Comparison of CNN and LSTM algorithms for solving the EIT inverse problem

Abstract. This article presents comparative research to verify the suitability of selected machine learning methods for the problem of solving the inverse problem in electrical impedance tomography. The research involved the use of a tomograph to image areas of moisture inside the walls. The measurement data collected by the tomograph was transformed into 3D spatial images using two types of artificial neural networks - convolutional neural network (CNN) and recurrent long short-term memory network (LSTM).


Keywords: electrical tomography; machine learning; moisture detection, neural networks
Słowa kluczowe: tomografia elektryczna; uczenie maszynowe; wykrywanie wilgoci, sieci neuronowe.

Introduction
Tomography belongs to the field of non-destructive testing, which is the only one that enables imaging of internal sections of walls in order to monitor moisture [1]. It can be used to create both 2D cross-section images and 3D spatial reconstructions. Contrary to standard methods, which enable humidity measurements only in selected points of the wall [2], tomographic images show larger areas. Thanks to the appropriate color calibration in the images, it is possible to effectively emphasize areas with higher humidity against the background of the fragments with a lower level of humidity, which can be considered as the background. So, tomography is a relative method that is not used to accurately measure the percentage of water content in porous walls, but it is a method that can monitor the spatial and relative distribution of moisture. In this study, the Electrical Impedance Tomography (EIT) was used to measure the humidity of the brick walls of the building [3–5]. The effectiveness of the tomographic system depends on the efficiency of the system for converting measurements to images. This is called an inverse problem that can be solved with deterministic or machine learning methods.

Deterministic methods rely on the appropriate selection of coefficients in the mathematical model. Examples of deterministic methods are Level Set, Gauss-Newton or Total Variation [6]. With appropriate iterative transformations, data from real or simulation measurements can be used to train machine learning-based models. In recent years, along with the development of information technology, machine learning methods have become increasingly popular. These are algorithmic methods that require a large amount of training data. Typically, the disadvantage of their use is the high computational complexity, which is associated with a high demand for computing power [7-11]. The most popular machine learning methods are artificial neural networks, SVM, logistic and linear regression, LARS and elastic net [12]. Artificial neural networks include, inter alia, classical networks, which include the multilayer perceptron, convolutional neural networks and recursive LSTM networks [13].

Tomography is the only known method of imaging areas of humidity inside walls. It is also a non-invasive, non-destructive method. Commonly used methods are limited in scope and frequently destructive. This paper is mostly about describing the algorithmic methods that improve the quality and resolution of a tomographic image [14,15].

The negative economic effects of damp buildings are related to the fact that they are degraded by water. The subject of identifying the dampness in the walls of buildings is therefore important both from the point of view of society as a whole and from the point of view of an individual person. The authors’ own contribution is the confirmation that both types of neural networks (CNN and LSTM) work well for tomographically identifying areas of moisture inside building walls where there is water damage.

Materials and Methods
Figure 1 shows the examined fragment of a wall of a historical building with a tomograph and electrodes applied to the wall. The tomograph with electrodes was entirely designed and manufactured in the research and development center of Netrix SA. It is a prototype unit.

Fig.1. The measuring station equipped with an electric tomograph and two metal strips with 16 electrodes each

Fig.2. View of a fragment of the wall - a photo taken with an ordinary camera

Figures 2 and 3 show the same fragment of a building wall, but the photograph in Figure 1 was taken with an ordinary photosensitive camera. Figure 3 shows the same
There are significant temperature differences in the range from 17.9 to 22 degrees Celsius. Damp surfaces evaporate more intensively, so their temperature is lower than that of dry surfaces. On this basis, it can be assumed that the lower the temperature, the more damp the wall surface is. The key word here is "surface". While infrared photography may serve as an approximate indicator of the moisture content of the external wall coatings, it does not answer the question about the distribution of moisture under their surface.

