

Improved regressive maintenance in smart Industry 4.0 using embedded systems with machine learning techniques

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ABSTRACT

Despite extensive research in this field, fourth generation of industrial revolution or the "Industry 4.0," remains rarely used. This technology enables sectors to make intelligent on taking decision, knowledge, problem-rectifying, self-diagnosis, configuration, and automation feasible. This research study proposes to transform the food sector into a smart Industry 4.0 by utilizing sensor and machine learning (ML) methods. The motive of this article is to use a variety of sensor data, such as motor temperature, oven temperature, gear pump temperature, vibration, current consumption, and motor speed, to forecast the likelihood of machine failure in the food processing business. We create models using artificial neural networks (ANN) and linear regression with the data collected from these sensors to estimate the likelihood of failure. The findings demonstrate that both of the generated models have excellent accuracy in forecasting the chance of failure. The technology could help the food sector transition to sector 4.0, where networked equipment exchanges data to maximize production efficiency. In summary, the present study showcases the potential of sensor-based analysis maintenance methods in the food sector and emphasizes the need to incorporate Industry 4.0 principles to enhance the effectiveness of food processing facilities.

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1. INTRODUCTION

The food industry is integral to global sustenance, continually evolving with advancements like Industry 4.0. This transformation integrates advanced technologies such as sensor systems and machine learning (ML), crucial for optimizing food production processes [1]. This literature review explores the application of these technologies, focusing on predictive maintenance and intelligent control systems in various industries. ML algorithms play a pivotal role in predicting maintenance needs in industrial methods. Studies have evaluated techniques like linear regression, artificial neural networks (ANN), and decision trees to forecast the remaining useful life of machines based on historical data and sensor readings [2]. These approaches aim to enhance efficiency, reduce downtime, and improve productivity by optimizing maintenance schedules. Decision support systems using ML have emerged to manage predictive maintenance

effectively across industries [3]. These systems optimize maintenance strategies, minimize downtime, and enhance equipment performance, demonstrating their applicability and efficacy in industrial contexts. Research efforts have combined wavelet analysis with ML to predict SF6 filling pressure in high-voltage circuit breakers [4]. Such predictive models are critical for ensuring reliable functioning and preventing failures in high-voltage systems. Similarly, a two-phase ML approach has been proposed for analysing maintenance of minimum-voltage industrial motors [5]. This method employs feature extraction and classification algorithms to accurately predict maintenance needs and optimizes motor performance in industrial environments. The integration of ML frameworks has furthered the development of robust models for predicting the rest useful life of industrial machines [6]-[10]. These frameworks provide insights into a developing maintenance strategies in optimize level and efficiency of enhanced operation in smart factory settings [11]-[15].

In recent research of Industry 4.0, these new technologies enable the transition from traditional production to smart, sensor-equipped facilities. Data analytics and decision support systems facilitate proactive maintenance planning and rapid failure recovery, crucial for maintaining operational continuity in smart factories. The proposed research aims to state gaps pointed in existing literature. While previous work have focused on individual ML techniques for predictive maintenance, there remains a need for integrated approaches that leverage diverse sensor data and advanced analytics to enhance efficiency and feasible in industrial operations. This study needs to fill this gap interval by developing an integrated predictive maintenance and intelligent control system tailored specifically for smart Industry 4.0 environments [16]-[19]. The decision support system gave rise to Industry 4.0's design support system, which uses ML algorithms to provide design help by suggesting, among other things, new product versions based on a product's attributes. PdM is another application that makes extensive use of data. With cyber-physical systems (CPSs) offering self-awareness and self-maintenance intelligence, this strategy enables the industry to forecast the deterioration of product performance and to independently manage and optimise product service requirements [20]-[22]. The smart sensors and Industry 4.0 technologies commonly utilized for maintenance in modern factories. It also facilitates the identification of novel patterns in intelligent and insightful predictive maintenance [23]-[25]. The proposed system uses different sensors to observe the real-time performance of industrial machines and then uses ML algorithms to analyse the sensor data and suggest the potential faults in the machines.

