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Performance Evaluation of Machine Learning Algorithms for Predictive Maintenance of Hydraulics System

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ABSTRACT: This article presents an assessment of how machine learning algorithms perform in the context of predictive maintenance (Pdm). With the increasing demand to minimize downtime and costs, Pdm has become a widely adopted approach for managing maintenance issues. The paper offers a comprehensive overview of the performance comparison among different machine learning algorithms employed in Pdm. The primary functions of Pdm are data gathering and analysis. The effectiveness and scope of analysis of large datasets should therefore be enhanced by using the appropriate data technique, like machine learning. But choosing the optimal machine learning algorithm among the various options can be challenging and time-consuming. Therefore, this paper conducts an analysis using a dataset obtained from the automated training of condition monitoring systems specifically designed for complex hydraulic systems. The authors' choice of algorithms includes Logistic Regression (LR), K-nearest Neighbors (KNN), Support Vector Classifier (SVC), Naive Bayes, Decision Tree, and Random Forest and the experiment was conducted using Colab Notebook. The study's findings led researchers to the conclusion that the top algorithm achieved 98.08% accuracy out of more than 48 000 test data records.

KEYWORDS: machinelearning, predictivemaintenance, hydraulicssystem, performancecomparison.

I. INTRODUCTION

The significance of monitoring the condition of hydraulic systems has escalated in industrial, power, and mobile applications [1, 2], driven by the need for condition-based maintenance to reduce equipment breakdowns and maintenance expenses. Two primary philosophies exist for condition monitoring: the model-based approach, which necessitates extensive understanding of the system's behavior but can be challenging to obtain in detail for complex systems, and the statistical approach, which relies on the analysis of historical fault data and associated measurements. Sufficient historical data is essential for the statistical approach to yield accurate predictions. [3].

Predictive maintenance (Pdm) involves monitoring equipment performance and condition during regular operation to minimize the likelihood of failures. Also known as condition-based maintenance, this approach has been widely adopted in industries since the 1990s. The primary objective of predictive maintenance is to accurately anticipate equipment failures based on specific factors and proactively prevent them by scheduling and implementing necessary maintenance activities.

Accurate failure prediction necessitates the analysis of large data sets, and with hundreds of potential variations occurring at the same time, this may be a challenging and time-consuming operation. In this scenario, machine learning is used. Machine learning (ML) is a data technology that uses artificial intelligence (AI) to train machines how to handle data more efficiently. The ML program analyses data sets and process parameters from many sources to detect patterns or warning indications of potential failures that the human eye would miss [22].

The utilization of machine learning algorithms has demonstrated significant advantages in terms of detecting failures and estimating the remaining useful life (RUL) of equipment. [4, 5, 6]. Machine learning algorithms find applications in diverse industries, such as predicting engine soot emissions [8], forecasting gearbox failures [7], and



anticipating failures in robotic manipulation [9]. Additionally, predictive models have widespread usage in various other technological domains.

This research paper undertook a comprehensive evaluation of predictive maintenance by comparing the performance of six machine learning algorithms with fine-tuned parameters.

II. RELATED WORK

The inception of predictive maintenance (Pdm) is credited by certain researchers to the Rio Grande Railway Company in the 1940s. [11]. Predictive maintenance has since been the subject of numerous researches.

Numerous studies have employed various approaches to the concept of predictive maintenance (Pdm) in order to attain the highest level of effectiveness.

In a previous study, G.A. Susto et al. (2012) [12] mentioned that the three primary categories of maintenance management approaches are as follows, increasing in complexity and effectiveness: i. The Run-to-Failure (R2F) approach entails deferring maintenance actions until equipment failures have taken place. While it is a straightforward method, it is widely acknowledged as the least effective approach to maintenance because the costs of interventions and the downtime that goes along with them are typically much higher. ii. Preventive Maintenance (Pvm): when the maintenance is performed routinely according to a schedule with the intention of foreseeing process breakdowns. This method typically prevents failures, albeit occasionally needless maintenance is carried out. iii. Predictive Maintenance (Pdm): Predictive Maintenance (Pdm) is a maintenance approach that involves performing tasks based on the assessment of the equipment's condition. Pdm systems offer prompt pre-failure modifications and advance identification of imminent problems.

