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ON THE PREMISE OF A NEW THEORY FOR FIRE-INDUCED SPALLING OF CONCRETE THROUGH EXPLAINABLE ARTIFICIAL INTELLIGENCE

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ABSTRACT

This paper presents preliminary results to describe the fire-induced spalling of concrete using explainable artificial intelligence (XAI). One thousand fire tests were collected from the literature consisting of twenty-two different mechanical, environmental, material, and geometrical parameters, creating the largest spalling database (up to date). This database was used to build, analyze, and verify an XAI model to identify the critical parameters influencing concrete spalling. This preliminary analysis is articulated around the top 5 factors influencing spalling and consists of two exogenous factors (maximum exposure temperature and heating rate) and three endogenous factors (compressive strength of concrete, degree of moisture content, and the amount of polypropylene fibre). The presented analysis showcases the linkage between these factors and quantifies them so that engineers can design a concrete mix that mitigates spalling.

Keywords: Concrete; Fire-induced spalling; Explainable AI; Fire test.

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1 INTRODUCTION

Concrete is one of the most widely used materials in the construction industry. During its service lifetime, concrete structures experience various extreme events that can cause damage to the structure. One such event is fire. Fire can adversely affect the integrity of concrete structures and may result in spalling-related damage, which is the breakage or separation of concrete chunks from the bulk of a structural member. Spalling can suddenly occur when the outside surface of the concrete members experiences a relatively high heating temperature (beyond 300^{o}C) [1].
The ramification of spalling varies, from forming a concrete matrix micro-crack to anticipating significant decreases in the compressive strength of concrete associated with temperature gradients. Such catastrophic events can harm the structure, and the structural members will suffer from a gradual reduction of the concrete capacity [2]. Such an event could trigger a structure to collapse. The degradation of compressive strength has been attributed to a combination of the decomposition of the hydrated pastes, deterioration of the aggregates, and the thermal incompatibilities between paste and aggregate, leading to stress concentrations and microcracking [2–6].

To further elaborate on the above, the moisture content of concrete is another critical factor that could influence concrete spalling, especially when present at above 2–3% of moisture content by weight of concrete [1, 7–9]. Polypropylene fibres have become an efficient solution for reducing the spalling risk of concrete due to fire exposure. Concrete with certain amounts of polypropylene fibre (PPF) and subjected to extreme heating conditions were observed to be free from thermal spalling [1, 10–12] with some exceptions[1]. Alternatively, the heating rate and maximum exposure temperature are considered exogenous critical factors and directly influence concrete spalling[4, 5, 13–16]. The contribution to spalling doesn't end here; many more parameters influence spalling, and the non-linearity nor the monotonic relation of spalling is escalating the complexity of understanding the concrete spalling phenomena.

To date, no consensus has been reached on fire-induced concrete spalling mechanisms [2]. Given the high nonlinearity of the spalling phenomenon, explainable artificial intelligence (XAI) could be perceived as an opportunity to explore the notion of a new theory [17–19]. This research work creates a model that accurately predicts and explains the fire-induced spalling of concrete – which is then can be thought of as the foundation for a possible theory on spalling [15].

2 DATABASE

The database contains more than 1000 test samples collected from the open literature. Twenty-two independent variables are known to be most acceptable for influencing fire-induced spalling in concrete. One dependent variable describes the occurrence of spalling by two labels: no spalling or spalling. The 22 independent variables are: 1) Water/binder ratio, 2) Aggregate type, 3) Aggregate/binder ratio, 4) Sand/binder ratio, 5) Heating rate, 6) Moisture content, 7) Maximum exposure temperature, 8) Silica fume/binder ratio, 9) Max aggregate size, 10) GGBS/binder ratio, 11) Fly ash/binder ratio, 12) Polypropylene fibre quantity, 13) Polypropylene fibre diameter, 14) Polypropylene fibre length, 15) Steel fibre quantity, 16) Steel fibre diameter, 17) Steel fibre length, 18) Shape, 19) Length, 20) Width, 21) Height, 22) Compressive strength. Table 1 shows the results of statistical analysis on this collected database.

