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Industrial IOT Framework Design For Predictive Maintenance In Intelligent Manufacturing Environments

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Abstract

In recent years, predictive maintenance is the best solution in many commercial and individual industries because it predicts the machine status before the failure occurs. But it contains some issues like high error, delay, and processing time also less prediction accuracy because of data complexity. So designed Honeybee-based Random Forest (HbRF) scheme to enhance the performance of predictive maintenance and is implemented using MATLAB tool. Initially, data are collected from the welding machine using IoT sensors and they are stored in the cloud. Then the collected data were sampled per second that are collected for one month or one week. Then preprocessing and decorrelator is performed to eliminate the errors, noise, missing values, and correlation in the input dataset. After that, feature extraction is utilized to extract the relevant information from the dataset. Moreover, update the honey bee fitness for continuous monitoring of machine features at a certain time. Finally, predict the machine status before the fault occurs. Consequently, the developed framework attained results are compared with other states of the techniques such as processing time, error, delay, prediction accuracy, precision, and recall.

Keywords: *Machine Failure, Predictive Analysis, Damage Prediction, Maintenance, Machine Learning, Optimization.*

Introduction

The Industrial Internet of Things (IIoT) denotes the use and extension of IoT in industrial applications and industrial sectors [1]. It includes industrial robots, medical devices, industrial applications, and software-defined construction processes [2]. Moreover, IIoT has been deployed to construct vehicles, sensor systems, robotics, wind, and solar power [3]. Furthermore, IIoT applications tend to do one thing which is deployed in challenging environments [4]. Using the camera, data analytics, and sensor, IIoT is able for determining a few pieces of equipment that may fail before it organizes [5]. Also, IoT enables systems are sense the damages, warning signs and use data for creating timeline maintenance and pre-emptively service equipment to overcome the problem [6]. Consequently, IIoT is the use of actuators and sensors for enhancing the industrial and manufacturing process which is used as the power of real-time analytics and smart machines for gathering data advantage [7, 8]. Thus the IIoT based smart machine is better than the human to analyze and capture data in real-time [9]. As well, improve the significant communication information which is helpful to fast and accurate drive business [10]. As well, the IIoT application is detailed in fig.1.

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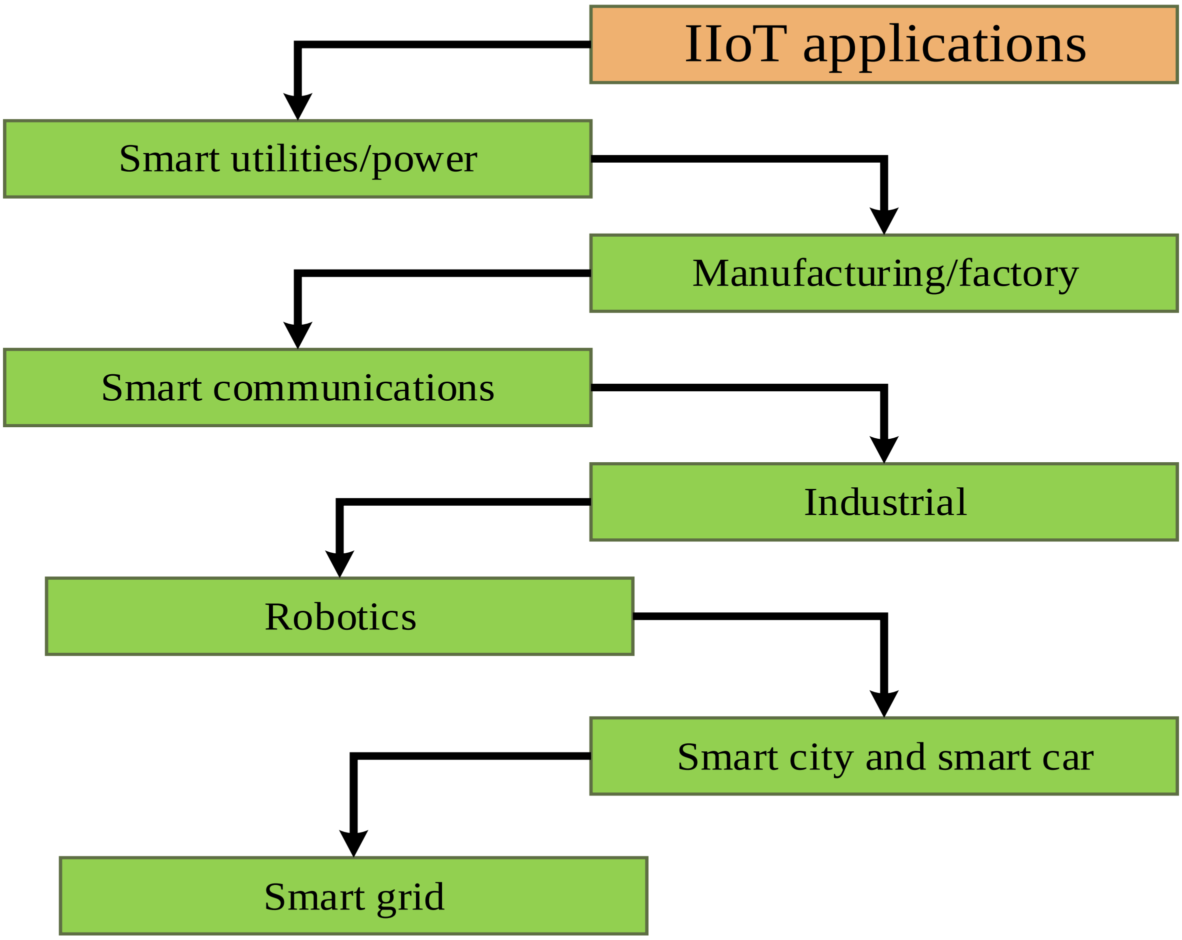

