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A Machine Learning Approach to the Classification of Engine Health

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Abstract—

Engine quality is the fulcrum of effective transportation and determines the health of the car. However, there are several parameters that need to be taken into consideration while estimating engine health which makes it cumbersome and tedious to always do it manually using techniques including but not limited to compression tests, leak down tests etc. This is where machine learning can step in. Machine learning uses historical data for prediction or classification tasks and can be extremely useful for this task of classifying the engine quality as normal, or, one with faults.

This can be an extremely useful tool to aid engine quality assessment either during testing phases or can be incorporated into the car for onboard diagnostics and early-stage detection and repairs making life comfortable for the user and increases the reputation of the automobile brand. In this paper, we therefore apply several machine learning techniques for classification of engine quality namely Logistic Regression, Artificial Neural Networks, Support Vector Machines, Decision Trees and Random Forest using several input features. We evaluate model performance using metrics such as training time, accuracy, precision, recall and model stability. We recommend the best model for this task of engine health classification and show that this is the way forward for intelligent maintenance services offered to the car owners in this digital age.

Keywords— Machine Learning, On-board Diagnostics, Engine Health

I. INTRODUCTION

This is the age of technological progress and empowerment. Automotive is one such sector which has come up leaps and bounds to the extent that we are now talking about driverless vehicles. However, it is imperative to note that full automation is achieved only when digital technologies are leveraged to its fullest potential and not only limited to hands-off steering.

For instance, on-board diagnostics is one such area where completed automation is desired. Powertrain components are the fulcrum of transportation, and it needs to be at the pink of its health to ensure hassle-free commutation from one place to another.

Engine in particular is critical, and its health dictates the quality of the automobile. However, ensuring its quality is now more often limited to manual tests using techniques such as compression tests, leak down tests etc. This has two drawbacks. Though these are effective these are not portable and require vehicle owners to visit the service stations to ascertain the health of the engines. Secondly, it is not possible to pre-empt the deterioration of the health of the engines, making vehicles susceptible to sudden-stop situations when the engine completely breaks down.

In this paper, we therefore leverage the application of machine learning techniques for classification of engine health using several input features. Specifically, we employ the Logistic Regression, Extreme Learning Machines (ELM), Support Vector Machines (SVM), Random Forests and Decision Trees for the task of classification. We use metrics such as model accuracy, precision, recall, training time and model stability to evaluate the performance of all models to the dataset of engine quality classification. We then recommend the best fitting model for this task.

This paper is organized as follows. The following section is devoted to the literature survey. The second section describes briefly the dataset used in this work. This is then followed by the section on the experimental approach followed in this work. This is succeeded by the section on the results obtained in this work. The last section is dedicated to the recommendation of the best fitting model for this task as well as future research work in this direction.

II. LITERATURE REVIEW

This section discusses the prior work done in this field of determination of engine health. [1] demonstrates the application of artificial neural networks, XG-Boost and Support Vector Machines for the task of predicting engine performance and emissions. However, they treat this as a regression problem and not a classification problem and hence use regression-specific techniques for evaluating model performance. [2] also treats this as a regression problem as opposed to a classification problem. Also, only a single model is applied and hence the focus is not on a comparative evaluation of the models' performance. [3] presents a machine learning approach to the classification of combustion events in a RCCI engine using a small subset of parameters. [4] presents machine learning as an alternative to Computational Fluid Dynamics (CFD) and laser diagnostics measurement for engine studies. [5] presents an overview of ML techniques for IC engine quality estimation. [6] presents three different models namely CatBoost, XG Boost and random forests for the task of classifying engine health. [7] present their work on the investigation of role of data quality in machine learning for classification of engine quality. [8] assessed six distinct machine learning methods, including Random Forest Classifier, Gradient Boosting Classifier, XGBoost Classifier, Logistic Regression, Voting Ensemble, and Stacked Ensemble models for the task of classifying engine quality and used classical metrics including but not limited to accuracy, precision and recall.

To the best of knowledge, little to no work has been done to classify engine quality using different ML techniques and then recommending the best fitting model. This paper addresses this research gap. Specifically, ELM, LR, SVM and Decision Trees and Random Forests are applied to the engine quality classification dataset, and several metrics are used to evaluate each model, namely, training time, model stability, precision, recall and model accuracy.

III. DATASET & PRE-PROCESSING

In this section, the data set used in our work is briefly described. The dataset was taken from Kaggle [9]. The problem and the dataset that we have is one of multi-class classification. The dataset is approximately nineteen thousand and five hundred rows long and comprises of the following main features –

a. Engine RPM
b. Lub Oil Pressure
c. Fuel Pressure
d. Coolant Pressure
e. Lub Oil Temperature
f. Coolant Temperature
g. Engine Conditions

There is not too much pre-processing required for this task except for dropping rows with at least one null valued column.

IV. EXPERIMENTAL APPROACH

The following is the experimental process followed for this paper. The same has been depicted in the form of a flow-diagram in Figure 1.

