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Verification of Non-Destructive Assessment of Moisture Content of Historical Brick Walls Using Random Forest Algorithm

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Abstract: The paper presents the results of verification of the suitability of the random forest algorithm for the non-invasive assessment of excessively damp and salty historical brick walls. A new method of such quantitative assessment was developed and recently published by the author for the purpose of conducting research in buildings where destructive intervention is not possible due to conservation restrictions. However, before implementing the developed method into construction practice, it requires further validation. The conducted research showed that among all analyzed machine learning algorithms, the random forest algorithm is the most predisposed for the non-invasive evaluation of the U_{mc} mass moisture content of brick walls. Data sets from archival research and experimental tests conducted in two historical buildings were used to verify the usefulness of this algorithm. This usefulness was confirmed by the obtained satisfactory values of the linear correlation coefficient R, which amounted to 0.801 for the first building and 0.803 for the second one. Moreover, it was also proved by the obtained low values of medians of the absolute errors $|\Delta f|$ equal to 1.79% and 1.46%, and also by the not too high (for an in situ study) medians of the relative errors $|RE|$ equal to 16.70% and 13.75%.

Keywords: historical brick walls; mass moisture; non-destructive testing; random forest algorithm

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1. Introduction

Machine learning is currently used to solve various types of engineering problems, especially in the area of materials science. Recently, machine learning techniques have also been increasingly used in relation to historical buildings as they are very useful in applications related to the monitoring of the condition of the structures of these buildings. These techniques are most often used to analyze data from non-destructive testing, data from sensors, or for the analysis of images obtained during the inspection of historical buildings.

For instance, Marni et al. [1], basing on non-destructive testing and the artificial neural networks, developed a mechanical characterization tool which may be used in connection with historic granite walls. Mishra et al. [2,3] applied non-destructive techniques such as the Schmidt hammer test, the ultrasonic pulse velocity method and compressive testing to assess the compressive strength of the brick–mortar masonry of historical constructions using three machine learning techniques. Barontini et al. [4] solved an inverse problem from changes in the elastic mechanical properties of the historical building by employing nature-inspired optimisation algorithms. Wang et al. [5] used mobile deep learning for detecting damage in the masonry of historical buildings. Another attempt to classify the damage of masonry historical structures based on convolutional neural networks and still images was presented by Wang et al. [6]. A systematic review of the various machine learning techniques that are used to assess the state of the preservation of historical buildings was conducted by Mishra [7].

The author's previous experience clearly shows that conducting moisture tests of brick walls in buildings under conservation protection is not an easy task, because interference in the structure of their historical tissue is possible to a very limited extent. This means that the free use of the destructive gravimetric method, which is currently considered to be the most reliable method of assessing the mass moisture content, is not possible [8,9]. At the same time, such a situation forces the use of non-destructive methods, such as the dielectric, microwave [10] or thermal imaging methods [11]. These methods have many limitations and produce less reliable results, which has already been described in the literature (e.g., [9,12,13]). Therefore, for some time, work has been carried out on the possibility of using non-destructive methods in conjunction with artificial intelligence in order to assess the moisture content of brick walls, e.g., the works of Rymarczyk et al. [14]. Their studies concerned a new method of testing moisture using electrical tomography and machine learning methods for the spatial analysis of wall moisture, the correctness and usefulness of which was confirmed by in situ tests. A prototype of the hybrid tomograph that was used in this method was constructed, but according to the authors of the indicated works, it is also necessary to conduct further research in order to create the final version of the device—a compact portable variation.

Likewise, the studies and analyzes carried out to date by the author of this paper have shown that artificial intelligence can be successfully used to reliably assess the moisture content of brick walls [15,16]. This is possible on the basis of several set parameters that are obtained during testing with the use of non-destructive methods in combination with machine learning algorithms. The method of such assessment, which was developed and recently published [16], may be particularly applicable in situations where moisture content tests are carried out on historical buildings. An undoubted advantage of this method is the possibility of obtaining reliable quantitative results with the least possible interference in the wall structure and in a large number of measurement points. It can therefore be expected that this method could be widely accepted by conservation services. Moreover, the test results obtained with this method are much more accurate than those obtained with the use of a single non-destructive method, which is a common practice when examining the moisture content of historical buildings.

Among all the machine learning algorithms analyzed by the author, which included a total of 11 different learning algorithms for artificial neural networks (ANN), the random forest algorithm (RF) and the support vector machine (SVM), the random forest algorithm turned out to be the most predestined for the non-destructive assessment of the moisture content of historical brick walls [16]. However, the mathematical model that is based on this algorithm requires validation on other historical objects. This is necessary before implementing the method of quantitatively assessing the moisture content in historical brick walls for construction practice. The article presents the results of such validation, which is a novelty because such research has not been conducted to date. Another novelty is a new data set, not used in previous research, which was created especially for the purpose of the verification. In order to build the data set, archival and experimental research was carried out on two newly selected historical buildings of different ages.