Fig.1 Industrial IoT application

Generally, connected actuators and sensors allow the companies for picking problems sooner, and inefficiencies also save money and time [11]. In the manufacturing field, IIoT plays a major role to enhance supply chain traceability, quality control, supply chain efficiency, and sustainable practices [12]. Thus the process of IIoT predictive maintenance improves asset tracking, energy management, and field service [13]. Subsequently, the working process IIoT is performed using network intelligent devices which are connected to the system for monitoring, collecting, analysing, and exchanging data [14]. Moreover, the IIoT ecosystem contains a connected device to sense, store and communicate information between them then store the data in the cloud [15]. Furthermore, intelligent assets and edge devices transfer the collected information directly to the data communication organization [16]. That converts the information into actionable information to operate some pieces in machinery [17]. Thus the information is helpful to predictive maintenance and optimized business process.

The benefit of IIoT device used in manufacturing industries enables predictive maintenance also real-time dataset is generated from the IIoT system for predicting the information when the machine needs service [18]. So needed maintenance has been performed before occurring failure. Also, it is well-organized in field service for helping the field service technicians to identify and detect potential issues in customer equipment before occurring major issues [19]. There are many techniques are designed in IIoT to enhance the predictive analysis but still have the problem of less prediction, errors, less accuracy, and vanishing gradient problem. So design a novel optimized machine learning framework to improve the predictive maintenance of Smart Manufacturing System (SMS).

The paper arrangement is ordered as; the literature review of this paper is discussed in session 2. Also, the analysed problem and the system model are elaborated in Session 3. The developed novel technique is explained in Session 4. Subsequently, the attained results and comparative analysis are mentioned in Session 5. The conclusion about the work is detailed in Session 6.

Related Works

A few recent literature survey based on IIoT is detailed below,

Zeinab and Yung [20] proposed IoT-based Machine Learning (ML) to monitor the manufacturing system. Moreover, data are collected using IoT sensor which includes humidity, accelerometer, temperature, and so on. Furthermore, the prediction technique helps to move outlier of sensor data also detect the fault in a manufacturing system. But error rate is high because of data complexity.

Nowadays SMS is the most growing technique for predicting the quality and reliability of the equipment. Shahbazi and Byun [21] developed blockchain-based ML for securing and handling system transactions and datasets. Moreover, analyze and manage the collected dataset using the developed technique. Finally, fault aspects are diagnosed using hybrid prediction but it has the problem of vanishing gradient.

Baotong Chen et al [22] proposed a new intelligent application of IIoT with ML for improving the cognitive capability of edge intelligence. Frequently, ML was developed for improving cognitive capability. Moreover, the developed technique mainly focuses on the reconfigurable production line through reinforcement learning. Furthermore, the designed model analyses the IIoT using a macroscopic view but it has data security and management issues.

The enhancement of network collaboration, flexibility, and sustainability play an important role in SMS also network collaboration enhances production efficiency. Lingguo Buo et al [23] developed an autonomous manufacturing machine for facilitating SMS also 3 terminal collaborative stages are developed for integrating IIoT technology. Finally, the designed technique facilitates optimization production but it has a defining problem.

Ameeth and Aditya [24] proposed an integrated autoregressive average technique for predicting quick defects and possible failures also enhancing the manufacturing process. Initially, various sensors are used to gather useful information and the data is captured with machines. The time-series data are collected using various sensors. Moreover, ML verifies vital components to minimize the cost, quality control but less accuracy.

The key contribution of the developed technique is detailed below,

- Initially, an IoT sensor is inserted into the welder machine to monitor the performance and identify the fault
- Then welding machine collected datasets are stored in the system using sensors
- Moreover, design a HbRF with a required parameter for enhancing predictive maintenance
- After that, preprocessing and decorrelate are performed to remove the error, noise, missing values, and correlation present in the input dataset.
- Consequently, feature extraction is utilized to extract relevant features to improve predictive analysis
- Furthermore, update honeybee fitness in the prediction phase to continuously monitor the temperature, pressure, and so on in the machine.
- Hereafter, the developed framework identifies the machine status before the fault occurs and the performances are compared with existing techniques.

System Model And Problem Definition

Nowadays ML is the most important area in SMS based on the efficiency of business function. Using ML enhances data analysis and product quality control. In the automotive industry, ML is essential for analysing problems and overcoming data classification. It includes data cleaning, model selection, feature preprocessing, and optimized parameter. Initially, data cleaning remove errors, missing data and remove duplicate. Then feature preprocessing is processed to split and acquire the data and feature scaling, etc. The basic system model and problem definition are detailed in fig.2.

