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Predicting machine failures using machine learning and deep learning algorithms

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ABSTRACT

Industry 4.0 emphasizes real-time data analysis for understanding and optimizing physical processes. This study leverages a Predictive Maintenance Dataset from the UCI repository to predict machine failures and categorize them. This study covers two objectives namely, to compare the performance of machine learning algorithms in classifying machine failures, and to assess the effectiveness of deep learning techniques for improved prediction accuracy. The study explores various machine learning algorithms and finds the XG Boost Classifier to be the most effective among them. Long Short-Term Memory (LSTM), a deep learning algorithm, demonstrates its superior accuracy in predicting machine failures compared to both traditional machine learning and Artificial Neural Networks (ANN). The novelty of this study is the application and comparison of machine learning and deep learning models to an unbalanced dataset. Findings of this study hold significant implications for industrial management and research. The study demonstrates the effectiveness of machine learning and deep learning algorithms in predictive maintenance, enabling proactive maintenance interventions and resource optimization.

1. Introduction

To align with Industry 4.0, traditional industrial automation approaches are evolving with the integration of new elements. The Internet of Things (IoT) and Cyber-Physical Systems (CPS) play crucial roles in enabling artificial intelligence and facilitating intelligent manufacturing, leading to the creation of innovative products and services [1]. Companies embracing this approach face increased competition in a dynamic market environment, where simply increasing production capacity does not guarantee success [2]. Despite various interpretations of industrial challenges, incorporating domain knowledge into understandable and explainable models remains challenging [3]. DSS, leveraging machine learning algorithms, aids in product design iterations and facilitates effective policymaking, potentially enabling quicker recovery from failures [4,5]. Furthermore, leveraging vast amounts of data, particularly in predicting machine failures and scheduling maintenance, allows industries to enhance performance and autonomously manage product requirements [6]. However, many manufacturing organizations struggle to embrace data-driven strategies due to various challenges, particularly during the data preprocessing stage [7]. As data generated within Industry 4.0 proliferate, machine learning algorithms play a vital role in extracting insights for improved understanding [8]. Nowadays ML can not only be used to diagnose problems, but can also be used to diagnose, prognosticate, and forecast problems [9,10].

In many instances, machines exhibit signs of deterioration and symptoms before they fail. Predictive maintenance (PdM) is a strategy used by engineers to anticipate failures before they occur, relying on sensor-based condition monitoring of machinery and equipment. However, implementing PdM requires substantial data and real-time monitoring, posing challenges such as latency, adaptability, and network bandwidth [11].

Implementing predictive maintenance at various stages of design offers several benefits but also presents challenges. Advantages include increased productivity, reduced system faults [12], decreased unplanned downtime, and improved resource efficiency [13]. Predictive maintenance also enhances maintenance intervention planning optimization [14]. However, managing data from multiple systems and sources within a facility is challenging, as is obtaining accurate data for predictive modelling [15,16].

Additionally, implementing machine learning models and artificial intelligence faces challenges such as collecting training data [17],

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managing dynamic environments [17], selecting suitable algorithms, and obtaining context-sensitive data, including working conditions [18,19,20]. Considering the data analytics challenges in predictive maintenance research domain, this study attempts to undertake analysis for an unbalance dataset of manufacturing machine available at UCI repository. Analysis of this study covers the following objectives:

a) Develop a data-driven model for predicting machine failure
b) Rank dataset features to improve model performance
c) Compare results from different machine learning algorithms
d) Optimize hyper parameters of deep learning algorithms
e) Compare results of the best machine learning model with artificial neural network (ANN) and long short-term memory (LSTM) models.

While numerous strategies exist to reduce losses from unnecessary maintenance tasks, there is a lack of comprehensive comparisons between them. This study addresses this gap by demonstrating how to handle unbalanced datasets and draw insights from analysis. Performance metrics such as AUC score, accuracy, recall, precision, and others are compared across various machine learning algorithms and deep learning models to evaluate outcomes.

The contents of this research are organized into six different sections. Section 2 details the in-depth literature review for understanding and analyzing the data analytics approached used in predictive maintenance domain. Section 3 discusses procedures to construct a machine learning model. In Section 4, this paper constructs the predictive model for the problem under consideration. Next, the findings about the machine learning models built during the study are presented in Section 5. The paper ends with Section 6, Conclusions and Future Work, which also offers a glimpse of potential managerial applications.

2. LITERATURE review

Maintenance can be broken down into two primary categories: reactive maintenance and proactive maintenance. These are the types of maintenance most performed in Industries. After a valued item has had a breakdown, the purpose of reactive maintenance is to return it to working order [21]. Through the utilization of preventative and predictive maintenance procedures, the purpose of proactive maintenance is to forestall the occurrence of expensive repairs and the early breakdown of assets. Corrective maintenance does not incur any upfront costs and does not need any prior preparation to be carried out [22]. In most cases, machines will experience some level of deterioration before finally breaking down. It is possible to monitor the trend of degradation to rectify any flaws that may exist before they cause any failure or the equipment to break down. Since machine maintenance is only carried out when it is necessary, this tactic results in greater levels of efficiency [22]. One such strategy that assists us in predicting failures before they take place is known as predictive maintenance (PdM). For this strategy to work, the asset in question needs to undergo condition monitoring, which employs sensor technologies to look for warning signs of deteriorating performance or impending breakdown. The PdM allows for the decision-making process to be examined from two different vantage points: the diagnosis and the prognosis. According to Jeong et al. [23], diagnosis is the process of determining the underlying cause of a problem, whereas prognosis is the process of estimating the likelihood that a failure will occur in the future [24]. Prognosis maintenance policy is further divided into statistical-based maintenance and condition-based maintenance. Industry 4.0 equipped digital model gives maintenance staff the ability to schedule repairs more effectively because it provides real-time equipment information.

It is evident that predictive maintenance is gaining more attention due to the recent advancements in data collection through Industry 4.0 technologies and data analysis capabilities using evolutionary algorithms, cloud technology, data analytics, machine learning and artificial intelligence. According to Ucar et al. [25] AI is the main component of PdM for next-step autonomy in machines, which can improve the autonomy and adaptability of machines in complex and dynamic working environments. It is comprehensible that predictive maintenance is getting additional consideration because of recent advancements in data accessibility and analytics capabilities brought on by expanding research into ML and AI algorithms.

