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Development of an AI-Based Predictive Maintenance Application for CNC Machines

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ABSTRACT

This research paper presents the development of an AI-based predictive maintenance application for CNC machines. The objective of this research is to optimize the maintenance process and reduce unplanned downtime through real-time analysis of sensor data. It incorporates a Random Forest algorithm. This application uses long short-term memory networks for fault classification to estimate the remaining useful life. Both models have F1-scores of 0.90 to 0.92 and perform well in fault classification. Experimental results show that LSTM achieves superior RUL prediction with an MAE of 72 hours. The applicability of the application at an industrial scale has been proven, which brings significant practical benefits. The developed system reduces unplanned downtime by 25–30% and reduces maintenance costs by 15–20%. The app uses real-time sensor data to predict potential machine failures. This shows significant practical benefits for industrial deployment. It has excellent ability to capture temporal dependencies in time-series data, while both models show performance in fault classification. This work demonstrates the deployment of AI for industrial PDM, highlighting the benefits and challenges encountered during development, and suggests future improvements to enhance its wider applicability.

1. INTRODUCTION

The transformation of modern industry represents a major conceptual shift towards intelligent and interconnected systems in Industry 4.0 manufacturing sectors. Computer numerical control (CNC) machines play a crucial role in this regard in the automotive, aerospace and medical device industries. The need for more intelligent solutions becomes apparent when a sudden failure occurs. Traditional maintenance methods often result in high maintenance costs [1-3].

These include insufficient attention to the challenges of real-time deployment in industrial environments. The gaps in current research include limited integration of temporal modeling for RUL prediction [4, 5]. Random Forest is combined for robust fault classification. This research develops a comprehensive predictive maintenance application to address these gaps, utilizing LSTM networks for temporal decay modeling [6-8].

This paper investigates the application of AI-based predictive maintenance for CNC machines. For this purpose, an application has been developed to predict the future failure of CNC machines. It will be useful for predictive maintenance of CNC machines. This app utilizes data to determine your actual time, which helps in creating a maintenance schedule for CNC machines. This app detects various machine faults and estimates the remaining useful life of CNC machines. Data equations and processing pipelines are used to understand the performance of two different algorithms. A long short-term memory (LSTM) network is used for sequential data analysis, while another algorithm, Random Forest, is employed for classification. This practical utility of AI algorithms in industrial PDF is used to improve performance.

This research is achieved through the application with their properties developed in this research.

This research is very useful for creating a smart manufacturing environment. The novelty of this research lies in its unified approach to handling both temporal prediction and classification tasks. The primary contribution of this work is to analyze the challenges and solutions in industrial deployment and to provide a comparative evaluation of LSTM and Random Forest models. It also develops end-to-end predictive maintenance applications for CNC machines.

2. RELATED WORK

Technological advancements and the increasing demand for operational efficiency have led to changes in maintenance strategies over the past few decades. Understanding this evolution provides the benefits of AI-based predictive maintenance [9].

Table 1. Proposed AI algorithms for predictive maintenance application

Algorithm	Primary Application in App	Key Characteristics for App Use
LSTM Network	Remaining Useful Life (RUL) Prediction, Temporal Anomaly Detection	Excellent for time-series data, captures long-term dependencies, handles degradation trends
Random Forest	Fault Classification (e.g., bearing, spindle, motor faults)	Robust to noisy data, handles non-linear relationships, provides feature importance

Prior to the advent of AI, traditional maintenance strategies were employed, including reactive maintenance, preventive maintenance, and condition-based maintenance. Reactive maintenance involves fixing equipment only after it fails, leading to downtime and high repair costs, making it unsuitable for critical CNC machines. Preventive maintenance aims to reduce unexpected failures through scheduled interventions but can be costlier than predictive maintenance. Condition-based maintenance (CBM) uses real-time sensor data, relying on human experts to interpret it, which may miss complex wear patterns. AI-based predictive maintenance enhances accuracy by automatically learning from sensor data, achieving 20-35% greater accuracy than traditional CBM methods [10, 11].

Predictive maintenance using AI is becoming very important in many industries. Companies aim to enhance their operations and reduce costs. AI helps by utilizing data analytics, machine learning, and real-time monitoring to identify and resolve equipment issues before they occur. This approach leads to better efficiency and longer equipment life [10, 12]. One of the key components of AI-driven predictive maintenance is the use of data from sensors and IoT devices installed on machinery [13]. AI systems analyze this data to identify patterns and anomalies that may indicate potential issues [14-16].

