IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

AN EFFECTIVE FRAMEWORK FOR AUTONOMOUS PREDICTIVE MAINTENANCE IN INDUSTRIAL ROBOTICS 4.0 USING MACHINE LEARNING

[1]Syed Azadar Hussain Zaidi, [2]Vikash Sharma, [3]Pankaj Prajapati

[1]MTech Research Scholar, [2]Assistant Professor, [3]Professor

[1]Department of Robotics

[1]Ambalika Institute of Technology, Lucknow

Abstract: The goal of predictive maintenance (PdM), a strategic strategy, is to effectively manage asset maintenance by employing data-driven strategies to predict problems. This process involves gathering data over time to monitor the condition of the equipment in order to identify patterns and correlations that can help anticipate and prevent problems. In the manufacturing sector, machinery is often run without a planned maintenance schedule, which leads to unexpected downtime due to unplanned malfunctions. In order to prevent unplanned breakdowns, scheduled maintenance entails inspecting the state of the machinery at predetermined intervals and replacing defective parts. This strategy, however, raises maintenance expenses and machine downtime. The emphasis on PdM techniques, which can lower downtime costs and increase the availability (utilization rate) of industrial equipment, has increased with the rise of Industry 4.0 and smart systems. Furthermore, by optimizing component useful life, PdM holds the potential to bring about sustainable practices in manufacturing. Analyses have been conducted on supervised learning methods such as Gradient Boosting Classifier, CatBoost Classifier, Light Gradient Boosting Machine, and Extreme Gradient Boosting.

Index Terms predictive maintenance, Industry 4.0, Industrial Robotics.

1.Introduction

"Industry 4.0" describes a dramatic change in the industrial sector characterized by enhanced automation, intelligent data analysis, and the integration of digital and physical systems. The underlying concept of this modification is predictive maintenance, which aims to anticipate and avoid equipment problems in advance. Industrial robots are essential components of automated manufacturing, and their longevity and continuous operation depend on robust maintenance procedures. Today, the global consumer requirement is increasing drastically. To fulfillment of this requirement industries have to increase drastically. Industries are working day and night but to do so machines should work without any breakdown. To avoid machine breakdown, industries perform scheduled maintenance. Scheduled maintenance increases operational costs. If these breakdown can be predicted on the basis of past parameter history, breakdown or failure may be reduced drastically. Proactive, Scheduled and reactive maintenance slow down production increase the cost hence overall performance degradation.

Prediction of Failure of industrial robots is possible with machine learning. After technology enhancement like Industry 4.0 and IoT the past data of machine environment that can be collected from different sensors and actuators. These data later on used to train the machine learning algorithms for prediction of malfunctioning. Predictive maintenance is possible after data collected from previous maintenance is used to train machine learning algorithms. Predictive maintenance can enhance the productivity of machines and also can reduce the manufacturing cost and delivery time. It also decreases the downtime and enhances the maintenance approach [1] - [5].

2. LITERATURE SURVEY

Archit P Kane has worked on the integration of water pump and IoT for failure detection to reduce the downtime [1]. The effectiveness of predictive maintenance has attracted many researchers to develop machine learning models. Number of work has been done in this field to improve the maintenance process. Many approaches have achieved reliable and cost effective industrial systems. Kumar et al. in 2005 has published his research work on neuro- fuzzy logic for controller parameters to enhance performance of machines in industrial robotics. [6]
Bustillo et al. has worked on prediction of surface roughness for deep drilling, based on artificial intelligence Bayesian Network on steel materials. They have taken cooling as a input parameter and made a predictive model for high speed conditions to streamline deep drilling work [7]. Praveen kumar et al. has worked on gearbox problem and makes a predictive model based on machine learning [8]. Kroll et al. has worked on model for anomaly identification based on machine learning predictive maintenance [9]. Coraddu et al. investigated the concept of condition-based maintenance, focusing specifically on naval propulsion systems. Their research provides a thorough examination of how maintenance might be optimized by taking into consideration the equipment's current state rather than following a predetermined plan. This technique aims to increase naval operations' efficiency and dependability by preventing unexpected breakdowns and extending the lifespan of critical components. The study stresses how condition-based maintenance has considerable potential for lowering maintenance costs and increasing operational readiness in naval propulsion systems [10]. Gombé et al. (2019) investigated wireless sensor networks and developed an innovative approach to predict maintenance requirements in order to reduce failures and future harm. Their findings highlight the application of these networks to monitor and assess equipment health in real time. Using sensor data, the model attempts to predict potential problems before they cause significant damage, hence improving the reliability and efficiency of maintenance tasks [10]. Venegas et al. presented a predictive maintenance system with a thermographic module based on infrared measurements. Their purpose is to improve maintenance operations by utilizing a machine learning framework that anticipates potential issues. This unique technology tries to improve equipment efficiency and dependability by anticipating potential problems before they occur [11].