Machine learning is frequently used by researchers to anticipate failure and improve output. Hesser and Markert [26] used an Artificial Neural Network (ANN) model embedded within a CNC-milling machine to monitor tool wear. Models like this one can be applied to older machinery that can be used in Industry 4.0, as well as for research purposes. Kamariotis et al. [27] found testing and validating AI-based PdM systems face a challenge due to the absence of standard evaluation metrics. This complicates the comparison of system performance and assessment of accuracy and reliability. Various evaluation metrics, including prediction accuracy, mean squared error, and precision and recall, have been suggested by researchers to address this issue. Sampaio et al. [28] created an ANN model based on vibration measurements for the training dataset. Additionally, they compare the outcomes of ANN to those of Random Forest and Support Vector Machine (SVM), two other ML techniques, and discover that ANN is superior. Binding et al. [29] created Logistic Regression, XG Boost, and Random Forest models to assess the machine’s operational status. By way of choice criteria, Random Forest and XG Boost execute far improved as compared to Logistic Regression, while all algorithms perform better than one another in terms of Receiver Operating Characteristic (ROC). It was developed by Falamarzi et al. [30] to track forecast data and measure variation.

SVM models predict curved segment gauge deviation better than ANN models do for straight segment gauge deviation. To recognize various rotary equipment scenarios, Biswal and Sabareesh [31] developed a Deep Neural Network (hereafter referred to as DNN) and Convolutional Neural Network (hereafter referred to as CNN). It can be used to monitor bearings in production lines and enhance the monitoring of online conditions in coastal turbines for wind energy. Data mining can be used to predict system behaviour based on historical data. A model-based approach that heavily relies on analytical models to illustrate how the system operates has a few benefits. In fields with an abundance of data, like industrial maintenance, machine learning may be used [32]. Actual results, answers based on cloud-based, and new algorithms are all becoming more popular.

Quiroz et al. [33] applied the Random Forest technique for fault identification and validity and reliability analysis with turned 98 % diagnostic accuracy rate. Yan and Zhou [34] use TF-IDF (Term Frequency - Inverse Document Frequency) and RF (Radio Frequency) data from aircraft speed and torque sensors to create ML models for defect prediction. After extracting the features with TF-IDF from the unprocessed data after the earlier flights, Random Forest had an accurate optimistic degree of 66.67 percent and a percentage of false positives of 0.13 percent. To predict wear and failures, Lee et al. [35] observed the spindle motor and cutting machine using data-driven machine learning modelling. It has been demonstrated that models using SVM and neural networks with artificial intelligence can forecast system health and longevity with high accuracy.

According to Palangi et al. [36], recurrent neural network (RNN) and long short-term memory networks (LSTM) algorithms perform well with data that is sequential, time-series data with dependencies that last a long time, and information from IoT flow sensors. LSTM and Naive Bayes models combined, according to the study, may effectively identify trends and produce forecasts. The Naive Bayes anomaly detector was created by the LSTM model. Learning through deep learning with Cox proportional hazard (CoxPHDL) was developed in a research study to address the common problems of data flexibility and filtering that occur when functional maintenance information is analyzed [37]. The main goal was to develop an integrated solution based on dependability analysis and deep learning. In Gensler et al. [38] IoT application that combines solar panel prediction, the Deep Belief Network (DBN) strategy performed well on time series data in addition to LSTM. Carvalho et al. [39] claim that because each recommended ML technique works with a different piece of equipment, comparisons are more challenging.

A significant portion of PdM's now revolves around planning maintenance events. Alimian et al. [40] created a framework for cross-organizational integration to assess the improvement of a single activity and the coordination of numerous maintenance jobs for predictive maintenance decision-making. Even though no algorithm can handle all the scenarios that are currently present in a company, Dalzochio et al. [41] still believe there is room for improvement and a need to apply theoretical learning in actual industrial settings. Zhai et al. [42] used unsupervised learning to circumvent the dearth of tagged failure data, which was one of the major barriers to the use of PdM in the industry. M-IPS the health prognostications model, which stipulates a quantitative evaluation of deterioration for a particular manufacturing system, enables PdM-IPS. Grating the output with virtual reality, Van Oudenhoven et al. [43] developed a PdM work system model which provides a transition between PdM implementation strategies on human factors and includes a glimpse of Industry 5.0 vision in PdM through this proposed model.

Oliosi et al. [44] explored various statistical and probabilistic modeling approaches, including HMMs, BNs, GMMs, XGBoost, DBSC, PCA, and K-means, for PdM tasks. Additionally, they introduced DNN models like LSTM and autoencoders. By analyzing data from multiple sensors, they identified deterioration events and predicted potential future failures based on interdependencies. Shahin et al. [45] utilized machine learning, deep learning, and deep hybrid learning techniques to detect machine failures in a synthetic predictive maintenance dataset, suggesting these algorithms can optimize maintenance processes and reduce reliability risks. Junjie et al. [46] created a machine learning model to predict Diabetic Nephropathy (DN) diagnosis using various techniques. The Random Forest model demonstrated the best predictive performance, enabling early diagnosis and screening of DN, with a ROC curve area under the curve of 0.912. Bezerra et al. [47] highlighted the significance of managing large amounts of data in Industry 4.0, using a few models such as Principal Component Analysis and Random Forest techniques to identify machine failure, enhancing production efficiency and minimizing disturbance. Derogar et al. [48] created a design model that predicts reinforced concrete slab punching shear using artificial intelligence. The model, based on 650 testing, predicted punched shear strength, and streamlined design. The study shows that AI can improve forecast accuracy and provide structural engineering insights. It needs more validation and development to work in different structural configurations and environments.

The summary of the systematic review of the literature is as follows:

- The researchers have put effort into determining the system's RUL, but they are yet to build a system that gives early warnings to help with better maintenance planning.
- Even though numerous maintenance strategies and methods have been developed, it has been found that there have not been many comparisons between them.
- Implementing the theoretical philosophies that have been developed in research need an additional assessment of their usefulness based on metrics, for instance, the amount of money and time saved on maintenance tasks.
- Scientific community have also paid a lot of attention to the use of machine learning models in PdM. In this way, it has been found that industries use many different models, each of which is suggested by a different person and put into action by a different group. Nevertheless, the outcomes of the assessment of the exhaustive work revealed that there is no algorithm that can handle all the possible situations that could happen in a business.

