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Fault Diagnosis of Gearbox Using Machine Learning Approach

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Abstract: *Gear box is crucial in industrial processes, enabling adjustments of speed and load conditions to meetoperational needs. As gearboxtechnologyadvances, their capabilities increase, but component failure can result in product losses and maintenance costs. Detecting potential failures before handis essential, and vibration measurementis a proven method for monitoring machine condition and predictinggearboxfaults. This study explores the use of machine learning to develop an automated fault diagnosis system for gear boxes using vibration signals. The performance of the developed model is compared with existing methods to determine the most effective algorithm. This research paper explores the application of machine learning techniques for faultdiagnosis of gear boxes using vibration signals. The study involved collecting vibration data fromgearboxes in both good and defective conditions, under various loading conditions. Statistical features were extracted from the collected data and used to develop a fault identification system. The performance of the developed model was evaluated and compared with existingmethods. The study also aimed to determine the mostsuitablealgorithm for the collected data. Overall, the paper provides insights into the effectiveness of using machine learning approaches for gear box fault diagnosis and identifies the best-performing algorithm for this task.*

Key Word: *Machine Learning, Gearbox, Vibration, Data preprocessing, Algorithms.*

I.INTRODUCTION

Gearboxes play an important role in many industries, including automotive, manufacturing, and energy production, by multiplying or decreasing drive train speed and torque. The quality and maintenance of the gearbox have a significant impact on the overall system's performance. However, the cost and effort required for installation and maintenance frequently cause scepticism about the sustainability of energy as a source. To overcome scepticism and promote consensus, it is necessary to demonstrate that there are opportunities to develop gearbox systems that are as material and energy efficient as possible.

Predictive maintenance has received a lot of attention and development in recent years as a way to supplement industry practices. The most recent trend is the shift to Industry 4.0, in which online data is used to monitor and predict conditions rather than relying on offline or onsite measurements. Transmission vibrations have been identified as the most frequently occurring data source in numerous research studies. However, these vibrations only occur after the damage has begun to spread, making it too late to plan maintenance work ahead of time. Alternative approaches to indicating changes in transmission operation conditions, such as using transmission error, oil temperature, or oil contamination, may be considered in such cases.

Machine learning is a critical tool in predictive maintenance. It entails teaching algorithms to learn from data, allowing them to make accurate predictions about future events. In the context of gearbox maintenance, machine learning algorithms can be used to analyze data from various sources, including vibration data, to identify patterns and detect anomalies that indicate potential gearbox failures. Machine learning algorithms, for example, can predict the remaining useful life of a gearbox and recommend maintenance schedules based on oil temperature and contamination data.

Predictive maintenance is an important tool for ensuring the long-term and efficient operation of gearbox systems. The most recent trend is the transition to Industry 4.0, in which online data is used to monitor and predict conditions rather than relying on offline or onsite measurements. Machine learning is a critical component of this trend, allowing for accurate predictions and recommendations regarding maintenance schedules, resulting in increased efficiency and lower costs.

II.LITERATURE REVIEW

Jagath Sri Lal Senanayaka, Huynh Van Khang, and Kjell G. Robbersmyr studied the use of convolutional neural networks (CNN) for diagnosing gearbox faults . They observed that previous machine learning algorithms for fault diagnosis were pattern recognition tools that didn't provide a direct interpretation of the physical phenomena involved in the faults. To address this, the authors proposed using CNNs for classifying gearbox faults and to visualize the learning features of the CNN filters, which could help understand the physical fault diagnosis phenomena better. They tested their proposed algorithm on an experimental setup that they developed in-house.

Van Bui, Van Hoa Nguyen, Huy Nguyen, Yeong Min Jang have studied on the importance of early detection of gearbox faults in industrial manufacturing. It also highlights the use of vibration signals and machine learning techniques for fault detection. The machine learning models used in the study are Artificial Neural Network, Logistic Regression, and Support Vector Machine. These models are selected due to their flexibility in adapting to a variety of data types. The paper does not provide a literature survey of previous research on the topic.

