An Ensemble Voting-Based Framework for Maintenance Decision Support in Mining Centrifuges

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ABSTRACT

Attaining environmental sustainability in industrial operations requires innovative solutions that optimize resource utilization and improve energy efficiency. Central to this initiative is intelligent predictive maintenance powered by AI and ML. Direct support for critical Sustainable Development Goals (SDGs), such as industrial innovation, responsible consumption, and climate action, is derived from mitigating unforeseen equipment failures and enhancing operational efficiency. This research builds on a preliminary investigation in which various ML and DL models—including Deep Neural Networks (DNN), Long Short-Term Memory (LSTM), K-Nearest Neighbors (KNN), Naïve Bayes (NB), Logistic Regression (LR), and XGBoost—were developed to predict equipment failures in industrial centrifuges utilized in mining. This study improves forecasting accuracy and reliability by using an ensemble voting mechanism that demonstrates remarkable performance with an accuracy of 99.80%, a precision of 1.00/0.99, a recall of 1.00/1.00, and an F1-score of 1.00/0.99. These findings emphasize the capacity of ensemble models in predictive maintenance to facilitate early and more precise problem detection, hence optimizing maintenance procedures and reducing operating costs. This study provides a scalable and practical

approach to improving operational efficiency and environmental accountability in the mining industry by integrating predictive maintenance with sustainability-focused methods.

Keywords-predictive maintenance; machine learning; deep learning; ensemble voting; industrial centrifuge; mining industry; sustainable development goals; industrial innovation

I. INTRODUCTION

Predictive Maintenance (PdM) has become a basic strategy in modern manufacturing and mining operations, leveraging advanced Machine Learning (ML) techniques and Internet of Things (IoT) data to predict equipment failures and maximize maintenance schedules. Since mining environments suffer from hostile operating conditions, variable loads, and unpredictable external factors, traditional maintenance approaches sometimes fail to offer consistent forecasts. This results in unnecessary maintenance interventions [1] or costly unplanned downtime. In these uncertain environments, integrating PdM presents unique challenges that conventional single-model solutions do not adequately address. Mining operations find the application of PdM especially difficult due to the complex interaction of environmental factors, equipment wear patterns, and operational variability. In such environments, maintenance strategies have major financial consequences as companies balance the possibility of long-term operational inefficiencies and reduced downtime with the upfront high costs of advanced predictive systems [2].

Single-model PdM systems often yield false positives or miss failures and are not resilient enough to handle the wide range of failure modes and operational conditions that can occur in mining environments. This work addresses these issues by utilizing decision threshold optimization strategies and ensemble learning techniques specifically designed for mining operations. The aim was to improve the accuracy, dependability, and cost-effectiveness of PdM systems in uncertain mining environments by combining several predictive models and finding the best decision thresholds based on the operational context. These efforts produced several significant developments in the field. First, a voting classifier ensemble combines several ML techniques to improve the accuracy of predictions in a range of operational situations. Second, an adaptive decision thresholding method chooses the best maintenance actions based on the operational environment, the importance of the equipment, and the available budget. Finally, a real-time system continuously updates the prediction models to accommodate changing environmental conditions, ensuring continuous performance in dynamic mining operations.

A. PDM in Uncertain Mining Environments

PdM in these operations faces particular challenges due to the uncertain nature of mining environments. In [3], the challenges of system-level PdM were discussed, showing that conventional data processing methods are less adequate as operational systems become more complex. Mining activities reflect this complexity and require more sophisticated predictive models to manage fleet-level maintenance planning across several operational environments. The application of PdM systems in industrial settings presents even greater challenges in terms of data quality, availability, and representativeness [4]. These problems are made worse in mining environments by the fact that the sites are far away, the conditions are harsh, and it is challenging to obtain balanced datasets. In [2], the financial aspects of PdM systems were highlighted, emphasizing the need to justify major expenditures through improved operational efficiency and reduced downtime. The study in [5] explored how strategic data augmentation techniques could help ML models make better predictions in smart manufacturing settings, highlighting that consistent data quality remains a fundamental challenge for the application of PdM, especially in environments where operational conditions vary significantly. Recent research has proven the effectiveness of ML methods in the field of PdM. In [6], a Random Forest (RF) model used sensor temperatures to estimate injection failures in diesel engines with a success rate of more than 97%.