2. MATERIALS AND METHOD

This research is conducted in the food industry at Madura wafer house in Coimbatore, where the production of wafer is highly dependent on the efficient operation of the wafer stick machine. The wafer stick machine, depicted in Figure 1, is a complex system that comprises three subsystems: dough and paste injection, baking, and rolling. The dough and paste subsystem consist of a gear pump that charges the dough and paste into the system, which is a dangerous step for the quality and dimension of the wafer. The baking area is responsible for maintaining an optimum temperature on the moulded paste to ensure proper baking. The rolling system utilizes a gearbox with an electric motor to roll the stick based on the thickness of the wafer. Therefore, the proper operation of each subsystem is crucial for producing high-quality wafers. If any one of the subsystems operates with less efficiency, the wafer cannot be produced correctly. To ensure optimal operation of the wafer stick machine, each subsystem should be operated under specific conditions. The gear pump in the dough and paste subsystem should be operated at a speed of 900 to 1200 RPM. The oven should maintain a temperature of 180 °C for 2 minutes, and the rolling system motor should be operated at 1400 to 1500 RPM with a fixed width of the wafer. The Madura wafer house in Coimbatore operates a critical wafer stick machine pivotal for the production of high-quality wafers. This machine, depicted in Figure 1, comprises three essential subsystems: dough and paste injection, baking, and rolling. The dough and paste subsystem involve a gear pump crucial for maintaining the quality and dimensions of the wafer. In our research, we focus on addressing the challenge of noisy data in predictive maintenance systems for the wafer stick machine. During preprocessing, data sanitizing, outlier identification, and normalization are implemented to confirm the model receives clean and consistent input data, thereby reducing noise effects.

2.1. Sensors

In this research, a comprehensive approach is taken to continuously monitor the wafer stick machine using various sensors to ensure optimal performance. Figure 1 illustrates the placement of these sensors throughout the machine. The selected sensors by adding temperature sensors, speed sensors, vibration sensors, and current sensors. To capture temperature data, three temperature sensors are strategically placed. One sensor is positioned at the gearbox to monitor the temperature in that area, while the remaining sensors are placed at the oven and the electric motor in the rolling subsystem. These temperature sensors provide

crucial insights into the thermal conditions within the machine. Vibration sensors are installed on each actuator of the machine. These sensors detect and measure the levels of vibration, enabling the identification of any abnormal vibrations that could indicate underlying issues such as misalignment, imbalances, or bearing faults. The speed sensor is employed to measure the rotation speed of the gearbox and the electric motor. By continuously monitoring the rotational speed, any deviations from the expected values can be detected, indicating potential problems with the rotational components of the machine. Current sensors are utilized to measure the current input taken by each actuator. Monitoring the current consumption helps in assessing the power usage and can offer insights into the performance and efficiency of the machine. The output from each sensor is communicated to a microcontroller, which serves as the CPU. The microcontroller receives and analyses the sensor data to utilise the performance of the machine. In this article, a Raspberry Pi is employed as an intersection communication medium between the user and the microcontroller. It provides the seamless transfer of data and commands between the system and the microcontroller. Figure 2 shows the sensor readings obtained from the wafer stick machine for a day after the installation of the predictive maintenance system. In this fitting, where the method learns to memorise the training data rather than generalise well to unseen data, is a common challenge in ML.

