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INTEGRATING SENSOR DATA AND MACHINE LEARNING FOR PREDICTIVE MAINTENANCE IN INDUSTRY 4.0

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A B S T R A C T

The availability of manufacturing machinery is crucial for having a productive production line. So, for industrialists, being successful in the field of maintenance is crucial if they want to make sure that key equipment is performing as it should and that unscheduled downtime is kept to a minimum. Predictive maintenance skills are viewed as being essential with the rise of complex industrial processes. The assistance that contemporary value chains may provide for a company's maintenance role is another area of focus. The development of sensors and Industry 4.0 technologies has greatly improved access to data from equipment, processes, and products. Electric motor condition monitoring and predictive maintenance help the industry avoid significant financial losses brought on by unforeseen motor breakdowns and significantly increase system dependability. This research offers Enhanced Nave Bayes Artificial Neural Network-based machine learning architecture for Predictive Maintenance. The system was tested in an industrial setting by building a data collection and analysis system using sensors, analyzing the data with a machine learning approach, and comparing the results to those generated by a simulation tool. With the help of the Azure Cloud, the Data Analysis Tool may access information collected by a wide variety of sensors, machine PLCs, and communication protocols. Preliminary results show that the method correctly predicts a wide range of machine states.

1. INTRODUCTION

Predictive maintenance (PM), often known as "online monitoring," "risk-based maintenance," or "condition-based maintenance," has been the focus of several recent research publications and has a long history (Erbiyik 2022). It speaks of the careful monitoring of machinery to prevent future breakdowns. The original method of predictive maintenance, visual inspection, has evolved into automated systems employing cutting-edge signal processing methodologies based on recognition of patterns and neural networks, fuzzy logic, machine learning, etc. (Benardos and Vosniakos 2003). Many companies can detect and gather sensitive information from equipment, primarily motors, using automated ways, although human eyes and ears may no longer be able to do so. Predictive maintenance, when used in conjunction with integrated sensors, may decrease machine downtime, prevent needless equipment replacement, identify the source of a problem, and ultimately save money and increase

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productivity (Daily and Peterson 2017) By way of planning the protection work to prevent machine breakdowns, predictive maintenance, and preventive maintenance has certain similarities. Predictive maintenance programs, as opposed rely on data acquired by sensors and analytical algorithms, as opposed to conventional preventive maintenance. (Cheng et al., 2020) Induction motors account for over seventy percent of all electricity-powered loads in process industries. In this context, there has been a lot of interest in finding enhanced techniques to assess the health of these motors. The most prevalent reason for motor failure and the most frequent upkeep issue are both recognized as bearing failure. Predictive maintenance hence primarily emphasizes two points: increased energy efficiency and less unplanned downtime (Nacchia et al., 2021)

The data-driven strategy sometimes addressed as the data mining strategy or the ML strategy employs historical data to develop a model of machinery performance. When using a model-based methodology, it is possible to include a physical comprehension of the intended result since the analytical model is used to depict the system's behavior (Utting et al., 2012). In fields where data availability is growing, like maintenance in the industrial sector, machine learning techniques are successfully applied. It is progressively offering efficient solutions, cloud-based solutions, and fresh algorithmic developments.

The following two primary classifications may be used to categorize machine learning-based PM: Unsupervised which procedure data is provided but no protection data exists and Supervised which the data on the incidence of fault is contained in the modeling dataset (Calabrese et al., 2019). The kind of present protection supervision policy mainly determines the convenience of maintenance data. The use of supervised solutions is advised wherever possible. Regression problems and classification problems are the two groups of supervised problems that are achievable from a machine-learning standpoint, based on the results of the data set. This research presents a novel PM strategy on a cutting machine based on PM machine learning. Given the growing requirement to reduce downtime and related costs, PM is an effective technique for handling maintenance difficulties. Based on a genuine industrial group, for instance, the ENBANN has been used in an experimental setting to provide accurate estimations.