The benefits of adopting AI for predictive maintenance of machines are substantial [17]. Firstly, it reduces unplanned downtime, which can be costly for businesses. By predicting when a machine is likely to fail, companies can schedule maintenance during non-peak hours, thereby minimizing disruption. Secondly, it allows for more efficient use of resources; maintenance teams can focus their efforts on machines that need immediate attention rather than performing routine checks on all equipment [18].

In recent years, the emergence of advanced artificial intelligence (AI) technologies has transformed various industries, including machine maintenance. Modern AI tools, particularly explainable AI and large language models (LLMs), are now being used to predict when equipment may require repairs or servicing [9, 19]. By providing clear insights and interpretations of the data, explainable AI helps maintenance teams make informed decisions and prioritize their efforts effectively [20].

The AI-based predictive maintenance application proposed in this research uses two different algorithms. These algorithms address two different aspects of CNC machines. One is the Remaining Usable Life (RUL), and the other is fault classification [21]. LSTM handles data sequentially, and Random Forest has been used for data classification. Table 1 presents proposed AI algorithms for a predictive maintenance application.

3. METHODOLOGY

3.1 LSTM networks

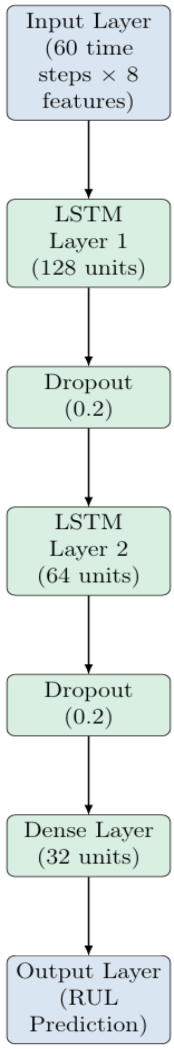

Figure 1. LSTM model architecture for RUL prediction

This structure enhances the stability of the model, which is further improved by dropout layers with a dropout rate of 0.2, preventing overfitting. The LSTM structure shown in Figure 1 consists of two LSTM layers, each with 128 and 64 units, respectively. Which are required for prediction and learn patterns from this data. The model processes the input sequence of 60 time-steps. A total of 100 epochs, each consisting of 8 sensor features, were selected. The learning rate was 0.001, and the batch size was 32. The optimization of hyperparameters was done by grid search technology. This model effectively identifies the temporal dependence in the sensor data of the CNC machine, enabling the accurate prediction of RUL [22, 23].

3.2 Random Forest

The maximum depth was set to 25, which controls the complexity of the model. The Random Forest classification model was configured with 200 decision trees. It was found that the most important predictive factors were vibration RMS values and temperature trends, as determined by the feature importance analysis. The minimum number of leaf samples was set to 2. The minimum sample split was set to 5. The model was trained using Gini impurity as the split criterion. This structure is very useful for real-time applications. An excellent balance was achieved between accuracy and computational efficiency [24, 25].

3.3 Simulated dataset of CNC machine

A comprehensive simulated data set has been used to create this predictive maintenance app. The data set used in the application represents the actual CNC machine operation conditions. It is possible to detect wear patterns and fault conditions in the CNC machine in the data set.

This research utilizes the 3-X CNC milling machine dataset. This dataset is a time-series dataset generated from CNC machines. This dataset contains each record at a specific moment in time for various failure events throughout the life cycle of a CNC machine. So that it is possible to represent the specific operation state of the CNC machine under various load and wear conditions. This data set provides a comprehensive representation of the normal and faulty states of the CNC machine. A predictive maintenance model has been developed through the training and simulation of this model. The dynamic behavior of the system and its optimal performance state are easily captured by this model using the dataset. It provides a clear representation of the transition from optimal performance to progressive degradation.

