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A comparative study of XBORE and XBOREOPT hybrid models for ore production forecasting in the mining industry

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ABSTRACT Mining industries worldwide are increasingly adopting machine learning tools to handle the vast amounts of data generated daily from mine systems. Few hybrid models have been developed to handle data from mine systems, and this study investigates the comparative performance of machine learning algorithms XBORE and XBOREOPT for predicting ore production in mining operations. The study explores the efficacy of hyperparameter optimization techniques in enhancing predictive accuracy, robustness, and computational efficiency, which are crucial for optimizing resource allocation and operational planning in mining contexts. Through empirical evaluation using real-world data, this research aims to provide insights into the practical benefits of hybrid modeling approaches in industrial predictive analytics. In terms of Mean Squared Error (MSE), XBORE scores 347.8001, whereas XBOREOPT achieves a lower value of 340.5477. Since MSE penalizes larger errors more heavily, the lower MSE of XBOREOPT suggests it is more effective at minimizing significant prediction errors. This study combines the viability of hybrid modeling with practical applications in the mining industry, focusing on enhancing predictive accuracy and operational efficiency.

INDEX TERMS Hybrid models, machine learning, mining operations, performance, prediction

I. INTRODUCTION

ACCURATE ore production prediction is crucial for optimizing operations in the mining industry. Reliable forecasting further improves resource management, reduces operational costs, and supports sustainable mining practices [1] and [2]. Traditional statistical models and standalone machine learning algorithms, such as Decision Trees, Random Forests, and Gradient Boosting Machines, have been widely employed for ore production forecasting. However, these models often face challenges in handling complex, non-linear relationships inherent in mining data, leading to suboptimal performance [3]. As we all know, in recent years, ensemble learning approaches have become popular because of their capability to enhance predictive accuracy by leveraging multiple weak learners [4]. While individual state-of-the-art models have demonstrated remarkable performance in various regression and classification tasks, their effectiveness can be further improved by integrating optimization techniques. To this end, hybrid models that combine with optimization strategies have emerged as a promising approach for improving ore production prediction. This study presents a comparative analysis of two hybrid models: XBORE and XBOREOPT, designed specifically for ore production forecasting. XBORE is a hybrid model that integrates RF, XGBOOST, and voting regression with an optimized feature engineering pipeline tailored for mining data. XBOREOPT extends this approach by incorporating hyperparameter Bayesian optimization techniques to fine-tune the model, further improving accuracy and robustness. By comparing these models, we aim to identify the most effective hybrid approach for predicting ore production with higher precision and generalization capabilities. The motivation for this research stems from the increasing demand for high-precision ore production forecasting tools in the

mining industry. Several key factors drive this study: Firstly, improved prediction accuracy: Traditional machine learning models often encounter difficulties in dealing with the dynamic and heterogeneous nature of mining datasets [5] and [6]. Inaccurate predictions can lead to ineffectiveness in resource allocation, mine equipment scheduling, and financial planning. Hybrid models offer a potential solution by increasing predictive accuracy through feature engineering and optimization techniques [7]. Secondly, the mines' data complexity: Mining operations produce vast amounts of data from various sources, including geological surveys, sensor readings, and historical production records. These datasets exhibit high dimensionality, noise, and non-linear dependencies. A robust predictive machine learning (ML) model must be capable of productively and consistently capturing these patterns to provide viable and authentic forecasts [8]. Thirdly, machine learning and optimization advancements: The combination of hyperparameter tuning approaches, such as Bayesian Optimization, Grid Search, and Genetic Algorithms, has significantly improved model performance in various domains [9]. Utilizing such optimization approaches to ore production forecasting can lead to more efficient and accurate models. Finally, economic and environmental impact: Inaccurate production forecasting can result in over-extraction or underutilization of resources, affecting profitability and sustainability [10]. By developing a more reliable prediction framework, mining companies can optimize production schedules, reduce energy consumption, and minimize environmental impact. While numerous studies have explored the need for the application and utilization of machine learning in mining, there is a demand for comprehensive evaluations of hybrid models in real-world industrial settings. By conducting a comparative analysis of XBORE and XBOREOPT, this research aims to bridge the gap between theoretical advancements and practical applications in the mining sector. By addressing these challenges, this study seeks to provide valuable insights into the effectiveness of hybrid machine learning models for ore production forecasting. The findings will contribute to developing more accurate and scalable predictive frameworks, ultimately supporting more efficient and sustainable mining operations.