It was claimed that significant research on predicting maintenance requirements had been conducted in recent years. Early prediction plays a crucial part in the transition to Industry 4.0, which will ultimately bring in a new way of working. It is not possible for a single maintenance approach to be the most cost-effective method for all the components and machines used in an enterprise. This study attempts to address certain gaps present in literature and examines a secondary unbalanced dataset and applied various machine learning and deep learning algorithms to compare the findings to suggest outcomes that may applicable in practical setting.

3. DATA analysis and research methods

This study develops a data-driven model for predicting machine failure and improves the scheduling of asset maintenance. The advantages of implementing a predictive maintenance strategy for the business are discussed in previous sections. The most crucial factor in creating a predictive model is having correct data. What data should be gathered using the various condition-based monitoring techniques is up to the modeler. The data can be obtained by the modeler either through their own data collection efforts or using external data sources like PHM (Prognostics and Health Management) or census records. Normally, projects applying regression and classification machine learning models cannot employ unprocessed data that has not been treated in any way because of following facts:

- The only type of data that the machine algorithms for learning may use is data that is numerical in nature.
- Some neural network algorithms are only operational when the input data meets certain requirements.
- The data may need to be adjusted to eliminate noise from statistical analysis and inaccuracies.
- A variety of techniques can be used to extract complicated nonlinear connections from the available information.

Consequently, pre-processing is necessary before using the raw facts for training and testing AI models. In the framework of a predictive modelling venture, this step is referred to as "data preparation," although it can also be referred to as "data wrangling," "data cleaning," "data pre-processing," and "feature engineering." [49]. In any case, organizing and cleaning the data is the goal of this phase that will be used in the subsequent stages. It's possible that some of these titles would work better as subtasks within the larger data research process.

"Data preparation" is the process of transforming unprocessed information to a format more suitable for modelling [50]. This is extremely dependent on the data, the objectives of the project, and the methods that will be utilized in the process of modelling this dataset. However, there are several tasks that can be employed or investigated throughout the data collection stage of a project related to machine learning that are thought of as conventional or common. This study uses the same dataset as mentioned in the study of Kaushik and Yadav [8]. However, this study has done more theoretical work and applied more numbers of machine learning algorithms and deep learning models to get more insights from the output models.

General Information about the Dataset

- The generated dataset has been suggested and provided as a replication of actual anticipatory maintenance information discovered in a manufacturing environment [8,51]. 10,000 observations are recorded as rows and six traits are grouped as divisions in the dataset.
- The dataset contains 10,000 points of data, that are listed as rows and contain the 14 attributes mentioned below as columns:
- A machine's UID, which ranges from 1 to 10,000, is its unique identification.
- Product ID: Low product quality variations are represented by the letters L, M, or H (which account for fifty percent of all goods; 30

percent of all items as medium quality, and 20 percent of all items as high, respectively).

- The air temperature was calculated through a nonlinear process and then normalized to a value of about 300 K, with a standard deviation of two K.
- Process temperature [K]: By increasing the air temperature by 10 K, the process temperature [K] was created using a one K standard deviation nonlinear process.
- A 2860 W power source with a layer of normally distributed noise on top is used to calculate rotational speed (rpm).
- There is a possibility that the torque [Nm] value will be negative, but since the values have a mean of 40 Nm and a standard deviation of 10, they are normally distributed and don't contain any negative values.
- Tool wear [min]: The standard variants H, M, and L each add 5/3/2 min to the implemented device's wear time during the operation.
- If any of the error criteria are correct, this label shows if the machine has failed at this data point. Tool Wear Failure (TWF), Heat Dissipation Failure (HDF), Power Failure (PWF), Overstrain Failure (OSF), and Random Failures (RNF) are five different types of failures.

Fig. 1 expresses the flowchart for data analysis used in this study. It starts with data preprocessing and is followed by Exploratory Data Analysis (EDA). Data Preprocessing is an iterative process for the transformation of the raw data into understandable and useable forms and should be done before performing EDA to address inconsistencies, if any. It majorly includes data cleaning like checking missing values, noisy data, and other inconsistencies. EDA is a technique used to gain insights from data. Using a variety of statistical charts and other visualization techniques, data scientists and analysts investigate a wide range of hidden patterns, relationships, and anomalies in the data. In EDA, there isn't a standardized set of techniques that are used. It's critical to remember that the EDA is an approach to how the data is evaluated rather than a set of predetermined procedures. It is intended to gain a broad understanding of the information provided without making any presumptions about what the data means. Instead of deciding whether a particular hypothesis about the data is true, an effort will be made to understand what the data is and what it might mean before investigation of it begins.

In order to perform exploratory data analysis using Python as the programming language, Python libraries like NumPy, Pandas, and Seaborn are necessary. The two libraries' Pandas and Seaborn are used in the visualization process.

1. Shape of data: (10,000, 14)
2. Absent values and the type of statistics in columns: Air temperature, process temperature, and torque have the data type "float64," while the rest of the columns have the data type "int64." The data type for the type of machine is "object." Additionally, the dataset contains no missing value.
3. Discrete variables count: The target variable is the only other discrete variable that counts. The type of machine is the discrete variable in the dataset. Fig. 2 shows the machine counts for the various types of machines.
4. Features that are continuous: The dataset contains five continuous features. These characteristics include "tool wear," torque, rotating speed, "air temperature," and "process temperature."
5. Every other feature, besides "Torque," is not randomly distributed.
6. Outliers: All other features are devoid of outliers, apart from "rotational speed" and "torque." Fig. 3 illustrates the two features' outliers, which are those that fall outside of the specified lower and upper limits.
7. Fig. 4 depicts the count plot for the training dataset's target variable, "Machine failure." In the machine failure count plot, the number "1″ indicates how many times the machine fails, while the number "0″ indicates how many times it does not fail.