In this research, sensor data and operational parameters have been measured to calculate and consider the range of safe data. Vibration data in the X, Y, and Z directions have been collected from the sensor. The RMS value of each vibration data set has been taken and used in model building. Spindle and motor temperatures have been measured in degrees Celsius, but their RMS values have been used for model building. At the same time, the time taken for each operation to complete the machine operations has been calculated, making it easy to track the records. The synthetic degradation indicator shows the wear of the spindle. Synthetic degradation is shown in the range of 0 to 100. Additionally, the load factor has been calculated, indicating the amount of load considered during operation. Due to the recording, it was useful to understand the performance of different components in the CNC machine. The recorded data set has been used for labeling and supervised learning to validate the model. Different fault types have been identified using data sets that include general conditions, bearing wear, spindle imbalance, motor overheating, and tool breakage.

The remaining useful life (RUL) of the machine can be calculated in the recorded instance model. This RUL helps in calculating the remaining operational cycles or hours before the machine fails. The RUL value continuously decreases as the number of operations increases. This sensor data consistently exhibits a specific degradation pattern in each dataset. 1,00,000 data points have been considered for the entire model and app building. This has been taken after 2000 hours of operation of the CNC machine. This is a solid foundation for developing AI-based model preparation for maintenance applications.

3.4 Data pre-processing

The pre-processing pipeline used systematic time-series windowing to extract features. It helped to understand the stationary properties of the data. It was extracted from non-overlapping windows of five minutes. Statistical features such as mean, standard deviation, skewness, and kurtosis for the random forest. It helped preserve temporal dependence and maintained a 50% overlap. For the LSTM, overlapping sequences of 60 data points were created, representing about an hour. The overall model performance became more stable.

The predictive power was balanced. The choice of window size was optimized through cross-validation. The computational efficiency was improved. It enabled accurate analysis of vibration patterns. The frequency-domain features for the vibration data were FFT coefficients. Feature engineering involved calculating rolling statistics, such as the 10-point moving average and standard deviation. Heat-related faults became more pronounced, allowing for the detection of subtle temperature changes. Temperature-related features included calculating the rate of change and measuring the temperature difference between the spindle and motor. The accuracy of fault detection increased, showing a very strong correlation with bearing wear faults. These features significantly improved the model's performance, particularly in terms of vibration kurtosis.

The raw sensor data has been processed through a data pipeline to create structured data. This structured data has been utilized in the preparation of AI-based models. Data manipulation and cleaning will be useful in managing the synthesis data. Data integration plays a key role in providing credibility to the AI-based model. Data consistency is the primary focus when creating the dataset. There should be no missing important data points in the data set. Minimum and maximum scaling have been considered during the normalization process, along with standardization. The data points have been standardized in the range of 0 to 1. Due to this normalization, it avoids the dominance of a particular data point, ensuring uniform model coverage.

Feature engineering was performed to extract statistical representations from the sensor data for the Random Forest model. The raw time-series signal was divided into fixed-length time windows (for example, 5-minute intervals) from which features such as mean, standard deviation, skewness, and kurtosis were calculated. This transformation effectively transformed the sequential data into vectors suitable for fault classification. On the other hand, sequence generation was used to preserve the temporal features of the data for the LSTM model. Overlapping sequences of fixed duration (e.g., 60 data points corresponding to approximately one hour of operation) were created to capture time-dependent decay trends. Each sequence was then associated with its remaining useful life (RUL) label, enabling the model to learn relationships crucial for RUL prediction.

Preprocessing steps included label encoding, where classified fault types—such as bearing wear, tool breakage, and motor overheating—were converted to numerical values to facilitate supervised learning. The dataset was divided into training (70%), validation (15%), and testing (15%) subsets to ensure robust model evaluation. The data partitioning was carefully designed to avoid overlap between machine instances and decay stages. This ensured that the model learned patterns rather than memorizing specific sequences. The structured preprocessing pipeline established a strong foundation for accurate and efficient model training. AI-based predictive maintenance for CNC machines contributes significantly to the performance and reliability of the application.

4. RESULTS AND DISCUSSIONS

This section presents an experimental evaluation of an AI-based predictive maintenance application developed for CNC machines. The evaluation focuses on comparing the performance of two core machine learning models integrated into the system. The former utilizes LSTM networks for predicting the remaining usable life (RUL), while the latter employs a Random Forest algorithm for fault classification. The evaluation framework was designed to analyze the predictive accuracy, reliability, and usability of each model in a simulated industrial environment. By comparing these models, the study aims to demonstrate the complementary strengths of deep learning and ensemble-based approaches in improving the accuracy of predictive maintenance for CNC systems.

