Soils and Rocks
An International Journal of Geotechnical and Geoenvironmental Engineering
www.soilsandrocks.com
ISSN 1980-9743
ISSN-e 2675-5475

Estimation of the permeability coefficient of recycled concrete aggregates using machine learning algorithms: AdaBoost and artificial neural networks

Justyna Dzięcioł[1#], Wojciech Sas[1]

Article

Keywords
Permeability coefficient
Machine learning
Recycled concrete aggregate
AdaBoost
Artificial neural network

Abstract

The development of the construction sector in recent decades and the systematic reduction of natural aggregate (NA) resources have obliged the search for alternatives and substitutes for these essential construction materials. Using anthropogenic aggregates as replacements for natural aggregates provides an opportunity to reduce landfills by recycling waste materials from construction and demolition (CDW), for civil engineering applications. It may also involve risks that undoubtedly include estimating geotechnical parameters based on solutions developed to date for natural aggregates. A significant factor affecting these estimates is that anthropogenic aggregates could have different properties and chemical compositions. This study analyzed the possibility of estimating the coefficient of permeability for recycled concrete aggregate (RCA) using machine learning algorithms - AdaBoost and artificial neural networks. The AdaBoost model demonstrated higher accuracy (R^2 was 0.959 for training data and 0.886 for test data), relative to neural networks (R^2 was 0.682 and 0.640). Shapley Additive Explanations (SHAP) analysis, which increased the interpretability of the results, showed that AdaBoost better reflected the influence of hydraulic properties such as gradient or bulk density, while the neural networks were more sensitive to aggregate grain size. The results indicate the effectiveness of machine learning algorithms in evaluating the coefficient of permeability for recycled materials and represent a promising perspective for supporting the design of sustainable construction solutions.

1. Introduction

Sustainability in the construction sector is becoming increasingly crucial as environmental concerns, regulatory policies, and resource limitations drive the industry toward more eco-friendly solutions. The construction sector is one of the largest consumers of natural resources and simultaneously generates significant waste, making the transition to a circular economy essential (Cassiani et al., 2021; Vieira et al., 2016). One key strategy for achieving this transformation is reusing construction materials, particularly recycled concrete aggregates (RCA), which substitute natural aggregates in various engineering applications. The utilization of RCA helps mitigate the environmental impact of construction activities by reducing landfill waste, minimizing the depletion of natural aggregate sources, and lowering transportation emissions (Danish & Mosaberpanah, 2022; Stengel & Kustermann, 2024; Yadav & Kumar, 2024). However, challenges remain in fully integrating RCA into construction applications due to variations in its physical and mechanical properties, including its increased porosity and potential impact on concrete strength (Dash et al., 2023; Hatungimana et al., 2020).

The history of RCA utilization dates back to the post-World War II reconstruction era, when Europe faced a significant shortage of raw materials, prompting the need to repurpose demolition waste (Buck, 1973). Today, the process of producing RCA involves crushing concrete from demolished structures, removing impurities such as rebar, bricks, and soft materials like wood, glass, or polystyrene, and grading the resulting material into fractions ranging from 0 to 63 mm (Oikonomou, 2005). RCA's mechanical and hydraulic properties, including density, moisture content, porosity, water absorption, grain size distribution, and filtration characteristics, determine its suitability for specific applications. The permeability coefficient is significant in road construction and dam engineering, as it influences drainage capacity and the material's ability to control water flow within infrastructure layers (Elhakim, 2016; Sas et al., 2019; Wang et al., 2008).

[#]Corresponding author. E-mail address: justyna_dzieciol@sggw.edu.pl
[1]Warsaw University of Life Sciences, Institute of Civil Engineering, Warsaw, Poland

Submitted on February 7, 2025; Final Acceptance on September 19, 2025; Discussion open until February 28, 2026.
Editor: Renato P. Cunha
https://doi.org/10.28927/SR.2025.002525

Life cycle assessments (LCA) comparing 100% recycled aggregate concrete with conventional concrete indicate that RCA can significantly reduce environmental impact (Stengel & Kustermann, 2024). Studies have shown that incorporating RCA into construction can lower greenhouse gas emissions, reduce the need for raw material extraction, and decrease the amount of construction and demolition waste sent to landfills (Moccia et al., 2022). Nevertheless, despite its environmental benefits, RCA is not yet widely used in structural concrete due to its strength and durability concerns. Increased porosity and residual cement paste on RCA particles can reduce compressive strength, making it necessary to explore methods for enhancing its mechanical performance (Dash et al., 2023). Construction authorities recognize the potential of RCA, and its adoption is encouraged through sustainability-driven policies aimed at reducing construction waste and promoting circular economy initiatives (Nedeljković et al., 2021).

One of the primary challenges in expanding the use of RCA is the lack of effective characterization methods that can accurately predict its mechanical, physical, and filtration properties. Traditional laboratory and field tests for determining the permeability coefficient are expensive and time-consuming, limiting their feasibility for large-scale applications. Machine learning (ML) offers a promising alternative by enabling the prediction of permeability characteristics based on easily measurable physical properties, reducing the reliance on costly experimental procedures (Dzięcioł & Sas, 2023; Mamirov et al., 2022; Nguyen et al., 2024).The potential of ML-based models in sustainable construction extends beyond predictive accuracy. By integrating ML techniques with RCA assessment, engineers and researchers can optimize material selection, improve parameter control and reduce the uncertainty associated with recycled aggregate performance. This approach aligns with the broader shift toward digital transformation in construction, where data-driven methodologies enhance efficiency and sustainability (Albuquerque et al., 2022; Trach et al., 2022). However, further research is needed to refine ML models for RCA characterization, taking into account additional material parameters such as cement paste content, microstructural properties, long-term durability assessments, or specifically the permeability coefficient (Dzięcioł & Sas, 2023; Sua-iam & Makul, 2023; Zhou et al., 2024). Moreover, hybrid ML models that combine multiple algorithms could further enhance prediction robustness and reliability.