The tomograph used consisted of 32 electrodes arranged on two metal strips, each with 16 sensors. The electrodes are specially designed. Thanks to soft elements such as rubber and sponge, good contact is ensured on the uneven and porous surface of the brick wall. Care was also taken to minimize the contact resistance of the wall with the electrodes.

Using 32 electrodes made it possible to obtain 448 voltage measurements. Such a number of measurements is possible thanks to the multiplexer built into the tomograph, which switches the electric current source successively to individual electrodes and measures the voltage on a single electrode, which is also changed before each subsequent measurement. So, the whole measuring cycle is a set of measurements that are done in the right order. Therefore, since we are dealing with measurement cycles, the measurements within a given cycle form a measurement sequence consisting of 448 measurements, which in turn explains the use of the LSTM network. LSTM networks are great for making predictions about time series and data sequences because they can learn a lot from past trends.

The general model of the neural networks implemented can be written as $448 \rightarrow \text{CNN} \rightarrow 10752$ and $448 \rightarrow \text{LSTM} \rightarrow 10752$. The 3D output image is created on a mesh of 10752 tetrahedral finite elements. The measurement cases were generated using an algorithm that was created. It was necessary in order to obtain the appropriate number of observations to train the neural networks. The training set consisted of 30,000 observations. The algorithm solves a forward problem, i.e., on the basis of a randomly assigned moisture distribution in the tested fragment of the wall, the voltages between the individual pairs of electrodes are calculated. The research used the Eidors toolbox, which cooperates with the Matlab software [12].

Table 1 shows the seven layers of the CNN network. The first layer is sequential and contains 448 channels. The second layer is a weave and contains six 112-element filters. The third layer is ReLu, which zeros the negative values. The next layer is used to normalize the mini-batches. Layer 5 is global max pooling, which does downsampling by outputting the maximum time dimension of the input. The sixth layer is a fully connected layer, which in fact, acts as a multilayer perceptron with no transfer function, i.e., one which only sums up the products of weights and input values. The last layer is the regression layer that computes the half-mean-squared-error loss for regression tasks.

Table 2 provides a description of the LSTM network layers. As with CNN, the first layer is sequential. It is aligned with a vector of 448 measured values. The second layer is a bidirectional LSTM with 2200 hidden units. The last two layers are the fully connected layer and the regression layer. The tasks of these layers are analogous to those of CNN.

Table 1. Layers of the CNN network

<table>
<thead>
<tr>
<th>Name</th>
<th>Activations</th>
<th>Learnable Properties</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 sequence</td>
<td>448(C) × 1(B) × 1(T)</td>
<td>-</td>
</tr>
<tr>
<td>2 conv2d</td>
<td>112(C) × 1(B) × 6(T)</td>
<td>weights 4 × 448 × 112 bias 112 × 1</td>
</tr>
<tr>
<td>3 ReLu</td>
<td>112(C) × 1(B) × 6(T)</td>
<td>-</td>
</tr>
<tr>
<td>4 batchnorm</td>
<td>112(C) × 1(B) × 6(T)</td>
<td>weights 0.0001 bias 112 × 1</td>
</tr>
<tr>
<td>5 preprocessed</td>
<td>112(C) × 1(B)</td>
<td>-</td>
</tr>
<tr>
<td>6 FC</td>
<td>10752(C) × 1(B)</td>
<td>weights 10752 × 112 bias 10752 × 1</td>
</tr>
<tr>
<td>7 regression</td>
<td>10752(C) × 1(B)</td>
<td>-</td>
</tr>
</tbody>
</table>

Table 2. Layers of the LSTM network

<table>
<thead>
<tr>
<th>Name</th>
<th>Activations</th>
<th>Learnable Properties</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 sequence</td>
<td>448(C) × 1(B) × 1(T)</td>
<td>-</td>
</tr>
<tr>
<td>2 biLSTM</td>
<td>4480(C) × 1(B)</td>
<td>weights 17000 × 4480 bias 17000 × 1</td>
</tr>
<tr>
<td>3 FC</td>
<td>10752(C) × 1(B)</td>
<td>weights 10752 × 1 bias 10752 × 1</td>
</tr>
<tr>
<td>4 regression</td>
<td>10752(C) × 1(B)</td>
<td>-</td>
</tr>
</tbody>
</table>
The graphs in Figure 6 show the training performance of CNN and LSTM networks. The regular shape of the hyperbola and the lack of fluctuations show that the learning process is going in the right direction and give us a strong reason to believe that there is no overfitting.

