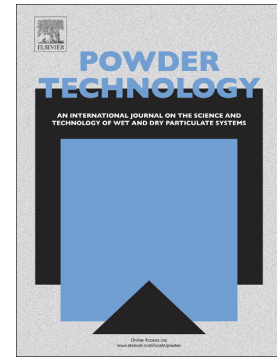


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Modeling industrial hydrocyclone operational variables by SHAP-CatBoost - a “conscious lab” approach

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Abstract

Undoubtedly hydrocyclones play a critical role in powder technology, which can considerably affect the plants' process efficiency. However, hydrocyclones were rarely modeled on an industrial scale, where a model can be used to train operators and minimize potential scale-up errors and lab costs. The novel approach for filling such a gap would be using conscious lab “CL” as a new concept that builds based on an industrial dataset and explainable artificial intelligence (XAI). As a novel approach, this study developed a CL and explored the interactions between hydrocyclone variables by the most recent XAI method called “SHapley Additive exPlanations (SHAP)”, and a novel machine-learning model, “CatBoost”. The hydrocyclone output and the particle size of the plant magnetic separator were modeled by SHAP-CatBoost. SHAP could successfully model all the relationships, and CatBoost could predict the O_{80} and K_{80} , where outcomes had a higher accuracy ($R^2 \sim 0.90$) than other conventional AIs.

Keywords: Hydrocyclone; Ultrafine particles; Random Forest; Support Vector Regression; XGBoost

1. Introduction

In mineral processing plants, hydrocyclones are the most typical tools for controlling and classifying particle size distribution (PSD) of powders (fine particles mostly in $<500\mu\text{m}$) generated by mills [1]. Since fine grinding of low-grade ore is essential to meet the minerals' liberation degree (vital for the efficient downstream separation processes), the hydrocyclone performance can directly affect the efficiency of upgrading units and the final products' quality.

In other words, the PSD of ground ores, besides minerals' properties, would dictate the selection of the upgrading method (such as gravity, magnetic, and froth flotation). Therefore, understanding relationships among hydrocyclone operational variables and their effects on the products' particle size would be crucial for any plant [2–4].

Modeling is a key to better controlling and determining these relationships. Thus, several theoretical models have been developed to explore correlations between operational parameters and model hydrocyclone performances [5,6]. Yet, the generated empirical-numerical models were mostly based on the laboratory scale experiment results [7], and they were limited to specific operating scenarios, could not show the level of variables' effectiveness on the hydrocyclone performance, and assessed each parameter unconnectedly [8–11]. Recently some investigations using artificial intelligence (AI) models have been conducted to model hydrocyclone performance (Table 1). Since ANN are mostly black box models, they still hold some fundamental challenges of empirical models. They cannot provide multi-correlation assessments within the operational hydrocyclone variables nor indicate the magnitude of relationships. Moreover, they were mostly based on small laboratory datasets, which would not generate inadequate confidence levels for industrial-scale processes. In some cases, no validation step was considered through those investigations that can develop overfitted models (Table 1).

Table 1. AI models and their conditions applied for modeling various hydrocyclone performances.

Model	Input Variables	Output	Data Type	Number of Records	Model Results (Testing Step)	Ref.
Feed-forward neural network	Pressure drop at the inlet, Solid percent vortex Apex diameter	Cut size Overflow Underflow	Laboratory	19 train 6 validation 5 test	R-square: 0.98	[11]
Feed-forward neural network	Inlet flow rate Overflow flow rate Underflow flow rate Pressure Volumetric solid concentration Solid density Overflow density Angle of discharge	Cut size	Laboratory	25 train 8 validation 8 test	R-square~0.81	[5]
Combination of Self-Organizing Map and Neuro-Fuzzy Inference System	Pressure drop Solid percent Size fraction Overflow densities Underflow densities	Cut size	Laboratory	150 train 19 test	Not reported	[12]

Back propagated neural network	Water-solid ratios Overflow densities Underflow densities Apex Spigot flowrates	Cut size	Laboratory	100 train 100 test	R-square~0.97	[13]
Conventional neural network	ImageNet data (300 images)	Underflow particle size	Laboratory	210 train 90 test	R-square~0.85	[14]
Feed-forward neural network	Vortex finder diameter Spigot diameter Inlet pressure	Solid recovery	Laboratory	100 train 50 validation 50 test	Not reported	[15]
Feed-forward neural network	Inlet flowrate Inlet density Spigot opening Vortex height Temperature of slurry	Cut size	Laboratory	~100 train ~100 test	R-square~0.94	[16]

Considering the “conscious lab (*CL*)” concept could potentially fill all these gaps. Exploring relationships in a simultaneous single and multivariable assessment using machine learning systems (which would reduce ANN limitations) based on industrial datasets called *CL* [17]. A *CL* can develop a comprehensive insight into the sensitivity of process performance to all monitored operational factors. In detail, *CL* is a new theory that suggests using explainable *AI* (*XAI*) to assess relationships within observed variables from industrial units and model their interactions [17,18]. *XAI* can consider linear and nonlinear relationships through a single-multivariable assessment and rank variables based on their effectiveness on the model outputs. That assessment will also determine the magnitude of relationships. Recently, *CL* has been successfully constructed based on different machine learning models with random forest (RF), support vector regression (SVR), and eXtreme Gradient Boosting (XGBoost)) for various industrial units. This work, as a unique approach, is going to develop a *CL* for an industrial hydrocyclone by using Shapley Additive exPlanations (SHAP) as a novel *XAI* structure.

Each generated model needs to be understandable for operators [19,20]. As a recently developed *XAI*, SHAP can unbox any black box model and translate relationships, bringing them to a human basis. Based on each record's local interpretability, SHAP can thoroughly explain the global average and model output and consider single and multi-correlations for linear and nonlinear interactions. Such an illustration facilitates the training of operators by breaking down *AI* complexity to the general level. In this study, SHAP was coupled with the CatBoost model to enhance its functionality. CatBoost is a newly established *AI* model for gradient boosting on decision trees. It has several advantages over other traditional machine learning methods, such as being faster in training, keeping the original structure of the data frame, and being sparse.

Catboost uses the “Ordered target statistics” principle, which solves the prediction shift and target leakage problem [21,22]. The core objective of this work is to emphasize the essential need to understand inter-correlations among hydrocyclone operational valuables and their effectiveness on the process performance by accurate and human basis methods (*XAI*) on an industrial scale. This approach can be implemented in various processes dealing with powder technology. This study is going to construct a *CL* for a hydrocyclone in the Fakoor Sanat iron ore processing plant using the SHAP-CatBoost model as a narrative approach and assess hydrocyclone’s performance on the magnetic separator response (Fig. 1). For comparison principles, random forest (RF), support vector regression (SVR), extreme gradient boosting (XGBoost), and Artificial Neural Network (ANN) as conventional statistical *AI* models, were also examined to assess the SHAP-CatBoost capability for modeling hydrocyclone performance.

