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Classification lung diseases with electrical impedance tomography

***Abstract**. This article analyzed the application of Electrical Impedance Tomography (EIT) in diagnosing lung diseases using the Lung Electrical Tomography System (LETS), which consists of a vest equipped with 32 electrodes and the LETSWEB analytical module. A comparison was made between the classification models Multi-layer Perceptron (MLP) and Gradient Boosting Classifier (GBC). In classifying pathological conditions based on simulated EIT data, the MLP model achieved a higher accuracy (87.5%) compared to the GBC model, which reached 80.5%. The study employed the Boruta algorithm for feature selection and dimensionality reduction techniques, significantly improving classification efficiency. The results highlight the potential of LETS and EIT as non-invasive diagnostic methods for detecting respiratory diseases.*

***Streszczenie.** W artykule dokonano analizy zastosowania tomografii impedancyjnej (EIT) w diagnostyce chorób płuc, z wykorzystaniem systemu Lung Electrical Tomography System (LETS), który składa się z kamizelki wyposażonej w 32 elektrody oraz modułu analitycznego LETSWEB. Porównano modele klasyfikacyjne Multi-layer Perceptron (MLP) i Gradient Boosting Classifier (GBC). W klasyfikacji stanów patologicznych na podstawie symulowanych danych EIT model MLP osiągnął wyższą dokładność (87,5%) w porównaniu z modelem GBC, który uzyskał 80,5%.. W badaniu zastosowano algorytm Boruta do selekcji cech oraz techniki redukcji wymiarowości, co znacząco poprawiło efektywność klasyfikacji. Wyniki wskazują na duży potencjał LETS i EIT jako nieinwazyjnych metod diagnostycznych w wykrywaniu chorób układu oddechowego (**Klasyfikacja chorób płuc z tomografią impedancji elektrycznej**).*

Keywords: electrical impedance tomography; chronic obstructive pulmonary disease; acute respiratory distress syndrome; pneumothorax; pneumonia; bronchospasm; pulmonary hypertension
Słowa kluczowe: tomografia impedancyjna; przewlekła obturacyjna choroba płuc; zespół ostrej niewydolności oddechowej; odma opłucnowa; zapalenie płuc; skurcz oskrzeli; nadciśnienie płucne

Introduction

The article discusses the research findings related to the development of a medical diagnostic system using electrical impedance tomography (EIT) [1-6] and machine learning algorithms [7-9]. One of the central features of this solution is its ability to assist in the diagnosis of respiratory diseases, with a particular focus on conditions such as chronic obstructive pulmonary disease (COPD), acute respiratory distress syndrome (ARDS), pneumothorax (PTX), pneumonia (PNA), bronchospasm, and pulmonary hypertension (PHTN).

Chronic Obstructive Pulmonary Disease (COPD) is characterized by irreversible airflow obstruction and lung tissue damage due to chronic inflammation, primarily from harmful exposures [10]. Acute Respiratory Distress Syndrome (ARDS) involves severe lung injury and inflammation with no effective pharmacological treatment, making early diagnosis crucial [11]. Pneumothorax (PTX) is the accumulation of air in the pleural cavity causing lung collapse, which can impede breathing if not promptly treated [12]. Pneumonia (PNA) is an infection that inflames the lungs and alveoli, often requiring early detection to prevent severe complications [13]. Bronchospasm involves sudden bronchial muscle constriction, commonly associated with asthma or allergies, requiring swift diagnosis to avoid respiratory failure [14]. Pulmonary Hypertension (PHTN) is marked by elevated blood pressure in the pulmonary arteries, potentially leading to heart failure if not identified early [15].

Diagnosing medical conditions often involves conducting multiple intricate tests, leading to prolonged waits for accurate diagnoses. The objective of the presented approach is to minimize the number of necessary tests for a precise diagnosis, resulting in time savings.

The article explores two classification models designed to distinguish between healthy individuals and those suffering from respiratory diseases. These models leverage data collected through the EIT system to classify the health status of patients more efficiently and accurately. By focusing on specific patterns in lung function and impedance, these models can provide preliminary diagnoses in a matter of minutes, helping clinicians prioritize patients who require immediate attention.

Methods

The Lung Electrical Tomography System (LETS) is an advanced solution in medical diagnostics, enabling real-time, three-dimensional impedance tomography. A key component of this system is a wearable vest designed with both comfort and measurement precision in mind. The vest is equipped with 32 electrodes arranged in two rows of 16, allowing for accurate imaging of internal organs, such as the lungs, by monitoring electrical impedance changes in the tissues.

