthy subjects, two advanced classification models were compared: a Multi-layer Perceptron (MLP) classifier and a Gradient Boosting Classifier (GBC).

The Boruta algorithm was used for feature selection by iteratively eliminating features deemed less relevant than random probes. By comparing the importance of the original features with shadow features, Boruta retained only those significantly more important [5]. Using this approach, the Boruta algorithm identified 300 of the most significant features out of 448. MLP, a feedforward artificial neural network, uses backpropagation for training and involves multiple layers of input nodes [3], with optimal parameters selected using the GridSearchCV function. GBC used decision trees as base learners, with each tree correcting the errors of the preceding ones through gradient descent [2].

The study's dataset was generated through simulations of electrical impedance tomography (EIT) data frames to model the electrical properties of lung tissue, providing detailed impedance variations associated with respiratory health and disease states.

RESULTS AND DISCUSS

A training model dataset was constructed with 30,240 cases, and a testing set with 9,072 cases. The training set had 21,168 observations after processing. The MLP classifier achieved 84.06% accuracy, while the Gradient Boosting Classifier achieved 83.18%. The study highlights the potential of EIT-based diagnostic systems in improving respiratory disease diagnosis efficiency and accuracy. This article presents the application of electrical impedance tomography (EIT) for diagnosing six lung diseases (COPD, ARDS, PTX, PNA, bronchospasm, PHTN). Future work will analyze temporal data with more complicated models and using recurrent and convolutional neural networks to understand temporal dependencies and detect spatial patterns.

REFERENCES

[1] Dielectric properties » it'is foundation. https://itis.swiss/virtualpopulation/tissue-properties/database/dielectric-properties. Accessed:2024-07-19.

[2] Gradient boosting classification explained through python | by vagif aliyev | towards data science. https://towardsdatascience.com/gradientboosting-classification-explained-through-python-60cc980eeb3d. Accessed: 2024-07-19.

[3] What is a multilayer perceptron (mlp)? - definition from techopedia. https://www.techopedia.com/definition/20879/multilayerperceptron-mlp. Accessed: 2024-07-19.

[4] Heather Baid, Fiona Creed, and Jessica Hargreaves. Respiratory assessment and monitoring, page 101–132. Oxford University Press, February 2016.

[5] Miron B. Kursa and Witold R. Rudnicki. Feature selection with theborutapackage. Journal of Statistical Software, 36(11), 2010.

[6] Mario C. Ponce; Abdulghani Sankari; Sandeep Sharma. Pulmonary Function Tests. StatPearls, 2023.