2. RELATED WORKS

The paper (Çınar et al., 2020) presented a systematic overview of the current developments of ML approaches that are extensively used in PM for smart manufacturing in I4.0 by categorizing the study according to the ML algorithms utilized. The article (Zonta et al., 2020) provided an examination of the literature on Industry 4.0 initiatives for preventative maintenance, identifying and categorizing methods, standards, and applications. A discussion of the current challenges and limitations in predictive maintenance, as well as a new taxonomy for classifying this area of research in light of Industry 4.0 needs, are among the survey's major contributions. The study (Butte et al., 2018) explored a cutting-edge PM tactic that makes use of machine learning. Several methods are explored for both posing and solving the PM issue. The effectiveness of various machine learning algorithms is assessed by analyzing equipment data. The article (Pech et al., 2021) presented a detailed review of current trends to aid in the organization and direction of future studies. At a similar moment, it provides answers to crucial questionnaires about current trends in protection procedures in smart factories. They identify which Industry 4.0 methodologies and intelligent sensors are often used in smart factories to offer maintenance.

The study (Zhang et al., 2019) aimed to give graduate students, businesses, and institutions a basic grasp of the recently published works by concentrating on data-driven approaches for predictive maintenance, providing a thorough assessment of its applications. The paper (Zenisek et al., 2019) provided a machine learning-based method for discovering errant patterns of thought, or "concept drifts," in real-time information flows. Predictive Maintenance (PM) is a proactive method of triggering service procedures for industrial machinery, and it is this issue that inspired our work. The research (Makridis et al., 2020) offered a method for anomaly identification on time-series data that makes use of machine learning on the sensor data from the vessel to enable predictive maintenance on the main engine. The research (Ayvaz and Alpay 2021) established a data-driven prognostic maintenance solution for manufacturing assembly lines was developed. The system is designed to utilize the real-time data collected by IoT sensors to detect signs of probable problems using machine learning techniques.

3. METHODOLOGY

The Predictive Maintenance is a useful maintenance device that anticipates problems by predicting the standards of certain quantities that illustrate a system using specific numerical models. The fundamental PM framework is as follows:

- Instantaneous measurement of physical quantities.
- Parameters that may be measured or estimated are estimated at time t + dt.
- Detection of the abnormal or malfunctioning state of the system.
- Preventative and corrective measures are planned for implementation before a system's critical condition is reached.

The following are some examples of predictive maintenance:

- Deterioration of bearings or mechanical part deformation can cause a machine to vibrate.
- When a motor's temperature and drown current start to rise, it might be a sign that friction and or mechanical failure are reducing its efficiency.

- The many particles in a lubricant may be used to determine how well rubbing contact components are holding up. It is feasible to test the lubricating oils composition and assess the machine's health using the right sensors.

The estimation of the parameters forms the foundation of the initial stage of these operations. The technique can produce accurate projections based on PM. It will be challenging to spot abnormalities and decide on maintenance and repair if the prediction algorithms generate inaccurate predictions or with too wide of reliability ranges. The forecasts often fall into one of two categories: Predicting trends across time and comparing different periods.

3.1. Cross-Sectional Prediction

In cross-sectional forecasting, factors for which there are no data are estimated using measurements on other variables that have been observed. By measuring the electric current that flows through an electronic component while it is used in a specific environment, for instance, it may be feasible to estimate how long it will last.

3.2. Predictions Based on Time Series

Predicting time series is the process of estimating variables that vary eventually. The parameters are measured up to time instantaneous t, and the forecasted variable is at time immediate t + dt. It is characteristically feasible to anticipate future values by taking regular intervals of measuring the variable of interest. The most straightforward illustration is the estimation of our cell phones' remaining battery life, which is based on our usage patterns and past consumption. It is common practice to identify: Trends or a long-term increase (or decrease) in values.

- The seasonal phenomena or the phenomena that determine value changes through time with a constant cycle of the same length.
- Cyclical phenomena create variations in values that don't always last for the same amount of time, or that aren't periodic.

The nature of the relationship between the measured numbers is one of the most crucial concepts to comprehend while interpreting data. This may be accomplished by using graphic visualization with dispersed plots to show how the data are interdependent. The idea behind linear regression is that the behavior of the evaluating phenomenon is linear. Analyzing the residuals is an easy technique to determine whether the signal we wish to anticipate is linear or includes data not included in our prediction model.