In some datasets, the target class has an uneven distribution of observations, with one class label having many observations and the other not. "Imbalanced data" refers to this. It is also possible to refer to data collection as "imbalanced" if the distribution of observations for the target class varies significantly. Fig. 4 shows that compared to the total number of machine failures, there are much fewer machine failures. Therefore, it can be said that the dataset is inherently unbalanced. Techniques for sampling are recommended to deal with the issue posed by datasets that are unbalanced.

Machine learning techniques either fail when applied to classification data with an uneven distribution of classes or produce results that are overly optimistic. This is because many machine learning algorithms are made to function best when used with classification data, which comprises the same number of instances for a piece of class. In situations where this is not the case, algorithms can learn that a small number of samples are insignificant and can be ignored to achieve high performance.

The data sampling methodology contains a collection of techniques that modify a training dataset to better balance or balance the classification algorithm [8]. Once the dataset has been rebalanced,

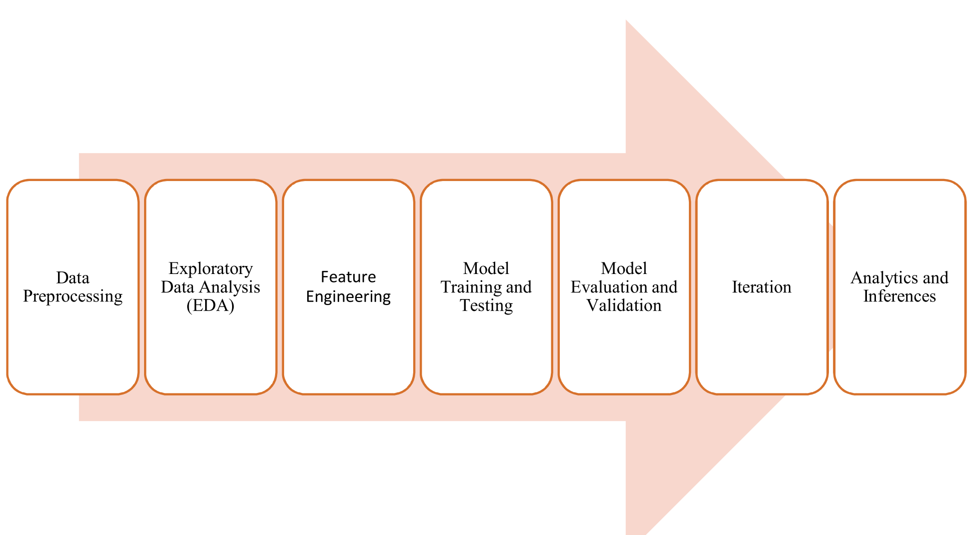

Fig. 1. Flowchart for the data analysis.

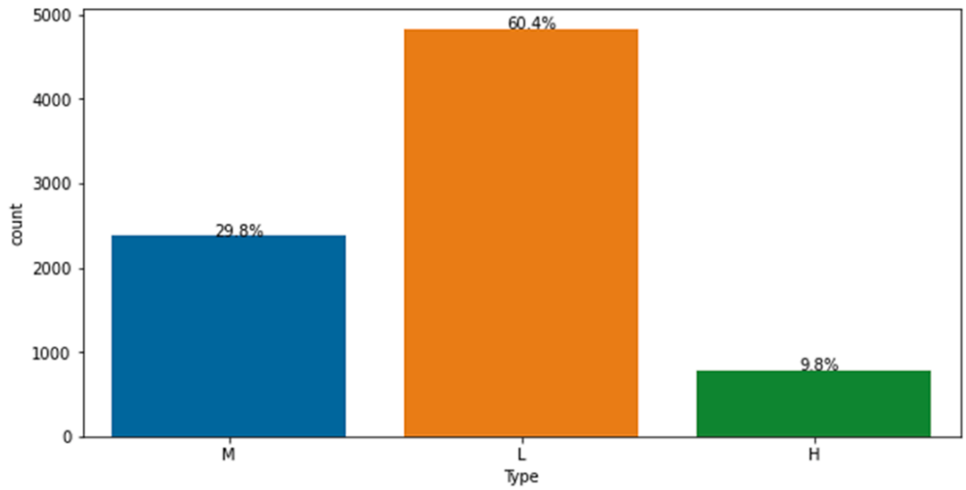

Fig. 2. Count-plot of the different types of machines.

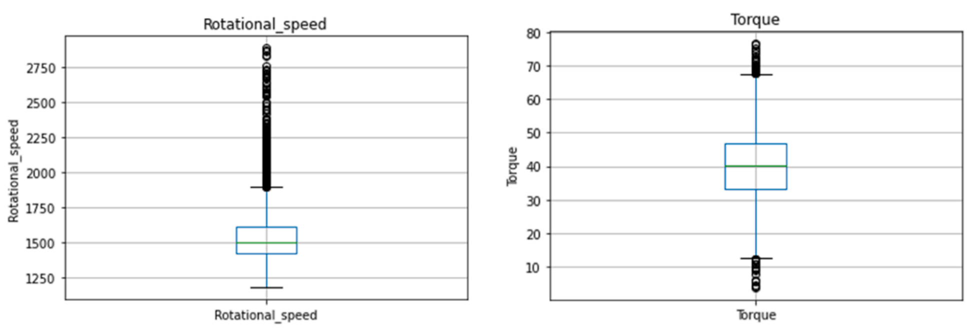

Fig. 3. Outliers present in rotational speed and torque.

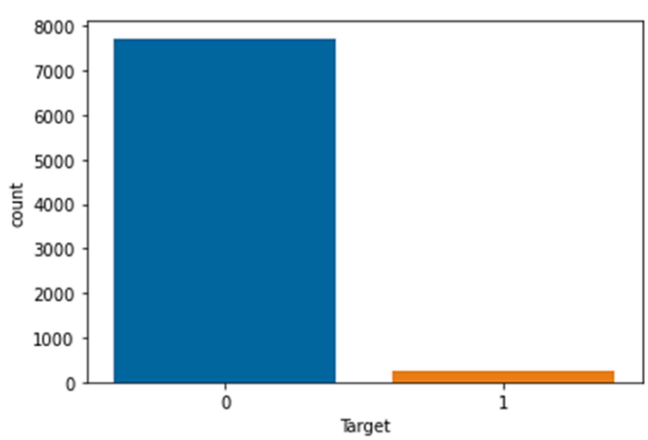

Fig. 4. Count plot of the target variable.

conventional machine learning methods can be trained directly on the modified version of the dataset with no additional modifications required. This enables the use of a data preparation technique to resolve the issue of imbalanced classification, even with the same amount of presence of extremely unbalanced class distributions.

