

# Useful Life Prediction of Bearings in Abrasive Environments through FEM Modeling, IoT Validation, and Visual Training Using Machine Learning

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**Abstract**— *The reliability of rolling bearings in mining machinery is essential for maintaining operational continuity in extreme environments such as Cerro de Pasco, Peru, where abrasive particles, humidity, and cyclic loads accelerate mechanical degradation. To overcome the limitations of conventional maintenance approaches, this study proposes a hybrid methodology for predicting the Remaining Useful Life (RUL) of industrial bearings by integrating Finite Element Modeling (FEM), IoT-based monitoring, and machine learning techniques. The analysis focuses on the SKF 22244 CC/W33 spherical roller bearing used in crushers and grinding mills. FEM simulations identified stress concentration zones under realistic loads, while vibration, temperature, and pressure data acquired through IoT sensors were used to train XGBoost and Random Forest models for RUL prediction. Additionally, a Convolutional Neural Network (CNN) classified wear severity from bearing images with accuracy above 93%. Results indicate that actual bearing lifespan in abrasive environments may decrease by up to 15% compared with ISO 281 theoretical predictions, highlighting the importance of predictive models adapted to real operating conditions. Cross-validation between simulations, sensor data, and intelligent algorithms confirmed the robustness of the proposed approach for early fault detection, maintenance optimization, and reliability improvement in mining systems.*

**Keywords**— *Remaining Useful Life (RUL); Bearing; Finite Element Modeling (FEM); IoT Sensors; Machine Learning.*

## I. INTRODUCTION

Mining operations in Cerro de Pasco, Peru, represent one of the most demanding environments for electromechanical components due to extreme conditions such as high altitude, temperature fluctuations, humidity, and airborne abrasive particles generated during mineral extraction and crushing [1]. Under these conditions, rolling element bearings—critical components in heavy rotating machinery—experience accelerated wear that compromises reliability, safety, and energy efficiency [2].

In equipment such as conveyors, crushers, mills, and ventilation systems, bearings are subjected to cyclic loads,

vibrations, dust contamination, and thermal variations that intensify fatigue, abrasion, lubrication degradation, and micro-spalling [3]. Consequently, actual service life is often shorter than theoretical predictions, leading to unexpected failures, downtime, and increased maintenance costs.

Many mining operations still rely on corrective or time-based preventive maintenance, replacing bearings according to operating hours or visual inspections without predictive diagnostics [4]. Such approaches do not adequately consider environmental variability and progressive internal damage, increasing failure risk in abrasive environments [5].

Recent advances in predictive maintenance have promoted the integration of numerical simulation, real-time sensing, and artificial intelligence techniques for fault diagnosis and Remaining Useful Life (RUL) prediction in rotating machinery [6]. Machine learning and deep learning methods have demonstrated significant improvements in rolling bearing fault diagnosis through automated feature extraction and adaptive classification under variable operating conditions [7].

In particular, deep learning architectures have shown strong performance in intelligent fault diagnosis due to their capability to process high-dimensional vibration and image data without requiring extensive manual feature engineering [8].

Finite Element Modeling (FEM) enables stress and fatigue analysis based on standards such as ISO 281 [9], while IoT monitoring provides continuous measurements of operational variables for early degradation detection and model validation [10]. In parallel, computer vision combined with deep learning has demonstrated high effectiveness in classifying bearing damage, enabling rapid diagnosis and improved Remaining Useful Life (RUL) estimation [11][12].

Therefore, integrating FEM, IoT monitoring, and machine learning enables robust hybrid diagnostic models for bearings

operating in abrasive mining environments, improving early fault detection, maintenance planning, and reliability of critical industrial assets.

## II. MATERIALS AND METHODS

This study followed a quantitative experimental–computational approach to predict the Remaining Useful Life (RUL) of bearings operating in abrasive mining environments through the integration of numerical simulation, real-time sensing, and machine learning techniques. Three main technological platforms were employed: SolidWorks for three-dimensional modeling and Finite Element Analysis (FEA), Python-based processing in Google Colab for data analysis and model training, and an IoT architecture for real-time acquisition of operational variables.

The methodology consisted of three complementary components. First, a three-dimensional bearing model was developed and subjected to representative dynamic loads associated with mining operating conditions. Finite Element simulations with refined meshing and defined boundary conditions were performed to evaluate stress distribution and estimate service life according to ISO 281 standards. Similar FEM-based approaches have been successfully applied in the structural and fatigue analysis of mining mechanical components subjected to complex loading conditions [16].