2. Description of the Model

The operation of random forests (RF) involves conducting of a classification using a group of decision trees. The bagging method is used to create a random forest composed of decision trees—the trees are independent of each other and have the same weight, whereas the result of the classifier is the mode (the most frequent value) of the classes detected by individual trees [17,18].

Each tree is constructed based on a random sample of n observations taken (with replacement) from the training set (bootstrapping). In addition, the attributes (variables) selected in the construction of each tree are also randomly chosen. During the construction of the tree, at each node, the splitting is performed by randomly selecting (without replacement) m out of p attributes ($m \leq p$). Parameter m is most often determined in the following way: $m = \sqrt{p}$, which is suggested in the subject literature [19]. This process is repeated at the subsequent node, and the building of the tree without cutting continues, if possible, until the leaves contain elements from just one class. A given observation vector is classified by all the trees, and it is then finally classified into the class in which it occurred most often.

The advantage of the random decision forest technique is the reduction in variance and the increase in the stability of the classification model. An example of a random forest with a simplified reasoning scheme is shown in Figure 1.

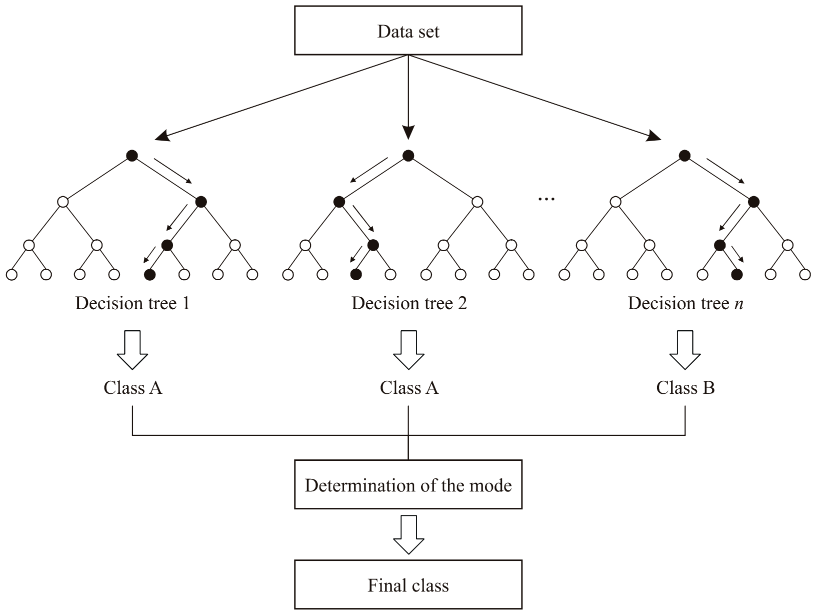

Figure 1. An example of a classification scheme using a random forest, which is built from many different decision trees.

In order to build a model for the non-destructive assessment of the moisture content of historical brick walls on the basis of the random forest algorithm, a data set was created as part of the research, which includes 290 sets of results. Each of the 290 sets of results contains seven numerical values, hereinafter referred to as parameters. This set was published as an appendix to paper [16].

For the purpose of creating the data set, archival and experimental research was carried out in ten historical buildings with walls made of ceramic bricks and lime mortar. These buildings were erected in different historical periods; the oldest is dated to the 1280s, and the youngest to the 1930s. First, in order to determine the Y (-) parameter which represents the year of building construction, for each of the buildings, archival research was carried out based on the analysis of available historical sources and documents. Parameter Y is related to the time of exposure of the walls to moisture and salts, as over time, an increasing volume of pores in the wall is filled with water, which is drawn up by capillary action and hygroscopically absorbed from the air [20,21].

Afterwards, experimental studies were conducted in the laboratory, as well as in situ in 290 measuring points located on brick walls and vaults. Two dimensionless parameters X_D (-) and X_M (-) which indirectly describe the humidity content of the wall were determined by non-destructive dielectric (Gann Hydromette Uni 2 m with an active ball probe) and microwave (Trotec T 600 m) methods. Parameters X_C (%), X_S (%) and X_A (%) which describe the molar concentration of the chloride, sulphate and nitrate salts in the wall were determined by the semi-quantitative method. These salts, which are commonly present in brick walls (penetrate into the structure of a wall along with capillary water from the environment surrounding the buildings), affect the results of tests conducted using the dielectric and microwave methods by overestimating or underestimating the measurement results [22]. Meanwhile, the U_m (%) parameter which describes the actual humidity of the wall was determined by the gravimetric method with the use of a laboratory dryer. The obtained results of the U_m tests fell within wide ranges, from ca. 1% (mass moisture content of a brick wall up to 3% is considered acceptable) up to 26% (in a state of full moisture saturation, the mass moisture content of a brick wall is twenty-odd percent), which proved the representativeness of the data set.