B. Rules of Single-Model Predictive Maintenance (PdM) Systems

Conventional PdM approaches rely on single-model systems that struggle to represent the complexity and fluctuation of mining activities. As noted in the literature, these systems have several significant critical limits that reduce their performance in uncertain surroundings. In [7], event-driven PDM was discussed using classification and regression methods, showing that single models do not always accurately predict failures in a wide range of operational settings. Similar studies reveal that models tuned for specific conditions may suffer when those conditions change—a common occurrence in mining environments where operating parameters vary continuously. In [8], the importance of decision support systems for PdM was highlighted, arguing that algorithmic methods do not always consider important contextual factors that human experts can find. This work suggested that in demanding operational environments, single-model systems without domain knowledge are particularly prone to data pattern misinterpretation. The study in [9] underscored even more the limitations of single-model approaches, investigating several ML methods used in PdM in the power sector and finding that generalizing models, extracting features, and adapting to changing operational conditions are always hard. Such problems arise in mining environments. Models trained on specific operational conditions often fail to generalize to new or changing conditions, degrading PdM over time.

C. Techniques of Optimal Decision Thresholds and Ensemble Learning

Ensemble learning methods have emerged to address the limitations of single-model PdM systems, especially under uncertain conditions. Several creative ensemble techniques have been proposed for industrial maintenance. The DOWELL framework aggregates an ensemble learning approach, selecting 20 DL models as accurate and varied base learners [10]. This framework optimizes the weights of these models to improve accuracy while maintaining diversity, leading to

shorter retraining times and less accuracy loss than traditional ensembles. The OPELRUL method predicts Remaining Useful Life (RUL) 23.4% better than other optimal weighting methods. These techniques show particular promise for mining environments where computational efficiency and adaptation to changing conditions are essential.

In [11], a hybrid model combined Bidirectional Long-Short-Term Memory (BiLSTM) with Convolutional Neural Networks (CNN), using attention mechanisms and a Kernel Density Estimate (KDE). This method can capture the spatial and temporal aspects of sensor data, helping to measure uncertainty and make accurate RUL predictions. Hybrid models are particularly helpful for mining applications where equipment degradation patterns show intricate temporal dependencies and spatial relationships between several sensors. In [12], an unsupervised ensemble approach combined the results of interpretable algorithms into a single health status indicator, offering a new way to predict when a wind turbine's main bearing will fail. This method provides great accuracy (95.1%) and flexibility, which may be suitable for other real-time monitoring systems. The unsupervised character of this method can solve a major issue in mining operations: the frequent lack of thoroughly labeled failure data.

D. Maximizing Threshold for Decision Making

Many studies confirm the necessity of decision threshold optimization for use in PdM. In [13], Random Forest (RF) was used with a dynamic threshold adjustment technique to reduce false positives by 40% and make the model more resilient. For mining operations, this approach is particularly crucial since false alarms could result in costly, unnecessary maintenance. In [11], a dynamic PdM system combined mission cycles and dependability measures to change decision thresholds. This approach, tested on NASA's turbofan engine dataset, outperforms stationary thresholding approaches. Different equipment use patterns and mission profiles allow dynamic thresholding to significantly increase maintenance efficiency for mining operations. In [14], an RF framework was used to develop an adaptive learning mechanism that changes model parameters to keep up with how the process is changing. This method can work especially well in mining systems that need to be optimized in real-time to avoid catastrophic failures and reduce unnecessary maintenance work.

E. Applications in Similar Disciplines

Threshold optimization techniques and ensemble learning can be used effectively in fields similar to mining. Voting classifiers can be used to examine the condition of the equipment. In [12], an ensemble-based health status indicator for wind turbine main bearings predicted failures with high accuracy (95.1%). In [15], a meta-learning approach was proposed for small-sample scenarios. In [16], a hybrid MLP-GRU model achieved 94% accuracy with federated learning, preserving data privacy. This approach can address crucial aspects of mining activities, where data may be spread across multiple sites or equipment fleets. PdM-FSA [17] uses RF, SVM, XGBoost, and KNN to determine what kind of maintenance to do next based on how serious the fault is. This approach demonstrates potential in mining tools where failure criticality varies significantly between components or systems.