This literature review highlights effectiveness of predictive maintenance in the field of industrial robotics. It also emphasize on predictive models based on different machine learning algorithms. This survey based on literatures has also suggested that they have also improved the performance and reliability of machines after using predictive models. The literatures have also discussed the various methodologies and outcomes.

3. Materials and Experiment Methods

In this work dataset is utilized the UCI Machine Learning repository, specifically the AI4I 2020 Predictive Maintenance dataset [16]. In the context of this study, the dataset was constrained to 6,000 data points falling under the category of the low type. The primary focus of this research revolves around five specific features: ambient temperature (K), process temperature (K), rotation velocity (RPM), torque (Nm), and tool wear (min). After finalizing the data set models Gradient Boosting Classifier (GBC), CatBoost Classifier, Light Gradient Boosting Machine, Extreme Gradient Boosting, Ada Boost Classifier, Random Forest Classifier, Extra Trees Classifier, Naive Bayes, Linear Discriminant Analysis, Logistic Regression, Decision Tree Classifier, K Neighbors Classifier, Quadratic Discriminant Analysis, Dummy Classifier and SVM - Linear Kernel are trained to predict the maintenance.

CMMS system handle maintenance personnel and service records, but it also records events pertaining to all kinds of malfunctions, overhauls, inspections, and other maintenance tasks.

The selected organization has been supporting maintenance management for a long time using a particular CMMS system that has been modified and updated to accommodate shifting production and organizational requirements. The system's purchasing, inventory control, materials and parts, breakdown handling, maintenance, and repair have all undergone substantial changes in recent years.The technician's action time, failure diagnosis time, and estimated time to solve the problem are all critical components of the failure report. The operator's report, specifically the technical facility operator's preliminary assessment of the defect's implications (and causes), has a direct impact on the technician's response time and the time at which the malfunction is discovered. Ninety percent of complaints are for mechanical or electrical issues, therefore it's critical to get a skilled specialist on the site as quickly as possible to reduce the amount of time needed to identify the problem.

3.1 IMPLEMENTATION DETAILS

This project focuses on utilizing data from a manufacturing company's industrial devices to predict maintenance needs, thereby preventing breakdowns and saving costs. As companies expand, manual maintenance tracking becomes challenging. Thus, an intelligent solution has been proposed using machine learning algorithm: leveraging sensor data to forecast when maintenance is required.

The objective is to analyze sensor data to determine the optimal maintenance schedule for these devices. Several algorithms have been analyzed on the data set. [16]

3.2 Data set Descriptions: [16]

The dataset utilized in this investigation is obtained from the UCI Machine Learning repository, specifically the AI4I 2020 Predictive Maintenance dataset [16]. This particular dataset comprises 10,000 data points, each characterized by 14 distinct features. In the context of this study, the dataset was constrained to 6,000 data points falling under the category of the low type. The primary focus of this research revolves around five specific features: ambient temperature (K), process temperature (K), rotation velocity (RPM), torque (Nm), and tool wear (min). The classification objective pertains to a binary target, wherein 0 denotes normal operational status while 1 signifies machine malfunction. Owing to the disproportionate distribution between the two target classes, under-sampling techniques were implemented. The features used in the study are detailed as follows:

1. **Product ID:** This feature consists of a letter (L, M, or H) representing low (50% of all products), medium (30%), and high (20%) product quality, along with a serial product number.
2. **Ambient temperature [K]:** Generated from a random walk process, normalized to a standard deviation of 2 K, and centered at 300 K.
3. **Process temperature [K]:** Derived from a normal distribution with a standard deviation of 1 K, added to the ambient temperature with an additional 10 K.
4. **Rotation velocity [RPM]:** Measured at 2860 W and covered by normal distribution noise.

	UDI	Product	Type	Air temp	Process	Rotatior	Torque	Tool we	Target	Failure Type
2	1	M14860	M	298.1	308.6	1551	42.8	0	0	No Failure
3	2	L47181	L	298.2	308.7	1408	46.3	3	0	No Failure
4	3	L47182	L	298.1	308.5	1498	49.4	5	0	No Failure
5	4	L47183	L	298.2	308.6	1433	39.5	7	0	No Failure
6	5	L47184	L	298.2	308.7	1408	40	9	0	No Failure
7	6	M14865	M	298.1	308.6	1425	41.9	11	0	No Failure
8	7	L47186	L	298.1	308.6	1558	42.4	14	0	No Failure
9	8	L47187	L	298.1	308.6	1527	40.2	16	0	No Failure
10	9	M14868	M	298.3	308.7	1667	28.6	18	0	No Failure
11	10	M14869	M	298.5	309	1741	28	21	0	No Failure
12	11	H29424	H	298.4	308.9	1782	23.9	24	0	No Failure
13	12	H29425	H	298.6	309.1	1423	44.3	29	0	No Failure
14	13	M14872	M	298.6	309.1	1339	51.1	34	0	No Failure
15	14	M14873	M	298.6	309.2	1742	30	37	0	No Failure
16	15	L47194	L	298.6	309.2	2035	19.6	40	0	No Failure