3.3. Investigation of the residuals

The residuals represent the discrepancy among the size's observed variables and those derived by fitting the prediction line.

$$f_j = x_j - x'_j \tag{1}$$

Here f_j is the measurement's residual, x_j is the value that was measured, and $z'_j = n's_j + r'$ 0 is the variable that was calculated at times_j. The least square approach is used to determine the coefficients m and q. Autocorrelation is a useful tool for determining either the generated regression model meets the signal to be forecasted. By counting the number of residuals whose values fall inside the interval, it is possible to compute the autocorrelation of the residues obtained above:

$$Int = \pm \frac{2}{\sqrt{M}} \tag{2}$$

Where M is the total value of capacity. Typically, it is assumed that if >95% of the residuals are contained within the $\pm Int$, then the noise may be classified as white noise since there is no correlation between the residuals. This method enables the development of algorithms for signal prediction using linear regression, is helpful for predictive maintenance, and automatically checks any alterations of the system being observed in real-time. The test of residuals may also be used to determine whether linear regression is the better option for the desired prediction model.

3.3. Predictive maintenance using machine learning

A plan outlining the steps and technical tasks needed to deploy PM is shown in Figure 2. The data gathered by the I4.0 and MES machine layers may be used to execute the Machine Learning phase of the PM (Figure 2). Three crucial data sources must be located to determine if an issue is suitable for a predictive maintenance solution.

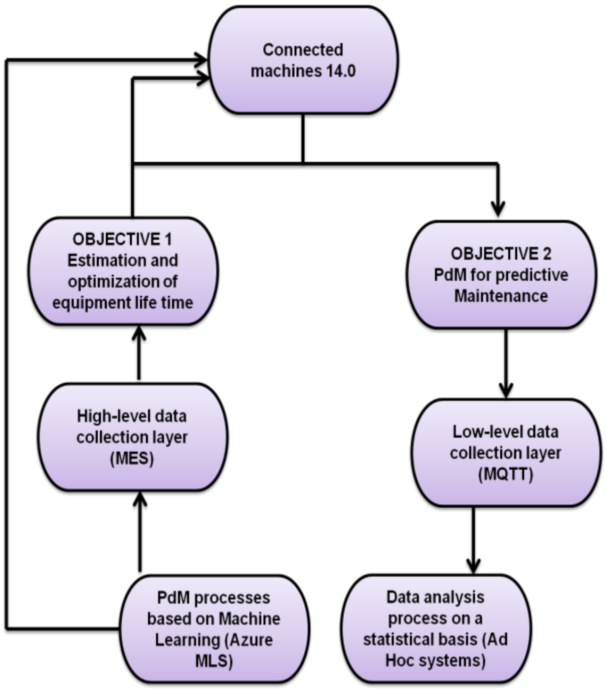

Figure 1. Flowchart of predictive maintenance

3.4. Problem history

In predictive maintenance systems, error occurrences are often quite infrequent. However, the algorithm must be trained to learn both the standard functioning system and the fault system to build predictive models that forecast failures. Therefore, the training data must have adequate several instances in each category.

3.4. Repair and maintenance history

The thorough asset of maintenance history, which includes data on replacement components, completed preventive maintenance chores, etc., is a crucial data source for solutions including predictive maintenance.

3.5. Repair and maintenance history

It is assumed that a machine's health condition deteriorates with time to calculate how many days (or hours, kilometers, etc.) it will endure before breaking down. Therefore, the data must include time-varying functions that develop aging patterns or other abnormalities that could lead to a decline in performance.

- It is important to carry out certain pre-processing processes to get the information into the format needed to make the functions that will be contained in the ml techniques.
- The first is to split the time required for data gathering into discrete units, with every record history representing a discrete unit of time for a given asset. The general data model may be:
- Maintenance history: This is the documentation of the upkeep tasks completed. Untreated protection data is often linked to an asset ID and a timestamp that contains details on the maintenance tasks completed at that moment. Maintenance actions need to be converted from unprocessed data each representing a particular kind of maintenance work, into category columns for time, maintenance, and asset IDs actions that will be included in the basic data structure for maintenance records.
- Failure Records: These are records that pertain to the evaluation aim, eg., failure or faults. They might be particular error messages or errors that are caused by particular operational circumstances. In other instances, the data contains many error codes, some of which are associated with important defects. Others are often used to develop functions that can be associated with failures because not all faults are the target of an estimate. The columns for time fault and asset ID, or cause for fault if a pattern is provided, will be included in the base data format for failure records.
- Machine specifications: Preferably real-time monitoring information on the data's operational circumstances.
- Machine and operator information: the assets controlled by a certain operator, as well as the attributes of the assets and the operator, may be identified by combining this data in a plan.

