OPEN ACCESS
International Journal of Innovations in Science & Technology

AI-Based Predictive Tool-Life Computation in Manufacturing Industry

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Citation | Aleem. M, Jawaid. M. M, Talpur. S, Junejo. A. Z, Khan. S. A, Ahmed. M, "AI Based Predictive Tool-Life Computation in Manufacturing Industry", IJIST, Vol. 6 Issue. 1 pp 132-142, Feb 2024
Received | Jan 31, 2024 **Revised |** Feb 22, 2024 **Accepted |** Feb 24, 2024 **Published |** Feb 25, 2024.

For maximum productivity and optimal utilization of tools, predictive maintenance serves as a standard operation procedure in the manufacturing industry. However, unnecessary or delayed maintenance both causes increased downtime and loss of revenue which should be optimized. Accordingly, this paper presents a method for predicting the maintenance requirement to ensure the optimal utilization of the tools. The experimental data for this research has been collected from a CNC lathe machine in a manufacturing plant for multiple days. The CNC machine equipped with three sensors leads to a detailed log for parameters related to tool wear including current, voltage, acceleration in 3D, motor rpm, and tool temperature respectively. Detailed experimentation has been performed to investigate the importance of different parameters. A direct relationship between current and tool temperature was observed leading to an immediate halt of machine operations. In the subsequent step, maintenance prediction was performed using Logistic regression and Random Forest technique respectively to validate the machine behavior. The retrospective data validated the performance with precise accuracy equal to 98% and 95% for both of methods respectively. The promising results predicting the maintenance schedule of the Lathe machine signify the effectiveness of Machine Learning towards advance scheduling for maintenance. The proactive maintenance strategy helps in potential benefits such as avoiding further costs, avoidance of disruptions, and increased efficiency productivity, thereby enhancing tool life cycles.

List of Abbreviations:
PdM: Predictive Maintenance
CNC: Computer Numerical Control
AI: Artificial Intelligence
SVM: Support Vector Machines
ML: Machine Learning
RPM: Revolution Per Minute

Keywords: Predictive maintenance (PdM); Cutting Factors; Tool Life; Manufacturing Industry and Computer Numerical Control (CNC).

Introduction:

On-going advancements in the field of Artificial intelligence (AI) have led to the revolution of various sectors, including the production and manufacturing industry [1]. One area where AI can make a significant impact is predictive maintenance (PdM) [2], which involves using data from sensors and other sources to predict when equipment is likely to fail and scheduled maintenance accordingly [3]. The accurate prediction of tool wear in machining operations is critical for achieving high-quality products and minimizing costs. The use of AI-based predictive tool-life computation can help manufacturers optimize their processes and reduce downtime.

Integration of complex data analytics, and decision-making techniques with PdM can greatly improve its performance. AI algorithms, including regression [4], neural networks [5], decision trees [6] and so on, acquire learning from historic data patterns to forecast tool life in production and manufacturing industries. Although such extensive work and remarkable can be seen in the literature related to predictive maintenance, however, the application of predictive maintenance in manufacturing industries is lacking. Hence, this study aims to bridge this existing gap in the literature by exploring the potential of AI-based PdM for such industries. The novelty statement of our study and major contributions of the paper include:

- Comprehensive literature survey to identify current state-of-the-art techniques and methods for monitoring and predicting the tool's life.
- Proposing a technique to increase efficiency, reduce costs, and optimize machining processes for prediction of tool life. This will in turn increase the life of the tool due to proper scheduled maintenance.

To achieve these contributions, the objectives of the study are:

- Identify various predictive maintenance algorithms in the literature.
- Utilize these algorithms to design and implement a framework to predict the tool life of a CNC lathe.
- Analyze and propose the best-performing method.

