Concrete Decisions: How XAI is Paving the Way for Future Construction Materials

Fiorella Cravero, PhD[1], Gustavo E. Vazquez, PhD[2] Ignacio Ponzoni, PhD[3], y Mónica F. Díaz, PhD[4]
[1,3]Instituto de Ciencias e Ingeniería de la Computación (ICIC), Universidad Nacional del Sur (UNS) - Consejo Nacional de Investigaciones Científicas y Técnicas (CONICET), Bahía Blanca, Argentina, *fiorella.cravero@cs.uns.edu.ar*
[1,2]Departamento de Informática, Universidad Católica del Uruguay (UCU), Montevideo, Uruguay, *gustavo.vazquez@ucu.edu.uy*
[3]Departamento de Ciencias e Ingeniería de la Computación - (DCIC-UNS) - CONICET, Argentina, *ip@cs.uns.edu.ar*
[4]Planta Piloto de Ingeniería Química (PLAPIQUI UNS-CONICET), and Departamento de Ingeniería Química (DIQ-UNS), *mdiaz@plapiqui.edu.ar*

Abstract– For approximately twenty-five years, machine learning methods have been used to develop predictive models applied to construction materials. Concrete in particular is widely studied as it is the core of this industry, seeking to improve its properties to comply with both safety standards and market demands for more competitive products. There are major challenges in this area, one is the need for reliable data for the correct training of models, and other is understanding the choices made by computational methodologies to achieve such accurate models. To increase confidence in these useful tools, for example, when deciding to change a formulation and estimate its mechanical profile, it is necessary to evaluate the behavior of the model. For this, explainable artificial intelligence methodologies are beginning to be used. In this paper we present problems and advances in the area, hoping to contribute to the decision-making of construction engineers.

Keywords– Construction industry, concrete, mechanical properties, machine learning, explainable artificial intelligence.

I. Introduction

Although the materials used in the construction industry are innumerable, concrete is and will continue to be a fundamental pillar for the execution of architectural and infrastructure projects [1]. Because of this, there is a large number of scientific studies focused on understanding the mechanical behavior of these materials and their possible applications. However, trial and error and empirical formulas have not been totally effective in developing new formulations of cementitious/mortar products, new combinations of materials, nor new geometries of the support pieces [2-5]. Predicting mechanical properties is essential in these cases, but the complex relationship between the variables involved exceeds the predictive capacity of linear empirical formulas. For this reason, the use of computer tools that have the ability to find non-linear relationships has become increasingly popular, although they require a large amount of reliable data and a clear design to achieve the objective [6].

Many artificial intelligence (AI) and machine learning (ML) methods, particularly modern deep learning algorithms, lack inherent explainability. This has led to skepticism in materials research, where experts criticize their reliability and scientific value [7]. The construction industry, traditionally conservative and reliant on established methodologies, has also been hesitant to adopt ML due to the difficulty of interpreting model predictions [8].

Despite achieving strong predictive performance in material property estimation and design optimization, ML models are often seen as black boxes, raising concerns about safety and reliability. However, this perspective is shifting with the integration of Explainable Artificial Intelligence (XAI) [9]. The adoption of AI in material design faced similar mistrust initially, but increasing regulatory demands and the need for transparency are driving the adoption of XAI in construction materials research.

While not all professionals actively implement interpretability techniques, there is a growing acknowledgment of their importance. XAI is increasingly seen as a key factor in ensuring AI models can be trusted and their decisions understood, particularly in safety-critical fields. As noted in [10], although XAI has received limited attention in the construction sector, its significance is expanding across various industries.

Moreover, broader discussions on AI interpretability emphasize that accuracy alone is not sufficient. It is crucial for humans to comprehend the decision-making process of ML models, reinforcing the necessity of XAI for practical deployment. This perspective aligns with the increasing emphasis on responsible AI development, where interpretability is not merely a technical challenge but an ethical and regulatory imperative [11].