Second, real-time monitoring was implemented using vibration, temperature, and pressure sensors connected to an ESP32 microcontroller, transmitting data to the cloud via the MQTT protocol. Third, worn-bearing images acquired through digital imaging and optical microscopy were processed and classified using a Convolutional Neural Network (CNN) implemented in Python with TensorFlow, Keras, and OpenCV.

Model validation followed a multi-source cross-validation strategy in which FEM results were compared with sensor measurements and machine learning predictions. This triangulation enabled calibration of simulation parameters and improved the predictive accuracy of the proposed maintenance framework. The combination of these approaches is consistent with recent studies demonstrating that the fusion of numerical simulation, online monitoring, and artificial intelligence significantly enhances bearing diagnostics in severe operating environments [11–15].

The complete methodological workflow was organized into five sequential phases, as illustrated in Fig.

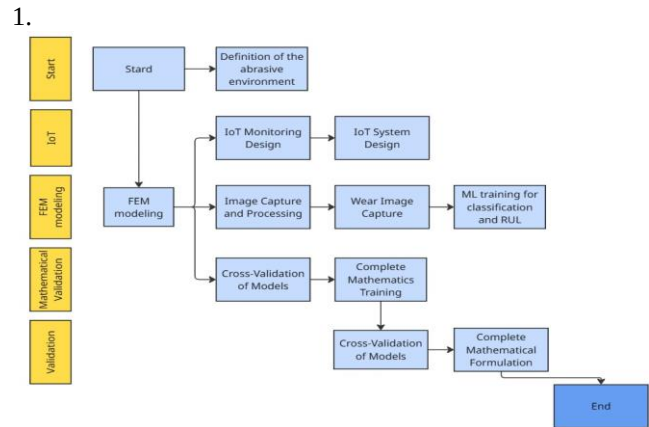


Fig. 1. Research Flowchart.

### A. Methodological Stages

#### • Finite Element Modeling and Simulation (FEM)

In this stage, a three-dimensional model of the bearing was developed using SolidWorks, considering its actual geometry and constituent material (AISI 52100 steel). Subsequently, dynamic loads representative of mining operating conditions were applied, including contact pressure, rotational speed (RPM), and cyclic stresses. The model was subjected to refined meshing and well-defined boundary conditions, followed by static structural and fatigue analyses to evaluate stress distribution and deformation behavior.

Additionally, contact interactions between rolling elements and raceways were considered to improve the accuracy of the simulation under realistic operating conditions. The theoretical service life was estimated according to ISO 281 standards using surface and subsurface fatigue resistance criteria [16].

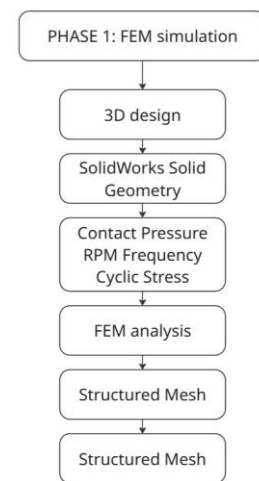


Fig. 2. Stage 1: FEM Simulation

- **Stage 2 – Implementation of the IoT-Based Monitoring**

Real-time monitoring was performed using MPU6050, Type K, and MPX5700AP sensors to measure vibration, temperature, and pressure, respectively. The sensors were interfaced with an ESP32 microcontroller responsible for data acquisition and wireless transmission to a cloud database through the MQTT protocol and Firebase platform.

Sampling rates were dynamically adjusted according to system operating conditions, enabling reliable acquisition of operational variables and continuous monitoring of bearing behavior under abrasive mining environments. The acquired sensor data were subsequently used for experimental validation of FEM results through comparison with real operating measurements [17].

- **Stage 3 – Wear Image Acquisition and Processing**

Worn bearings were inspected using high-resolution digital imaging and optical microscopy under controlled illumination and focal distance conditions to ensure image consistency and repeatability. The acquired images were preprocessed in OpenCV through cropping, grayscale conversion, normalization, and contrast enhancement to improve feature visibility and reduce noise.

Subsequently, the images were manually labeled into three wear categories (mild, moderate, and severe) to construct a supervised dataset for machine learning model training and classification tasks [18].