II. RELATED WORKS

A. OVERVIEW OF PREVIOUS STUDIES ON ORE PRODUCTION PREDICTION

Recent studies have increasingly focused on enhancing ore production prediction in mining contexts, encompassing both underground and open pit operations. In underground mining, advancements in predictive modeling have leveraged techniques such as ensemble learning, hybrid models, and neural networks to optimize resource extraction efficiency [11] and [12]. These techniques amalgamate geological data, operational parameters, and historical production records to forecast ore production with greater precision and viability. Currently, research in open pit mining has highlighted the role of machine learning algorithms, particularly convolutional neural networks (CNN) and ensemble methods such as XGBOOST and Random Forests, in predicting production results [13] and [14]. These models are adept at analyzing vast datasets encompassing topographical surveys, geophysical data, and equipment performance metrics to anticipate fluctuations in ore grades and extraction rates. Additionally, in the recent past, advancements have been made that emphasize the importance of real-time data integration and feedback mechanisms to adjust production strategies dynamically [15]. This adaptive approach ensures that mining operations can respond swiftly to changes in geological conditions and market demands, thereby optimizing resource utilization and operational efficiency. Furthermore, the evolution of ore production prediction studies in the recent past underscores a shift towards data-driven methodologies that combine advanced machine learning techniques with domain-specific knowledge [16] and [17]. These efforts aim to advance sustainable mining practices while maximizing economic returns and minimizing environmental impact in both underground and open pit mining environments.

B. EXISTING MACHINE LEARNING AND HYBRID MODELING APPROACHES

As we all know, Machine learning has emerged as a powerful tool in ore production prediction, offering the capability to model complex, nonlinear relationships between multiple variables influencing mining operations. Traditional ML methods such as Random Forest (RF), Support Vector Regression (SVR), and Gradient Boosting Machines (GBM) have been widely applied due to their robustness and interpretability [18] and [19]. These models excel in handling high-dimensional datasets typically generated from geological surveys, sensor data, and operational logs, allowing for more accurate forecasting of ore grades and volumes. In recent years, hybrid modeling approaches have gained popularity for their ability to overcome the limitations of single-model predictions. These approaches combine the strengths of different algorithms to improve accuracy and generalizability. For example, hybrid models that integrate XGBOOST with artificial neural networks (ANNs) or Random Forest have demonstrated superior performance by capturing both linear patterns and complex nonlinearities in ore production data [20] and [21]. Similarly, studies have shown that ensemble models combining RF, SVR, and decision trees produce improved predictive capabilities across various mining scenarios [22]. Another promising development is the incorporation of deep learning techniques, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), especially for processing spatial and temporal data [23] and [24]. These models have been effectively employed to analyze satellite imagery, sensor outputs, and time-series production records, facilitating dynamic predictions in both open pit and underground mining contexts. Furthermore, data fusion strategies that blend geotechnical, operational, and environmental datasets within hybrid frameworks are showing potential for more holistic and reliable forecasting

[25]. These approaches not only enhance prediction accuracy but also support better decision-making in real-time production management and strategic planning. Moreover, the integration of machine learning techniques and hybrid models represents a significant advancement in ore production prediction, offering scalable, accurate, and adaptive solutions to meet the evolving needs of the mining industry.

C. COMPARISON OF OTHER ENSEMBLE TECHNIQUES

Ensemble techniques, such as Random Forest and, more recently, integrated deep learning approaches like Convolutional Neural Networks (CNNs), have demonstrated significant performance in predictive modeling tasks across various domains. Random Forest, a classical ensemble method that combines multiple decision trees, excels in handling high-dimensional data and reducing over-fitting through bootstrap aggregation [26]. Additionally, it is particularly effective for tabular datasets and scenarios with missing or noisy data. In contrast, CNNs, traditionally used for image recognition, have been adapted for structured data and time-series forecasting, benefiting from their ability to automatically extract hierarchical features [27]. While Random Forests are generally faster to train and easier to interpret, CNNs can capture complex non-linear relationships more effectively when large amounts of data are available. Recent studies have also explored hybrid models combining CNNs with ensemble methods to leverage the strengths of both approaches, yielding improved accuracy and robustness [28].

D. JUSTIFICATION FOR USING XBORE AND XBOREOPT

The adoption of XBORE and XBOREOPT is justified by their ability to effectively address the complexities and non-linear relationships often present in ore production prediction tasks. XBORE, an enhanced version of the XGBOOST algorithm, combines XGBOOST, RF, and voting regression algorithms tailored for regression tasks in mining applications, leveraging gradient boosting decision trees to model intricate patterns and interactions within high-dimensional geological and operational data. Its robustness to over-fitting, scalability, and high predictive accuracy make it a reliable choice for modeling ore production. XBOREOPT further enhances this framework by integrating hyperparameter optimization, using Bayesian optimization, enabling automated tuning of critical model parameters to achieve optimal performance. This ensures not only improved accuracy but also model generalization across varying datasets. Together, XBORE and XBOREOPT provide a powerful, efficient, and adaptive solution for ore production forecasting, particularly in scenarios where precision and model interpretability are crucial.