Table: 1 Data set Descriptions

3.3 Data set Analysis using EDA:

Finding patterns in data, identifying anomalies like outliers, and testing preliminary hypotheses and assumptions using various statistics and visual aids are all important steps in the essential EDA process. EDA is a technology used to gain a deeper understanding of the dataset and optimize its preparation for the subsequent deployment of machine learning algorithms. In fact, EDA is a first and essential stage in identifying patterns in your data, which you can subsequently use to develop precise algorithms that emphasize onboard capabilities to aid in scientific research [17-19]

a. Displot: Displot also known as distribution plot is an advanced form of common histogram**.**

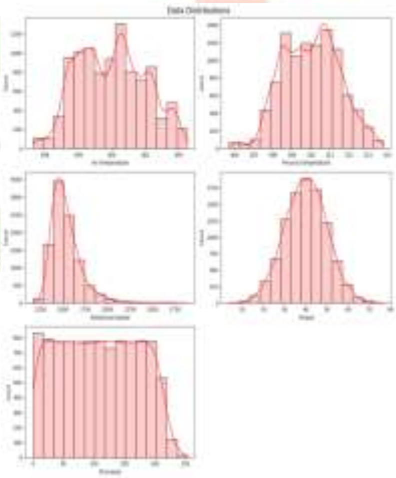

Figure: 1 data distribution plot with various parameters

b. **Box plot:** box plot, also known as a box-and-whisker plot, is a standardized way of displaying the distribution of data based on a five-number summary: minimum, first quartile (Q1), median, third quartile (Q3), and maximum

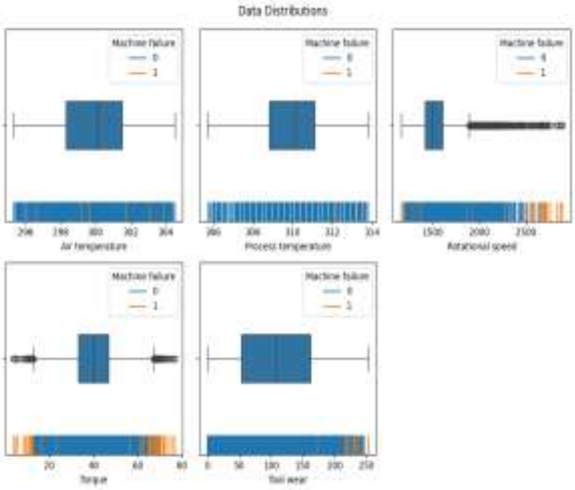

Figure: 2 Box plot for various measuring industrial parameter with target value

c. **Heatmap:** The construction of the matrix can be achieved by incorporating all feature variables, where these variables are denoted as both the row and column headers, and each variable is juxtaposed with itself along the diagonal. This method proves to be especially proficient in illustrating the interrelations among variables within spaces of high dimensionality.

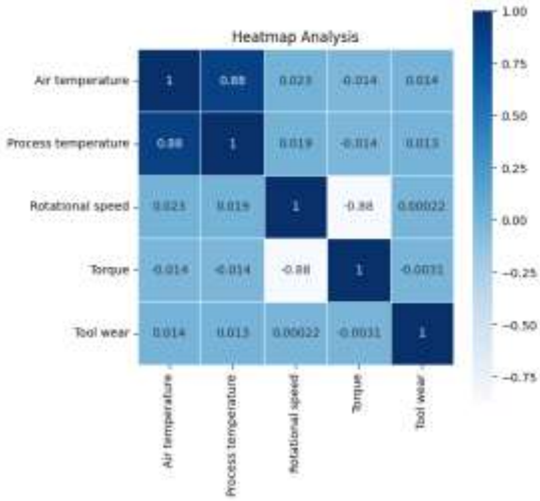

Figure: 3 Heat map analysis of measuring industrial parameter

d. **Hexbin Plot:** This kind of plots serve as a multifaceted instrument in the realm of data visualization, adept at illustrating the correlation between two continuous variables and the spatial distribution of data points. The entire graphing space is divided into hexagons (similar to a honeycomb), and all points are assigned to specific hexagonal regions. Each hexagon's density (or average Z value) is indicated by a color gradient. Hexbin plots shown in Figure No 4 can take lists of X, Y, and optional Z values with measuring industrial parameter. The end result is something like a scatter plot.