Nowadays, the advantages of using XAI are widely recognized [2, 7, 9]. By improving interpretability, XAI helps engineers, materials scientists, and other professionals gain trust in AI-driven decisions, facilitating broader acceptance in the industry [9]. This growing awareness is particularly relevant in fields like construction, where safety, compliance, and accountability are critical. Although XAI adoption is still evolving, the expanding discourse on AI transparency is pushing industries toward greater integration of interpretability techniques, aligning both scientific and practical standards.

While this article is not intended to be a review, it analyses selected works on construction materials such as concrete and related reinforced structures, which have been published in recent years and which show how XAI methodologies have been adopted, highlighting the barriers that still persist and the advances that are being promoted. For the selection of the studies, Mendeley browser (https://www.mendeley.com/) was used to perform a systematic search with keywords such as XAI and construction materials, among others that these authors consider encompass the concepts to be studied such as interpretable and concrete. This analysis provides an understanding of the current state of XAI adoption in the industry and provides insight into future opportunities for interdisciplinary teams in the area.

II. Artificial Intelligence

As a field based on mathematics and computer science, AI is dedicated to developing systems capable of replicating abilities attributed to human intelligence. In recent decades, AI has advanced significantly, driving innovations across multiple industrial and scientific sectors [6] excelling in pattern recognition, problem-solving, understanding natural language, perception and decision-making.

To achieve these advancements, AI employs various modeling paradigms, with ML being one of the most widely adopted approaches. ML enables the construction of models capable of detecting patterns and establishing relationships from data without explicit programming or prior knowledge of these relationships or phenomena. When experimental data is available, predictive models can be developed to anticipate the properties of new materials, thereby facilitating their optimization and application across various industries. Moreover, this capability allows for the exploration of new material designs through in silico simulations, reducing the need for physical testing and accelerating the innovation process. Additionally, safety is enhanced, as these models can anticipate potential material failures, helping to prevent structural defects and ensuring better performance in practical applications. These advancements have been made possible through the continuous development of new predictive models, increased computational power, and the ability to store digitally large volumes of data.

One of the most important features of ML is its ability to develop predictive models using only a set of examples with their associated target properties; then, a ML algorithm will try to find the best formulation for the predictive model. As previously mentioned, this process occurs even without knowing the actual relationships governing the phenomena. Special care is taken to avoid overfitting of these training examples, reserving a separate set of validation examples for model evaluation on unseen data. Although this ensures a numerical validation by measuring the difference between actual and predicted values, a subtle question arises: what is the underlying explanation for why the model predicts a particular value? This is very important to validate the model in terms of its interpretability, ensuring that its predictions are not only accurate but also auditable. Even more, explainability could show if the model aligns with ethics and compliance. So, ML models offer a wide range of methods, starting, for example, with linear regression. In this case, this model is perfectly explainable because coefficients show the contribution of each variable to the target value. However, these methods are limited to explaining only linear relationships within the data.

On the other hand, modeling approaches such as ensembles or deep neural networks [12] can handle complex non-linear relationships but at the cost of producing black-box prediction models, meaning that no clear explanation exists for each prediction. In recent years, there is an effort to develop new explainability methods, even for black-box models, creating a new discipline named explainable artificial intelligence. Fig. 1 illustrates a standard ML pipeline (left) and an XAI-ML workflow (right). In the standard ML pipeline, a model is trained on data and target predictions are generated. In contrast, the XAI-ML workflow not only provides predictions but also incorporates explanations, improving the interpretability and reliability of the model's outputs.