F. Transparency and Contributions

Despite the progress in the study of ensemble learning and decision threshold optimization for PdM, there are still some problems that need to be resolved, especially in mining environments. The extreme variability and demanding conditions specific to mining operations are beyond the scope of most modern ensemble techniques. Often lacking operational context, equipment criticality, and financial considerations unique to mining environments, current decision threshold optimization methods also fail. The real-world adaptation of ensemble models to respond to rapidly changing operational and environmental conditions in mining environments remains underexplored. Few studies investigate how combined domain knowledge with ensemble learning methods might enhance interpretability and practical applicability in mining operations. This work aimed to fill these gaps by developing a Voting Vlassifier ensemble for mining equipment and a real-time logic framework that updates to adapt to new situations. This is performed using an adaptive decision thresholding technique that takes into account the operational context and financial concerns. Combining these elements can increase the dependability, economy, and practical applicability of PdM in uncertain mining environments.

II. METHODOLOGY

A. Data Collection

Data were acquired from an ABB 800xA Distributed Control System (DCS) that monitors the operation of mining centrifuges using oil temperature, triaxial vibration, and torque sensors mounted in recommended locations on bearings and driving mechanisms. Alarm limits were set at 85°C for oil temperature, 12 mm/s RMS for vibration, and 85% of nameplate torque load values. The raw signal streams were recorded in the DCS history and duplicated in parallel to an analytics server for analysis. Before training the models, data preprocessing involved synchronization to a uniform time, handling missing data, and creating features to capture short-term dynamic processes. The final data was marked with Normal or Fault flags according to maintenance information to maintain realistic supervisory control consistent with the real-world processes being supervised. Data integrity was validated through checksum verification and cross-sensor consistency checks before model training, minimizing noise propagation.

B. Data Preprocessing

Data preparation began with a thorough review to identify and address missing values. Mean imputation was used for numerical columns and placeholders for non-numeric fields aimed at maintaining dataset integrity. The dataset was labeled to differentiate between faults and normal operations following verification. To improve anomaly detection, feature engineers used a 10-lag window to monitor trends in important metrics. The datetime conversion improved model performance by exposing operational patterns in temporal data.

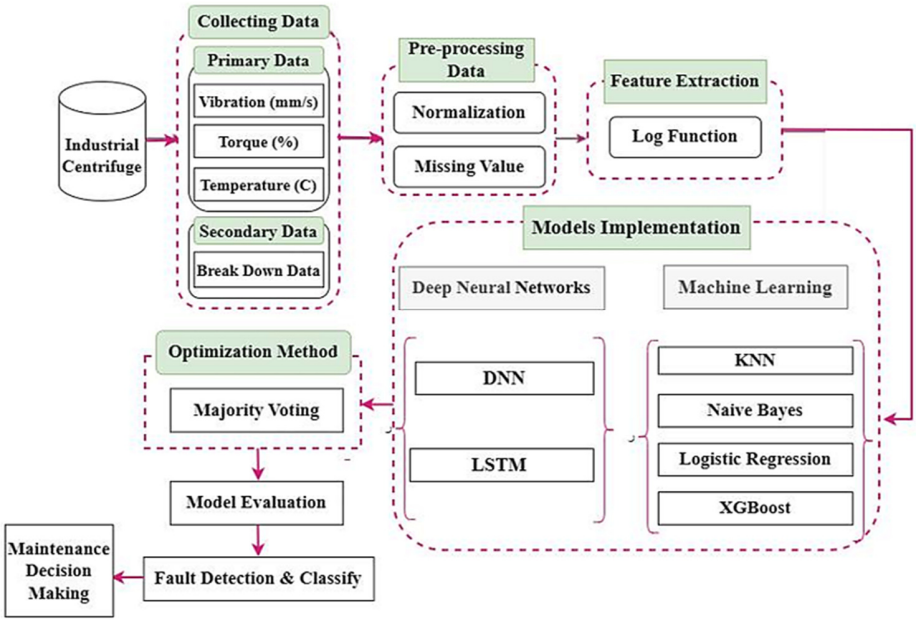

Fig. 1. The architecture of the proposed I-PdM platform.