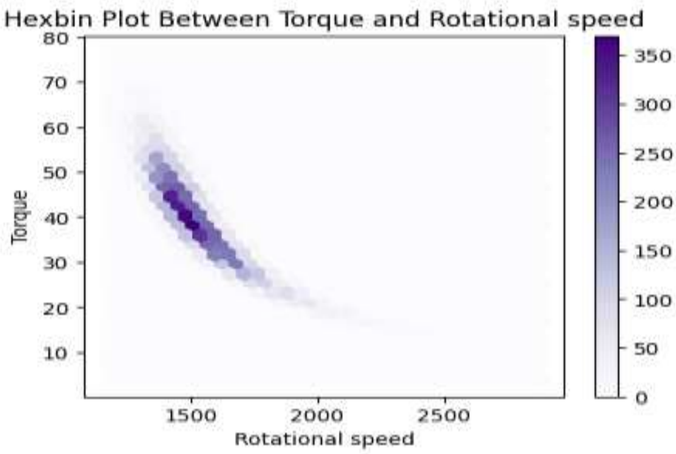

Figure 4: (a) Hexbian plot between Torque and Rotational speed

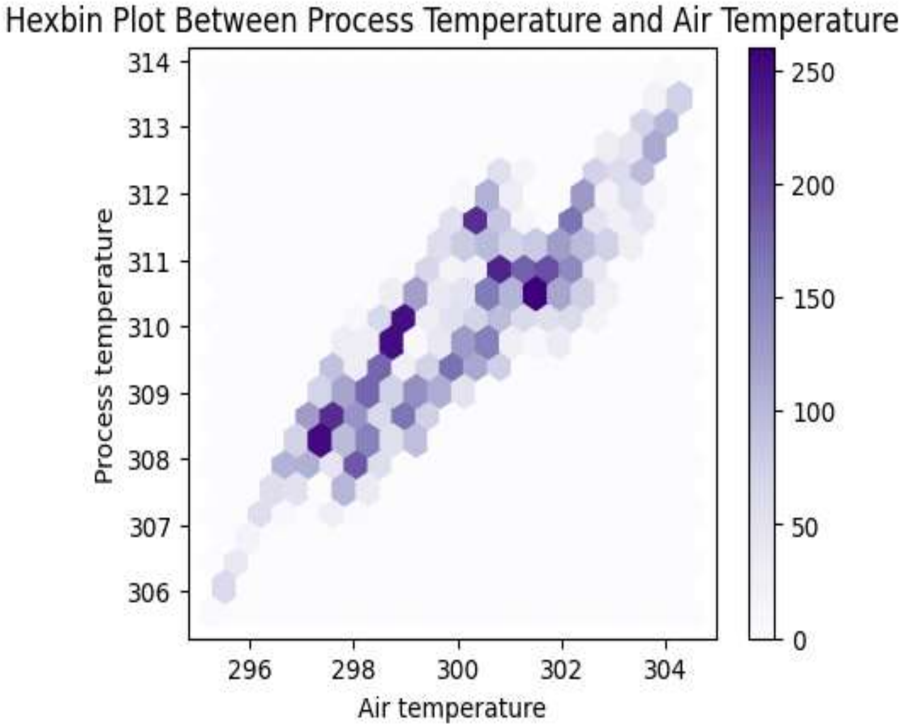

Figure No 4 (b) Hexbian plot between Process and Air temperature

3.4 **Industrial machine Failure**: Industrial machinery and vehicles have to work in challenging environments with heavy weights, high pressure, extreme temperatures, wetness, and a lot of dust. Their components have a much shorter lifespan and are more prone to failure due to the continuous exposure to such severe work environments. When industrial machinery malfunctions, it is called a machine failure. A common misconception is that this phrase only applies to total mechanical breakdown. It might also be connected to less severe issues with performance, like when an equipment item becomes less useful and effective. Thus, we might infer that a machine failure can be a sign of an unforeseen outage or performance problem. Figure No type of machine versus failure listed graphical form and Figure No shown the reason of machine failure.