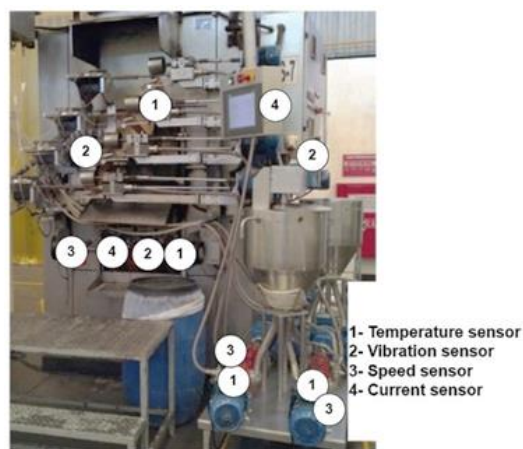


Figure 1. Wafer stick machine with various sensor locations

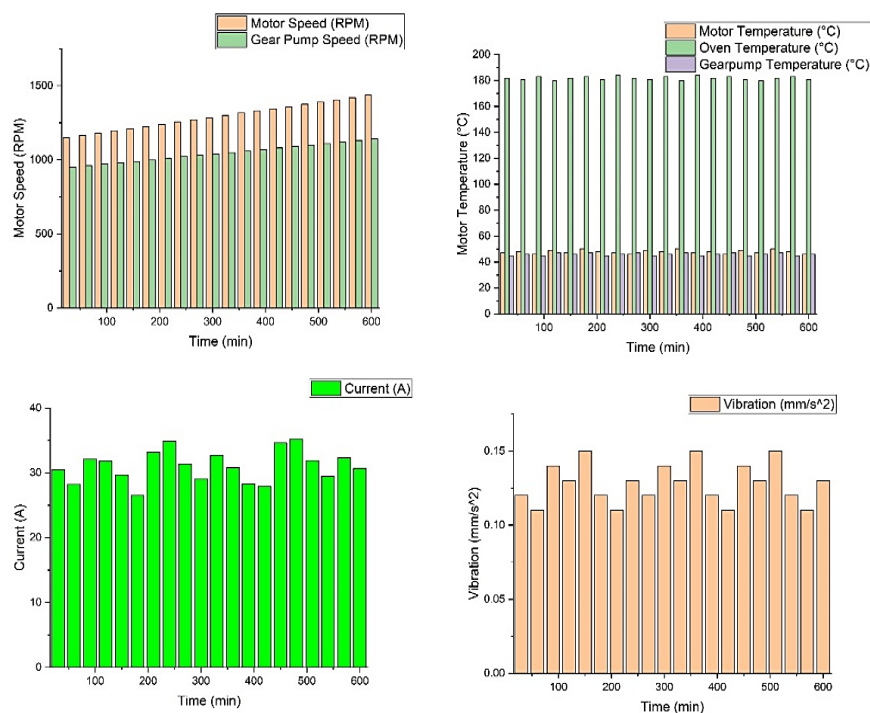


Figure 2. Sensor readings at a half an hour interval basis for a one complete day

2.2. Probability of failure equations for predictive maintenance

In this research, the probability of failure is determined using the exponential distribution equation, which is based on historical data. After the installation of various sensors in the wafer stick machine, the readings are continuously monitored for a month. Specifically, attention is given to the readings when any of the critical components, such as the oven temperature, gear pump speed, current consumption, motor speed at the rolling subsystem, or excessive vibration, indicate improper operation. By proactively addressing potential issues flagged by sensor data, the research contributes to minimizing downtime, increasing product quality, and upgrading maintenance schedules in the food manufacturing industry.

To calculate the probability of failure, the exponential distribution equation is utilized. This equation is derived from the exponential probability density function and represents the time between failures. The equation is as follow:

$$P(t) = 1 - e^{-\lambda t}$$

In this equation, $P(t)$ represents the probability of failure occurring within a given time period t ; λ (lambda) is the failure rate parameter, which reflects the rate at which failures occur; and e is the mathematical constant approximately equal to 2.71828.

2.3. Machine learning approach for prediction of maintenance

In this work, ML algorithms, including linear regression and ANN, were employed to analyse the given sensor readings and identify the probability of failure. Historical data was utilized to construct a dataset for training and testing the algorithms. It was observed that whenever the system deviated from the pre-set optimum values, either higher or lower, the probability of failure rate increased. By capturing these patterns, the ML models were able to identify critical operating conditions that could lead to higher failure probabilities. This insight enables proactive maintenance interventions to mitigate numerical failures and to enrich the definitive and execution of the wafer stick machine. Figure 3 says the flow illustration of the proposed method which illustrate the use of sensor based internet of things (IoT) system and ML approach for automating the machinery.

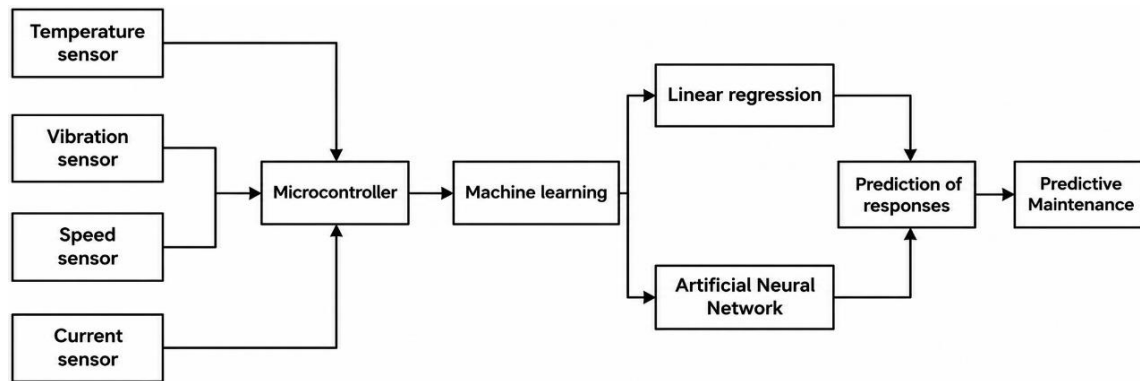


Figure 3. Working of the proposed system

2.4. Artificial intelligence using linear regression

In this research, a linear relapse ML approach was employed to analyse the probability of failure in the wafer stick machine based on sensor readings. Linear relapse is a supervised learning algorithm that gives the contact with a dependent variable (in this case, the probability of failure) and one or more free variables (sensor readings).