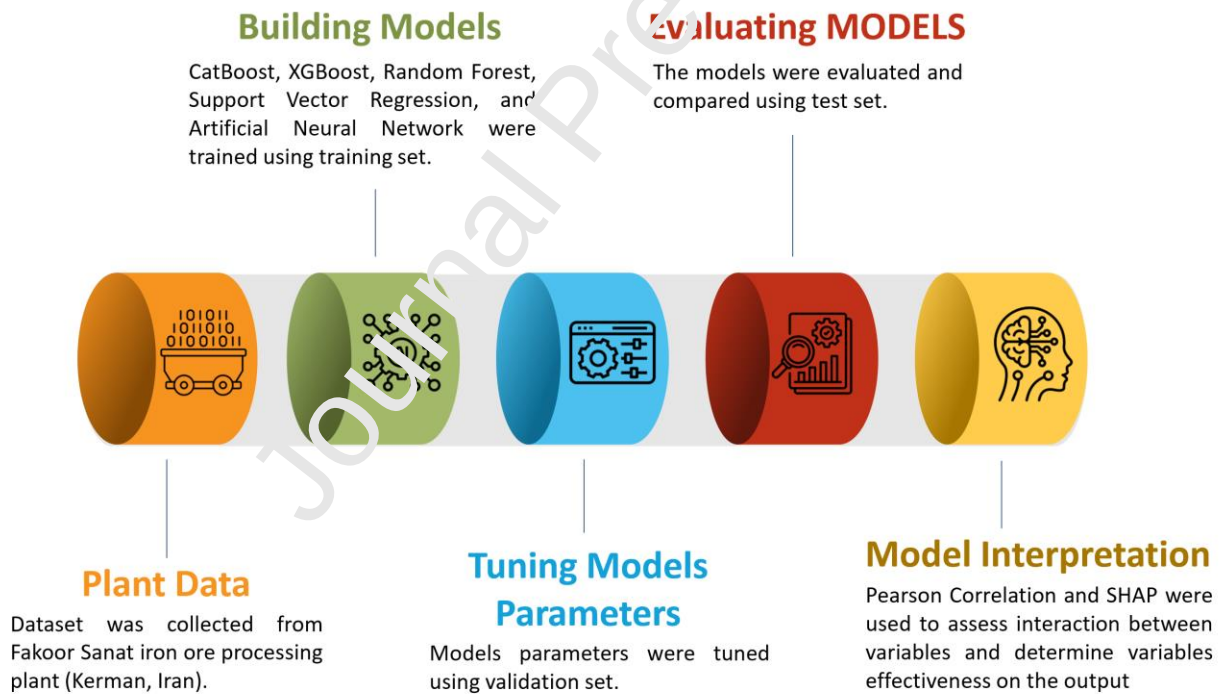


Fig. 1. The methodology used for constructing the *CL* for a hydrocyclone using the SHAP-CatBoost model.

2. Materials and methods

2-1. Dataset

A dataset from the Fakoor Sanat iron ore processing plant (Kerman, Iran) based on daily monitoring of a hydrocyclone for over 6 months (22 December 2019 to 20 June 2020) was gathered to explore the interactions between its operational variables and their effects on the final magnetic concentrators' particle size (magnetite separate from silicates and phosphates) (Fig. 2). The dataset consisted of 185 samples. In the plant, the ball mill's product is subjected to a hydrocyclone, and then, the overflow of the hydrocyclone feeds to medium-intensity magnetic separators (MIMS). The hydrocyclone's cluster consists of four hydrocyclones, and in each case, the main body, apex, and vortex diameter are 660, 220, and 110 mm, respectively. The maximum operating pressure is around 1 bar. Daily measurements were taken, and their mean numbers (for each day) were considered. The parameters (Table 2) of particle size and solid wt% are the mean value of different recorded parameters of representative samples during each shift. The laboratory determined them by sampling and physical tests (wet and dry sieving and filtration, respectively). The working pressure and density of hydrocyclone's feed were monitored from the plant's central control room. SHAP and Pearson's correlation assessed the relationships within the hydrocyclone variables, and its outcome "O₈₀" and MIMS particle size "K₈₀" were modeled with different machine learning methods.

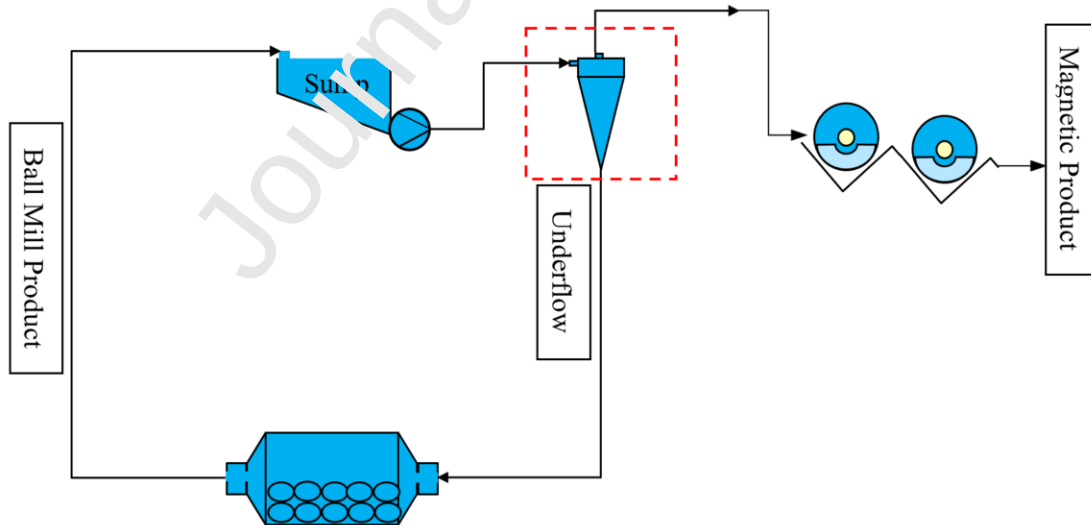


Fig. 2. Schematic of the Fakoor Sanat iron ore processing plant.

Table 2. Descriptive analyses of the considered hydrocyclone operating parameters.