The procedure leading to the construction of the data set is graphically presented in Figure 2. More detailed information on the method of conducting the research can be found in paper [16].

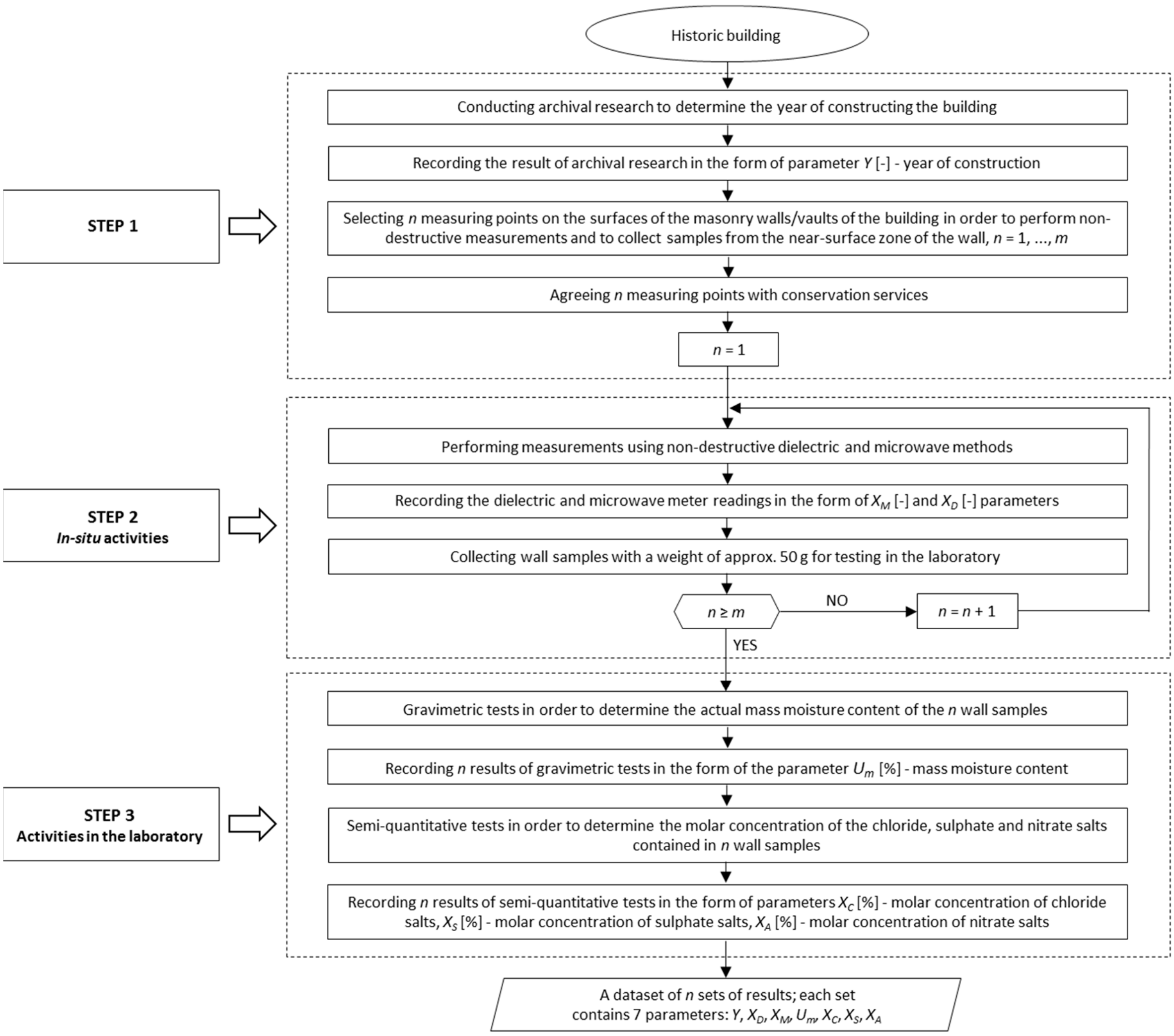

Figure 2. The procedure leading to the construction of the data set.

After eliminating the outliers from the data set, a total of 273 sets were used for the numerical analyses. Parameters Y, X_D, X_M, X_C, X_S, X_A were used as the input variables for learning and testing of the algorithm, and the U_m parameter was used as a model in the learning processes. In turn, the evaluated output variable was the U_{mc} parameter, which described the value of the mass moisture that was generated by the model. The training and testing process was carried out on the basis of a 10-fold cross-validation, which involved the performing of numerical analyzes (for 10 times) in which nine data sets were used in the training process, and one set was used in the testing process. As a result of numerical work, on the basis of the random forest algorithm (with the number of decision trees equal to 500, the number of attributes considered for each split equal to 6 and the smallest subset that can be split equal to 3), a model for the non-destructive assessment of the moisture content of historical brick walls was built. The complete results of the carried out numerical analyzes that were performed with the use of the MATLAB software are presented in [16].