1. Remove null valued rows in the dataset.

2. Perform linear correlation study.

3. Divide the dataset into training – test set ratio of 60-40%.

4. Train the ML models and cross validation is also performed.

5. Evaluate the models based on the training time, model accuracy and model stability.

6. Recommend the best model for this task.

The mean is represented by μ and the standard deviation is represented by σ in this work borrowing from standard literature.

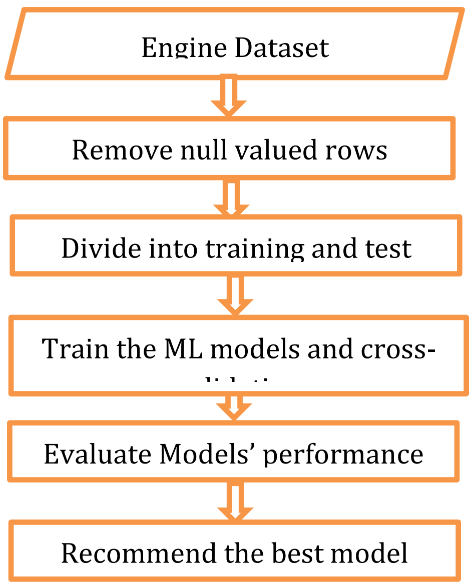

Figure 1 – Experimental Approach Flow Diagram

V. RESULTS

a. Random Forest Classifier

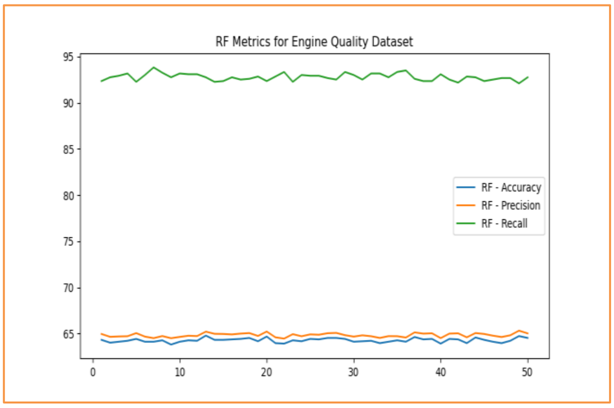

Figure 2 – Metrics for Random Forest Classifier

Table I

μ (Training Time Per Iteration)	1.22s
σ of model accuracy	0.25
σ of model precision	0.23
σ of model recall	0.34

Inference - It can be seen from Figure 2 that the model accuracy is not that high. However, from table I the mean training time for fifty iterations / cycles is low and the standard deviation of model metrics is negligible, indicating little variability in model performance.

b. Decision Tree Classifier

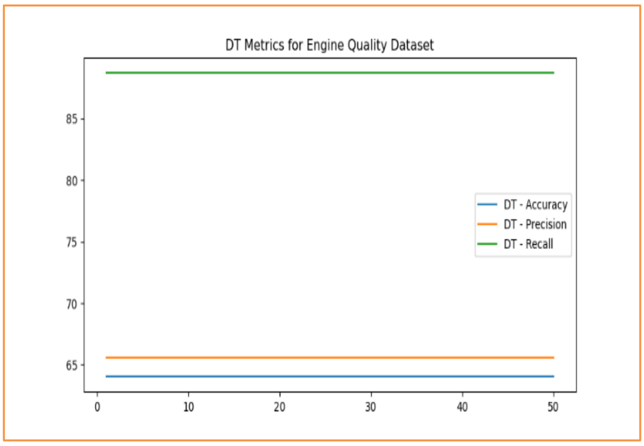

Figure 3 – Metrics for Decision Tree Classifier.

Table II

μ (Training Time Per Iteration)	0.040s
σ of model accuracy	0.0
σ of model precision	0.0
σ of model recall	0.0

Inference: It can be seen from Figure 3 that while the accuracy and precision are not high enough, the recall is high and hovers around 89% though not as much as Random Forest classifier. Table II shows that the training time is lower than the Random Forest as we are training a single tree as opposed to several trees.

c. Support Vector Machines Classifier

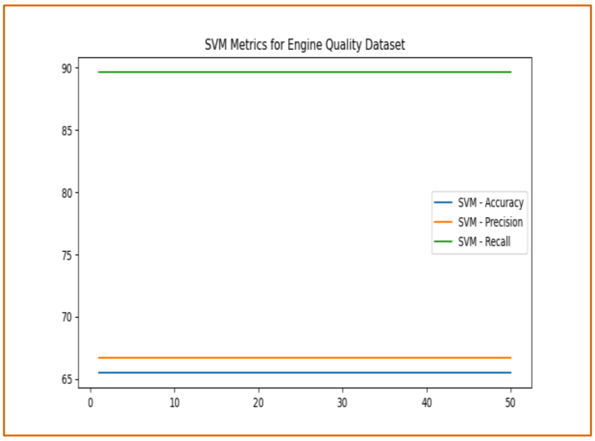

Figure 4 – Metrics for SVM Classifier

Table III

μ (Training Time Per Iteration)	18.09s
σ of model accuracy	0.0
σ of model precision	0.0
σ of model recall	0.0