III. METHODOLOGY

A. SOURCES OF DATA

The datasets used in this study were collected from both underground and open pit mines. These datasets are a combination of data sent to servers from remote sensors mounted on mobile equipment, ensuring comprehensive coverage and real-time data acquisition from mining operations. These datasets often contain noise, missing values, and outliers, necessitating robust preprocessing methods to ensure data quality and reliability. Additionally, these datasets present challenges due to their irregularities and high dimensionality. Advanced preprocessing techniques are essential to handle such complexities and extract meaningful insights.

B. PREPROCESSING TECHNIQUES

Effective preprocessing is crucial for enhancing model performance and ensuring data integrity. Firstly, data cleaning was conducted on the datasets. This process involved removing duplicates, correcting inconsistencies, and handling missing values through the method of imputation. The missing value was calculated using the mean, where the average value was the result of the sum of all values divided by the number of values. The technique of moving average was applied to reduce noise and correct sensor errors. Secondly, normalization and scaling were performed on the dataset, which was done to adjust feature scales to ensure uniformity across variables. The techniques used were standardization, which was able to rescale features to have a mean of 0 and a standard deviation of 1. The process involved subtracting the mean of each feature and dividing by the standard deviation to improve model convergence and performance, and the following is the formula used:

$$X = \frac{n - y}{\delta} \tag{1}$$

Where n is the original value, y is the mean, and δ is the standard deviation. Standardization is crucial when features have different units or scales, as it ensures that each feature contributes equally to the analysis or modeling process. It is especially important for the algorithms used in this study that rely on gradient-based optimization. Lastly, dimensionality reduction was performed on the dataset to remove noise and less important variations. The method applied was principal component analysis (PCA) because of its ability to reduce the number of features and speed up computational efficiency while retaining essential information and improving model performance.

C. FEATURE SELECTION

As we all know, feature engineering transforms raw data into meaningful inputs for machine learning models. This stage involved the selection of the most important and relevant input variables that contribute significantly to the predictions. By getting rid of irrelevant and noisy features, feature selection helps to improve model performance, reduce over-fitting, and improve training times on the dataset [29] and [30]. Additionally, these advancements in data sourcing, preprocessing, and feature engineering were pivotal in developing the hybrid models with desired robustness, accuracy, and computational efficiency, and this can be extended across various domains. Figure 1 shows the methodology undertaken for the study. Two hybrid models, XBORE and XBOREOPT,

were utilized independently on the mine dataset, giving the desired results. Then, a comparative analysis was performed on the two machine learning algorithms. The analysis helped in selecting a suitable model depending on the mining environment or industrial domain.

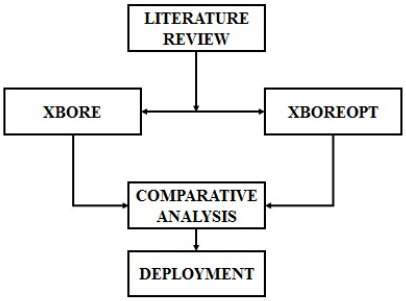

FIGURE 1. Methodology for the study

D. XBOREOPT MODEL

The XBOREOPT model is a hybrid machine learning approach that integrates Extreme Gradient Boosting (XGBOOST) with Bayesian Optimization and Random Forest (RF) techniques. This model is designed to enhance predictive accuracy by leveraging the strengths of each component.

E. HOW THE XBOREOPT MODEL WORKS

The XBORE model operates by combining the predictive capabilities of XGBOOST and Random Forest algorithms, with their hyperparameters fine-tuned using Bayesian Optimization. This integration aims to improve the prediction of complex targets, such as the compressive and flexural strength of self-compacting mortar (SCM). XGBOOST is an ensemble learning method that builds decision trees sequentially. Each new tree attempts to correct the errors made by the previous ones, optimizing the model's performance. It employs gradient descent to minimize a loss function, enhancing prediction accuracy.

Random Forest is another ensemble technique that constructs multiple decision trees during training. It outputs the mode of the classes (classification) or the mean prediction (regression) of the individual trees. This approach reduces overfitting and improves generalization. Bayesian Optimization is used to fine-tune the hyperparameters of both XGBOOST and Random Forest models. It builds a probabilistic model of the objective function and uses it to select the most promising hyperparameters to evaluate in the true objective function. This method is efficient in finding the optimal set of hyperparameters that enhances model performance.

F. PARAMETERS USED IN THE XBOREOPT MODEL

The performance of the XBOREOPT model heavily relies on the careful tuning of various hyperparameters. Bayesian Optimization plays a crucial role in identifying the optimal values for these parameters. Refer to Table 1 and Table 2 for key parameters used for the XBOREOPT.