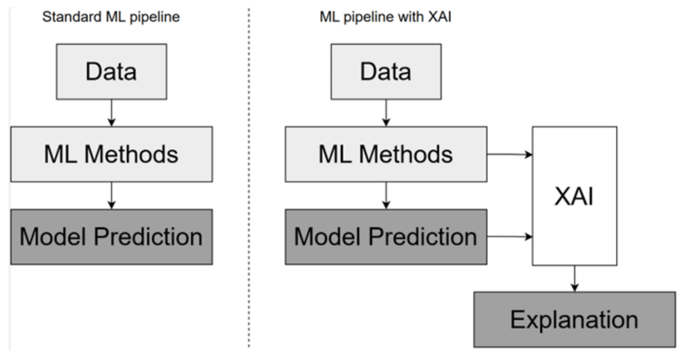

Fig. 1 In the standard ML pipeline (left), data is processed using an ML method, generating predictions without explicit explanation. In the XAI-assisted workflow (right) predictions are improved by showing explanation data, thus enhancing transparency and understanding of the decision-making process. (Own elaboration)

III. XAI Applied to Construction Materials

A. *Construction Materials*

Among the most important tasks of a construction engineer is the correct choice of materials, and in particular of concrete and its varieties. Depending on the type of structure, it is common to find special needs regarding the mechanical profile of the materials, with compressive strength being one of the most useful properties for decision-making, as well as tensile and flexural strength, among others. These properties are obtained in universal testing machines such as the one shown in Fig. 2, using appropriate test specimens. The objective is to characterize the performance of both the different materials involved in the structure and the different geometries (Fig. 3). It is intuitive to think of the enormous time consumption that would be needed to test multiple combinations of these variables, and from here arises the need to estimate the mechanical profile using ML. Therefore, with all the data obtained experimentally, that is, the mechanical properties associated with the different formulations of concrete mixtures, different reinforcement materials, and different geometries, the databases are created with which the predictive models are trained. In this regard, for approximately twenty-five years [3], predictive models with neural networks and other ML methods have been developed to predict mechanical properties.

Particularly, today, there is great interest in improving the understanding of these ML models with explainability methodologies [2]. Some of the most studied materials and structures in this emerging area are listed in Table I, indicating the XAI method applied. Although there is a wide variety of cementitious materials studied, in general we can find in the literature those related to concrete and its varieties, especially those where the formulation contains many ingredients. An example is high-performance concrete [3], which outperforms conventional concrete since its formulation contains superplasticizer, silica fume, and fly ash aggregates, among others, which significantly improve its properties. In addition, we can cite other cases such as composite concretes, for example, mixed with graphene [13], aerogel [14], and iron ore tailings [15], and mortars with textile fiber aggregates [4].

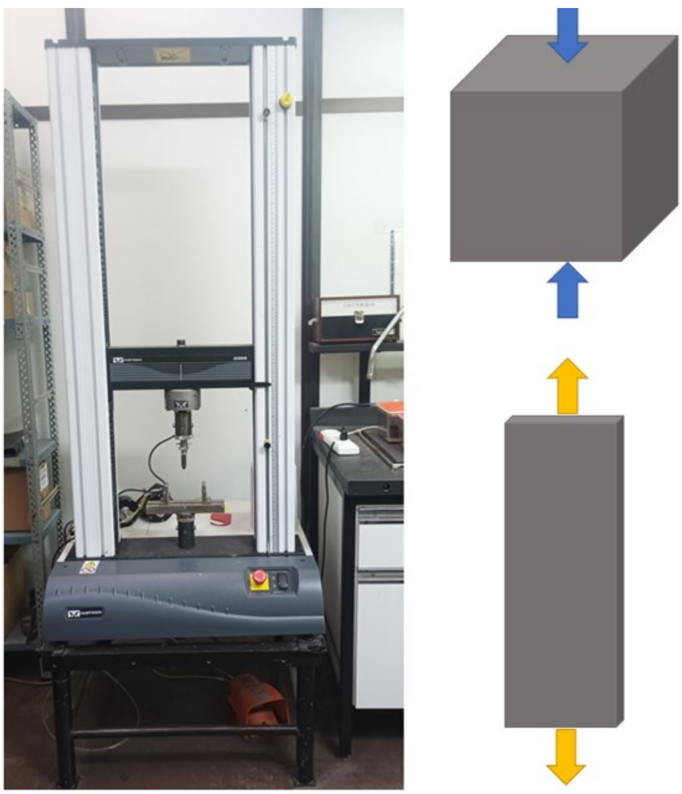

Fig. 2 Left: Photo of a universal testing machine (INSTRON 3369), prepared to flexural testing as an example. Right: Schematics of the forces involved in compression (blue arrows) and tensile (orange arrows) tests. The data obtained from these mechanical tests serves as input for the ML models. (Own elaboration)