Up Sampling, Down Sampling, and SMOTE are the three sampling methods used for this dataset. From literature, it was determined that the SMOTE technique is superior to the other two sampling methods. When algorithm names are bandied about, it is simple to get confused given that there are simply too many different machine learning procedures around and it is assumed that one knows what they are and where they belong. There are two ways of considering and classifying algorithms that can be encountered in the field.

- The foremost is a classification of algorithms according to their learning mechanisms.
- The subsequent step involves categorizing algorithms according to their shape or application. (Similar to group creatures with similar characteristics).

Machine learning algorithms come in four different flavors: Unsupervised, reinforcement, semi-supervised, and supervised learning.

1. Unsupervised Learning: The machine learning algorithm looks for patterns in the data in this phase. There is no available solution key or human operator to provide instruction. On the contrary, a machine analyses the information to find connections and linkages between the different variables.
2. Reinforcement learning is primarily concerned with structured learning processes, wherein a predetermined list of acts, variables, and final outcomes are provided for use with a machine learning algorithm. After the rules have been defined, the machine learning algorithm will attempt to explore a variety of alternatives and opportunities while continuously monitoring and evaluating the outcomes to identify the most effective solution.
3. Semi-supervised learning uses simultaneously identified or unidentified information, just like supervised learning. Data that has been given significant tags so that an algorithm can comprehend it is referred to as labeled data. On the other hand, unlabeled data lacks these labels. This allows machine learning algorithms to discover how to label data that was previously unlabeled.

4. In supervised learning, the computer gains knowledge by observing its human trainers. It could be a classification task (for discrete target variables) or a regression task (for continuous target variables), depending on the characteristics of the target variable. The operator provides the machine learning algorithm with access to a well-known dataset containing favorite inputs, and the algorithm's job is to figure out how to access those inputs and outputs using a technique that it discovers on its own. While only the operator knows the correct problem solutions, the algorithm may recognize patterns in the data, acquire knowledge through observations, and generate hypotheses. Due to the nature of the dataset, only supervised learning was used to develop the model for this study.

A brief discussion on deep learning and hyperparameters tuning is also added for reading purposes.

3.1. Deep learning

Artificial neural systems and representational learning are both used in the machine learning process known as deep learning. It is also known as "deep structured learning." Learning can occur with or without direct supervision. It is a set ML technique that abstracts complex-level characteristics from initial data using multiple layers. The lower levels, for instance, are used in the processing of images, may be able to identify boundaries, whereas higher layers may be able to identify human-important objects, such as letters, numbers, and faces. Each deep learning level gains knowledge about transforming its input data into a representation that is slightly more abstract and composed of other elements. It can achieve different levels of abstraction, for instance, by varying the number of layers and the dimension of each layer. The LSTM technique has been used exclusively to train the model in this work.

3.2. Hyper-Parameter tuning

Data scientists and researchers believe that determining the appropriate values for the hyperparameters is the most challenging aspect of developing machine learning and artificial intelligence models. When developing a model for the first time, it can be challenging to make guesses about which parameters to use. Always experiment with the hyperparameters to determine which combination of values yields the best results. This method is ineffective, however, when applied to high-dimensional data, as the training time increases when the quantity of iterations grows. Grid Search and Random Search are two of the most common and straightforward training techniques used for tuning hyperparameters.

Grid search is a technique that can be used to determine the optimal hyperparameter combination for a given model. Since hyperparameters are not considered model parameters, it is impossible to choose the best setup based on the training data. Model parameters are learned through the process of optimizing a loss function during training by employing gradient descent or a similar method. Using this method of tuning, a model is built for every possible combination of hyperparameters, and then each model is analyzed [52]. The objective of random search is to identify the optimal solution for a constructed model by randomly combining the hyperparameters. It is comparable to grid search but has been shown to yield superior results. When it comes to computers, a problem with random search is that it can produce a wide variety of results [53].

This section represented the findings of the exploratory data analysis carried out on the dataset. In addition, it is determined whether the dataset contains any null values, and then the datatypes of each of the dataset's features are validated. Following this analysis, it was determined whether the dataset contains any characteristics that can be classified as outliers. Elimination of outliers was accomplished by calculating the Interquartile range and then replacing data points that exceeded the upper or lower bounds with new ones. In addition, the count plot of the target variable was constructed, and it was determined that when compared to the number of instances of the majority class, the minority class is extremely underrepresented. It indicates many unbalanced fundamentals in the dataset. Before resampling the dataset, sampling techniques must be employed. In addition, this section explains how various ML-based methods are applied to test the model. The algorithm is trained specifically so that it can be evaluated based on its performance on previously unseen data.

4. Development of model

In the previous section, it was revealed that the dataset used in this study contains a significant amount of imbalance and that a variety of sampling strategies have been implemented to address the issues associated with the dataset. Guo et al. [54] state that SMOTE is the most effective sampling technique used in this instance to correct the unbalanced data set. After using the SMOTE, a new set of data was produced; this data will serve as the basis for the further stages of our algorithm training.

The following are the steps taken during data preparation and feature engineering:

Step 1: Divide database into training and testing datasets: The ratio used to split the dataset is 4:1. Therefore, the training dataset has a size of (8000, 13) and the testing dataset has a size of (2000, 13). Moving forward, only the training dataset can be applied to develop the various ML algorithms.

Step 2: Normalization: Since each attribute has its own distinct range of possible values, the min-max scaling method is used to calculate the normalization value. To calculate the normalization, the following formula is applied:

$$X_n = \frac{X - X_{minimum}}{X_{maximum} - X_{minimum}}$$

Where,

- X_n = Value of Normalization
- $X_{maximum}$ = Maximum value of a feature
- $X_{minimum}$ = Minimum value of a feature

Step 3: Feature Selection: Once the data has been subjected to normalization, the next step is to select the features. As shown in Fig. 5, a heatmap of the training data is plotted to accomplish this. This will allow us to examine the degree to which the variables are correlated with one another.