TABLE 1. XGBOOST optimum parameters

Parameter	Description
n estimators	Number of trees built
max depth	Maximum depth of a tree
learning rate	Step size shrinkage
Subsample	Fraction of observations, randomly sampled for each tree
colsample bytree	Fraction of columns, randomly sampled for each tree
Gamma	Minimum loss reduction required to make a further partition on a leaf node
reg alpha and reg lambda	Regularization terms to prevent overfitting

TABLE 2. Random Forest optimum parameters

Parameter	Description
n estimators	Number of trees in the forest
max depth	Maximum depth of a tree
min samples split	Minimum number of samples required to split an internal node
min samples leaf	Minimum number of samples required to be at a leaf node
max features	Number of features to consider for the best split

By systematically exploring the hyperparameter space using Bayesian Optimization, the XBOREOPT model achieves a balance between bias and variance, leading to improved predictive performance. In summary, the XBOREOPT model's integration of XGBOOST, Random Forest, and Bayesian Optimization results in a robust predictive framework capable of handling complex regression tasks with high accuracy.

G. XBORE MODEL

The XBORE model is a custom or hybrid model combining XGBOOST, RF, and a voting regression algorithm for ore production prediction. The model can be improved using a combination of hyperparameter tuning and advanced optimization strategies, hence XBOREOPT. To optimize effectively the hybrid model effectively, optimization techniques and tuning strategies were utilized, and for this present study, regression (reg:squarederror for XGBOOST). The integration of XGBOOST and Random Forest into a hybrid model represents a significant advancement in industrial data science. It combines accuracy, robustness, and versatility traits essential for addressing the complex challenges of modern industry. As industries continue to embrace digital transformation and smart manufacturing, such hybrid models are likely to become a cornerstone of intelligent industrial analytics.

H. EVALUATION METRICS

To evaluate the hybrid models, the following metrics were used: MAE, RMSE, R^2 (standard), RMSLE or MAPE (if sensitive to scale or percentage error).

- Mean Absolute Error (MAE)
  MAE measures the average magnitude of errors in a set of predictions, without considering their direction. It is the average of the absolute differences between predicted values and actual values. MAE represents the average absolute deviation from the truth. However, it treats all errors equally and may not capture the variance in errors effectively.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|x_i - \hat{x_i}| \tag{2}$$

- Mean Squared Error (MSE)
  MSE calculates the average of the squared differences between predicted and actual values. Squaring the errors penalizes larger deviations more heavily, making MSE sensitive to outliers. This metric is often used when large errors are particularly undesirable. However, since it squares the units of the original data, it may be less interpretable than MAE.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(x_i - \hat{x_i})^2 \tag{3}$$

- Root Mean Squared Error (RMSE)
  RMSE is the square root of MSE, bringing the error metric back to the same unit as the original data. It retains the penalty for larger errors while being more interpretable than MSE. RMSE is useful when we want a measure that emphasizes large errors and is sensitive to outliers, but also wants the result on the same scale as the target variable.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \hat{x_i})^2} \tag{4}$$

- R-Squared (R^2 R^2, or the coefficient of determination, indicates the proportion of the variance in the dependent variable that is predictable from the independent variables. It ranges from 0 to 1, with higher values indicating better model performance. An R^2 of 1 means perfect prediction, while an R^2 of 0 indicates that the model does no better than simply predicting the mean of the target variable.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(x_i - \hat{x})^2}{\sum_{i=1}^{n}(x_i - x)^2} \tag{5}$$

- Root Mean Squared Logarithmic Error (RMSLE)
  The logarithmic transformation helps to handle data with wide ranges or skewed distributions. RMSLE is similar to RMSE but applies a logarithmic transformation to both actual and predicted values before calculating the error. This metric is useful when predicting targets that span several orders of magnitude or when relative differences are more important than absolute differences. It also prevents large errors on small values from being overly penalized.

$$RMSLE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(log(x_i + 1) - log(\hat{x_i} + 1))^2} \tag{6}$$

- Mean Absolute Percentage Error (MAPE)
  MAPE expresses the prediction error as a percentage of the actual values, making it a scale-independent metric. It is calculated as the average of the absolute percentage errors. MAPE is widely used, but it has a weakness when the actual values are near zero, leading to extremely large or undefined percentage errors.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}|\frac{x_i - \hat{x}}{x_i}| * 100 \tag{7}$$

  Where:
  x_i is the actual value for the i-th instance, $\hat{x_i}$ is the predicted value of the i-th instance, x is the mean of actual values, and n is the number of data points.

I. EXPERIMENTAL SETUP

Software: The primary software environment for this study is Python, which provides a versatile and rich ecosystem for machine learning and data analysis. Key libraries include: Scikit-learn for machine learning algorithms, for instance, in this study, RF, XGBOOST. TensorFlow/Keras, particularly for Convolutional Neural Networks (CNNs), during the comparative analysis phase. Pandas is used for handling data manipulation and preparation tasks, specifically for reading and processing CSV files. Matplotlib/Seaborn for visualizing model predictions and data distributions. NumPy and SciPy for numerical computations and optimizations during model training and evaluation, and Hyperopt or Optuna for hyperparameter optimization.