This study aims to demonstrate the predictive capabilities of AdaBoost and Neural Network algorithms in estimating the permeability coefficient of RCA. By comparing these two approaches, the research seeks to evaluate their accuracy, generalization ability, and suitability for practical applications in construction. Additionally, SHAP analysis will identify the key features influencing permeability predictions, providing insights into the underlying physical mechanisms governing RCA behavior (Hart, 1989; Zargari Marandi, 2024). The findings of this study contribute to the growing body of knowledge on sustainable material reuse, supporting the integration of ML-driven methods in the circular economy framework for construction.

2. Materials and methods

The recycled concrete aggregate used in the study originated from the demolition of a repaired road surface. A constant head method was applied to test the coefficient of permeability. The grain size range is presented below in Table 1.

Figure 1 presents the results of the coefficient of permeability tests with a compaction energy of 0.59 J/cm^3 and 2.65 J/cm^3. The boxplot illustrates the distribution of permeability values for both energy levels, with a notable decrease in permeability observed at the higher compaction energy. The mean permeability coefficient at 0.59 J/cm^3 is approximately 0.007 m/s, whereas at 2.65 J/cm^3, it is significantly lower, around 0.0041 m/s. Increasing the energy of compaction reduces the permeability of the soil due to the compaction of the soil structure and the reduction of voids.

Table 1. A summary of the material's grain size range.

Description and unit	Minimum	Maximum
Particle size (d_5), [mm]	0.15	0.17
Particle size (d_{10}), [mm]	0.28	0.30
Particle size (d_{17}), [mm]	0.60	0.80
Particle size (d_{20}), [mm]	0.98	1.30
Particle size (d_{30}), [mm]	1.90	2.20
Particle size (d_{50}), [mm]	3.30	3.90
Particle size (d_{60}), [mm]	5.50	7.80
Particle size (d_{90}), [mm]	9.80	12.50

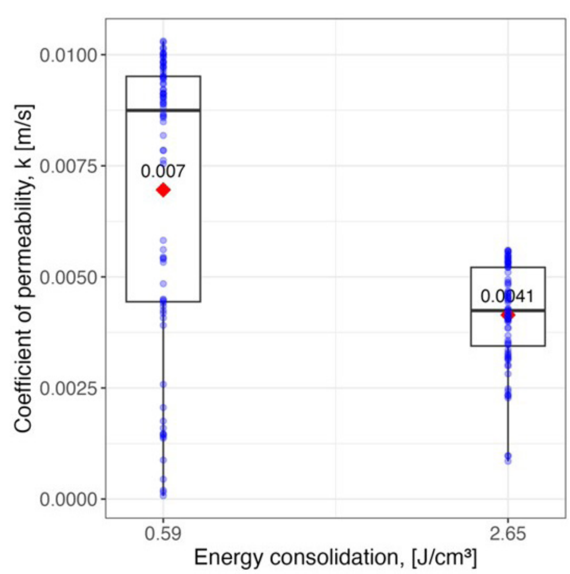

Figure 1. The results of the coefficient of permeability tests.

Figure 2 presents a 3D scatter plot correlating filtration velocity, gradient, and compaction energy. The colour gradient represents variations in filtration velocity, with higher values observed at lower compaction energy levels. The data points show a nonlinear trend, where permeability decreases as the compaction energy increases.

A total of 160 laboratory measurements of the coefficient of permeability were performed, with each observation including the particle size distribution, compaction energy, and hydraulic gradient values. These data formed the basis for training and testing the machine learning models. The input features selected for the model were: the grain size parameters d_5 to d_{90}, compaction energy, volumetric density, porosity, grain size curvature index (C_C), homogeneity index (C_U) and hydraulic gradient. The permeability coefficient was used as the target variable. The choice of features was based on established relationships in soil mechanics, particle size distribution affects pore structure and flow paths, compaction energy influences the density and thus void ratio. In contrast, the hydraulic gradient controls flow behavior in the medium. The dataset was randomly split into a training set (80%) and a test set (20%). To validate the model's robustness, 10-fold cross-validation was applied during the training process. This study implemented two machine learning algorithms to estimate the permeability coefficient of recycled concrete aggregates: Artificial Neural Networks (ANN) and AdaBoost. The Artificial Neural Network (ANN) model was implemented as a feedforward architecture trained using backpropagation. Its structure, including the number of neurons and layers, was optimized through cross-validation. The AdaBoost algorithm, using decision tree stumps as weak learners, underwent hyperparameter tuning with grid search. The results were verified with the use of error analysis, for individual models were estimated:

Root Mean Square Error (RMSE):

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

Mean Squared Residuals (MSR):

$$MSR = \frac{\sum_{i=1}^{n}\left(\widehat{y_i} - y_i\right)^2}{n} \tag{2}$$

Mean Absolute Error (MAE):

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - y_t^P\right| \tag{3}$$

Coefficient of determination (R^2):

$$R^2 = \frac{\sum_{i=1}^{N}\left(\hat{y}_i - \overline{y}\right)^2}{\sum_{i=1}^{N}\left(y_i - \overline{y}\right)^2} \tag{4}$$

To enhance the interpretability of the machine learning models developed in this study, SHAP (Shapley Additive Explanations) analysis was applied. SHAP is a widely adopted explanatory technique for interpreting predictions made by machine learning algorithms. It quantifies the contribution of each input feature to a model's output by assigning importance scores, thereby offering detailed insight into the internal decision-making process of the model (Dzięcioł & Sas, 2024; Hart, 1989). In this context, SHAP enabled the identification of the most influential parameters affecting the predicted permeability coefficient of recycled concrete aggregates (RCA), revealing distinct patterns between the AdaBoost and Neural Network algorithms.

