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COMPARATIVE ANALYSIS OF DIFFERENT MACHINE LEARNING ALGORITHMS IN MECHANICAL DATASET

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ABSTRACT

In this paper we created a data set for tool wear of a lathe machine. In data set we have taken 29 observations that means there are 29 rows in our data set and 4 variables that means data set have 4 columns i.e. Cutting speed (rpm), Feed rate (mm/min), Radial depth of cut (mm) and Tool wear (mm).For this particular data set we are using different machine learning algorithms to train the model and find out the comparative model accuracy. decision tree, generalization of ordinary linear regression and Random forest models has been used in this paper for comparative analysis using R programming language.

KEYWORDS: Machine learning (ML), data set, R programming.

1. INTRODUCTION

Machine learning is an part of artificial intelligence that provides systems the ability to improve itself and automatically learn, improve and update from experience without being crystal clear programmed. ML focuses on the development of computer programs that can a way of entering the data and use it to learn for themselves. For creating the model we have used R programming language, R is a programming language and freeware software environment for statistical computing, Data science ,Machine learning and graphics.

In this paper we had used a data set of lathe machine having 29 observation and 4 variables, out of all the variables tool wear was output variable and speed , Feed rate and Radial depth of cut were dependent variables. For the particular data set we have used 7 steps to build a ML model the steps are :

Step 1: Collect Data / Problem formulation
Step 2: Prepare the data and preprocessing
Step 3: Split train and test data
Step 4: Choose the model
Step 5: Train your machine model / model building
Step 6: Parameter Tuning / validation / model accuracy

2. LITERATURE REVIEW

Dazhong Wu al., [2017] Manufacturers are faced with a growing need for the development of predictable models that predict mechanical failure and the remaining useful life (RUL) of production systems or components. Predictability based on classic or physics-based models often requires a deep physical understanding of the interest system in order to develop mathematical models of closed forms. However, prior knowledge of system behavior is not always available, especially in complex production systems and processes. In line with model-based predictions, data-driven methods have been increasingly used in machine prediction and adjustment management, transforming asset production systems into intelligent production systems. Although previous research has shown the effectiveness of data-driven methods, many of these predictors are based on learning techniques for older machines, such as artificial network networks (ANNs) and support vector regression (SVR). With the rapid development of artificial intelligence, various machine learning algorithms have been developed and widely used in many fields of engineering. The purpose of this study is to present a forest-based forecasting method (RFs) for predicting aging tools and comparing RF performance with feed-forward back propagation (FFBP) ANN and SVR.

A.Gouarir al., [2018] This paper introduces an in-process tool wear prediction system, which uses a power sensor to monitor device flank continuity and machine learning (ML), in particular, the Convolutional Neural Network (CNN) as a tool for predicting the aging of tools. . The proposed method is demonstrated by testing using grinding as a test procedure. The test was performed using a dry machine with a closed ball endmill and a stainless steel working piece. Flank wear measurement is done in-situ using a digital microscope. ML model predictions are based on an information database that contains all the pre-test data. The proposed system of injecting in-process tool wear will be strengthened over time with a flexible control system (AC) that will continuously interact with the ML model to seek the best adjustment of feed level and spin speed that allows for the development of flank aging and expansion. tool life. The AC model decisions are based on predictions delivered by the ML model and the information response provided from the energy sensor, which captures changes in cutting strength as a function of continuous flank aging. In this work, only part of the ML model is shown to measure the aging of tools based on CNN. The proposed methodology showed an average accuracy of 90%. Additional tests will be performed to confirm the duplication of results and to increase the scope of measurement to improve the accuracy of the measurement system.

Yan Shen al., [2017] The need to monitor the aging of tools is important, especially in the advanced manufacturing industry, as it aims to increase The life of the cutting tool while ensuring the quality of the working piece to be performed. Although there were many studies conducted by monitoring the health of cutting tools under certain cutting conditions, monitoring the aging of the tools in all multiple cutting cases it is still a challenging proposition. In dealing with this, this paper presents an outline monitor the health of the cutting tool, which works under most cutting conditions. Predictable model, using Advanced Machine learning methods with a combination of multi-dimensional models and a flexible sliding system, are being developed. I Framework that takes into account machine parameters, including cutting depth, cutting speed as well the feed rate, as input into the model, thereby produced important speculative features. Actual data from machine testing were collected, investigated and analyzed, with predictive results showing high compliance with the principles of predictive styles and central root accuracy mean square error values.

Dazhong Wu al., [2016] Increased real-time monitoring systems and the arrival of Industrial Internet of Things (IIoT) over a few years ago needed scalable development again compatible algorithms help predict machine failures as well useful remaining life of a production system or system parts. Predictions based on the old model require depth physical understanding of the system of interest as well they usually take some stochastic or random procedures. To overcome model-based, data-driven methods methods such as machine learning have been increasing used in prognostics and health management (PHM). While machine learning algorithms are able to create precision predictable models, a lot of training data is required. Therefore, machine learning methods do not exist works well on PHM data driven computer. The purpose of this research is to develop a new mechanical method prognostics using the same cloud-based machine learning algorithm. Specifically, one of the most popular machines learning algorithms (i.e., random forest) is used for prediction wear of tools in dry grinding operations.