Looking at the heatmap, it is evident that 'Air temperature' and 'Process temperature' have a strong positive correlation with one another. In addition, "Torque" and "Rotational speed" have a significant inverse relationship. Consequently, one of the characteristics from each set is eliminated. In addition, the five distinct breakdown types that have occurred will be eliminated, as they are ultimately responsible for the failure of the machine, as indicated in the column titled "Machine failure." In addition, the 'UDI' feature is removed from the dataset because it does not distinguish between any of the machines and is not crucial for training the algorithms. Therefore, the total size of the training dataset will be (8000, 5) for future research purposes.

Step 4: Examine the multicollinearity of the characteristics: It refers to the existence of a strong correlation between two or more explanatory factors. To confirm this, the Variation Inflation Factor (VIF) is calculated for each of the independent variables. The Variance Inflation Factor, also known as VIF, is a tool for identifying instances

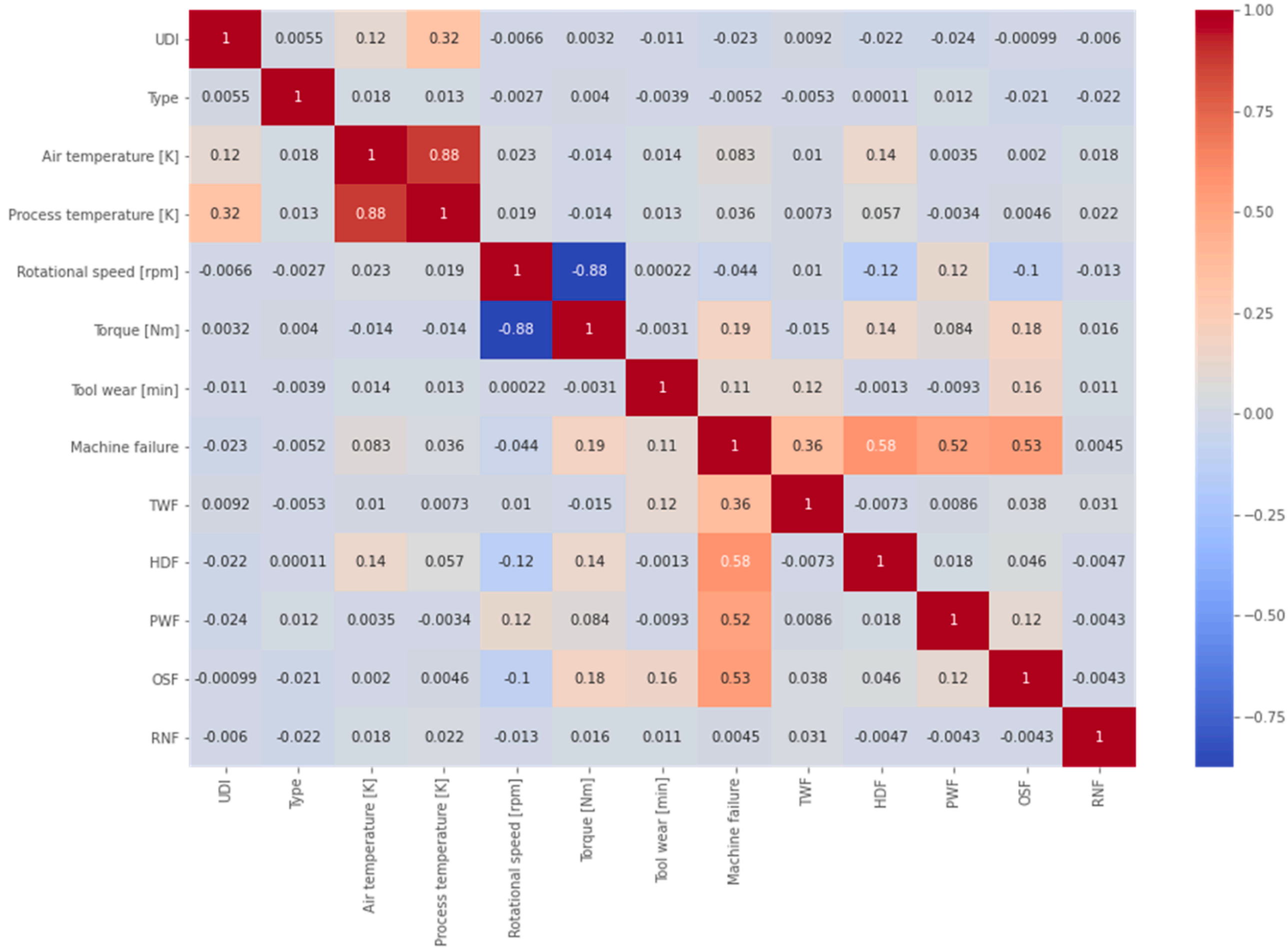

Fig. 5. Correlation heatmap of the attributes.

of multicollinearity. The variance inflation factors (VIF) show how inflated the predicted regression coefficients' variance is compared to what it would be in the absence of a linear relationship between the explanatory variables. Generally, multicollinearity could be present and further research is necessary if a value of VIF is above 4 or if the tolerance level is below 0.25. When the tolerance is smaller than 0.1 or the numerical value (VIF), surpasses 10, there is significant multicollinearity that needs to be corrected. Fig. 6 shows the VIF number for each independent variable.