- **Stage 4 – Machine Learning Model Training**

Two machine learning models were developed in Python using the Google Colab environment: a Convolutional Neural Network (CNN) for wear classification and an XGBoost regressor for Remaining Useful Life (RUL) prediction. The image dataset and sensor-derived features were divided into training, validation, and testing subsets to ensure model generalization and performance evaluation.

The CNN model was trained using labeled wear images, while the XGBoost model employed operational variables obtained from IoT monitoring and FEM simulations as predictive inputs. Model performance was evaluated using Accuracy, Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the coefficient of determination ( $R^2$ ) metrics [19].

- **Stage 5 – Cross-Validation and Hybrid Model Integration**

Results obtained from FEM simulations, IoT sensor measurements, and machine learning predictions were statistically compared using correlation analysis, relative error evaluation, and predictive performance metrics. This multi-source validation strategy enabled calibration of simulation parameters and verification of consistency between numerical, experimental, and intelligent prediction models. The integration of these complementary approaches contributed to the consolidation of a robust predictive maintenance framework applicable to abrasive mining environments and complex industrial operating conditions [20].

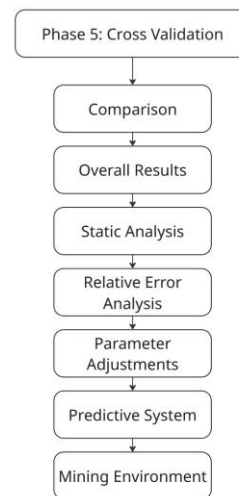


Fig. 6 Stage 5: Cross-Validation

### B. Mathematical and Computational Analysis

This study integrates physical, statistical, and computational models to predict the Remaining Useful Life (RUL) of bearings operating under extreme abrasive conditions. The mathematical framework estimates variables associated with fatigue behavior, contact mechanics, cumulative damage, and predictive accuracy, considering mining environments characterized by high altitude, dust exposure, vibration, and cyclic loading conditions.

#### Contact Pressure Calculation (Hertzian Contact Theory)

Stress distribution at the rolling element–raceway interface was evaluated using Hertzian contact theory, which is applicable to elastic and frictionless elliptical contact conditions commonly found in rolling bearings. The maximum contact pressure, calculated according to Equation (1), serves as a key indicator for identifying stress concentration zones associated with surface fatigue initiation, one of the primary failure mechanisms in abrasive mining environments [14][15].

This approach is widely employed in rolling bearing analysis because localized contact stresses directly influence crack initiation, material degradation, and reduction of bearing service life under severe operating conditions.

$$p = \frac{2F}{\pi ab} \quad (1)$$

### Basic Rating Life Calculation (L10)

The basic bearing life was determined according to the ISO 281 standard, which estimates the number of revolutions that 90% of a bearing population is expected to complete without fatigue failure under specified operating conditions. This theoretical life, commonly referred to as the L10 life, is calculated as expressed in Equation (2).

The L10 formulation is widely used in rolling bearing engineering because it provides a standardized criterion for evaluating fatigue resistance and estimating service life under dynamic loading conditions typical of industrial rotating machinery.

$$L_{10} = \left(\frac{C}{P}\right)^p \quad (2)$$

Since actual mining conditions differ significantly from controlled laboratory environments, an adjustment factor is applied as indicated in Equation (3).

$$L_{10} = a_{10} \cdot L_{10} \quad (3)$$

### Miner's Cumulative Damage Model

The behavior of bearings under variable and irregular loading conditions was modeled using Miner's cumulative damage rule, which evaluates the progressive accumulation of cyclic fatigue damage over time. This approach is particularly suitable for mining systems that experience frequent start-stop cycles, variable dynamic loads, and occasional overload conditions during ore transportation, all of which contribute to nonlinear component degradation [18].

Miner's rule enables estimation of the remaining fatigue resistance of the bearing by relating the number of experienced load cycles to the total number of cycles required for failure under different stress levels. The total accumulated damage is calculated as expressed in Equation (4).

Furthermore, this model provides an effective approximation of fatigue evolution in rotating mechanical systems operating under severe abrasive conditions, supporting predictive maintenance strategies and Remaining Useful Life (RUL) estimation.

$$D = \sum_{i=1}^n \frac{n_i}{N_i} \quad (4)$$

### FEM Analysis: Meshing and Convergence Study

The bearing geometry was modeled in SolidWorks and analyzed using Finite Element Modeling (FEM) with a second-order tetrahedral mesh refined in critical contact regions to improve stress distribution accuracy. A radial load of 12 kN was applied to the inner ring to represent representative conveyor belt operating conditions commonly encountered in mining environments.