G.A. Susto et al. (2015) [6] later introduced a new Pdm methodology for integral type faults, demonstrated for a maintenance task involving an Ion-Implanter in semiconductor manufacture. This facilitated the training of multiple classification (MC) modules with different prediction horizons, allowing for a range of performance trade-offs in terms of reducing unforeseen failures and maximizing equipment utilization. The collected data was then utilized in an operational cost-based maintenance decision system to minimize projected expenses. SVM and KNN were employed as the classifiers, and the data was gathered using the traditional R2F approach. Susto's research revealed not only does Pdm routinely beat Pvm techniques, but SVMs outperforms KNN classifiers when adopting the MC Pdm.

In a study conducted by Felix et al. (2017) [13], condition-based monitoring for hydraulic excavators was performed using data gathered from particle sensors and physical oil samples. Specialist programs (Matlab and Statistical Package for the Social Science, more commonly known as SPSS) were used to refine the data set for further visual and mathematical analysis. They used the Inductively-coupled Plasma/Optical Emission Spectrometry (ICP/OES) method for a greater resolution and more precise evaluation of fluctuation and origin of particles. The analysis showed that metallic particles like Cu and Fe should be the primary emphasis, making it possible for a machine to receive more focused diagnostic assistance and service planning. A significant conclusion drawn from this research is that there is a need for the development and testing of advanced in-line particle sensors specifically tailored for mobile applications in the construction industry. This is because the dynamic data captured by existing in-line particle sensors lacks the required level of detail to effectively support a successful condition-based monitoring (CBM) strategy.

Magargle et al. (2017) [14] presented an overview of Modelica and reduced order models for heat monitoring and preventive maintenance of automobile brake stems (ABS). In order to take use of previous modeling efforts and linkages with other ANSYS finite element programs, the Modelica models were integrated in the ANSYS Simplorer simulation. Simulation was used to record distinct ABS activation and speed-slip signals for mechanical failure of the wheel sensor's teeth.

In order to create simulation-based digital twins, various techniques such as system modeling, circuit modeling, and reduced-order modeling were illustrated. This involved employing 3-D finite element analysis and 0-D multi-domain circuit simulation to achieve accurate representations of the systems being modeled.

Orošnjak et al. (2017) [15] projected the framework for the development and discussion of a contamination control program as a component of the CBM strategy with the aim of preserving and extending the lifespan of hydraulic systems. The study has examined the CBM guidelines, which include three essential steps: data collecting,

data processing, and maintenance decision-making. For a more thorough understanding of the persistence and steadfastness of hydraulic system maintenance, the authors suggest an algorithm that is a contamination control program. The following steps make up the program: System monitoring, diagnostics, data collection and cleaning, Data Analysis: Pattern recognition, Degradation failure: Transient or misuse failure, Decision-making, Maintenance action, Prognosis. The method discussed is closed-loop that provides information feedback on probable errors or fault detection after each cycle. Through the use of complex non-linear programming, artificial intelligence, or reliability theory, various models can be created based on data.

Rivera et al. (2018) [16] implemented a model-based approach to hydraulic pump in an injection molding machine that was in active production. The primary focus of their study was to forecast the failure of a crucial component, the radial-piston pump, which is integral to the injection molding process. A predictive maintenance system was created using an iterative-hierarchical design technique, with three layers: process understanding, methods selection, and implementation. The first layer dealt with suggestions from various subject-matter specialists and technical manuals and drawings, creating strategies for the project's execution and establishing a standpoint from which to assess whether concepts are practical. The second layer contrasted current and target states, and available software and hardware tools were scrutinized and approved. The third layer has to deal with all sorts of practical implications of tools and analytical techniques.