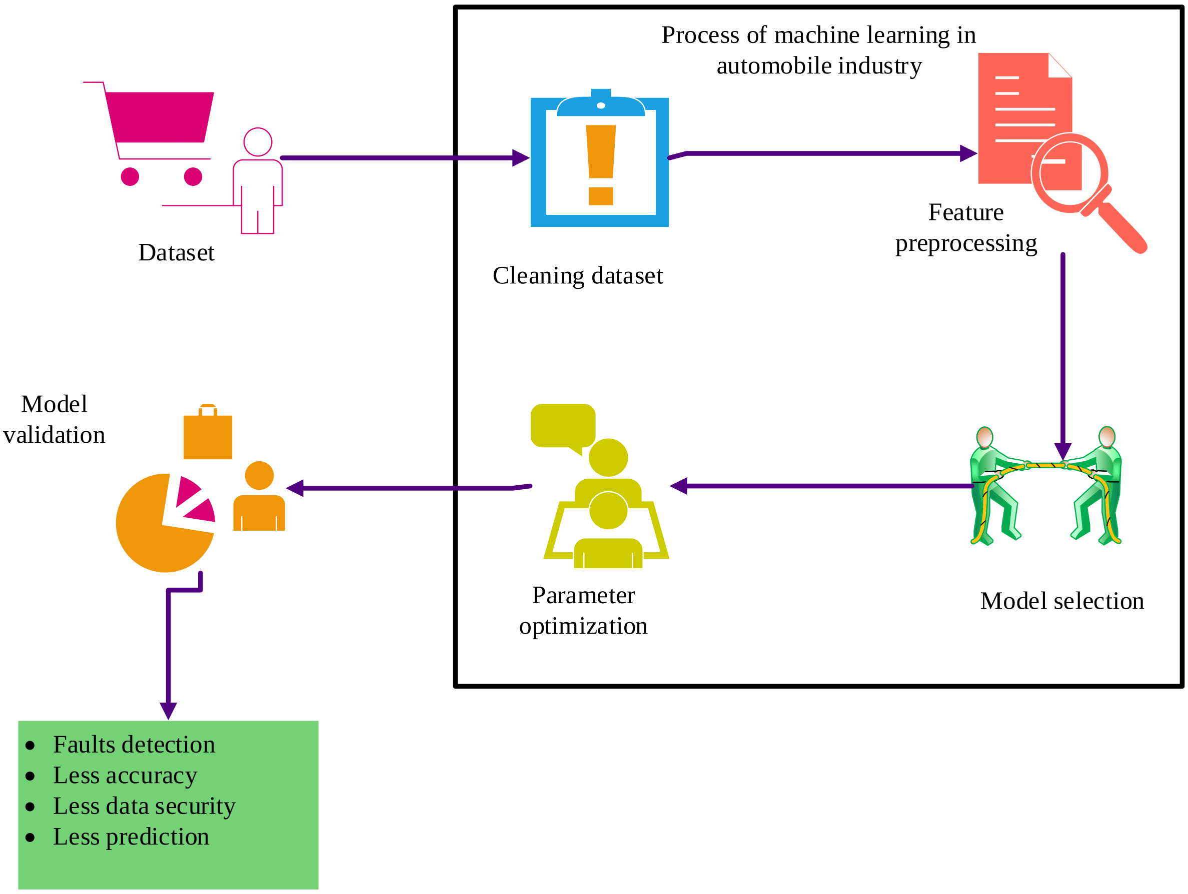

Fig.2 System model and problem definition

Moreover, ML performed model selection and parameter optimization to enhance the data quality control and so on. But it has some issues to validate the design such as less data security, less accuracy, high fault detection, and less prediction. However, the main issue in the automotive system is improper prediction so it causes the overall performance. So design a new research work to enhance the performance of the predictive analysis.

Proposed Methodology

Initially, data are collected from the welding machine or slitting machine using IoT sensors and they are stored in the cloud. Then the collected data were sampled per second that are collected for one month or one week. Then preprocessing is performed to eliminate the errors, noise, and missing values in the dataset. Moreover, a decorrelator is used to remove the correlation among inputs and outputs. After that, feature extraction is utilized to extract the relevant information from the machine. Moreover, update the honey bee fitness for continuous monitoring of machine features at a certain time. Finally, predict the machine status before the fault occurs. The architecture of the developed HbRF is shown in fig.3.

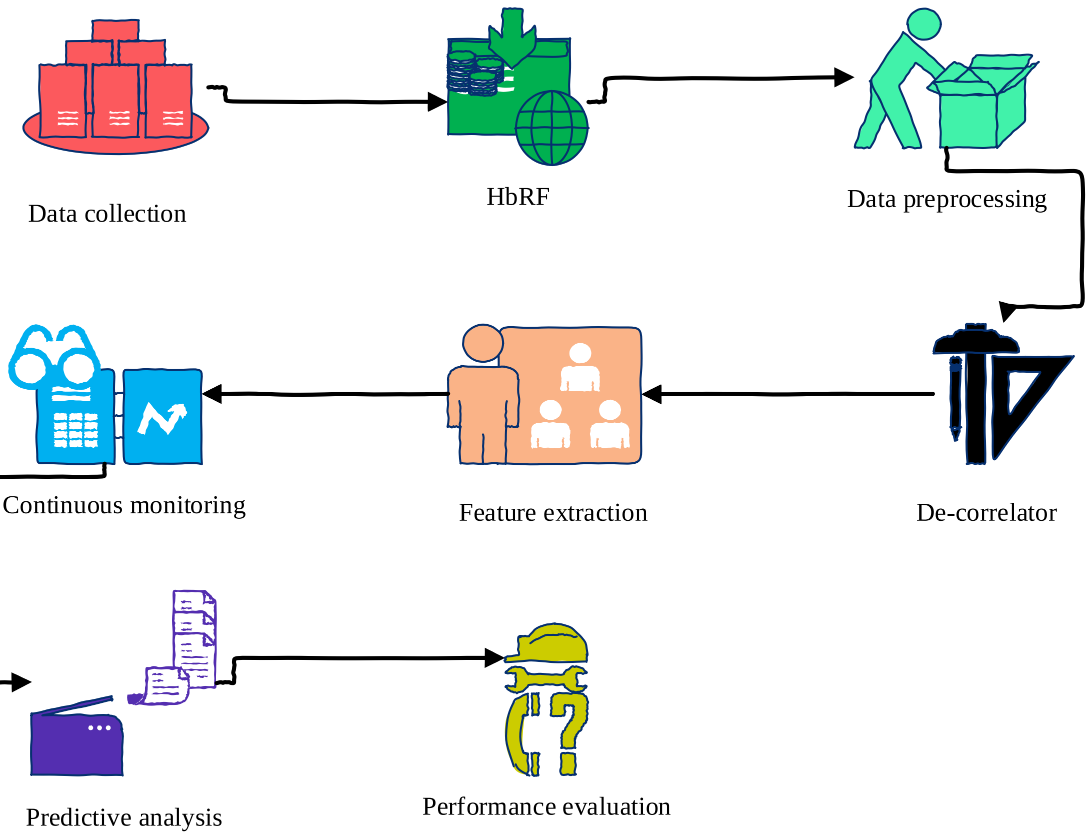

Fig.3 Proposed methodology

The main aim of the designed framework is to enhance productivity, provide prognostics, prevent quality failures and enhance predictive maintenance. Because it operates the parts of the machine by diagnosis and data analysis also detect the remaining service of machine parts. Moreover, predictive maintenance is the capability for ensuring maximum time intervals among minimum occurrences and maintaining tasks.