Literature Review:

Predictive maintenance is a need of the current era and the most advanced approach for enhancing the reliability, accuracy, and accessibility of production systems for optimizing performance. This involves forecasting time predicting the lifespan of a machine or its components and managing maintenance tasks accordingly [7]. To construct reliable, accurate, precise, and efficient predictive maintenance models, Artificial Intelligence (AI) methodologies have garnered significant attention in recent times [8]. There have been multiple inquiries, works, and examinations conducted to assess the effectiveness of AI-driven predictive maintenance within the industrial domain [9]. To stop or minimize unplanned and unscheduled downtime and reduce maintenance cost is the pivotal benefit when implementing AI-based predictive maintenance [3].

A statistically meticulous designed and enhanced predictive maintenance management trick for continuous monitoring of industrial systems was presented in research by You et al. [7] which showed analysis that when the machine isn't in a good state it uses extra raw material which is also a big loss. The proposed approach successfully results in reducing maintenance expenses while boosting system reliability, efficiency, and accuracy. Similarly, Lee et al. used AI techniques on machine-generated datasets to suggest a maintenance strategy for machine tool systems which results in optimizing maintenance cycles and improving machine reliability [10].

One more efficient method in supporting the durability of multi-component systems is the implementation of multi-level predictive maintenance [2]. In addition to ensuring the accuracy, efficiency, and reliability of the machine and its components, Nguyen et al. [3] worked extremely hard to achieve a multi-level predictive maintenance model that integrates both prognostic & diagnostic data. Their study showed the success of this approach in not only reducing maintenance costs but also elevating the overall availability and performance of the system.

Further making well-informed judgments on maintenance tasks can also be aided by AI-based predictive maintenance. An intelligent predictive decision support system for condition-based maintenance was given by Yam et al. [11] and can assist maintenance managers in making well-informed run-time decisions on the scheduling of maintenance tasks. Nowadays industrial sector has shown interest in using ML approaches for predictive maintenance. Çınar et al. [2] performed an in-depth examination of ML methods in predictive maintenance within the framework of Industry 4.0. The author's works underscore the importance of using ML methods to analyze extensive data generated by machines used in the industrial sector, specifically emphasizing improving predictive maintenance plans. Recently Carvalho et al. [12] worked comprehensively on machine learning techniques used in predictive maintenance in another research. According to his finding's Neural networks, SVM support vector machines, and decision trees were the most often utilized ML approaches for predictive maintenance in the industrial domain.

In addition to that, a physical manufacturing model for producing intricate data for AI-based predictive maintenance study was described by Klein and Bergmann [13]. They emphasized on importance of leveraging data in crafting accurate, reliable, and efficient predictive maintenance models. A study by Traini et al. [4] suggested an ML framework for milling predictive maintenance. This helped in identifying issues within milling machines by analyzing acoustic and vibration data. Lastly, a thorough evaluation of the literature on predictive maintenance in Industry 4.0 was carried out by Zonta et al. [14]. They focused that in order to create precise and effective predictive maintenance models, it is important to combine data-driven and physics-based models.

Overall, the research points to the possibility that AI-based predictive maintenance holds promise in augmenting and enhancing the availability and dependability of industrial systems. There is massive growth in the popularity of predictive maintenance using machine learning approaches and has strong potential to completely transform the industrial sector. Creating precise, accurate, and effective predictive maintenance models for complex systems in Industry 4.0 requires further dedicated research and exploration. This is how our first objective is to identify the importance of ML algorithms for the predictive maintenance of machines in industrial systems.

Material and Methods:

In this section, the proposed ML-based approach for computing tools like predictive maintenance, is described in detail. The section also discusses the research materials and methods used to conduct this research.

Proposed Framework:

This paper aims to propose a framework that will efficiently predict tool life for manufacturing industries. This framework exploits machine learning algorithms for accurate prediction of maintenance, such that system downtime is reduced and the overall production efficiency is increased. The flowchart in Figure 1 Show the overall picture of the framework.