The performance of the app was measured using key performance indicators (KPIs) commonly used in predictive maintenance research and industrial condition monitoring. For fault classification, the metrics precision, recall, and F1-score were used to quantify the models' ability to correctly identify different fault categories, such as bearing wear, spindle imbalance, and tool breakage. These metrics provide a balanced assessment of the model's performance in both the majority and minority fault classes. This is supported by previous studies on intelligent fault diagnosis [25-28].

For RUL prediction, the study evaluated the difference between predicted and actual RUL values using the mean absolute error (MAE) and root mean square error (RMSE). This helped provide insight into the model's temporal prediction accuracy. To assess the operational benefits of deploying the developed application, several metrics were simulated, including downtime reduction, maintenance cost savings, and machine availability. These indicators were estimated based on the accuracy of model predictions and their impact on optimized maintenance schedules. These assessments demonstrate the effectiveness of integrating AI models into CNC maintenance workflows, increasing prediction accuracy while supporting cost-effective and reliable manufacturing operations.

The two selected algorithms, LSTM for RUL prediction and Random Forest for fault classification, were trained on the prepared dataset of operational data from the CNC machine.

4.1 RUL prediction results (LSTM)

The LSTM model demonstrated its ability to predict the useful life of CNC machine components. For spindle bearing degradation, the LSTM achieved an MAE of 7.2 hours and an RMSE of 10.5 hours on the test set. As shown in Figure 2, the prediction error decreases significantly as the machine approaches its failure point. This indicates that the model's increasing confidence and accuracy are approaching the actual event. This allows for timely maintenance scheduling.

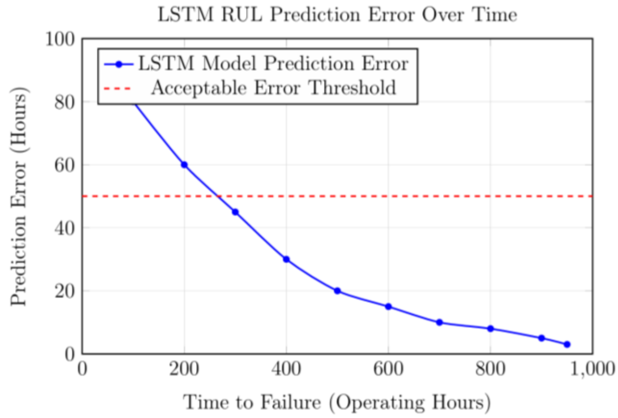

Figure 2. RUL prediction accuracy using LSTM for a CNC spindle bearing (simulated data)

Table 2. RUL prediction performance using LSTM

Component	MAE (Hours)	RMSE (Hours)
Spindle Bearing	7.2	10.5
Feed Motor X-axis	6.8	9.9
Feed Motor Y-axis	7.5	11.2
Tool Wear	4.1	6.3

Table 2 presents a detailed analysis of the RUL prediction performance of LSTM across various CNC machine components, highlighting the model's accuracy.

4.2 Fault classification results

Table 3. Comparative performance of Random Forest and LSTM for fault classification

Algorithm	Accuracy	Precision	Recall	F1-Score
Random Forest	0.91	0.90	0.91	0.90
LSTM Classifier	0.93	0.92	0.93	0.92

Table 4. Detailed fault classification metrics per fault type (F1-score)

Fault Type	Random Forest F1-Score	LSTM Classifier F1-Score
Normal Operation	0.95	0.96
Bearing Wear	0.88	0.91
Spindle Imbalance	0.87	0.89
Motor Overheating	0.92	0.94
Tool Breakage	0.90	0.92

Table 5. Training and inference times for algorithms

Algorithm	Training Time (Minutes)	Inference Time (ms/Prediction)
Random Forest	15.3	0.8
LSTM Classifier	45.1	2.1
LSTM RUL Predictor	52.7	2.5