Due to the absence of multicollinearity in the independent variables, principal component analysis will not be conducted. Instead, the

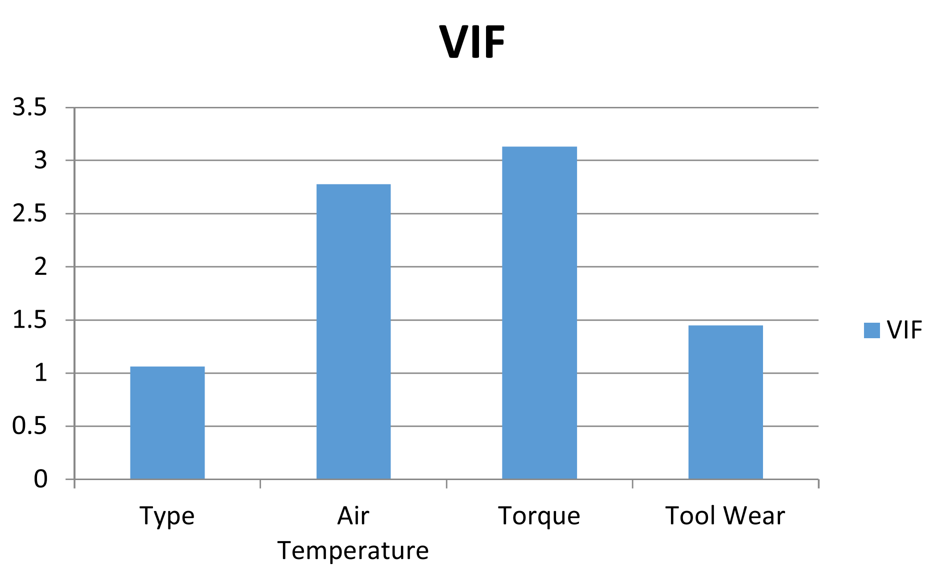

Fig. 6. VIF number of independent variables.

subsequent phases will involve the modelling of different machine-learning techniques.

Step 5: Data Analysis using machine Learning Algorithms: A technique of supervised machine learning called classification employs the training of datasets to categorize the output into some classes. In the classification process, the ML model first picks up knowledge from a dataset or set of provided observations before classifying new data into a variety of categories or groups. Examples include "Yes" and "No", "0″ and "1″, "Spam" and "Not Spam", "Cat or Dog", etc. Classes are referred to by the term's categories, objectives, and labels. The categorical nature of the objective variable in this study's corresponding dataset indicates that the machine will either fail or succeed. Because there are only two different answers that might be correct, the classification issue is referred to as a Binary Classifier. The "Sklearn" Python library will be used to invoke all the metrics and algorithms. In addition, the performance measurement of executing the code for various algorithms will be compared and interpreted. Following this, the AUC score will be utilized to select the optimal model. The optimal model is then selected by adjusting the hyperparameters.

This section provided an in-depth discussion of the meticulous step-by-step method involved in the development of predictive maintenance models.

5. Results and discussion

The primary goal of the classification model is to predict whether the machine will break down within the allotted time. It is possible to forecast the residual usable life of the machine by utilizing the regression model; nevertheless, the value of the prediction shifts with the deterioration of the asset. They can go down significantly or up significantly. However, if many assets need to be tracked, it will not be possible to do so on an individual basis for each asset. As a result, a classification model has been developed that provides certain early warnings with precision and within a predetermined time frame. The performance metrics of several machine learning models are displayed in Table 1.

After obtaining the results for the various ML models, the hyperparameters of these models will be modified to attain a greater degree of precision and accuracy. As the tuning of hyperparameters was discussed in the previous section and it is known that the "Random Search CV" method is superior to the other commonly employed parameter optimization techniques, we can move on to the next step. The effects of hyperparameter tuning and optimization on the performance metrics of multiple machine learning models are displayed in Table 2.

Based on the data presented in Table 2, it can be concluded that the XG Boost classifier is the most effective of all the algorithms used in the modeling process. It is primarily because it has the highest AUC score and the highest accuracy among all the models. The ROC curve for an XG Boost model illustrates its ability to discriminate between positive and negative classes across various threshold values, serving as a pivotal tool for evaluating its classification performance. The ROC-curve corresponding to the XG Boost model is depicted in Fig. 7, and the confusion matrix for the XG Boost model applied to the validation dataset is shown in Table 3.

Table 1
Evaluation metrics of a classification model.

Model	Accuracy	Precision	Recall	F1-Score	AUC-Score
Logistic Regression	0.6453	0.4419	0.9625	0.6057	0.5331
KNN	0.7168	0.6709	0.6831	0.6769	0.7007
SVC	0.7293	0.7809	0.8027	0.7916	0.7138
Decision Tree (Gini)	0.6998	0.7713	0.7668	0.769	0.7237
Decision Tree (Entropy)	0.6998	0.7713	0.7668	0.769	0.7237
Bagging Classifier	0.8239	0.8859	0.5799	0.701	0.7842
Adaptive Boosting	0.7786	0.8551	0.8657	0.8604	0.7814
Gradient Boosting	0.7671	0.852	0.8557	0.8538	0.7817
Random Forest Classifier	0.7964	0.9054	0.9234	0.9143	0.8202
XG Boost Classifier	0.848	0.946	0.9466	0.9463	0.8544

Table 2
Evaluation metrics of classification model after hyperparameters tuning optimization.

Model	Accuracy	Precision	Recall	F1-Score	AUC-Score
Logistic Regression	0.6692	0.4693	0.9976	0.6383	0.5532
KNN	0.7407	0.6983	0.7182	0.7081	0.7208
SVC	0.7532	0.8083	0.8378	0.8228	0.7339
Decision Tree (Gini)	0.7237	0.7987	0.8019	0.8003	0.7438
Decision Tree (Entropy)	0.7237	0.7987	0.8019	0.8003	0.7438
Bagging Classifier	0.8478	0.9133	0.615	0.7353	0.8043
Adaptive Boosting	0.8025	0.8825	0.9008	0.8916	0.8015
Gradient Boosting	0.7910	0.8794	0.8908	0.8850	0.8018
Random Forest Categorization	0.8203	0.9328	0.9585	0.9455	0.8403
XG Boost Classifier	0.8719	0.9734	0.9817	0.97756	0.8745

Following the investigation of the machine learning models, the ANN and LSTM models of AI are trained. Tables 4-5 detail the 'Accuracy' of the LSTM and ANN models respectively.

This section examined the effectiveness of several machine learning methods. The best result for this unbalanced dataset is provided by XG Boost Classifier. In addition, the performance measurement of ANN and LSTM were analyzed and presented in Table 4-5. Results also show that increasing layers in ANN model could not help in improving accuracy and precision with respect to LSTM model.

6. Conclusions and future work

Predictive maintenance appears as an essential method for accomplishing the goals of Industrial Revolution 4.0 in the worldwide industrial sector. The classification models created in this study greatly improve maintenance planning by providing early indications of asset breakdown. Critical tracking of multiple assets at the same time is now possible using these models. However, implementing predictive maintenance presents obstacles, such as addressing dataset imbalance and optimizing hyperparameters for greater performance.