The adjustment of the model to the training data and the accuracy of the mapping were assessed using the coefficient of determination R^2, the root mean square error *RMSE*, the absolute error *MAE*, and the absolute percentage error *MAPE*, which were determined on the basis of the following formulas [23]:

$$R^2 = \frac{\sum_{i=1}^{n}(x_i - x_{mean})^2 - \sum_{i=1}^{n}(x_i - \hat{x}_i)^2}{\sum_{i=1}^{n}(x_i - x_{mean})^2}, \quad (1)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \hat{x}_i)^2}, \quad (2)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|(\hat{x}_i - x_i)|, \quad (3)$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{(x_i - \hat{x}_i)}{x_i}\right| * 100, \quad (4)$$

where x_i is the *i*th real value obtained from the experimental studies, $\hat{x}_i$ is the *i*th value evaluated using the random forest algorithm.

The obtained satisfactory values of these parameters, namely R^2 = 0.968, *RMSE* = 1.080%, *MAE* = 0.791 and *MAPE* = 14.28%, indicate the correct mapping of the verification data by the algorithm. This is also confirmed by the distribution of points on the scatterplot shown in Figure 3, where the relationship between the values of the U_{mc} mass moisture content generated by the algorithm and the actual U_m values obtained experimentally using the gravimetric method is presented.

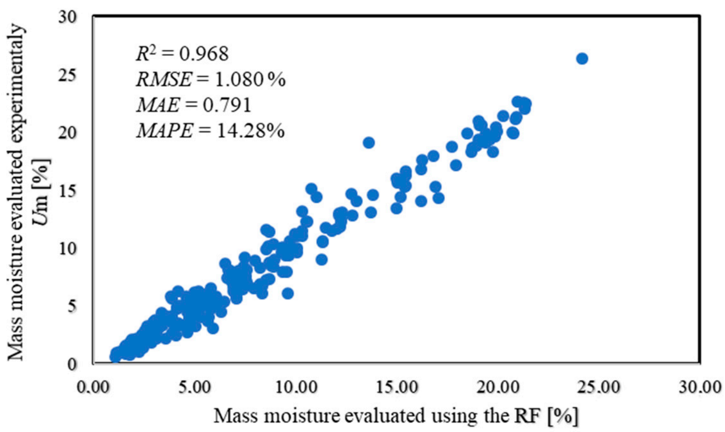

Figure 3. Relationships between the mass moisture content U_m assessed experimentally and the mass moisture content U_{mc} assessed using the random forest algorithm [10].

The usefulness of the RF model is also proved by the value of the *a*20-*index*—an indicator that has been recently suggested for the reliable assessment of the developed soft computing techniques [24–26]:

$$a20 - index = \frac{m20}{M}, \quad (5)$$

where *M* is the number of the data set sample, *m*20 is the number of samples with a value of the "experimental value/predicted value" ratio between 0.80 and 1.20.

For the analyzed model, the value of this index is high and amounts to 0.77 (perfect *a*20-*index* = 1), which means that 77% of the generated U_{mc} values correspond to the U_m values obtained experimentally (with a deviation of ±20%).

3. Data Collected to Verify the Model

In order to carry out the experimental verification of the model, which is based on the random forest algorithm and presented in Section 2, experimental and archival research was carried out (with the methods described in Section 2) on excessively wet and saline brick walls in two historical buildings. They are the Golden Gate in Gdansk (Pomerania, Poland) and a residential and commercial tenement house in Katowice (Silesia, Poland). Brief descriptions of these buildings and the research sites, together with exemplary photographs, are provided below.

Tables 1 and 2 show the data sets that were obtained as a result of the tests conducted in both buildings for the purpose of verifying the RF model. Therefore, 18 sets of results were obtained from the Golden Gate building, and 17 sets were obtained from the tenement house. In accordance with the methodology presented in Section 2, each set includes seven parameters: the dimensionless parameter Y, which describes the year of construction of the building; the two dimensionless parameters X_D and X_M, which were defined non-destructively, and which describe the moisture content of the wall; the three parameters X_C, X_S, and X_A, which describe the percentage of the molar concentration of the chloride, sulphate and nitrate salts in the wall; and also the reference parameter U_m, which describes the actual mass moisture content of the wall (in percent). The obtained results of the U_m fall in the range from 4.97% up to 21.92%, so they can be considered quite representative. Tables 3 and 4 present selected descriptive statistics that characterize the collected data.

Table 1. Data sets collected during the tests carried out in the Golden Gate building for the purpose of verifying the RF model.