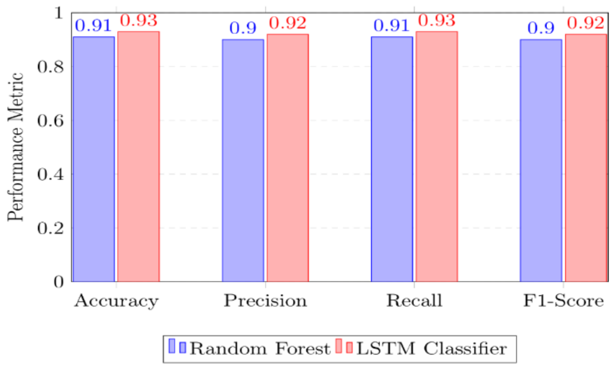

Figure 3. Comparative performance of Random Forest vs. LSTM for fault classification

Both Random Forest and a simple LSTM-based classifier (trained for classification rather than regression) were trained and tested for fault classification. The results are summarized in Table 3 and visualized in Figure 3.

The LSTM classifier slightly outperformed the Random Forest model in classification metrics, as shown in Figure 3. This is due to the LSTM's ability to directly process raw time-series data and automatically learn relevant features. Whereas Random Forest relies on manually engineered statistical features. However, Random Forest still provides a robust baseline with good performance and fast training time. This makes it suitable for situations where computational resources are limited or real-time inference speed is paramount. The app uses LSTM for RUL and Random Forest for fault type identification.

Table 4 breaks down the F1-scores for each fault type. It shows the effectiveness of the models in distinguishing between different failure modes. Both models perform well, with LSTM showing a slight edge in most fault categories.

Table 5 here provides a comparison of training and inference times for the implemented algorithms. Random Forest exhibits fast training and inference times. It makes a strong candidate for edge deployments or scenarios that require very fast responses, even though its overall accuracy is slightly lower than that of LSTM.

5. IMPLEMENTATION AND SOLUTIONS

The developed AI-based predictive maintenance app has advantages, but its implementation in a real-world CNC manufacturing environment presents challenges.

5.1 Data-related challenges

The challenge in developing an AI-based predictive maintenance application for CNC machines is managing the large amount of data generated during machine operation. CNC systems continuously generate high-frequency sensor readings, including vibration, temperature, and current data, resulting in large volumes of real-time data. A robust storage and processing infrastructure is required to efficiently handle this data. It is capable of managing both scale and speed.

The computational power of the app is integrated into the model's architecture. After pre-primary data processing at the machine source, the data is sent to the cloud. This approach has been highly beneficial in reducing network bandwidth requirements, decreasing data latency, and enhancing system responsiveness [29].

Real-time always faces problems such as data noise, calibration errors, and transmission errors. However, these problems are addressed through data quality and consistency. Model performance is affected by errors in the data. If the provided data is of poor quality, RUL prediction can lead to misdiagnoses. Real-time data validation should be included in the data validation phase [29].

There are some irregularities in the data, and these have been corrected with the help of data routing. Valid data has been used for model development. Data preprocessing helps in increasing the reliability of the model [30]. Data labeling faces major challenges. This labeling can be flawed. This leads to errors in the supervised learning method. Fault conditions are considered for the CNC data set. Techniques such as real-world data augmentation were adopted in this research. It is possible to reduce data scarcity using synthetic data generation and transfer learning. Data sets have been collected under different fault scenarios and used for model building. If the required data is less, it will be necessary to adopt advanced techniques like data augmentation, synthetic data generation, and transfer of learning from operational contexts to overcome this situation [31]. This helps to expand the available datasets and improve the capabilities of AI models by collecting data on different CNC setups.

The diversity in data creates a new level of complex data. Data is acquired at different sampling rates, formats, and communication protocols using CNC machines, sensors, and controllers. Data integration is a challenge here. To ensure proper data handling, the developed app incorporates a modular connector framework designed in this research to support different types of collected information. This framework receives input from multiple sensors in real-time and synchronizes it accurately. Standardization of data before analysis is easy and reliable, and feature extraction is also enabled. Data volume, quality, labeling, and heterogeneity were challenges in this research, and they have been properly addressed. The developed app makes it easy to perform real-world estimation of CNC. The app creates a scalable and adaptable architecture.