Bo Qin – Zixian Li –Yan Qinthey studied a new method for fault diagnosis in planetary gearboxes using transient feature learning. The authors have conducted a literature survey on the existing methods for fault diagnosis in gearboxes and have identified that most of the existing methods rely on frequency domain analysis. However, these methods have limitations in detecting transient faults. Therefore, the authors propose a new method that uses a transient feature learning approach to detect transient faults in planetary gearboxes. The proposed method is compared with the existing Empirical Mode Decomposition (EMD) method to validate its effectiveness.

Wang Hao , Dong Guangming , Chen Jin, Hu Xugang , and Zhu Zhibing have studied the method for fault diagnosis of gearboxes using dictionary learning and hidden Markov model. The authors have conducted a literature survey on the existing methods for gearbox fault diagnosis and have highlighted the limitations of traditional methods in dealing with complex fault types. They have also discussed the advantages of using sparse representation and HMM for fault diagnosis. The authors have cited several previous studies on dictionary learning and HMM for fault diagnosis in different domains, such as motor bearing fault diagnosis and wind turbine gearbox fault diagnosis.

Chong Tak Yaw1, Siew Li Teoh ,Siaw Paw Koh, KeemSiah Yap, Kok Hen Chong and Foo Wah Low have studied on Extreme Learning Machine (ELM) for fault diagnosis in wind energy. The authors searched two databases to identify relevant articles and included 14 studies in their review. The studies showed that ELM produced superior accuracy results in fault diagnosis of wind turbines compared to other algorithms. However, the authors found that there was insufficient reporting on the methodology of data collection, feature extraction, and type of data used in the studies. They recommended that future studies should improve reporting on these components to better inform study design.

T Praveenkumar, M Saimurugan, P Krishnakumar, and K I Ramachandran has conducted experimental studies by collecting vibration signals for both good and faulty conditions of the gearbox, using good gears and face wear gears. The authors extracted statistical features from the collected vibration signals and employed support vector machine (SVM) for the identification of faults. They discussed and compared the performance of the fault identification system utilizing vibration signals. The utilization of vibration signals for automated fault diagnosis of gearboxes has been studied.

VenkatNavneeth , K S. Vinod and K. Yagna studied on the use of different machine learning and deep learning algorithms for fault diagnosis of an automobile gearbox. The literature survey of the paper includes a review of previous research on gearbox fault diagnosis and the use of artificial intelligence techniques for the same. The paper also discusses the limitations of previous research and the need for more accurate and efficient fault diagnosis methods.

Jan Vrba, MatousCejnek, Jakub Steinbach, and Zuzana Krbcova developed a fully automated method for diagnosing faults in gearboxes. To do this, they conducted a literature review to identify existing methods for gearbox fault diagnosis, and discussed their limitations. They then explained how their proposed approach overcomes these limitations. Finally, the authors compared their proposed method with two reference methods to demonstrate its effectiveness.

Mohamad HazwanMohdGhazali and Wan Rahiman conducted a study on vibration analysis for machine monitoring and diagnosis. They reviewed various approaches proposed by researchers, including time domain analysis, frequency domain analysis, time-frequency domain analysis, and artificial intelligence-based approaches. The authors discussed the advantages and disadvantages of each approach in their survey.

ZhiQiang Chen, ChuanLi , and Rene-Vinicio Sanchez studied on the application of convolutional neural network (CNN) for fault identification and classification in gearboxes. The literature survey of the paper includes a review of previous studies on fault diagnosis of gearboxes using different machine learning algorithms such as support vector machine (SVM), artificial neural network (ANN), and decision tree (DT). The paper also discusses the limitations of these algorithms and how CNN can overcome these limitations. Additionally, the paper provides a detailed explanation of CNN and its advantages over other machine learning algorithms.

