PREDICTIVE MAINTENANCE FOR SMART MACHINES

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Abstract

Maintenance is generally done to maintain or restore the functionality of a system. Maintenance strategy for any product can be classified in three major categories:

a) Fault oriented maintenance: In this type of approach system undergo maintenance when there is any fault in entire system. This type of approach requires more downtime for the system.

b) Time based maintenance: In this approach maintenance is done at regular pre-defined interval irrespective of the need or the condition of component of the system.

c) Conditional maintenance: In this approach components of the systems are regularly monitored and maintenance is done only when it is absolutely required for the continued operation.

Above three traditional maintenance strategy, either leads to more downtime of the system or the cost of maintenance is more. With the advent of AI, the better strategy is predictive maintenance. In this approach, the health status or performance data of all the relevant components of the system is continuously recorded. Recorded data is statistically analyzed to predict the future malfunction. This type of strategy is more of just in time approach which enables minimum downtime of machine with minimum cost. Also maintenance can be pre planned to minimize the effect of downtime.

The purpose of this paper is to describe the implementation of the predictive maintenance application. Predictive maintenance represents an important component of the smart machines, which ensures high availability of system and minimum machine failures. Our approach involves the application of Machine learning techniques such as prediction, classification, Anomaly detection and Survival analysis to provide solutions for different use cases under predictive maintenance as well as generation of model performance metrics. Application uses Aircraft Engine parameter data to build and validate Machine Learning models and is developed using MySQL DB for persistent storage, R Machine Learning libraries and R Shiny API on Windows platform.

Index Terms

Predictive Maintenance, Machine Learning, Models, Prediction, Classification, Anomaly Detection, Survival Analysis

N.1 INTRODUCTION

Predictive analytics is the technique of using history data analysis to make intelligent decisions This process uses data along with analysis, statistics, and machine learning techniques to create a predictive model for forecasting future events. The workflow for predictive maintenance application development is shown in Figure 1. Typically, the workflow for a predictive analytics application follows the steps listed

A. Data Preparation step involves importing data from various sources, such as different hardware systems and software logs. This is followed by data pre-processing which involves cleaning of data thereby converting data into a form that is required for application of machine learning models.

Data is segregated into Training data (used for training the models), Test data (used to validate the models) and Truth data (used to evaluate models and generate metrics). MySQL database is used for persistent storage

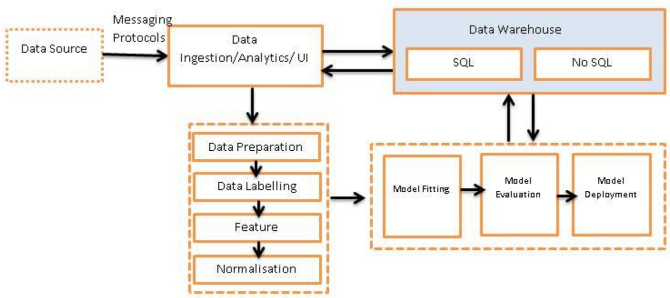

Figure 1

B. Data Labeling involves tagging the data which conveys special meaning to each entry in data sample. Our application involves generation of three labels namely RUL(Remaining Useful Life), Class Label1for binary classification and Class Label2 for multiclass classification

C. Feature Engineering involves feature selection and feature extraction , which results in elimination of unwanted features from the data sample

D. Training data will be used to train different machine learning models. Our application encompasses Prediction, Classification, Clustering and Survival models.

E. Models will be evaluated and performance metrics will be generated by comparing predicted output with truth data

F. R Shiny API has been used to develop user interface to interact with the models

N.2 PREDICTION

One of the essential use cases is to predict RUL (Remaining Useful Life) of machines. Our application uses Random Forest, Boosted Decision Tree, Poisson model and Neural Networks to predict RUL of engines. The predictions can be plotted along with truth data as shown in Figure 3.The truth data can also be used to calculate metrics such as MAE, RMSE, RAE, RSE, Co-efficient of Determination to evaluate performance of individual models as shown in Table 1.

