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Integration of machine learning algorithms with electrical impedance tomography-based wearable sensors

Abstract. The article describes a solution integrating machine learning algorithms and electrical impedance tomography-based wearable sensors. The main aim of the project was to develop a device that can assess the state of the urinary bladder in a non-invasive way. The research methods included XGBoost, Extremely Randomized Trees, Elastic Net, NNNET, and RPART Decision Tree. The obtained reconstructions of the simulated urinary bladder were presented, and a comparative analysis of the algorithms was performed.

Streszczenie. *W artykule opisano rozwiązanie integrujące algorytmy uczenia maszynowego i czujniki noszone na ciele oparte na elektrycznej tomografii impedancyjnej. Głównym celem projektu było opracowanie urządzenia, które może oceniać stan pęcherza moczowego w sposób nieinwazyjny. Metody badawcze obejmowały XGBoost, Extremely Randomized Trees, Elastic Net, NNNET i RPART Decision Tree. Przedstawiono uzyskane rekonstrukcje symulowanego pęcherza moczowego i przeprowadzono analizę porównawczą algorytmów. (**Integracja algorytmów uczenia maszynowego z czujnikami noszonymi na ciele opartymi na elektrycznej tomografii impedancyjnej**).*

Keywords: machine learning, electrical impedance tomography, wearable sensors, urinary bladder
Słowa kluczowe: uczenie maszynowe, tomografia elektryczna impedancyjna, czujniki do noszenia, pęcherz moczowy

Introduction

Electrical impedance tomography (EIT) is an innovative imaging technique that allows for non-invasive monitoring and assessment of the urinary bladder's function and structure. EIT involves placing electrodes around the examined area and measuring changes in electrical impedance, which are then processed into tomographic images. This method uses differences in the electrical conductivity of tissues, allowing for real-time visualization of changes [1-8].

In the urinary bladder, EIT can monitor its filling and emptying. This is particularly useful in diagnosing and treating urological disorders such as urinary incontinence, overactive bladder, or chronic urinary retention. EIT allows for tracking dynamic changes in bladder volume and assessing the function of the smooth muscles of the bladder wall, which can provide valuable diagnostic information.

One of the main advantages of EIT is its non-invasiveness and the lack of the need for contrast agents, which minimizes the risk of complications and makes it safe for patients, including children and pregnant women. In addition, EIT can be used multiple times, allowing for continuous monitoring of the patient's condition without exposing them to ionizing radiation.

The article discusses a project that combines machine learning algorithms with wearable sensors based on electrical impedance tomography (EIT). The primary goal was to create a non-invasive device to evaluate the condition of the urinary bladder. The research compared several machine learning techniques, including XGBoost, Extremely Randomized Trees, Elastic Net, NNNET, and RPART Decision Tree [9-14].

The device

The important aspect of the project is the wearability. It is designed as normal underwear (Fig. 1), in which the electrodes collecting the measurements are implemented (Fig. 2). Such a solution makes it much easier for a doctor to check the state of the urinary bladder, without the unnecessary stress of the patient. It can be used to assess the effectiveness of surgical therapy, monitor patients after urological procedures, and search for early stages of bladder disease. The device enables more precise treatment decisions, significantly improving patient care quality [15-19].

Fig. 1. The designed device

Fig. 2. The measurement module

Methods and Reconstructions

The XGBoost (Extreme Gradient Boosting) model is an advanced machine learning technique based on the gradient boosting algorithm. XGBoost is particularly valued for its efficiency and effectiveness in classification and regression tasks. The basic idea of gradient boosting is to build a predictive model in the form of an ensemble of weak models, usually decision trees, that are trained sequentially. Each successive tree tries to correct the errors made by the previous trees, leading to a gradual improvement in the model's accuracy. XGBoost introduces several key improvements over traditional gradient boosting algorithms. First of all, XGBoost uses a technique called “shrinkage”, which involves scaling each tree's contribution, which helps avoid overfitting. Furthermore, XGBoost implements regularization, which penalizes the complexity of the model. Another significant feature of XGBoost is its ability to process data in parallel, which significantly speeds up the model training process. The advantages of the XGBoost model are numerous. First of all, XGBoost is extremely efficient and scalable, making it ideal for analyzing large data sets.

Thanks to advanced regularization techniques and overfitting control, XGBoost often achieves very high predictive accuracy. Furthermore, XGBoost is very flexible and can be applied to various types of problems, including classification, regression, and ranking. However, the XGBoost model also has its defects. One of the major drawbacks is its computational complexity. Training XGBoost models can be time-consuming and require significant computational resources, especially for large data sets. Furthermore, XGBoost can be challenging to tune because it has many hyperparameters that must be appropriately configured to achieve optimal performance. Another drawback is that XGBoost, like other gradient-boosting algorithms, can be prone to overfitting if proper regularization techniques are not applied. Fig. 3 and Fig. 4 present the reconstructions obtained using the XGBoost model.