Achyuth Kothuru al., [2017] Due to the needs of Computer-Integrated Manufacturing (CIM), Tool Condition Monitoring (TCM) system, as a major program. As part of the CIM, it is important to improve productivity, increase labor and maintenance costs, and reduce productivity. production is lost with increasing production. Looking for a reliable, efficient, and inexpensive solution, varied Monitoring techniques using a variety of sensory enhancement techniques to detect device conditions such as monitoring unusual cutting conditions. This paper examines the use of audible sound signals as a hearing aid to detect sound cutting aging and tool failure during grinding operations using the Learning Vector Machine (SVM) learning model as decision-making algorithm. In this study, the sound signals collected during the process of the machine are regularly analyzed background to extract signal features that link to a real cutting event. The SVM method seeks to provide a language model by measuring the wear of the tools from the information embedded in this machine learning method. Performance test results of the proposed algorithm has shown accurate prediction in obtaining wearable tools under various fast cutting conditions response rate, which provides a good in-depth TCM solution. In addition, the proposed monitoring system is trained with sufficient signals collected at various locations have proven to be independent in monitoring the aging of the instruments conditions.

3. MATERIALS AND METHODS

Step 1: Collect Data / Problem formulation

We have been collected data of lathe machine and formulate a data set 29 observation and 4 variables, sample of data set as follows:

Table 1: sample of data set

Exp.nos.	Cutting speed(rpm)	Feed rate(mm/min)	Radial depth of cut(mm)	Tool wear
1	150	50	1.5	0.226
2	150	100	1.5	0.286
3	150	150	1.5	0.26
4	150	50	1	0.293
5	150	100	1	0.237
6	150	150	1	0.296
7	150	50	0.5	0.272
8	150	100	0.5	0.299
9	150	150	0.5	0.34
10	200	50	1.5	0.409

Step 2: Prepare the data and preprocessing

Pre-data processing in Machine Learning is an important step that helps to improve data quality in order to improve the output of meaningful data. Pre-processing Data in Mechanics refers to the process of preparing (cleaning and editing) raw data to suit the structure and training of Machine Learning models. This dataset has no missing values but it has more outliers.

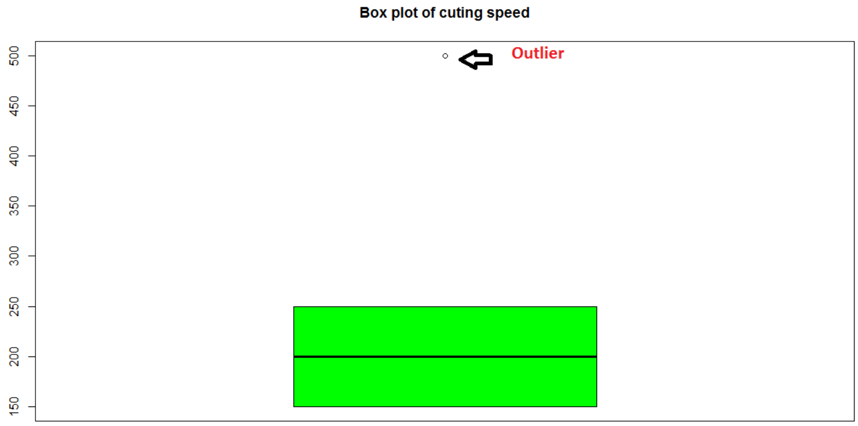

Fig. 1 : box plot of Cutting speed

In fig. 1 it is clearly visible that cutting speed has a outlier so we can delete the raw or replace the value of outlier by median (200) so in this paper we had replaced outlier by median. similarly In fig. 2 it is clearly visible that Radial depth of cut has a outlier so we can delete the raw or replace the value of outlier by median so in this paper we had replaced outlier by median (1).column number 1 is only showing experiment number or number of

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observation so we can delete it. Now data has no missing values and outlier after that we made a machine learning model.

Step 3: Split train and test data
To build model we are using R programming, in R programming there is a library Catools available to slit the data into test data set and train data set. for this paper we are using 80% data for training propose and reaming 20% data for testing propose.

As per random selection by software out of 29 observations 21 observations has been used for training propose that means to train the model and 8 observations has been used for testing propose.

Step 4: Choose the model
The data set had tool wear variable as a output variable and the variable had only numeric values that means this a regression model problem for that we can using multi linear regression model , logistic regression and decision tree and random forest algorithms.