A. M. Umbrajkaar, A. Krishnamoorthy and R. B. Dhumale they studied a machine learning-based approach for condition monitoring of shaft misalignment. The authors conducted a literature survey to identify the existing methods for shaft misalignment detection and found that most of the methods rely on vibration analysis. They also found that machine learning-based approaches are becoming increasingly popular for condition monitoring in the Industry 4.0 revolution. The authors then proposed a combined approach of artificial neural network and support vector machine for identification and measurement of shaft misalignment.

III.METHODOLOGY

We have gather vibration data from kaggle. Once we've collected the data, we need to preprocess it to remove any noise or inconsistencies that could potentially impact the delicacy of our model. This involves filtering out high frequency noise, homogenizing the data, and testing it.

Next, we need to recognize applicable features from the preprocessed data that will serve as input to our machine learning algorithm. The features that are generally used in vibration analysis include breadth, frequency, and phase. After that, we need to elect the most applicable features to use in our model. This can be done using statistical styles similar as correlation analysis or by experimenting with different combinations of features.

Once we've named our features, it's time to choose the right machine learning algorithm for our analysis. Some popular algorithms for vibration analysis include decision trees, support vector machine, arbitrary timbers, and grade boosting. We also need to train our chosen machine literacy model using the preprocessed and point- named data. After training, we must estimate the performance of our model using criteria similar as delicacy, perfection, recall, and F1- score.

Still, we can OK - tune the hyper parameters of our chosen machine literacy algorithm to optimize the performance of our model, If necessary. Eventually, once we've a trained and optimized machine literacy model, we can emplace it for real-time vibration analysis of the gearbox, helping to insure optimal performance and help mechanical failures.

IV.DATA PREPROCESSING

We have imported various libraries for performing exploratory data analysis, data visualization, data preprocessing, machine learning modeling, hyper parameter tuning, and model evaluation. The code also imports numpy and pandas for numerical operations and handling data in data frames, matplotlib, seaborn, and plotly for data visualization, sklearn for machine learning modeling, preprocessing, hyperparameter tuning, and evaluation, IPython.display, and warnings for displaying output and handling warnings. It imports Decision Tree Classifier, Random Forest Classifier, Gradient Boosting Classifier for machine learning modeling, GridSearchCV for hyper parameter tuning, confusion_matrix, and precision_score for model evaluation.

By traversing through the directory and subdirectories and prints the absolute path of each file. The CSV files starting with 'h30hz' or 'b30hz' and ending with a number between 0 and 90 in increments of 10 are imported.

By setting the 'load' and 'failure' columns of different data frames to simulate different load and failure conditions for a system. The data frames contain information about the system under different load conditions, and the code is likely being used to simulate failure scenarios and evaluate the performance of the system.

Now by concatenates multiple data frames into two data frames: healthy30hz and broken30hz using pd.concat function with axis=0 and ignore_index=True. The resulting data frames contain all the rows from the original data frames concatenated together.

Concatenating two data frames (broken30hz and healthy30hz) along axis 0 (vertically) using pd.concat() function, and assigns the result to a new data frame called "data". Then it prints the info of "data" using the data.info() method, the shape of "data" using data.shape, and displays the first three rows of "data" using data. head(3) method.

We usedseaborn to create a figure with 4 subplots, displaying kernel density plots for variables 'a1', 'a2', 'a3', and 'a4' in the 'data' DataFrame, with 'failure' distinguishing between broken and healthy bearings.

