A Novel Intelligent Approach for Predicting Wear of Excavator Bucket Teeth Based on Hybrid ICA-XGBoost Model

Godwin Ativor
University of Mines and Technology

Yao Yevenyo Ziggah
University of Mines and Technology

Victor Temeng
University of Mines and Technology

A Novel Intelligent Approach for Predicting Wear of Excavator Bucket Teeth Based on Hybrid ICA-XGBoost Model*

[1]G. Ativor, [1]Y. Y. Ziggah, and [1]V. A. Temeng
[1]University of Mines and Technology, Tarkwa, Ghana

Ativor, G., Ziggah, Y. Y. and Temeng, V. A (2025), "A Novel Intelligent Approach for Predicting Wear of Excavator Bucket Teeth Based on Hybrid ICA-XGBoost Model", *Ghana Journal of Technology*, Vol. 9, No. 1, pp. 77-.92

Abstract

The wear of the excavator bucket teeth is a significant operational issue in the mining industry, negatively impacting material production and increasing costs. Accurate prediction of this wear is crucial in mitigating its effects. This study introduces, for the first time, a hybrid intelligent approach that leverages four metaheuristic optimisation algorithms: Imperialistic Competitive Algorithm (ICA), Grasshopper Optimisation Algorithm (GOA), Antlion Optimiser (ALO), and Artificial Fish Swarm Algorithm (AFSA), to optimise the parametric weights of the Extreme Gradient Boosting (XGBoost) technique, enhancing its ability to predict excavator bucket tooth wear. The hybrid models, named ICA-XGBoost, GOA-XGBoost, ALO-XGBoost, and AFSA-XGBoost, were developed using a data set of 579 wear records from a surface mine in Ghana. Furthermore, the study implemented standalone models, such as XGBoost, Gradient Boosting Regressor (GBR), Random Forest (RF), and Categorical Boosting Regressor (CatBoost), to benchmark the performance of the various hybrid XGBoost models. To evaluate the predictive performance of these models, six statistical metrics were employed: Variance Accounted for (VAF), Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Square Error (MSE), Correlation Coefficient (R), and Coefficient of Determination (R^2). In addition, the Akaike Information Criterion (AIC) was used to identify the most effective model. The results demonstrated that ICA-XGBoost outperformed the other models, achieving the lowest MAE, RMSE and MSE values (0.065536, 0.050359, and 0.002536, respectively) as well as the highest VAF, R, and R^2 values (99.9997, 0.999998, and 0.999996, respectively). Furthermore, ICA-XGBoost exhibited the lowest AIC value (-447.060), confirming its superior predictive capability for the wear of excavator bucket teeth. Finally, after evaluating the various models, a sensitivity analysis was performed to assess the influence of the input variables.

Keywords: Imperialistic Competitive Algorithm, Extreme Gradient Boosting, Excavator Bucket Teeth, Wear, Metaheuristic Optimisation

1 Introduction

Excavators play a crucial role in surface mining operations by excavating and transporting large quantities of blasted ore and waste materials, even in challenging environments. The excavator bucket, equipped with cutting teeth, faces severe wear due to its constant contact with abrasive rock and soil. This wear primarily results from two mechanisms: abrasive wear, which occurs as hard particles scratch against the bucket teeth, and impact wear, caused by the high impact forces during excavation (Ren *et al.*, 2019; Hawk *et al.*, 2002; Singh *et al.*, 2013). Over time, these wear mechanisms lead to a significant deterioration of the bucket teeth, affecting the excavator's performance and increasing maintenance costs. Efficient management of wear is crucial for optimising the operational efficiency and economic feasibility of mining operations, as it impacts both productivity and cost-effectiveness (Holmberg *et al*., 2023; Holmberg *et al.*, 2017). Therefore, the development of effective wear prediction models is essential to assist maintenance engineers in the mining industry.

A variety of laboratory studies have focused on improving the durability of excavator bucket teeth to reduce maintenance needs and operational downtime. For example, Singla (2012) concentrated on enhancing the durability of excavator bucket teeth to minimise their replacement frequency. Similarly, Bolobov *et al.* (2020) conducted a comprehensive analysis of the effects of high-temperature thermomechanical treatment on steel structures, aiming to strengthen the bucket teeth assembly. Other material-based studies, such as those by Keles and Yildirim (2020), evaluated the impact of titanium (Ti) additions (0.15–0.20 wt%) on the wear resistance of bucket teeth, while Suryo *et al*. (2018) explored optimal heat treatment settings for mild carbon steel to improve wear resistance. Despite these contributions to enhancing durability, these laboratory studies primarily focus on material properties under controlled conditions, which often do not reflect the dynamic and

**Manuscript received September 15, 2024*
Revised version accepted March 22, 2025

unpredictable wear encountered in actual mining environments. Moreover, these studies lack predictive insights into wear over time, which is crucial for maintenance engineers in the mining industry.

In addition to laboratory experiments, numerical analysis techniques have been employed to assess the strength and durability of excavator bucket teeth. Kumar and Alam (2016) numerically examined the impact of stress on fixed joints of bucket teeth in large-scale excavators, such as the P & H 1900 electric shovel and Kartex-10 mining shovel. While valuable in understanding stress distributions, these studies did not focus on wear predictive modelling. Zhang (2016) used discrete element modelling to evaluate the performance of bucket teeth on the WK-75 rope shovel, focusing on stress and material endurance. Yu *et al*. (2018) expanded this approach by using EDEM software to simulate the influence of the number of bucket teeth on the drag forces experienced during excavation. Choudhry (2020) further explored the durability of bucket teeth at the Boliden Aitik copper mine, noting that the middle teeth were subjected to the highest levels of mechanical stress. While these numerical studies offer important insights into the structural durability of excavator bucket teeth, they are often computationally intensive and lack real-time predictive capabilities for variable field conditions (Rackl *et al*., 2017).

Despite the insights gained from both laboratory and numerical studies, a significant gap remains untapped in the ability to predict wear of excavator bucket teeth in real-world scenarios. The reviewed approaches primarily focused on improving durability, without offering insights into the prediction of excavator bucket teeth wear under actual operational conditions. To address this gap, this study proposes the development of predictive models using advanced machine learning techniques, shifting the focus from durability testing to real-time wear prediction. Specifically, the research emphasises the need for models that can predict wear based on key excavation parameters such as rock compressive strength, quartz content, interaction duration, and rock fragment sizes. These factors significantly influence wear patterns, and their integration into predictive models is essential for optimising the usage of excavator bucket teeth (Dong *et al*. 2023).

In recent years, artificial intelligence (AI) has demonstrated significant potential in predictive analysis for industrial applications by efficiently modelling complex relationships in large datasets (Colantonio *et al*., 2021; Cheng *et al*., 2020; Cheng *et al*., 2022). A commonly used AI technique is the extreme gradient boosting (XGBoost), known for its ability to approximate intricate mappings between input and output features. However, despite its wide applicability, XGBoost has limitations, including its susceptibility to local minima during training, which can result in suboptimal predictions. To overcome this challenge, metaheuristic algorithms have been developed to optimise the training process, enabling more accurate predictions by locating global optima (Chong *et al*., 2021; Carvalho *et al*. 2011, 2005; Tran-Ngoc *et al*., 2021; Ojha, 2017; Askarzadeh and Rezazadeh, 2013; Mirjalili, 2019). Metaheuristics, particularly swarmed-based and evolutionary methods, have demonstrated significant promise to improve prediction accuracies in various engineering applications (Hussain *et al*., 2019; Han *et al*., 2019; Qiu *et al*., 2022; Monga *et al*., 2022), making them well-suited for adoption in this research to predict excavator bucket teeth wear.

In light of this insight, the study introduces and assesses new hybrid models that integrate metaheuristic algorithms with XGBoost to predict wear on excavator bucket teeth. To develop the wear prediction models in this research, metaheuristic algorithms are specifically employed as surrogate training algorithms to fine-tune the parametric weights and biases of the XGBoost model. For the first time, the performance of four hybrid models: ICA-XGBoost (Imperialist Competitive Algorithm-XGBoost), GOA-XGBoost (Grasshopper Optimisation Algorithm-XGBoost), ALO-XGBoost (Ant Lion Optimiser-XGBoost), and AFSA-XGBoost (Artificial Fish Swarm Algorithm-XGBoost) will be evaluated for their effectiveness in predicting excavator bucket teeth wear. These optimisers (ICA, GOA, ALO, and AFSA) have been selected due to their demonstrated success in helping the model development better fit the data and improve prediction accuracy (Duan *et al*., 2021; Afzal *et al*., 2024; Pradeep *et al*., 2022; Alhndawi *et al*., 2024; Jahed Armaghani *et al*., 2016). The predictive performance of these four hybrid models will be compared against the standalone XGBoost and other machine learning methods, including Gradient Boosting Regressor (GBR), Random Forest (RF), and Categorical Boosting Regressor (CatBoost), to assess their robustness and suitability for wear prediction in mining operations. The selection of GBR, RF, and CatBoost as baseline techniques for comparison in this study is based on their proven performance and widespread use in predictive modelling tasks, particularly in the context of handling non-linear relationships and complex datasets (Qui *et al*., 2022; Zhou *et al*., 2024; Mustapha *et al*., 2024; Jia *et al*., 2022; Ha *et al*., 2021; Song *et al*., 2024).