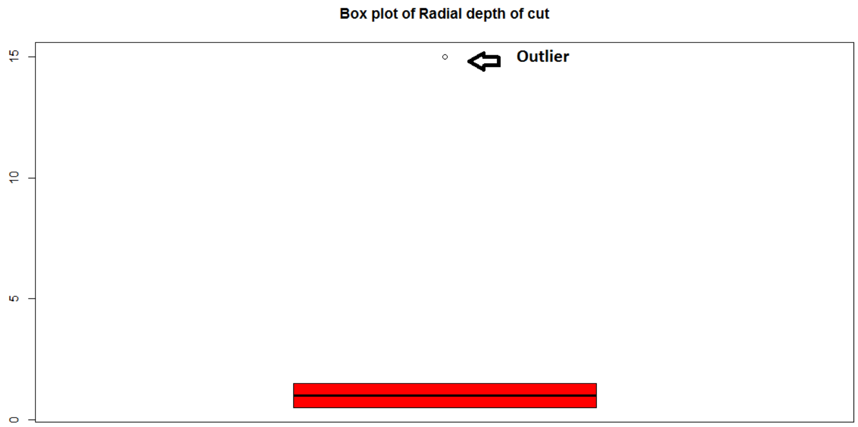

Fig.2 : box plot of Radial depth of cut

Step 5: Train your machine model / model building
After the model selection we built model first using multi linear regression model, Multiple regression is a method of predicting dependent variables with the help of two or more independent variables. In conducting this analysis, the main objective of the researcher is to discover the relationship between dependent variables and independent variables. To predict dependable variables, many independent variables are selected, which can help predict dependent variability. It is used where the reversal of the line cannot achieve the purpose. The retrospective analysis assists in the process of ensuring that the prediction variables are accurate enough to help predict dependent dependencies. After multi linear regression model we created Decision tree model With mathematical complexity the decision tree model is a calculation model in which the algorithm is considered a decision tree, that is, a sequence of questions or randomized controlled trials, so that the result of previous tests can influence the test. For model creation in R we had used rpart library. After Decision tree model we have created Random forest, Random forests or randomly forested forests are an integrated learning method for segregation, retrieval and other activities that work by building a number of deciduous trees during training. With segregation activities, random forest clearing is a class selected by many trees. For model creation in R we had used randomForest library.

Step 6: Parameter Tuning / validation / model accuracy
Medium square error (MSE) error tells you how close the regression line is to a set point. It does this by taking the distances from the points to the backbone (these distances are “errors”) and combining them. Squaring is

needed to remove any bad symptoms. It also gives extra weight a big difference. It is called a square error as you get a set of error sets. The lower the MSE, the better the forecast.

4. RESULTS AND DISCUSSION

MSE formula = (1/n) * Σ(actual – forecast)2
Where:
n = number of items,
Σ = summation notation,
Actual = original or observed y-value,
Forecast = y-value from regression.
using above formula based on R programming we got Mean Squared Error for multi linear regression model is 0.0085 , for decision tree model it is 0.0072 and for random forest it is 0.0090 shown in fig.2 bar chart of Mean Squared Error of different models.

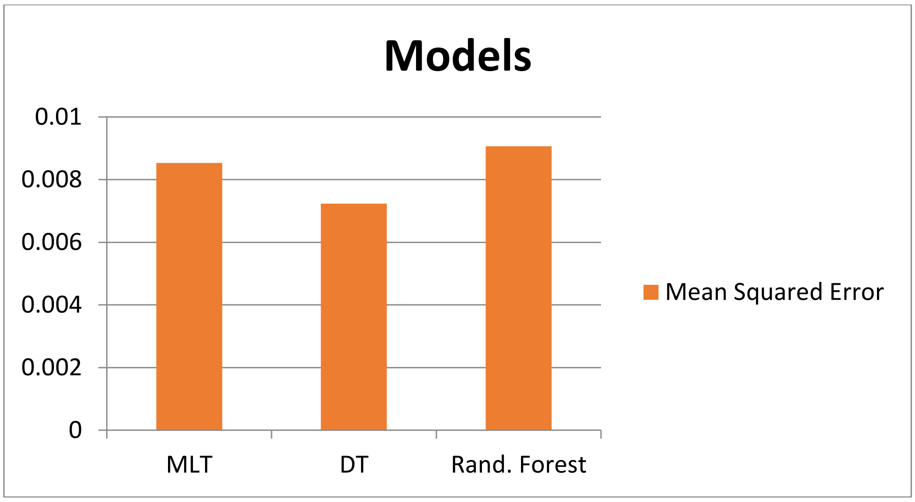

Fig.3 : Mean Squared Error of different models

5. CONCLUSION

As per fig.3 bar chart Mean Squared Error (MSE) of different models. It is clearly visible that decision tree model had the value of MSE 0.0072 means decision tree model had more accuracy for that particular data set the value of MSE for multi linear regression was 0.0085 means multi linear regression had more accuracy than random forest and the value of MSE for random forest was 0.0090 but all 3 models have the value of MSE below 0.01 that means all models were good.

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