Variables	Symbol	Min	Max	Mean	STD
Feed density (g/cm ³)	ρ	1.35	1.74	1.59	0.08
Feed Solid (wt%)	Xf	23.87	76.11	59.86	7.63
Working Pressure (kpa)	WP	85.00	99.00	91.42	2.73
Mill Feed (μm)	F ₈₀	198.15	763.72	467.98	125.50
Underflow (μm)	U ₈₀	203.87	684.36	357.99	98.68
Overflow (μm)	O ₈₀	56.52	230.98	108.54	25.35
Underflow Solid (wt%)	Xu	37.19	80.09	74.24	4.21
Overflow Solid (wt%)	Xo	11.99	42.18	26.48	5.67
MIMS products (μm)	K ₈₀	53.05	154.40	111.44	22.07

2-2. Pearson Correlation Coefficient

The Pearson correlation coefficient measures the strength of the linear dependence between two random variables [23]. In other words, the Pearson correlation coefficient measures the closely related two variables and how well they can be described using a linear equation. It is a widely used measure in statistics and is defined as the covariance of the two variables divided by the product of their standard deviations. Pearson correlation coefficient can be computed as follows:

$$r_{xy} = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2} \sqrt{\sum_{i=1}^n (y_i - \bar{y})^2}} \quad (1)$$

where n represents the sample size, x_i and y_i are sample points, and $\bar{x}$ and $\bar{y}$ denote the sample mean.

2-3. Artificial Intelligence Models

2-3-1. Shapley Additive Explanations

The Shapley Additive exPlanations (SHAP) is a game theory approach for quantifying the marginal effects of individual features and the interaction/joint effects of two features [24]. It has been demonstrated that SHAP is useful in explaining different machine-learning models [25]. SHAP can explain any machine learning model's output by computing each variable's contribution to the output. This is done by SHAP assigning a score to each variable, which indicates how important it was in making the output. This score is called the SHAP value

[26,27]. SHAP satisfies the following properties: local accuracy, missingness, and consistency [28]. Local accuracy means the explanation model should match the original model. The missingness property enforces that missing variables in the dataset are attributed no importance. Consistency indicates that the attribution given to a variable will never decrease, even if we modify a model to increase the impact of a variable on the model. SHAP defines the output of a model as follows:

$$f(\mathbf{x}) = g(\mathbf{z}') = \phi_0 + \sum_{i=1}^M \phi_i z'_i \quad (2)$$

where $g(\mathbf{z}')$ denotes the SHAP explanation model, ϕ_i represents the SHAP value, and $z_i \in \{0,1\}$ is a binary variable. In other words, SHAP decomposes the prediction into a linear function that is comprised of binary variables [29]. Two methods can be used to approximate SHAP values, i.e., Kernel SHAP and Tree SHAP. In this study, Tree SHAP was used to approximate SHAP values as it is much faster than Kernel SHAP and can be used with tree-based methods like CatBoost.

2-3-2. CatBoost

CatBoost is a novel variant of the gradient-boosting decision tree method developed by Prokhorenkova et al. in 2018 [21]. Its main idea is that a strong regressor can be created by iteratively combining weak regressors [30]. CatBoost has strong learning capabilities to deal with highly nonlinear data [31]. It can be trained by minimizing the expected loss function ($L(\cdot)$) through gradient descent:

$$h^t = \arg \min_{h \in H} \mathbb{E}\{L(y, F^{t-1}(\mathbf{x}) + h(\mathbf{x}))\} \quad (3)$$

where y denotes the output and h is a gradient step function selected from H , i.e., a family of functions. The step function can be calculated as follows:

$$h(\mathbf{x}) = \sum_{j=1}^J b_j \mathbb{I}_{\{\mathbf{x} \in R_j\}} \quad (4)$$

where R_j denotes the disjoint regions that correspond to the tree's leaves. b_j is the predictive value of the region, and $\mathbb{I}$ is an indicator function [32].

The expectation in Eq. (3) is approximated by the same dataset, which leads to prediction shift and gradient bias. These issues result in overfitting. CatBoost resolves them by employing the ordered boosting method, which causes improving the robustness and generalization ability of the model [31,32]

2-3-3. Extreme Gradient Boosting

Extreme gradient boosting (XGBoost) is a tree-based ensemble method. It integrates several weak regression trees and sequentially combines their prediction to increase the overall accuracy [33,34]. XGBoost supports parallel and distributed computing and can use the CPU's multithreading feature, which speeds up the computational process [34,35]. Researchers widely use it due to its high robustness and sufficient flexibility [36]. XGBoost adds regularization term to the loss function that smoothens the learned weights and avoids overfitting [37].

XGBoost output can be computed as follows:

$$\hat{y} = \sum_{k=1}^K f_k(\mathbf{x}), f_k \in \Gamma(5)$$

where $\hat{y}$ denotes the predicted output, $\mathbf{x}$ is the input vector, f_k represents the output of the k th tree, and Γ denotes the function space containing every potential regression tree [29]. Eq. (6) shows XGBoost's objective function:

$$Obj(\theta) = L(\theta) + \Omega(\theta)(6)$$

where $L(\cdot)$ is the loss function that computes the error between the predicted value and target value, and $\Omega(\cdot)$ represents the regularization function that controls the complexity of the model and prevents overfitting [29].

2-3-4. Random Forest

Random Forest (RF) is a nonparametric, ensemble regression method developed by Breiman in 2001 [38]. RF is a modification of bagging that creates a collection of K -randomized regression trees and averages them. It combines the random subspace method with bagging [39]. The least relevant features can be reduced using RF based on their importance [40].

Solving regression problems by RF has several advantages: low bias, having very few hyperparameters, and minimized risk of overfitting [41]. RF builds an ensemble of K decision trees (DT) as base learners. Each DT predicts the output independently, and then the predictions are averaged to generate the final result (Eq. 6):

$$\hat{T}(\mathbf{x}) = \frac{1}{K} \sum_{k=1}^K \hat{T}_k(\mathbf{x}) \quad (6)$$

where $\mathbf{x}$ denotes input and $\hat{T}_k(\mathbf{x})$ is the estimation produced by the k th tree [36].

2-3-5. Support Vector Regression

Support vector regression (SVR), proposed by Drucker [42], is a supervised learning method based on statistical learning theory [43]. SVR is widely used in data-driven problems due to its powerful capability of nonlinear predictions [44]. The advantages of modeling by SVR are: a) It is robust to outliers, b) It has lower computational cost compared to other methods, and c) It is effective when dealing with high-dimensional problems with a small number of samples [45].

The main fundamental concept behind SVR is to map input vectors into an N -dimensional feature space using a mapping function ($\phi(\mathbf{x})$) so that in this space, a linear function can model the relationship between input ($\mathbf{x}$) and output (y) as follows:

$$f(\mathbf{x}) = \mathbf{w}\phi(\mathbf{x}) + \mathbf{b} \quad (7)$$

where $\mathbf{w}$ and $\mathbf{b}$ represent weights vector and bias, respectively. Eq. (8) shows SVR's objective function:

$$\phi(\mathbf{w}, \xi) = \frac{1}{2} \|\mathbf{w}\|^2 + C \sum_{i=1}^n (\xi_i^- + \xi_i^+) \quad (8)$$

where C represents the regularization constant, and ξ_i^- and ξ_i^+ are slack variables, i.e., margin constraints allowed to be violated [46,47].