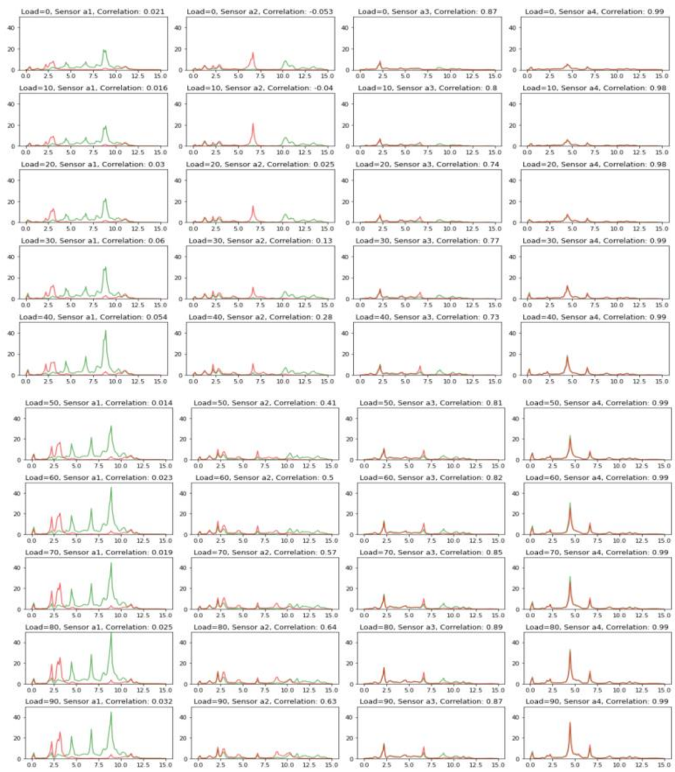

Fig1. Data Visualization

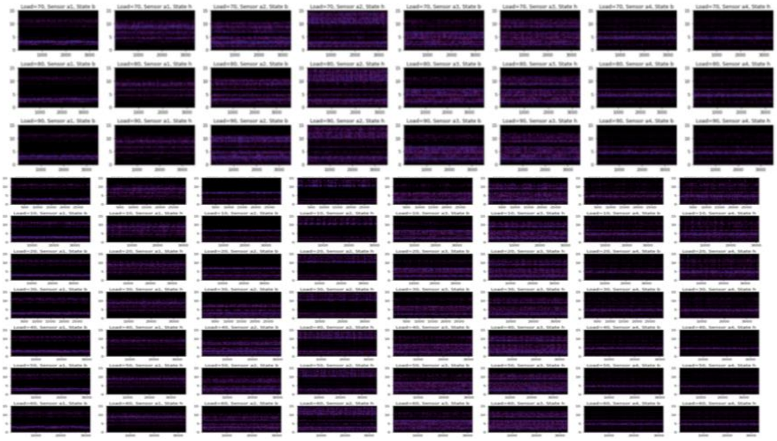

Fig2. Data Visualization

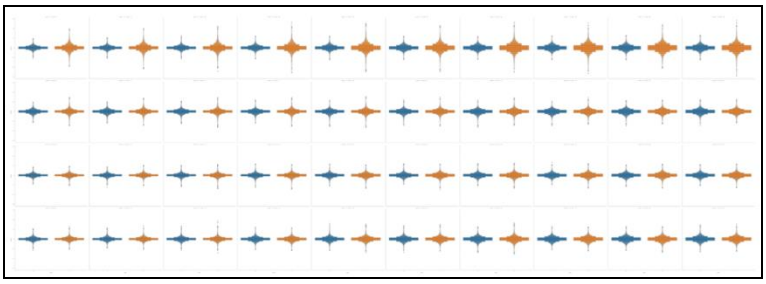

Fig 3. Data Visualization

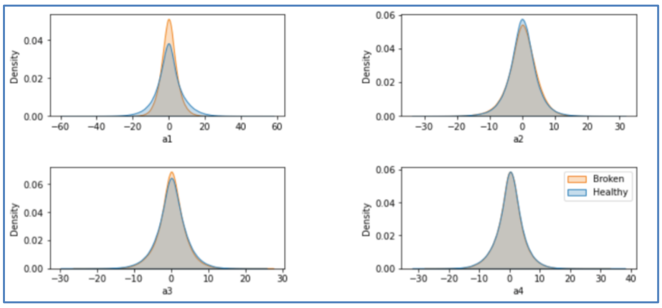

Fig 4. Visualization of all 4 sensors

We can observe that maximum difference is seen in the sensor a1 as compared to other 3 sensors i.e. a2, a3, a4.