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Table 1. Summary of statistical insights for the parameters of the database

Parameter	Min	Max	Median	Mean	Standard deviation	Skew
Water/binder ratio (%)	0.13	0.63	0.30	0.31	0.13	0.78
Aggregate/binder ratio (%)	0.00	5.10	1.66	1.42	1.16	0.34
Sand/binder ratio (%)	0.48	3.41	1.20	1.37	0.51	1.40
Heating rate (C/min)	0.10	200.00	10.00	26.02	35.70	1.93
Moisture content (%)	0.000	0.089	0.035	0.035	0.019	-0.311
Maximum exposure temperature	75	1200	600	578	228	0
Silica fume/binder ratio (%)	0.00	0.23	0.00	0.06	0.08	0.82
Max aggregate size (mm)	0.50	32.00	13.00	10.60	7.84	-0.03
GGBS/binder ratio (%)	0.00	0.48	0.00	0.04	0.12	2.92
FA/binder ratio (%)	0.00	0.40	0.00	0.02	0.07	3.60
Compressive strength (MPa)	20	214	84	91	40	1
PP fibre quantity (Kg/m^3)	0.00	16.00	0.00	1.09	2.60	3.91
PP fibre diameter (μm)	0.00	150.00	0.00	10.84	21.19	3.49
S fibre length (mm)	0.00	60.00	0.00	5.02	10.74	3.04
S fibre quantity (Kg/m^3)	0.00	180.00	0.00	18.92	37.68	2.32
S fibre diameter(mm)	0.00	90.00	0.00	1.10	9.51	9.26
PP fibre length (mm)	0.00	30.00	0.00	3.18	5.64	2.00
Length (mm)	28.0	3600.0	100.0	198.2	401.5	6.3
Height (mm)	0.0	3360.0	150.0	203.8	348.0	7.3
Width (mm)	0.0	1200.0	50.0	91.2	162.1	3.5

3 METHODOLOGY

This section describes the methodology used to explore the spalling phenomena and establishes a holistic understanding of the main factors of fire-induced spalling by building, training, and validating an XAI model. This model is then augmented by the explainability methods to identify the key parameters influencing fire-induced spalling to find patterns in our spalling database and quantify them. Figure 1 illustrates a flowchart to detail the process boundaries of this analysis. A multi-step process starts with collecting the database and ends with identifying and quantifying fire-induced spalling influencing parameters.

In the first step, the database is collected and pre-processed to be used as input for the model, which is created to predict spalling. The next stage starts by splitting the data into two sets; the larger set will be used for training purposes, while the testing set will be used to evaluate the model's predictions of spalling. In the subsequent stage, the model will be assessed based on different evaluation metrics to establish its validity. Poor evaluation will lead to repeating the process to the training stage, at which we will need to evaluate the data processing. However, a good evaluation will take the model to its final stage, at which the explainability tools and methods are applied, and the top five parameters are identified and quantified.

3.1 XAI model

In this work, an XAI model was built using Extreme Gradient Boosting (XGBoost) as a decision-tree-based algorithm that uses a gradient boosting framework [20, 21]. It is known as one of the fastest implementations compared to the gradient boosting family, focusing on enhancing the model performance and processing rapid numerical and mathematical computations. XGBoost was used herein to establish a limestone of this preliminary analysis based on building a binary classification predictive model.

The first step in creating a prediction model starts by fitting the algorithm to the training set. In our model, the probability of spalling in the trained dataset is initially predicted to be 50%, regardless of the spalling dataset's default parameters. After which, the residuals (i.e., observations subtracted from the predictions) are calculated. At this point, the model's output has been accurately predicted and validated. However, at this stage, it is considered a 'black-box' model.