2-3-6. Artificial Neural Networks

Artificial Neural Networks (ANN) are mathematical modeling approaches comprised of artificial neurons inspired by research on the human brain system [48,49]. The first computational model of a neuron was proposed by McCulloch and Pitts in 1943 [50]. Due to

their good nonlinear mapping capability, ANNs have achieved tremendous success in various domains [51]. Formally, a neuron output signal can be computed as follows:

$$O = f(\text{net}) = f\left(\sum_{j=1}^n w_j x_j + b\right) \quad (9)$$

where $\mathbf{w}$ and b denote weight and bias, respectively, n represents the number of inputs and $f(\cdot)$ is the activation function. Rectified linear unit (ReLU) and Sigmoid are two activation functions that are widely used in ANNs [52,53].

3. Results and discussions

3-1. Intercorrelations

Pearson correlation “r” was used for the initial single linear inter-correlation assessments within hydrocyclone operational variables throughout the entire dataset (Fig. 3). F_{80} indicated a low positive correlation with O_{80} (r: 0.20), which showed hydrocyclone performance was slightly dependent on the ball mill feed size (F_{80}) and mostly relied on the ball mill product size. Pearson assessments also indicated that the working pressure (WP) decreased marginally when bigger particles were fed to the line (F_{80}). F_{80} and X_f also showed a positive correlation (r: 0.59). Overflow solid wt% (X_o) demonstrated a substantial positive correlation with O_{80} (r: 0.78).

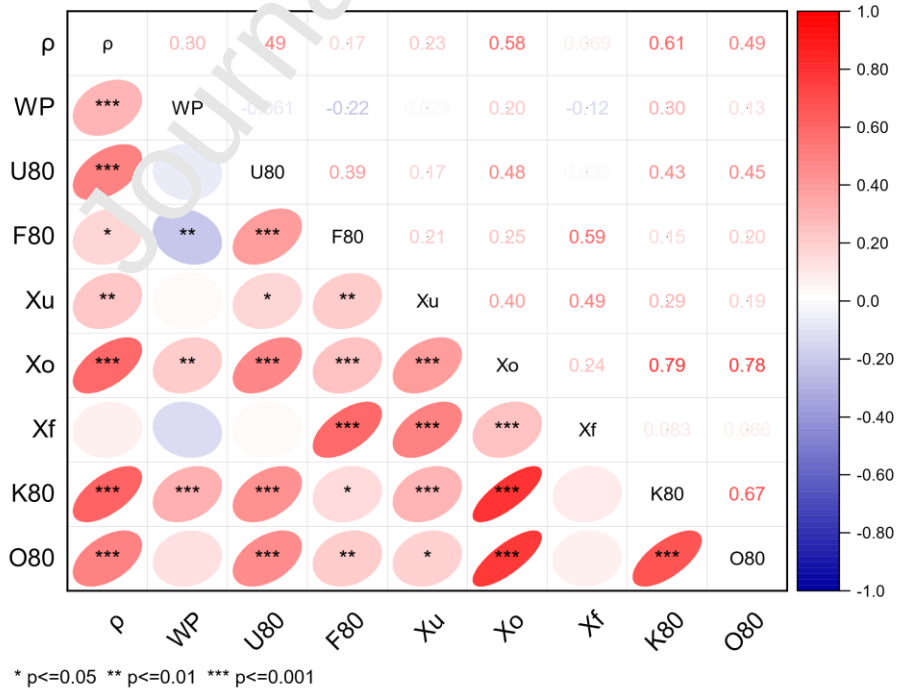


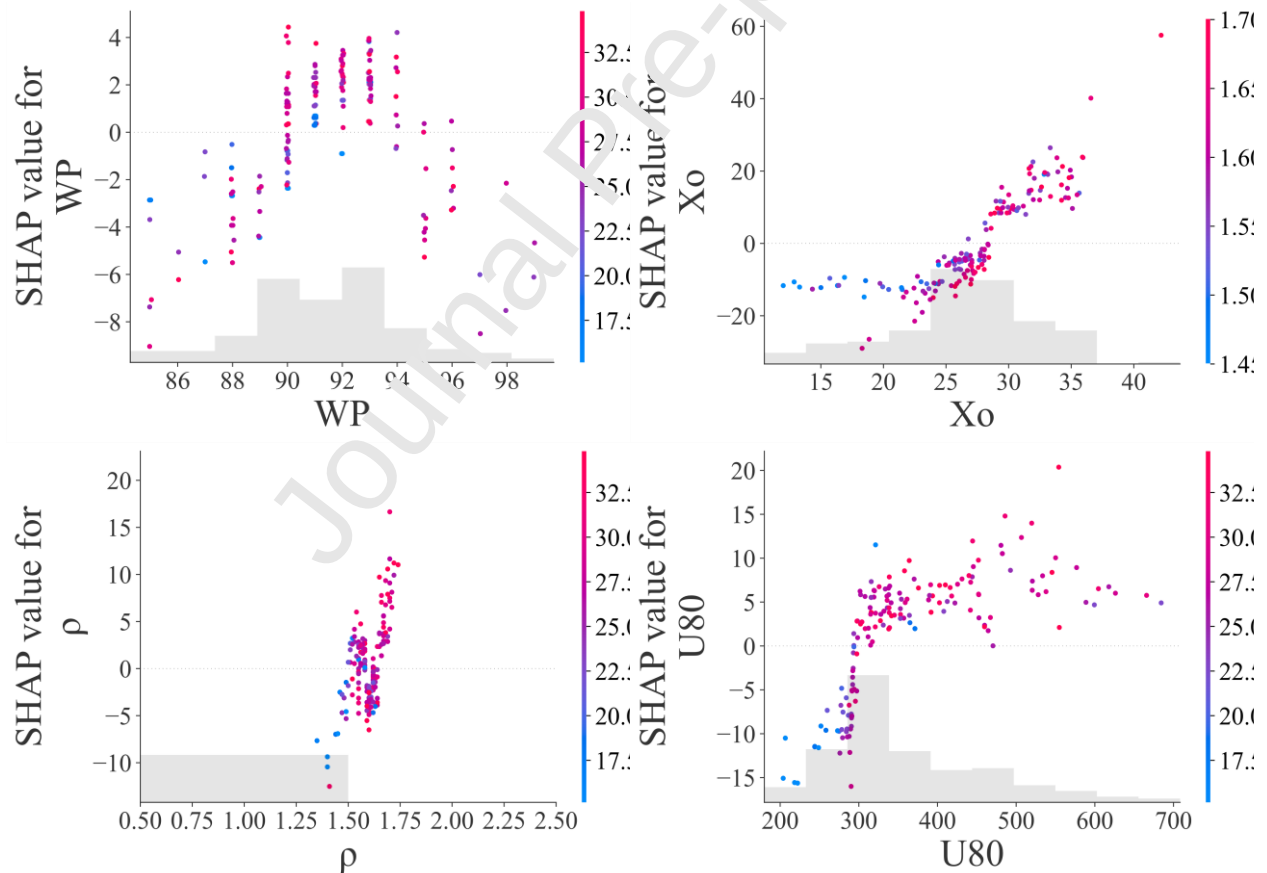
Fig. 3. Pearson correlation among hydrocyclone variables.

