1. Marcin DZIADOSZ[3], 2. Mariusz MAZUREK[4], 3. Barbara STEFANIAK[1], 4. Dariusz Wójcik[1,2], 5. Konrad Gauda[2]

R&D Center Netrix S.A. Lublin, Poland (1), WSEI University Lublin, Poland (2),
Lublin University of Technology Lublin, Poland (3), Polish Academy of Science Warsaw, Poland (4)
ORCID: 1. 0000-0002-0506-6653; 2. 0000-0002-9646-6897; 3. 0000-0001-6555-8230, 4. 0000-0002-4200-3432, 5. 0000-0002-7300-6978

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A comparative study of selected machine learning algorithms for electrical impedance tomography

***Abstract**. The main purpose of the article is to compare selected machine learning methods in Electrical Impedance Tomography. The paper studies the relationship between a number of training cases and Root Mean Squared Error loss in the EIT image reconstruction problem. The research was conducted with the Elastic Net, Least Angle Regression and Artificial Neural Network algorithms in R environment. Various tests have been performed, leading to many results and a discussion about a plateau in the model training plot.*

***Streszczenie.** Głównym celem artykułu jest porównanie wybranych metod uczenia maszynowego w tomografii impedancyjnej. Artykuł bada związek między liczbą przypadków treningowych a utratą RMSE w problemie rekonstrukcji obrazu EIT. Badania przeprowadzono z wykorzystaniem algorytmów Elastic Net, Least Angle Regression oraz Artificial Neural Network w środowisku R. Przeprowadzono różne testy, które doprowadziły do wielu wyników i dyskusji na temat plateau na wykresie treningowym modelu. (**Badanie porównawcze wybranych algorytmów uczenia maszynowego w elektrycznej tomografii impedancyjnej**).*

Keywords: electrical impedance tomography, machine learning, inverse problem, image reconstruction
Słowa kluczowe: tomografia elektryczna impedancyjna, uczenie maszynowe, problem odwrotny, rekonstrukcja obrazu

Introduction

In this work, various algorithms for optimising and reconstructing images were developed and compared [1-9]. Specifically, the paper presents a solution to the inverse problem of Electrical Impedance Tomography [10-15]. The article also studies the relationship between the number of training cases and Root Mean Squared Error (RMSE) loss. The EIT data were simulated and consisted of three datasets, each containing 10,000 observations with identical inclusions ranging from 1 to 3. There were 8 electrodes and 5,870-pixel mesh elements. The research was performed on several different models, including Elastic Net, Least Angle Regression (LARS), and a neural net with a single hidden layer (Artificial Neural Network) in the R environment. Various tests were performed, leading to interesting results. The one with the lowest Root Mean Squared Error (RMSE) was chosen out of the tested models.

Materials and Methods

For the research, the sample size from the dataset was systematically increased (100, 500, 1000, 2000, 3000, 4000, and 5000 cases). Subsequently, every sample was divided proportionally – $\frac{3}{4}$ of the observations went to the training dataset, while $\frac{1}{4}$ of them created the test dataset. To avoid cases where the values for a specific pixel are constant, Gaussian noise was added with a mean of 0 and a standard deviation of 0.001. In order to receive an image reconstruction, a model was built for predicting each pixel of the image. The next step consisted of calculating the Root Mean Squared Error for each model and then determining the average value for the metric. RMSE is defined as:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y})^2}, \quad (1)$$

where $\hat{y}$ is the predicted value of y.
Implementing the Elastic Net model in R comes from the glmnet package, with the Gaussian family chosen. Independent variables were standardized, and an intercept was included. Multiple tests were conducted to achieve the best-performing model, each using a different value of alpha (the mixing parameter) and lambda (the regularization parameter). Eventually, alpha was set to 0.8, and lambda was set to 0.0000007. The penalty function for the model is defined as:

$$(1-\alpha)/2\left||\beta|\right|_2^2 + \alpha\left||\beta|\right|_1. \quad (2)$$

The Least Angle Regression (LARS) was carried out using the R lars package. LARS is one of the feature selection methods similar to stepwise regression (backwards or forward). L2 normalization was performed for every variable, and an intercept was fitted.
The Artificial Neural Network (ANN) model was created with the R nnet package. Firstly, before the model development, the data were normalized. The ANN model consists of a single hidden layer with two units. The range parameter (defining the initial weights interval) was set to 0.1, and the weights decay parameter was set to 0.0005. A maximum of 200 iterations was allowed.