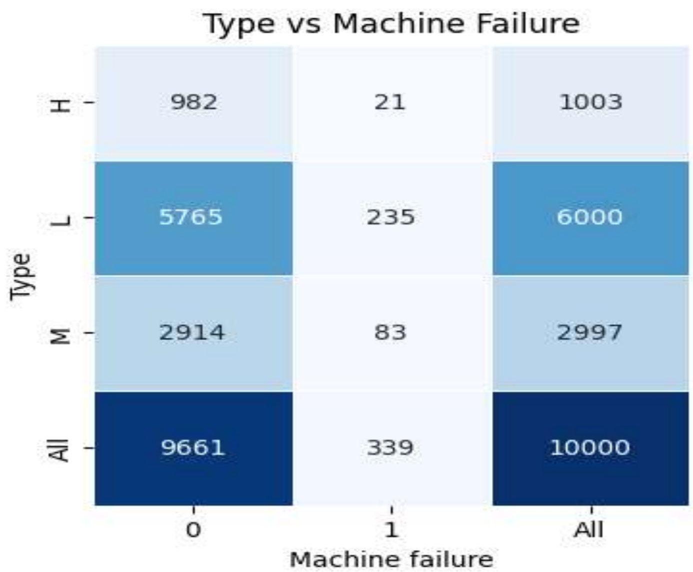

Figure 5: Type of machine versus machine failure

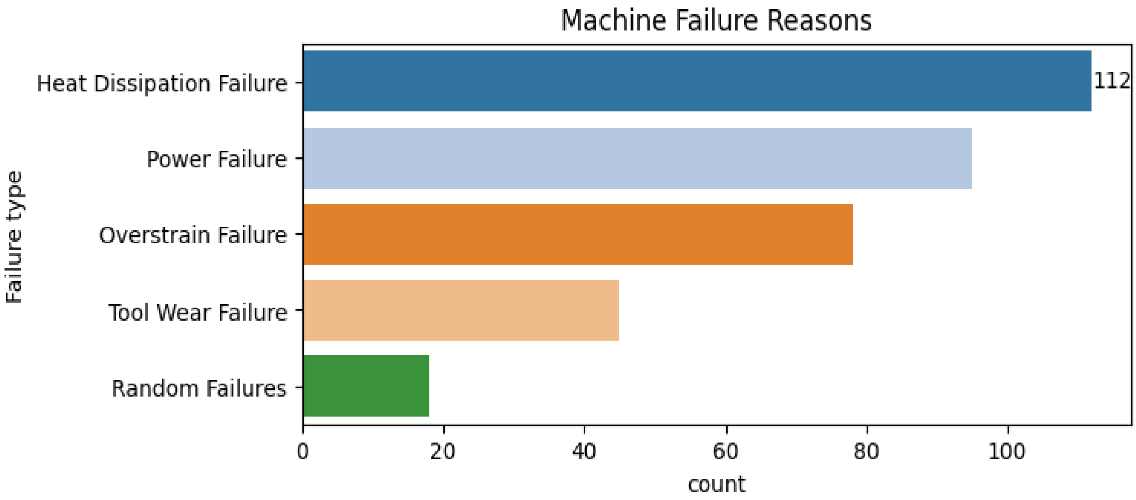

Figure 6: Listed Machine failure reasons

3.5 Step involved in predictive Maintenance:

A strong foundation must be in place before utilizing preprocessed data to train machine learning models. Regression, classification, clustering, and reinforcement learning are some pertinent methods for predictive maintenance. Evaluation and validation procedures would be utilized to guarantee the dependability and effectiveness of the models. Model performance and usefulness can be evaluated using cross-validation methods and performance metrics such as accuracy, precision, recall, and the F1-score.Align evaluation criteria with your key performance indicators (KPIs), such as minimizing downtime, extending equipment longevity, and optimizing maintenance expenses. Manufacturing businesses that prioritize measurements in accordance with overall goals can assess the efficacy of predictive maintenance programs and make sound decisions to improve operational efficiency.

This paper focuses on utilizing data from a manufacturing company's industrial devices to predict maintenance needs, thereby preventing breakdowns and saving costs. As companies expand, manual maintenance tracking becomes challenging. Thus, we propose an intelligent solution: leveraging sensor data to forecast when maintenance is required. The objective is to analyze sensor data to determine the optimal maintenance schedule for these devices. We will employ advanced techniques to achieve this efficiently. Key components of the paper include data collection from industrial robots equipped with sensors, preprocessing of raw sensor data to extract meaningful features, and the application of ML algorithms for predictive modeling. Supervised learning techniques such as Random Forest, Support Vector Machines (SVM), and Gradient Boosting Machines (GBM) will be explored to develop predictive models tailored to different types of failure modes. Figure No shown all step involved in this work

Evaluation criteria should align with the organization's Key Performance Indicators (KPIs), which may involve reducing maintenance costs, prolonging equipment lifespan, and minimizing downtime.