The main contributions of this paper are as follows: First, it explores the effectiveness of four novel metaheuristic optimisation algorithms, including ICA, GOA, ALO, and AFSA, in enhancing the predictive performance of the XGBoost model for predicting excavator bucket teeth wear. Second, the research assesses and compares the prediction outcomes of these metaheuristic-based hybrid models (ICA-XGBoost, GOA-XGBoost, ALO-XGBoost, and AFSA-XGBoost) with the standalone XGBoost model, as well as three additional baseline models: GBR, RF, and CatBoost. Lastly, it performs a sensitivity analysis on the input features to identify the parameter that has the greatest impact on the wear of excavator bucket teeth.

2 Resources and Methods

2.1 Study Area

The study was carried out at an open-pit mine located in Ghana. More precisely, the site is situated roughly 133 km to the west of Koforidua, which is the regional capital, and around 3 km to the west of New Abirem, the district capital. According to Kaba (2013), it is located approximately 180 km northwest of Accra. Tarkwaian sediments, comprising conglomerate, sandstone, and phyllite, are found in the northwestern section of the mining area, where they unconformably overlay the Birimian volcanic belts. Figure 1 illustrates the precise position of the study site.

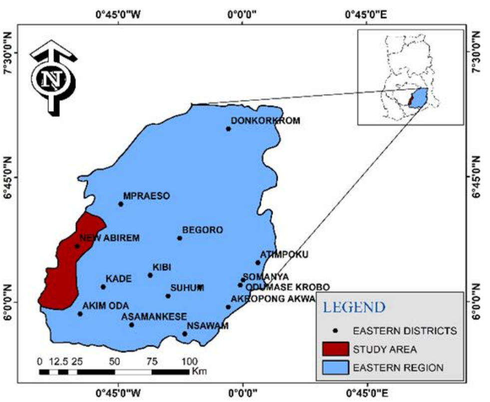

Fig. 1 Study Area

The mining operation features a fleet comprising two Liebherr 9400 hydraulic shovels and two hydraulic backhoes for mucking. It also includes eighteen Caterpillar 785 rear dump trucks, each capable of transporting up to 134 tonnes of ore to stockpiles or crushers, or moving non-economical blasted materials to the waste dump. The loading process uses a single backup loading method and involves excavating a 9-metre bench through a series of 3-metre sequential flitch excavations. The mine operates seven Pantera drill rigs: five with 165-mm drill bits, primarily for blasting, and two with 115-mm drill bits, mainly for wall control holes. A staggered drill design is employed, with a burden and spacing of 4.0 m × 4.0 m in the ore zone and 5.2 m × 5.2 m in the waste zone.

2.2 Data Description

A dataset consisting of 579 historical data points, gathered over a period of 289.5 effective working days, was utilised for the development of predictive models. The dataset contained a number of variables, including the digging duration during rock-tool interaction (DD), the equivalent quartz content (EQC), the average rock fragment sizes (FS), and the uniaxial compressive strength (UCS). These factors served as input parameters, with the average wear of excavator bucket teeth (W) at five positions as the output parameter. The FRAGTrack™ device, incorporating sophisticated image processing technology, was installed on the excavator's rollover protection structure (ROPS) to capture and analyse rock fragment sizes. The measurements of average fragment sizes were utilised for the developing of the model. The study examined the operation of a Liebherr 9400 excavator in an area characterised by phyllite, sandstone, and greywacke rock formations. The uniaxial compressive strength was tested in accordance with the norms set by the International Society for Rock Mechanics (ISRM) (Aydin, 2014), while the equivalent quartz content was assessed using X-ray diffraction tests. The duration of the excavator's cycle, which includes the time it takes to scoop with the bucket, was tracked using a dispatch system that relies on GPS technology. The longitudinal dimensions of the bucket teeth were measured as they wore down, using a ground-engaging tool (GET) measurement device, essentially a well-graded or calibrated ruler. Measuring the on-site wear of excavator bucket teeth is crucial in this research, as it provides essential data for understanding wear patterns. It offers direct, practical insights into actual working conditions, aiding in the development of more reliable predictive models. The dataset's statistical features are presented in Table 1, while Figure 2 depicts the correlation matrix among the variables. Table 2 presents a sample of the datasets collected for this study.

Table 1 Statistical Features of the Data Variables

Parameters (Unit)	Category	Mean	Min	Max
DD (min)	Input	298.2	164.3	407.6
FS (cm)		22.2	12.2	41.8
UCS (MPa)		87.1	58.0	157.0
EQC (%)		35.4	24.0	60.0
Wear (mm)	Output	36.1	24.0	56.0

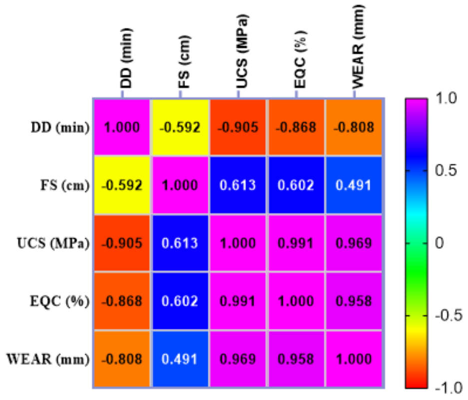

Fig. 2. Correlation Matrix for the Dataset

Table 2 Sample of Datasets

Symbol		DD	FS	UCS	EQC	W
Datapoint	1	315.40	16.20	58	24	29
	2	258.40	22.58	128	54	45
	3	209.35	29.18	157	60	55
	4	335.75	17.60	58	24	29
	5	185.68	28.10	157	60	54
	6	290.23	23.69	128	54	46
	7	331.38	14.99	58	24	29
	8	178.50	35.58	157	60	52
	9	322.63	28.92	58	24	25
	10	293.65	23.09	128	54	48
	11	192.47	29.17	157	60	51
	12	341.53	20.10	58	24	29
	13	261.30	23.67	128	54	47
	14	356.58	15.59	58	24	33
	15	186.05	26.97	157	60	54

2.3 Methodology

This section provides a brief overview of the optimisation techniques employed in this study, along with standalone extreme gradient boosting and baseline non-hybrid models.

2.3.1 Imperialistic Competitive Algorithm (ICA)

The Imperialist Competitive Algorithm (ICA) was introduced by Atashpaz-Gargari and Lucas (2007) as a simulation of human social evolution to address optimisation problems. Recognised for its high performance in decoding continuous functions, ICA is a global search algorithm rooted in imperialist competition and social dynamics (Hosseini *et al.*, 2014; Elsisi, 2019; Zadeh Shirazi and Mohammadi, 2017). The algorithm operates on the principle that the strongest empire can dominate various colonies and their resources. When an empire falls, other territories vie to claim the land. The fundamental process of ICA can be outlined in the following eight steps:

i. Initialise Empires and Search Spaces: Randomly generate initial empires and their associated search spaces;

ii. Colony Assimilation: Adjust the positions of colonies based on their respective empire locations;

iii. Revolutionary Changes: Implement random modifications to each empire’s features as a form of revolution;

iv. Territorial Swapping: A colony with a superior position may rise to control the empire, replacing the previous empire;

v. Empire Competition: Empires compete to seize control of each other's colonies;

vi. Elimination of Weaker Empires: Weaker empires are defeated and eliminated, along with their colonies, applying natural selection principles; and

vii. Termination Check: Assess whether the stopping criteria are met. If so, conclude the process; otherwise, return to the colony assimilation step (Step 2).