Silvestrin et al. (2019) [17] used a modestly large dataset for the condition monitoring of hydraulic systems to test and contrast a variety of machine learning (ML) and deep learning (DL) algorithms. The Long Short-Term Memory model (LSTM) and Temporal Convolutional Neural Network (TCN) were contrasted with three simpler feature-engineered machine learning models: K-Nearest Neighbors Algorithm, Random Forest and Decision Tree. The algorithms were first tested on a fixed-sized dataset, and their individual performance was then evaluated using datasets of varied sizes. It was learned that employing fundamental machine learning techniques along with a straightforward feature engineering strategy can be highly effective in predictive maintenance (Pdm) scenarios with limited data availability. Furthermore, the Temporal Convolutional Network (TCN) demonstrated strong performance even with a restricted dataset, while the Long Short-Term Memory (LSTM) model struggled to learn from the same volume of data.

Gupta et al. (2019) [18] investigated a pseudo-spectrum method to analyze the level of particle pollution in hydraulic filters. The objective was to effectively predict and diagnose potential weak or faulty conditions in the system. Oil filter soundtracks were captured by the sound recorders of three well-known mobile phone brands and transmitted over mobile phone networks for estimation over MATLAB(2017b) using the MUSIC (multiple signal classification) algorithm. Observations led to the following two conclusions: (1) 12.5 kHz relative peak energy (12.5RPE) compared to the clean stage and (2) the lower band energy (LBE) of the pseudo-spectrum have been identified as reliable indicators. The LBE value decreases to approximately one-third of its original value in comparison to the clean stage. is a generally trustworthy feature. The LBE decreases to roughly one-third of the clean stage's value after a certain level of pollution, and rises to two-thirds as the hydraulic system becomes clogged. The 12.5RPE exhibits its progressive growth in a manner similar to how the particle pollution gradually grows. The occurrence of choking is identified when the 12.5 kHz relative peak energy (12.5RPE) reaches a value of zero, as it approaches nearly twice the clean stage.

Through the analysis of 2.8 million sensor data points, Hus et al. (2020) [19] applied statistical process control and machine learning algorithms for fault diagnosis and maintenance of wind turbines. Rotating blades, gearboxes, generators, and hydraulic oil systems were the four categories of wind turbine disputes found by statistical program control. The authors then applied decision tree and random forest classifications, two machine learning methods, to forecast wind turbine anomalies. The decision tree model's accuracy rate is 92.68%, while the random forest model's accuracy rate is 91.98%, according to the results.

Khan et al.'s (2021) [20] analysis of recent research on predictive maintenance of an aircraft's hydraulic setup and engine, identifies emerging issues and trends. The most often employed AI algorithms are neural networks and support vector machines. Window-based pattern identification is used to increase prognostic accuracy and predict faults before they arise.

Linto et al. (2022) [21] proposed a practical approach for fault diagnostics in hydraulic systems by developing a five-dimensional digital twin framework. The researchers highlighted that users can monitor the real-time state of the system through a digital interface. Remarkably, without relying on historical fault data, the diagnostic accuracy for ten



prevalent hydraulic cylinder issues can reach approximately 89%. This represents a notable improvement of 9% compared to a non-interactive simulation model.

In conclusion, the majority of the studies referenced indicate that predictive maintenance (Pdm) is the most efficient approach for maintaining hydraulic systems. However, there aren't many comparisons made between various machine learning algorithms to show how accurate each model is. The accuracy and precision ratings of six distinct algorithms are thus compared by the writers in this research.

III. METHODOLOGY

This section of the paper discusses in detail methodology employed in this study.

A. Dataset

The dataset used in this paper is freely accessible from the machine learning repository at UCI at <https://archive.ics.uci.edu/ml/datasets/Condition+monitoring+of+hydraulic+systems>. The data was gathered by experimentation with hydraulic test equipment. This test rig is composed of two circuits: a working circuit and a cooling-filtration circuit connected by an oil tank [1], [2]. The system cycles through 60-second constant load cycles, measuring process data such as pressures, volume flows, and temperatures while numerically altering the condition of four hydraulic components (cooler, valve, pump, and accumulator).