The growing applications of machine learning in all domains of science and technology attempts better prediction through applying well-known models and comparing their performances. Though the models applied in this study are well known machine learning and deep learning models, the focus of this work was on trying to explore the models that ensure accurate prediction with an imbalance dataset. The researchers can apply the same set of algorithms for predicting machine failure in any type of industrial setting. Additionally, this study has developed a data-driven model for predicting machine failure and compared results from different machine learning algorithms. Practitioners and policy-makers can take note that these algorithms require availability of large amount of error-free data to predict failure accurately. Many industries do not invest in data collection through IOT and sensor devices and face frequent breakdowns and interruption in their production lines. Analytics of collected manufacturing and operations data can help in saving huge amounts of time and money of manufacturing and service industries.

Additionally, while a relevant problem, this paper does not focus on exploring why some algorithms and techniques are individually better than others. Still, the techniques considered represent the most used approaches, and the algorithms used for the meta-learner also provide a decent insight into the performance that can be expected.

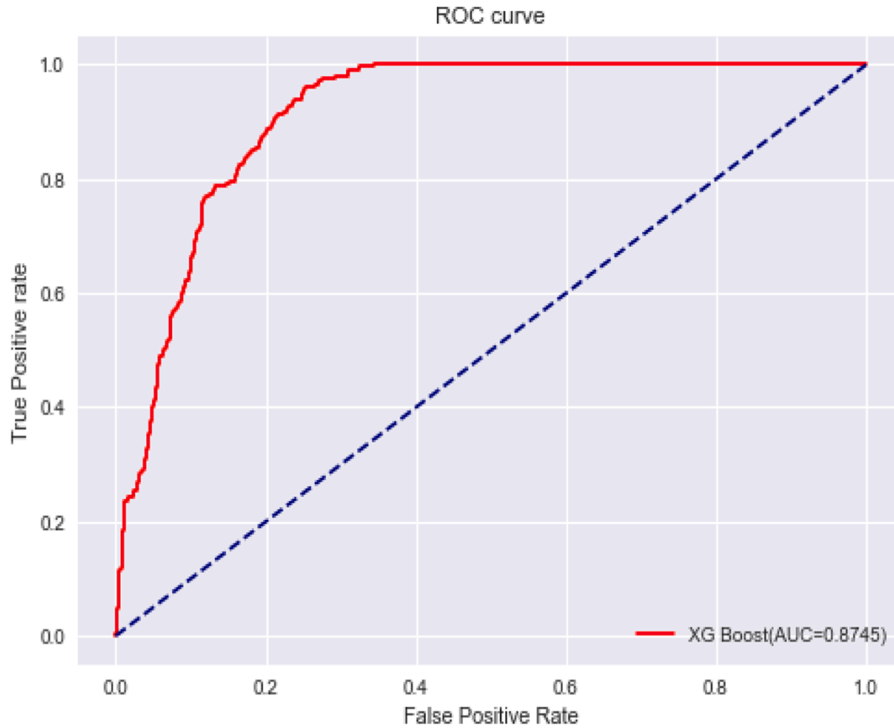

Fig. 7. ROC curve of XG Boost model.

Table 3
Confusion matrix.

CONFUSION MATRIX		Actual	
		Positive	Negative
Predicted	Positive	1339	41
	Negative	28	56

Table 4
Performance measures of the LSTM model.

Model	Accuracy	Precision	Recall	F1-Score	AUC- Score
LSTM	0.96540	0.97	0.9438	0.957	0.9732

The SMOTE approach effectively resolved the imbalance in the dataset, allowing for the comparison of different machine-learning methods. The results show that the XG Boost Classifier outperforms other ML algorithms in terms of performance measures, even after hyperparameter adjustment. This emphasizes the significance of balancing datasets and fine-tuning model parameters to ensure accurate predictions. Furthermore, the use of deep learning models, notably Long Short-Term Memory (LSTM), outperforms typical machine learning approaches. Although the accuracy of Artificial Neural Networks (ANN) initially fell short, layer-based optimization has the potential to improve.

Despite its efficiency, predictive maintenance remains very expensive due to the use of advanced monitoring technology. Future efforts should focus on creating low-cost sensor technologies to reduce monitoring costs. Furthermore, future work will focus on optimizing hyperparameter tweaking in machine learning models. Furthermore, investigating a range of deep learning algorithms other than LSTM could improve the modelling process and provide more reliable forecasting capabilities. In conclusion, while predictive maintenance provides significant benefits for maintenance planning and efficiency, overcoming problems such as dataset imbalance and cost considerations is critical. Continued R&D efforts will help to advance and widely adopt predictive maintenance solutions in the industry.

Predicting machine failures through predictive models, one of the goals of Industry 4.0, provides timely warnings of potential equipment failures and helps organizations to schedule maintenance activities. The results of this study demonstrate the effectiveness of machine learning and deep learning algorithms in predictive maintenance, enabling proactive maintenance interventions and resource optimization. It also contributes to the growing body of research on machine learning applications in industrial settings, advancing theoretical understanding and paving the way for further refinement of predictive maintenance methodologies.

Compliance with ethical standards

- The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.
- The authors declare that they have no conflict of interest.
- This study is not received any financial support from any organization.

Table 5
Performance measures of the ANN model.

Model	Number of layers	Number of neurons	Accuracy	Precision	Recall	F1-Score	AUC- Score
ANN	5	16	0.6491	0.5620	0.6836	0.6179	0.6730
	10	32	0.5524	0.4682	0.5510	0.5062	0.6018
	16	64	0.6520	0.5832	0.6940	0.8228	0.6826

- This study does not involve human participants and/or animals for data.

CRediT authorship contribution statement

Devendra K. Yadav: Writing – review & editing, Validation, Supervision, Project administration. **Aditya Kaushik:** Resources, Methodology, Formal analysis, Data curation. **Nidhi Yadav:** Writing – review & editing.

Declaration of competing interest

The author hereby affirms that there are no financial interests or affiliations with any organisations, institutions, or enterprises that may derive potential benefits from the dissemination of this research work. There are no financial conflicts of interest that need to be disclosed

Data availability

Data will be made available on request.

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