C. Training and Evaluating Models

In the first phase, multiple models were trained and tested, including KNN, Naive Bayes (NB), Logistic Regression (LR), and XGBoost, to evaluate their effectiveness in PdM. This selection was aimed at handling nonlinear patterns and temporal dependencies in time-series data. Model training involved a 5-fold cross-validation process to enhance robustness and minimize overfitting, ensuring reliable performance assessment.

D. Majority Voting for Model Optimization

The majority voting aggregation method served to enhance the accuracy of the forecast, deriving it by amalgamating the predictions of various models, leveraging the strengths of each. This cohort comprised KNN, NB, LR, XGBoost, deep neural networks, and long short-term memory networks. This technique operates by aggregating forecasts from many models and deriving the outcome based on the majority vote principle. This mitigates the risk of overfitting, enhancing model robustness and overall forecasting accuracy.

E. Evaluation Metrics

Confusion matrices, accuracy, precision, recall, and F1 score were employed to assess the performance of the trained models [18]. The confusion matrix offers a summary of classification performance by displaying the counts of True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN) [19]. Accuracy assesses the general correctness of forecasts, while precision, or positive predictive value, exclusively evaluates the accuracy of positive predictions [20]. Recall, also known as sensitivity, is the model's ability to reliably detect positive instances [21]. The F1 score, determined as the harmonic mean of precision and recall, provides a fair assessment of model efficacy.

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+FP+TN+FN}} \times 100 \quad (1)$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \times 100 \quad (2)$$

$$\text{Recall} = \frac{\text{TN}}{\text{TN+FP}} \times 100 \quad (3)$$

$$\text{F1} - \text{score} = \frac{2\times(\text{Precision}\times\text{Recall})}{\text{Precision}\times\text{Recall}} \times 100 \quad (4)$$

F. Maintenance Decision

The model sets the optimal threshold, which drives the maintenance decision. If the model predicts a probability of a fault higher than the set optimal threshold, the system triggers an alarm because such a situation shows a critical level of centrifuge condition deterioration. This threshold provides a decision point that allows a good balance between the trade-off of FP—necessary maintenance—and FN—missing faults [22].

The maintenance team initiates corrective action once they have crossed this threshold. Due to the centrifuge losing stable conditions, the apparatus may need to be inspected for possible damage, and replacement or readjustment of operating parameters may have to be performed accordingly. This criterion prioritizes maintenance interventions based on the likelihood of equipment failure, ensuring efficient allocation of resources [23]. Condition-based monitoring with dynamic scheduling can allow for more active maintenance because decisions are made based on the actual conditions of the equipment instead of fixed schedules. This will make the equipment last longer with lower long-term maintenance costs [24].

III. RESULTS

A. Ensemble Method-Voting Classifier

To enhance accuracy and reliability, a Voting Classifier combined KNN, NB, LR, and XGBoost. Table I illustrates the performance of the voting classifier. The confusion matrix demonstrates the Voting Classifier's capacity in classifying

both normal and faulty conditions, with very few misclassifications.

TABLE I. MODEL PERFORMANCE

Model	Accuracy	Precision (Normal/Fault)	Recall (Normal/Fault)	F1-score (Normal/Fault)
Voting Classifier	99.80%	1.00/0.99	1.00/1.00	1.00/0.99

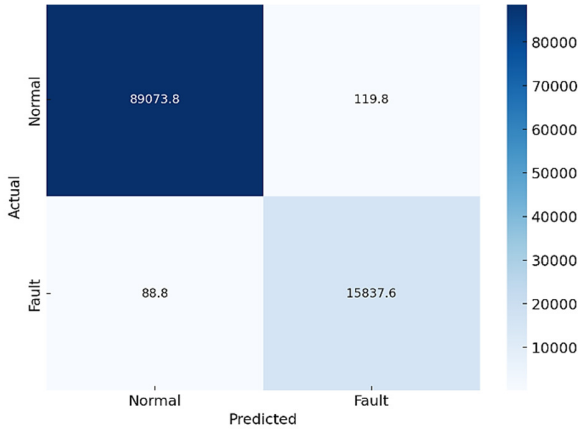

Fig. 2. Average confusion matrix for voting classifier.