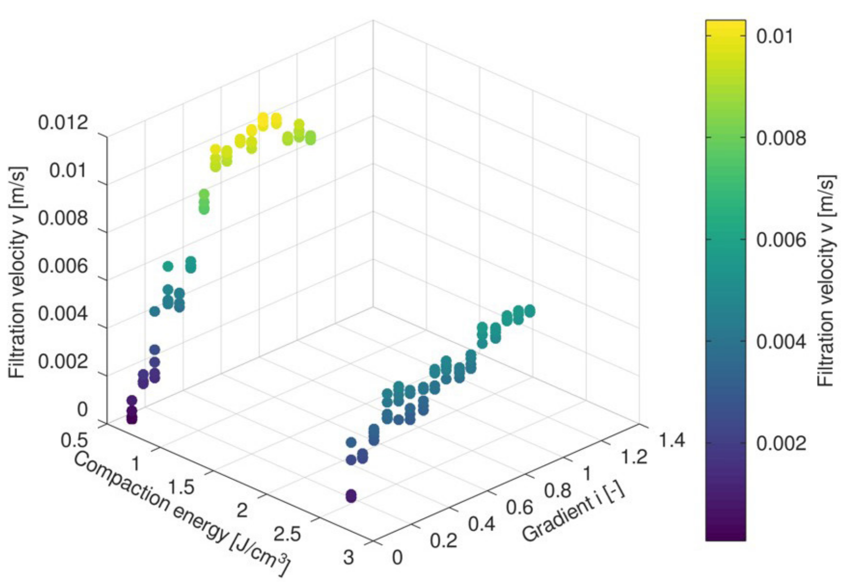

Figure 2. Results of filtration velocity versus gradient and compaction energy tests.

3. Results

Table 2 presents the prediction results of the permeability coefficient for both algorithms. The following physical characteristics of the investigated Recycled Concrete Aggregate (RCA) were used to determine models based on AdaBoost and Neural Network algorithms: grain sizes at selected percentage content, including smaller sizes (d_5, d_{10}, d_{17}, d_{20}, d_{30}, d_{50}, d_{60}, d_{90}), grain size curvature index, homogeneity index, volumetric density, porosity, and compaction energy. In the case of the training sample, better results of fitting to the observation data were obtained for the AdaBoost algorithm, in its case the R^2 was 0.959, for Neural Network the R^2 was 0.682.

In the test sample (Table 3) the R^2 results obtained for the algorithms were lower for AdaBoost the coefficient of determination was 0.886, and for Neural Network it was 0.640.

Figure 3 presents a comparison between the predicted and actual permeability coefficient (k) values obtained using the AdaBoost regression model. The left plot corresponds to the training set, while the right plot represents the test set. The coefficient of determination (R^2) for the training set is 0.959, indicating an excellent fit of the model to the training data. The test set shows a slightly lower R^2 value of 0.886, suggesting that the model generalizes well to unseen data, though with minor deviations. The strong alignment of data points along the regression line in both cases highlights the high accuracy of AdaBoost in predicting the permeability coefficient.

Figure 4 illustrates the performance of a Neural Network model in predicting the coefficient of permeability. Similar to Figure 3, the left plot represents the training set, while the right plot corresponds to the test set. The training set exhibits an R^2 value of 0.682, indicating a moderate fit to the data. However, the test set has an even lower R^2 value of 0.640, reflecting a weaker generalization capability than AdaBoost. The increased spread of data points around the regression line suggests that the Neural Network model struggles to accurately capture the permeability coefficient trends, potentially due to insufficient training data or the complexity of the underlying physical processes.

Table 2. Evaluation of the training set.

Model	RMSE	MSR	MAE	R^2
AdaBoost	0.001	3.04×10^{-7}	3.62×10^{-4}	0.959
Neural Network	0.002	2.39×10^{-6}	1.26×10^{-3}	0.682

Table 3. Evaluation of the test set.

Model	RMSE	MSR	MAE	R^2
AdaBoost	0.001	8.07×10^{-7}	6.34×10^{-4}	0.886
Neural Network	0.002	2.53×10^{-6}	1.30×10^{-3}	0.640