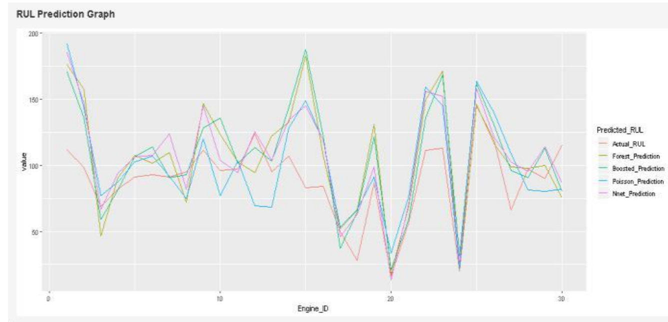

Figure 3

The screenshot of application dashboard is shown in Figure 2.

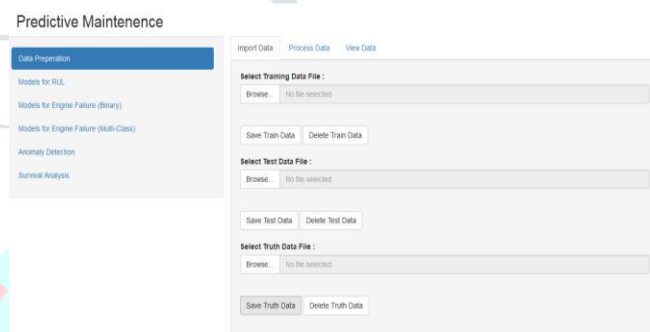

Figure 2

The subsequent sections discuss different use cases under predictive maintenance and their solutions.

Table 1

Algorithms	Mean.Absolute.Error	Root.Mean.Squared.Error	Relative.Absolute.Error	Relative.Squared.Error	Coefficient.of.Determination
Decision Forest	[illegible]	[illegible]	0.5531418	0.4667725	0.5332275
Boosted Decision Tree	[illegible]	29.53229	0.5761778	[illegible]	0.4949495
Poisson Regression	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Neural Network	18.31517	25.30458	0.4981388	0.3707992	0.6292008

N.3 CLASSIFICATION

Predicting whether a machine will undergo failure within a stipulated time period is an important use case under predictive maintenance. This will help businesses to plan scheduled maintenance/replacements effectively and improve their efficiency. Our application uses Logistic Regression, Boosted Decision Tree and neural networks to classify whether machine will fail or not. Binary classifications as well as multi class classification have been carried out based on user defined time intervals. Classification plots are displayed in Figure 4. Precision and Accuracy

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metrics for classification algorithms have also been generated to evaluate models as shown in Table 2.