The ROC curve analysis further confirmed the exceptional performance of the proposed ensemble method. The Voting Classifier's average AUC-ROC score of 1.00 across all folds shows that it can perfectly distinguish normal and fault conditions. The Voting Classifier outperformed the best individual model (XGBoost), which achieved an accuracy of 99.00%, effectively leveraging the strengths of individual models to produce highly accurate predictions.

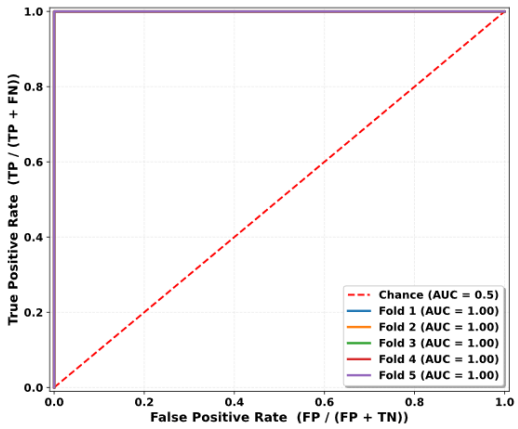

Fig. 3. ROC curves for cross-validation folds.

Figure 3 compares the performance of the models. The ensemble method's ability to use the strengths of multiple classifiers elucidates its superior accuracy by mitigating the deficiencies of individual models. This outcome reinforces the established advantage of ensemble learning in enhancing robustness and predictive efficacy. In conclusion, while individual models showed strong performance, the Voting Classifier proved to be the most effective approach for the PdM of industrial centrifuges. The exceptional accuracy and reliability of this method make it a highly valuable tool to improve maintenance strategies in the mining industry, potentially leading to significant reductions in downtime and maintenance costs.

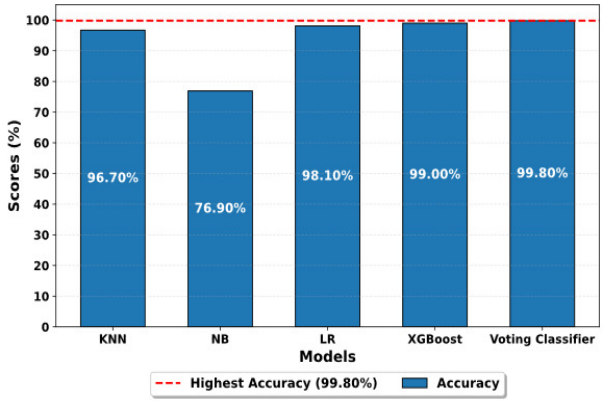

Fig. 4. Model performance comparison.

B. *Practical Implications for Maintenance Decision-Making*

These results reveal several significant practical implications for industrial maintenance.

1) *High-Confidence Fault Detection*

With 99.80% accuracy and 1.00 AUC score, maintenance teams can rely on model predictions. An extremely low false alarm rate of 0.13% implies that there would be negligible wasteful maintenance operations, and a high TP rate means that serious faults are practically never missed.

2) *Early Anomaly Detection*

The model's ability to effectively differentiate between normal operations and possible malfunctions enables the recognition of subtle irregularities that may not be visible to conventional monitoring systems. The early warning system provides maintenance personnel with valuable time to plan interventions before catastrophic failures occur.

3) *Optimized Maintenance Scheduling*

The probability scores generated by the model allow the prioritization of maintenance activities according to the likelihood and severity of faults. This functionality enhances the resource utilization and maintenance scheduling by using equipment conditions instead of pure time-based schedules.

4) *Optimal Threshold for Decision-Making*

The average optimal threshold of 0.0371 provides a clear decision-making point. When the model's prediction probability exceeds this threshold, it signals a potential fault. This threshold balances the trade-off between FP and FN, optimizing the decision to intervene. The ROC curves in Figure 5 show the best thresholds for all folds used in the Voting Classifier.