Pearson correlation (a linear assessment) results showed the potential of several multivariable relationships among the hydrocyclone' variables. The potential of multi-interactions between hydrocyclone operational variables was reported in various investigations [5,12]. SHAP assessments can determine these multi-correlations, illustrate them (Fig. 4), rank them based on their importance (Fig. 5), and represent the mean magnitude of their impacts. The SHAP variable importance ranking evaluation revealed a similar pattern to the Pearson correlation assessment (Fig. 3 and 5). SHAP analyses (Fig. 5) demonstrated that X_o has the highest effectiveness on O_{80} modeling. The mean magnitude of this correlation is positive (increasing overflow solid wt% increased the percentage of coarser particles in the overflow “ O_{80} ”). In general, lower solid wt% (lower X_o means higher water content) would transport the fine particles of the slurry to the hydrocyclone center and direct them to the overflow [54].

SHAP also showed the interaction between X_o and W_P (Fig. 4). It was reported that increasing W_P would be enhanced X_o [55–57]; however, after a certain point, higher W_P can partially discharge more water through the overflow and decrease X_o [57]. Farghaly et al. (2020) claimed that by increasing W_P , the X_o would decrease, and the cut size could be reduced [58]. SHAP analyses demonstrated only in a specific range (W_P : 90-94 kpa and $X_o \geq 28\%$), their interactions had a positive correlation with O_{80} (Fig. 4). Their increase in that range would increase the overflow PSD. Out of these ranges, the SHAP value was negative (O_{80} was finer). It was documented that high W_P would increase the turbulence in the hydrocyclone, which can reduce the sharpness of classification by increasing the entrainment of fine particles through coarse particles during their settlement [56,57,59–62].

U_{80} showed the second highest positive effectiveness on O_{80} (Fig. 5). This effectiveness could be explained by its interaction with X_o (Fig. 4). SHAP analyses indicated that for U_{80} below 300 μm and X_o below $\sim 24\%$, the SHAP value was negative. In contrast, the SHAP value showed a positive effect for their higher values. This relationship can be due to the fact that when the mill product size was generally increased, coarser particles were processed by the hydrocyclone, and subsequently, both U_{80} and O_{80} were raised [63]. It was stated that a fraction of fine particles is regularly subjected to underflow, which supports the negative SHAP value of U_{80} for $<300 \mu\text{m}$. SHAP mean value assessment also indicated that by increasing ρ , the O_{80} increases (Fig. 5). Although ρ did not show any significant linear correlation (Fig. 3), SHAP

indicated its high interactions with other operational variables (Fig. 4) and positive contribution on O_{80} modeling (Fig. 5). Although ρ and X_o has a negative relationship, by increasing ρ and X_o their negative correlations decreased. For ρ and X_o higher than $1.54 \text{ (g/cm}^3\text{)}$ and 26% (respectively), their interactive effectiveness is positive for O_{80} modeling (Fig. 4). It is well understood that unsteady feeding and feed slurry density would be detrimental to the hydrocyclone performances [64]. Increasing density generally causes settling to be hindered, and particle interactions lead to fine particle entrainment [54]. These results indicated that although variables monitored online in the plant's controlling room (WP and ρ) have several interactions with other essential variables, they are not the most effective on hydrocyclone performance. Thus, process operators showed train based on the correlations (linearly and nonlinear) [1] among operational variables and understand interactions (multivariable), something that *CL* has been provided and can have a direct effect on the product properties.



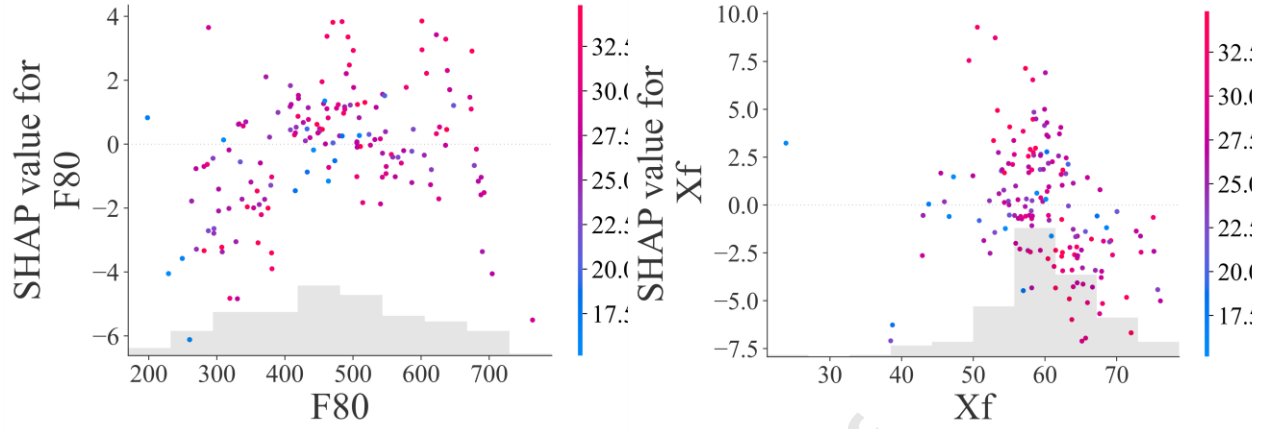


Fig. 4. SHAP values for multi-interactions among hydrocyclone operational variables.