The test system is equipped with sensors that monitor process values, including pressure (PS1- 6), flow (FS1, FS2), temperature (TS1-5), electrical power (EPS1), vibration (VS1), efficiency factor (SE), virtual cooling efficiency sensor (CE), and virtual cooling power sensor (CP). With digital EIA232 and EIA-485 bus interfaces, particle contamination sensors (CS and MCS, COPS, and oil parameter monitoring) are also included. Sampling rates can be as high as 1 Hz for temperature and 100 Hz for pressure, depending on the dynamics of the underlying physical variables. [10]. The data for each sensor is provided in separate files. These sensors are the predictor (independent) variables of the dataset. The results of the test are divided as follows (Fig.1.) which are the target variables for the dataset:

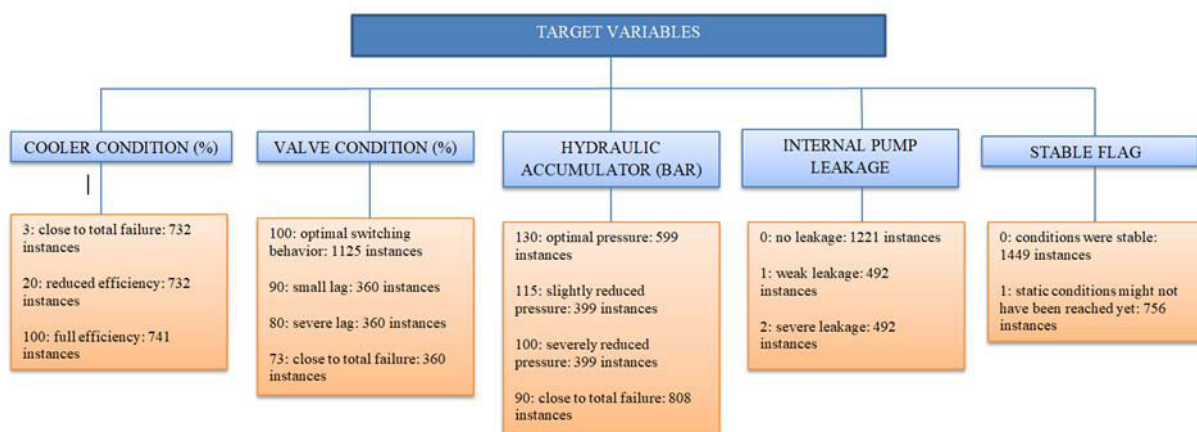


Fig.1. Target Variables

B. Algorithms

There are various machine learning algorithms used for various purposes but only few simple one are fitted for predictive maintenance. Deep learning algorithms like LSTM not only require huge amount of data to be trained but are also outperformed by simple algorithms like KNN and random forest [17]. Other algorithms like XGBoost are also not appropriate for use due to over-fitting.



Thus six machine learning algorithms employed in the methodology are Logistic Regression, K- nearest neighbor, Support Vector Classifier, Decision Tree, Random Forest and Naïve Bayes which are not only simple to implement but require comparatively smaller dataset to train and give high accuracy.

C. Processing

The following processing steps were carried out and analyzed by the authors using Colab Notebook.

A "predictor variable" is a variable whose values will be used to predict the target variable's value. A dataset's "target variable" is the aspect of the dataset that must be predicted or about which deeper knowledge is to be gained.

The data is processed by calculating the mean value for each and every independent parameter (PS1-PS6, ESP1, FS1, FS2, TS1-TS4, VS1, CE, CP, SE). Next, the mean value for these independent variables, are merged together. The target variables (cooler, valve, pump, and accumulator) are also combined with the above merged data along with the final target (stable flag). So, the final dataset contains 22 attributes and 2205 instances.