The first step in implementing linear regression is to develop an equation that represents the contact with the input variables (sensor readings) and the output variable (probability of failure).

Probability of failure = $\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n$ are the coefficients corresponding to each independent variable (sensor reading). Here, β_0 is the y-interdict, $\beta_1, \beta_2, \dots, \beta_n$. To obtain the volumes (β values), the linear regression algorithm analyses the training dataset, which contains of historical sensor readings and their matching probability of failure.

3. RESULTS AND DISCUSSION

In this research, a linear regression model is created in MATLAB to confine the probability of failure based on the sensor data sets. The steps involved in developing the linear regression model are as follows. First, the historical data is collected, which includes the sensor readings and the corresponding probability of failure. Finally, the trained linear regression model is evaluated by metrics such as mean squared error or -squared (R^2) to assess its performance. The model helps to find the probability of failure for new sensor readings, providing valuable insights for maintenance and decision-making in the wafer stick machine industry. The developed regression equation for finding the probability of failure ($P(t)$) is shown in (1).

$$P(t) = 2.427 - 0.00244 * Mt - 0.01002 * Ot - 0.00538 * Gt - 0.965 * V - 0.00218 * C + 0.000061 * Ms \quad (1)$$

In the equation mentioned, the variables represent different sensor readings and measurements. The variable "Mt" represents the temperature of the motor in °C; "Ot" represents the temperature of the oven in °C, and "Gt" represents the temperature of the gear pump in °C. The variable "V" represents the vibration level in millimeters per second squared, while "C" represents the current in Amperes. In Figure 4, the usual distribution point in the predicted $p(t)$ is depicted, showcasing the performance accuracy is forecasting in the machine's response. The plot demonstrates that the identified values are closely monitored with the expected distribution, shows the effectiveness of the proposed model.

The R^2 value of 98.2% further substantiates the accuracy of the model. The R^2 value measures the proportionality of the variance can be elaborated by the predictor variables. High R^2 value signifies the proposed model captures a important part of the variability in the probability of failure based on the sensor readings. The obtained R^2 value of 98.2% demonstrates the developed linear relapse model is highly successive in predicting the probability of failure using the sensor readings as input. The high R^2 value implies that the majority of the variations in the probability of failure can be elaborated by the selected sensor variables. Figure 5 presents a comparison is presented between the actual and forecast values obtained from the linear model over a period of 600 minutes.

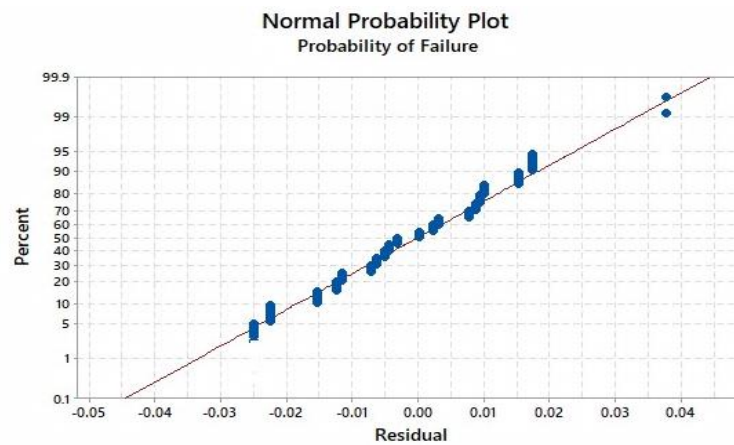


Figure 4. Normal probability plot for predicting the responses

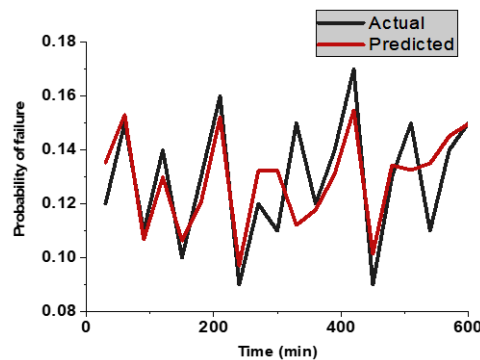


Figure 5. Comparison of actual and predicted value from linear regression

Here, an ANN model is utilized to forecast the responses in the wafer stick machine. Figure 6 depicts the architecture of the popular ANN model specifically designed for this work. The number of neurons and layers (hidden) in each layer is determined based on experimentation and optimization.