Data Set No.	Year of Construction Y (-)	Dielectric Meter Reading X_D (-)	Microwave Meter Reading X_M (-)	Chloride Concentration X_C (%)	Sulfate Concentration X_S (%)	Nitrate Concentration X_A (%)	The Real Humidity of the Wall U_m (%)
1.	1610	133.20	40.70	0.455	0.550	0.500	7.88
2.	1610	157.00	56.80	0.122	0.800	0.010	8.88
3.	1610	124.30	55.80	0.042	0.250	0.010	9.35
4.	1610	140.90	53.20	0.230	0.500	0.500	10.19
5.	1610	161.60	53.40	0.255	0.650	0.050	10.89
6.	1610	167.20	60.00	0.080	0.400	0.010	11.34
7.	1610	117.60	36.70	0.040	0.250	0.000	11.60
8.	1610	138.50	68.10	0.024	0.600	0.050	12.87
9.	1610	151.60	56.00	0.152	0.600	0.400	13.26
10.	1610	170.00	73.20	0.110	0.450	0.100	15.60
11.	1610	144.00	72.40	0.039	0.350	0.025	16.73
12.	1610	134.30	72.50	0.500	0.500	0.300	16.98
13.	1610	134.20	63.60	0.035	0.200	0.350	17.70
14.	1610	132.30	49.00	0.161	0.900	0.150	18.29
15.	1610	161.80	74.40	0.096	0.450	0.100	18.36
16.	1610	168.90	68.00	0.073	0.400	0.025	20.28
17.	1610	150.80	76.50	0.045	0.500	0.050	21.59
18.	1610	160.00	76.60	0.115	0.700	0.000	21.92

Table 2. Summary of the selected descriptive statistics that characterize the data collected during the research conducted in the Golden Gate building—grouped as parameters X_D, X_M, X_C, X_S, X_A and U_m.

Name of the Statistic	Parameter Symbol					
	X_D (-)	X_M (-)	X_A (%)	X_C (%)	X_S (%)	U_m (%)
Arithmetic average $\bar{x}_i$	147.12	61.49	0.143	0.503	0.146	14.65
Maximum value $x_{\max}$	170.00	76.60	0.500	0.900	0.400	21.92
Minimum value $x_{\min}$	117.60	36.70	0.024	0.200	0.000	7.88
Standard deviation S_x	16.06	12.16	0.138	0.187	0.178	4.51

Table 3. Data sets collected during the tests carried out in the tenement house for the purpose of verifying the RF model.

Data Set No.	Year of Construction Y (-)	Dielectric Meter Reading X_D (-)	Microwave Meter Reading X_M (-)	Chloride Concentration X_C (%)	Sulfate Concentration X_S (%)	Nitrate Concentration X_A (%)	The Real Humidity of the Wall U_m (%)
1.	1870	153.1	74.6	0.042	0.500	0.025	13.09
2.	1870	152.6	58.1	0.160	1.600	0.050	12.95
3.	1870	133.2	46.3	0.040	0.200	0.000	4.97
4.	1870	162.2	62.2	0.280	1.600	0.500	10.15
5.	1870	160.70	74.80	0.152	0.700	0.025	10.38
6.	1870	167.00	81.20	0.105	0.400	0.010	9.36
7.	1870	141.90	58.00	0.058	1.600	0.500	6.98
8.	1870	135.60	53.60	0.124	1.600	0.100	5.06
9.	1870	167.30	61.70	0.140	0.450	0.250	6.66
10.	1870	148.40	63.10	0.420	0.650	0.500	6.63
11.	1870	160.90	56.30	0.190	0.600	0.500	8.96
12.	1870	165.60	75.50	0.185	1.600	0.150	16.28
13.	1870	157.00	74.40	0.082	1.600	0.050	14.41
14.	1870	138.60	51.80	0.035	1.600	0.025	8.84
15.	1870	130.20	58.00	0.100	1.600	0.250	9.35
16.	1870	150.20	87.30	0.115	1.600	0.250	11.29
17.	1870	130.80	58.00	0.060	1.600	0.050	11.8

Table 4. Summary of the selected descriptive statistics that characterize the data collected during the research conducted in the tenement house—grouped as parameters X_D, X_M, X_C, X_S, X_A and U_m.

Name of the Statistic	Parameter Symbol					
	X_D (-)	X_M (-)	X_A (%)	X_C (%)	X_S (%)	U_m (%)
Arithmetic average $\bar{x}_i$	150.31	64.41	0.135	1.147	0.190	9.83
Maximum value $x_{\max}$	167.3	87.3	0.42	1.600	0.500	16.28
Minimum value $x_{\min}$	130.2	46.3	0.035	0.200	0.000	4.97
Standard deviation S_x	13.05	11.42	0.098	0.568	0.196	3.22

3.1. Golden Gate in Gdansk, Poland

The Golden Gate was erected in 1612 as a representative gate of the main city of Gdansk, and is now considered one of the most splendid monuments of the Old Town of Gdansk. It was designed by architect Abraham van den Blocke, and represents the Dutch mannerism style. The building has two above-ground stories. There are three passages on the ground floor: the main one, located on the front facade axis, and two side passages. The upper floor is used, and there is a room with an office function. There is an unused basement under the building. The facades of the building have a rich cornice and column arrangement, and are crowned with an attic in the form of a stone balustrade with figural sculptures. During the war, in 1945, the Golden Gate was damaged. It was restored in the years 1957–1962, and in 1967 it was entered into the Registry of Cultural Property of Poland. In 1978, the facade was renovated, and in 1995–1998, conservation and fragmentary reconstruction of the facade took place.