The FEM model incorporated defined boundary conditions and contact interactions between rolling elements and raceways to simulate realistic operating behavior. Model validity was verified through a mesh convergence study using the relative energy error (Eq. 5), where  $\sigma_i$  and  $\sigma_{i+1}$  represent Von Mises stresses obtained from successive mesh refinements.

Convergence was considered acceptable when the relative error  $\varepsilon$  became lower than the predefined tolerance threshold, ensuring numerical stability, mesh independence, and reliability of the stress distribution results. This procedure enabled accurate identification of peak stress zones associated with fatigue initiation and progressive bearing degradation [16][19].

$$\varepsilon = \left| \frac{\sigma_{i+1} - \sigma_i}{\sigma_i} \right| 100\% \quad (5)$$

### Machine Learning Model Validation Metrics

Experimental data obtained from IoT sensors and classified images of worn bearings were used to train machine learning models. Model performance was evaluated using three key metrics:

#### Mean Absolute Error (MAE)

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (6)$$

#### Root Mean Square Error (RMSE)

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (7)$$

#### Coefficient of Determination (R<sup>2</sup>):

$$R^2 = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y})^2} \quad (8)$$

These metrics assess the goodness-of-fit of the Remaining Useful Life (RUL) prediction model. Desirable performance

corresponds to  $R^2$  values greater than 0.9 and absolute errors below 5%. Their application in this study demonstrates the high capability of the proposed hybrid system to anticipate failures based on sensed and visual patterns [19][20].

### III. RESULTS

#### A. FEM Modeling Applications

FEM simulation of the SKF 22244 CC/W33 bearing was performed under representative mining operating loads (726 kN radial load, 140 kN axial load, 58 kNm torque, and 600 RPM rotational speed) using a refined second-order tetrahedral mesh. The maximum Von Mises stress reached 188.6 MPa at the inner ring contact region, remaining well below the material yield strength of 620 MPa, which indicates safe elastic operating conditions under the simulated loading scenario.

The maximum displacement obtained was 0.004 mm, confirming high structural stiffness and dimensional stability of the bearing during operation. Furthermore, the mesh convergence study verified numerical stability and mesh independence, supporting the reliability and consistency of the stress distribution results and enabling accurate identification of critical regions associated with fatigue initiation.



Fig. 7 Cross-sectional view of a precision bearing

#### • Bearing Displacement Analysis

The displacement map illustrates the structural deformation of the bearing under dynamic and torsional loading conditions. The maximum recorded displacement was 0.003 mm, located at the contact region between the rolling elements and the outer ring, where axial and radial loads are concentrated.

This deformation remains within acceptable design limits, indicating that the bearing maintains its structural integrity and alignment during operation. The low displacement values also confirm high structural stiffness and reduced risk of excessive vibration under severe mining operating conditions.

These results validate the bearing's suitability for continuous operation in aggressive environments such as rod mills and conveyor systems in Cerro de Pasco.

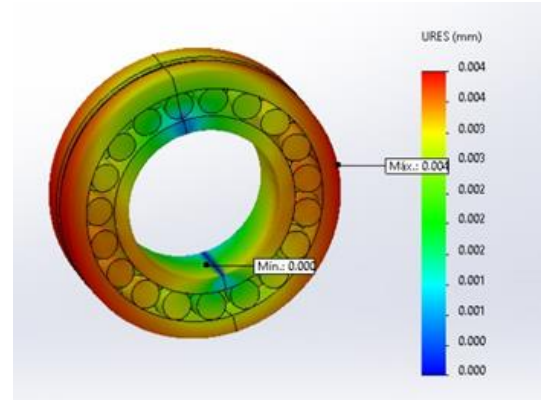


Fig. 8 Bearing displacement analysis

#### • Bearing Wear Perception

Wear visualization analysis was performed using the SolidWorks Design Insight module to identify regions susceptible to stress accumulation and progressive damage. Deformation was scaled by 11.19 $\times$ , highlighting critical contact zones between the rolling elements and the inner ring. The affected volume was estimated at 5.31%, indicating acceptable structural performance under the simulated operating conditions. However, continuous monitoring is recommended to account for environmental factors such as abrasive contamination and temperature fluctuations. This analysis supports predictive maintenance by enabling computational estimation of progressive wear and potential service life reduction in mining operating environments.