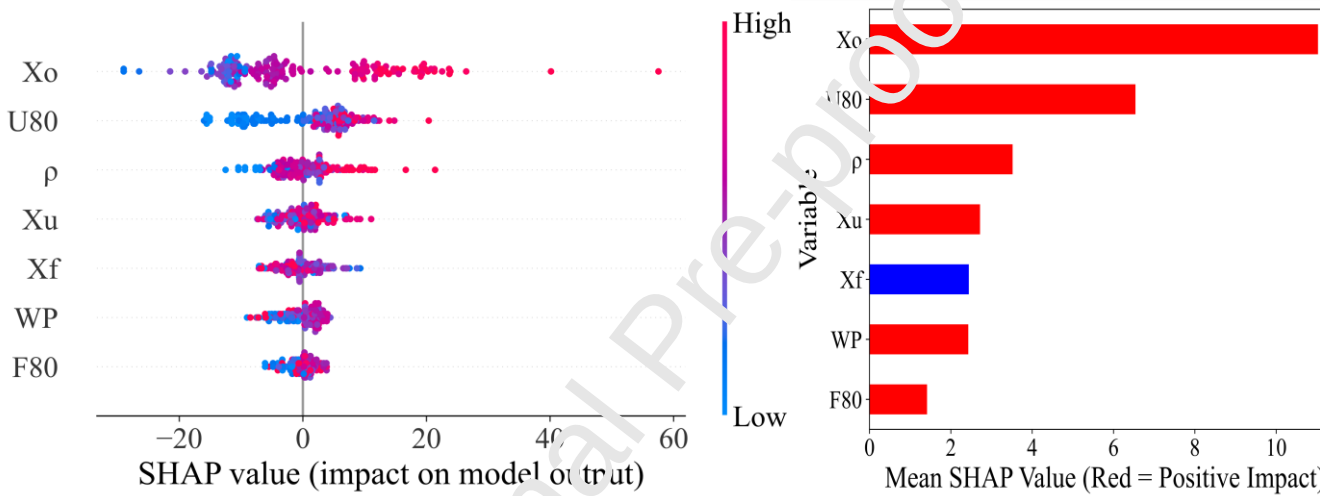


Fig. 5. Ranking variables based on their mean SHAP value and their relationship magnitude for O_{80} prediction.

The MIMS operating condition was mostly constant when the process (Fig. 1) was steady in the plant. Thus, its performance could be linked to the hydrocyclone operation and its overflow properties. A meaningful positive relationship ($r: 0.67$) was observed between O_{80} with K_{80}

(Fig. 3). In other words, by increasing the particle size of overflow (O_{80}) of the hydrocyclone, the particle size of (K_{80}) recovered particles would be increased. Such an interaction would be evident since it meant that coarser particles fed into the MIMS (O_{80}) caused an increase in the product particle size (K_{80}). X_o had the highest positive linear correlation with K_{80} ($r: 0.79$). Single and multiple assessments showed a nonlinear multivariable correlation between O_{80} and X_o with K_{80} (Fig. 6). These interactions highlighted the potential of K_{80} prediction based on the

hydrocyclone operating parameters, while SHAP ranked the potential effectiveness of all the variables (Fig. 7).

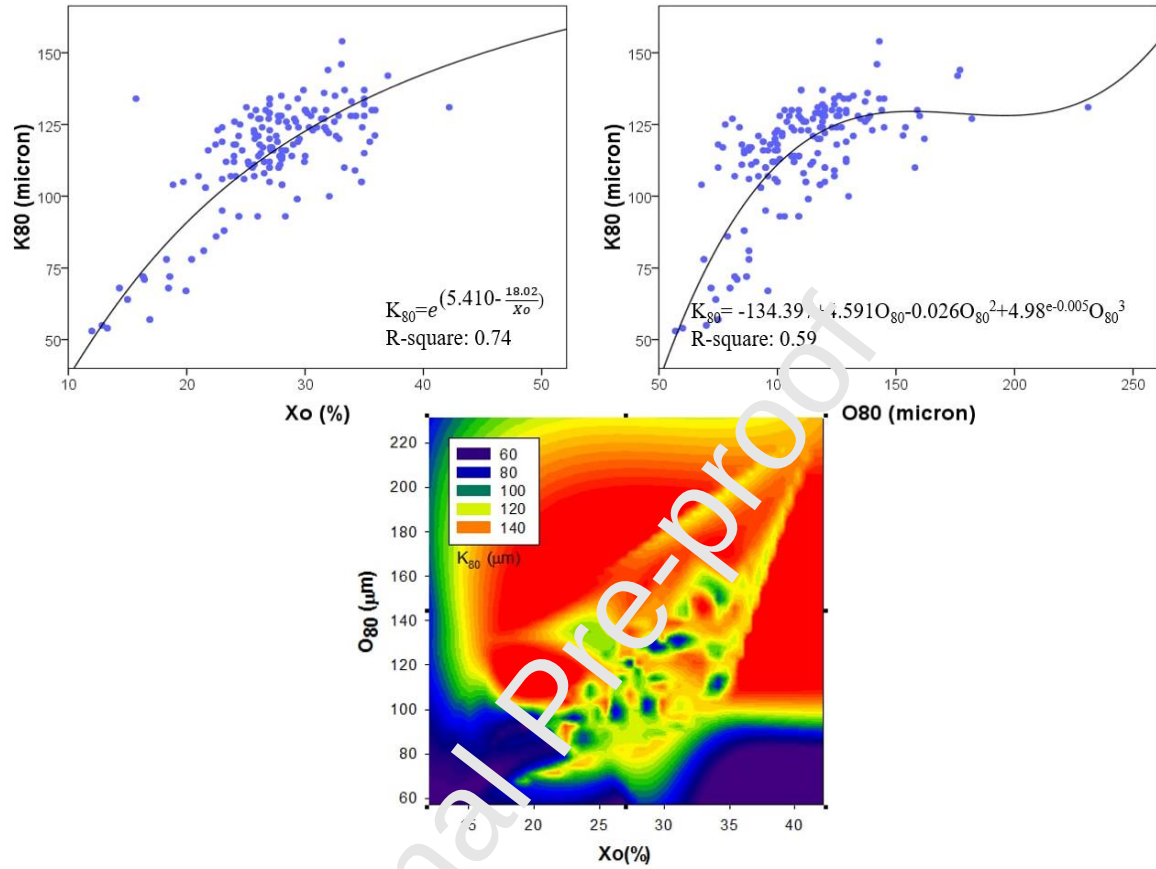


Fig. 6. Relationships between overflow variables with MIMS product size.