A legend is added. It generates a kernel density plot for 'a1' with 2 vertical dashed lines at -7 and 7. The code creates 3 pie charts to visualize healthy and broken cases based on 'a1' values, highlighting broken cases and displaying percentages. It creates a binary threshold column 'a1_thr' based on 'a1' values.

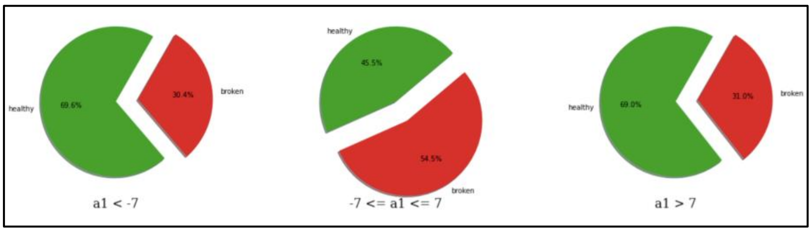

Fig 5. Pie Chart of a1 sensor health

From the above pie charts, it can be found that sensor "a1" is more informative. If we consider -7 and 7 as thresholds for a1 these results may appear:

1. If a1 is lower than -7 or higher than 7 there is a high probability (~70% and 69% respectively) that system continues working without failure.
2. If a1 is between -7 and 7 there is a little more chance for system failure.

```
Data_result shape: (22456, 12)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 22456 entries, 0 to 22455
Data columns (total 12 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   a1_median     22456 non-null  float64
 1   a1_std        22456 non-null  float64
 2   a2_median     22456 non-null  float64
 3   a2_std        22456 non-null  float64
 4   a3_median     22456 non-null  float64
 5   a3_std        22456 non-null  float64
 6   a4_median     22456 non-null  float64
 7   a4_std        22456 non-null  float64
 8   load_median   22456 non-null  float64
 9   load_std      22456 non-null  float64
 10  a1_thr_mode   22456 non-null  float64
 11  failure       22456 non-null  float64
dtypes: float64(12)
memory usage: 2.1 MB
None
```

Fig 6. Extracted Features

By splitting the data_result data frame into training, validation, and test sets. First, it selects the features (independent variables) and target variable (dependent variable) using indexing with [['a1_median', 'a1_std', 'a2_median', 'a2_std', 'a3_median', 'a3_std', 'a4_median', 'a4_std', 'load_median', 'load_std', 'a1_thr_mode']] and ['failure'], respectively, and assigns them to X and y.Then, train_test_split function from sklearn.model_selection is used three times to split the data into training, validation, and test sets.

In the first train_test_split call, X_train_val and y_train_val are obtained by randomly splitting X and y into training and validation sets with a test size of 0.15 (15%) and a random state of 1.

In the second train_test_split call, X_train and y_train are obtained by splitting X_train_val and y_train_val into training and validation sets again, but this time with a test size equal to the size of the X_test (which was obtained from the first split). This means that the validation set will be empty, and all the data will be used for training.

Finally, the sizes of the resulting sets are printed to the console. The training set has 15,718 rows and 11 columns, the validation set has 3,369 rows and 11 columns, and the test set has 3,369 rows and 1 column (the target variable).

```
X_train shape: (15718, 11)
y_train shape: (15718,)
X_validation shape: (3369, 11)
y_validation shape: (3369,)
X_test shape: (3369, 11)
y_test shape: (3369,)
```

Fig 7. Train Test Data Shape

Creating a pie chart to show the ratio of broken and healthy samples in the training set. The code first specifies the size of the figure as 7 by 7 inches. Then, it uses the pie function from matplotlib to create a pie chart with two sections, one for the number of broken samples and one for the number of healthy samples in the training set. The explode parameter specifies how much each section of the pie should be separated from the rest of the pie. In this case, the explode parameter is set to [0.1,0], which means that the section for broken samples will be separated from the rest of the pie by a small amount. The shadow parameter is set to True to add a shadow to the pie chart.