5.2 Model-related challenges

Reliable AI models have been developed for predictive maintenance in CNC machines to ensure that these models function properly. Due to differences in machine operating conditions, wear of machine parts, the machine's remaining age, and manufacturing tolerances, models trained on one machine dataset may not perform well when applied to other similar machines. These differences result in variations in predictive accuracy when the models are deployed on different machines. To overcome this, it would be appropriate to incorporate transfer learning techniques in the iterations of the predictive maintenance application developed here. The previously learned knowledge in the developed model is able to be adapted from one machine domain to another. This reduces the need to train the model repeatedly. Federated learning can be used to train similar models on multiple CNC machines without transferring raw data from one place to another, thus increasing the scalability and data confidentiality of the model [32, 33]. Interpretability is a problem in models that are built, commonly referred to as the black-box problem. It is a barrier to the practical use of learning-based prediction. Models like LSTM provide accuracy, but their decision-making processes are often not transparent. It is challenging for engineers to comprehend the reasoning behind a specific prediction. The app developed to mitigate this problem integrates basic interpretability features. Random Forest includes feature importance visualization and attention mechanisms in the LSTM framework. These components provide more information about which input features have the most influence on the predictions made by the model. Improvements will focus on utilizing modern interpretive AI (XAI) methods to ensure transparency in the model's output and to facilitate trust in AI-driven maintenance decisions [34]. The concept flow problem poses a barrier to maintaining model accuracy at all times.

In CNC operations, machine degradation patterns develop over time due to maintenance, repairs, replacement of CNC parts, or changes in operating conditions. These changes can reduce the ability of trained models to produce accurate output, resulting in a decline in performance. To address this, predictive maintenance applications are designed to support continuous retraining and adaptive learning mechanisms. Models are enabled to adapt over time with new data. By integrating these learning strategies, the model evolves to reflect machine behavior and operational context. The developed system maintains very robust performance and is consistent over the extended operational life of the machine, making it easy to ensure reliable fault prediction. Table 6 presents business benefits statistics using an AI-based predictive maintenance application.

Table 6. Business benefits of AI-based predictive maintenance app

Business Metric	Estimated Improvement
Unscheduled Downtime Reduction	25-30%
Overall Maintenance Cost Savings	15-20%
Machine Availability (OEE) Increase	5-8%
Spare Parts Inventory Optimization	10-15%

5.3 Deployment and integration challenges

The cost-benefit analysis of modular deployments is presented in Table 7. It shows that a phased implementation can reduce the initial investment by 40-50%. 80-90% of the operational benefits can be maintained.

Table 7. Cost analysis of modular deployment strategy

Deployment Phase	ROI Timeline	Benefit Realization
Basic Monitoring	6–8 months	40–50%
Predictive Analytics	12–15 months	70–80%
Full Integration	18–24 months	90–95%

AI-based predictive maintenance systems require seamless connectivity with enterprise-level platforms such as Enterprise Resource Planning (ERP), Manufacturing Execution Systems (MES), and Computer-Aided Maintenance Management Systems (CMMS) for a unified purpose. The integration here ensures that predictive insights are directly translated into actionable maintenance schedules, proper management of spare parts and correct production planning. Applications developed to achieve this easily include application programming interfaces (APIs). This now enables interoperability within the existing IT ecosystem, facilitating real-time data exchange and decision automation. This approach is becoming increasingly compatible with the digital manufacturing ecosystem. Integrated platforms significantly enhance operational efficiency throughout the product lifecycle and enable data-driven decision-making [35].