2.3.2 Grasshopper Optimisation Algorithm (GOA)

In this technique, the exploration process is modelled after the erratic movements of grasshoppers when searching for food, while the exploitation process simulates their behaviour of moving toward and consuming food at a local source (Mafarja *et al*., 2018). These behaviours are naturally exhibited by grasshoppers. The algorithm captures these behaviors using a location update formula. The position of each grasshopper is updated based on its current location, the global target value, and the locations of other grasshoppers. The updated mathematical model for simulating grasshopper positions in a D-dimensional space is as follows:

$$A_i = c_n\left(\sum_{\substack{j=1\\ j\neq i}}^{z} c_n\left(\frac{a_j - a_i}{d_{ij}}\right)\cdot\left(\frac{\varepsilon-\delta}{2}k(d_{ij})\right)\right) + T_d \qquad (1)$$

where the position vector of the *i*-th grasshopper is denoted as A_i; the parameter c_h, analogous to the inertial weight in the particle swarm technique, helps maintain a balance between the exploration and extraction activities of the entire group around the target; ε and δ represent the upper and lower limits of the search range, respectively; *k* is the attraction function; d_{ij} =| a_i - a_j | represents the distance between the *i*-th and *j*-th grasshoppers; a_i and a_j are the location vectors of the *i*-th and *j*-th grasshoppers, respectively; the current ideal goal value sought is denoted as T_d ; and the parameter c_n represents the decreasing coefficient of the repulsive, contraction comfort, and attraction zones. The computation formula is as follows:

$$c_n = \frac{c_{\min} - c_{\max}}{L}(t) + c_{\max} \qquad (2)$$

The variables in the Equation (2) are defined as follows: C_{max} represents the highest possible value, *t* represents the current number of iterations, *L* represents the maximum number of iterations, and C_{min} represents the lowest possible value.

$$ue^{-\frac{t}{\tau}} = k(r) - e^{-(r)} \qquad (3)$$

where *k(r)* represents the function of attraction between objects, *u* represents the intensity of this attraction, *r* represents the distance between the objects, and τ represents the maximum range of this attraction. When the function *k(r)* yields a positive value, the grasshoppers exhibit attraction towards one another, creating an attraction zone. When the function *k(r)* has a value below 0, grasshoppers are in a condition of exclusion from one another, which is known as the repulsion zone. Equation (4) represents the distance that separates *j*-th and *i*-th grasshoppers.

$$d_{ij} = \left|a_j - a_i\right| \qquad (4)$$

Equation (5) represents the unit vector that goes between the *i*-th grasshopper to the *j*-th grasshopper.

$$\bar{d}_{ij} = \frac{a_j}{d_{ij}} - \frac{a_i}{d_{ij}} \qquad (5)$$

The model leverages the interaction among grasshoppers to progressively move toward and eventually access the food source (Mafarja *et al*., 2018). This is accomplished through a linearly decreasing mechanism that fine-tunes parameters to search for the optimal global value.

2.3.3 Ant Lion Optimisation Algorithm (ALO)

Mirjalili (2015) came up with an algorithm called Ant Lion Optimiser (ALO) that is based on nature and copies the way ant lions hunt in their natural environment. The ALO algorithm also finds better optimal designs for most standard problems in engineering, which shows that it can be useful for finding solutions with limited search spaces. The main idea behind the ALO algorithm comes from how antlion's larvae finds food. Two important steps in the life cycle of ALO are the larvae phase and the adult phase. When they are larvae, ant lions hunt, and when they are adults, they reproduce. The larvae stage is where the ALO algorithm got its idea.

Ant lions move in a circle and throw sand out with their sharp jaws to make a cone-like hole in the sand. Once the hole is dug, the larvae wait for the prey or ant. No matter how hungry the ant lion is or how big the moon is, the size of the trap will change. Larger moons or levels of hunger mean bigger traps, and smaller moons mean smaller traps. It is easy for pray to fall into the cone if it hits the top. If the ant lion finds the prey in the trap, it will definitely catch it. There are five major steps in the ALO algorithm: ants moving randomly, setting up a trap, ants getting caught in the trap, catching prey, and setting up the traps again (Mirjalili, 2015).

2.3.4 Artificial Fish Swarm Algorithm

The Artificial Fish Swarm Algorithm (AFSA) is a local optimisation technique that enhances the ability to exploit the search space. In biological terms, fish can locate more nutritious areas through individual search or by following another fish. Generally, areas with a higher concentration of fish are the fullest of nutrients. AFSA is an effective, parallel and random search method that was first proposed by Neshat *et al*. (2014). The technique simulates fish behaviors such as preying, swarming, and following to achieve the global best solution through the local exploration of fish individuals. Each artificial fish's position signifies a potential solution. The present position of artificial fish *i* is denoted as $F_i = (f_{i1}, f_{i2}, \ldots, f_{in})$. The fitness of artificial fish *i* at this position is represented by $P_i = f(F_i)$, with P_i being the objective function. The updated position $F_i^{'}$ can be described as follows:

$$F_i^{'} = F_i + Rand() \times \frac{step \times (F_j - F_i)}{\left\| F_j - F_i \right\|} \tag{6}$$

Here, the function Rand ( ) generates a random number between 0 and 1. The variable step represents the length of each movement, whereas F_j is the position within the visible range. Here, F_j is characterised by several behaviors as follows (Neshat *et al*. 2014):

i. Following: The artificial fish engages in trailing behaviour by following a neighboring fish within its visual range that has discovered the most reliable food source, in order to find additional food. The position of the partner with the highest food consistency is visible within the fish's field of vision;

ii. Swarming: The artificial fish exhibits a tendency to cluster around the center of a group, similar to the behavior observed in natural organisms. This swarming behavior helps enhance the survival of the group and reduces potential threats, serving as the focal point of the gathering; and

iii. Preying: The artificial fish uses its vision or sensory capabilities to detect food sources and make movement decisions based on the consistency of food availability. When it identifies an area with a higher concentration of food, it will immediately move toward that location.

2.3.5 Extreme Gradient Boosting (XGBoost)

XGBoost is a computational package that integrates a novel algorithm with gradient-boosting decision trees techniques, as proposed by Chen *et al*. (2015), to effectively enhance gradients. XGBoost, which is based on the concepts of regression and classification trees, is a highly successful approach for solving classification and regression constraints (Zhang *et al*., 2022; Zhou *et al*., 2015).

The objective function of XGBoost is comprised of two main components after optimisation. These components capture the deviation and include a regularisation term designed to prevent overfitting (Chen and Guestrin, 2016). Given a dataset $D = \{(x_i, y_i)\}$ with *n* samples and *m* features, the predictive model is an additive model consisting of *k* basic models. The results of the sample predictions are as follows:

$$p = \sum_{z=}^{z} f_z(a_i).f_z \in \ell \tag{7}$$

$$\ell = \{ f(a) = w_h(a) \} h : R^m \to K,\ \mathrm{w}_h \in R^k) \tag{8}$$

where *p* denotes the prediction label, a_i represents a specific sample, and $f_z(a_i)$ denotes the predicted score for that sample. The symbol ℓ stands for the set of regression trees, which are the parameters of *h*. The symbols $f(a)$ and *w* refer to the weight of the leaves and the number of leaves, respectively. The objective function of XGBoost includes both the standard loss function and a term for model complexity, which together assess the algorithm's operational effectiveness. The second term in Equation (9) corresponds to the standard loss function, while the last term addresses the model's complexity.

$$\mathrm{Obj} = \sum_{i=1}^{t} b(\hat{p}_i\ , p_i^{(k-1)} + f_i(a_i)) + \beta(f_z) \tag{9}$$

$$\beta(f_z) = (0.5 \times w^2 \times \lambda) + K\gamma \tag{10}$$

In these formulas, *i* represents the index of samples in the dataset, and *z* denotes the total number of data points fed into the *t*-th tree. The parameters γ and λ are used to regulate the complexity of the tree. The regularisation term helps to prevent overfitting and smooth the final network weights. For more detailed information, refer to the research by Chen and Guestrin (2016).

2.3.6 Gradient Boosting Regressor (GBR)

The GBR model has recently become a popular choice for its effectiveness in machine learning. GBR excels with structured data, which is typically organised into rows and columns, and is particularly suitable for datasets of moderate size, generally up to a few million records. As an ensemble technique, GBR builds a series of decision trees sequentially rather than in parallel. Each tree in GBR learns from the errors of the previous one, and by combining the outputs of many weak learners, GBR creates a robust ensemble model using Gradient Descent. This iterative approach focuses on reducing errors, although it can occasionally lead to overfitting if outliers are overemphasised (Zhang and Haghani, 2015).

2.3.7 Random Forest (RF)

The Random Forest, an ensemble machine learning method that falls within the decision tree category was developed by Breiman (2001). Suitable for both regression and classification tasks, the RF regressor is specifically designed for regression problems. It operates by generating multiple decision trees through a technique called bootstrapping, or bagging, and then averaging their predictions to derive the final outcome. This involves creating a source matrix from various features of the training data, building a set of K regression trees, and computing the average of their predictions (Breiman, 2001; Guo *et al*., 2010; Rodriguez-Galiano *et al*., 2015). While the RF regressor is known for its accuracy, it often requires longer training times compared to single decision trees due to the large number of trees it constructs, making it a more complex model (Mbaabu, 2020).

2.3.8 Categorical Boosting (CatBoost)

CatBoost, a recent gradient boosting technique introduced by Prokhorenkova *et al*. (2018), excels in handling categorical features with minimal information loss. It stands out from other gradient-boosting methods by incorporating ordered boosting, a specialised variation designed to address target issues (Dorogush *et al*., 2018). This approach proves especially effective for datasets with limited size. CatBoost processes categorical features by converting them into numerical values during pre-processing. Bakhareva *et al*. (2019) have shown that CatBoost efficiently manages various data types and formats. It has been successfully applied across different fields, including fault classification (Ogar *et al*., 2022), and for analysing time series data (Diao *et al*., 2019; Fan *et al*., 2020). Notably, CatBoost replaces the original variable with a binary attribute for each category and uses random permutations to estimate leaf values during tree structure selection, which helps mitigate overfitting commonly associated with traditional gradient boosting algorithms. CatBoost relies on binary decision trees as its core predictor. The output estimation, as defined by Huang *et al*. (2019), is as follows:

$$P = C(x_i) = \sum_{j=1}^{j} b_j \; \{x = R_j\} \tag{11}$$

where $C(x_i)$ represents a decision tree operator that depends on the variables that explain the phenomena x_i. R_j refers to the disjoint zone that corresponds to the leafy part of the tree.