The vertical axis shows the root mean square error (RMSE) values. The RMSE is calculated according to the formula (1)

The graphs in Figure 7 show the reconstructions obtained from simulation-generated measurements.
where $y_i$ is the reference value of the $i$-th finite element of the reconstruction, $\hat{y}_i$ is the reconstruction value, and $n$ is the total number of the image voxels (tetrahedrons).

**Results**

Figure 7 shows the comparative results of four selected four simulation test cases. The "Pattern" column contains reference images, while the next two columns contain reconstructions obtained using the CNN and LSTM methods, respectively. To increase the objectivity of the assessments, the reconstruction index analysis based on reconstructions obtained using the CNN and LSTM reference images, while the next two columns contain four simulation test cases. The "Pattern" column contains indicators. Networks with simple architecture were used in the results obtained with the use of quantitative (objective) validation methods, so image validation was based on infrared images (see Figure 3).

The conducted comparative experiments have shown that both LSTM and CNN networks can be successfully used to convert measurements into images in EIT in the problem of moisture detection in building walls. Visual (subjective) observation of the images in Figure 7 confirms the results obtained with the use of quantitative (objective) indicators. Networks with simple architecture were used in the research. CNN contained only one convolutional layer, and the LSTM network contained only one biLSTM layer. Despite this, it was quite easy to train effective machine learning-based models. In the future, research will focus on how to choose the best reconstruction techniques by taking into account different criteria and model parameters.

REFERENCES


Table 3. Indicators characterizing the quality of reconstructions for individual methods and observations.

<table>
<thead>
<tr>
<th>Observation</th>
<th>Indicator</th>
<th>Methods</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>CNN</td>
</tr>
<tr>
<td>I</td>
<td>MSE</td>
<td>8.58</td>
</tr>
<tr>
<td></td>
<td>ICC</td>
<td>0.89</td>
</tr>
<tr>
<td>II</td>
<td>MSE</td>
<td>3.33</td>
</tr>
<tr>
<td></td>
<td>ICC</td>
<td>0.87</td>
</tr>
<tr>
<td>III</td>
<td>MSE</td>
<td>6.40</td>
</tr>
<tr>
<td></td>
<td>ICC</td>
<td>0.83</td>
</tr>
<tr>
<td>IV</td>
<td>MSE</td>
<td>13.31</td>
</tr>
<tr>
<td></td>
<td>ICC</td>
<td>0.77</td>
</tr>
</tbody>
</table>

Figure 8 shows an example of an EIT reconstruction based on actual measurements with the use of CNN. Due to the lack of a reference image, the correctness of the reconstruction cannot be verified. To do this, a direct method should be used (e.g., drying-weighing method), which, however, would injure the wall. Indirect point-by-point methods are less accurate (e.g., dielectric or microwave methods), so image validation was based on infrared images (see Figure 3).

**Conclusions**

The conducted comparative experiments have shown that both LSTM and CNN networks can be successfully used to convert measurements into images in EIT in the problem of moisture detection in building walls. Visual (subjective) observation of the images in Figure 7 confirms the results obtained with the use of quantitative (objective) indicators. Networks with simple architecture were used in the research. CNN contained only one convolutional layer, and the LSTM network contained only one biLSTM layer. Despite this, it was quite easy to train effective machine learning-based models. In the future, research will focus on how to choose the best reconstruction techniques by taking into account different criteria and model parameters.