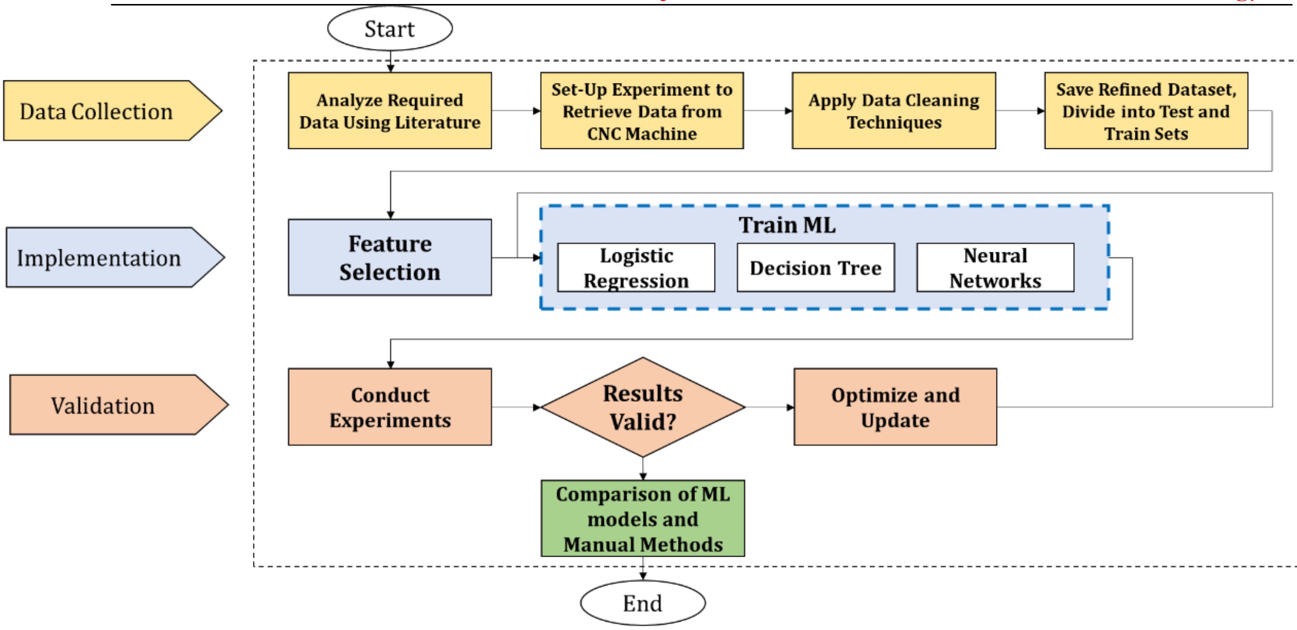

Figure 1: Proposed Framework

The diagram is divided into three phases i.e., data collection, implementation of machine learning algorithms, and validation of results. For each of these phases, various steps are proposed. The very first step is dataset acquisition. After a comprehensive literature study, we found a number of datasets using features like time, rpm, c1, c2, c3, v1, v2, v3, accx, accy, ambient_temp, tool_temp, and unnamed. Since the application of PdM is relatively new in the field manufacturing industry, hence we acquired the required data from real-time experiments of CNC machines at our institution. The details of this data are given in upcoming sections. Once this dataset is obtained, data cleaning is applied to it, where redundant data and missing value fields are deleted. The preprocessed dataset is then split into training and testing sets. The training set was then chosen for further processing.

Similarly, moving on to the next step, here the main models of the framework were implemented. First feature selection is done, with which we skillfully reduced extra fields from data to yield a more concise and relevant dataset and filtered dataset based on a threshold criterion, specifically 'c1' values exceeding 1. Subsequently, we undertook a profound transformation, categorizing 'Tool Life' into a binary classification schema—a '1' denoting tool life below 5 units and a '0' for tool life equal to or exceeding 5 units. This transformation brought clarity and precision to our data which is an essential demand for precise predictions. We corrected our data, and we made a smooth transition to the world of machine learning.