Data collection

The IoT-based sensor data is inserted in the different fragments of the welding machine for predictive maintenance of machine parts. The sensor collects the information of the welding machine such as current, air pressure, vibration, temperature, and so on. Then the collected dataset from the sensor is stored in the cloud. Next, they are distributed to the developed model. Thus the data has been samples per second which are collected for a period of one week or one month.

Design of Honeybee based Random Forest (HbRF)

After the collection of the dataset from the welding machine, a dataset is delivered to the developed HbRF design to enhance predictive maintenance, productivity and prevent quality failures. It involves preprocessing, feature extraction, continuous monitoring, and predictive analysis. Consequently, update the honeybee fitness in the developed framework to continuously monitor the machine failure before occurs. Thus the sensors send the information of the machine while changes occur in a machine that is commonly sampled per second.

Preprocessing

Additionally, the collected dataset contains null values, errors and noise hence preprocessing is executed to remove the errors and noise present in the dataset. Preprocessing can improve data quality and remove missing values, unwanted data, and errors in the dataset. Furthermore, preprocessing is obtained using Eqn. (1)

$$p_r(s)=\frac{k_o(s)-m(s)}{q(s)} \tag{1}$$

Where, $k_o(s)$ is denoted as input dataset and $m(s)$ is represented as error and noise present in the dataset. Additionally, $q(s)$ is denoted as the probability of the original dataset.

De correlator

Consequently, de correlator is utilized to eliminate the correlation between i inputs and j inputs. Where, i inputs include input current, noise level and difference among temperature, and pressure. Moreover, j inputs contain humidity, device altitude, vibration, and light intensity. Thus the de correlator removes or eliminates the difference owed to environmental conditions. Then the de correlator matrix of β was defined using uncorrelated output CR_o which is obtained using Eqn. (2)

$$CR_o = i-\beta j[CR(s)]^t \tag{2}$$

Let, $CR(s)$ is denoted as i and j input parameters based on uncorrelated output, t is represented as the time interval of inputs i and j.

Feature extraction

After that, the uncorrelated output is sent to the feature extraction process to extract the relevant features from the dataset. It includes the process of acquiring data, splitting data, extracting relevant information, and feature scaling. In this stage, data are separated or divided into six features temperature, current, pressure, air pressure, humidity, vibration, and flow rate. Furthermore, the developed framework analyses relevant features during the process. Then splitting the selected features into testing and training processes to identify the features to avoid and predict failure. Thus the relevant features based on air pressure features, pressure features, temperature features, humidity features, current features, flow rate features, and vibration features are obtained using Eqn. (3)

$$F_e(s)=\sum_{i=1}^{j} p(t)[CR_o(t-1)]+H_p(s)[D_p]+\alpha(H_p) \tag{3}$$

Let, $p(t)$ is denoted as training and testing of the real dataset, and $H_p(s)$ is represented as task of all iteration. Moreover, D_p is considered as relevant feature in all iteration and α is represented as a variable.

Predictive analysis

Update the fitness of honeybees in the prediction phase to enhance the predictive maintenance of machines also increase productivity. The purpose of the honeybee is to identify the best search space to best brood that is used for the developed technique for continuously monitoring the machine status before the fault occurs. Moreover, it continuously monitors the problem in the machine using selected features. While the problem has occurred in machine means predict the problem using the fitness of honeybee. By measuring and monitoring data from the sensors based on-trend value to perform maintenance tasks. The use of enhancing predictive maintenance is monitoring a large amount of data and pushed into the analytical tool for predicting the overload, machine failure, downtime, and other problems. Thus the prediction is performed using Eqn. (4)

$$P_m(s)=\begin{cases} D_p h(t) & l_p \le F_e(s) \\ H_p(s)+[l_p-F_e(s)] & l_p > F_e(s) \end{cases} \tag{4}$$

Let, $h(t)$ is denoted as the fitness of honeybee and l_p is represented as a threshold value. Moreover, the design of the developed technique is detailed in algorithm.1.

Algorith.1 Proposed HbRF model for predictive maintenance

Start

{

Design HbRF

//increase productivity and enhance predictive maintenance

Initialization

{

Update the dataset *// Different parts of machine using IoT sensor*

}

Pre-processing

// remove the noise, null values, error in the dataset

{

For all $m(s)$

{

Remove errors

}

End for

}

De correlator

//eliminate input correlation

{

$CR_o \rightarrow i, j$ *with* t

// i, j *-input parameter*

// t *- time interval*

}

Feature extraction

{

```
                Extract the relevant features
                // Temperature, Current, Pressure, Vibration, Flow rate, and so on
                        For all D_p
                        // D_p - relevant features
                        {
                        Extract features
                        }
                        End for
        }
Predictive analysis
        // predict the machine failure and machine status
        {
                        Update fitness function of honeybee
                        Predict machine status using eqn.6
                        if (l_p > 500)
                        {
                        Machine problem
                        }
                        Else if (l_p ≤ 500)
                        {
                        Normal
                        }
                        end if
            }
        }
stop
        Output: finest solution
```

While the threshold value is greater than the mathematical value of relevant features means machine problems otherwise machine conditions become normal. Based on the predictive results, the machine has been maintained and replaced.