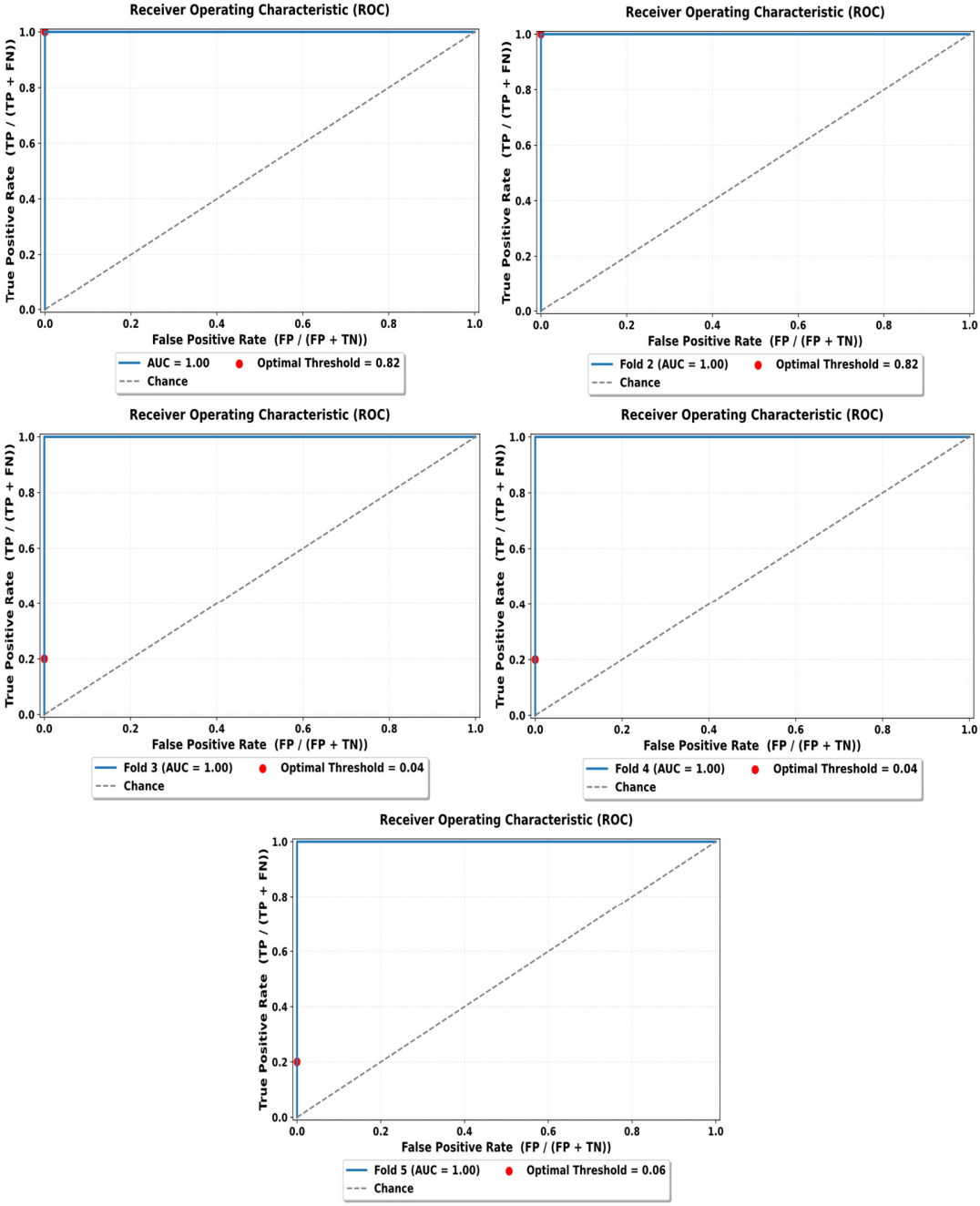

Fig. 5. ROC curves showing the optimal thresholds for all folds used in the Voting Classifier, with each fold achieving an AUC of 1.00.

5) Minimizing False Alarms and Missed Faults

The confusion matrices show very few misclassifications, with high TP and TN rates. This minimizes both false alarms, which could lead to unnecessary maintenance, and missed faults, which could result in unexpected breakdowns.