Reconstructions and Results

Conducting the research led to various results. The first part of the study focused on training the models using EIT data with only one inclusion. Figure 1 presents a comparison between the Artificial Neural Network's image reconstruction based on 3,750 training observations and the original image with a single inclusion.

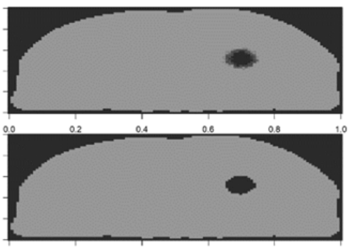

Fig. 1. The upper panel - Artificial Neural Network image reconstruction on 3750 training observations, the lower panel - the original image with one inclusion.

Table 1 contains the sample size, the training simple size and the values of the Root Mean Squared Error metric for the case with only one inclusion ($k = 1$).

Table 1. Root Mean Squared Error values for one inclusion (k=1)

Sample size	Training sample size	Elastic Net	Least Angle Regression	Artificial Neural Network
100	75	0.11131	0.13119	0.07194
500	375	0.07937	0.08024	0.05253
1000	750	0.07844	0.07838	0.04200
2000	1500	0.07815	0.07816	0.03524
3000	2250	0.07820	0.07814	0.03210
4000	3000	0.07823	0.07868	0.03087
5000	3750	0.07846	0.07844	0.03016

The table shows that, generally, as the number of cases in the training set increases, the RMSE decreases. Out of all the tested models, the Artificial Neural Network clearly provides the best results. With 1,500 cases in the training dataset, the RMSE already reaches a value of less than 0.04. Considering small training sample unit sizes, such as 75 or 375, the Elastic Net method gives better results than the LARS one; overall, they perform quite similarly. With 750 training cases, the RMSE for Elastic Net and LARS is in approximation 0.0784. Interestingly, by doubling the number of cases from 750 to 1,500, we do not see a significant improvement. As the training sample grows, both models' Root Mean Squared Error stabilizes, balancing around a constant value. The next step in the research relied on analyzing images with two inclusions present. An example of the two inclusions' image reconstruction by the Least Angle Regression model based on 3,750 training observations is shown in Figure 2.

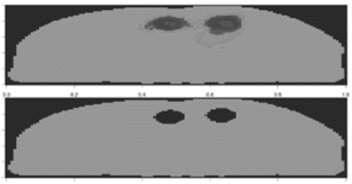

Fig. 2. The upper panel - Least Angle Regression image reconstruction on 3750 training observations with two inclusions - the original image- and the lower panel.

The sample size, the training simple size and the Root Mean Squared Error for the case with two inclusions ($k = 2$) have been collected in Table 2.

Table 2. Root Mean Squared Error values for two inclusions (k=2)

Sample size	Training sample size	Elastic Net	Least Angle Regression	Artificial Neural Network
100	75	0.13425	0.13613	0.13808
500	375	0.11485	0.11514	0.11229
1000	750	0.11010	0.11011	0.10176
2000	1500	0.11122	0.11123	0.09649
3000	2250	0.11053	0.11046	0.09417
4000	3000	0.11086	0.11125	0.09138
5000	3750	0.11125	0.11118	0.09059

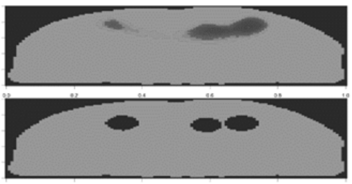

Fig. 3. The upper panel - Elastic Net image reconstruction on 3750 training observations with three inclusions,
The lower panel - the original image.