AI models are uninterpretable by themselves, which is why they are called 'black-box' models; they are directly created from big 'data,' and users are unable to understand or explain the approaches that the models are proposing as a solution. Still, advanced techniques and explainability methods have been introduced to the computer science domain. These techniques (i.e., XAI) allow us to explain our models and understand the model's outcomes both visually and graphically. With the help of explainability tools and frameworks, engineers can interpret and deliver a transparent model. To investigate our model's behaviour, we are adopting the feature importance plot, summary plot, and partial dependence plot, which will be discussed accordingly.

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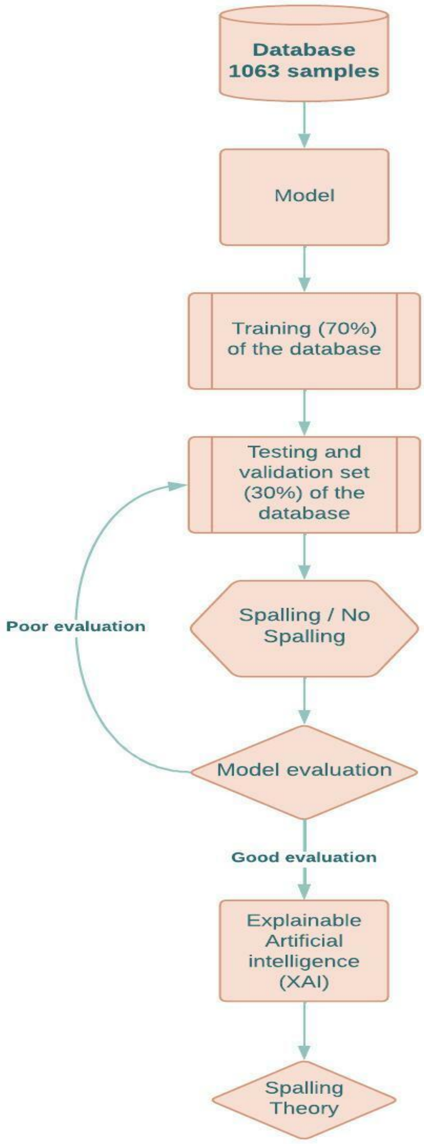

Figure 1. Flowchart for the model process

First, the feature importance plot is the plot where the parameters are ordered in descending order based on how high the impact is on the prediction [22]. Despite its advantages, the major cons related to this figure is that it does not provide information regarding the direction of impact. To overcome this con, the summary plot was put forward with the leverage to combine feature importance and their direct and indirect impact on the model's output [22]. Such an advanced plot explains how the model reached its prediction. However, the summary plot was unable to quantify them. This is where the partial dependence plot (PDP) comes in handy. Finally, the partial dependence plot works by producing a relationship between the parameter's value and its corresponding prediction. At each value of the parameter, the model is evaluated for all observations of the other model inputs, and the output is then averaged. Thus, the relationship they depict is only valid if the parameter of interest does not have a strong correlation with the other parameters.

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3.2 XAI model technical details

The developed algorithm was trained and validated over the 1000 specimens mentioned in the previous section. The dataset was split into two sets; the large set contains 70% of the database and is used to train and cross-validate the model, while the smaller set consists of 30% of the database and is used to test and evaluate the trained model. Then, a k-fold cross-validation approach is used to further refine the training process and to prevent the model's overfitting.

In addition, confusion matrices are also used. Confusion matrices measure the quality of the model's predicted values compared to the original values to produce a 2D matrix (Fig. 2) and visualize the model's performance. The most accurate model with the highest accuracy should have a high number of samples in the diagonal line from the top left to the lower right. Similarly, the diagonal line from the lower left to the higher right should have the lowest number of samples.