Results and Discussion

The designed paradigm was implemented in a MATLAB tool and the welding machine datasets are collected and stored in the system using sensors. Consequently, a novel proposed HbRF was designed with all required parameters; here the optimal solution of the honeybee algorithm is incorporated in all functioning steps to obtain the finest expected result. Then the dataset is updated to the developed technique to predict the fault before occurs also enhances the predictive maintenance. Moreover, primarily, the preprocessing process was functioned to remove training errors and noises in the input dataset. Next, extract the relevant features from the dataset and then predict machine status while the problem is occurring from the machine. Thus the developed framework attains better performance in predictive maintenance of machines using IIoT.

Case study

The developed framework is implemented for various purposes such as detecting machine damage, increasing productivity, enhancing machine lifetime, and so on. Moreover, a designed case study is valid and implemented in the production of oil and gas fields. Generally, an IoT sensor is inserted into the oil and gas machine. Hereafter, the sensor collected the information of the machine which is approximately collect more than 18,900 information per day. Furthermore, sensor collected information are well pressure, oil production levels, temperature, and so on. Then the collected dataset is stored in the CSV file of the cloud which consists of certain columns like pressure, temperature, and production levels. Additionally, the process of the designed HbRF in the oil and gas production field is shown in fig.4.

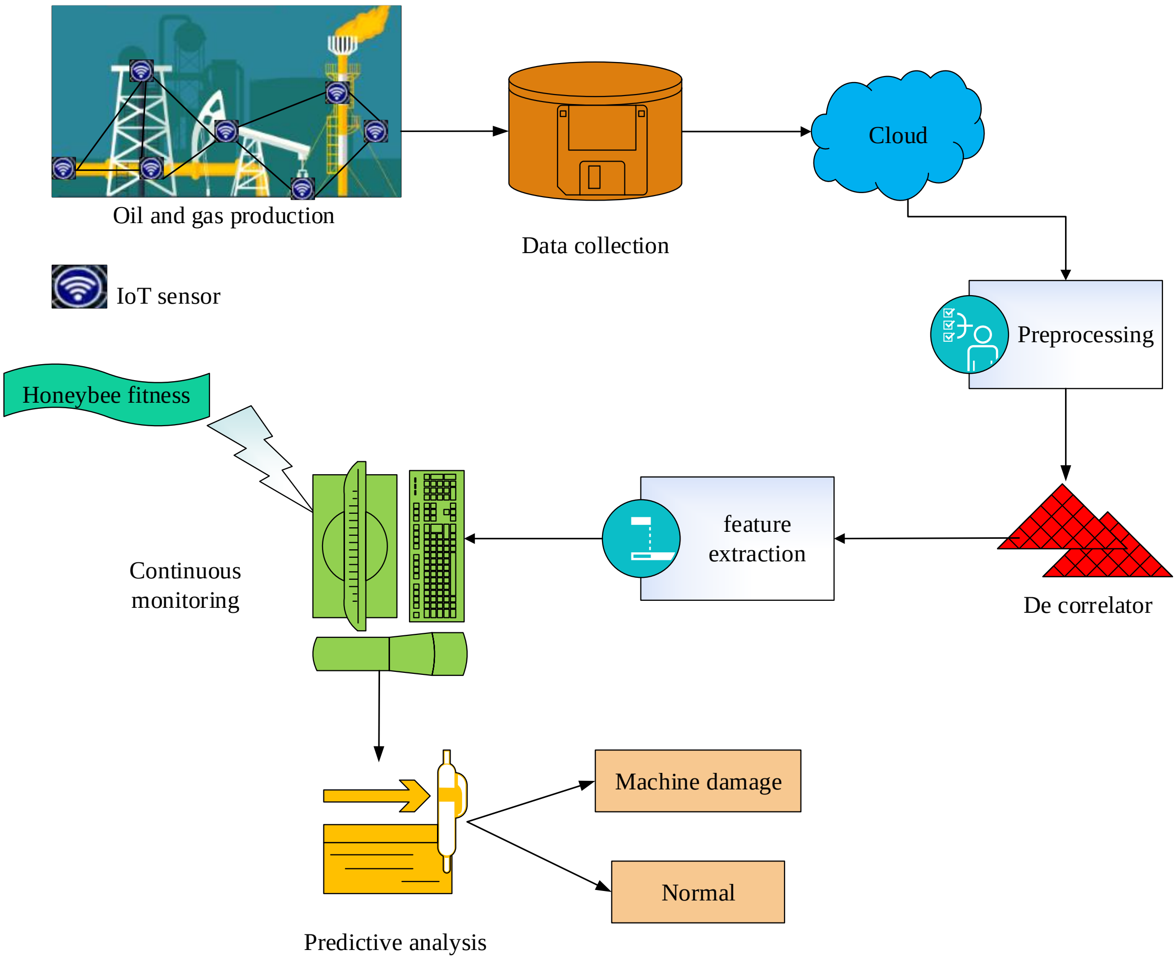

Fig.4 Process of designed HbRF using IIoT in oil and gas field

Additionally, the stored dataset is delivered to the developed design HbRF to predict the failure in the machine also enhance the performance of predictive maintenance. Thus the developed technique executes the process of preprocessing, feature extraction, decorrelator, and predictive analysis. The errors, noise, missing value, and correlation have been removed and eliminated using preprocessing and decorrelator. Then extract the relevant features from the machine to identify the failure or damage in the machine. Consequently, update the fitness function of the honeybee to enhance the performance of predictive maintenance. Thus the developed technique continuously monitors the machine status and machine behavior using the threshold value. In the prediction phase, identify the machine failure and machine damage before occur. While the threshold value is greater than the mathematical values means predicted as machine damage and the threshold value is less than the mathematical value means predicted as normal. The prediction is obtained by,

$l_p > 500 \rightarrow$ Machine damage

$l_p \leq 500 \rightarrow$ Normal

Finally, the developed framework predicts the machine status before the damage occurs also enhances the performance of IIoT by attaining better results for predictive maintenance. As well, the designed framework enhances the productivity, prevents quality failures, also enhance predictive maintenance.