For the overall prediction mechanism of the machine's behavior, we used different ML algorithms starting with Logistic Regression, in which we began our analysis with a firm foundation of the train-test split, an infundibular process that occurs during model development on the bedrock of our data set was thoughtfully split into training and testing subsets, as well we defined 'x' to represent the feature matrix and 'y' as the target variable, after feature extraction we kept highest affecting parameter as the dependent variable and keeping all others as an independent variable because in our case in the feature extraction part, it shows c1 variable or parameter is highly involve in machine shutdown or in unexpected machines behavior, so using logistic regression algorithm we kept c1 current variable as dependent and all other as independent to train our model – an approach that aimed at optimal model building & evaluation.

Followed, by the Decision tree classifier which contributes mainly to identifying the importance of different parameters from a data set and provides valuable insights into processes of decision-making. Lastly, Random Forest algorithms, which helped in building multiple decision trees and show the combined result of all predictions to enhance overall predictive accuracy and considering the essential importance of feature extraction and of all parameters collected from the CNC lathe machine. After that, in the validation phase, experiments are conducted using test data. The results obtained in this section are compared with those of existing methods for predictive maintenance and this is how our second objective is achieved.

Research Methodology:

The research methodology for this research is shown in Figure 2 and described as follows:

Literature Review:

A literature study was conducted for this work to understand and analyze the state-of-the-art in the domain of predictive maintenance. The comprehensive study insights into the different techniques and algorithms used for predictive maintenance in the manufacturing industry.

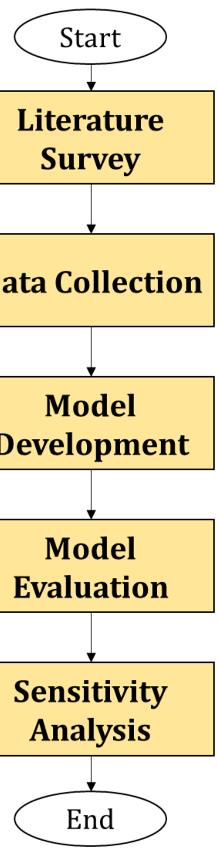

Figure 2: Research Methodology

Data Collection and Preprocessing:

The data for this research work was collected from a manufacturing plant at our institute. The data comprises attributes such as tool wear and other influencing factors. The data collection process involved choosing the most suitable parameters based on the literature survey. After the collection of data, it was preprocessed using several methods, removing all the errors and inconsistencies. These methods include data cleaning, data integration, and data transformation. The pre-processed data was then divided into training and testing sets.

Model Development:

In this phase, the proposed model is developed. Various AI and ML algorithms such as logistic regression, decision trees, and neural networks are implemented. Further, these algorithms are fed the training data to learn from. This learned model is then tested using the testing part of the dataset.

Model Evaluation:

The developed model was evaluated based on the accuracy of its predictions. The evaluation involved comparing the predicted results with the actual results obtained from the manufacturing plant. The evaluation metrics used include mean absolute error, root means squared error and R-squared value.

Sensitivity Analysis:

A sensitivity analysis was conducted to identify the factors that have the most significant impact on tool wear. The analysis involved varying the parameters related to the tool wear and observing the effect on the predicted tool life.

Dataset:

The dataset was obtained using a manufacturing plant. The machine used was a CNC lathe. The parameters acquired through experimentation were related to tool wear and other factors affecting it. The dataset is open-sourced for people who would like to work further in this domain our Github repository: https://github.com/muhibaleem/dataset_cnc. Table 1 shows the summary of the CNC lathe machine dataset and Table 2 provides a description of the dataset and parameters involved in this study.

Table 1: CNC lathe machine dataset.

Time	Time.1	Rpm	C1	C2	C3	V1	V2	V3	Accx	Accy	Accz	Ambient_Temp	Tool_Temp
22-02-20	9:03:01 AM	0	0.06	0.3	0.34	231.52	231.82	231.76	596	16032	-1664	26.21	26.2
22-02-20	9:03:04 AM	15	0.05	0.32	0.37	231.53	231.5	231.89	532	16128	-1616	26.21	26.21
22-02-20	9:03:07 AM	33	0.06	0.3	0.3	231.51	231.64	231.69	548	16180	-1688	26.21	26.21
22-02-20	9:03:10 AM	49	0.07	0.35	0.33	231.88	231.59	231.51	568	15976	-1684	26.21	26.22
22-02-20	9:03:13 AM	78	0.06	0.35	0.3	231.55	231.86	231.93	584	16004	-1664	26.21	26.22

Table 2: Description of Dataset.