The autopct parameter specifies the format of the percentage values that are displayed on the chart. In this case, the %.2f %% format is used, which means that percentages will be displayed with two decimal places. The text props parameter specifies the font properties for the text on the chart. In this case, plt_font is a dictionary of font properties that is used to set the font size, weight, and style. The legend function is used to add a legend to the chart, with labels for the broken and healthy sections. Finally, the title function is used to set the title of the chart to "Broken Vs healthy ratio", using the plt_font dictionary to specify the font properties. The show function is used to display the chart.

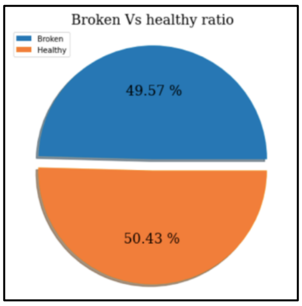

Fig 8. Gearbox Health

V.MACHINE LEARNING IMPLEMENTATION

1) Decision tree classifier

Decision tree classifier were trained on a dataset with different maximum depths, selects the best depth value based on the highest validation accuracy, and evaluates the trained classifier's accuracy and precision on the test data. It displays a heatmap of the confusion matrix and the precision score of the trained classifier on the test data. The accuracy of the Decision Tree Classifier Model is 91.3%.

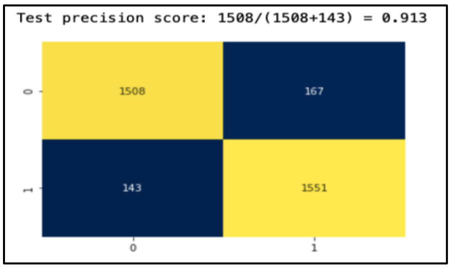

Fig 9. Confusion Matrix of Decision Tree

2) Random Forest Classifier

Random Forest Classifier model were trained using specified hyper parameters. It uses Grid SearchCV to perform a grid search over hyper parameters and cross-validation folds to find the optimal model with the highest accuracy score. It also calculates precision scores on the training, validation, and test sets, and generates a heat map of the confusion matrix with annotated values using the Seaborn library. The precision score is calculated using the precision_score() function, which measures the proportion of true positives among all positive predictions. The accuracy of the model is around 93%, which indicates the percentage of correct predictions made by the model on the test set.

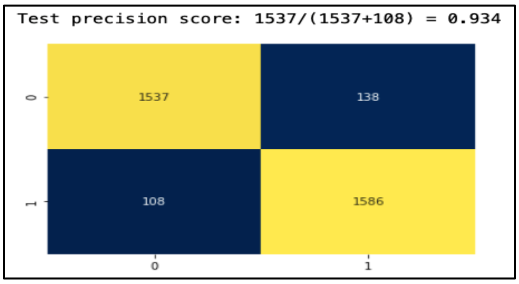

Fig 10. Confusion Matrix of Random Forest

3) Gradient Boosting Classifier

A Grid SearchCV was performed to tune hyper parameters for a Gradient Boosting Classifier model. An instance of the model was created with a random_state of 1 for reproducibility. A dictionary of hyper parameters to be searched was defined, including n_estimators, learning_rate, subsample, and max_depth. GridSearchCV was then instantiated with the estimator parameter set to the Gradient Boosting Classifier model, cv set to a cross-validation strategy, param_grid set to the hyper parameters dictionary, scoring set to 'accuracy', and verbose set to 3 to display progress. The fit() method was called on the Grid Search CV object to fit the best model with optimal hyper parameters to the training data. The best_params_ attribute was used to output the hyper parameters that achieved the highest accuracy score during cross-validation, while the best_score_ attribute was used to output the mean cross-validation accuracy score achieved by the best set of hyperparameters found. The resulting accuracy of the Stochastic Gradient Boosting (SGB) Model was around 93%.