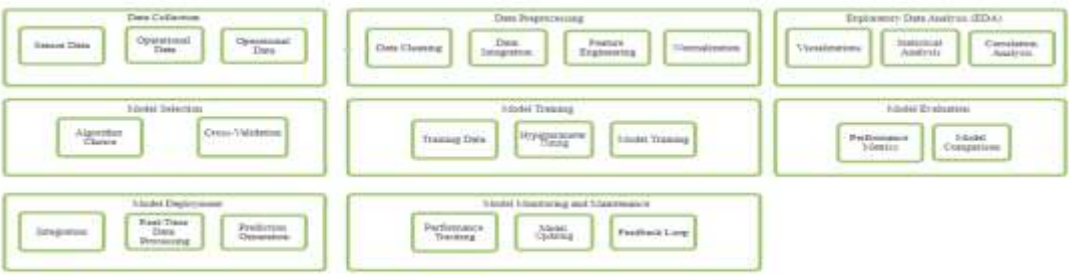

Figure 7: shown all step involved in predictive maintenance system

4. Results and Discussion:

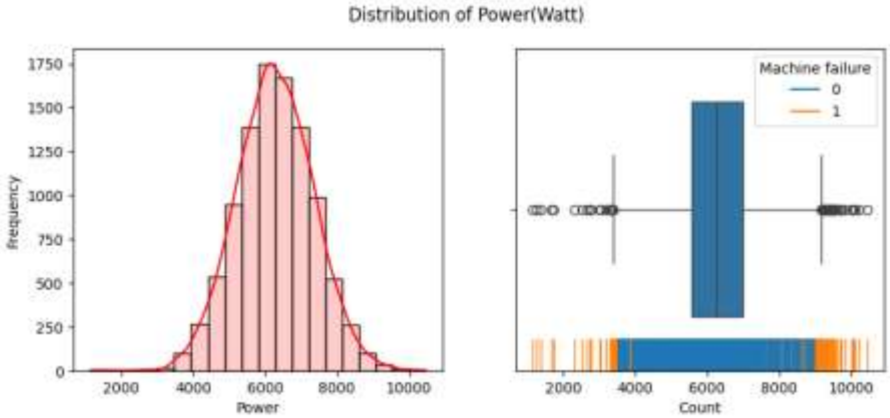

Figure: 8 Data distribution and box plot of Power

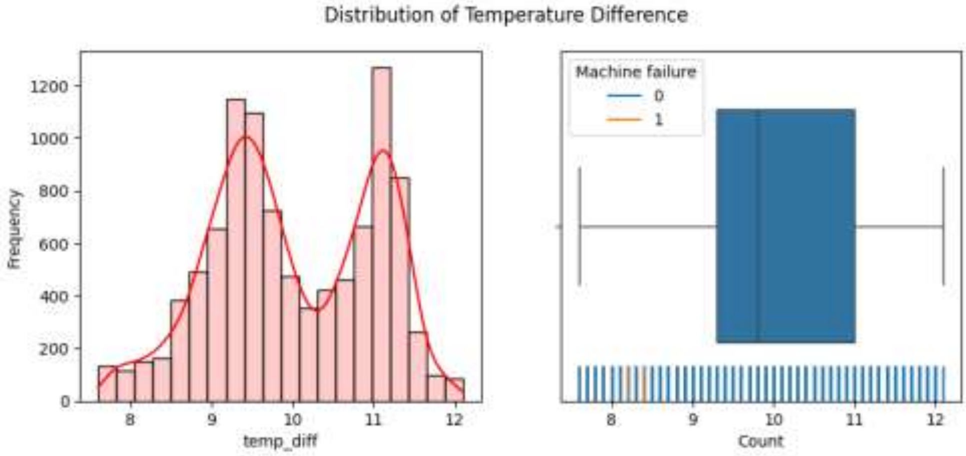

Figure: 9 data distribution and box plot of Temperature Difference plot

Model	AUC	Recall	Prec.	F1	Kappa	MCC	TT (Sec)
Gradient Boosting Classifier	0.9807	0.9692	0.5264	0.8461	0.6412	0.6321	0.6545
CatBoost Classifier	0.9789	0.9665	0.5228	0.7855	0.622	0.6118	0.628
Light Gradient Boosting Machine	0.9774	0.9575	0.5359	0.7266	0.6111	0.6	0.6102
Extreme Gradient Boosting	0.978	0.9523	0.5353	0.7523	0.6176	0.6068	0.62
Ada Boost Classifier	0.9749	0.9482	0.4636	0.7108	0.5534	0.5412	0.5581
Random Forest Classifier	0.9801	0.9467	0.523	0.8332	0.6302	0.621	0.6442
Extra Trees Classifier	0.975	0.9263	0.371	0.7888	0.4967	0.4858	0.5255
Naive Bayes	0.9711	0.8675	0.1641	0.8967	0.2712	0.2641	0.3667
Linear Discriminant Analysis	0.9671	0.8106	0.0337	0.65	0.0637	0.0615	0.1433
Logistic Regression	0.9666	0.806	0.0254	0.4667	0.0474	0.0452	0.1022
Decision Tree Classifier	0.9707	0.771	0.5569	0.5729	0.5586	0.5437	0.5469
K Neighbors Classifier	0.9769	0.7569	0.3712	0.872	0.5132	0.5038	0.5552

Quadratic Discriminant Analysis	0.5711	0.5282	0.4326	0.073	0.0576	0.0099	0.0122
Dummy Classifier	0.9661	0.5	0	0	0	0	0
SVM - Linear Kernel	0.9624	0	0.0043	0.1	0.0083	0.0044	0.0168