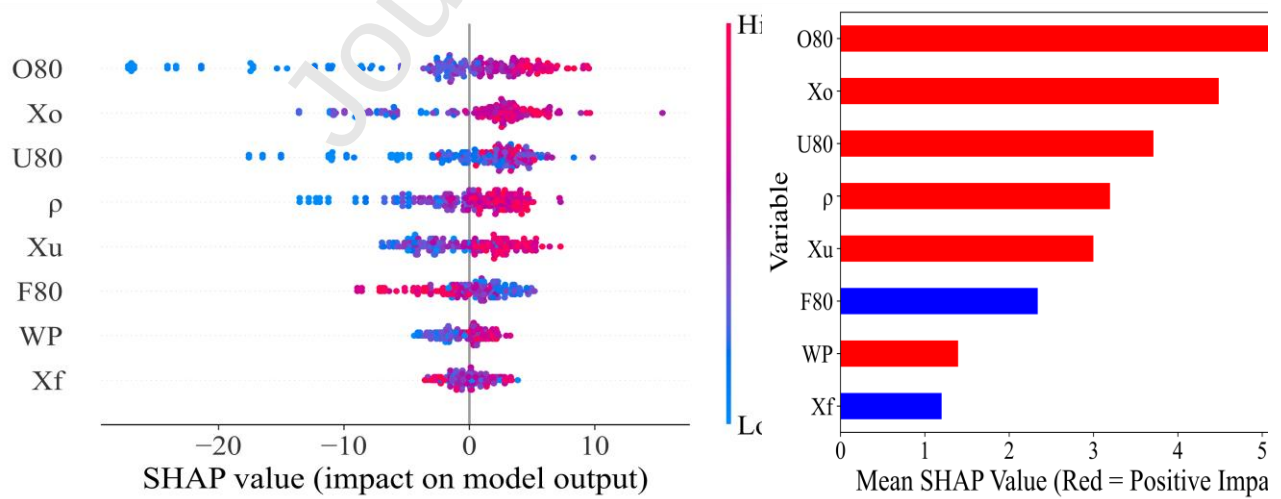


Fig. 7. Ranking variables based on their mean SHAP value and their relationship magnitude for K_{80} prediction.

3-2. O_{80} and K_{80} prediction

The entire dataset was randomly split into 80, 10, 10% for training, validating, and testing the AI models used to predict the O_{80} and K_{80} . Different CatBoost features were examined to find the values of the optimum hyperparameters, adjusted, and tuned the CatBoost model for the training stage. The three main CatBoost hyperparameters are the learning rate, maximum number of trees, and maximum depth of trees. The optimum model parameters were adapted and used for training after the tuning procedure (a try-and-error system) (Table 3). The CatBoost outcomes in the testing stage (Table 4) indicated that this model could accurately estimate the O_{80} and K_{80} based on the plant's operational variables. SHAP could assess all individual records and illustrate each variable contribution level through the prediction (Fig. 8).

Table 3
The parameter settings for the predictive models.

Parameter	Value (K_{80})	Value (O_{80})
CatBoost		
Learning rate	0.897	0.394
Maximum number of trees	105	64
Maximum depth of trees	6	6
XGBoost		
Learning rate	0.285	0.279
Maximum number of trees	26	20
Maximum depth of trees	6	6
γ	1.97	0.94
Random Forest		
Maximum number of trees	183	8
Support Vector Regression		
Kernel	RBF	RBF
Artificial Neural Network		
Activation Function	ReLU	ReLU
Training Epochs	1000	500
Batch Size	10	10

* Radial basis function (RBF) ** Rectified linear unit (ReLU)

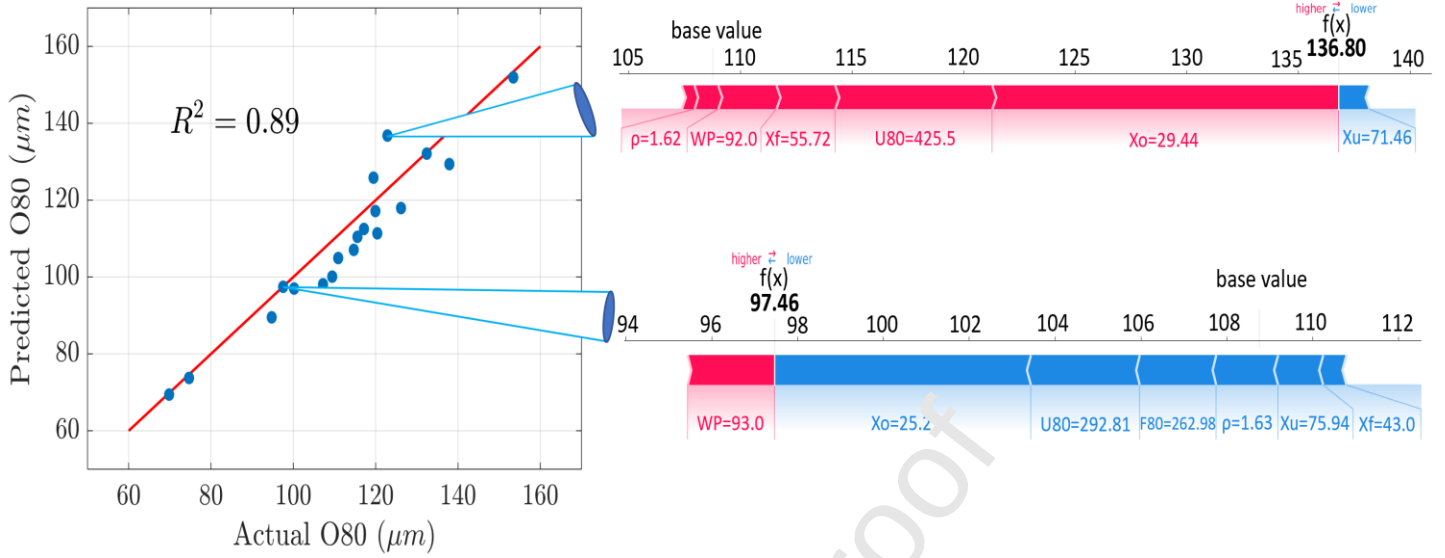


Fig. 8. SHAP analyses of each individual record in the test set.

Other traditional machine learning models (RF and SVR) and XGBoost were examined to O_{80} and K_{80} with the same training and testing records for comparison purposes. Results (Table 4) released that the CatBoost model can produce the highest accuracy for the O_{80} and K_{80} . RF, XGBoost, and CatBoost are ensemble methods. RF is a bagging model, while XGBoost and CatBoost are boosting approaches and require less feature engineering. ANNs can learn complex nonlinear relationships but must adjust several parameters and find an optimal architecture [31]. The kernel function limits SVR. XGBoost suffers from prediction shift and gradient boosting bias, while CatBoost solves prediction shift by employing the ordered boosting method. It also overcomes gradient-boosting biases by using oblivious DTs and applying the same splitting criterion at each tree level. The results obtained by other studies [65–68] also indicated that CatBoost outperformed other ML methods (i.e., SVR, DT, RF, and XGBoost) in the regression task. These results would highlight that SHAP-CatBoost can productively construct a *CL* for a hydrocyclone performance modeling as a commanding *XAI* system. The robust structure of the generated *CL* hypothetically portrayed that this approach could be used for modeling, monitoring, and maintaining different grinding circuits on the industrial scale.

Table 4

Outcomes of different machine learning methods in various modeling stages for the O_{80} and K_{80} prediction.