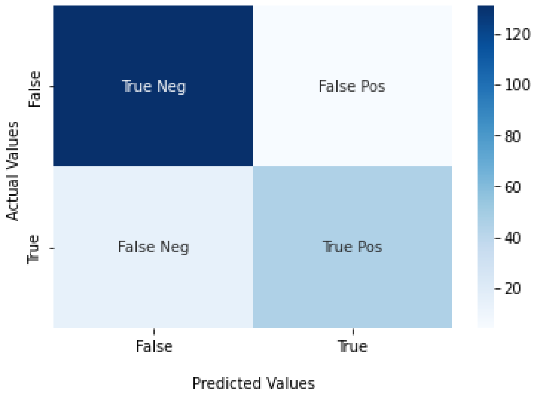

Figure 2. Confusion matrix

Similar to the model that was developed and recently published by the authors with an accuracy of 92% [15], this model consisted of almost identical tuning parameters and was tweaked with the following settings: 1. Objective: binary: logistic, which specifies the learning task and the corresponding learning objective. 2. Seed = 52, used for generating reproducible results and parameter tuning. 3. Learning rate = 0.3, which makes the model more robust by shrinking the weights on each step. 4. Max depth = 4, the maximum depth of a tree, which is used to control over-fitting, as higher depth will allow the model to learn definite relations to a particular sample.

The following settings were used for the data fitting stage: 1. Verbose = True, when the verbose parameter is set to 'True', then the evaluation metric on the validation set is printed at each boosting stage. 2. Early stopping rounds=50 is a technique used to stop training when the loss on the validation dataset starts to increase. 3. Eval metric='AUCpr'. The evaluation metric is to be used for validation data. Which is the Area under the curve in our model. Lastly, the following settings were used in the k-folds validation stage: The number of splits = 10 represents the equal portions of the split datasets. Random state = 7; it shuffles the data before splitting it to avoid the model's overfitting.

4 RESULTS AND DISCUSSION

After examining 22 different parameters, we are focusing our discussion on the top 5 influential parameters that govern concrete spalling thru XAI. Further analysis is ongoing to analyze the resulting parameters.

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4.1 Model validation

The model's performance is the key to proving the model's power to predict spalling, and the proposed model prediction accuracy was 92%. Figure 3 demonstrates the confusion matrix for both testing and training datasets. As one can see, both training and testing sets performed well in the confusion matrix evaluation method. The diagonal line, which showcases the true labels in the training set, presents 518 (no spalling) and 215 (spalling), while the model mispredicted only ten samples. Similarly, on the testing dataset, the diagonal line which shows the true labels shows 208 (no spalling) and 86 (spalling), both of which are predicted correctly, in contrast to only 25 samples that have been miss-predicted.

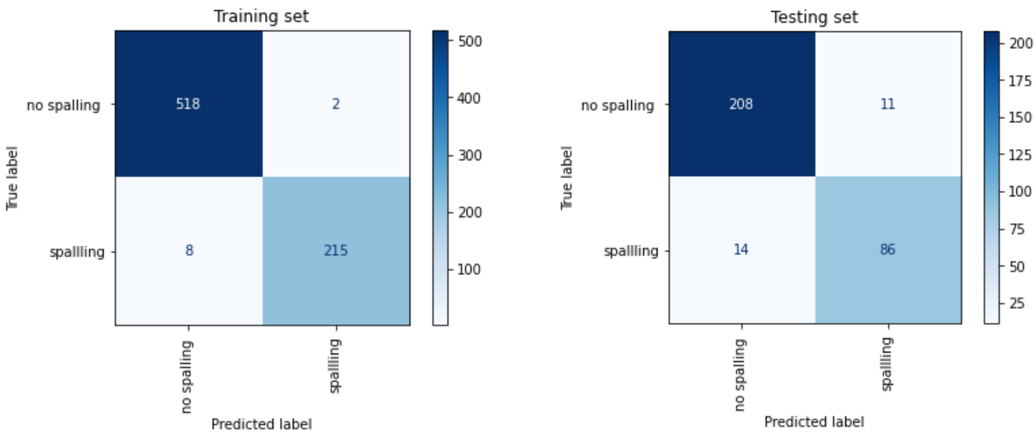

Figure 3. Model's confusion matrix for training and testing sets

4.2 Feature importance plot

Figure 4 shows that the compressive strength of concrete is the most important factor among the five factors included in this study, followed by maximum exposure temperature, moisture content, heating rate, and PP fibres, respectively. The downside of the feature importance plot is that it can only show the order of the influencing parameters. We were able to identify the feature importance, and at this point, we are obliged to define the direction of the feature and how each feature influences spalling to resist or trigger spalling, which introduces the SHAP summary plot.