Among the most studied structures are reinforced concrete beams and columns, and the focus is on mechanical properties such as compressive strength. In the case of reinforced concrete beams, they can be reinforced with steel bars [16], polymer bars/sheets [2, 17, 18], and fiberglass [19, 20]. In the case of columns, there are those constructed of concrete [5], steel filled with concrete [21, 22], and fiberglass reinforced concrete columns [19]. Sometimes the interest is focused on studying the bond between the components of a structure such as profiled steel–concrete [5].

Other works study the punching shear strength, for example, of FRP reinforced concrete slabs [23] and also reinforced concrete with FRP bars [24]. In addition, case studies of sprayed concrete linings [25], auxetic cementitious cellular composites [26], and cement rammed earth [27] were found.

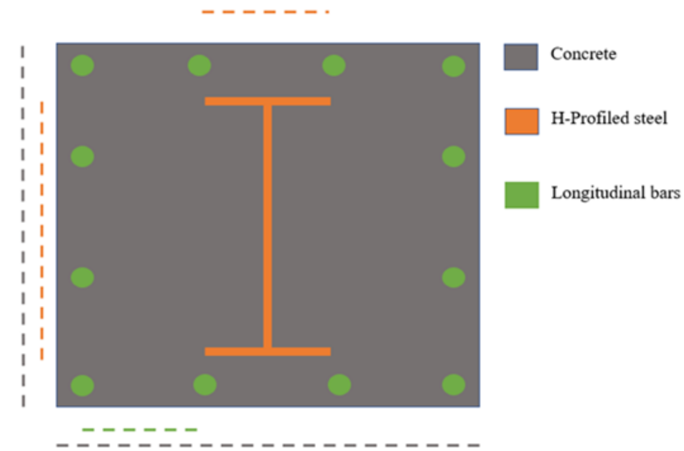

Fig. 3 Schematic example of a reinforced concrete column with an H-profiled steel showing some of the dimensions (dashed line) that must be considered as variables within the geometry item in predictive modeling. (Own elaboration)

TABLE I
PAPERS THAT WORK ON MODELING PROPERTIES OF CONSTRUCTION MATERIALS APPLYING XAI METHODOLOGIES.

[Ref]	Authors (year)	Material	XAI method
[2]	M.Z. Naser (2021)	Reinforced concrete beams strengthened with fiber-reinforced polymer (FRP) composite laminates	SHAP; Perturbation-based
[3]	D. Chakraborty, I. Awolusi and L. Gutierrez (2021)	High-performance concrete	SHAP
[4]	Y. Song, K. Kim, S. Park, S.K. Park, and J. Park (2023)	Textile-reinforced mortar	SHAP
[5]	S.Zhang, J. Xu, T. Lai, Y. Yu, and W. Xiong (2023)	Profiled steel-concrete in steel reinforced concrete composite structures	SHAP
[13]	J.Yang, B. Zeng, Z. Ni, Y. Fan, Z. Hang, Y. Wang, C. Feng, and J. Yang (2023)	Graphene oxide/cement composites	Perturbation-based
[14]	F. Han, Y. Lv, Y. Liu, X. Zhang, W. Yu, C. Cheng, and W. Yang (2023)	Aerogel-incorporated concrete	SHAP
[15]	Z. Cheng, Y. Yang, H. Zhang (2022)	Cementitious materials supplemented with iron ore tailings	SHAP
[16]	T.G. Wakjira, M. Ibrahim, U. Ebead, and M.S. Alam (2022)	Reinforced concrete beams strengthened with fabric	SHAP