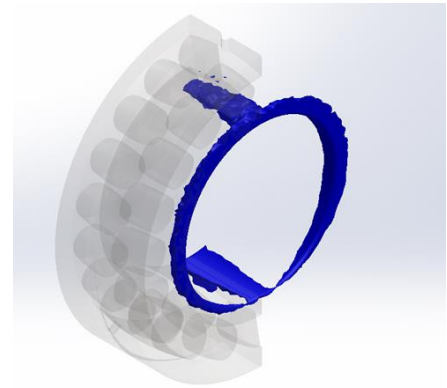


Fig. 9 Bearing wear perception

#### B. Monitoring with IoT Sensors in Rotating Systems

Real-time monitoring of rotating machinery was implemented using IoT sensors to support predictive

maintenance under severe mining operating conditions. Bearings used in equipment such as mills, conveyors, and crushers are continuously exposed to dynamic loads, vibration, and thermal stress that directly affect their performance and service life.

An IoT-based sensing system was deployed to continuously acquire vibration, temperature, and pressure data through sensors installed at critical machine locations. This monitoring strategy enabled detection of operational deviations and early-stage degradation associated with wear, lubrication instability, and abnormal operating conditions.

TABLE I  
TYPES OF SENSORS

| Component                                      | Description                                                                                                                                                                              |
|------------------------------------------------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| MPU6050<br>(Vibration Sensor)                  | Accelerometer and gyroscope sensor used to measure vibration signals along the X, Y, and Z axes for dynamic condition monitoring.                                                        |
| Type K<br>Thermocouple<br>(Temperature Sensor) | High-precision temperature sensor capable of measuring temperatures ranging from $-200\text{ }^{\circ}\text{C}$ to $1372\text{ }^{\circ}\text{C}$ under industrial operating conditions. |
| MPX5700AP<br>(Pressure Sensor)                 | Pressure sensor employed to monitor lubrication system pressure within a measurement range of 0 to 700 kPa.                                                                              |
| ESP32<br>(Microcontroller)                     | Microcontroller with integrated Wi-Fi and Bluetooth communication capabilities used for sensor data acquisition and cloud transmission.                                                  |
| Firebase (Cloud<br>Data Platform)              | Cloud-based platform used for real-time storage, processing, visualization, and remote monitoring of sensed operational data.                                                            |

The table presents the main components of the IoT-based monitoring system implemented for real-time analysis of SKF 22244 CC/W33 bearings operating in the mining environment of Cerro de Pasco. Each selected sensor plays a critical role in operational data acquisition, enabling continuous monitoring of vibration, temperature, and lubrication pressure conditions. This sensing architecture supports early fault detection and predictive maintenance strategies by providing real-time information associated with bearing degradation and abnormal operating behavior.

### C. Computer Vision in Wear Analysis

Computer vision has emerged as an essential tool for wear analysis in industrial components, enabling automated assessment of bearing condition without the need for physical interventions or disassembly. In this study, advanced Machine Learning (ML) techniques, specifically Convolutional Neural Networks (CNNs), were employed to classify and predict the wear level of SKF 22244 CC/W33 bearings.



Fig. 10 Bearing wear

Bearing images representing three wear levels (mild, moderate, severe) were captured using high-resolution digital imaging and optical microscopy under controlled lighting and focus conditions. A deep CNN architecture with convolutional, pooling, and fully connected layers was trained using a labeled dataset of 100 images (80% training, 20% validation) in Google Colab with TensorFlow and Keras. Data augmentation techniques including rotation, scaling, and translation were applied to improve robustness and reduce overfitting.

Model performance reached 96.2% validation accuracy, with confusion matrix results showing correct classification in most cases and minor errors primarily between mild and moderate wear levels.



Fig. 11. Inner ring wear

### D. Machine Learning for RUL Prediction

The achieved correlation was  $R^2 = 0.945$ , with an MAE of 18.6 hours and an RMSE of 22.9 hours, indicating a high degree of predictive accuracy. In comparison, the Random Forest model achieved an  $R^2$  of 0.915 and an MAE of 24.1 hours, while a simpler Linear Regression model obtained an  $R^2$  of 0.81 with an MAE of 41.3 hours. These results demonstrate the superior predictive capability of ensemble machine learning approaches, particularly XGBoost, under nonlinear operating conditions typical of abrasive mining environments.