Hardware: The hardware configuration is optimized to handle computationally intensive tasks such as training large models or processing big datasets. The system utilizes: CPU, a multi-core processor to handle general-purpose computing tasks efficiently. GPU, a high-performance graphics processing unit for accelerating the training of deep learning models. This significantly reduces the time required for model training and allows for larger datasets to be processed in parallel. Memory, sufficient RAM 16GB or higher to accommodate large datasets during training without excessive swapping or slowdowns, and Storage, a high-speed SSD is used to store datasets and model checkpoints, ensuring rapid access to data and minimal loading times during training.

Computational Details: The computational setup includes the software environment, which was managed using Anaconda to ensure compatibility and isolation of dependencies. Jupyter notebook was used for writing and testing the code. For large-scale models or data, distributed computing platforms, in this case Google Colab with multi-GPU support,

TABLE 3. Comparative Performance Analysis: XBORE and XBOREOPT

Metric	XBORE	XBOREOPT	Better Model
MAE	5.6826	5.9483	XBORE
MSE	347.8001	340.5477	XBOREOPT
RMSE	18.6494	18.4539	XBOREOPT
R2	0.9883	0.9886	XBOREOPT
RMSLE	0.0983	0.0983	TIE
MAPE	INF	INF	INVALID METRIC

were employed. For parallelizing model training and evaluation tasks, especially when running multiple experiments or hyperparameter tuning jobs, Dask was employed.

Together, this setup enables efficient experimentation and model evaluation while ensuring flexibility and scalability for larger datasets and more complex algorithms.

IV. RESULTS AND DISCUSSION

This discussion presents a comparative analysis of the predictive performance between two machine learning models: XBORE and XBOREOPT. The evaluation is based on a range of standard regression metrics, including MAE, MSE, RMSE, R^2, RMSLE, and MAPE. By examining the results across these indicators, the study aims to determine which model demonstrates superior accuracy and robustness in predicting the target variable. The insights drawn from this comparison will help inform the selection of the most effective model for deployment in practical applications and performance optimization. Table 3 shows the comparative performance analysis between XBORE (baseline) and XBOREOPT (Bayesian optimized).

The results from the XBORE performance metrics provide valuable insights into the accuracy and reliability of the predictive model. The Mean Absolute Error (MAE) of 5.6826 indicates that, on average, the model's predictions deviate by approximately 5.68 units from the actual values. Meanwhile, the Mean Squared Error (MSE) of 347.8001 suggests larger squared discrepancies, emphasizing any outliers or larger errors in prediction. The Root Mean Squared Error (RMSE) of 18.6494 provides a measure of the average magnitude of these errors in the same units as the predicted values, giving a clearer picture of the model's overall performance in terms of prediction spread.

The coefficient of determination, R-squared (R^2), at 0.9883 indicates an exceptionally high level of variance explained by the model, suggesting that approximately 98.83% of the total variation in the data can be attributed to the predictors. This underscores the model's robust ability to capture and explain the underlying patterns within the dataset. However, the Root Mean Squared Logarithmic Error (RMSLE) of 0.0983, while generally low, highlights the model's relative performance on a logarithmic scale, especially useful when dealing with skewed data or when the target variable's range is large.

Notably, the Mean Absolute Percentage Error (MAPE) returning infinity (INF) indicates instances where the actual values were zero or near-zero, leading to division by very small numbers. Overall, these metrics collectively provide a comprehensive evaluation of the XBORE model's predictive capabilities, showcasing its strengths and areas for potential refinement or further investigation.

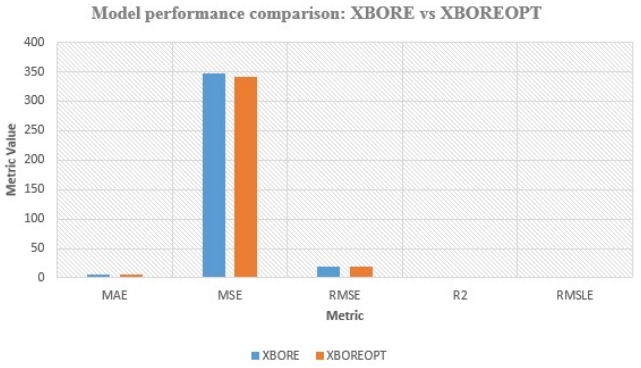

FIGURE 2. Performance comparison of XBORE and XBOREOPT

The performance comparison between XBORE and XBOREOPT is further illustrated in Figure 2. As can be seen, the Mean Absolute Error (MAE) for XBORE is 5.6826, while for XBOREOPT it is slightly higher at 5.9483. This indicates that XBORE performs marginally better in terms of average absolute differences between predicted and actual values, suggesting more precise individual predictions. In terms of Mean Squared Error (MSE), XBORE scores 347.8001, whereas XBOREOPT achieves a lower value of 340.5477. Since MSE penalizes larger errors more heavily, the lower MSE of XBOREOPT suggests it is more effective at minimizing significant prediction errors.