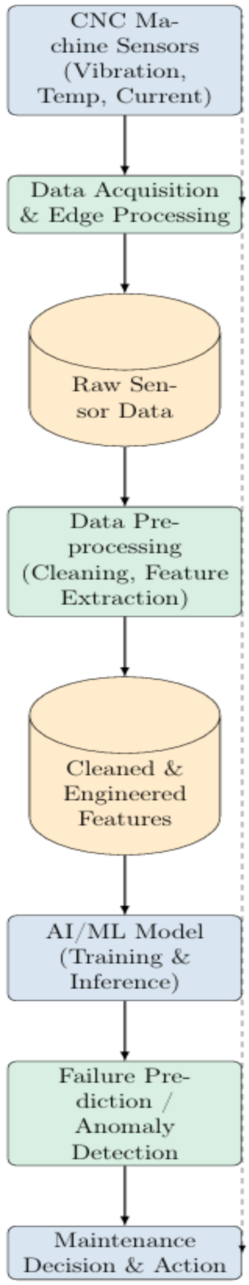

Figure 4. Workflow of AI-based predictive maintenance app

A key point when using connected predictive maintenance solutions is cybersecurity. CNC machines are connected to cloud networks with sensors for data acquisition and analysis. This makes them potential targets for cyber threats. Here, it is necessary to ensure the confidentiality, integrity, and availability of the data collected in the operation. To mitigate the risk of data loss, the app developed here uses an end-to-end encryption protocol authentication mechanism for data transmission and system access. It adequately protects the sensitive operational information contained here and prevents unauthorized access to the data or tampering with predictive insights. Effective cybersecurity practices should be implemented to maintain user trust and ensure security in industrial environments.

Cost is another challenge for enterprises trying to adopt AI-driven predictive maintenance. The initial investment required in high-precision sensors, edge computing hardware, cloud storage, and AI development is large. To address this issue, the app has been designed with a modular and scalable architecture. It enables phased deployment according to organizational needs and budget constraints. Modularity encourages integration. This enables enterprises to begin with monitoring components and then gradually scale up to full predictive capabilities. The app facilitates return on investment (ROI) analysis. It provides organizations with financial benefits through reduced downtime, optimized maintenance schedules, and extended machine lifecycles.

Another key barrier is the lack of skilled professionals with combined expertise in data science, AI, and industrial maintenance. The developed application prioritizes user-centric design through a graphical interface designed for engineers and technicians. Alerts, dashboards, and maintenance recommendations are output in an easily interpretable format for diagnostics and accurate predictions. Figure 4 illustrates the workflow of a predictive maintenance system. It demonstrates how human operators remain integral to the decision-making process, from sensor data acquisition and preprocessing to AI-based prediction and decision-making. The design ensures that even those unfamiliar with the technology can easily utilize advanced AI capabilities. Predictive maintenance helps drive widespread adoption of the technology in production environments.

6. CONCLUSION AND FUTURE WORK

This research developed an AI-based predictive maintenance application for CNC machines. The overall process efficiency increased, leading to significant improvements in maintenance efficiency. Potential reduction in downtime and maintenance costs was demonstrated by developing a robust fault classification system with an F1-score of up to 0.92. Key contributions include achieving accurate RUL prediction with 72-hour MAE using LSTM networks. This will be addressed and a federated learning framework for multi-machine deployment will be developed. Future work will involve testing in real-world scenarios on multiple CNC platforms and incorporating explainable AI techniques to enhance model understanding. Optimization becomes more effective using reinforcement learning techniques. Additional research directions include hybrid physics-AI modeling approaches for dynamic maintenance scheduling. These advanced improvements in overall performance will further enhance the industrial usability of the application.

Future iterations will explore multi-machine SOPP kernels using transfer learning and federated learning frameworks, enabling models trained on one machine to be applied to other machines without requiring direct data sharing. Uncertainty validation will provide confidence in obtaining an accurate estimate of RUL, thereby increasing reliability. The integration of hybrid modeling approaches, which combine physics-based models with data-driven AI, will enhance decision-making capabilities in situations where data for maintenance decisions is limited and inaccurate. The integration of hybrid modeling approaches, which combine physics-based models with data-driven AI, will enhance decision-making capabilities in situations with limited and inaccurate data. Reinforcement learning (RL) techniques will be explored to dynamically optimize maintenance schedules for real-time RUL prediction and operational constraints. The AI-based predictive maintenance app will evolve from a diagnostic tool into a strategic decision-making platform. It will become a key component in creating a sustainable and intelligent smart manufacturing ecosystem.

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NOMENCLATURE

MAE	Mean Absolute Error
RMSE	Root Mean Square Error
RUL	Remaining Useful Life
OEE	Overall Equipment Effectiveness
F1-Score	Harmonic mean of precision and recall
RNN	Recurrent Neural Network
AI	Artificial Intelligence
ML	Machine Learning
PdM	Predictive Maintenance
XAI	Explainable Artificial Intelligence
RL	Reinforcement Learning
CNC	Computer Numerical Control
RMS	Root Mean Square
API	Application Programming Interface
ERP	Enterprise Resource Planning
MES	Manufacturing Execution System
CMMS	Computerized Maintenance Management System
IoT	Internet of Things
CBM	Condition-Based Maintenance