2.4 Model Development and Selection

The workflow used to set up the hybrid and standalone AI models in the present investigation is depicted in Figure 3.

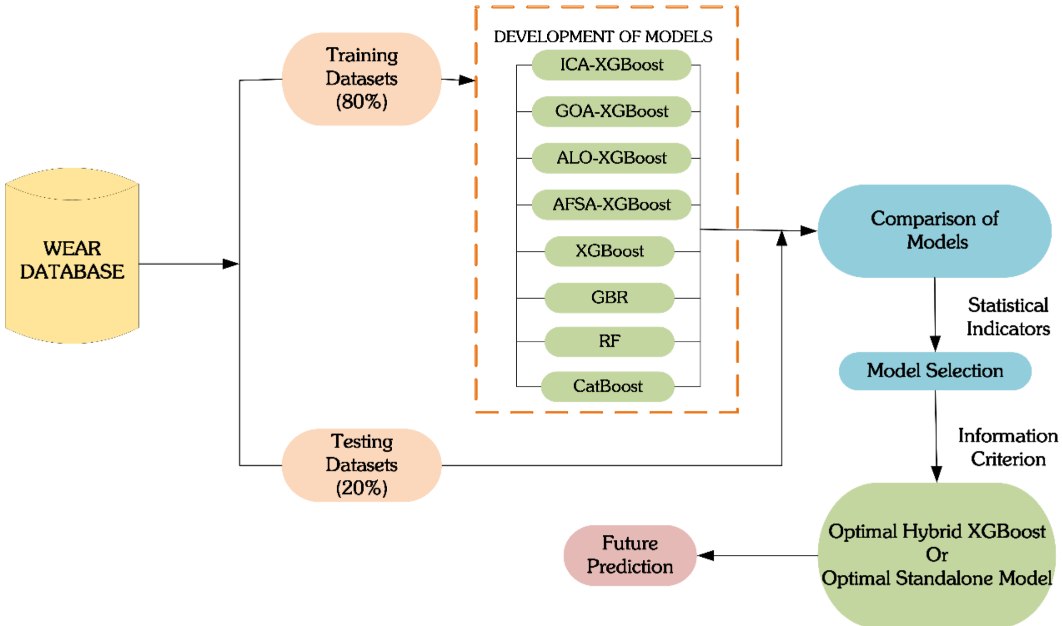

Fig. 3 Workflow Adopted in This Study to Predict Wear of Excavator Bucket Teeth

2.4.1 Developed Hybrid Models with Optimisation

The data was split into training and testing sets using a holdout cross-validation method for the development of optimised hybrid models (ICA-

XGBoost, GOA-XGBoost, ALO-XGBoost, and AFSA-XGBoost). Specifically, 80% of the 579 total dataset points were randomly selected for model development, while the remaining 20% were reserved for model evaluation. These models were built using the XGBoost framework, focusing on finding the optimal values for parametric weights and biases to minimise errors. Given the stochastic nature of the optimisation methods (ICA, GOA, ALO, and AFSA), performance varied with each run, and this procedure was iterated till the optimal solution was achieved. The optimal factor settings for each optimiser (ICA, GOA, ALO, and AFSA) are summarised in Table 3.

2.4.2 Developed Standalone Models

A grid search was employed to systematically find the optimal parameter combinations by varying step sizes for the standalone models. This method, widely used for hyperparameter optimisation (Chen *et al*., 2018; Fan *et al*., 2020), explores a predefined range of values to fine-tune parameters. In this study, three parameters for the XGBoost model were optimised: the number of trees (100 to 1000), the maximum tree depth (2 to 40), and the learning rate (0.002 to 0.4). For the Gradient Boosting Regression (GBR) model, the grid search focused on tuning two parameters: the number of rounds, ranging from 50 to 500 with a step size of 50, and the maximum tree depth, ranging from 2 to 40 with a step size of 5. This study involved tuning two parameters: the number of rounds, which went from 50 to 500 with a step size of 50, and the maximum tree dimensions, which ranged from 2 to 40 with a step size of 5, for the random forest model. The CatBoost model was trained with varying settings, including the number of rounds (100 to 600, increasing by 100), the maximum tree depth (2 to 20, increasing by 2), and the subset ratio of the datasets (0.5 to 1, increasing by 0.05).

2.5 Model Performance Assessment

The prediction accuracies of the derived predictors were evaluated using statistical indicators. The metrics used in this analysis were variance accounted for (VAF), mean absolute error (MAE), root mean square error (RMSE), mean square error (MSE), correlation coefficient (R), and coefficient of determination (R^2). These measurements assess the accuracy, association, and fit between expected and observed data. Smaller values of MAE, RMSE, and MSE imply superior performance, whereas larger values of R and R^2 indicate strong relationships. The mathematical expressions for these measures are denoted by Equations (12) to (17) (Kong *et al*., 2018; Kanake and Ahuja, 2022). In addition, the Akaike information criterion (AIC) (Bozdogan, 1987) (Equation (18)) was used as a tool for model selection in order to choose the most accurate technique.

$$\text{VAF} = \left[\frac{1-(\text{var}(L_i - T_i))}{\text{var}(T_i)}\right] \times 100 \tag{12}$$

$$\text{MAE} = \frac{1}{m} \times \sum_{i=1}^{m} | L_i - T_i | \tag{13}$$

$$\text{RMSE} = \sqrt{\frac{1}{m} \times \sum_{i=1}^{m} (L_i - T_i)^2} \tag{14}$$

$$\text{MSE} = \frac{1}{m} \times \sum_{i=1}^{m} (L_i - T_i)^2 \tag{15}$$

$$\text{R} = \frac{\sum_{i=1}^{m}(L_i - T_{av})(L_i - T_{av})}{\sqrt{\sum_{i=1}^{m}(L_i - T_{av})^2} \times \sqrt{\sum_{i=1}^{m}(L_i - T_{av})^2}} \tag{16}$$

$$\text{R}^2 = \left(\frac{\sum_{i=1}^{m}(L_i - T_{av})(L_i - T_{av})}{\sqrt{\sum_{i=1}^{m}(L_i - T_{av})^2} \times \sqrt{\sum_{i=1}^{m}(L_i - T_{av})^2}}\right)^2 \tag{17}$$

$$\text{AIC} = m \left[\text{In}\left(\frac{1}{m} \times \sum_{i=1}^{m} (L_i - T_i)^2\right)\right] + 2\gamma \tag{18}$$

The assessment metrics taken into account include features such as the overall count of samples for testing (m), observed values (L_i), response values (T_i), averaged of observation values (L_{av}), and average of response data (T_{av}).

3 Results and Discussion

This study presents novel methods to enhance the optimisation of XGBoost for accurately predicting of wear in excavator bucket teeth utilised in surface mining settings. To ascertain the most efficient solution, four optimisation algorithms (ICA, GOA, ALO, and AFSA) that draw inspiration from nature were utilised. The metaheuristic algorithms were utilised to optimise the mathematical relationship within the XGBoost framework, with the objective of reducing errors and enhancing prediction accuracy.

Table 3 displays the adjusting or regulating factors and their respective values for each optimisation technique that yielded the most optimal outcomes, whereas Table 4 presents the optimal values of the hyperparameters which were fine-tuned in the standalone models. High Performance desktop computer system equipped with 64 GB of RAM and a 3.2 GHz processor was employed to run the individual models using the Matrix-based and Python programming languages

Table 3 Optimal Settings of the Optimisation Regulating Factors

Algorithm	Parameter	Value
ICA	Number of Empires	15
	Number of Countries	100
	Revolution Rate	0.07
	Colonial Competitive Rate	0.5
	Damping Coefficient	0.95
	Assimilation Coefficient	1.6
GOA	Number of Grasshoppers	11
	Iterations	200
	Attraction Coefficient	0.5
	Convergence Rate	0.7
ALO	Search Agents (Ant lions)	4
	Iterations	200
	Hidden Neurons	25
	Lower Bound	-1
	Upper Bound	1
AFSA	Population Size (Artificial Fish)	50
	Iteration	300
	Visual Distance	2.5
	Crowd Factor	0.7
	Try Number	10
	Prey Probability	0.8

Table 4 Optimal Settings of the Standalone Regulating Factors

Algorithm	Parameter	Value
XGBoost	Number of Trees	500
	Maximum Tree Depth	15
	Learning Rate	0.1
Gradient Boosting Regressor	Number of Rounds	300
	Maximum Tree Depth	10
Random Forest	Number of Rounds	200
	Maximum Tree Depth	15
CatBoost	Number of Rounds	400
	Maximum Tree Depth	8
	Subset Ratio of Datasets	0.8

3.1 Comparison of Models

The predictive performances of all the methods formulated were examined using the computational metrics given in Equations (12) to (17). Table 5 provides the findings per the models developed using the testing datasets.