Table 1. Feature data set.

Features	Significance
X Current	X-axis absorption of current.
Y Current	Y-axis absorption of current.
Z Current	Z-axis absorption of current.
Spindle Velocity	Rate of spindle rotation
Spindle power	The spindle's sucked-up energy
Spindle position	Angle of the spindle
X Speed	Axis X Velocity
Y Speed	Axis Y Velocity
Z Speed	Axis Z Velocity
StatoRot	Spindle rotor functionality (c).
Timestamp	Data Collected
Machine	Mechanics in Action
Location Variation X	Ratio of actual to nominal X-axis position
Location Variation Y	Ratio of actual to nominal Y-axis position
Location Variation Z	Ratio of actual to nominal Z-axis position

A list of data is presented in Table I together with the statoRot status value, which serves as the variable for machine condition in the outcome section. Designing the functions is the initial stage in modeling. Conceptually speaking, the concept of generating functions entails leveraging past data amassed up to that point to describe and abstract the integrity status of a machine at a specific moment. However, the approaches for designing the functions that are given here can be utilized as a starting point for developing functions. The creation of delay (lag) functions from data sources, such as timestamps, as well as standing operations from static sources of data, with instances from the illustrative use cases, is required in the following. The chronological data used for preventative maintenance often include timestamps that show when each data point was collected. A window with the size "W" that corresponds to the several time units for which we wish to evaluate the chronological aggregations is chosen for each asset record. The W periods before the record's creation date are then used to construct the aggregate sequencing functions. Examples of sequential aggregations include peaks, trend changes, and level changes using methods that identify anomalies, mean, and outliers based on normal deviations, increasing total observations, maximum and minimum window values, etc.

3.5. Enhanced naïve bayes artificial neural network (ENBANN)

The Enhanced Naive Bayesian method was developed based on Bayesian decision theory. The variables of the dependent and prior probabilities are calculated based on historical data. The Bayesian formula is then used to calculate the posterior probability distribution, and the likelihood that an event belongs to a certain category may be detected by comparing the possibilities. The basic framework is

$$O(Y) = O(D)\frac{O(C)}{O(Y)}, \tag{3}$$

Where O is the probability. We assume that there are m judgment categories $D = \{D_1, D_2, \ldots D_n\}$ and n characteristic features $Y = \{Y_1, Y_2, \ldots, Y_m\}$ in each fire dataset. By assuming that $O(Y)$ is constant over all possible categories, we may arrive at the naive Bayesian classification model.

$$D_{MA}(W) = argmaxo(D_j) \prod_{l=1}^{m} \quad o(D_j) \tag{4}$$

Here $o(D_j)$ is the expected value of the choice categories and (D_j) is the possibility that W_l has the value x if Ci is the decision category. For every given dataset, Y, the prior probability of assigning it to one of the classes $\Upsilon = \{z_1, z_2, \ldots z_m\}$ is obtained from the data itself. The conditional possibility of every feature is compounded under every option categoryD_j. Multiplying the prior possibility $o(\Upsilon)$by the conditional possibility $o(\Upsilon)$yields the posterior probability$o(\Upsilon)$. The highest posterior probability is chosen as the class the item belongs to $o(\Upsilon)_{max}$.

The ENBANN is a collection of neurons with unidirectional links between them that may mimic the brainpower capacity for pattern recognition and association learning in data. Each neuron j has an activated function θ_i associated with it, and each connection among neurons j,i has a weight u_{ji} given to it that regulates how much impact neuron j has on neuron$i$. The weighted connections between the neurons, which stand in for the fundamental processing units of an ENBANN, enable the modeling of complicated interactions. Normally, the neurons are arranged in layers, and each layer's neurons are connected directly to the layers above it (Figure 2). The levels in between are referred to as "hidden layers," while the initial layer is well-known as the "input layer" and the final one as the "output layer." The initial hide layer receives the input information from the input layer, where it aggregates and transforms them as follows:

$$net_i = \sum_{j \in O_i} \quad u_{ji} P_j \tag{5}$$

Where O_i is the collection of neurons that had linked to neuron i, P_j is the output of neuron I, and wij is the weight of the link connecting neuron j and i. The following formula is used to determine a neuron's output.

$$P_j = \phi\,(net_j) \tag{6}$$

Where ϕ represents neuron j is an activated function. The hyperbolic tangent function, with the formula$e(y) = \frac{f^y - f^{-y}}{f^y + f^{-y}}$, is a typical activation function. This function is very helpful since it may be both continual and distinct, which are requirements for determining the network error gradient. The neurons in the subsequent layer get each neuron's output after that. This process is continued for each additional layer until the network's output layer is reached. The output layer's output corresponds to the network's overall output.