		reinforced cementitious matrix composites	
[17]	S.Y. Zhang, S.Z. Chen, X. Jiang, and W.A. Han (2022)	FRP strengthened reinforced concrete beams	SHAP
[18]	C. Cakiroglu, K. Islam, G. Bekda, S. Kim. and Z.W. Geem (2022)	FRP reinforced concrete columns	SHAP
[19]	A.S. Bakouregui, H.M. Mohamed, A. Yahia, and B. Benmokrane (2021)	FRP reinforced concrete columns	SHAP
[20]	T.G. Wakjira, A. Al-Hamrani, U. Ebead, and W. Alnahhal (2022)	FRP reinforced concrete beams	SHAP
[21]	X. Zhao, J. Chen, and B. Wu (2022)	Concrete-filled steel tubular columns	SHAP
[22]	C. Cakiroglu, K. Islam, G. Bekdas¸ U. Isikdag, and S. Mangalathu (2022)	Concrete-filled steel tubular columns	SHAP
[23]	Y. Shen, J.Sun and S.Liang (2022)	FRP reinforced concrete slabs	SHAP
[24]	P. Pan, R. Li, and Y. Zhang (2023)	Reinforced concrete interior flat slabs with steel and FRP reinforcements	SHAP
[25]	X. Yin, F. Gao, J.X. Huang, Y. Pan, and Q. Liu (2022)	Sprayed concrete lining	Perturbati on-based
[26]	G.A. Lyngdoh, N.K. Kelter, S. Doner; N.M. Anoop Krishnan, and S. Das (2022)	Cementitious cellular composites	SHAP
[27]	H. Anysz, Ł. Brzozowski, W. Kretowicz, and P. Narloch (2020)	Cement-stabilized rammed earth	Perturbati on-based
[30]	N. Uddin, N. Shanmugasundaram, S. Praveenkumar, and L.Z. Li (2023)	Engineered cementitious composite	SHAP

A very clear example of the application of XAI methodologies can be found in the work of Anysz et al. [27], who studied the influence of different components of cement-stabilized rammed earth (CSRE) on the compressive strength. CSRE is a sustainable construction material, which allows to save the cost of a structure, since the soil used for the rammed mix is generally excavated close to the construction site. Furthermore, for ecological reasons, there is a tendency to limit the addition of cement. The components of the mix are: clay, silt, sand, gravel, cement and water content, and it is crucial to know which ones determine to a greater extent an optimal compressive strength. Based on 434 samples, and using different machine learning tools to predict compressive strength, and then XAI methods to assess which variables are most influential, they found that the order of impact on the mix is given by: A - cement and water (considered together), B - clay and silt (also considered together), C - sand and D - gravel. This means that the higher the cement content, the higher the compressive strength, which contributes to the decisions made by builders. In this case, the use of XAI enabled robust, high-performance models while preserving interpretability, allowing the exploration of nonlinear relationships and interactions that white-box models could not capture without sacrificing validity or clarity.

B. *XAI and its Role in Construction Materials*

The integration of XAI in the construction industry helps overcome barriers to AI adoption in critical processes like material design. Traditionally, the industry has relied on established methodologies and has been skeptical of new technologies due to risk concerns. XAI addresses this by enhancing the transparency of AI/ML models, enabling engineers to understand model reasoning and verify predictions. This transparency is essential in safety-critical applications, fostering trust and facilitating the validation of results.

Beyond interpretability, XAI aids engineers in optimizing designs and improving system performance. By highlighting key features and their relationships with material properties, it provides deeper insights into model behavior. Additionally, XAI helps detect spurious correlations, ensuring that predictions align with fundamental physical principles rather than artifacts in the data, an essential step in identifying potential model biases or anomalies [2, 9].