The strong results of the model in each of the five cross-validation tests demonstrate its capacity to adjust to new data. Once that happens, this model can identify many different fault states, even very mild and subtle ones that are not detected by normal monitoring methods. It does this by combining multi-sensor data with cutting-edge ML models. The threshold score generated by the model might be used to rank maintenance tasks according to these probability scores, as higher scores could indicate more serious problems. Thus, maintenance teams can use their resources more effectively and efficiently. Furthermore, since the model evaluates real-world sensor data, it offers ongoing centrifugal health monitoring, allowing dynamic maintenance scheduling based on the actual state of the equipment, instead of static schedules.

IV. DISCUSSION

Unlike previous studies that evaluated single-model PdM systems, this study introduces a hybrid ensemble integrating ML models within an adaptive decision-thresholding framework specifically optimized for mining centrifuges. The findings underscore the substantial improvements in predictive maintenance accuracy and reliability that can be achieved through the integration of ML models, particularly when employing an ensemble voting technique. The evaluation of individual models, including KNN, LR, and XGBoost, demonstrated their robustness and reliability. However, the ensemble model, which aggregates predictions from these diverse models, consistently outperformed them, achieving near-perfect evaluation metrics.

The ensemble voting model exhibited an unparalleled level of predictive accuracy, attaining an AUC-ROC score of 1.0000 and an accuracy rate of 99.80%, providing a strong foundation for confident decision-making in PdM. The high level of precision enables maintenance teams to proactively schedule interventions, allowing for early detection of operational anomalies. Furthermore, the optimal decision threshold was determined at 0.0371, effectively balancing the trade-off between FP and FN rates. The negligible misclassification rates indicate a significant reduction in both FP and FN, which is vital for preventing unexpected equipment failures and optimizing maintenance strategies, thereby eliminating unnecessary interventions and reducing operational downtime.

A. Comparative Analysis and Theoretical Implications

Although numerous previous studies have established the benefits of PdM, most have focused on single-model approaches. Although these models offer certain advantages in terms of computational efficiency and interpretability, they often fail to fully capitalize on the strengths of multiple algorithms. This study aligns with contemporary research that advocates ensemble techniques as a means to improve predictive performance and enhance model generalization. By systematically combining the strengths of multiple classifiers, ensemble methods mitigate overfitting, increase model robustness, and provide more reliable forecasts compared to single-model approaches. From a theoretical perspective, these findings contribute to the growing body of literature on PdM by offering empirical evidence that supports the superiority of ensemble learning frameworks. The results validate the assumption that aggregating weak learners in a structured ensemble framework yields superior predictive power. This aligns with ensemble learning theory, which postulates that diverse and complementary models reduce bias and variance, leading to more accurate and generalizable predictions. The findings empirically support the bias–variance trade-off theory in ensemble learning, confirming that diversity among base learners improves generalization.

B. Practical Implications and Industrial Applications

The implications of this study extend beyond theoretical contributions, offering substantial practical benefits for industrial maintenance strategies. PdM is a critical component of modern industrial operations, where equipment failures can result in substantial financial losses and operational disruptions. The adoption of an ensemble voting approach presents an opportunity to refine maintenance strategies by providing early and precise fault detection mechanisms.

In industrial settings, maintenance schedules are often dictated by periodic inspections or rudimentary threshold-based alerts. These traditional methods, while effective to some extent, lack the adaptability required to handle complex and dynamic operational conditions. By implementing an advanced ensemble-based predictive maintenance framework, organizations can move toward a more data-driven and proactive maintenance paradigm. The high accuracy and recall rates achieved suggest that maintenance teams can better allocate resources, reducing unnecessary inspections and interventions while simultaneously mitigating catastrophic equipment failures. These findings are particularly relevant to industries with high capital investments in heavy machinery, such as mining, manufacturing, and energy production. By integrating PdM models that utilize ensemble learning, these industries can enhance operational efficiency, minimize unplanned downtime, and extend the lifespan of critical equipment. Additionally, improving PdM capabilities contributes to sustainability goals by reducing resource waste and optimizing energy consumption.