Dataset Columns	Description
Time and Time.1	These two columns likely represent the timestamp or time interval at which the data was collected.
RPM	This column represents the spindle speed in revolutions per minute (RPM) at which the lathe machine was running.
C1, C2, and C3	These columns likely represent sensor readings or measurements from different sensors (force sensor, vibration sensor, position sensor) on the lathe machine.
V1, V2, and V3	These columns likely represent voltage readings or measurements from different sensors (force sensor, vibration sensor, position sensor) on the lathe machine.
Accx and Accy	These columns likely represent acceleration readings along the x-axis and y-axis, respectively. These readings may provide information about the vibration or movement of the lathe machine during operation.
Ambient_Temp and Tool_Temp	These columns likely represent temperature readings from different locations on the lathe machine. ambient_temp may represent the ambient temperature of the machine, while tool_temp may represent the temperature of the cutting tool or workpiece.

Evaluation Parameters:

To measure the performance of our AI-based tool-life computation system we used different evaluation parameters. Primarily, the Accuracy shows the comprehensive overview of our model's performance by calculating how many predictions are correct overall. While Precision & Recall furnishes how well our model captures actual positives. Then majorly the F1 Score combines Precision & Recall which shows an idea of the overall correctness of predictions. Then Confusion Matrix breaks down the model's prediction into true positive, false positive, true negative, and false negative which helps us in seeing that actually where the model excels and where it fails. And lastly, the Feature Importance tells us about the factors which have the most impact on our predictions. The chart in Figure 3 Shows the feature importance analysis or dependency of individual parameters from the dataset involved in this study.