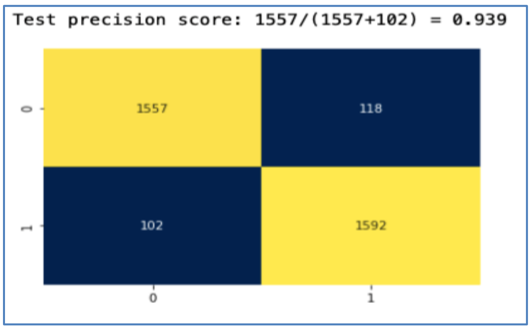

Fig 11. Confusion Matrix of Stochastic gradient boosting

VI.RESULT

The aim of this machine learning project was to predict gearbox vibration levels using different algorithms: Decision Tree Classifier, Random Forest classifier, and Stochastic Gradient Boosting (SGB). The vibration signals dataset was pre-processed, and the data were divided into training and testing sets for model development and evaluation.

The models were assessed based on accuracy, precision, and recall scores. The decision tree algorithm achieved 91.3% accuracy, while the random forest classifier achieved a slightly higher accuracy score of 93.4%. The Stochastic Gradient Boosting algorithm achieved the highest accuracy score of 93.9%. All three models performed well in predicting the gearbox vibration levels.

The precision and recall scores were also used to evaluate the models' performance. Precision score measures the true positives among all positive predictions made by the model, while the recall score represents the true positives among all actual positive instances in the dataset.

Table no 1: Shows the Precision, Recall and Accuracy rate of the algorithms

Sr. No	Algorithm	Precision	Recall	Accuracy
1	Decision Tree Classifier	0.913	0.91	0.908
2	Random Forest Classifier	0.934	0.93	0.92
3	Stochastic Gradient Boosting	0.939	0.93	0.934

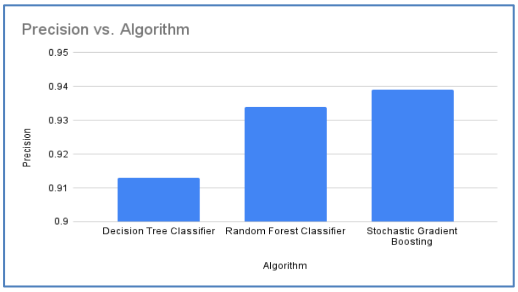

Fig 12. Plotting of algorithms as per their precision

By plotting the three algorithms in a graph of Accuracy and Precision

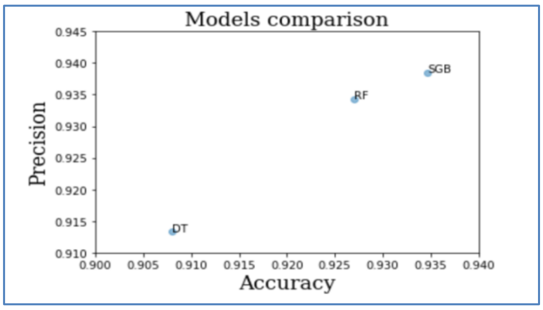

Fig 13. Plotting Algorithms as per their precision and accuracy

We can observe that the Stochastic Gradient Boosting shows the highest precision and accuracy among all three algorithms.

VII.CONCLUSION

In conclusion, this project demonstrated that decision tree, random forest classifier, and Stochastic Gradient Boosting algorithms are effective in predicting gearbox vibrations. The results showed that Stochastic Gradient Boosting achieved the highest accuracy, while Decision Tree Classifier had the lowest accuracy but still performed well. These findings have practical applications in predictive maintenance of machinery to prevent unexpected failures.

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