The electrodes in LETS have specific features that make them particularly effective. They are designed to ensure stable measurements even when the patient is moving, which is crucial in practical medical applications where patients cannot always remain still. Thanks to the flexible design of the vest, the electrodes conform to the body, minimizing the risk of signal interference caused by movement.

Another advantage of the LETS electrodes (figure 1) is their ability to function on both dry and wet skin. This means that the system can be used in a variety of clinical conditions without the need for prior skin preparation, such as moistening or applying special conductive gels. This feature enhances the convenience of using the system, shortens the preparation time for the examination, and increases its applicability in a wide range of clinical cases, from routine check-ups to emergency patient monitoring.

An integral part of the LETS system is the advanced LETSWEB analytical module, which collects and processes data from the electrodes. This software enables the real-time analysis of large amounts of information, allowing for the rapid and precise diagnosis of pathological conditions, such as Chronic Obstructive Pulmonary Disease (COPD), Acute Respiratory Distress Syndrome (ARDS), Pneumothorax

(PTX), and many other respiratory diseases. LETSWEB assists doctors in making diagnostic decisions by offering visualizations and detailed measurement data analyses, making the LETS system a precious tool in modern medicine.

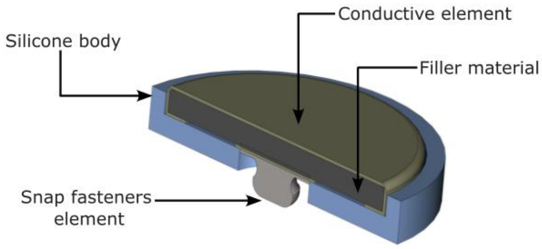

Figure 1. Structure electrode

The LETS system represents the future of non-invasive diagnostic testing, combining advanced technology with intuitive operation. Its innovative approach to monitoring respiratory functions opens new possibilities for treating and diagnosing lung diseases.

Models

Numerical models were developed to include cases of both healthy and diseased individuals (see Figures 1 - 7). These models were designed to highlight differences between healthy and diseased states, with a particular focus on the lung areas. Subsequently, as part of the research, material parameters for the human body were identified [16]. This process involved a detailed determination of material properties in areas suspected of disease presence.