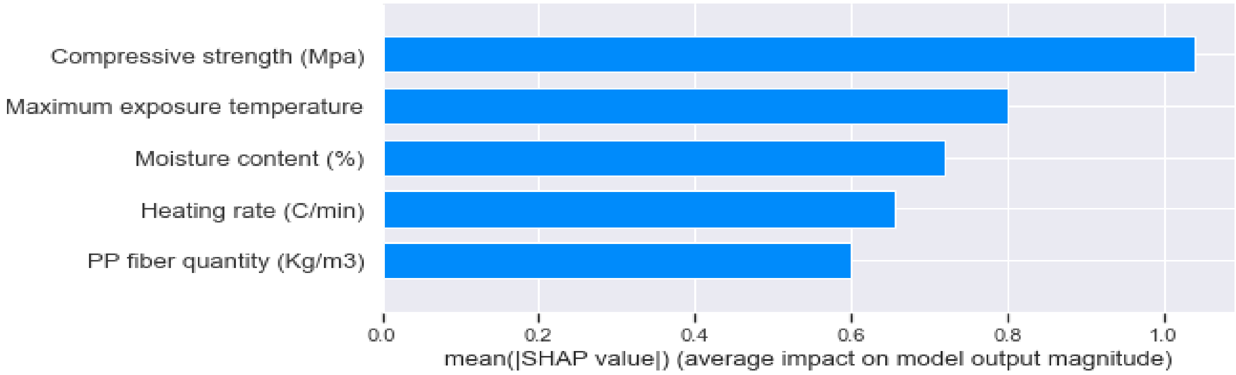

Figure 4. Feature importance plot of SHAP values

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4.3 Summary plot

Figure 5 shows the five factors used in this study that influence spalling. Focusing on the compressive strength and its position at the top of the figure indicates how significant the impact is on the model's prediction. In addition, red dots (high compressive strength values) are on the positive SHAP values, which shows that the higher the compressive strength, the higher the chances of spalling. Additionally, maximum exposure temperature, moisture content, and heating rate factors show the exact same direction of impact on the model as the red dots are on the positive side of the SHAP values, but its impact power is correspondingly lower than the compressive strength.

Alternatively, polypropylene fibre quantity in a concrete mix shows an entirely different impact on spalling. The red dots, which indicate a higher amount of PP fibre in the mixture, lay on the negative side of the summary plot indicating that higher quantities of pp fibre negatively impact the spalling occurrence, which will mitigate spalling. Now, quantifying the features is a must, and we must continue our analysis to be able to quantify the feature and create a concrete mix that can mitigate spalling.