TABLE III

RUL PREDICTION PERFORMANCE OF MACHINE LEARNING MODELS

| MODEL             | R <sup>2</sup> | MAE (HOURS) | RMSE (HOURS) |
|-------------------|----------------|-------------|--------------|
| LINEAR REGRESSION | 0.81           | 41.3        | 48.7         |
| RANDOM FOREST     | 0.915          | 24.1        | 29.6         |
| XGBOOST           | 0.945          | 18.6        | 22.9         |

### E. Methodological Process

A modular architecture was implemented for bearing monitoring and Remaining Useful Life (RUL) prediction through integration of IoT sensing, FEM analysis, and machine learning techniques (Fig. 14). The system was structured as interoperable functional modules operating synchronously within a unified predictive maintenance framework.

The sensing module acquired real-time vibration, temperature, and lubrication pressure using MPU6050, Type K, and MPX5700AP sensors, enabling continuous condition monitoring and detection of degradation patterns. These data were used as input for the FEM module, which simulated operating conditions under radial and axial loads to generate stress and displacement maps for structural assessment and life estimation.

The machine learning module employed XGBoost and Random Forest algorithms to predict RUL by correlating sensor measurements with simulation outputs, improving prediction accuracy and supporting maintenance decision-making to reduce unplanned downtime.

Finally, a monitoring module provided real-time supervision through a visualization dashboard and PLC-based control system, enabling remote access, automated response to operating conditions, and continuous optimization. This integrated architecture enhances predictive maintenance efficiency while increasing reliability and availability of mining equipment.

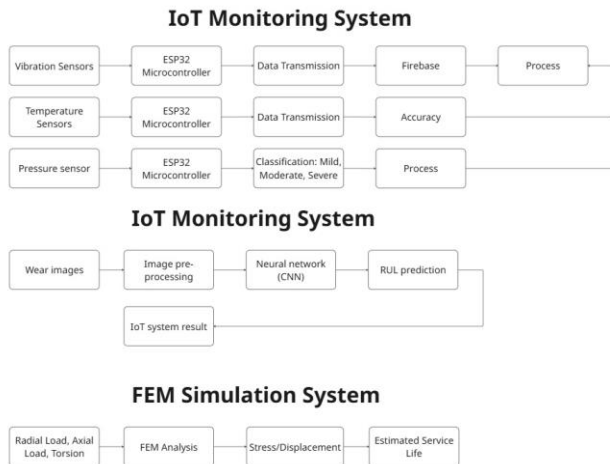


Fig. 12 IoT and FEM monitoring systems.

### A. IoT Sensor Results in the Mining Field

Real-time monitoring of the SKF 22244 CC/W33 bearing under simulated mining conditions recorded vibration, temperature, and lubrication pressure (Fig. 15). Vibration ranged from 1.0 to 2.4 mm/s over 60 min, remaining below the ISO 10816 limit (2.5 mm/s) and indicating stable operation [18]. Temperature increased from 45 °C to ~60 °C, below the 80 °C critical threshold, though suggesting progressive friction or lubrication inefficiency [19][20]. Pressure decreased slightly from 2.8 to 2.3 bar, possibly indicating minor leakage or viscosity changes [21].

These results confirm reliable real-time data acquisition for Remaining Useful Life prediction when integrated with FEM and machine learning models [22].



Fig. 13 Monitoring results.

### B. Computer Vision and IoT-Based Wear Analysis

A Convolutional Neural Network (CNN) was implemented to automatically classify bearing images into three wear categories: mild, moderate, and severe. The dataset consisted of 100 images obtained from maintenance inspections, which were preprocessed using resizing, normalization, and edge enhancement techniques in OpenCV [23].

The dataset was divided into 70% training, 15% validation, and 15% testing subsets. Additionally, a 5-fold cross-validation strategy was implemented to improve model robustness, reduce overfitting, and ensure stable predictive performance during training. The network architecture included three convolutional layers with ReLU activation functions, max-pooling layers, and a fully connected softmax output layer. Model training employed categorical cross-entropy loss and the Adam optimizer with a learning rate of 0.001 [24].

Model evaluation achieved an overall classification accuracy of 93.5%, with class sensitivities of 96% for mild

wear, 91% for moderate wear, and 94% for severe wear conditions. Misclassifications were primarily observed between mild and moderate categories, likely due to gradual visual transitions between intermediate damage states [25].

Training convergence was achieved after 30 epochs, reaching a minimum validation loss of 0.18 and validation accuracy of 94%, indicating stable learning behavior; however, the limited dataset size should be considered as a methodological limitation for future validation [26].