1	PS1	PS2	PS3	PS4	PS5	PS6	ESP1	FS1	FS2	TS1	TS2	TS3	TS4	VS1	CE	CP	SE	Cooler_Co	Valve_Cor	Internal_F	Hydraulic	Stable_Flag
2	160.678	109.467	1.99148	0	9.84217	9.7281	2538.93	6.70982	10.3046	35.622	40.9788	38.471	31.7453	0.57695	39.6014	1.86275	59.1572	3	100	0	130	1
3	160.608	109.355	1.97623	0	9.63514	9.52949	2531.5	6.71531	10.4031	36.677	41.5328	38.979	34.4989	0.56585	25.7864	1.25555	59.3356	3	100	0	130	1
4	160.352	109.159	1.97222	0	9.53055	9.42795	2519.93	6.71852	10.3663	37.8808	42.4425	39.632	35.6462	0.57653	22.2182	1.11322	59.5432	3	100	0	130	1
5	160.193	109.065	1.94658	0	9.43883	9.33743	2511.54	6.72056	10.3027	38.8791	43.404	40.4034	36.5795	0.56927	20.4598	1.06215	59.7949	3	100	0	130	1

Fig.2. Processed Data Set

Next, variance (var()) Fig.2. and correlation (corr()) between each attribute is calculated in form of a heat-map Fig.3. for data analysis.

```
df_final.var()
PS1      22.084591
PS2      24.866035
PS3       0.063454
PS4      18.312876
PS5       0.332117
PS6       0.302048
ESP1     5451.855603
FS1       1.066847
FS2       0.201822
TS1       63.871000
TS2      54.704580
TS3      55.530634
TS4      65.737688
VS1       0.003631
CE       133.988270
CP        0.077430
SE       80.284993
Cooler_Condition 1796.330820
Valve_Condition  114.100893
Internal_Pump_Leakage 0.667869
Hydraulic_Accumulator 270.137114
Stable_Flag      0.225408
dtype: float64
```

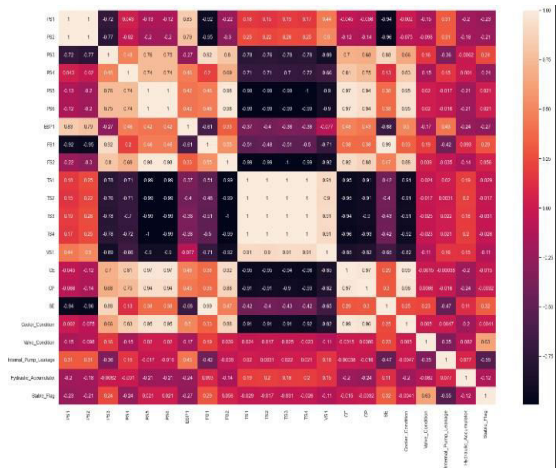


Fig.3. Variance of each attribute Fig.4 Heat-map of attributes

Then the ML models are applied in two stages:

Stage 1: Take predictor variables as PS1-PS6, ESP1, FS1, FS2, TS1-TS4, VS1, CE, CP and SE to predict the target variables Cooler, Valve, Pump, and Accumulator. Each target variable is predicted separately.

Stage 2: Take predictor variables as Cooler, Valve, Pump, and Accumulator to predict the final target variable Stable Flag.

At each stage the data is split between target values and independent attributes (called predictors). The predictors(x) and the corresponding target(y) are further divided into train_data(trains_x,train_y) and test data (test_x, test_y). It is a



general practice to consider 20% of data for testing (test_size = 0.2). These train and test data are then analyzed with six machine algorithms mentioned above. For each algorithm accuracy and precision is measured and the best model is obtained. Once the above process is done for all four targets, this process is again repeated for stage 2.

In stage 2 it was observed that the stable flag data was imbalanced where true instances were 65.8% and false instances were only 34.2%. Due to this the models did not have sufficient data to train on. To overcome this problem an oversampling technique SMOTE was employed. SMOTE stands for Synthetic Minority Oversampling Technique. It helps to generate synthetic data for the classifiers to train on. The synthetic data generated contained 1449 instances for both true and false values and was used by the models.

The roc_auc_score (overall efficiency throughout the process) of each of the algorithms was evaluated to find the best model.