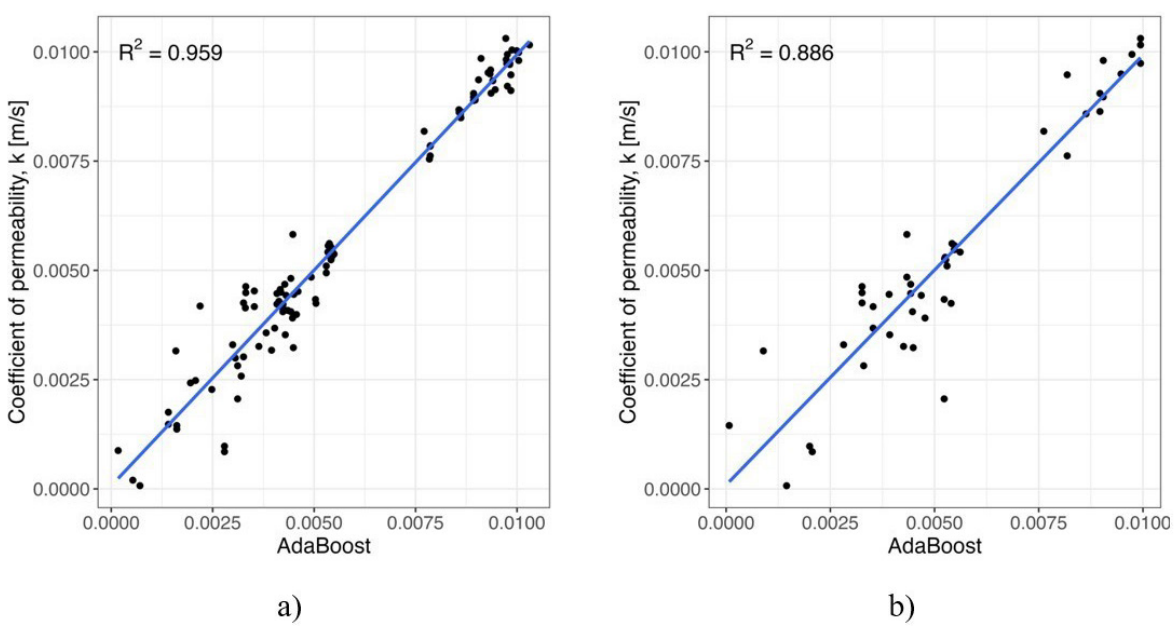

Figure 3. AdaBoost prediction results: (a) training set; (b) test set.

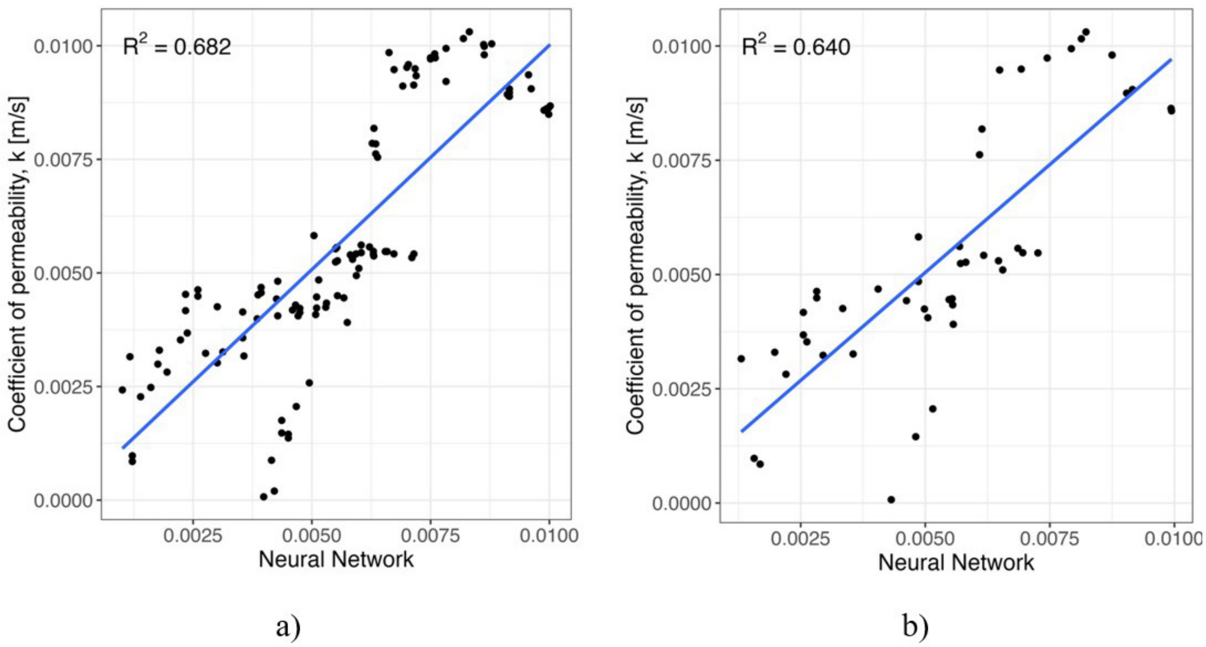

Figure 4. Neural Network prediction results: (a) training set; (b) test set.

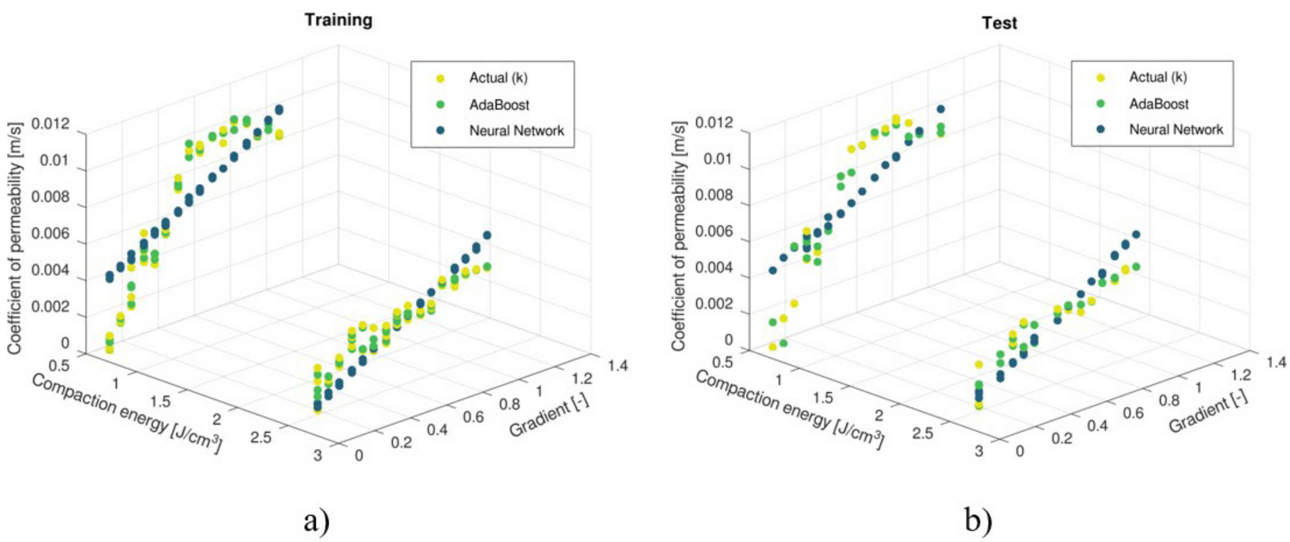

Figure 5. Comparison of actual permeability coefficient (k) values with predictions from AdaBoost and Neural Network models: (a) training set; (b) test set.