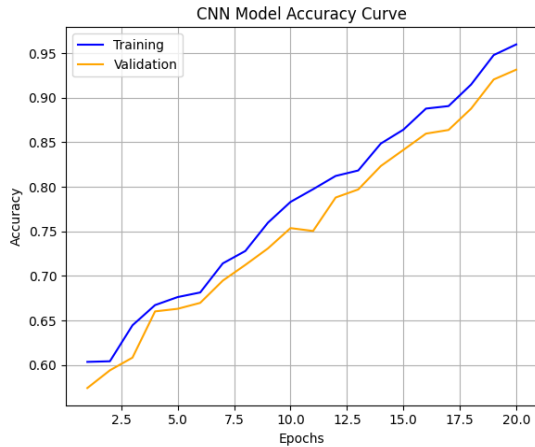


Fig. 14 IoT sensor results (A)

These results demonstrate that automated vision-based diagnosis significantly improves inspection efficiency and supports predictive maintenance by enabling rapid severity assessment and prioritization of corrective actions, consistent with recent studies on AI-driven fault detection in rotating machinery [27].

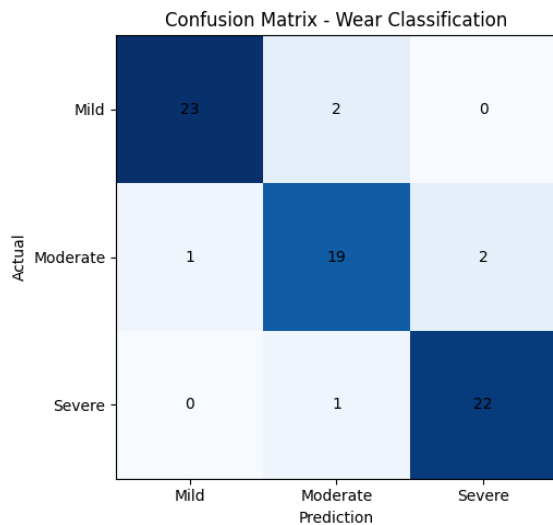


Fig. 15 IoT sensor results (B)

#### A. RUL Prediction Results Based on IoT Sensor Data

Accurate prediction of the Remaining Useful Life (RUL) of industrial bearings subjected to severe mining conditions is a cornerstone of predictive maintenance. In this study, a regression model based on Machine Learning algorithms, specifically Random Forest and XGBoost, was developed and trained using historical IoT sensor data (vibration, temperature, and pressure) and labels derived from wear inspections and FEM simulations.

The target variable was RUL expressed in operating hours, defined based on accumulated wear and the evolution of sensor-monitored conditions. The training dataset included 1,500 records processed from mining stations located in Cerro de Pasco, structured using 60-minute time windows. Predictor variables selected after feature importance analysis included vibration RMS, moving average temperature, average pressure, and dominant spectral frequency [28].

Fig. 17 and Fig. 18 show the comparison between real RUL values obtained in the field (measured after failure or replacement) and predictions generated by the XGBoost model. The achieved correlation was  $R^2 = 0.945$ , with an MAE of 18.6 hours and an RMSE of 22.9 hours, indicating a high degree of predictive accuracy. In comparison, the Random Forest model achieved an  $R^2$  of 0.915 and an MAE of 24.1 hours, showing slightly lower performance but serving as a useful cross-validation reference.

This prediction was contrasted with the theoretical L10 life estimation determined using ISO 281, incorporating equivalent dynamic radial load (P) and the life adjustment factor (aISO) adapted to operating conditions. While theoretical L10 values indicated a service life of up to 36,000 hours for the SKF 22244 CC/W33 bearing, ML models yielded average values of 31,200 hours under real operating conditions, highlighting the impact of non-ideal factors such as abrasive dust, misalignment, and lubrication irregularities [29].

Furthermore, an additional comparison was performed with stress maps obtained from the FEM model (see Fig. 15), revealing spatial correspondence between high-load zones and lower RUL predictions, thereby validating the model through triangulation of three sources: sensor data, simulation, and Machine Learning [30].

This multi-source validation approach strengthens the reliability of the predictions generated by the intelligent system, promoting its applicability as a preventive tool in the maintenance of industrial mill bearings. The integration of these tools has been supported by recent studies in Maintenance 4.0, where the fusion of physical data, simulated models, and intelligent algorithms is consolidated as a trend in hostile production environments [31].