As we described in the previous sections, the use of XAI techniques in problems related to the use of AI in the construction industry is still in its infancy. In this sense, although in recent years a wide variety of different XAI approaches were proposed in the literature, only very few methods have been applied in this application field. So much so that all works compiled in the previous section exclusively use techniques belonging to the feature attribution XAI branch. In this family of methods, the contribution of each feature (input variable) of a model to the predictions of a given instance (sample) is weighted by numerical values known as attribution scores. These values are proportional to the contribution of the feature to the predicted value, and can be computed in different ways depending on the XAI method used.

One of the most popular techniques within Feature Attribution approaches is the Shapley Additive Explanations, more commonly known as SHAP [28]. This is based on Shapley values [29], which use game theory to assign the importance of each feature (input variable) of a model in the predictions it generates for a given instance (input sample). SHAP method decomposes the output of a model by the sum of the impact of each feature and calculates a value that represents the contribution of each feature to the model output. These values can be used to understand the importance of each input variable as a methodology for explaining the output of the model to a person. SHAP is the XAI method predominantly used by the publications surveyed in the previous section, being used in 17 of the 20 works cited [2-5, 14-24, 26, 30].

Another type of feature attribution method that is also used in the construction industry is the perturbation-based ones [31]. These approaches work by systematically perturbing parts of the input features, by altering their values, and observing the effect generated in the output of the model. In this way, the importance of each feature is weighted based on how its alteration impacts the prediction obtained by the model. If a feature is strongly altered and this does not modify the output of the model, we can conclude that it is unimportant for generating the prediction. On the other hand, if the perturbation in the value of a feature, even if it is a small variation, modifies the result of the model, we will know that this input variable is an important feature for the prediction. This type of explanation strategy is used in four papers [2, 13, 25, 27].

From a critical analysis of the solutions explored in all these works, we can conclude that the efforts of experts in AI applied to the construction industry focused on building explanations centered on determining the importance of each input variable in the predictions obtained by AI models, without considering other types of approaches used in cheminformatics [32, 33]. In this regard, while understanding the relevance of each input feature is undoubtedly valuable to comprehend how a model decides an output value, this type of approach becomes limited when the input variables do not have clearly established semantics, as happens for example when input variables extracted from chemical data through AI are used by the predictive model, as is the case with molecular embeddings [34]. For this reason, we believe that there is still a long way to go in the use of XAI methods for AI models trained for application in the construction industry. In this sense, other approaches such as those based on graph topologies [35] can provide different and even complementary explanations to those provided by feature attribution techniques [33].

C. Explainability in Practice: An Example of XAI Visualization

Visualization tools play a key role in presenting and understanding the results of an explainability method. As XAI becomes increasingly important in ML projects, the need to communicate the results to expert and non-technical audiences is crucial. To illustrate this, we consider the case of the Shapley Values method and the tools it provides. We will analyze a simple example on predicting concrete compressive strength [36], not as a full case study, but to showcase the type of plots produced by the method. This analysis is conducted using open-source tools (Python standard shap library), lowering adoption barriers for new practitioners and making XAI more accessible to both researchers and industry professionals.

For example, Fig. 4 shows a beeswarm SHAP plot generated by the authors using publicly available data from [36] and tools from the SHAP library (GitHub repository: [https://shorturl.at/KiHsw]), that provides a graphical way for global explanation of the feature contributions in a trained ML model. On the y-axis, features are ordered according to their contribution, with more influential features appearing higher in the list. As expected, the number of days the cement has been left to set and harden (Age) is the most important feature, followed by the amount of cement used in the concrete mix (Cement) and amount of water added to the mix (Water).