The R^2 results for both algorithms translate into a distance of the individual results from the reference line, thus larger residuals' values. Comparing all the graphs, one can notice a greater concentration of results around the reference line in the case of the AdaBoost algorithm, which harmonizes with the obtained high R^2 results and low error results for this algorithm. Figure 5 compares the actual and predicted permeability coefficient values using AdaBoost and Neural Network models for training and test sets. The left plot represents the training set, while the right plot corresponds to the test set. The yellow markers represent actual permeability coefficient values, while the green and blue markers correspond to AdaBoost and Neural Network predictions. In both plots, the AdaBoost model aligns more closely with the actual permeability coefficient values than the Neural Network model, particularly at lower permeability coefficient values. This further confirms the predictive performance of AdaBoost observed in previous analyses.

In the test set (right plot), the Neural Network model shows more deviation from actual values, especially at higher permeability ranges, indicating potential generalization issues. In contrast, the AdaBoost predictions remain consistently aligned with observed permeability coefficient trends, suggesting better adaptability to unseen data.

Figure 6 presents the prediction error distribution for the AdaBoost and Neural Network models in both the training (top) and test (bottom) datasets. The x-axis represents the actual permeability coefficient, while the y-axis shows the prediction error, calculated as the difference between predicted and actual permeability values. In the training dataset (top plot), the AdaBoost model (green points) exhibits a more concentrated distribution of errors around zero, indicating a better fit to the training data. The Neural Network model (blue points) shows more variability, particularly for higher permeability values, suggesting a greater prediction error. Both models show slightly increased error variability in the test dataset (bottom plot), which is expected due to the model's exposure to unseen data. However, the AdaBoost model maintains a lower spread of errors, reinforcing its superior generalization ability compared to the Neural Network. The Neural Network model shows higher prediction deviations for lower and higher permeability values, which may indicate a mismatch or limitation in capturing complex dependencies on the permeability coefficient.

Figure 7 presents the residual error distributions for the AdaBoost and Neural Network models in both the training and test datasets. The residual error represents the difference between the predicted and actual permeability coefficient values. The histograms provide insights into the error distributions and model performance. The top row shows the residuals for the training dataset, with AdaBoost on the left (green) and Neural Network on the right (blue). The bottom row displays the residuals for the test dataset, with the same model assignments. In the training set, the AdaBoost model exhibits a more symmetrical and concentrated residual distribution around zero, indicating a well-fitted model with minimal bias. The Neural Network model, however, has a broader spread and an asymmetric shape, suggesting a higher degree of error. In the test set, the AdaBoost residuals remain relatively centered around zero, though with a slightly broader distribution than the training set, which is expected due to the model's exposure to unseen data. The Neural Network residuals, however, display an even wider spread and more extreme errors, reinforcing the findings from previous figures that this model struggles with generalization.

To assess potential overfitting of the AdaBoost model, which achieved a very high R^2 coefficient, an in-depth statistical analysis was applied. As a result, it was found that the limited decrease in performance on the test set, as well as the concentrated distribution of residuals (Figure 7) and low prediction error (Figure 6), support the conclusion that AdaBoost retains strong generalization ability. Compared to the neural network model, which shows a lower R^2 and wider distribution of residuals on the test set, AdaBoost performs more reliably on unseen data.

Figures 8 and 9 in this study leverage SHAP to evaluate feature importance for permeability coefficient prediction models trained using both machine learning algorithms. SHAP estimates the influence of each feature on model predictions, allowing for a deeper understanding of key factors affecting permeability.

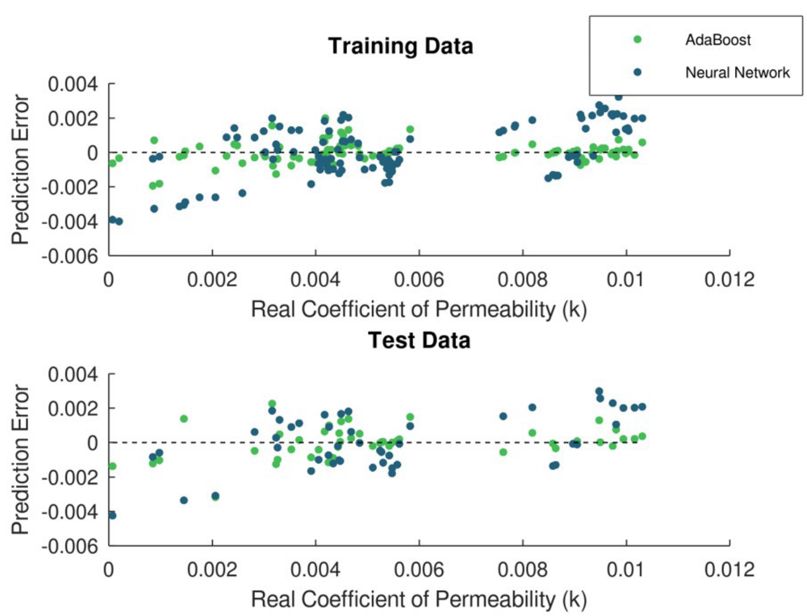

Figure 6. Prediction error comparison for the AdaBoost and Neural Network models in the training dataset (top) and test dataset (bottom).