IV. EXPERIMENTAL RESULTS

The performance of any machine learning algorithm is evaluated through accuracy and precision score. Accuracy tells how close the predicted values to the actual values are whereas precision depicts how close the predicted values to each other were. Both accuracy and precision are computed using confusion matrix Fig.4. which summaries the performance of a classification algorithm.

		ACTUAL VALUES	
		Positive	Negative
PREDICTED VALUES	Positive	True Positives (TP) Actual value is Positive and Predicted value is Positive.	False positives (FP) Actual value is negative and Predicted value is Positive.
	Negative	False negatives (FN) Actual value is Positive and Prediction value is Negative	True negatives (TN) Actual value is Negative and Predicted value is Negative.

Fig.5. Confusion Matrix Sample

Using confusion matrix accuracy and precision score are calculated using the following formulas:

$$\text{Accuracy} = \frac{TN+TP}{TN+FP+TP+FN} \quad \text{Precision} = \frac{TP}{TN+FP}$$

Based on this the accuracy score, precision score and confusion matrix of each algorithm was evaluated in each stage out of which the results of stages 2 are displayed below.

A. LOGISTICREGRESSION

AccuracyScore:0.9426108374384237
 PrecisionScore:0.9177553684933416

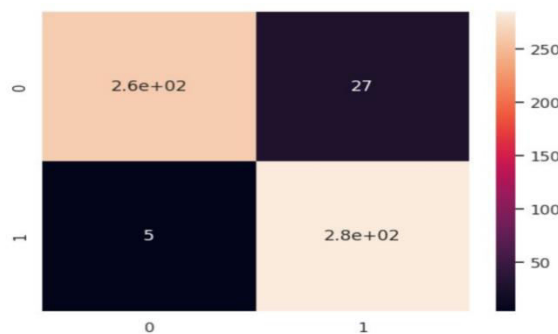


Fig.6. Confusion Matrix for Logistic Regression



B. KNN

AccuracyScore:0.942179802955665
PrecisionScore:0.9212950930079662

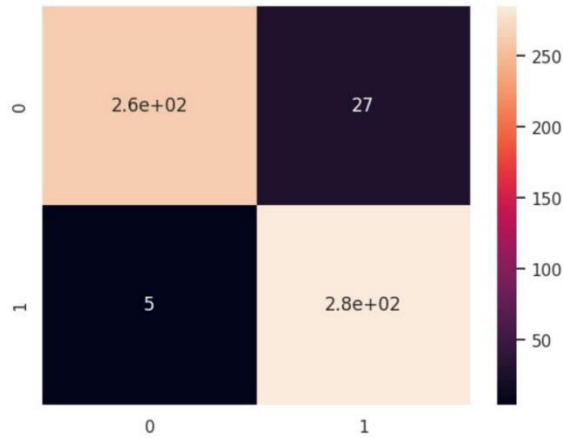


Fig.7. Confusion Matrix for KNN

C. SVC

AccuracyScore:0.9400227645917301
PrecisionScore:0.9173492831870067

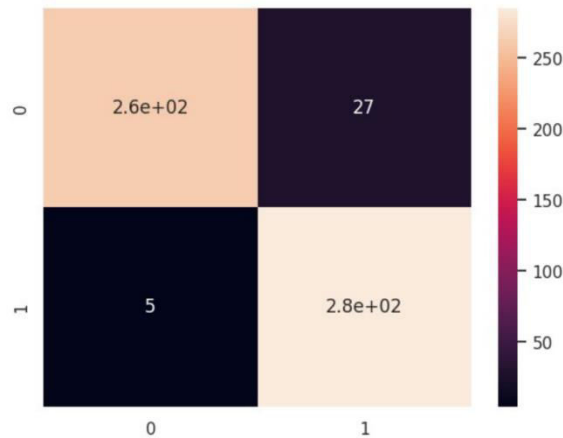


Fig.8. Confusion Matrix for SVC

D. NAÏVEBAYES

AccuracyScore:0.9098360655737705
PrecisionScore:0.8555389221556886



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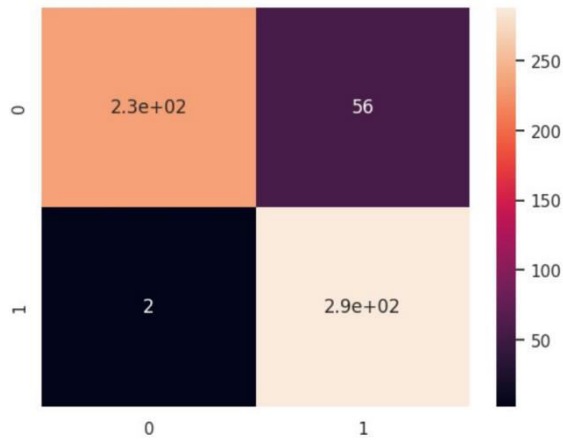


Fig.9. Confusion Matrix for NaïveBayes

E. DECISION TREE

AccuracyScore:0.9464938796835348

PrecisionScore:0.9183817205409186