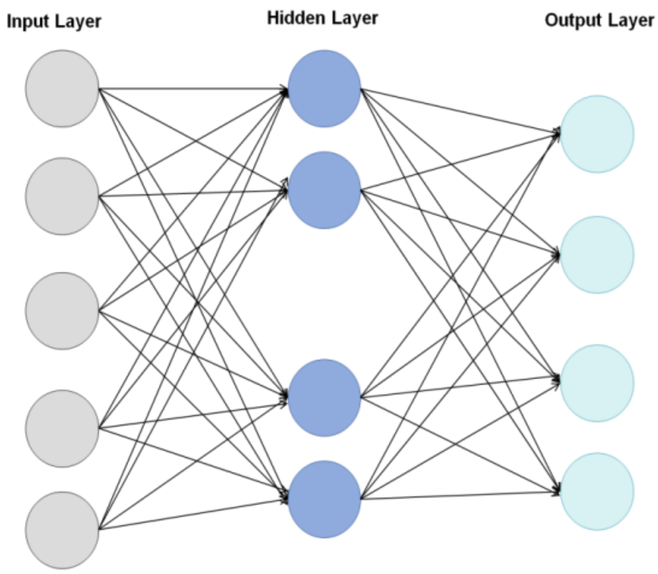

Figure 2. Three layers of ANN

An ENBANN connection weights must be changed to simulate non-linear relations. The usual method for doing this entails two steps. Back propagation is used to determine each neuron's error signal for a specific observation in the initial step. The error function determines the error signal. Regression's error function is written as $F = \frac{1}{2}\sum_{j=1}^{m} \quad (s_i - P_j)^2$, where m is the overall number of goal values, P_j is the output neuron j and s_i is the goal value. The error function leads to the calculation of the error signal as follows:

$$\delta_i = \{\phi'(net_i)(P_i - s_i) \quad if\ is\ an\ output\ neuron\ \ \phi'(net_i)\sum_l \quad \delta_l u_{il} \quad otherwise \tag{7}$$

Here P_i is the neuron i output, s_i is the neuron j's target value, u_{il} is the weight of the link among neurons j and k, k is the neuron error signal, net_i is the input from the network system to neuron j, and ϕ' is the derived activated function

$$\Delta u_{ji} = -\eta \frac{\partial F}{\partial u_{ji}} = -\eta \delta_i P_j \quad (8)$$

The linked weights are modified by use of Training Algorithm in the second phase. Where u_{il} is the weight of the connection among neuron j and neuron i, E stands for error function, P_j for neuron j output, and i for neuron i error signal. Continue all steps till a termination requirement is satisfied. To enhance the network's training, several gradient expansions and modifications have been suggested. To increase the training's resistance to noise, the error gradients are often added across a "mini-batch" of data. The cumulative modifications are then used to modify the connection weights. Also, utilizing an accelerated gradient while modifying the connection weights may significantly enhance training results.

$$\delta_i = \{\phi'(net_i)(P_i - s_i) \quad if\ is\ an\ output\ neuron\ \ \phi'(net_i)\sum_l \quad \delta_l u_{il} \quad otherwise \quad (9)$$

Where P_i is the neuron i output, s_i is the neuron j's target value, u_{il} is the weight of the link between neurons j and k, k is the neuron error signal, net_i is the input from the network system to neuron j, and ϕ' is the derived activated function

$$\Delta u_{ji} = -\eta \frac{\partial F}{\partial u_{ji}} = -\eta \delta_i P_j \quad (10)$$

The linked weights are modified by use of training algorithm in the second phase. Where u_{il} is the weight of the link between neuron j and neuron i, E stands for error function, P_j for neuron j output, and i for neuron i error signal. Continue all steps till a termination requirement is satisfied. To enhance the network's training, some gradient expansions and modifications have been suggested. To increase the training's resistance to noise, the error gradients are often added across a "mini-batch" of data. The cumulative modifications are then used to modify the connection weights. Also, utilizing an accelerated gradient while modifying the connection weights may significantly enhance training results.