Table 5 Evaluation Performance Results for the Developed Models Based on Testing Dataset

Method	Performance Metrics					
	MAE	RMSE	MSE	VAF	R	R^2
ICA-XGBoost	**0.065536**	**0.050359**	**0.002536**	**99.9997**	**0.999998**	**0.999996**
GOA-XGBoost	0.070735	0.098158	0.009635	99.9802	0.999879	0.999758
ALO-XGBoost	0.096011	0.178916	0.032011	99.9670	0.999746	0.999492
AFSA-XGBoost	0.074586	0.102401	0.010486	99.9622	0.999794	0.999588
XGBoost	0.259175	0.443052	0.196295	99.8399	0.998257	0.996517
GBR	0.155537	0.265832	0.070667	99.8361	0.998684	0.997369
RF	0.104685	0.256134	0.065605	99.7701	0.998701	0.997403
CatBoost	0.203773	0.375224	0.140793	99.7500	0.998357	0.996716

A model is considered exceptional when it achieves values near zero for the MAE, RMSE, and MSE metrics. Table 5 presents the evaluation results, where ICA-XGBoost emerged as the top performer, exhibiting the lowest MAE, RMSE, and MSE values. Specifically, ICA-XGBoost achieved MAE of 0.065536 (Fig. 4), outperforming the other hybrid models, GOA-XGBoost (0.070735), ALO-XGBoost (0.096011), and AFSA-XGBoost (0.074586), as well as standalone models such as XGBoost, GBR, RF, and CatBoost, which recorded MAE values of 0.259175, 0.155537, 0.104685, and 0.203773, respectively. These findings suggest that ICA-XGBoost provided the most accurate predictions of the wear of excavator bucket teeth.

Furthermore, the RMSE values in Table 5 reveal that ICA-XGBoost demonstrated a closer alignment between the predicted and actual wear values compared to other methods, with the lowest RMSE of 0.050359 (Fig. 5). This further highlights its superior predictive accuracy. In contrast, the RMSE values of the remaining models ranged from 0.070735 to 0.259175, underscoring the lower error margin of ICA-XGBoost.

The MSE results presented in Table 5 further reinforce this trend. ICA-XGBoost had the smallest error margin between predicted and observed wear, with an MSE of 0.002536, followed by GOA-XGBoost (0.009635), ALO-XGBoost (0.010486), and AFSA-XGBoost (0.032011). These results confirm the superior performance of the hybrid models over the standalone approaches, as visualised in Fig. 6.

In theory, a prediction model achieves perfection when its VAF (Variance Accounted For) reaches 100%, indicating complete accuracy. All the models listed in Table 5, both hybrid and standalone, exhibited VAF values above 99%, affirming their high predictive accuracy. Among them, ICA-XGBoost produced the highest VAF value of 99.9997% (Fig. 7). The following models, in descending order, were GOA-XGBoost (99.9802%), AFSA-XGBoost (99.9670%), ALO-XGBoost (99.9622%), RF (99.8399%), GBR (99.8361%), CatBoost (99.7701%), and XGBoost (99.75%).

Furthermore, Table 5 reveals that both the hybrid and baseline models (ICA-XGBoost, GOA-XGBoost, ALO-XGBoost, AFSA-XGBoost, XGBoost, GBR, RF, and CatBoost) achieved R values exceeding 0.9 (Fig. 8), indicating a strong linear relationship between predicted and observed wear values. ICA-XGBoost recorded an exceptionally high R value of 0.999998, showcasing the strongest correlation.

Consistently, the hybrid ICA-XGBoost model outperformed all others in capturing the diverse patterns within the dataset, delivering the highest out-of-sample R^2 statistic of 0.999996. This result underscores the model's ability to accurately characterise the dynamic patterns of wear over time. The R^2 values are visually presented in Fig. 9.

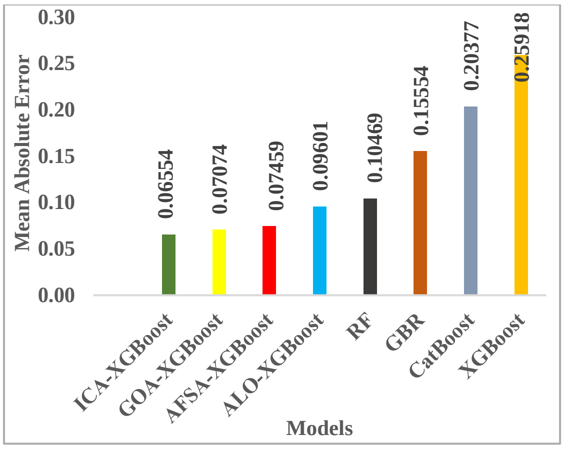

Fig. 4 Mean Absolute Error Results for the Models

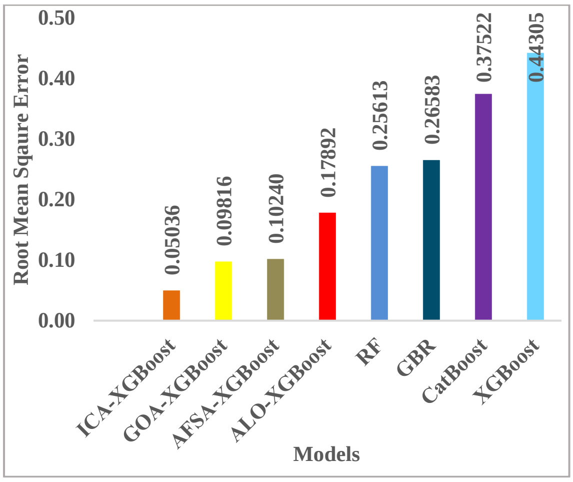

Fig. 5 Root Mean Square Error Results for the Models

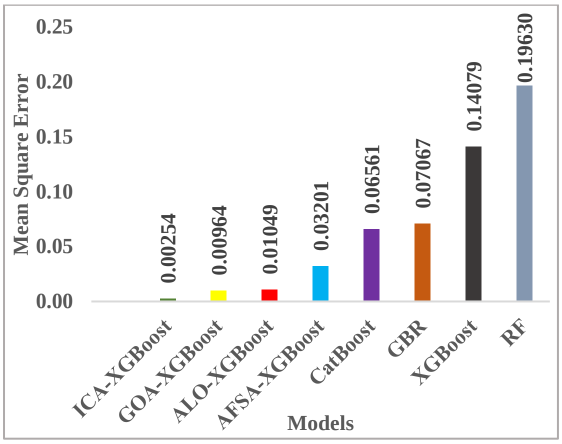

Fig. 6 Mean Square Error Results for the Models

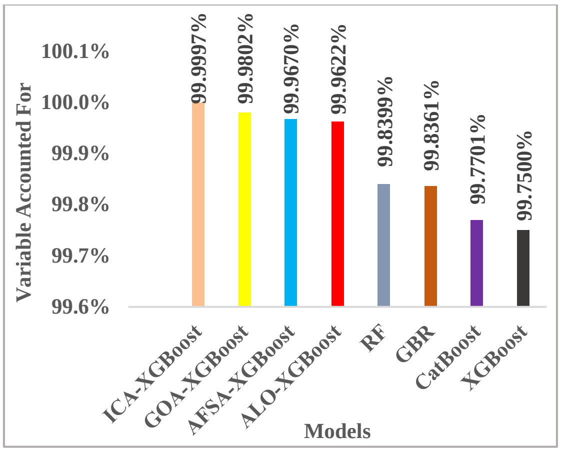

Fig. 7 Variable Accounted for Results for the Models

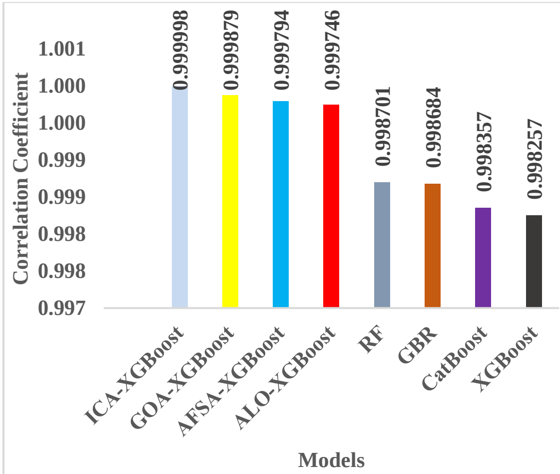

Fig. 8 Correlation Coefficient Results for the Models

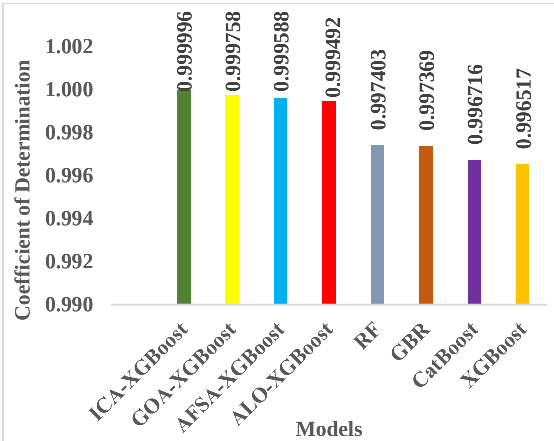

Fig. 9 Coefficient of Determination Results the Applied Models

3.2 Selection of the Best Performing Model

The Akaike Information Criterion (AIC) was used to choose the most efficient model among the techniques that were studied. The model or technique that has the lowest AIC value is considered the most favourable approach. A lower

AIC value suggests a better fit to the observed data compared to models with higher values. Based on the AIC results presented in Table 6, it is clear that the ICA-XGBoost technique demonstrates superior performance compared to all other methods to predict the wear of excavator bucket teeth in the study mine. The ICA-XGBoost model, with an AIC value of -447.060, which is the lowest among the methods analysed in Table 6, confirms this evaluation and establishes it as the technique of choice above the GOA-XGBoost, ALO-XGBoost, AFSA-XGBoost, XGBoost, GBR, RF, and CatBoost methods. The result visualisation is additionally illustrated in Fig. 10.