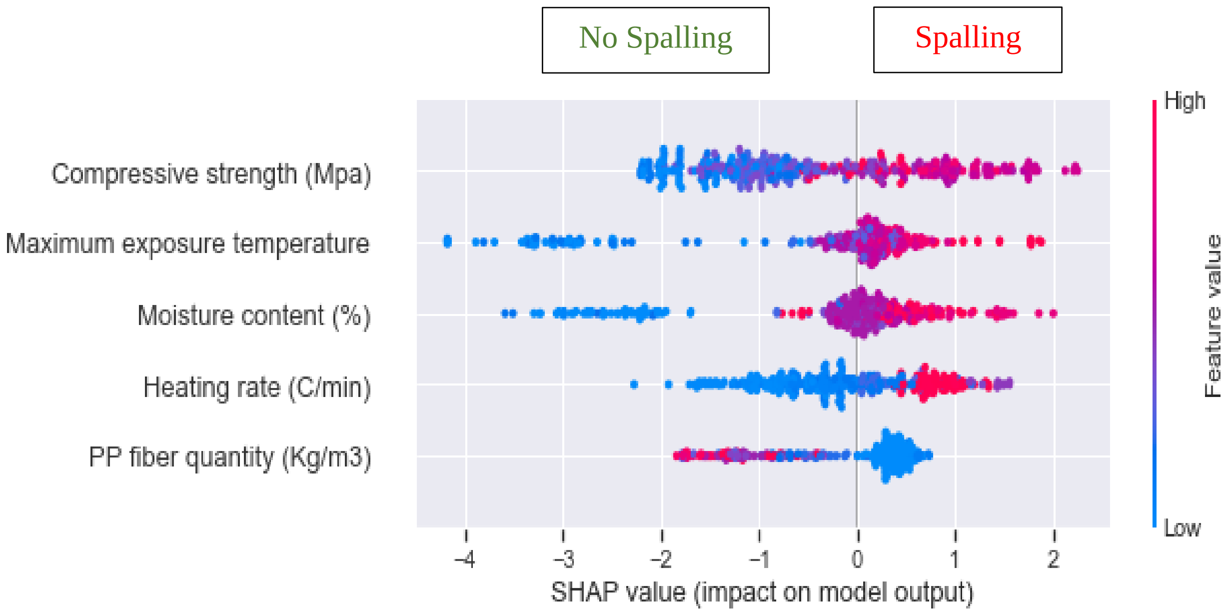

Figure 5. Summary plot of SHAP values

4.4 Partial dependence plot

Figure 6 represents the PDPs for the top five influencers to spalling. One can see some trends which are of interest to the reader. Looking at the compressive strength, PDP confirms the outcome of the SHAP summary plot that the tendency of spalling increases as the compressive strength increases because higher compressive strength increases the density matrix of concrete and decreases the permeability, which makes concrete that is more sensitive to spalling [1, 2, 23]. It should be noted that there are three critical values where the trend increases sharply. Those values lay at (47, 86, and 110 MPa). These values lay where the concrete class roughly changes from normal-strength concrete to high-strength concrete to ultra-high-performance concrete.

A closer look at the maximum exposure temperature plot shows a direct correlation between temperature and concrete spalling. Also, the trend increases sharply between the temperature of 320-380°C, and this

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temperature lays at the aggregate dehydration temperature and stabilizes before and after this range. Kang and Hertz [2, 16] mentioned the explanation for such a unique trend. Further, the rise in heating rate (upward of 5 °C/min and from 10-15°C/min) positively correlates with spalling; when the values increase, the likelihood of spalling occurrence also increases. The plot for PP quantity shows a different trend which shows that adding 0.75-0.9kg/m^3 will significantly mitigate spalling in the concrete mix.