Table: 2 All parameter compressions of different model algorithms

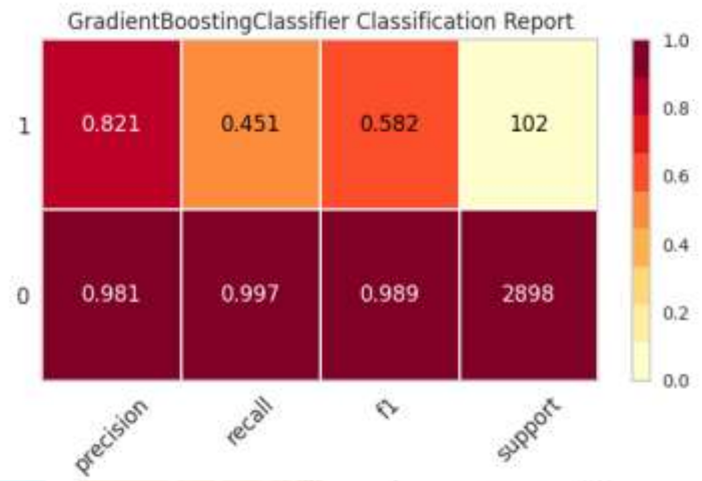

Figure: 10 Gradient Boosting Classifier Classification Report

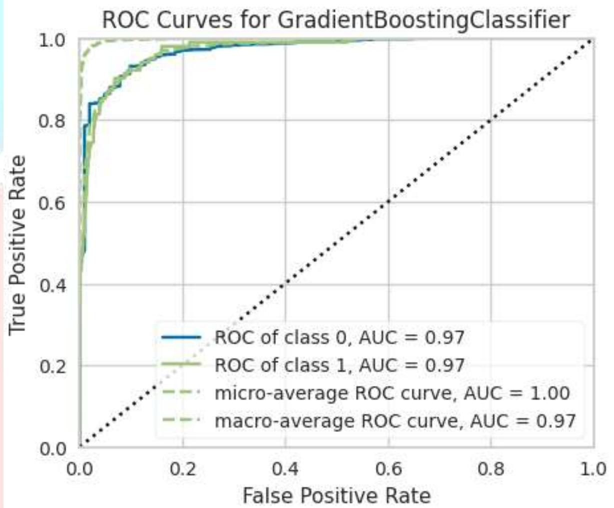

Figure: 11 ROC Curve for Gradient Boosting Classifier

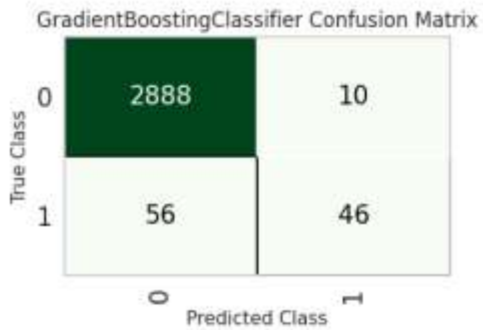

Fig: 12 Confusion Matrix for Gradient Boosting Classifier

5. CONCLUSION AND FUTURE SCOPE:

The model based on Gradient Boosting Classifier (GBC), CatBoost Classifier, Light Gradient Boosting Machine, Extreme Gradient Boosting, Ada Boost Classifier, Random Forest Classifier, Extra Trees Classifier, Naive Bayes, Linear Discriminant Analysis, Logistic Regression, Decision Tree Classifier, K Neighbors Classifier, Quadratic Discriminant Analysis, Dummy Classifier and SVM - Linear Kernel are trained with UCI Machine Learning repository, specifically the AI4I 2020 Predictive Maintenance dataset [16]. It has been found that GBC classifier achieving AUC is 0.9807, Recall 0.9692, Kappa 0.6412, MCC 0.6321 and TT 0.6545. It can be observed from Table: 02. The performance in predicting faults is best of the Gradient Boosting Classifier.

In this work, particular machine learning models or classifiers are applied to a single dataset. Subsequent studies should be investigated the utilization of numerous datasets using diverse classifiers. We can find the most dependable and robust predictive maintenance algorithms by contrasting how various models perform on various datasets. By taking this technique, the models will be more accurate and generalizable to a wider range of industrial situations and equipment kinds.

A limited features, including process temperature, rotational speed, torque, tool wear, and ambient temperature, are usually included in the predictive maintenance frameworks that are now in use. For more precise predictions, future developments must to take into account incorporating a wider variety of process characteristics. These characteristics could include electrical factors like surge, harmonics, voltage and current changes, and vibration level, humidity, pressure, oil quality, running hours, machine age, and maintenance history. Predictive models can offer a richer understanding of machine health by capturing a wider range of characteristics. This can result in more accurate maintenance scheduling and less downtime.