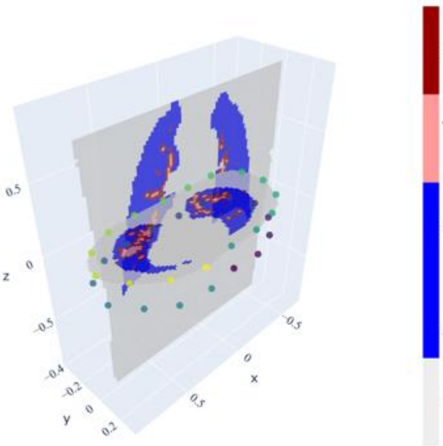

Figure 2. Model of healthy case

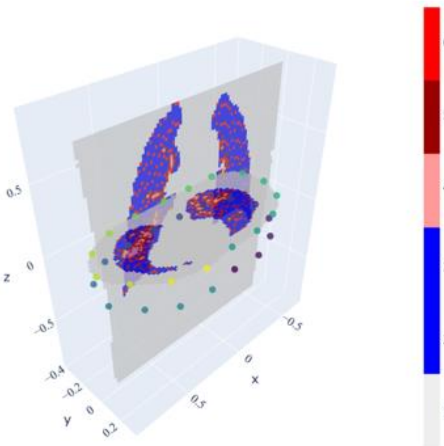

Figure 3. Model of ARDS disease

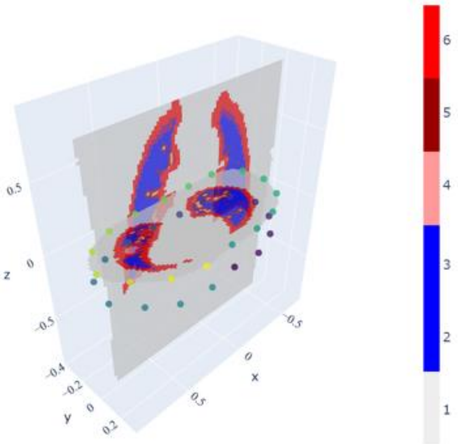

Figure 4. Model of COPD disease

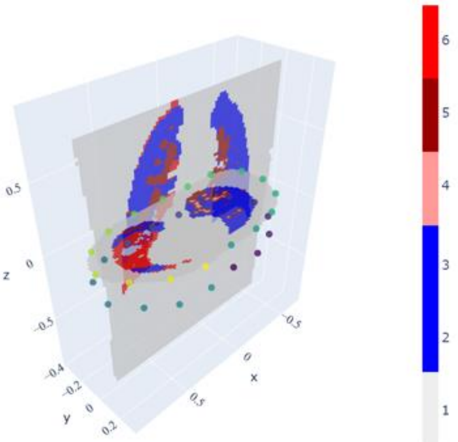

Figure 5. Model of PTX disease

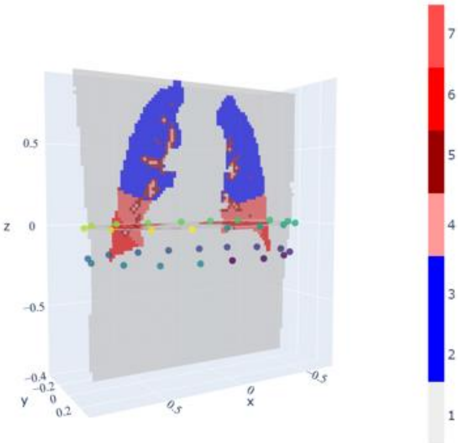

Figure 6. Model of pneumonia disease

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, 7 – area showcasing a secondary lesion (specifically utilized for pneumonia).

Coefficients for areas affected by pathology were determined as linear or non-linear combinations of relevant values in Figures 2-8. For COPD, ARDS, and PNA, the coefficient corresponded to consolidation with varying degrees of density, depending on the electrical conductivity of lung tissue. In the case of PTX, the air-filled area was assigned a numerical value of zero, corresponding to the absence of electrical resistance in the air. In PHTN, the coefficient was a linear combination of values assigned to blood and vessel walls, reflecting their electrical properties. In the case of bronchospasm, modeling involved a non-linear combination of values for the bronchial wall and air, taking into account their electrical interactions.

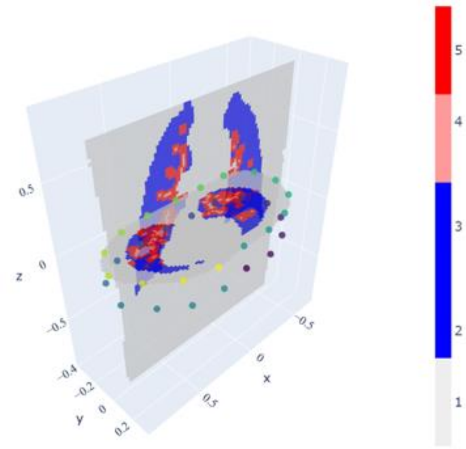

Figure 7. Model of PHTN disease

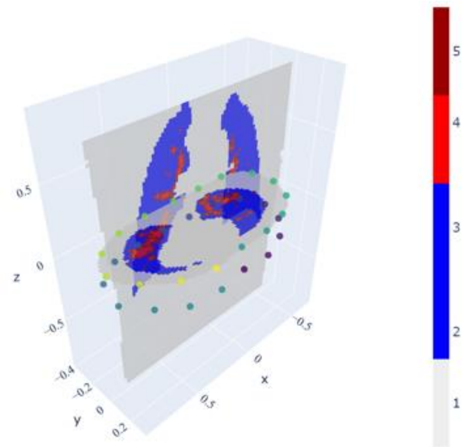

Figure 8. Model of bronchospasm disease

Modeling the measurement process

Compared to random probes, the Boruta algorithm was used for feature selection by iteratively eliminating those deemed less important. The functioning of Boruta is based on comparing the importance of original features with so-called shadow features, which are randomly generated variables. The original features that prove to be more significant than the shadow features are retained. In this way, the algorithm effectively removes irrelevant features, leaving only those that have a real impact on the model. As a result of this analysis, the Boruta algorithm selected 300 of the most significant features from an initial pool of 448 variables [17].

The importance of feature selection in data analysis cannot be overstated, especially in complex models with a large number of input variables. Choosing the right features allows for increased model efficiency, reduces the risk of overfitting, and shortens the computation time. Unlike many other feature selection methods, Boruta not only eliminates random variables but does so in a way that preserves information about the underlying data structure. By selecting only the most significant features, the algorithm ensures that the model operates on the most valuable data, which translates into better classification and prediction results.