Performance metrics

The planned HbRF model is implemented in the MATLAB tool and the success rate of the designed scheme was analysed with comparison assessment in terms of, prediction accuracy, precision, recall and processing time, delay, and error. Thus the achieved performance is compared with other existing techniques such as Smart Manufacturing (SM) based Blockchain (SMbB) [20], Multistage Quality Device in SM (MQD) [21], Cognitive Ability of Edge Intelligent in IIoT (CAEI) [22], and Edge Computing (EC) [25].

Processing time

The term processing time is defined as the total time taken for completing the task which can increase the output through decreasing processing time. Also, it is the time among machine activity while the prediction time before the failure occurs. It is calculated based on the various quantity of the control over the processing time. Moreover, a comparison of processing time is detailed in table.1.

Table.1 Validation of processing time

No. of. features	**Processing time (ms)**				
	SMbB	**MQD**	**CAEI**	**EC**	**Proposed**
5	58	15	25	8	2
10	62	20	31	14	4
15	67	28	37	21	6
20	73	35	44	28	10

The gained performances of the developed framework are compared with other existing techniques such as SMbB, CAEI, MQD, and EC. Moreover, SMbB and MQD attained processing time is 58ms and 15ms for using 5 features. Furthermore, CAEI and EC achieved 25ms and 8ms. While comparing other techniques developed HbRF attain less processing time as 2ms. The comparison of processing time is detailed in fig.5.

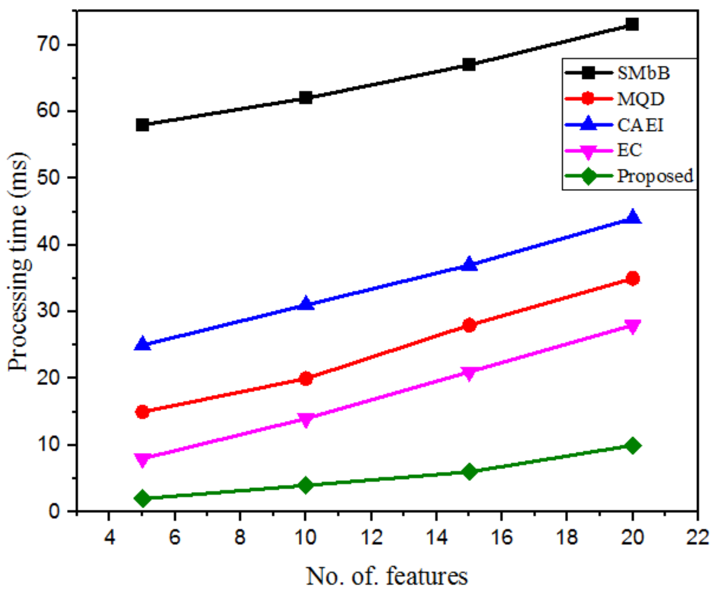

Fig.5 Comparison of processing time

Prediction accuracy

The numerical value of the accuracy denotes the proportion of true positive outcomes for the prediction of machine damage or machine failure using IIoT. Also, it is defined as the degree of the result of accurate measurement value to the standard or correct value. The accuracy is measured using closeness among measured true amount value and measured quantity value which is calculated using Eqn. (5,

$$PA = \frac{IP + IN}{IP + IN + AP + AN} \qquad (5)$$

Where, IP is denoted as the quantity of correct prediction rate and IN is represented as the quantity of correct negative prediction rate. Moreover, AP and AN are denoted as incorrect predictions of true and positive rates. The comparison of prediction accuracy is detailed in table.2.

Table.2 Validation of prediction accuracy

No. of. features	**Prediction accuracy (%)**				
	SMbB	**MQD**	**CAEI**	**EC**	**Proposed**
5	95	95.56	80	85.12	98.65
10	93.12	93	78.16	83	98.12
15	89	90.04	75	79.28	97.74
20	85.7	88.3	71.05	77.7	97

The prediction accuracy of the developed technique is compared with other existing techniques such as SMbB, MQD, CAEI, and EC. Moreover, SMbB and MQD techniques attain 95% and 95.56% for 5 features. Additionally, CAEI and EC models gained 80% and 85.12%. Finally, the developed framework HbRF attains 98.65% in predictive maintenance, which is high while comparing other existing replicas. The comparison of prediction accuracy with other existing techniques is detailed in fig.6.

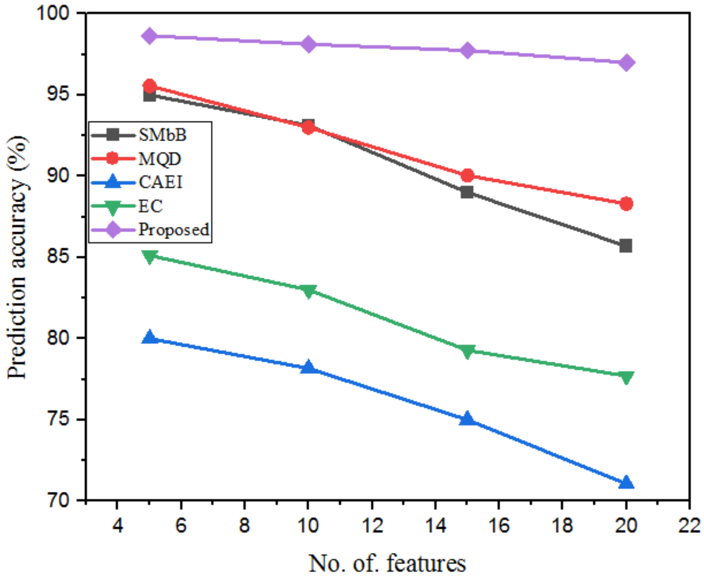

Fig.6 Comparison of prediction accuracy

Delay

The total time required for transmitting the data packets is known as delay and the delay is calculated based on the post ponding and causing actions to occur more slowly than normal action. Moreover, the delay is calculated based on the arrival rate of incoming information and transmission capacity. Thus the delay comparison is detailed in table.3.