4. RESULT AND DISCUSSION

The aforementioned techniques for predictive maintenance have been applied to actual cutting-edge woodworking technology that is a machining center for the firewood industry. The primary goals of the suggested test are to assess the suggested method for machine learning PM of the machine using analysis of Fingerprints, which includes vibration data analysis to gauge spindle health status and drive data analysis for axis monitoring. A data set of 530731 data reading on 15 distinct machine features were adjusted for the suggested feature set, which is presented in Table I, and the data was acquired from the tried and true cutter in real-time. The method of gathering data takes into account several data sources, and the following general architecture was created:

- **Flight Recorder:** The MCM machine tool is equipped with an industrial PC. It's having conversations with different parts of the system to get the information it needs for the study.
- **IT Accelerometer***:* A vibration data-collecting accelerometer with an interface for simple data export, the Information Technological Accelerometer may be attached to the spindle head of MCM machines.

As for the introduction of the top-level architecture:

- The computer hosting the analysis of data software that can be used is known as the data analysis unit.
- Simulation Unit is a Machine Learning Studio-based Azure Cloud architecture that houses the ML software.

The three distinct data sources for the Flight Recorder system are listed below.

Drive data: Through a D.Electron-developed communication protocol, they are sampled in real-time by the CNC and prepared accessible to the Flight Recorder. The CNC at the moment of sampling associates this data with a time reference (timestamp).

Input/output signal: Similar to drive data, they are collected in actual time by the machine PLC and made available to the Flight Recorder.

Vibration data: To effectively monitor the spindle unit, vibration analysis in the frequency domain is carried out. The Flight Recorder needs a specialized sensor/electronic system that, after each fingerprinting or operational incident, provide both raw data about the trend in the vibration spectrum and an assessment of how much the detected spectrum deviates from the typical spectrum contain under ideal functioning conditions.

The suggested architecture was used to analyze all the data obtained, with 40% of the data set serving as a training set and the remaining 60% being used to assess the findings. Using various metrics, including accuracy, precision, and recall, we compared some of the current approaches, such as CNN, RNN, and A2LSTM, with our novel approach, ENBANN.

Predictive maintenance accuracy refers to a model's or system's capacity to correctly forecast the occurrence of equipment faults or maintenance requirements. The comparison of accuracy between the current and our suggested methods is shown in Figure 3 and Table 2. And it depicts that our proposed method is higher than other existing methods.

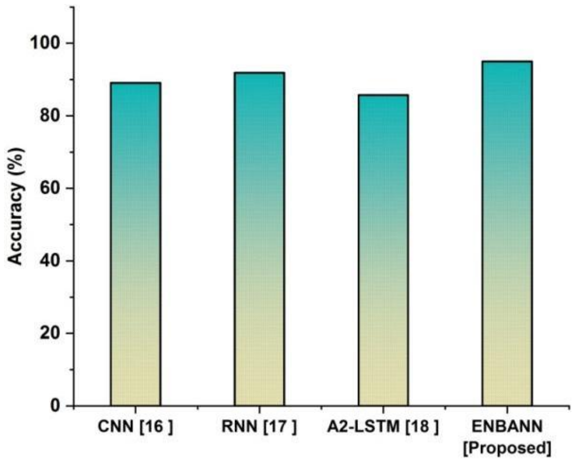

Figure 3. The comparison of accuracy between the current and our suggested methods

Table 2. Comparison of accuracy.

Methods	Accuracy (%)
CNN (Silva and Capretz 2019)	89.08
RNN (Rivas et al., 2020)	91.91
A2-LSTM (Jiang et al., 2022)	85.75
ENBANN [Proposed]	95

The capacity of a predictive maintenance model or system to precisely identify true positive situations, or in other words, to properly forecast equipment failures or maintenance requirements, is referred to as precision in predictive maintenance. The percentage of optimistic forecasts that come true positively is measured by this performance statistic. The comparison of precision between the current and our suggested methods is shown in Figure 4 and Table 3. And it depicts that our proposed method is higher than other existing methods.