The building is made of ceramic brick, sandstone and granite. The fragments of the walls of the basements and ground floor, which are made of solid ceramic bricks and lime mortar, were subjected to the study (samples were taken from bricks). The measuring points were placed at different heights above the floor level in order to increase the probability of obtaining results within the widest possible range of the moisture content and salinity values. This is due to the fact that usually, the closer to the floor or ground level, the higher the mass moisture U_m of the brick wall due to capillary action. Since the sampling involved interference with the historic tissue of objects under conservation protection, the location of the measuring points was agreed upon with the conservation services.

The view of the eastern facade of the Golden Gate, exemplary views of the basements, and a view of a fragment of the tested brick wall are shown in Figure 4. Table 1 contains 18 sets of data, which were collected during the tests for the purpose of experimental verification of the RF model.

(a) (b) (c) (d)

Figure 4. The Golden Gate in Gdansk: (**a**) eastern facade; (**b**,**c**) exemplary views of the basements; (**d**) a fragment of the brick wall of the basement wall.

Table 2 summarizes the selected descriptive statistics that characterize the data collected during experimental research conducted in the Golden Gate building. The arithmetic average $\bar{x}_i$ and standard deviation S_x were determined, and the minimum x_{min} and maximum x_{max} values are also provided.

3.2. Residential and Commercial Tenement House in Katowice, Poland

A corner residential and commercial tenement house located in the northern frontage of the market square in Katowice was built in 1869 by the builder Abraham Goldstein. The building has three floors aboveground and one underground, and it is covered with a flat roof. The tenement house was partly rebuilt several times, e.g., in 1900, 1911 and 1933. The last renovation, which included works conducted on the facades, took place in 2017. As a result of these works, the building lost its original appearance, especially when it comes to the facade decoration, and is now referred to as a styleless building (it has no decoration that would allow the building to be placed in a specific historical context). The tenement house is listed in the municipal register of monuments of the city of Katowice.

The external and internal walls of the basements, which are made of ceramic bricks and lime mortar, were subjected to the tests (samples were taken from bricks). Same as in the Golden Gate building, the measurement points were placed at different heights above the floor level and the location of the measuring points was agreed upon with the conservation services. The view of the tenement house, an example view of the basements, and a view of a fragment of the tested wall are shown in Figure 5. Table 3 shows 17 sets of data collected during the tests for the purpose of experimental verification of the RF model.

(**a**) (**b**) (**c**)

Figure 5. The tenement house in Katowice: (**a**) picture of the building; (**b**) exemplary view of the basements; (**c**) a fragment of the brick wall of the basement.

Table 4 summarizes the selected descriptive statistics that characterize the data collected during the experimental research that was carried out in the tenement house. The arithmetic average $\bar{x}_i$ and standard deviation S_x were determined, and the minimum x_{min} and maximum x_{max} values are also provided.

4. Results

The results of the experimental verification of the model, which was based on the random forest algorithm, and taught and tested on the database presented in [16], are presented below. The verification was carried out on two independent data sets obtained as a result of testing excessively damp brick walls in two historical buildings, the description of which is provided in Section 3.

The values of the mass moisture content U_{mc} generated by the algorithm were compared with the real U_m values that were obtained experimentally with the use of the gravimetric method, with the relationships between them shown in Figure 6. The obtained results indicate that the random forest algorithm correctly mapped the verification data. This is evidenced by the location of the points along the regression line, which corresponds with the ideal mapping. Moreover, satisfactory values of the linear correlation coefficient R equal to 0.801 for the Golden Gate, and 0.803 for the tenement house, were also obtained.