1 REFERENCES

[1] Archit, P., Kane., Ashutosh, S., Kore., Advait, N., Khandale., Sarish, S., Nigade., Pranjali, Joshi. (2022). Predictive Maintenance using Machine Learning. arXiv.org, doi: 10.48550/arXiv.2205.09402

[2] (2022). Predictive Maintenance Algorithm Based on Machine Learning for Industrial Asset. doi: 10.1109/codit55151.2022.9803983

[3] Angel, J., Alfaro-Nango., Elías, N., Escobar-Gómez., Eduardo, Chandomí-Castellanos., Sabino, Velázquez-Trujillo., Héctor, R., Hernández, De, León., L., M., Blanco-Gonzalez. (2022). Predictive Maintenance Algorithm Based on Machine Learning for Industrial Asset. doi: 10.1109/CoDIT55151.2022.9803983

[4] Anisha, Chazhoor., Y, Mounika., M., Vergin, Raja, Sarobin., M, V, Sanjana., R, Yasashvini. (2020). Predictive Maintenance using Machine Learning Based Classification Models. doi: 10.1088/1757-899X/954/1/012001

[5] (2022). Predictive Maintenance using Machine Learning. doi: 10.48550/arxiv.2205.09402

[6] Manish Kumar; Devendra P. Garg; "Neuro-fuzzy Control Applied to Multiple Cooperating Robots", IND. ROBOT, 2005. (IF: 3)

[7] Andrés Bustillo; Maritza Correa; "Using Artificial Intelligence to Predict Surface Roughness in Deep Drilling of Steel Components", JOURNAL OF INTELLIGENT MANUFACTURING, 2012. (IF: 3)

[8] T. Praveen kumar; M. Saimurugan; P. Krishnakumar; K. I. Ramachandran; "Fault Diagnosis of Automobile Gearbox Based on Machine Learning Techniques", PROCEDIA ENGINEERING, 2014. (IF: 3)

[9] Bjorn Kroll; David Schaffranek; Sebastian Schriegel; Oliver Niggemann; "System Modeling Based on Machine Learning for Anomaly Detection and Predictive Maintenance in Industrial Plants", PROCEEDINGS OF THE 2014 IEEE EMERGING TECHNOLOGY AND ..., 2014. (IF: 3)

[10] Andrea Coraddu; Luca Oneto; Aessandro Ghio; Stefano Savio; Davide Anguita; Massimo Figari; "Machine Learning Approaches for Improving Condition-based Maintenance of Naval Propulsion Plants", PROCEEDINGS OF THE INSTITUTION OF MECHANICAL ENGINEERS, ..., 2016. (IF: 4)

[11] Nan Tian; Matthew Matl; Jeffrey Mahler; Yu Xiang Zhou; Samantha Staszak; Christopher Correa; Steven Zheng; Qiang Li; Robert Zhang; Kenneth Y. Goldberg; "A Cloud Robot System Using The Dexterity Network and Berkeley Robotics and Automation As A Service (Brass)", 2017 IEEE INTERNATIONAL CONFERENCE ON ROBOTICS AND ..., 2017. (IF: 3)

[12] Bérenger Ossété Gombé; Gwenhael Goavec-Mérou; Karla Breschi; Hervé Guyennet; Jean-Michel Friedt; Violeta Felea; Kamal Medjaher; "A SAW Wireless Sensor Network Platform for Industrial Predictive Maintenance", JOURNAL OF INTELLIGENT MANUFACTURING, 2019. (IF: 3)

[13] Tianwen Zhu; Yongyi Ran; Xin Zhou; Yonggang Wen; "A Survey of Predictive Maintenance: Systems, Purposes and Approaches", ARXIV-EESS.SP, 2019. (IF: 4)

[14] P. Venegas; E. Ivorra; M. Ortega; G. Márquez; J. Martínez; I. Sáez de Ocáriz; "Development of Thermographic Module for Predictive Maintenance System of Industrial Equipment", 2020.

[15] Sulaiman Aburakhia; Tareq Tayeh; Ryan Myers; Abdallah Shami; "Similarity-Based Predictive Maintenance Framework for Rotating Machinery", ARXIV-EESS.SP, 2022.

[16] Andrea Torcianti and Stephan Matzka. Explainable artificial intelligence for predictive maintenance applications using a local surrogate model. In 2021 4th International Conference on Artificial Intelligence for Industries (AI4I), pages 86–88. IEEE, 2021.

[17] Harinakshi., A., Annie, lydia., Mahizharuvi, Poongundran., Syeda, Masarath., P.Vivek, Karthick., I., M., Zayats. (2022). EDA and its Impact in Dataset Discover Patterns in the Service Sector. doi: 10.1109/ICIRCA54612.2022.9985599

[18] (2023). Towards High-Performance Exploratory Data Analysis (EDA) Via Stable Equilibrium Point. doi: 10.48550/arxiv.2306.04425

[19] Victoria, Da, Poian., Bethany, Theiling., L., Clough., Brett, McKinney., Jonathan, Major., Jingyi, Chen. (2023). Exploratory data analysis (EDA) machine learning approaches for ocean world analog mass spectrometry. Frontiers in Astronomy and Space Sciences, 10 doi: 10.3389/fspas.2023.1134141