Table 6 AIC Results for the Various Applied Models

Methods	AIC Values
ICA-XGBoost	**-447.060**
GOA-XGBoost	-405.631
AFSA-XGBoost	-361.263
ALO-XGBoost	-328.721
RF	-304.851
GBR	-267.205
CatBoost	-214.458
XGBoost	-180.864

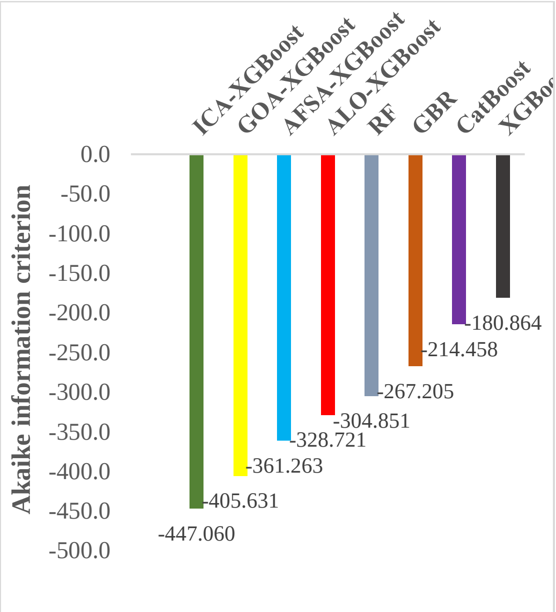

Fig. 10 AIC Results of the Various Applied Models

3.3 Sensitivity Analysis

A sensitivity analysis was conducted in this study to assess the relative influence of input features, including bucket digging duration (DD), mean fragment sizes (FS), equivalent quartz content (EQC) of the fragmented rock mass, and the uniaxial compressive strength (UCS) of the rocks, on the output feature: the wear of excavator bucket teeth. The significance of each input variable on the output was quantified using the Cosine Amplitude Method (Equation (19)) (Parsa *et al.*, 2017).

$$S_{ij} = \frac{\left| \sum_{k=1}^{M} D_{ik} R_{jk} \right|}{\sqrt{\left(\sum_{k=1}^{N} D_{ik}^{2} \right)} \times \sqrt{\left(\sum_{k=1}^{M} R_{jk}^{2} \right)}} \tag{19}$$

where S_{ij} represents the sensitivity index, D_{ik} denotes the input feature matrix, R_{jk} describes the output feature matrix, k signifies the data sample sequence number, and M exemplifies the total number of datasets considered. Consequently, it is crucial to note that the higher the sensitivity index of an input feature, the greater its influence on the output feature. The computed sensitivity indices for these input features are presented in Table 7 and are visually represented in Fig. 11.

Table 7 Sensitivity Analysis Results on Input Features Used

Input Feature	Category	Sensitivity Index
Digging Duration	DD	0.8079
Mean Fragment Sizes	FS	0.4910
Equivalent Quartz Content	EQC	0.9579
Uniaxial Compressive Strength	UCS	0.9694

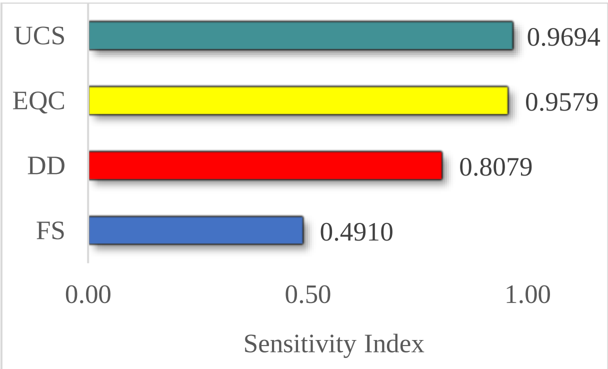

Fig. 11 Influence of Each Parameter on Bucket Teeth Wear

Figure 11 reveals that the input variables had a significant impact on the excavator bucket teeth wear. Uniaxial compressive strength had the highest influence with a sensitivity index of 0.9694, followed by equivalent quartz content (0.9579), digging duration (0.8079), and mean fragment sizes (0.4910), in descending order of importance.

4 Conclusions

This study explores the application of four metaheuristic optimisation algorithms (ICA, GOA, ALO, and AFSA) as alternatives to the traditional gradient-boosting tree algorithm for training the parametric weights and biases of XGBoost. The performance of the resulting hybrid models, including ICA-XGBoost, GOA-XGBoost, ALO-XGBoost, and AFSA-XGBoost, was assessed using metrics such as MAE, RMSE, MSE, VAF, R, and R^2. After evaluation, these hybrid models were compared against the conventional XGBoost algorithm and three baseline machine learning models (GBR, RF, and CatBoost) to determine their technical superiority. In addition, the Akaike Information Criterion (AIC) was applied to identify the most effective predictive model. The bucket teeth wear models were constructed using input variables, including the equivalent quartz content of blasted rock, rock fragment sizes, excavator digging duration, and uniaxial compressive strength of the rocks. The evaluation results showed that, ICA-XGBoost achieved the lowest MAE (0.065536), RMSE (0.050359), and MSE (0.002536). In contrast, the other methods, including GOA-XGBoost, ALO-XGBoost, AFSA-XGBoost, XGBoost, GBR, RF, and CatBoost, exhibited higher MSE, RMSE, and MAE values, ranging from 0.0707 to 0.2592, 0.0981 to 0.4431, and 0.0096 to 0.1963, respectively. Furthermore, ICA-XGBoost achieved the highest VAF (99.9997%), R (0.999998), and R^2 (0.999996) scores compared to the other techniques. The AIC results further reinforced the superiority of ICA-XGBoost, as it recorded the lowest AIC value of -447.060, while the other models exhibited AIC values between -180.864 and -405.631. Based on all the assessments, this study concludes that the hybrid ICA-XGBoost model is the most effective for predicting on-site excavator bucket teeth wear in mining operations. This model demonstrated strong predictive capability and can be adopted as a cost-effective tool for the maintenance practices of excavator bucket-teeth assembly in the mining industry. The sensitivity analysis also demonstrated that the input variables had a considerable impact on the output feature, which is the wear of excavator bucket teeth. However, uniaxial compressive strength emerged as the most influential factor in predicting the wear of the excavator bucket teeth.

Acknowledgements

The authors would like to thank the Ghana National Petroleum Corporation (GNPC) for providing funding to support this work through the GNPC Professorial Chair in Mining Engineering at the University of Mines and Technology (UMaT), Ghana. Also, the authors would like to express their gratitude to the management of the studied mine for providing the necessary data and access to conduct this research.

References

Afzal, S., Shokri, A., Ziapour, B. M., Shakibi, H. and Sobhani, B. (2024), “Building Energy Consumption Prediction and Optimisation Using Different Neural Network-Assisted Models; Comparison of Different Networks and Optimisation Algorithms”, *Engineering Applications of Artificial Intelligence*, Vol. 127, pp. 1-24.

Alhndawi, A. H., Alshorman, H. and Alkhadrawi, S. (2024), “A Hybrid Approach to Water Potability Prediction: Leveraging Artificial Fish Swarm Algorithm and Convolutional Neural Networks”, *Asian Journal of Civil Engineering*, Vol. 25, No. 3, pp. 2715-2727.

Askarzadeh, A. and Rezazadeh, A. (2013), “Artificial Neural Network Training Using A New Efficient Optimisation Algorithm”, *Applied Soft Computing*, Vol. 13, No. 2, pp. 1206-1213.

Atashpaz-Gargari, E. and Lucas, C. (2007), “Imperialist Competitive Algorithm: An Algorithm for Optimisation Inspired by Imperialistic Competition”, In *2007 IEEE Congress on Evolutionary Computation*, pp. 4661-4667.

Aydin, A. (2014), “ISRM Suggested Method for Determination of The Schmidt Hammer Rebound Hardness: Revised Version”, *The ISRM Suggested Methods for Rock Characterisation, Testing and Monitoring: 2007-2014*, pp. 25-33.