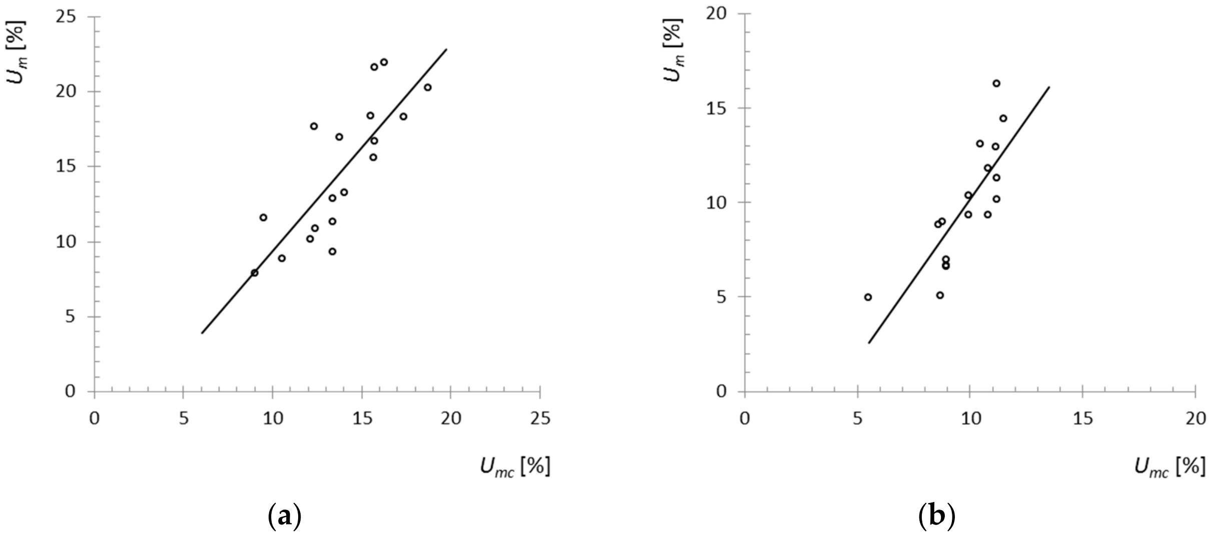

Figure 6. Relationship between the actual mass moisture content U_m gained on the basis of the tests performed using the gravimetric method, and the moisture content U_{mc} identified by the random forest algorithm: (**a**) for the Golden Gate; (**b**) for the tenement house.

Tables 5 and 6 present a comparative summary of the U_m and U_{mc} humidity content values, which were determined with the use of the gravimetric method and the random forest algorithm, respectively. The values are provided for each building separately.

Table 5. The Golden Gate building in Gdansk: U_m and U_{mc} values determined with the use of the gravimetric method and the RF algorithm, respectively, and also the values of the absolute and relative measurement errors.

Data Set No.	The Real Humidity Content U_m (%)	The Humidity Content Determined with the Use of RF U_{mc} (%)	Absolute Error $\lvert \Delta U_m \rvert$ (%)	Relative Error $\lvert RE \rvert$ (%)
1.	7.88	9.03	1.15	14.59
2.	8.88	10.52	1.64	18.47
3.	9.35	13.38	4.03	43.10
4.	10.19	12.13	1.94	19.04
5.	10.89	12.37	1.48	13.59
6.	11.34	13.38	2.04	17.99
7.	11.60	9.50	2.10	18.10
8.	12.87	13.38	0.51	3.96
9.	13.26	14.01	0.75	5.66
10.	15.60	15.68	0.08	0.51
11.	16.73	15.74	0.99	5.92
12.	16.98	13.75	3.23	19.02
13.	17.70	12.32	5.38	30.40
14.	18.29	17.35	0.94	5.14
15.	18.36	15.53	2.83	15.41
16.	20.28	18.75	1.53	7.54
17.	21.59	15.74	5.85	27.10
18.	21.92	16.28	5.64	25.73
Arithmetic average $\bar{x}_i$	14.65	13.82	2.15	16.18
Median *Me*	-	-	1.79	16.70

Table 6. The tenement house in Katowice: U_m and U_{mc} values determined with the use of the gravimetric method and the RF algorithm, respectively, and also the values of the absolute and relative measurement errors.

Data Set No.	The Real Humidity Content U_m (%)	The Humidity Content Determined with the Use of RF U_{mc} (%)	Absolute Error $\lvert\Delta U_m\rvert$ (%)	Relative Error $\lvert RE\rvert$ (%)
1.	13.09	10.45	2.64	20.17
2.	12.95	11.17	1.78	13.75
3.	4.97	5.50	0.53	10.66
4.	10.15	11.20	1.05	10.34
5.	10.38	9.96	0.42	4.05
6.	9.36	9.96	0.60	6.41
7.	6.98	8.93	1.95	27.94
8.	5.06	8.67	3.61	71.34
9.	6.66	8.93	2.27	34.08
10.	6.63	8.93	2.3	34.69
11.	8.96	8.78	0.18	2.01
12.	16.28	11.20	5.08	31.20
13.	14.41	11.50	2.91	20.19
14.	8.84	8.59	0.25	2.83
15.	9.35	10.81	1.46	15.61
16.	11.29	11.20	0.09	0.80
17.	11.8	10.81	0.99	8.39
Arithmetic average $\bar{x}_i$	9.83	9.80	1.65	18.50
Median *Me*	-	-	1.46	13.75

The results of the experimental verification presented in Tables 5 and 6 indicate that there is a correct identification of the validation data. This is evidenced by the fact that low median of the absolute error $\lvert\Delta U_m\rvert$ (amounting to 1.79% for the Golden Gate in Gdansk and 1.46% for the tenement house in Katowice) and not very high (for in situ research) values of the median of the relative error $\lvert RE\rvert$ (amounting to 16.70% and 13.75%, respectively) were obtained. It is also worth to note that the average values of the U_{mc} humidity content, which were identified using the RF algorithm, are close to the average U_m values obtained using the gravimetric method. In the case of the Golden Gate, these values are 13.82% and 14.65%, respectively, and in the case of the tenement house, the values are 9.80% and 9.83%.