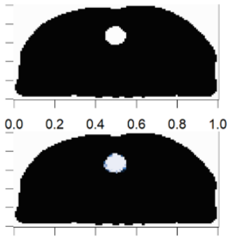

Fig. 3. Example comparison of the simulated urinary bladder and the reconstruction – XGBoost

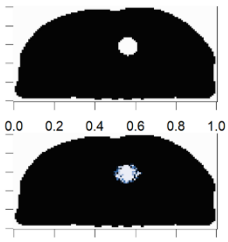

Fig. 4. Example comparison of the simulated urinary bladder and the reconstruction - XGBoost

Extremely Randomized Trees is an advanced machine learning technique that, like Random Forest, relies on the construction of multiple decision trees to improve prediction accuracy. However, Extra Trees introduces an additional layer of randomness when building decision trees, which distinguishes it from traditional Random Forest algorithms. In the Extra Trees model, both the selection of features to split and the threshold values for these features are randomly selected, without optimizing the splitting criteria. This makes the structure of the trees more diverse, which can lead to better generalization of the model to new data. The basic architecture of Extra Trees consists of multiple decision trees that are trained on the entire dataset, but with different subsets of features. Each tree in the Extra Trees model is built independently, and the final prediction is obtained by aggregating the results of all trees, typically by majority voting in the case of classification or by average in the case of regression. The random selection of features and split thresholds makes the model less prone to overfitting and can better handle diverse data. Extra Trees are computationally very efficient, flexible and can be applied to various types of problems. One of the major drawbacks is that the random selection of features and split thresholds can lead to less interpretable decision trees, which can be problematic in applications requiring model explainability. Furthermore, although Extra Trees are less prone to overfitting, they may still require hyperparameter tuning to achieve optimal performance. Another disadvantage is that this model, like other ensemble algorithms, can be resource-intensive, especially for large data sets. In summary, the Extremely Randomized Trees model is a powerful data analysis tool with many performance, scalability, and generalization advantages. However, its random nature and resource requirements can be challenging in practical applications. Fig. 5 and Fig. 6 present the reconstructions obtained using the Extremely Randomized Trees model.

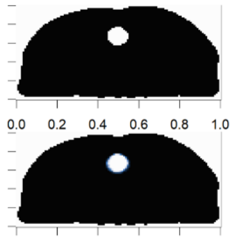

Fig. 5. Example comparison of the simulated urinary bladder and the reconstruction – Extremely Randomized Trees

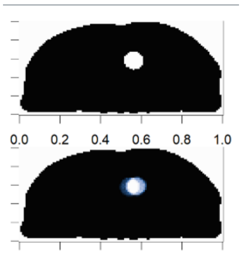

Fig. 6. Example comparison of the simulated urinary bladder and the reconstruction – Extremely Randomized Trees

Elastic Net is a regularized regression method that combines the L1 and L2 penalties used in the lasso and ridge methods. It is beneficial for high-dimensional data, where the number of variables is much larger than the number of observations. Elastic Net helps overcome the limitations of the lasso method, which can select only one variable from a group of highly correlated variables, ignoring the rest.

The basic architecture of Elastic Net consists of adding two terms to the loss function: the L1 penalty (the absolute value of the coefficients) and the L2 penalty (the square of the coefficients). This allows the model to combine the advantages of both methods: lasso (variable selection) and ridge (coefficient stability). In practice, Elastic Net is often preferred over either the ridge or lasso methods alone, because it combines their advantages while minimizing their disadvantages. Combining the L1 and L2 penalties makes the model more flexible and can better handle high-dimensional data.

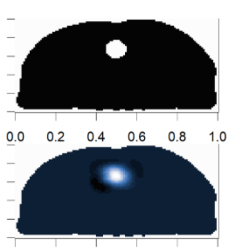

Fig. 7. Example comparison of the simulated urinary bladder and the reconstruction – Elastic Net

One of the main drawbacks is that it can be computationally more resource-intensive, especially for very large datasets, due to the need to tune two hyperparameters: alpha and lambda. Selecting these parameters can be difficult and time-consuming, as there is no clear-cut method to optimize them. Furthermore, Elastic Net, like other regularization algorithms, can be less interpretable, which can be problematic in applications requiring model explainability. Fig. 7 and Fig. 8 present the reconstructions obtained using the Elastic Net model.

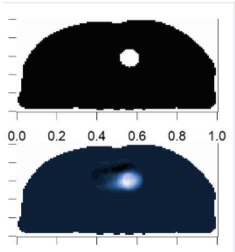

Fig. 8. Example comparison of the simulated urinary bladder and the reconstruction – Elastic Net

The NNET model is an implementation of a neural network that allows for the creation of classification and regression models. Its architecture consists of an input layer, one hidden layer, and an output layer. Each neuron in the hidden and output layers calculates a value based on the weights assigned to the connections to the neurons in the previous layer and an activation function. The model is trained using a backpropagation algorithm that adjusts the connection weights to minimize the prediction error.