This time, with 75 training observations, The Artificial Neural Network has the biggest RMSE out of all the models, meaning it performs the worst on such a sample. However, as the training sample size increases, the ANN model reaches a Root Mean Squared Error value under 0.1, while the Elastic Net and the Least Angle Regression stabilised and fluctuated around a bigger value. Subsequently, the models were trained on EIT data with three identical, same size inclusions in each image. Fig. 3 compares the Elastic Net image reconstruction on 3750 training observations and the original image with three inclusions.

Table 3 shows the sample size, the training simple size and the Root Mean Squared Error for the case with three inclusions ($k = 3$).

Table 3. Root Mean Squared Error values for three inclusions (k=3)

Sample size	Training sample size	Elastic Net	Least Angle Regression	Artificial Neural Network
100	75	0.13909	0.13584	0.15790
500	375	0.13447	0.13457	0.13848
1000	750	0.13449	0.13507	0.13035
2000	1500	0.13466	0.13523	0.12531
3000	2250	0.13417	0.13463	0.12198
4000	3000	0.13371	0.13423	0.11981
5000	3750	0.13423	0.13473	0.11863

The table contains some interesting results. With 75 and 375 cases in the training dataset, the Elastic Net and Least Angle Regression models yield lower RMSE, indicating better performance. Even so, as the training sample size increases, the Artificial Neural Network model achieves the best value for the RMSE metric (0.11863). While Elastic Net and Least Angle Regression techniques perform similarly, the Artificial Neural Network provides the largest RMSE loss. In order to study the relationship between the number of inclusions and the number of cases in the training dataset for EIT image reconstruction, the same model methods were compared for different numbers of inclusions (different k values). Table 4 contains the Elastic Net model sample size, the training sample size, and the Root Mean Squared Error metric values for one inclusion, two inclusions, and three inclusions.

Table 4. Root Mean Squared Error values for Elastic Net model with different number of inclusions

Sample size	Training sample size	k=1	k=2	k=3
100	75	0.11131	0.13425	0.13909
500	375	0.07937	0.11485	0.13447
1000	750	0.07844	0.11010	0.13449
2000	1500	0.07815	0.11122	0.13466
3000	2250	0.07820	0.11053	0.13417
4000	3000	0.07823	0.11086	0.13371
5000	3750	0.07846	0.11125	0.13423

First of all, Table 4 shows that the more identical, same-sized inclusions there are, the larger the RMSE becomes. As the training sample size increases, the RMSE begins to 'stabilize,' meaning it balances around a constant value. In other words, it reaches a plateau in the model learning plot, above which additional training cases do not provide a better-performing model. It is worth noting that the largest RMSE loss occurs when there is only one inclusion. With 75 training observations, the RMSE is around 0.11131; with 1,500 training units, it is about 0.07815, indicating a 30% loss. With two inclusions present, there is an 18% RMSE loss. The Root Mean Squared Error loss is only about 4% for three inclusions. Furthermore, the RMSE value for 75 training units with only one inclusion and the RMSE for a training sample size of 3,750 with two inclusions present are almost equal, meaning that the two inclusions case is a much more complex machine learning task. Table 5 contains the Least Angle Regression model sample size, the training sample size, and the Root Mean Squared Error metric values for one inclusion, two inclusions, and three inclusions.

Table 5. Root Mean Squared Error values for LARS model with different number of inclusions

Sample size	Training sample size	k=1	k=2	k=3
100	75	0.13119	0.13613	0.13584
500	375	0.08024	0.11514	0.13457
1000	750	0.07838	0.11011	0.13507
2000	1500	0.07816	0.11123	0.13523
3000	2250	0.07814	0.11046	0.13463
4000	3000	0.07868	0.11125	0.13423
5000	3750	0.07844	0.11118	0.13473

In most cases, the Root Mean Squared Error for the same training sample grows as the number of inclusions in the EIT data increases. However, the RMSE value for 75 training observations is actually the biggest for $k = 2$. Again, as the training sample size increases, the RMSE reaches a plateau point, above which additional training cases do not provide a better performance. For example, in the case of one inclusion the RMSE stabilizes around 0.078 value, in approximation. Overall, the Least Angle Regression method returns quite similar results to the Elastic Net one. Table 6 contains the Artificial Neural Network model sample size, the training simple size and the Root Mean Squared Error metric values for one inclusion, two inclusions and three inclusions.