Bakhareva, N., Shukhman, A., Matveev, A., Polezhaev, P., Ushakov, Y. and Legashev, L. (2019), “Attack Detection in Enterprise Networks by Machine Learning Methods”, In *2019 International Russian Automation Conference (RusAutoCon)*, pp. 1-6.

Bolobov, V. I., Chupin, S. A., Bochkov, V. S., Akhmerov, E. V. and Plaschinskiy, V. A. (2020), "The Effect of Finely Divided Martensite of Austenitic High Manganese Steel on the Wear Resistance of The Excavator Buckets Teeth", *Key Engineering Materials*, Vol. 854, pp. 3-9.

Bozdogan, H. (1987), “Model Selection and Akaike's Information Criterion (AIC): The General Theory and Its Analytical Extensions. *Psychometrika*, Vol. 52, No. 3, pp. 345-370.

Breiman, L. (2001), “Random Forests”, *Machine Learning*, Vol. 45, pp. 5-32.

Cao, W., Wang, X., Ming, Z. and Gao, J. (2018), “A Review on Neural Networks with Random Weights” *Neurocomputing*, Vol. 275, pp. 278-287.

Carvalho, A. R., Ramos, F. M. and Chaves, A. A. (2011), “Metaheuristics for The Feedforward

Artificial Neural Network (ANN) Architecture Optimisation Problem", *Neural Computing and Applications*, Vol. 20, No. 8, pp. 1273-1284.

Chen, T. and Guestrin, C. (2016), "Xgboost: A Scalable Tree Boosting System", In *Proceedings of the 22nd International Conference on Knowledge Discovery and Data Mining*, pp. 785-794.

Chen, T., He, T., Benesty, M., Khotilovich, V., Tang, Y., Cho, H., Chen, K., Mitchell, R., Cano, I. and Zhou, T. (2015), "XGBoost: Extreme Gradient Boosting", *R Package Version 0.4-2*, Vol. 1, No. 4, pp. 1-4.

Chen, H., Liu, Z., Cai, K., Xu, L. and Chen, A. (2018), "Grid Search Parametric Optimisation for FT-NIR Quantitative Analysis of Solid Soluble Content in Strawberry Samples", *Vibrational Spectroscopy*, Vol. 94, pp. 7-15.

Cheng, M., Jiao, L., Shi, X., Wang, X., Yan, P. and Li, Y. (2020), "An intelligent prediction model of the tool wear based on machine learning in turning high strength steel", *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, Vol. 234, No. 13, pp. 1580-1597.

Cheng, M., Jiao, L., Yan, P., Jiang, H., Wang, R., Qiu, T. and Wang, X. (2022), "Intelligent Tool Wear Monitoring and Multi-Step Prediction Based on Deep Learning Model", *Journal of Manufacturing Systems*, Vol. 62, pp. 286-300.

Chong, H. Y., Yap, H. J., Tan, S. C., Yap, K. S. and Wong, S. Y. (2021), "Advances of Metaheuristic Algorithms in Training Neural Networks for Industrial Applications", *Soft Computing*, Vol. 25, No. 16, pp. 11209-11233.

Choudhry, J. (2020), "A Study of Wear and Load Behaviour on Bucket Teeth for Heavy-Duty Cable Shovels", *Published MSc Thesis*, Lulea University of Technology, 70 pp.

Colantonio, L., Equeter, L., Dehombreux, P. and Ducobu, F. (2021), "A Systematic Literature Review of Cutting Tool Wear Monitoring in Turning by Using Artificial Intelligence Techniques", *Machines*, Vol. 9, No. 12, 54 pp.

Diao, L., Niu, D., Zang, Z. and Chen, C. (2019), Short-Term Weather Forecast Based on Wavelet Denoising and Catboost", In *2019 Chinese Control Conference (CCC)*, pp. 3760-3764.

Dong, Z., Jiang, F., Tan, Y., Wang, F., Ma, R. and Liu, J. (2023), "Review of the Modelling Methods of Bucket Tooth Wear for Construction Machinery", *Lubricants*, Vol. 11, No. 6, pp. 1-19.

Duan, J., Asteris, P. G., Nguyen, H., Bui, X. N. and Moayedi, H. (2021), "A Novel Artificial Intelligence Technique to Predict Compressive Strength of Recycled Aggregate Concrete Using ICA-Xgboost Model", *Engineering with Computers*, Vol. 37, pp. 3329-3346.

Elsisi, M. (2019), "Design of Neural Network Predictive Controller Based on Imperialist Competitive Algorithm for Automatic Voltage Regulator", *Neural Computing and Applications*, Vol. 31, No. 9, pp. 5017-5027.

Guo, L., Chehata, N., Mallet, C. and Boukir, S. (2011), "Relevance of Airborne Lidar And Multispectral Image Data for Urban Scene Classification Using Random Forests", *ISPRS Journal of Photogrammetry and Remote Sensing*, Vol. 66, No. 1, pp. 56-66.

Ha, N. T., Manley-Harris, M., Pham, T. D. and Hawes, I. (2021), "Detecting Multi-Decadal Changes in Seagrass Cover in Tauranga Harbour, New Zealand, Using Landsat Imagery and Boosting Ensemble Classification Techniques", *ISPRS International Journal of Geo-Information*, Vol. 10, No. 6, pp. 1-8.

Halim, A. H., Ismail, I., and Das, S. (2021), "Performance Assessment of The Metaheuristic Optimisation Algorithms: An Exhaustive Review", *Artificial Intelligence Review*, Vol. 54, No. 3, pp. 2323-2409.

Han, F., Jiang, J., Ling, Q. H. and Su, B. Y. (2019), "A Survey on Metaheuristic Optimisation For Random Single-Hidden Layer Feedforward Neural Network", *Neurocomputing*, Vol. 335, pp. 261-273.

Hawk, J. A., Wilson, R. D., Danks, D. R., and Kiser, M. T. (2002), "Abrasive Wear Failures", *Failure Analysis and Prevention*, pp. 906-921.

Holmberg, K., Ronkainen, H., Andersson, P., Juoksukangas, J., Valtonen, K., Lehtovaara, A., Säynätjoki, M., Salonen, P. and Sundquist, H. (2023), "History of Tribology in Finland 1881–2023 and the Finnish Society for Tribology 1977-2023", *Tribologia-Finnish Journal of Tribology*, Vol .40, No. 3, pp. 4-38.

Holmberg, K., Kivikytö-Reponen, P., Härkisaari, P., Valtonen, K. and Erdemir, A. (2017), "Global Energy Consumption Due to Friction and Wear in The Mining Industry", *Tribology International*, Vol. 115, pp. 116-139.

Hosseini, S., and Al Khaled, A. (2014), "A Survey on The Imperialist Competitive Algorithm Metaheuristic: Implementation in Engineering Domain and Directions for Future Research", *Applied Soft Computing*, Vol. 24, pp. 1078-1094.

Huang, G., Wu, L., Ma, X., Zhang, W., Fan, J., Yu, X. and Zhou, H. (2019), "Evaluation of CatBoost Method for Prediction of Reference Evapotranspiration in Humid Regions", *Journal of Hydrology*, Vol. 574, pp. 1029-1041.

Hussain, K., Salleh, M. N. M., Cheng, S. and Shi, Y. (2019), "On the Exploration and Exploitation in Popular Swarm-Based Metaheuristic Algorithms", *Neural Computing and Applications*, Vol. 31, No. 11, pp. 7665-7683.

Jahed Armaghani, D., Hasanipanah, M. and Tonnizam Mohamad, E. (2016), "A Combination of the ICA-ANN Model to Predict Air-Overpressure Resulting from Blasting", *Engineering with Computers*, Vol. 32, pp. 155-171.

Jia, J. F., Chen, X. Z., Bai, Y. L., Li, Y. L. and Wang, Z. H. (2022), "An Interpretable Ensemble Learning Method to Predict the Compressive Strength of Concrete", *Structures*, Vol. 46, pp. 201-213.

Kaba, F. A. (2013), "Student Internship Technical Report on Newmont Golden Ridge Limited, Akyem", *Internship Report, Ghana,* pp. 1-15.

Keles, A. and Yildirim, M. (2020), "Improvement of Mechanical Properties by Means of Titanium Alloying to Steel Teeth Used in The Excavator", *International Journal of Engineering Science and Technology*, Vol. 23, No. 5, pp. 1208-1213.

Kumar, B. and Alam, T. (2016). "Excavator Bucket Tooth Wear Analysis", In *2016 International Conference on Electrical, Electronics, and Optimisation Techniques (ICEEOT),* pp. 3364-3366.

Mafarja, M., Aljarah, I., Heidari, A. A., Hammouri, A. I., Faris, H., Ala'M, A. Z. and Mirjalili, S. (2018), "Evolutionary Population Dynamics and Grasshopper Optimisation Approaches for Feature Selection Problems", *Knowledge-Based Systems*, Vol. 145, pp. 25-45.

Mirjalili, S. (2015), "The Ant Lion Optimiser", *Advances in Engineering Software*, Vol. 83, pp. 80-98.