The advantages of the NNET model include the ability to model complex nonlinear relationships between variables, which often leads to better prediction accuracy compared to traditional statistical models. The NNET model is also flexible and can be adapted to different types of problems, such as classification, regression, and time series analysis.

One of the main disadvantages is that neural networks are often viewed as “black boxes.” This can be problematic in applications where model explainability is important. Furthermore, the NNET model can require large amounts of training data and computational resources, especially for more complex problems. Fig. 9 and Fig. 10 present the reconstructions obtained using the NNET model.

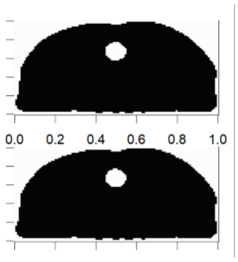

Fig. 9. Example comparison of the simulated urinary bladder and the reconstruction – NNET

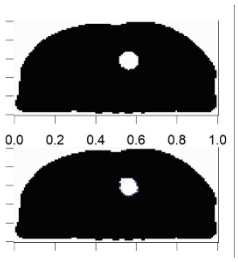

Fig. 10. Example comparison of the simulated urinary bladder and the reconstruction – NNET

RPART is a popular machine-learning technique used to build decision trees. This model works by iteratively splitting the data into smaller subsets, maximizing the homogeneity of the resulting groups. Unlike more advanced algorithms such as Extra Trees, RPART uses a deterministic approach for selecting features and splitting thresholds, which makes it more transparent and interpretable. Each node represents a decision based on one of the features, and each leaf represents the final outcome. This process is repeated until the maximum depth of the tree or another stopping criterion is reached, such as the minimum number of observations at a node.

One of RPART's main advantages is its simplicity and interpretability. The model results are easy to understand and explain, which is especially important in applications requiring transparency. Furthermore, RPART is versatile and can be applied to both classification and regression problems. The model is also relatively fast and computationally efficient, making it suitable for analyzing large data sets.

One of the main drawbacks is its susceptibility to overfitting, especially in the case of deep trees. To prevent this, tree pruning techniques are often used to remove less important branches. Furthermore, the deterministic approach to feature selection and splitting thresholds can lead to less diverse trees. It can then limit the model's ability to generalize. Compared to more advanced algorithms such as Extra Trees, RPART may also require more hyperparameter tuning to achieve optimal performance. Fig. 11 and Fig. 12 present the reconstructions obtained using the RPART Decision Tree model.

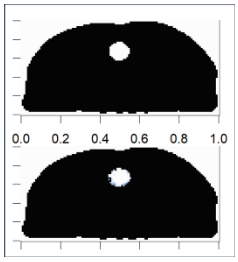

Fig. 11. Example comparison of the simulated urinary bladder and the reconstruction – RPART Decision Tree

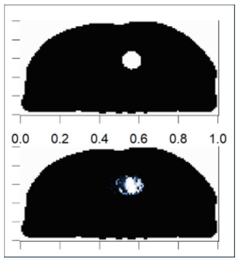

Fig. 12. Example comparison of the simulated urinary bladder and the reconstruction – RPART Decision Tree

Results and Conclusions

The algorithms were compared in terms of training time, prediction time, total time, mean absolute error (MAE), mean squared error (MSE), and root mean squared error (RMSE). The results are summarized in Tables 1 and 2.

Table 1. The comparison of algorithms in terms of time

Model	Training Time [s]	Prediction Time [s]	Total time [s]
XGBoost	92.42	11.55	103.97
Extremely Randomized Trees	283.39	110.97	394.38
RPART	186.7	25.19	211.89
Elastic Net	15.81	4.03	19.86
NNET	531.39	9.09	540.5

The Elastic Net model turned out to be the fastest one (total time 19.86 s). However, it is important to note that the prediction time is a more important indicator once the model is trained. The prediction time for the NNET neural network is also less than 10 seconds (9.09 s).

Table 2. The comparison of algorithms in terms of error

Model	MAE	MSE	RMSE
XGBoost	0.06043	0.00458	0.06486
Extremely Randomized Trees	0.00248	0.00082	0.00911
RPART	0.00383	0.00226	0.01462
Elastic Net	0.01540	0.00461	0.02224
NNET	0.00121	0.00043	0.00652

The two methods with the smallest error values are Extremely Randomized Trees and NNET. However, the prediction time for Extremely Randomized Trees was the longest. These conclusions indicate that the NNET neural network is the appropriate algorithm for the discussed task.

A solution integrating machine learning algorithms and electrical impedance tomography-based wearable sensors was presented. The device can assess the state of the urinary bladder in a non-invasive way. A comparative analysis of the algorithms was performed, which highlighted the NNET neural network as the optimal algorithm for the project.

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