Table 6. Root Mean Squared Error values for ANN model with different number of inclusions

Sample size	Training sample size	k=1	k=2	k=3
100	75	0.07194	0.13808	0.15790
500	375	0.05253	0.11229	0.13848
1000	750	0.04200	0.10176	0.13035
2000	1500	0.03524	0.09649	0.12531
3000	2250	0.03210	0.09417	0.12198
4000	3000	0.03087	0.09138	0.11981
5000	3750	0.03016	0.09059	0.11863

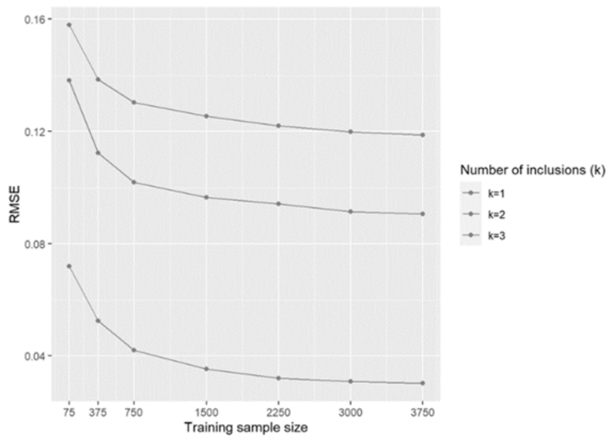

Fig. 4. Root Mean Squared Error plot for ANN model with different number of inclusions.

Table 6 shows that as the number of training units increases, the Root Mean Squared Error begins to 'stabilize' and reaches a plateau; however, this time, it is a much slower process. It is worth mentioning that the Artificial Neural Network, in comparison with the Elastic Net and the Least Angle Regression techniques, clearly provides the largest RMSE percentage decrease for every number of inclusions analyzed (k value in the table). For the one-inclusion case, with 75 training observations, the RMSE is around 0.07194, while with a training sample size of 3,750, it is about 0.03016, indicating about a 58% loss. With two inclusions present, there is a 34% RMSE loss. The Root Mean Squared Error loss is only about 25% for three inclusions.

Fig. 4 presents an Artificial Neural Network comparative Root Mean Squared Error loss plot for all three cases of inclusion number ($k = 1$, $k = 2$ and $k = 3$). The curves signal a correct learning process.

Discussion about the plateau

One of the main conclusions from the research is that in the described model learning processes, a plateau point has been reached, above which additional training cases do not significantly improve the model's performance. In order to optimize the time of the model training process and reduce the size of the training sample in Electrical Impedance Tomography image reconstruction, a mathematical assumption must be made to detect the plateau point precisely. In an effort to determine the plateau, the RMSE percentage points difference from the previous value in the table was calculated, with the percentage values computed in relation to the RMSE value for 75 training units. The last drop from the previous value above 2 percentage points was the aim of the search. Due to the fact that the Artificial Neural Network provided the best results in the study, the discussed analysis was conducted based on the ANN model. Table 7 contains the Artificial Neural Network model sample size, training sample size, the Root Mean Squared Error percentage values for one inclusion, and the percentage points drop from the previous value. The RMSE for the case with 75 training units (the first value in the table) is assumed to be 100%.

Table 7. Root Mean Squared Error percentage values for ANN model with one inclusion (k=1)

Sample size	Training sample size	Percentage RMSE values for one inclusion	RMSE percentage points drop from the previous value
100	75	100 %	-
500	375	73.02 %	26.98 p.p.
1000	750	58.38 %	14.64 p.p.
2000	1500	48.99 %	9.39 p.p.
3000	2250	44.62 %	4.37 p.p.
4000	3000	42.91 %	1.71 p.p.
5000	3750	41.92 %	0.99 p.p.