Mirjalili, S. (2019), "Evolutionary Algorithms and Neural Networks", *Studies in Computational Intelligence*, Vol. 780, pp. 43-53.

Monga, P., Sharma, M. and Sharma, S. K. (2022), "A Comprehensive Meta-Analysis of Emerging Swarm Intelligent Computing Techniques and Their Research Trend", *Journal of King Saud University-Computer and Information Sciences*, Vol. 34, No. 10, pp. 9622-9643.

Mustapha, I. B., Abdulkareem, M., Jassam, T. M., AlAteah, A. H., Al-Sodani, K. A. A., Al-Tholaia, M. M. and Ganiyu, A. (2024), "Comparative Analysis of Gradient-Boosting Ensembles for Estimation of Compressive Strength of Quaternary Blend Concrete", *International Journal of Concrete Structures and Materials*, Vol. 18, No. 1, pp. 1-24.

Neshat, M., Sepidnam, G., Sargolzaei, M. and Toosi, A. N. (2014), "Artificial Fish Swarm Algorithm: A Survey of The State-Of-The-Art, Hybridisation, Combinatorial and Indicative Applications", Artificial *Intelligence Review*, Vol. 42, No. 4, pp. 965-997.

Ogar, V. N., Hussain, S. and Gamage, K. A. (2022), "Transmission Line Fault Classification of Multi-Dataset Using CatBoost Classifier", *Signals*, Vol. *3*, No. 3, pp. 468-482.

Ojha, V. K., Abraham, A., and Snášel, V. (2017), "Metaheuristic Design of Feedforward Neural Networks: A Review of Two Decades of Research", *Engineering Applications of Artificial Intelligence*, Vol. 60, pp. 97-116.

Parsa, M., Maghsoudi, A. and Yousefi, M. (2017), "An Improved Data-Driven Fuzzy Mineral Prospectivity Mapping Procedure; Cosine Amplitude-Based Similarity Approach to Delineate Exploration Targets", *International Journal of Applied Earth Observation and Geoinformation*, Vol. 58, pp. 157-167.

Pradeep, T. and Samui, P. (2022), "Prediction of Rock Strain Using Hybrid Approach of ANN and Optimisation Algorithms", *Geotechnical and Geological Engineering*, Vol. 40, No. 9, pp. 4617-4643.

Prokhorenkova, L., Gusev, G., Vorobev, A., Dorogush, A. V. and Gulin, A. (2018), "CatBoost: Unbiased Boosting with Categorical Features", *Advances in Neural Information Processing Systems*, Vol. 31, pp. 1-9.

Qiu, Y., Zhou, J., Khandelwal, M., Yang, H., Yang, P. and Li, C. (2022), "Performance Evaluation of Hybrid WOA-XGBoost, GWO-XGBoost and BO-XGBoost Models to Predict Blast-Induced Ground Vibration", *Engineering with Computers*, Vol. 38, No. 5, pp. 4145-4162.

Rackl, M. and Hanley, K. J. (2017), "A Methodical Calibration Procedure for Discrete Element Models", *Powder Technology*, Vol. 307, pp. 73-83.

Ren, Z., Wang, J., Chen, J., Zhang, J., Liu, J., Liang, Y. and Sun, H. (2019), "Active-Side Calculation Method for A Backhoe Hydraulic Excavator with Incomplete Digging Resistance in A Normal State", *Mathematical Problems in Engineering*, Vol. 2019, No. 1, pp. 1-12.

Rodriguez-Galiano, V., Sanchez-Castillo, M., Chica-Olmo, M. and Chica-Rivas, M. J. O. G. R. (2015), "Machine Learning Predictive Models for Mineral Prospectivity: An Evaluation of Neural Networks, Random Forest, Regression Trees and Support Vector Machines", *Ore Geology Reviews*, Vol. 71, pp. 804-818.

Shaikh, B. P. and Mulla, A. M. (2015), "Analysis of Bucket Teeth of Backhoe Excavator Loader and Its Weight Optimisation", *International Journal of Engineering Research and Technology*, Vol. 4, No. 5, pp. 289-295.

Singh, S. P., Alam, T. and Chattopadhyaya, S. (2013), "A Review on The Excavator Tool Bits Wear", In *Proceedings of the 1st International and 16th National Conference on Machines and Mechanisms (iNaCoMM2013), IIT Roorkee,* India, pp. 823-829.

Song, T., Zhu, W., Pan, B., Song, H., Chen, Z. and Yue, M. (2024), "Development of Ensemble Learning Techniques and Sequential Model-Based Optimisation For Enhancing the Generalisability of Shale Wettability Predictions", *Marine and Petroleum Geology*, Vol. 168, pp. 1-12.

Singla, S., Kang, A. S. and Grewal, J. S. (2012), "Enhancing Wear Resistance of Low Alloy Steel Applicable on Excavator Bucket Teeth Via

Hardfacing", *Asian Review of Mechanical Engineering*, Vol. 1, No. 2, pp. 51-54.

Suryo, S. H., Widyanto, S. A., Paryanto, P. and Mansuri, A. S. (2018), "Hardness Optimisation of Heat Treatment Process of Bucket Teeth Excavator", *Civil Engineering Journal*, Vol. 4, No. 2, pp. 294-304.

Tran-Ngoc, H., Khatir, S., Ho-Khac, H., De Roeck, G., Bui-Tien, T. and Wahab, M. A. (2021), Efficient Artificial Neural Networks Based on A Hybrid Metaheuristic Optimisation Algorithm for Damage Detection in Laminated Composite Structures", *Composite Structures*, Vol. 262, pp. 113339.

Tylczak, J. H., Hawk, J. A. and Wilson, R. D. (1999), "A Comparison of Laboratory Abrasion and Field Wear Results", *Wear*, Vol. 225, pp. 1059-1069.

Zadeh Shirazi, A. and Mohammadi, Z. (2017), A Hybrid Intelligent Model Combining ANN and Imperialist Competitive Algorithm for Prediction of Corrosion Rate In 3C Steel Under Seawater Environment", *Neural Computing and Applications*, Vol. 28, No. 11, pp. 3455-3464.

Yu, X., Chen, Y. and Xie, G. (2018), "The Simulation Analysis of Different Tooth Numbers of Loader Bucket Based On EDEM", *IOP Conference Series: Materials Science and Engineering*, Nanchang, China, pp. 1-6.

Zhang, Y. (2016), "Wear Analysis and Structure Improvement on Bucket Tooth of Wk-75 Mining Excavator", *Published Doctoral Dissertation*, Taiyuan University of Technology, Shanxi Province, China, 167 pp.

Zhang, W., Zhang, R., Wu, C., Goh, A. T. and Wang, L. (2022), "Assessment of Basal Heave Stability for Braced Excavations in Anisotropic Clay Using Extreme Gradient Boosting and Random Forest Regression", *Underground Space*, Vol. 7, No. 2, pp. 233-241.

Zhang, Y. and Haghani, A. (2015), "A Gradient Boosting Method to Improve Travel Time Prediction", *Transportation Research Part C: Emerging Technologies*, Vol. 58, pp. 308-324.

Zhou, J., Li, X. and Mitri, H. S. (2015), "Comparative Performance of Six Supervised Learning Methods for The Development of Models of Hard Rock Pillar Stability Prediction", *Natural Hazards*, Vol. 79, pp. 291-316.

Zhou, J., Wang, Q., Khajavi, H. and Rastgoo, A. (2024), "Sensitivity Analysis and Comparative Assessment of Novel Hybridised Boosting Method for Forecasting the Power Consumption", *Expert Systems with Applications*, Vol. 249, pp. 1-21.

Authors

Godwin Ativor is a Postgraduate Research Assistant at the Department of Mining Engineering of the University of Mines and Technology (UMaT), Tarkwa. He holds a BSc (Hons.) degree in Mining Engineering and is currently a Doctoral candidate in Mining Engineering at UMaT. His current research interests include modelling and simulation of mine production and equipment systems, application of artificial intelligence, discrete element modelling, and drill and blast design and optimisation.

Yao Yevenyo Ziggah is a Senior Lecturer at the Geomatic Engineering Department of the University of Mines and Technology (UMaT). He holds a BSc in Geomatics Engineering from Kwame Nkrumah University of Science and Technology, Kumasi, Ghana. He obtained his Master of Engineering degree and PhD in Geodesy and Survey Engineering from China University of Geosciences (Wuhan). His research interests include artificial intelligent application in engineering, geodetic coordinate transformation, gravity field modelling, height systems and geodetic deformation modelling.

Victor Amoako Temeng is an Associate Professor of Mining Engineering at the University of Mines and Technology (UMaT), Tarkwa. He obtained his BSc (Hons.) and PgD in Mining Engineering degrees from UMaT. He holds MSc degree from the University of Zambia and PhD degree from the Michigan Technological University. He is a member of the Society of Mining, Metallurgy and Exploration (MSME) and a member of the Ghana Institution of Engineers (GhIE). His areas of specialisation include Operations Research, Materials Handling and Computer Applications.