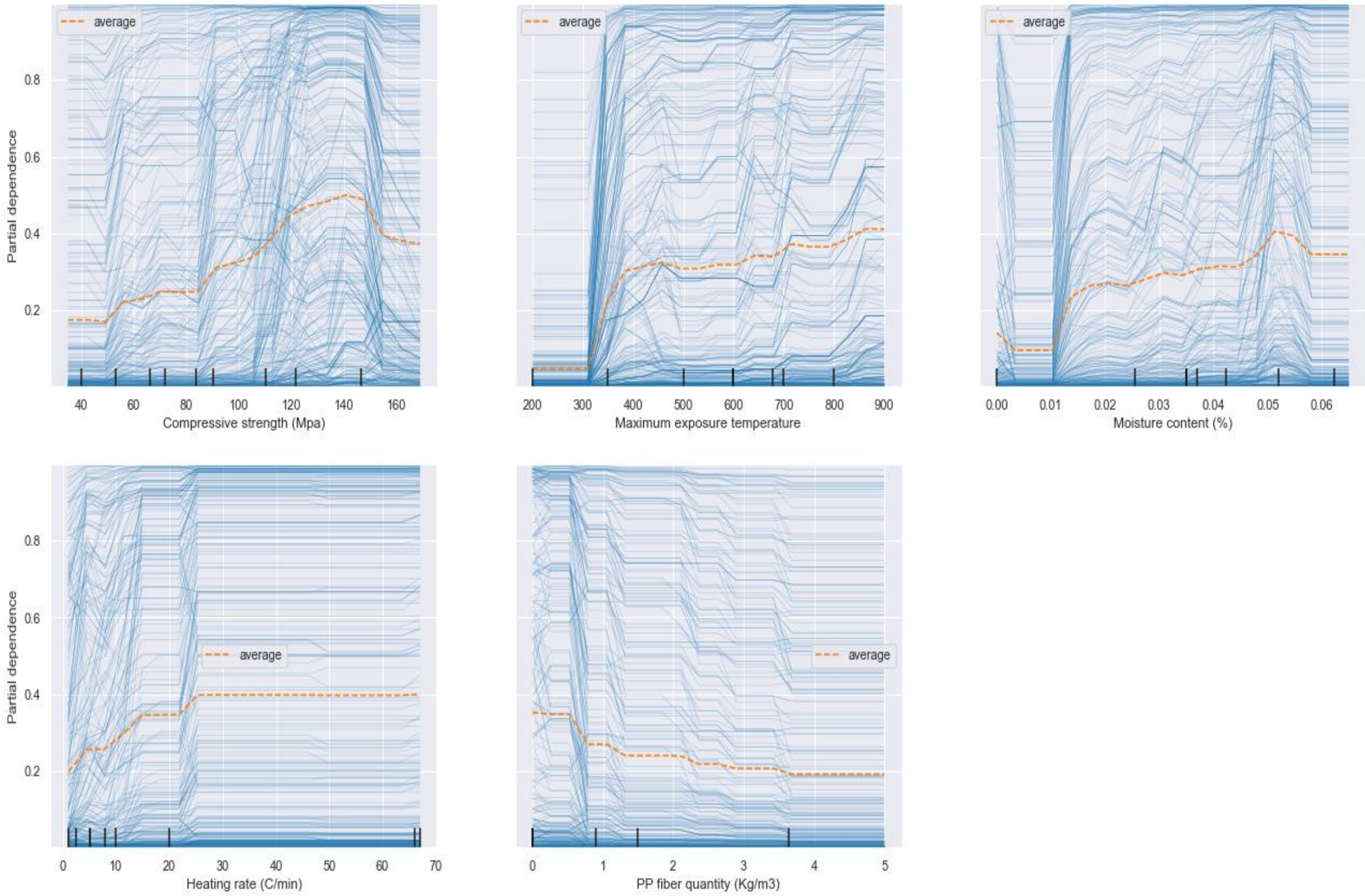

Figure 6. Partial dependence plot for the top five influencers of spalling.

5 CONCLUSIONS

This work presented a preliminary analysis en route to obtaining a spalling-free concrete mixture by analyzing 1000 fire tests (the largest in the literature review) using XAI. We were able to create a model that can predict concrete spalling with high accuracy (i.e., 93%). The following conclusions can be drawn.

- Compressive strength, maximum exposure temperature, moisture content, heating rate, and pp fibre quantity are considered the top 5 influencers of fire-induced spalling of concrete.
- The analysis of this paper confirms that compressive strength has a direct correlation to spalling and can be critical above 85 MPa.
- Maximum exposure temperature is ranked second most critical factor with a critical limit of 300^{o}C, the chances of spalling increase beyond this limit
- Reducing the moisture content below 1% by the weight of concrete is an effective way to improve the spalling resistance.
- Spalling was detected under high and low heating rates; however, limiting the heating rates below 5oC/min can minimize the spalling risk.

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- Adding PP fibres to the concrete mix can reduce the spalling tendency (especially in mixtures of > 0.9 kg/m3).

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