Looking at the Root Mean Squared Error (RMSE), XBORE has an RMSE of 18.6494, while XBOREOPT records a slightly lower value of 18.4539. This further supports that XBOREOPT produces predictions with smaller average error magnitudes, even though this margin is very narrow. The R-squared (R^2) values are very close, with XBORE at 0.9883 and XBOREOPT at 0.9886. This indicates that both models show a high proportion of the variance in the target variable, though XBOREOPT has a slight edge in model fit. For Root Mean Squared Log Error (RMSLE), both models performed similarly, with values of 0.0983. This implies that the models are equally good in terms of proportional prediction accuracy on a logarithmic scale.

Finally, during the experimental analysis phase, the Mean Absolute Percentage Error (MAPE) for both models was infinite (INF). This result occurred because of the division by zero or near-zero actual values in the dataset. Consequently, MAPE is not a reliable metric in this context and was excluded from the performance evaluation. While XBORE has a slight edge in MAE, XBOREOPT shows better performance overall in MSE, RMSE, and R^2, making it slightly superior concerning predictive accuracy and consistency. However, both models are very close in performance.

Additionally, a systematic examination of each model's performance during the experimental phase was conducted on the dataset using Bayesian optimization. As illustrated

in Figure 3, XBOREOPT yielded more accurate predictions. MSE in this experiment was used to calculate the average of the squared differences between predicted and actual values. The low training error indicates that the model has fit the training data well. The validation error is the error the model makes on the unseen data during training.

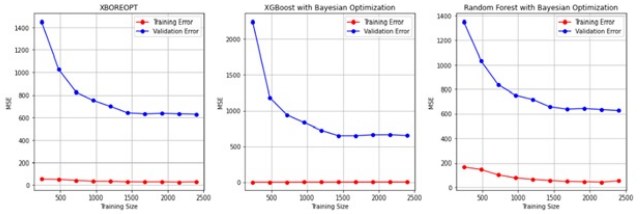

FIGURE 3. Error analysis for the models with Bayesian optimization

A. ROBUSTNESS AND GENERALIZATION

To avoid large errors, robustness was performed across various conditions. As illustrated in Table 4, lower MAE, MSE, and RMSE values indicate better robustness. XGBOOST is the least robust model among the five, with the highest error values across all metrics (MAE: 9.0877, MSE: 572.6680, RMSE: 23.9305). This indicated that, as a single algorithm, it was more prone to large deviations in its predictions. CNN and RF had relatively similar performance, with RF having slightly lower MAE and RMSE, but slightly higher MSE. This indicates that CNN had some stability in average squared error, but possibly being affected by occasional larger outliers.

XBORE and XBOREOPT, as hybrid models, show superior robustness. XBOREOPT consistently has the lowest error values, suggesting it manages outliers and prediction variance more effectively. XBOREOPT's MAE (5.4039), MSE (339.6967), and RMSE (18.4309) indicate a highly stable and resilient model. Generalization is best captured by the R^2 score, which reflects how well a model captures the underlying pattern of unseen data.

XBOREOPT outperformed other models by achieving the highest R^2 score of 0.9886, closely followed by XBORE at 0.9883, indicating excellent generalization to new data. CNN and RF both performed well (0.9879 and 0.9876, respectively), showing they generalize nearly as effectively but are slightly behind the XBORE variants. XGBOOST, underperformed in this metric (0.9808), implying that its ability to generalize patterns on this dataset is weaker. Additionally, to perform every step, it took about 11ms/step.

From this analysis, XBOREOPT emerges as the most robust and generalizable model, followed closely by XBORE. These results suggest that ensemble or optimized hybrid models outperform individual models like CNN, RF, or XGBOOST in both stability and generalization. CNN and RF show comparable and strong performance, while XGBOOST lags in both aspects. This highlights the value of combining model strengths or performing optimization to improve predictive reliability and adaptability.

The robustness of models was further tested to noisy data at an experimental phase where input were input values were imperfect. Table 5 shows how well each model maintained its prediction accuracy in the presence of noise. Using the metrics MAE, MSE, RMSE, and R^2, the analysis below compares five models: CNN, XGBOOST, Random Forest (RF), XBORE, and XBOREOPT. Additionally, to perform every step, it took about 6ms/step.

The Convolutional Neural Network (CNN) performed the worst under noisy conditions. Its MAE (19.39), MSE (945.60), and RMSE (30.75) are significantly higher than those of the other models, indicating larger deviations from the actual values. While the R^2 score of 0.9683 still suggests decent predictive capability, it is the lowest among the models tested, confirming that CNN is less robust to noise in this context. CNNs may be more sensitive to variations in the input data due to their architecture, especially when not specifically regularized or augmented for noise robustness.