The proposed ensemble Voting Classifier demonstrates clear improvements over single-model predictive-maintenance approaches. While individual algorithms such as LSTM or XGBoost reached high accuracy, combining them through a weighted voting mechanism reduced both bias and variance, resulting in 99.80 % accuracy and an AUC of 1.00. Beyond performance metrics, the framework introduces an optimal decision threshold (0.0371) that explicitly balances false-positive and false-negative rates under the plant's operational cost structure—transforming probabilistic outputs into actionable maintenance triggers. Economically, early fault detection translates into lower unplanned downtime and reduced maintenance expenses, supporting data-driven asset-management policies.

Moreover, while the ensemble model demonstrated exceptional predictive capabilities, there is room for improvement by incorporating advanced DL techniques such as reinforcement learning and transfer learning. These approaches can enhance model adaptability and learning efficiency, enabling predictive maintenance systems to operate effectively across different industrial contexts with minimal retraining requirements. Future studies should also explore hybrid ensemble strategies that combine traditional ML models with DL architectures to further enhance predictive performance.

Despite promising results, this study is not without limitations. The dataset used was derived exclusively from industrial centrifuges operated by the Arab Potash Company. Thus, the findings may be contextually constrained and not necessarily generalizable to all industrial settings or types of equipment. Additionally, the data, collected over twelve months, may not encompass all possible operational scenarios or failure patterns. Future work should seek to address these limitations by incorporating a more diverse set of industrial equipment and expanding the data collection timeframe to ensure model robustness under varied operational conditions.

Economically, each one-hour reduction in unplanned downtime corresponds to an estimated saving of USD 1,500–2,000 in lost production and maintenance labor at APC. Thus, the proposed ensemble's ability to predict faults several hours in advance provides tangible financial benefits in addition to operational reliability.

Finally, to reduce the implementation complexity, the proposed ensemble can be deployed as a modular system, where each base model runs in a separate microservice environment. This design simplifies maintenance, allows independent updates, and ensures scalability.

V. CONCLUSION

This study underscores the effectiveness of integrating ML models within an ensemble voting framework to improve PdM accuracy for industrial centrifuges. The ensemble model demonstrated superior recall, precision, and overall accuracy compared to individual models, reinforcing the advantages of ensemble techniques in industrial applications. These findings suggest that the adoption of ensemble methods can significantly improve the effectiveness of PdM strategies, particularly in industrial environments where equipment reliability is paramount.

By proposing an ensemble voting method, this work contributes to the advancement of PdM by improving fault detection accuracy and model resilience. The results indicate that the integration of multiple predictive models within a unified ensemble framework can yield near-optimal classification performance, surpassing the limitations of traditional single-model approaches. This method supports more informed decision-making, reduces maintenance costs, and enhances operational efficiency, offering a practical and scalable solution for mining and industrial operations. Furthermore, by addressing the challenges associated with PdM in demanding industrial environments, this study adds valuable insights to the existing literature and lays a strong foundation for future advances in smart maintenance technologies.

Unlike previous techniques that relied on a single model and had issues of overfitting or lack of generalizability under different operating conditions, the proposed ensemble model maintains a balance between bias and variance and is interpretable and scalable as well. Methodologically, its originality is embedded in its use of the decision threshold mechanism (0.0371) that helps translate predictive probabilistic outcomes into actual decision outcomes, thus reducing false alarms and missed signals resulting from such PdM activities, as has not been explicitly documented within pertinent research on mining centrifuges. In comparison, while previous models achieved accuracies of 90%-96%, the proposed ensemble model achieved an accuracy of 99.80% and an AUC of 1.00, marking a substantial improvement. There is no doubt that ensemble learning of varied ML algorithms, such as XGBoost, LSTM, and LR, has proven its worth through this model.

This study also has practical applications, as it is a scalable framework that can be deployed in any industrial setting. Every learner can run standalone based on a microservice architecture, providing flexibility and ease of maintenance and development. The proposed method is of great economic value, as it can reduce downtime due to faults, thus lowering maintenance costs, especially for industries with great capital investment, such as mining and power generation. In conclusion, this study offers significant progress on the theoretical foundations and applications of PdM based on ensemble methods, providing a roadmap to intelligent and sustainable maintenance systems for industries.

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