O_{80}	Train			Validation			Test		
Method	R^2	RMSE	MSE	R^2	RMSE	MSE	R^2	RMSE	MSE
CatBoost	0.99	0.86	0.74	0.89	7.34	53.89	0.89	6.55	42.94
XGBoost	0.98	3.51	12.35	0.89	7.73	59.74	0.88	6.75	45.51
Random Forest	0.91	7.79	60.69	0.89	7.71	59.42	0.82	8.31	68.98
Support Vector Regression	0.74	13.40	179.58	0.81	9.86	97.24	0.77	9.31	86.61
Artificial Neural Network	0.59	16.72	279.43	0.86	8.46	71.59	0.78	8.46	71.59

K_{80}	Train			Validation			Test		
Method	R^2	RMSE	MSE	R^2	RMSE	MSE	R^2	RMSE	MSE
CatBoost	0.99	0.0003	7.62	0.94	5.18	27.83	0.93	6.61	43.72
XGBoost	0.99	1.0	1.09	0.92	6.35	40.33	0.90	7.99	63.97
Random Forest	0.96	4.1	16.58	0.92	6.10	37.28	0.89	8.59	73.94
Support Vector Regression	0.89	6.74	45.41	0.71	11.75	138.80	0.81	11.39	129.73
Artificial Neural Network	0.59	13.31	177.14	0.61	13.57	184.11	0.69	13.57	184.10

*Mean Square Error (MSE) **Root Mean Square Error (RMSE)

4. Conclusion

Constructing models that can show interactions between operational variables on the industrial scale and transforming generated data from complicated knowledge-based systems to human-basis insight would assist plant operators in optimizing production and enhancing process efficiency. The outcomes of this investigation indicated that industries that deal with power technology and use hydrocyclones could implement a *conscious lab* for modeling their processes and translate the monitored and recorded dataset to educative information for their operators in the controlling rooms. The generated *conscious lab* in this study indicated several linear and nonlinear multivariable interactions within a hydrocyclone's variables, which affects its performance. Overflow solid wt% has high importance on the overflow product size (O_{80}) within all the monitored variables. The magnitude of this effectiveness was positive. It was also

indicated that for a steady-state plant, the overflow variables (particle size and solid wt%) of a hydrocyclone can markedly affect the production properties of the downstream magnetic separator (K_{80}). Overflow solid wt% and O_{80} showed a significant positive correlation with the magnetic separator product size (K_{80}). They demonstrated that their increase would raise the K_{80} . The CatBoost model could accurately predict the O_{80} and K_{80} in the testing step (R^2 : 0.89 and 0.93, respectively). The capability of CatBoost has been argued with typical machine learning methods (random forest and support vector regression) and advanced (XGBoost) AI models. The models' outcomes cleared that CatBoost can accurately model the O_{80} and K_{80} (root mean square errors of the models for O_{80} prediction were CatBoost 6.57, XGBoost 6.75, random forest 8.31 and SVR 9.31, and ANN 8.46, and for K_{80} were CatBoost 6.61, XGBoost 7.99, random forest 8.59 and SVR 11.39, and ANN 13.57). In general, these results highlighted that the developed *CL* could be considered for any similar approaches.

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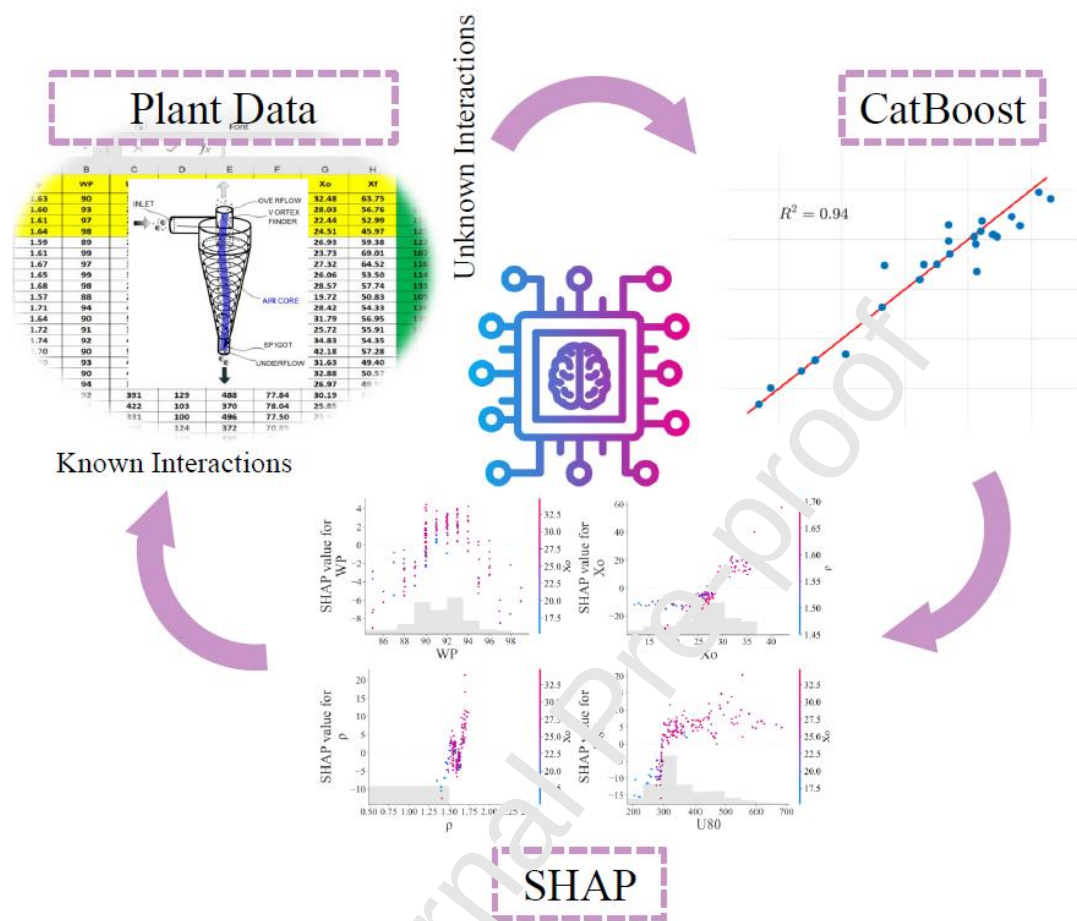
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S. Chehreh Chelgani: conceptualization, software, investigation, writing and editing original and review draft preparation, methodology, and supervision; H. Nasiri: conceptualization, investigation, software, writing and editing original and review draft preparation, and methodology; A. Tohry: conceptualization, writing draft preparation, methodology, and visualization; H. R. Heidari: supervision, software, visualization.

Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐ The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:



Highlights

- The conscious lab “*CL*” concept was used to model an industrial hydrocyclone
- SHAP and CatBoost, as novel explainable artificial intelligence, were used for constructing the *CL*
- Based on SHAP value, overflow solidity had the highest effectiveness on O_{80}
- CatBoost could predict overflow outcomes better than conventional AIs