It can be observed that the difference in percentage points becomes smaller and smaller. The last drop from the previous value above 2 percentage points occurred with 2,250 training observations, so it is safe to assume that additional training observations do not significantly improve performance. Fig. 5 shows the plateau point in the Artificial Neural Network model training plot for the case with only one inclusion.

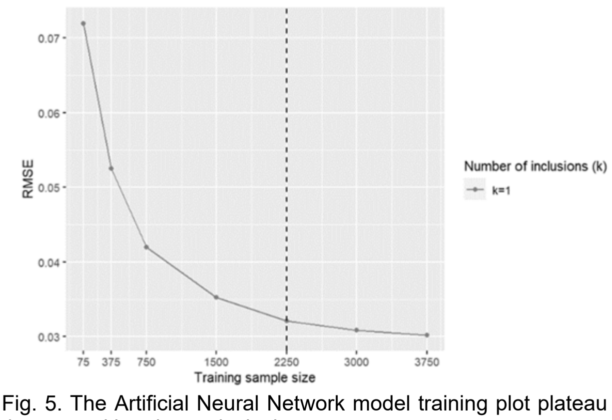

Fig. 5. The Artificial Neural Network model training plot plateau for the case with only one inclusion.

Table 8 consists of the Artificial Neural Network model sample size, training sample size, the Root Mean Squared Error percentage values for two inclusions and the percentage points drop from the previous value. The RMSE for the case with 75 training units (the table's first value) is assumed to be 100%.

Table 8. Root Mean Squared Error percentage values for ANN model with two inclusions (k=2)

Sample size	Training sample size	Percentage RMSE values for one inclusion	RMSE percentage points drop from the previous value
100	75	100 %	-
500	375	81.32 %	18.68 p.p.
1000	750	73.70 %	7.62 p.p.
2000	1500	69.88 %	3.82 p.p.
3000	2250	68.20 %	1.68 p.p.
4000	3000	66.18 %	2.02 p.p.
5000	3750	65.61 %	0.57 p.p.

Conclusions

The article presents a comparative study of selected machine learning algorithms for Electrical Impedance Tomography (EIT). For the research, Elastic Net, Least Angle Regression (LARS), and Artificial Neural Network (ANN) models were chosen and tested for EIT applications. The paper contains exemplary image reconstructions, various comparative tables, and training plots. Different training sample sizes and various amounts of inclusions were considered during the research. To sum up, the Elastic Net and Least Angle Regression techniques performed very similarly, while the Artificial Neural Network achieved the best results in the task. It provided the largest Root Mean Squared Error (RMSE) loss and better overall performance. ANN facilitated the reconstruction of the images with the highest quality, making it an optimal method for effectively solving the inverse problem in EIT tomography. In addition, a plateau point was found for the Artificial Neural Network model in each inclusions case, based on an assumption. A larger training sample size does not provide a significantly better-performing model. Reducing training units optimizes the model's training time in Electrical Impedance Tomography image reconstruction. Further research in this direction will be performed.

***Authors**: Marcin Dziadosz, M.Sc. Eng., Lublin University of Technology, Nadbystrzycka 38, Lublin, Poland, E-mail: m.dziadosz@pollub.pl; Mariusz Mazurek, Ph.D., Institute of Philosophy and Sociology of the Polish Academy of Science Warsaw, Poland, E-mail: mmazurek@ifispan.edu.pl; Barbara Stefaniak, M.Sc., Research and Development Centre Netrix S.A E-mail: barbara.stefaniak@netrix.com.pl, Dariusz Wójcik, Phd, WSEI University, Projektowa 4, Lublin, Poland/ Research & Development Centre Netrix S.A. E-mail: dariusz.wojcik@netrix.com.pl; Konrad Gauda, Phd, WSEI University, Projektowa 4, Lublin, Poland/ E-mail: konrad.gauda@wsei.lublin.pl.*

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