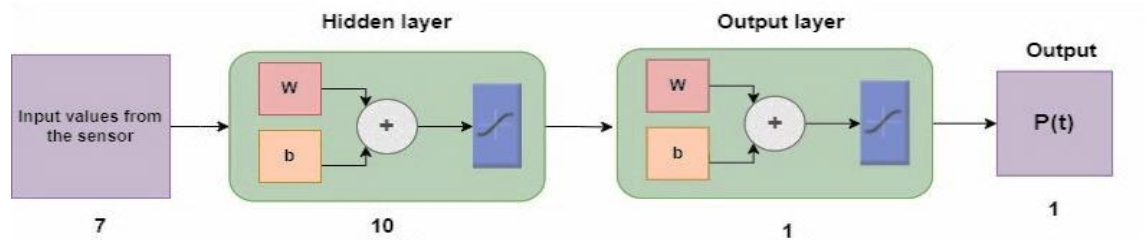


Figure 6. Developed ANN model

In this particular ANN model, 10 neurons are employed in the hidden layer. The choice of neurons in the layer (hidden) is based on the difficulty of the problem, the size of the dataset, and the prescribed level of fidelity. The next process involves training the ANN model. The training process entails iteratively balancing the weights and biases of the network to reduce the ratio between the confined output and the actual target values. This is achieved through a streamlining algorithm, such as gradient descent, which updates error parametric identified for every iteration. After the ANN model is completed, it should predict on new unidentified data. The trained model takes the sensor readings as input and produces the predicted probability of failure as output. The effectiveness of the developed neural network can be seen in Figure 7, where it is shown that the network is able to confine the response with a fidelity of 100%. The model was instructed, validated, and tested with the dataset, and at each stage, the accuracy was found to be 100%. It is evident from the graph that the predicted values closely resemble the experimental outcomes. The measurement analysis of the proposed with existing method is shown in Table 1. The model's forecasting align well with the actual values, indicating the accuracy and reliability of the ANN model in estimating the probability of failure depends on the sensor data's. The close correspondence between the projected and actual values further validates the efficiency of the developed ANN model identifying the underlying patterns and trends in the data. This close agreement demonstrates the model's ability to perform fidelity predictions and give valuable insights into the maintenance needs of the wafer stick machine.

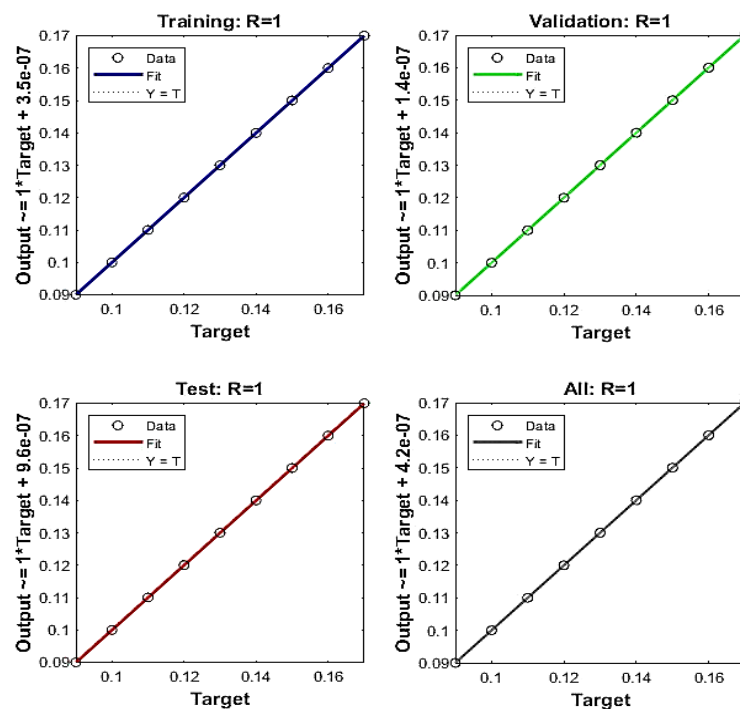


Figure 7. Efficacy of developed ANN model

Table 1. Performance analysis of proposed and existing method

S. No	Time (Mins)	Probability of failure	
		Proposed method	Existing method
1	200	0.16	0.22 [5]
2	400	0.17	0.21 [8]
3	600	0.15	0.18 [13]

Trained, ANN model can confine the probability of failure for new sensor readings. Figure 7 illustrates the effectiveness of the developed neural network, demonstrating a 100% accuracy in predicting the response. Throughout the training, validation, and testing phases, the model consistently achieved this high accuracy level.