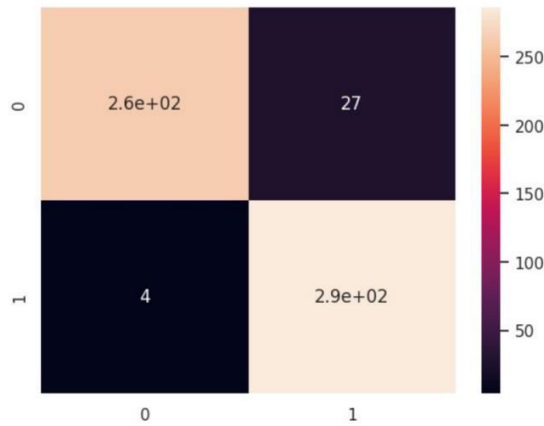


Fig.10. Confusion Matrix for Decision Tree

F. RANDOM FOREST

AccuracyScore:0.9447660098522167

PrecisionScore:0.9181094177194729

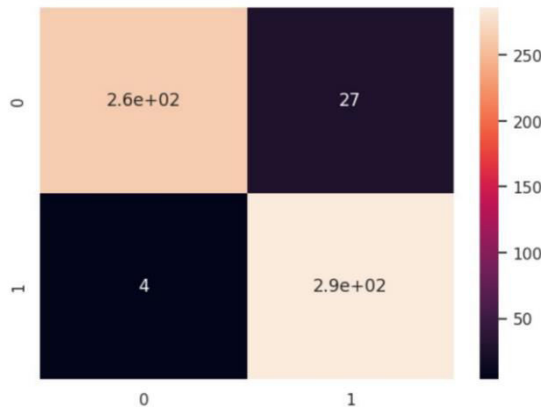


Fig.11. Confusion Matrix for Random Forest



The overall efficiency of a model throughout a program is given through the roc_auc_score. A roc_auc_score is the probability with which the model can distinguish between positive and negative class.

In this research the highest roc_auc_score was of 0.9808323424494648 that is approximately 98.08% for Random Forest Classifier.

V. CONCLUSION

The performance comparison of various machine learning algorithms used for predictive maintenance (Pdm) is the major topic of this article. These machine learning approaches include Logistic Regression (LR), K-nearest Neighbours (KNN), Support Vector Classifier (SVC), Naive Bayes, Decision Tree, and Random Forest. The experiment used data collected from automatically trained condition monitoring systems for complex hydraulic systems.

The data was processed to filter out anomalies, obtain correlation, and separate the training from the testing data. The algorithms were implemented in two stages, the first using sensors as predictors and hydraulic components as target variables, and the second using hydraulic components as predictors and the stability flag as the ultimate target variable. The optimal algorithm was founded by combining and analysing all of the results.

The final results demonstrate that the Random Forest Classifier, which has an accuracy score of 98.08%, is the best algorithm in contrast to the articles previously studied. Machine learning methods for predictive maintenance thus offer a far more reliable, robust and cost-effective solution when taking into account the need to manage the quality of the equipment and organise routine maintenance to minimise the likelihood of failures and potential losses.

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