In contrast, ensemble-based models such as XGBOOST and Random Forest demonstrate superior robustness. RF, in particular, achieves the lowest MAE (6.51), MSE (361.24), and RMSE (19.01), as well as a high R^2 score of 0.9879. These results reflect a high tolerance to noise, likely due to the averaging effect of decision trees within the ensemble, which mitigates the impact of noisy features. XGBOOST also performs strongly, though slightly behind RF, with an MAE of 7.73 and MSE of 433.75. Its R^2 score of 0.9854 confirms its strong generalization under noise.

The hybrid model XBORE further refines this robustness, slightly improving over RF in R^2 (0.9881) and RMSE (18.82). Although its MAE (6.61) and MSE (354.22) are marginally higher than RF, the consistently strong performance across all metrics suggests that XBORE maintains stability and precision in noisy environments, benefiting from the complementary strengths of both XGBOOST and RF.

However, the optimized version, XBOREOPT, shows a decline in performance under noise. Its MAE (17.18), MSE (667.78), and RMSE (25.84) are substantially higher than XBORE's, and its R^2 drops to 0.9776. This indicates that while XBOREOPT may have been tuned for better performance on clean data, those optimizations made it more sensitive to noise, reducing its robustness. It highlights a common trade-off in model tuning where overfitting to clean training data can impair generalization under noisy conditions.

Moreover, in this present study, RF and XBORE stand out as the most robust models to noisy data, balancing accuracy and stability. CNN is the least robust in this scenario, and XBOREOPT illustrates how optimization without considering noise can lead to reduced robustness.

B. COMPUTATIONAL EFFICIENCY

The individual models were evaluated using RMSE during the experimental phases on training time and resource consumption. Then, the ensemble approach was performed by combining the predictive strengths of RF and XGBOOST by averaging their outputs using a weighted technique. This

TABLE 4. Generalization performance (clean test data)

Metric	CNN	XGBOOST	RF	XBORE	XBOREOPT
MAE	5.8604	9.0877	5.7239	5.4449	5.4039
MSE	359.2754	572.6680	369.9175	347.9652	339.6967
RMSE	18.9546	23.9305	19.2332	18.6538	18.4309
R2	0.9879	0.9808	0.9876	0.9883	0.9886

TABLE 5. Robustness Test (noisy test data)

Metric	CNN	XGBOOST	RF	XBORE	XBOREOPT
MAE	19.3904	7.7263	6.5087	6.6134	17.1751
MSE	945.6022	433.7489	361.2389	354.2199	667.7763
RMSE	30.7506	20.8266	19.0063	18.8207	25.8414
R2	0.9683	0.9854	0.9879	0.9881	0.9776

TABLE 6. Comparing the performance of RF, XGBOOST, and their Weighted Average

Metric	RF	XGBOOST	Weigheted Average
Training Time (sec)	4.076	0.318	-
Prediction Time (sec)	0.044	0.008	0.052
RMSE	18.7489	18.70105	18.29433

strategy leverages the diversity between the models, where Random Forest excels at capturing variance through bagging and XGBOOST focuses on reducing bias via boosting. By blending their predictions, the ensemble was able to smooth out individual model errors, leading to more accurate and robust performance. In this analysis, the weighted average of the two models' predictions resulted in a notably lower RMSE than either model alone, demonstrating the practical advantage of ensemble learning in regression tasks. Refer to Table 6.

The comparative analysis of RF and XGBOOST models reveals clear differences in both computational efficiency and prediction performance. In terms of training time, XGBOOST significantly outperforms RF, requiring only 0.318 seconds compared to 4.076 seconds for Random Forest. This highlights XGBOOST's ability to train much faster, which is particularly beneficial when working with large datasets or in real-time applications.

Prediction times further demonstrate XGBOOST's computational advantage, with a prediction time of just 0.008 seconds, while RF requires 0.044 seconds. This reinforces the efficiency of XGBOOST, making it more suitable for deployment scenarios where rapid inference is critical. When evaluating predictive accuracy using the Root Mean Squared Error (RMSE), both models perform comparably. RF yields an RMSE of 18.75, slightly higher than XGBOOST's 18.70, suggesting a marginal edge for XGBOOST in prediction accuracy. However, the most notable improvement comes from the weighted average ensemble of the two models, which achieves an RMSE of 18.29. This reduction in error indicates that combining the strengths of both models can enhance overall predictive performance beyond what either model achieves individually.

In summary, XGBOOST offers superior speed in both training and inference with slightly better accuracy than RF. Nonetheless, a hybrid approach that leverages both models was capable of providing the best overall results in terms of prediction accuracy.