Table.3 Validation of delay

No. of. features	Delay (ms)				
	SMbB	**MQD**	**CAEI**	**EC**	**Proposed**
5	45	40	60	80	8
10	49	43	64	84	11
15	52	47	69	89	14
20	58	53	73	91	18

The gained performances of the developed framework are compared with other existing techniques such as SMbB, CAEI, MQD, and EC. Moreover, SMbB and MQD attained delay are 45ms and 40ms for using 5 features. Furthermore, CAEI and EC achieved 60ms and 80ms. While comparing other techniques developed HbRF attain less delay as 8ms and the comparison is shown in fig.7.

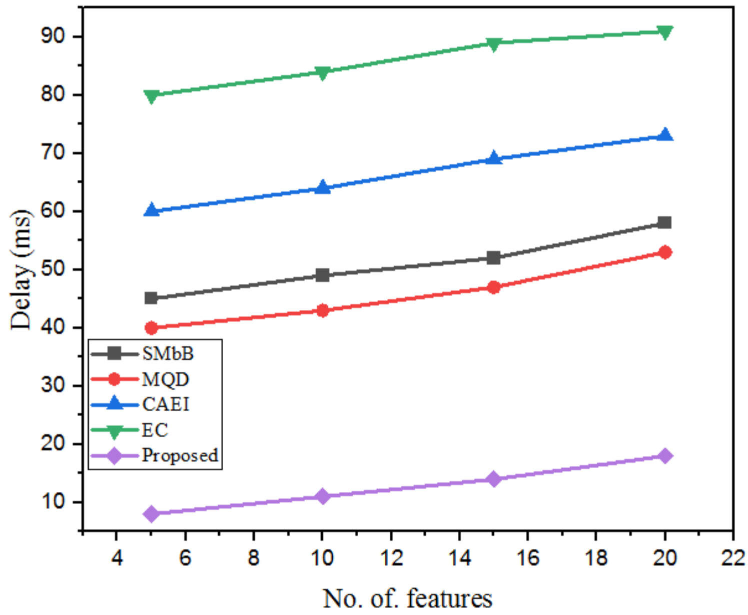

Fig.7 Comparison of delay

Precision

The computation of precision (P) is operated for recognizing the success of the proposed HbRFtechnique while predictive maintenance. Furthermore, precision is the ratio of the quantity of true positives to the total quantity of positive detection of intrusion. In addition, the measurement of precision rate is obtained using Eqn. (6) and comparison of precision has shown in table.4.

$$P = \frac{IP}{IP + AP} \quad (6)$$

Table.4 Validation of precision

No. of. features	Precision (%)				
	SMbB	**MQD**	**CAEI**	**EC**	**Proposed**
5	93.2	96	81	84	98.88
10	91	93.2	79.03	81.11	98.60
15	88.4	90.62	77.7	78	98.32
20	84	88	75	76.92	98

Thus the SMbB replica attained 93.2% in precision, and the MQD method gained 96% precision for using 5 features. Moreover, the CAEI, and EC methods attained 81% and 84% precision and the developed HbRF technique archives 98.88% in precision. The comparison of precision is detailed in fig.8.

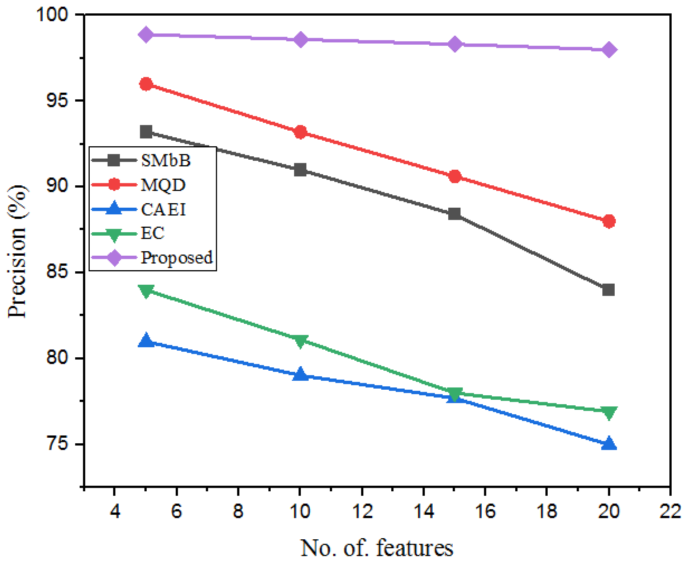

Fig.8 Comparison of precision

Recall

Measurement of recall (R) is developed to predict failure in a machine of the developed HbRF technique. Additionally, recall is the term of quantity of true positive value to the total quantity of relevant objects. Moreover, the recall calculation of the HbRF method was obtained using Eqn. (7),

$$R = \frac{IP}{IP + AN} \tag{7}$$

Table.5 Validation of recall

No. of. features	Recall (%)				
	SMbB	**MQD**	**CAEI**	**EC**	**Proposed**
5	94.6	95	82	84	98.4
10	92.12	92.17	79.12	82.17	98
15	90	89	77.7	80	97.8
20	87.7	87.3	75	79.72	97.3

The achieved recall rate of the proposed HbRF technique is compared with other existing replicas such as SMbB, MQD, CAEI, and EC. Thus the SMbB replica attained 94.6% recall, and the MQD method gained 95% recall for using 5 features. Moreover, the CAEI method attained 82% recall, and the EC technique achieved 84%. Additionally, the developed HbRF technique achieves 98.4% in recall and the comparison of recall with the exciting technique is detailed in fig.9 and table.5.