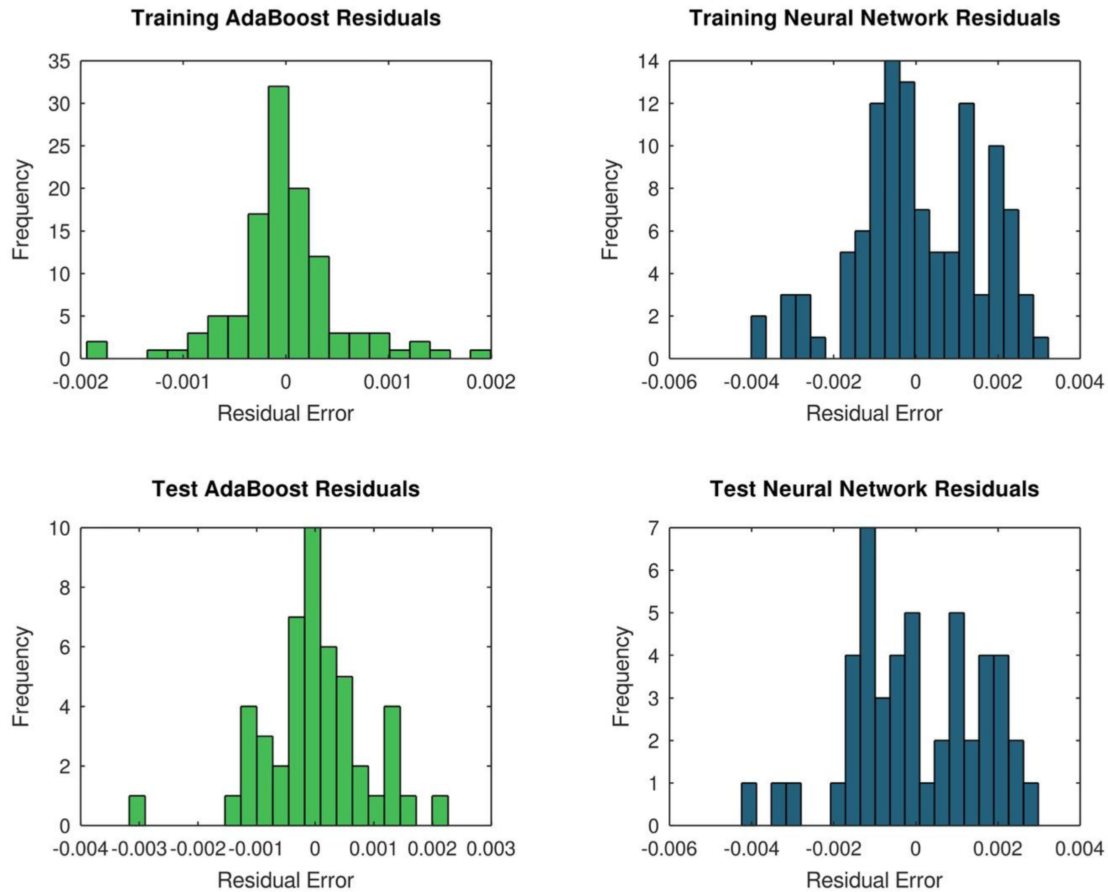

Figure 7. Residual error distributions for AdaBoost (left) and Neural Network (right) models in the training dataset (top) and test dataset (bottom).

Figure 8 presents the SHAP-based feature importance analysis for the AdaBoost regression model. The results indicate that the hydraulic gradient is the most influential feature, exhibiting the highest SHAP value and thus the strongest contribution to the model's predictions. Volumetric density also demonstrates a measurable influence, underscoring the role of compaction in controlling permeability. In contrast, features related to fine-grained particle size distribution (d_{10}, d_{30}, d_{17}, d_5) show limited overall impact. Nevertheless, these features may contribute to subtle variations in model output, affecting the precision of individual predictions.

Figure 9 illustrates the feature importance analysis for the Neural Network model using SHAP values. In contrast to Figure 8, the Neural Network model exhibits a stronger dependence on particle size variables. Features such as d_{20}, d_{50}, and d_5 have the highest SHAP values, indicating their crucial role in permeability predictions. This suggests that the Neural Network model relies more heavily on granular structure than hydraulic properties. Additionally, porosity (n) and particle diameters (d_{60}, d_{90}) contribute to permeability predictions, albeit to a lesser extent. The variance in SHAP values across different particle sizes suggests that the Neural Network model captures complex, nonlinear relationships in the dataset, making it more sensitive to granular properties.

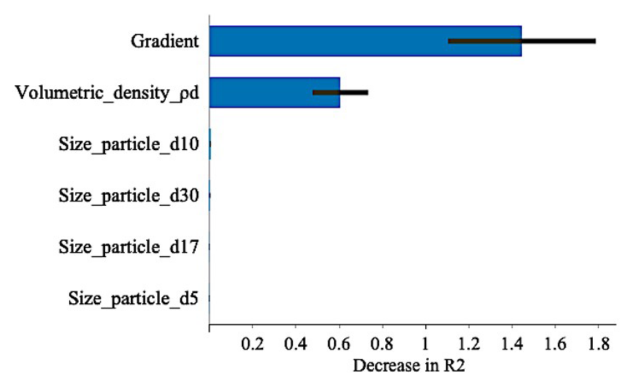

Figure 8. Feature Importance – AdaBoost.