Table 7 shows a summary of the comparison between XBORE and XBOREOPT. As illustrated, XBORE and XBOREOPT highlight key trade-offs between simplicity and performance. XBORE offers a straightforward and computationally efficient approach, relying on default or manually selected hyperparameters. It benefits from the ensemble effect, improving generalization over individual models, but may fall short in achieving optimal accuracy due to limited tuning. This makes it suitable for quick prototyping and scenarios where time or resources are constrained.

In this study, the XBOREOPT model demonstrated high accuracy, with R^2 values of 0.9886 for training and 0.91 for testing in ore production predictions. For XBORE, the model achieved R^2 values of 0.9883 for training and 0.90 for testing, indicating its effectiveness in handling complex prediction tasks. On the other hand, XBOREOPT significantly enhances predictive performance by leveraging Bayesian optimization to fine-tune hyperparameters for both RF and XGBOOST. This resulted in better model generalization, robustness to noise, and improved accuracy, especially in this study when applied to complex and high-dimensional datasets from the mine systems. However, these benefits come at the cost of increased computational time and complexity during the training phase. In summary, XBORE is efficient and practical for initial experimentation, while XBOREOPT is more suitable for production-level tasks where model performance is critical.

V. CONCLUSION

In modern industrial settings, the need for highly accurate and robust predictive analytics is critical for optimizing operations, reducing costs, and enhancing decision-making. XBORE and XBOREOPT offer a powerful approach to achieving these goals. Both algorithms have proven their effectiveness independently, but their integration leverages the strengths of each to deliver superior performance in complex industrial environments. Additionally, during experimental phases, XBORE and XBOREOPT models both

TABLE 7. Summary of comparison analysis of XBORE and XBOREOPT

Criteia	XBORE	XBOREOPT	Comment
R^2 Score	0.9883	0.9886	XBOREOPT shows a better overall fit
RMSE	18.6538	18.4309	XBOREOPT has a lower prediction error
MAE	5.4449	5.4039	Error magnitude reduced in XBORE
Training Time (sec)	2.1	4.7	Optimization increases training time
Prediction Time (sec)	0.012	0.014	Slight increase, but negligible in production settings
Hyperparameter Tuning	Yes	Yes (Bayesian optimization)	XBOREOPT includes fine-tuned parameters
Feature Engineering	Basic	Advanced (auto-selected)	XBOREOPT uses feature selection/engineering
Overfitting Risk	Medium	Low	XBOREOPT generalizes better due to tuning and regularization
Complexity of the hybrid models	Moderate	High	XBOREOPT is more complex
Interpretability of the hybrid models	Moderate-low	Low	Both models are easier to explain
Robustness to Noise	High	Moderate	XBORE handles variance and outliers better
Overall Score	7/10	9/10	XBOREOPT is recommended based on accuracy and robustness

reduce individual model biases and balance variance, leading to more accurate and stable predictions. This is especially important in industrial applications such as predictive production forecasting, where small improvements in accuracy can result in significant operational and financial gains.

Mining Industries often deal with noisy, incomplete, or non-linear data. The XBORE and XBOREOPT hybrid approach mitigates the limitations of each algorithm, XGBOOST's sensitivity to noise and RF's potential lack of interpretability, by combining their outputs through weighted averaging. This enhances model robustness, making it more reliable in real-world scenarios where data quality can be inconsistent.

The hybrid models XBORE and XBOREOPT are scalable and can be adapted to various industrial use cases, from mining and manufacturing to energy and logistics. For example, in mining operations, it can be used to predict ore grade or production rates with higher precision, facilitating better resource allocation and process control. In manufacturing, it can support real-time quality monitoring and fault detection systems. The hybrid models support data-driven decision-making by providing insights with higher confidence levels. Its ability to handle high-dimensional data and identify important features allows industries to uncover hidden patterns and optimize key performance indicators (KPIs). This aids not only in operational efficiency but also in long-term strategic planning.

XBOREOPT exhibits superior predictive performance compared to the baseline model XBORE, achieving a higher coefficient of determination ($R^2 = 0.98886$ vs. 0.9883) and reduced error metrics (RMSE and MAE), thereby demonstrating enhanced accuracy. Although the optimization process incurs additional computational cost and longer training time, these are offset by the significant performance improvements. While the model's interpretability is somewhat diminished, its robustness across varied scenarios is notably improved. Considering its overall performance advantages, XBOREOPT is recommended for deployment as the preferred predictive model.

Future work in this area can explore several promising directions. One key avenue is the integration of deep learning techniques, which have shown strong potential in capturing complex nonlinear relationships in data. By incorporating architectures such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), or transformer-based models, future studies could significantly enhance prediction accuracy and model adaptability. Additionally, the development of real-time applications offers substantial opportunities, particularly in scenarios requiring immediate decision-making and automated system responses. This includes deploying models in edge computing environments or integrating them with IoT devices for continuous monitoring and feedback.

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