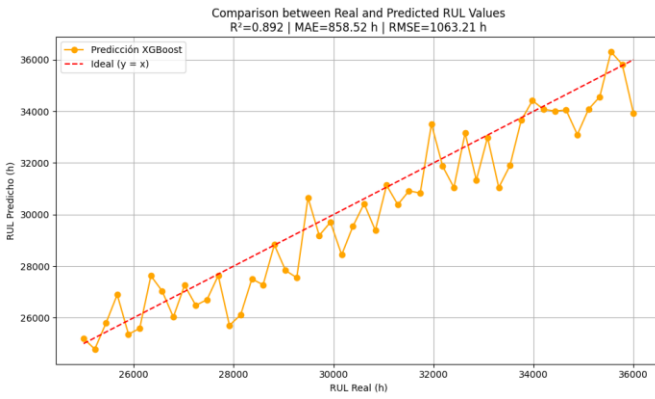


Fig. 16 Sensor-based prediction results

#### IV. DISCUSSION

The results demonstrate that the integration of Finite Element Modeling (FEM), IoT-based monitoring, and machine learning provides a robust framework for predicting bearing service life under abrasive mining operating conditions. FEM analysis identified stress concentration zones in critical contact regions, consistent with previous studies reporting that uneven load distribution accelerates fatigue crack initiation and progressive bearing degradation [32]. Furthermore, the use of ISO 281 theoretical life estimation (L10) provided a standardized reference for comparison with real operating measurements.

IoT sensor data revealed operational trends such as gradual temperature increases and slight pressure reductions that, although remaining within acceptable operating limits, suggest early-stage degradation mechanisms that are difficult to identify through conventional inspection techniques. When combined with intelligent diagnostic algorithms, these signals provide valuable predictive information for condition-based maintenance strategies [33].

The CNN model achieved wear classification accuracy above 93%, demonstrating strong capability for automated fault recognition in rotating machinery applications [34]. Similarly, the XGBoost-based Remaining Useful Life (RUL) predictor achieved a correlation coefficient of  $R^2 = 0.945$  using real operating data, confirming high predictive reliability and consistency between sensed variables and degradation progression.

The combined analysis of FEM, IoT, and machine learning results indicated that actual bearing lifespan may be reduced by approximately 10–15% compared with theoretical predictions obtained under ideal operating conditions. This deviation is primarily associated with abrasive particle contamination, thermal fluctuations, lubrication instability, and cyclic loading effects commonly encountered in high-altitude mining environments [35].

From an operational perspective, the proposed framework supports reduction of unplanned shutdowns, optimization of maintenance scheduling, and implementation of condition-based replacement strategies. These capabilities are aligned with intelligent maintenance paradigms associated with Industry 4.0 and emerging Industry 5.0 systems focused on adaptive, connected, and resilient asset management [36].

Overall, the proposed methodology constitutes a scalable and replicable approach for predictive diagnostics in harsh industrial environments, providing a foundation for future developments involving hybrid real-time monitoring systems, adaptive learning models, explainable artificial intelligence techniques, and cloud-based predictive analytics.

#### V. CONCLUSIONS

This study developed a hybrid predictive framework for estimating the Remaining Useful Life (RUL) of bearings operating under abrasive mining conditions through the integration of Finite Element Modeling (FEM), IoT-based sensing, and machine learning techniques. FEM simulations identified critical stress concentration zones in the SKF 22244 CC/W33 bearing and provided reliable reference values for theoretical life estimation based on ISO 281 standards.

Real-time IoT monitoring enabled continuous measurement of vibration, temperature, and lubrication pressure, allowing detection of degradation trends that are difficult to identify using conventional inspection methods. In parallel, the computer vision module achieved automated wear classification accuracy above 93%, while the XGBoost model predicted RUL with high reliability ( $R^2 = 0.945$ ), demonstrating strong predictive capability under variable operating conditions.

Cross-validation between numerical simulation, sensor measurements, and intelligent prediction models confirmed strong agreement in wear localization and degradation evolution. The obtained results demonstrated that actual bearing lifespan in abrasive mining environments may be reduced by approximately 10–15% compared with nominal design estimates due to abrasive contamination, thermal variability, and lubrication instability.

Overall, the proposed framework provides a scalable and reliable predictive maintenance strategy capable of improving maintenance planning, reducing unexpected failures, and enhancing operational reliability in mining systems. Furthermore, the methodology can be adapted to other rotating mechanical components and industrial systems operating under severe or highly variable conditions.

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