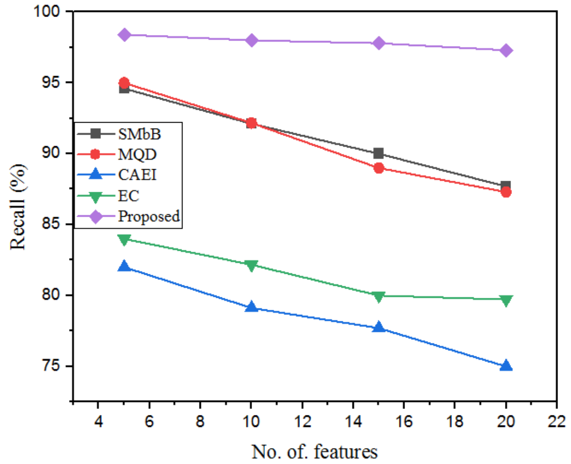

Fig.9 Comparison of recall

Error

Error is the action of incorrect and inaccurate results with mistakes. Moreover, the error is defined as the difference among values that are computed based on the correct value. As the result of the error occurs failure. Furthermore, the error is measured based on the estimated difference among the calculated or observed values of true value and quantity. Additionally, a comparison of errors is detailed in table.5.

Table.5 validation of error

No. of. features	**Error (%)**				
	SMbB	**MQD**	**CAEI**	**EC**	**Proposed**
5	24	33	17	22	8
10	28	36	19	25	11
15	32	39	22	29	15
20	37	42	26	32	17

The achieved error of the proposed HbRF technique is compared with other existing replicas such as SMbB, MQD, CAEI, and EC. Thus the SMbB replica attained 24% error, and the MQD method gained 33% error for using 5 features. Moreover, the CAEI method attained 17% error, and the EC technique achieved 22% of error for using 5 features. Additionally, the developed HbRF technique achieves 8% in error which is low while comparing other existing techniques and the comparison of error with the exciting technique is detailed in fig.10.

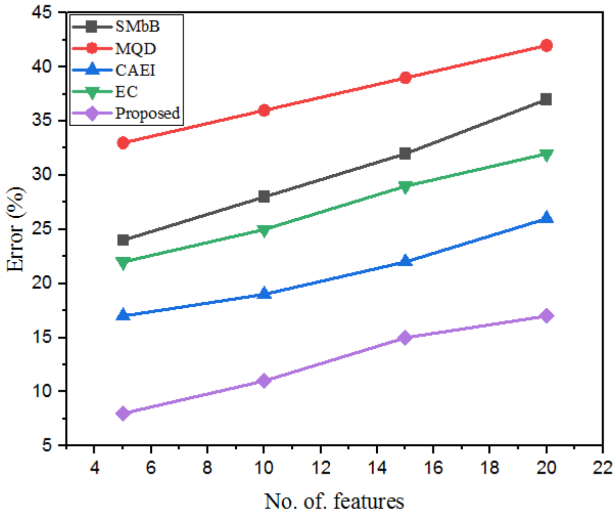

Fig.9 Comparison of recall

Discussion

From all performance evaluations, the robustness of the designed model is verified by achieving the best results than other models. In addition, the processing time of the designed approach is used to estimate the performance. InIIoT, some inefficient techniques have taken more duration to finish the execution because of the large dataset and complexity.The overall performance metrics of the designed approach were evaluated separately to prove the reliability of the illustrated model.

Table.6 Metrics assessment

Methods	Performance assessment					
	Prediction Accuracy (%)	Recall (%)	Precision (%)	Error rate (%)	Delay (ms)	Processing time (ms)
SMbB	95	94.6	93.2	24	45	58
MQD	95.56	95	96	33	40	15
EC	85.12	84	84	22	80	8
Proposed (HbRF)	98.65	98.4	98.88	8	8	2

The performance metrics of the designed model were evaluated in table.6. Hence, the proficient score of the presented model is verified and it is appropriate for IIoT to predictive maintenance and secure the machine before the damage occurs.

Conclusions

The main aim of the research is to predict the machine damage and machine fault also enhance the predictive maintenance to secure the machine from damage or fault. So, design an HbRF framework to improve predictive analysis and increase productivity. Moreover, an IoT sensor is inserted into the machine for collecting the features of the machine. Thus the collected dataset is stored in the cloud and they are updated to the developed framework for improving prediction. So, preprocessing and de correlator are performed to remove the error, correlation in the input, next, feature extraction is utilized to extract the relevant features from the dataset. Finally, predict the machine damage before occurs using the fitness of honeybee, and the prediction is happened based on the threshold value. At last, attained results of the developed framework are compared with other existing techniques. Moreover, the developed framework attains accuracy as 98.65%, precision as 98.88%, and recall as 98.4%. Also, it attains a low error rate of 8%, low delay as 8ms, and less processing time as 2ms. So, the proposed model is suitable for predicting machine damage and improving productivity.

Compliance with Ethical Standards

Conflict of interest

The authors declare that they have no conflict of interest.

Human and Animal Rights

This article does not contain any studies with human or animal subjects performed by any of the authors.

Informed Consent

Informed consent does not apply as this was a retrospective review with no identifying patient information.

Funding: Not applicable

Conflicts of interest Statement: Not applicable

Consent to participate: Not applicable

Consent for publication: Not applicable

Availability of data and material:

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

Code availability: Not applicable.

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