Figure 7 shows the histograms of the relative measurement error $\lvert RE\rvert$ determined for the RF-generated U_{mc} values in the case of the Golden Gate (Figure 6a) and the tenement house (Figure 6b). The distribution visible in the graph (a) is rather symmetric and the relative error values $\lvert$RE$\rvert$ are mostly in the range of 15% to 20% with the arithmetic average value of this error equal to 16.18% for the Golden Gate in Gdansk. The distribution visible in the graph (b) is right-skewed, which indicates the presence of outliers. Most $\lvert RE\rvert$ values are therefore concentrated below the arithmetic mean value, and the median value of this error is equal to 13.75% for the tenement house in Katowice.

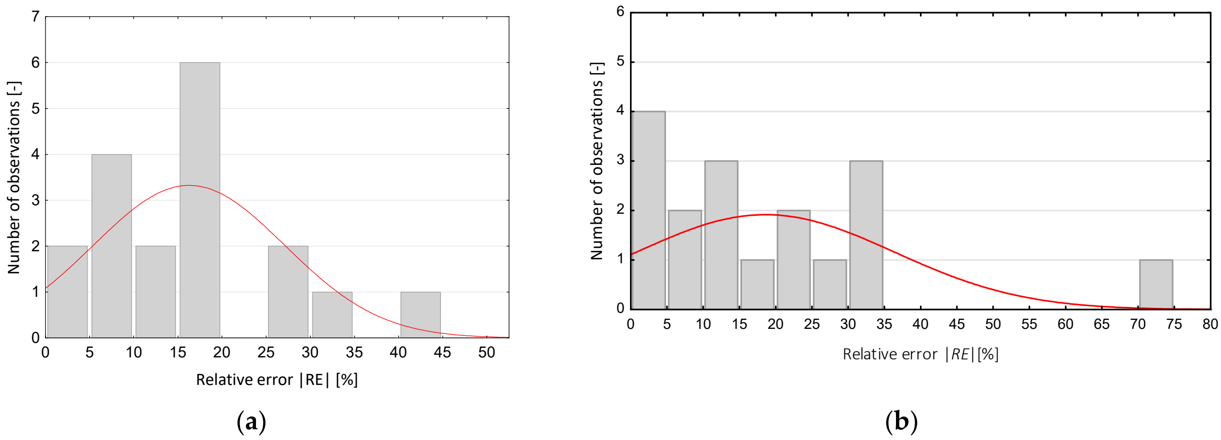

Figure 7. Histograms of the relative error $|RE|$ determined for the RF-generated U_{mc} values in the case of: (**a**) the Golden Gate building in Gdansk, and (**b**) the tenement house in Katowice.

5. Conclusions

The article presents the results of the experimental verification of the mathematical model that is based on the random forest algorithm for quantitatively assessing the moisture content in historical brick walls. Such validation is a novelty because similar research has not been conducted to date. It is, however, necessary before implementing the method to construction practice. The verification was carried out on a newly built data set based on archival and experimental research conducted on two newly selected historical buildings of different ages.

Based on the conducted research and analyzes which aimed to validate the suitability of the model based on the random forest algorithm for the method of the non-destructive quantitative assessment of the humidity content of historical brick walls (developed earlier by the author), the following conclusions can be drawn:

– It is possible to reliably assess the mass moisture content of a historical brick wall using the model based on the random forest algorithm, and also using parameters assessed using the non-invasive dielectric and microwave methods, the semi-quantitative method, and archival research;
– The correct mapping by the RF model of the actual mass moisture content U_m is evidenced by the low values of the median of absolute error $|\Delta U_m|$ amounting to 1.79% for the Golden Gate in Gdansk and 1.46% for the tenement house in Katowice, and the not too high (for in situ tests) median of the relative error $|RE|$ amounting to 16.70% and 13.75% for these buildings, respectively. The height of the error may be the result of the inaccuracy of the data entered into the model. It should be noted that the conditions of conducting in situ tests in historical buildings are often difficult, which is associated with possible inaccuracies in measurements conducted with the use of experimental methods;
– The average values of the humidity content U_{mc} identified with the use of the RF model are close to the average values of the humidity content U_m gained during the research using the gravimetric method.

Further validation works are planned for different historical buildings, and they may result in the implementation of the developed model into construction practice. Based on the obtained results, decisions will be made regarding the possible continuation of work in order to better match the algorithm to the data, e.g., by optimizing the model parameters, or by using other machine learning algorithms such as deep neural networks. At present, it seems that the accuracy of the developed model is sufficient for the needs of the construction industry, and the results of the analyzes obtained to date are satisfactory.

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