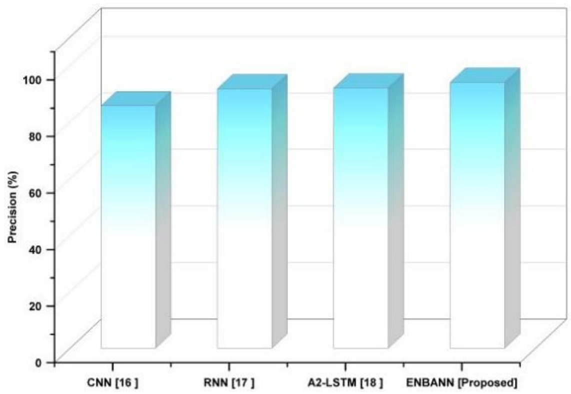

Figure 4. The comparison of precision between the current and our suggested methods

Table 3. Comparison of precision.

Methods	Precision (%)
CNN (Silva and Capretz 2019)	85.71
RNN (Rivas et al., 2020)	91.75
A2-LSTM (Jiang et al., 2022)	92.02
ENBANN [Proposed]	94

Recall, often referred to as sensitivity or the real positive rate is a performance indicator used in predictive maintenance that assesses a model's accuracy in identifying all positive instances, particularly the percentage of actual equipment failures or maintenance requirements that are accurately anticipated. The comparison of recall between the current and our suggested methods is shown in Figure 5 and Table 4. And it depicts that our proposed method is higher than other existing methods.

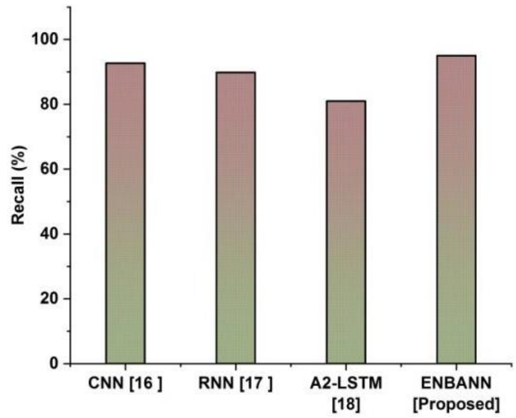

Figure 5. The comparison of recall between the current and our suggested methods

Table 4. Comparison of recall.

Methods	Recall (%)
CNN (Silva and Capretz 2019)	92.71
RNN (Rivas et al., 2020)	89.85
A2-LSTM (Jiang et al., 2022)	81.01
ENBANN [Proposed]	95

5. CONCLUSION

This research presents a novel ENBANN strategy on a cutting machine based on PM machine learning. Given the growing necessity to reduce downtime and related costs, PM is an effective technique for handling maintenance difficulties. The approach has been used in an experimental setting using a real-world industrial group as an example, yielding precise estimates. Data analysis tool offers access to data that has been collected by a variety of sensors, machine PLCs, and protocols for communication. By training an ENBANN technique on Azure Machine Learning Studio, the PM methodology enables the adoption of dynamic decision rules for maintenance management. The first results show that the approach works as intended by accurately predicting different states of the machine with a high accuracy of 95% using a dataset of 530731 data readings on fifteen dissimilar machine variables obtained in actual duration from the tested cutting machine. The main spindle rotor state prediction accuracy achieved by the papers is high, and the basic cloud architecture for Industry 4.0 is shown. Additionally, ML approaches are used to a factual data set from machines in the field. Future studies will concentrate on improving data reliability, exploring other failure situations, and studying an expanded range of features, especially in the frequency domain.

References:

Ayvaz, S., & Alpay, K. (2021). Predictive maintenance system for production lines in manufacturing: A machine learning approach using IoT data in real-time. Expert Systems with Applications, 173, 114598. https://doi.org/10.1016/j.eswa.2021.114598

Benardos, P. G., & Vosniakos, G. C. (2003). Predicting surface roughness in machining: a review. *International journal of machine tools and manufacture*, *43*(8), 833-844. https://doi.org/10.1016/S0890-6955(03)00059-2

Butte, S., Prashanth, A. R., & Patil, S. (2018, April). Machine learning based predictive maintenance strategy: a super learning approach with deep neural networks. In 2018 IEEE Workshop on Microelectronics and Electron Devices (WMED) (pp. 1-5). IEEE. https://doi.org/10.1109/WMED.2018.8360836