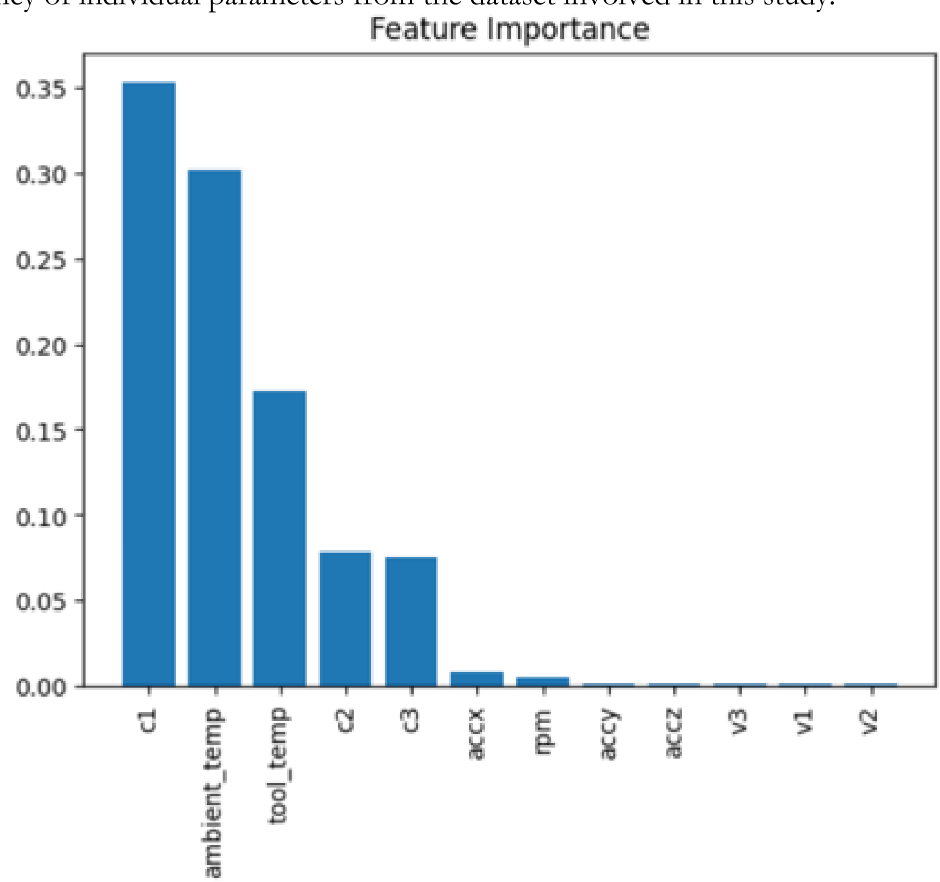

Figure 3: Feature Importance Analysis

Results:

The overall conducted experiments aimed to develop AI AI-based predictive maintenance model using sensor data from a CNC lathe machine. This section shows the outcomes of the experiments for enhancing accuracy and efficiency in manufacturing industries through proactive maintenance strategies.

Analysis of Results:

Several ML algorithms were applied including Logistic Regression, Random Forest Classifier, and Decision Tree Classifier. Leveraging features from the dataset encompassing current readings, voltage readings, temperature, accelerometer, and rpm was employed to predict tool lifespan. These experiments showed promising results Logistic Regression showcased an accuracy of 98% while the Random Forest Classifier showcased an accuracy of 95% and the Decision Tree Classifier showcased an accuracy of 94%, respectively precision, recall & f1 score for each determined for each algorithm which indicates respective strength in predicting tool-life.

Finally, the obtained result signifies the effectiveness of the ML algorithm in predicting the remaining useful tool life of the machine and helps us in maximizing productivity, reducing extra cost, reducing disruptions, and optimizing the overall tool lifespan and this is how our third objective is achieved. The results of experiments for this research are shown in Table 3.

Table 3: Results of experiments.

Algorithm	Accuracy	Precision	Recall	F1 Score
Logistic Regression	98	0.97	0.99	0.98
Decision Tree Classifier	94	0.94	0.93	0.94
Random Forest Classifier	95	0.95	0.96	0.95