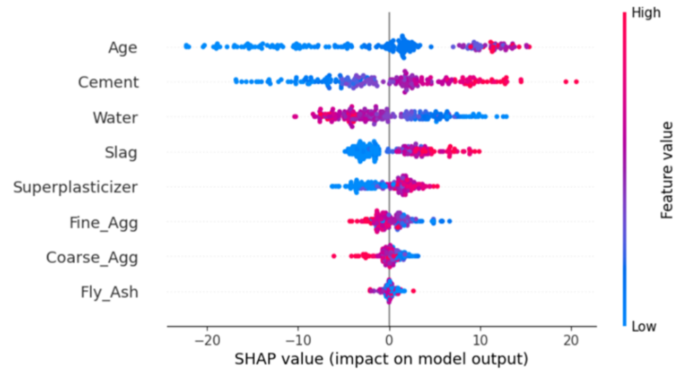

Fig. 4 A beeswarm SHAP figure that provides global interpretation of the feature contributions. (Own elaboration: see https://shorturl.at/KiHsw)

The x-axis represents the SHAP values, which measure the impact of each feature on the model's output. Positive SHAP values indicate that the feature increases the predicted numerical output, while negative values decrease it. Each dot in the plot represents a single instance from the dataset and the color indicates the feature value. For example, high values (red) of Age impact on higher cement compressive strength prediction. The horizontal position of the points indicates the variability in its effect across different instances.

Another kind of plot that illustrates how individual features contribute to a specific model prediction is waterfall, as shown in Fig. 5, also made by the authors (GitHub repository: [https://shorturl.at/KiHsw]).

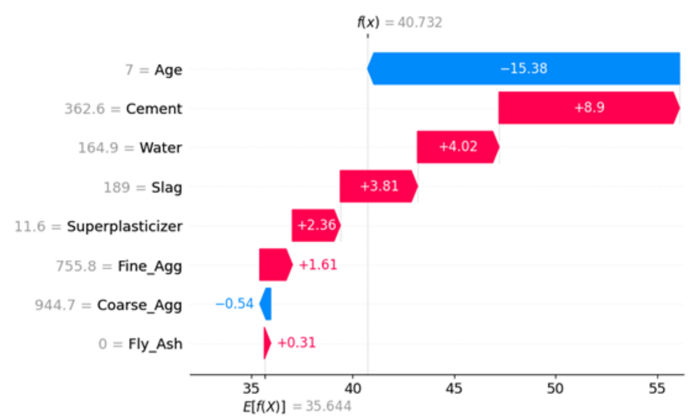

Fig. 5 A waterfall SHAP figure that provides local interpretation of the feature contributions for a specific prediction. (Own elaboration: see https://shorturl.at/KiHsw)

As it was mentioned in the last section, SHAP expresses a model's output as the sum of each feature's impact, assigning a value to represent its contribution. Following this idea, each feature increases (red and positive values) or decreases (blue and negative) the prediction, with the most important ones listed at the top, in a similar way to the previous figure. In this case, the feature Age significantly lowers the target prediction, i.e., as the number of days the cement has been left to set and harden increases, the compressive strength of the concrete is reduced. Meanwhile, Cement, Water, Slag and Superplasticizer (in a decreasing order) contribute positively. This is a simple example on how SHAP helps research and development teams to identify most important features and how their variations influence ML decisions. It provides a valuable way to verify if a model aligns with the domain knowledge and the expected feature importance. Also, this could uncover unexpected dependencies and genuine patterns when there is no prior knowledge about the problem, offering opportunities for new hypothesis generation.

IV. CONCLUSIONS

In this work we have focused on briefly presenting how the decisions of construction engineers can be assisted by predictive models that estimate the mechanical property profile of construction materials such as concrete and its derivatives. To do this, it is necessary to increase confidence and understanding of the decisions made by predictive models. In this sense, this paper presents an example of how visualization tools help to better understand the contribution of the XAI models.

The adoption of XAI methodologies in the construction industry presents a key opportunity to overcome traditional barriers that have hindered the integration of advanced technologies in material design and optimization. XAI is a relatively new field, and there is a need for user-friendly tools and libraries that incorporate domain knowledge from materials science, ultimately enabling informed decision-making based on solid evidence. While challenges remain, the potential of XAI in this field is significant, and it is necessary for working groups to be interdisciplinary, so that decisions on both model design and evaluation are shared between experts in engineering science and computer science.

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