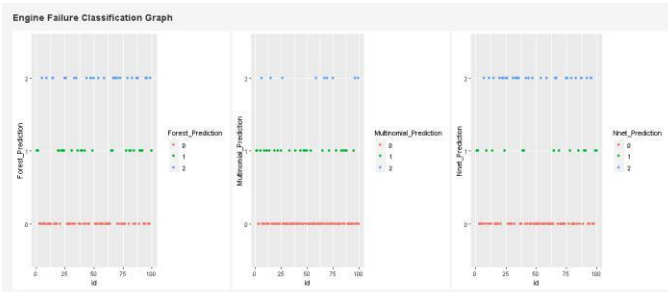


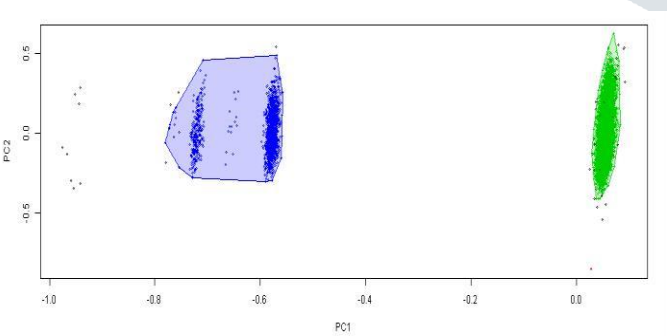
Figure 4

Algorithms	Overall.accuracy	Average.accuracy	Micro.averaged.Precision	Macro.averaged.Precision	Micro.averaged.Recall	Macro.averaged.Recall
Decision Forest	0.58	0.7200000	0.58	0.5635080	0.58	0.5558616
Multinomial	0.42	0.6133333	0.42	0.3121516	0.42	0.4013267
Neural Network	0.58	0.7200000	0.58	0.5036046	0.58	0.5100712

Table 2

N.4 ANOMALY DETECTION

Anomaly detection is the identification of rare items, events or observations which raise suspicions by differing significantly from the majority of the data. This is especially useful for detecting failures/faults in machinery and take appropriate preventive or corrective actions. Sample Data is grouped into clusters using Clustering algorithms to detect anomalies/outliers (Figure 5).Anomaly plots for individual attribute (Figure 6) data can give significant insights into operational status of different subcomponents of machines.



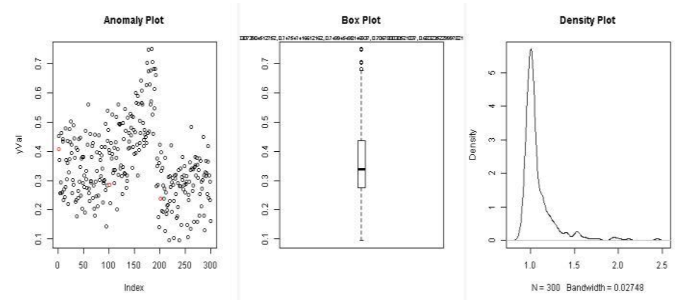


Figure 6

N.5 SURVIVAL ANALYSIS

Survival analysis is carried out to ascertain the proportion of population which is going to survive past a certain time. It is also used to determine the importance of different attributes on survival of population. Thus Survival analysis can provide valuable insights regarding the health of systems and provide valuable inputs for maintenance/replacement.

Survival analysis has been carried out in the application using Survival models. Kaplan-Meier curve indicating survival rate is shown in Figure 7. A Survival tree indicating the importance of selected attributes is shown in Figure 8.

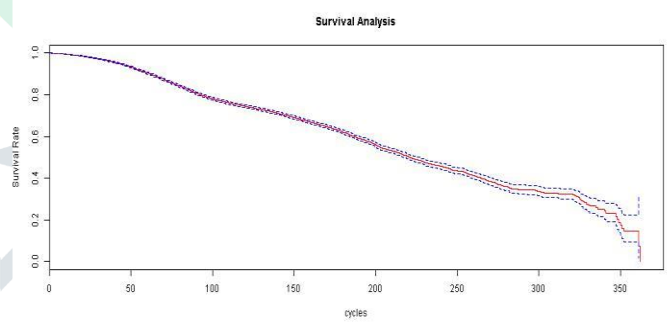


Figure 7

Figure 5

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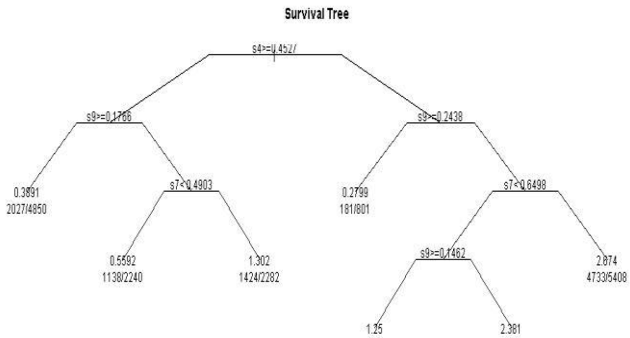

Figure 8

Thus the application comprehensively covers the different use cases under predictive maintenance and can be used for effective and smart maintenance of mechanical systems.

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