Calabrese, M., Cimmino, M., Manfrin, M., Fiume, F., Kapetis, D., Mengoni, M., ... & Toscano, G. (2019, August). An event-based machine learning framework for predictive maintenance in Industry 4.0. In International Design Engineering Technical Conferences and Computers and Information in Engineering Conference (Vol. 59292, p. V009T12A037). American Society of Mechanical Engineers. https://doi.org/10.1115/DETC2019-97917

Cheng, J. C., Chen, W., Chen, K., & Wang, Q. (2020). Data-driven predictive maintenance planning framework for MEP components based on BIM and IoT using machine learning algorithms. *Automation in Construction*, *112*, 103087. https://doi.org/10.1016/j.autcon.2020.103087

Çınar, Z.M., Abdussalam Nuhu, A., Zeeshan, Q., Korhan, O., Asmael, M. and Safaei, B., 2020. Machine learning in predictive maintenance towards sustainable smart manufacturing in industry 4.0. Sustainability, 12(19), p.8211. https://doi.org/10.3390/su12198211

Daily, J., & Peterson, J. (2017). Predictive maintenance: How big data analysis can improve maintenance. Supply Chain Integration Challenges in Commercial Aerospace: A Comprehensive Perspective on the Aviation Value Chain, 267-278. 10.1007/978-3-319-46155-7_18

Erbiyik, H. (2022). Definition of Maintenance and Maintenance Types with Due Care on Preventive Maintenance. 10.5772/intechopen.106346

Jiang, Y., Dai, P., Fang, P., Zhong, R. Y., Zhao, X., & Cao, X. (2022). A2-LSTM for predictive maintenance of industrial equipment based on machine learning. Computers & Industrial Engineering, 172, 108560. https://doi.org/10.1109/SNPD.2019.8935752. https://doi.org/10.1109/SNPD.2019.8935752

Makridis, G., Kyriazis, D., & Plitsos, S. (2020, September). Predictive maintenance leveraging machine learning for time-series forecasting in the maritime industry. In 2020 IEEE 23rd International Conference on Intelligent Transportation Systems (ITSC) (pp. 1-8). IEEE. https://doi.org/10.1109/ITSC45102.2020.9294450

Nacchia, M., Fruggiero, F., Lambiase, A., & Bruton, K. (2021). A systematic mapping of the advancing use of machine learning techniques for predictive maintenance in the manufacturing sector. *Applied Sciences*, *11*(6), 2546. https://doi.org/10.3390/app11062546

Pech, M., Vrchota, J., & Bednář, J. (2021). Predictive maintenance and intelligent sensors in smart factories. Sensors, 21(4), 1470. https://doi.org/10.3390/s21041470

Rivas, A., Fraile, J. M., Chamoso, P., González-Briones, A., Sittón, I., & Corchado, J. M. (2020). A predictive maintenance model using recurrent neural networks. In 14th International Conference on Soft Computing Models in Industrial and Environmental Applications (SOCO 2019) Seville, Spain, May 13–15, 2019, Proceedings 14 (pp. 261-270). Springer International Publishing. 10.1007/978-3-030-20055-8_25

Silva, W., & Capretz, M. (2019, July). Assets predictive maintenance using convolutional neural networks. In 2019 20th IEEE/ACIS International conference on software engineering, artificial intelligence, networking and parallel/distributed computing (SNPD) (pp. 59-66). IEEE. https://doi.org/10.1109/SNPD.2019.8935752

Utting, M., Pretschner, A., & Legeard, B. (2012). A taxonomy of model- based testing approaches. *Software testing, verification and reliability*, *22*(5), 297-312. https://doi.org/10.1002/stvr.456

Zenisek, J., Holzinger, F., & Affenzeller, M. (2019). Machine learning-based concept drift detection for predictive maintenance. Computers & Industrial Engineering, 137, 106031. https://doi.org/10.1016/j.cie.2019.106031

Zhang, W., Yang, D. and Wang, H., 2019. Data-driven methods for predictive maintenance of industrial equipment: A survey. IEEE Systems Journal, 13(3), pp.2213-2227. https://doi.org/10.1109/JSYST.2019.2905565

Zonta, T., Da Costa, C. A., da Rosa Righi, R., de Lima, M. J., da Trindade, E. S., & Li, G. P. (2020). Predictive maintenance in Industry 4.0: A systematic literature review. Computers & Industrial Engineering, 150, 106889. https://doi.org/10.1016/j.cie.2020.106889

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