The Multilayer Perceptron (MLP), a widely used artificial neural network model, was applied in the classification process. MLP is a feedforward network where information flows through multiple layers of neurons, from the input layer, through one or more hidden layers, to the output layer. The MLP network was trained using the backpropagation algorithm, which optimizes the weights within the network based on error gradients. The GridSearchCV method was employed to select the optimal model parameters, such as the number of neurons or activation function [18]. This technique allowed the MLP model to be fine-tuned for optimal performance, using the previously selected features better.

Another model used in the analysis was the Gradient Boosting Classifier (GBC), which relies on decision trees as base learners. In this method, each successive model, in the form of a decision tree, learns from the errors of its predecessor. A key mechanism in GBC is the use of gradient descent, which gradually minimizes prediction error by adding more trees to the model. Through this process, the GBC model becomes increasingly precise, with each iteration correcting the mistakes of previous steps, leading to more accurate results [19].

Classification

Two classification models, namely a Multi-layer Perceptron classifier (MLP) and a Gradient Boosting Classifier, were developed and compared for their effectiveness in distinguishing between individuals with respiratory diseases and healthy subjects. The models were trained on a comprehensive dataset encompassing various stages of disease progression. EIT data frames were simulated using the finite element method.

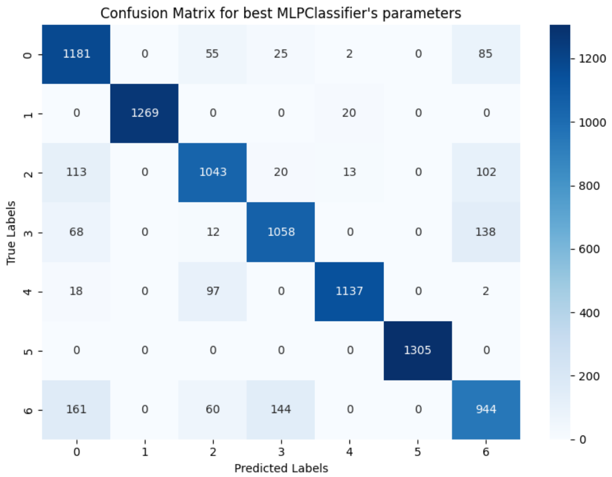

Figure 9. Confusion matrix for MLP, 0 – healthy, 1 – COPD, 2-ARDS, 3 – PTX, 4 – PNA, 5 – PHTN, 6 - bronchospasm

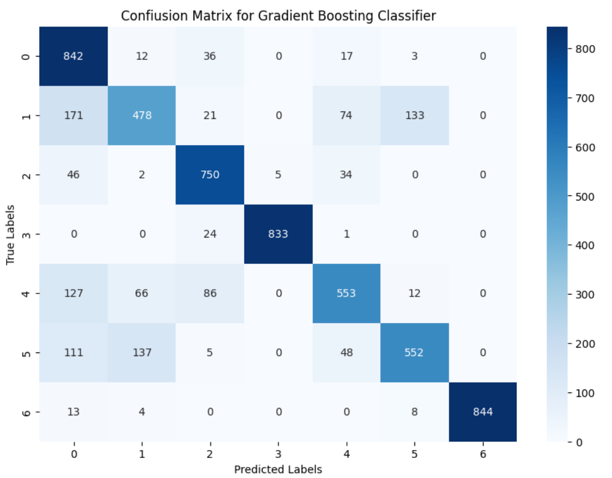

Figure 10. Confusion matrix for GBC, 0 – healthy, 1 – COPD, 2-ARDS, 3 – PTX, 4 – PNA, 5 – PHTN, 6 – bronchospasm

Each classification model was evaluated based on its accuracy in diagnosing specific lung conditions, with the MLP achieving an accuracy of 87.5% and the Gradient Boosting Classifier achieving 80.5%. The confusion matrices, corresponding to the MLP and GBC models, are shown in Figures 9 and 10.

Conclusions

The article presents a comparison of two classification models, the Multi-layer Perceptron (MLP) and Gradient Boosting Classifier (GBC), in the context of diagnosing respiratory diseases based on data obtained through Electrical Impedance Tomography (EIT). The models were tested on a dataset of simulated data representing different stages of lung disease development, using the finite element method (FEM). The MLP classifier achieved higher accuracy (87.5%) in distinguishing disease states than the GBC model (80.5%).

The results highlight the high effectiveness of neural network-based models and the potential of EIT in medicine, particularly in lung disease diagnosis. The article also emphasizes the importance of further research into optimizing dimensionality reduction methods and integrating measurements from different breathing phases to achieve even more precise pathology detection.

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