The SHAP-based feature importance analysis revealed notable differences in how each model utilizes input features to predict permeability. In the case of AdaBoost, features related to hydraulic conditions and compaction (e.g., gradient, volumetric density, compaction energy) were dominant, while particle size distribution appeared to have a limited impact. In contrast, the Neural Network model assigned higher importance to granular parameters such as d_{20}, d_{50}, and d_5, which aligns more closely with classical geotechnical understanding of

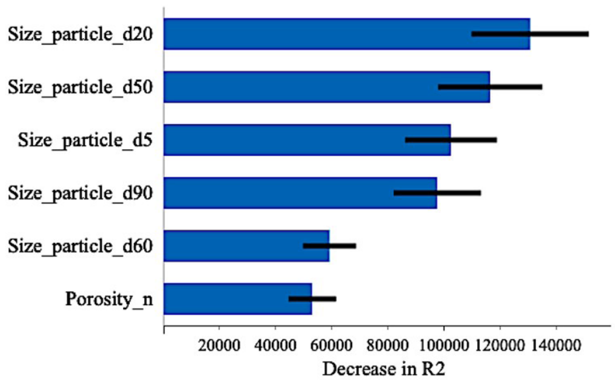

Figure 9. Feature Importance – Neural Network.

how pore structure affects flow. This divergence suggests that while AdaBoost may rely more on global patterns in the data, including strongly expressed relationships with compaction and gradient, the Neural Network model is potentially more sensitive to microstructural variation captured by the grain size distribution. However, despite this capacity to model detailed dependencies, the Neural Network exhibited lower predictive performance compared to AdaBoost. This may be attributed to factors such as limited training data and high input dimensionality, which may impair the model's ability to generalize effectively to unseen data.

4. Conclusions

This study explored sustainable practices in recycling concrete aggregates, focusing on predicting the permeability coefficient for recycled concrete using machine learning techniques. Two regression models, AdaBoost and Neural Networks, were evaluated and compared. Results showed that AdaBoost outperformed the Neural Network model, achieving an R^2 of 0.959 for the training set and 0.886 for the test set, indicating strong generalization capabilities. In contrast, the Neural Network model exhibited lower accuracy, with R^2 values of 0.682 (training) and 0.640 (test), suggesting limited generalization despite its ability to capture complex permeability-related patterns. To improve interpretability, Shapley Additive Explanations (SHAP) were applied, allowing detailed analysis of feature importance. In the AdaBoost model, hydraulic properties such as gradient and volumetric density emerged as key features, highlighting the role of compaction and hydraulic conditions in determining permeability behavior. Conversely, the Neural Network model relied predominantly on particle size variables (d_{20}, d_{50}, d_5), indicating a greater sensitivity to granular structure than hydraulic conditions. The findings confirm that machine learning offers a data-driven approach to predicting the permeability of recycled concrete aggregates, supporting sustainable material design and reuse strategies. By applying SHAP for feature interpretation, the study enhances understanding of the predictive process and improves the interpretability of machine learning models of machine learning models in geotechnical applications. The results suggest that AdaBoost is better suited for permeability prediction in the studied dataset due to its high accuracy and adaptation to hydraulic properties. At the same time, while still useful, neural networks may require further tuning or working with new data ranges to improve generalization.

These insights have significant implications for the sustainable use of recycled concrete aggregates, reinforcing the importance of AI-driven approaches in optimizing material performance. By identifying the dominant predictors of permeability, the study provides a framework for selecting and refining machine learning models in civil engineering applications. Furthermore, the ability to analyze feature contributions through SHAP facilitates model validation and ensures that predictions are consistent with established permeability theories.

The results demonstrate strong predictive performance, particularly for the AdaBoost model. It is important to note that the models were trained on RCA samples with specific origins and characteristics. As such, the generalizability of these models to all recycled concrete aggregates cannot be assumed without additional calibration or retraining using local data. From a design perspective, the observed prediction errors, particularly for AdaBoost, fall within ranges considered acceptable for preliminary geotechnical assessments. These models could therefore support early-stage evaluations, material screening, or comparative studies. However, further validation would be required for critical design applications or regulatory compliance to ensure reliability under varying field conditions and RCA compositions.

While this study demonstrates the potential of machine learning in permeability prediction, future research should further explore additional factors such as chemical composition or temperature effects to refine predictive models. Optimizing Neural Network architectures and exploring hybrid machine learning approaches could enhance accuracy and generalization. Validating these models in real-world construction scenarios would further strengthen their applicability in sustainable infrastructure projects.

In conclusion, this study highlights the effectiveness of machine learning in sustainable materials engineering, providing a scientifically sound methodology for optimizing recycled concrete applications. By improving the accuracy of permeability prediction, these insights contribute to developing sustainable construction practices, reducing environmental impacts and promoting the principles of a circular economy in the construction industry.

Declaration of interest

The authors have no conflicts of interest to declare. All co-authors have observed and affirmed the contents of the paper and there is no financial interest to report.

Authors' contributions

Justyna Dzięcioł: conceptualization, data curation, visualization, writing – original draft, methodology, supervision, validation, writing – review & editing. Wojciech Sas: supervision.

Data availability

Datasets generated and analyzed in the current study can be made available upon inquiry to the corresponding author.

Declaration of use of generative artificial intelligence

This work was prepared without the help of generative artificial intelligence (GenAI).

List of symbols and abbreviations

i	Index of observation in the dataset
n	Total number of observations in the dataset
y_i	Actual observed value of the permeability coefficient
$\widehat{y_i}$	Predicted value of the permeability coefficient
$\overline{y}$	Mean value of the actual permeability coefficient
N	Total number of samples considered for evaluation

References

Albuquerque, E., Borges, L., Cavalcante, A., & Machado, S. (2022). Prediction of soil water retention curve based on physical characterization parameters using machine learning. *Soils and Rocks*, 45(3), 1-13. http://doi.org/10.28927/SR.2022.000222.

Buck, A.D. (1973). *Recycled concrete* (Highway Research Record, No. 430, pp. 1-8). Retrieved in February 7, 2025, from https://onlinepubs.trb.org/Onlinepubs/hrr/1973/430/430-001.pdf

Cassiani, J., Martinez-Arguelles, G., Peñabaena-Niebles, R., Keßler, S., & Dugarte, M. (2021). Sustainable concrete formulations to mitigate Alkali-Silica reaction in recycled concrete aggregates (RCA) for concrete infrastructure. *Construction & Building Materials*, 307, 124919. http://doi.org/10.1016/j.conbuildmat.2021.124919.