The high fidelity of the ANN model is assigned to several factors:

- The feedforward algorithm's capability to learn underlying specimen in the dataset.
- The selection of an exact number of neurons (10 in this case), which strikes a balance between underfitting and overfitting the data.
- The rigorous training and verification process, which make sure the model accomplish well to new data.

Figure 8 portray the comparison in between actual and forecast values obtained from the ANN model, showing a close alignment between predicted and experimental outcomes. This close correspondence validates the model's fidelity and reliability in estimating the probability of failure based on sensor readings.

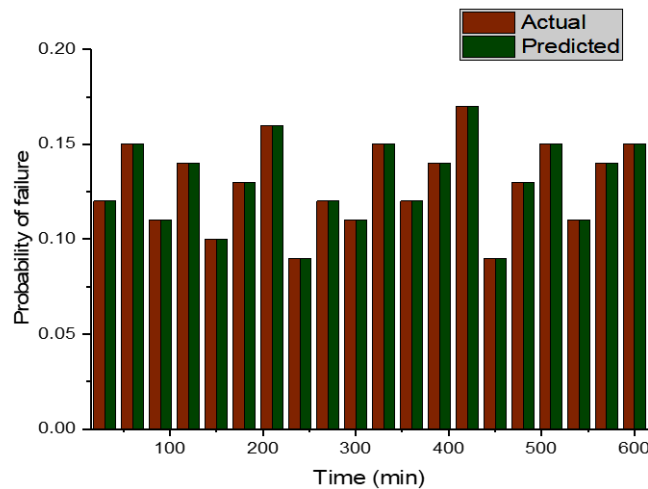


Figure 8. Actual and predicted value from ANN

4. CONCLUSION

This work mainly highlights on the implementation of predictive maintenance for a wafer stick machine in the food industry, leveraging sensor data and ML models. We utilized temperature, vibration, speed, and current sensors to continuously monitor the machine's health and predict failure probabilities. Both linear relapse and ANN models were expanded in MATLAB to forecast failure risks based on sensor inputs. The linear regression model provided a straightforward estimation linking sensor values to failure likelihood, while the ANN model employed a foresight approach with 10 neurons in the invisible layer to capture complex patterns, achieving exceptional accuracy. The high R^2 values of 98.2% for linear regression and 100% for ANN demonstrated the models' effectiveness in explaining variability and predicting failure probabilities accurately. These models enable proactive maintenance by alerting operators to potential issues before they cause downtime or quality issues in wafer stick production. Implementing predictive maintenance not only minimises unplanned leisure and maintenance costs but also enhances overall machine efficiency and product quality. The incorporation of sensor technologies and ML paves the way for smart industry applications in the food sector, promoting competitiveness and sustainability. Future research can prospect several points to further enhance predictive maintenance and smart industry applications.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Gokulachandar	✓	✓	✓	✓		✓			✓	✓	✓	✓		
Velmani Ramasamy		✓				✓				✓				
Maragatham	✓		✓	✓				✓	✓					
Anbuselvan		✓			✓					✓				
Anandan		✓		✓	✓				✓					
Tamilselvan Senthil	✓		✓	✓		✓				✓				

C : **C**onceptualization

M : **M**ethodology

So : **S**oftware

Va : **V**alidation

Fo : **F**ormal analysis

I : **I**nterpretation

R : **R**esources

D : **D**ata Curation

O : **O**riginal Draft

E : **E**diting

Vi : **V**isualization

Su : **S**upervision

P : **P**roject administration

Fu : **F**unding acquisition

CONFLICT OF INTEREST STATEMENT

There is no conflict of interest.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

ETHICAL APPROVAL

The research related to human use has been complied with all the relevant national regulations and institutional policies in accordance with the tenets of the Helsinki Declaration and has been approved by the authors' institutional review board or equivalent committee.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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