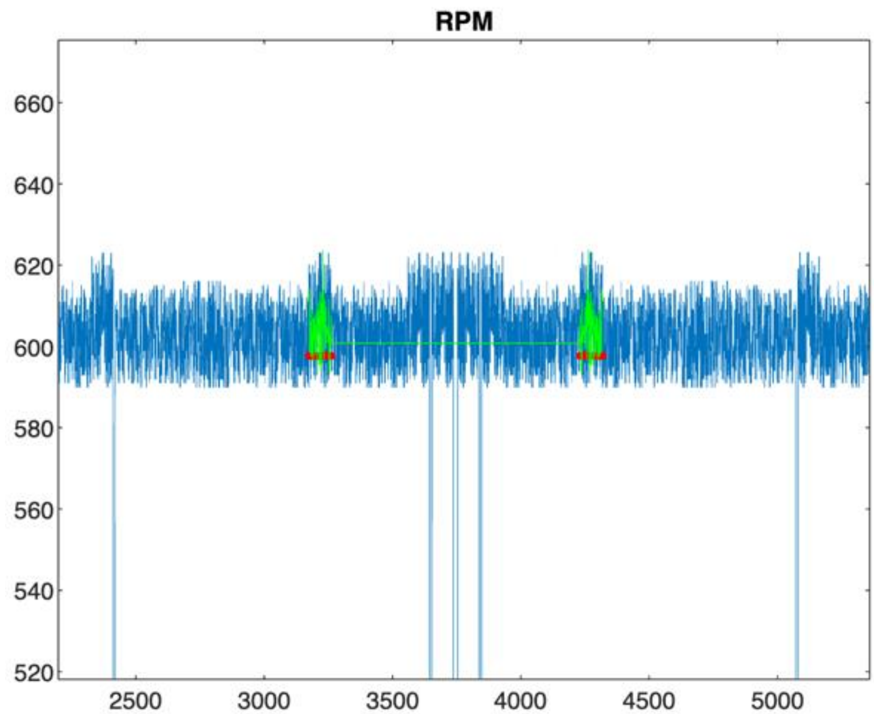

Figure 4: RPM Analysis

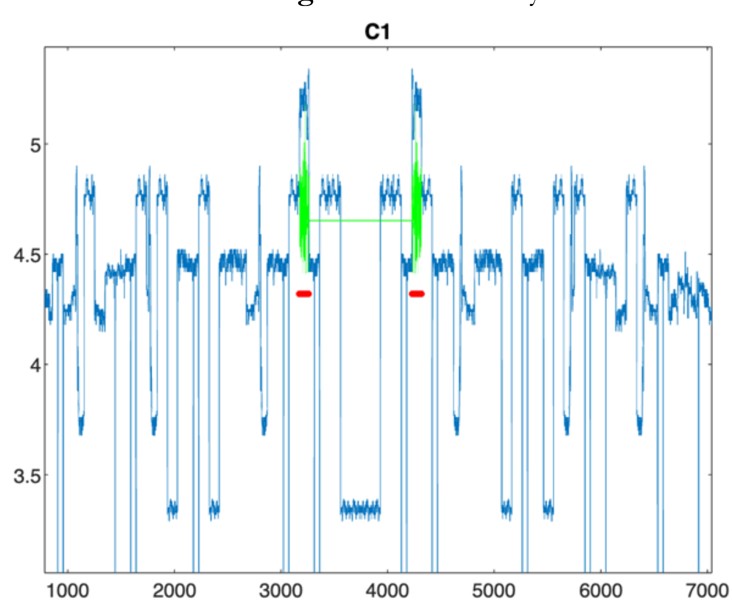

Figure 5: C1 Analysis

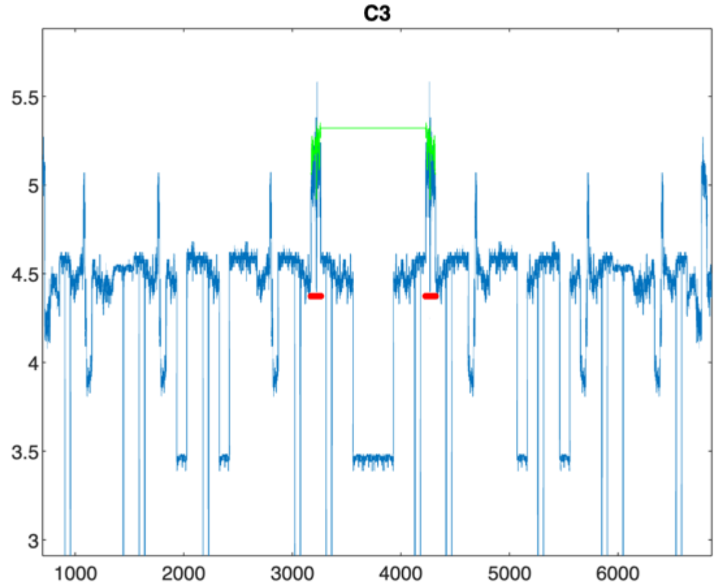

Figure 6: C3 Analysis

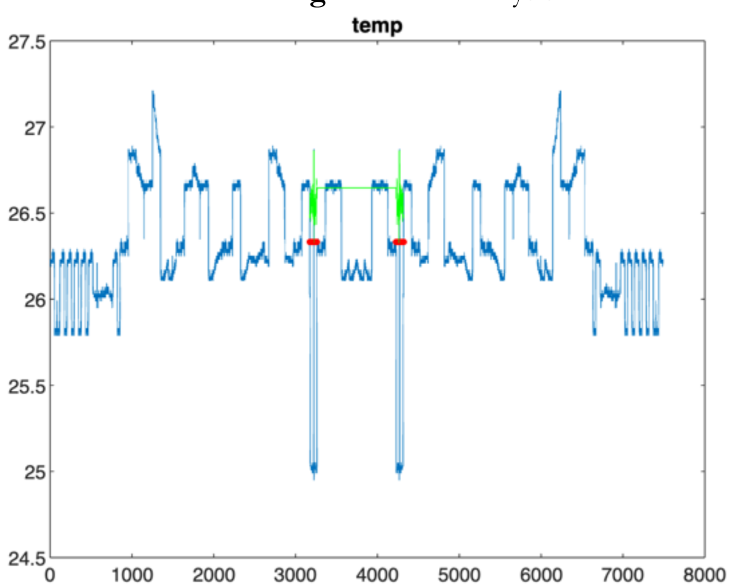

Figure 7: Temp Analysis

These graphs Figure 4, 5, 6, and 7 are extracted important features/columns that impact our overall situation. From our collected data we have closely examined their performances and in this visual representation, red points are strategically placed to highlight areas of concern or issues within the data. Meanwhile, green and blue points serve as data values, with blue representing actual values and green indicating predicted values. The distinction between actual and predicted values is crucial for assessing the performance of a machine, as the green points ideally represent what the values should be for error-free machine operation.

Discussion:

These results provide a convincing basis for the industries that have CNC lathe machines on an industrial scale to adopt AI-based predictive maintenance models. Additionally, the fact that machine learning algorithms like Logistic Regression have already shown impressive results regarding accuracy levels shows substantial potential to help improve tool life prediction and increase overall manufacturing efficiency. In order to reap the full benefits of AI-based predictive maintenance, industries should adopt these models into Industry 4.0 practices. Furthermore, the study states that a predictive maintenance model should be developed gradually and regularly updated. It is necessary to fine-tune the model regularly, to maintain its accuracy and reliability over time because it has a relationship with what changes were made as operating conditions changed tool specifications or other parameters relevant. Furthermore, the research considers establishing partnerships with CNC machine producers to make sure that AI-powered predictive maintenance is smoothly integrated into an internal part of a control system. This would enable real-time adjustments to be made so that the manufacturing environment could become more responsive and efficient by working in tandem.

Conclusion & Future Work:

Such key areas in the development of predictive maintenance are presented themselves for future work. 1st, the current model needs to be widened by incorporating data from different sensors. There will be various parameters from humidity and composition of the tool material to ambient conditions that may require clarification of this instrument's wear and improved accuracy predictions. Another significant solution is the establishment of real-time predictive maintenance mechanisms. This way of operation will enable us to take immediate action if tool performance is suspected and minimize downtime significantly thus making the maintenance strategies even more proactive. It is also necessary to investigate more advanced machine learning approaches including deep learning or ensemble methods. This includes experimentation with various algorithms to discover the best approach for particular manufacturing situations, thereby providing better accuracy and reliability of the model. Lastly, attention should be paid to the intuitive user interfaces of the predictive maintenance system. This strategic vision is about making the system easy to be available for manufacturing personnel from all levels of technical knowledge, facilitating easier implementation and full adoption within every single operating practice in a universal manner.

As onward advancements in technology occur further studies should develop and broaden these models by adding more intricate techniques along with real-time possibilities. The joint efforts between industries, the CNC machine makers could be involved in developing a more streamlined and intelligent manufacturing ecosystem, and then integrating these predictive maintenance features would happen much faster. It is evident here that commitment to research and development in this area will persist, determining the future trends in predictive maintenance for manufacturing.

Acknowledgement:

We extend our sincere appreciation to Mehran University of Engineering & Technology and its faculty for their support and for providing the necessary resources that have been instrumental in the successful competition of this research.

Author's Contribution: Manuscript preparation and conceptualization (Muhib Aleem, M Moazzam Jawaid); **Research methodology design and data analysis and visualization** (Muhib Aleem, M Moazzam Jawaid, Shahnawaz Talpur).; **Comparison, validation framework design** (Muhib Aleem, M Moazzam Jawaid, Shahnawaz Talpur, Aisha Zahid Junejo); **Proof-reading, editing and formatting** (Sheheryar Ahmed Khan, Muhammad Ahmed); All authors have read and agreed to the published version of the manuscript.

Conflict of Interest. There is no conflict of interest.

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