Danish, A., & Mosaberpanah, M.A. (2022). A review on recycled concrete aggregates (RCA) characteristics to promote RCA utilization in developing sustainable recycled aggregate concrete (RAC). *European Journal of Environmental and Civil Engineering*, 26(13), 6505-6539. http://doi.org/10.1080/19648189.2021.1946721.

Dash, B., Giri, J.P., & Raju, P.M. (2023). Assessing strength and durability: a performance evaluation of jute fiber-reinforced recycled aggregate concrete. *International Journal of Environmental Sciences*, 9(2), 102-112.

Dzięcioł, J., & Sas, W. (2023). Perspective on the application of machine learning algorithms for flow parameter estimation in recycled concrete aggregate. *Materials*, 16(4), 1500. http://doi.org/10.3390/ma16041500.

Dzięcioł, J., & Sas, W. (2024). Estimation of the coefficient of permeability as an example of the application of the Random Forest algorithm in Civil Engineering. *Archives of Civil Engineering*, 70(2), 119-134. http://doi.org/10.24425/ace.2024.149854.

Elhakim, A.F. (2016). Estimation of soil permeability. *Alexandria Engineering Journal*, 55(3), 2631-2638. http://doi.org/10.1016/j.aej.2016.07.034.

Hart, S. (1989). Shapley value. In J. Eatwell, M. Milgate & P. Newman (Eds.), *Game theory* (pp. 210-216). London: Palgrave Macmillan. http://doi.org/10.1007/978-1-349-20181-5_25.

Hatungimana, D., Yazıcı, Ş., & Mardani-Aghabaglou, A. (2020). EFfect of recycled concrete aggregate quality on properties of concretE. *Journal of Green Building*, 15(2), 57-69. http://doi.org/10.3992/1943-4618.15.2.57.

Mamirov, M., Hu, J., & Cavalline, T. (2022). Geometrical, physical, mechanical, and compositional characterization of recycled concrete aggregates. *Journal of Cleaner Production*, 339, 130754. http://doi.org/10.1016/j.jclepro.2022.130754.

Moccia, I., Farina, I., Salzano, C., Ruggiero, M., Petrillo, A., Colangelo, F., & Cioffi, R. (2022). Environmental assessment of concretes containing construction and demolition waste. *Key Engineering Materials*, 913, 131-135. http://doi.org/10.4028/p-5bebj7.

Nedeljković, M., Visser, J., Šavija, B., Valcke, S., & Schlangen, E. (2021). Use of fine recycled concrete aggregates in concrete: a critical review. *Journal of Building Engineering*, 38, 102196. http://doi.org/10.1016/j.jobe.2021.102196.

Nguyen, X.H., Phan, Q.M., Nguyen, N.T., & Tran, V.Q. (2024). Interpretable machine learning model for evaluating mechanical properties of concrete made with recycled concrete aggregate. *Structural Concrete*, 25(4), 2890-2914. http://doi.org/10.1002/suco.202300614.

Oikonomou, N.D. (2005). Recycled concrete aggregates. *Cement and Concrete Composites*, 27(2), 315-318. http://doi.org/10.1016/j.cemconcomp.2004.02.020.

Sas, W., Dzięcioł, J., & Głuchowski, A. (2019). Estimation of recycled concrete aggregate's water permeability coefficient as earth construction material with the application of an analytical method. *Materials*, 12(18), 2920. PMid:31509937. http://doi.org/10.3390/ma12182920.

Stengel, T., & Kustermann, A. (2024). Life cycle assessment of concrete made of 100% recycled aggregate compared to normal concrete. *Beton- und Stahlbetonbau*, 119(10), 712-721. http://doi.org/10.1002/best.202400043.

Sua-iam, G., & Makul, N. (2023). Potential future direction of the sustainable production of precast concrete with recycled concrete aggregate: a critical review. *Engineered Science*, 28, 1075. http://doi.org/10.30919/es1075.

Trach, R., Moshynskyi, V., Chernyshev, D., Borysyuk, O., Trach, Y., Striletskyi, P., & Tyvoniuk, V. (2022). Modeling the quantitative assessment of the condition of bridge components made of reinforced concrete using ANN. *Sustainability*, 14(23), 15779. http://doi.org/10.3390/su142315779.

Vieira, D.R., Calmon, J.L., & Coelho, F.Z. (2016). Life cycle assessment (LCA) applied to the manufacturing of common and ecological concrete: a review. *Construction & Building Materials*, 124, 656-666. http://doi.org/10.1016/j.conbuildmat.2016.07.125.

Wang, S., Tang, Z., Ning, X., Wu, P., & Xing, P. (2008). Permeability testing of drilling core sample from pavement. *Frontiers of Architecture and Civil Engineering in China*, 2(4), 391-394. http://doi.org/10.1007/s11709-008-0045-3.

Yadav, N., & Kumar, R. (2024). Performance and economic analysis of the utilization of construction and demolition waste as recycled concrete aggregates. *International Journal of Engineering*, 37(3), 460-467. http://doi.org/10.5829/IJE.2024.37.03C.02.

Zargari Marandi, R. (2024). ExplaineR: an R package to explain machine learning models. *Bioinformatics Advances*, 4(1), vbae049. PMid:38577543. http://doi.org/10.1093/bioadv/vbae049.

Zhou, X., Zhou, J., & Ohl, J.P. (2024). Improved prediction accuracy for compressive strength of recycled aggregate concrete using optimization-based algorithms and cascade forward neural network. *Journal of Environmental Management*, 371, 123068. PMid:39476676. http://doi.org/10.1016/j.jenvman.2024.123068.