Inference: It can be seen from Figure 4 that while the accuracy and precision are not high enough, the recall is high and hovers around 90% though not as much as Random Forest classifier. Table III shows that the training time is significantly higher than the random forest and decision tree classifiers used earlier.

d. Logistic Regression

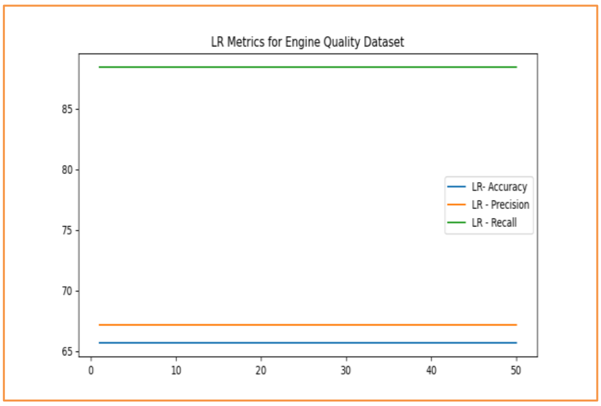

Figure 5 – Metrics for Logistic Regression

Table IV

μ (Training Time Per Iteration	0.016s
σ of model accuracy	0.0
σ of model precision	0.0
σ of model recall	0.0

Inference: It can be seen from Figure 5 that while the accuracy and precision are not high enough, the recall is high and hovers around 89% though not as much as Random Forest classifier. Table IV shows that the training time is significantly lower than the Support Vector Machines Classifier described earlier.

e. Extreme Learning Machines

Extreme Learning Machines or ELM was originally proposed by [10] to offset some of the bottlenecks of conventional gradient based iterative learning algorithms.

Choice of Activation Function – Sigmoid

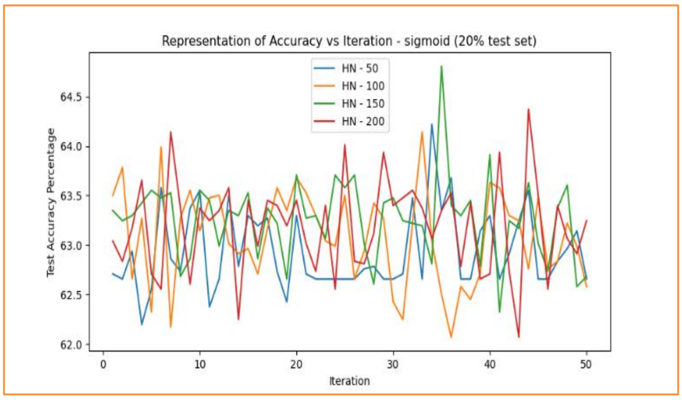

Figure 6 – Accuracy for ELM Sigmoid Activation Function.

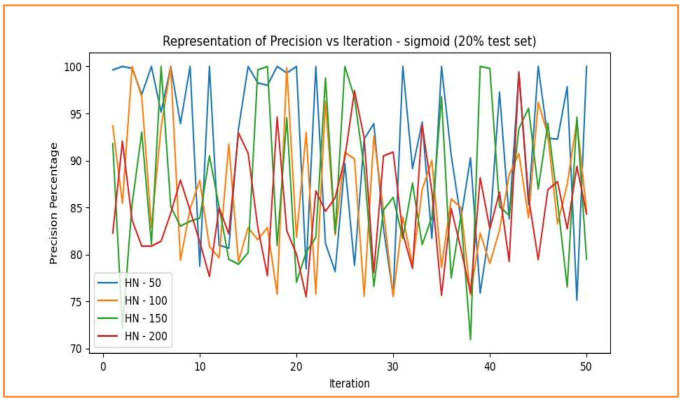

Figure 7 – Precision for ELM Sigmoid Activation Function

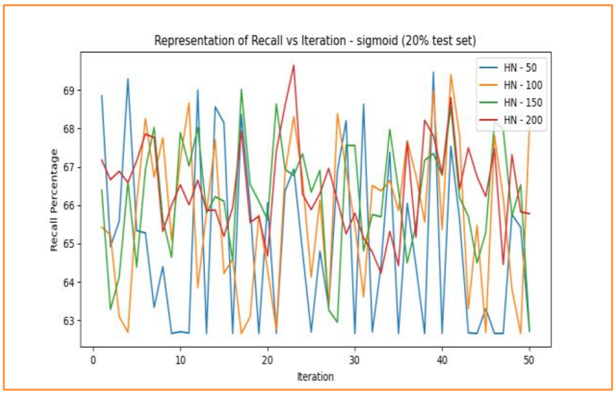

Figure 8 – Recall for ELM Sigmoid Activation Function

Table V

Number of Hidden Neurons	μ(Training Time Per Iteration)	σ of Model Accuracy	σ of Model Precision	σ of Model Recall
50	0.0421s	0.3974	8.296	1.581
100	0.0683s	0.4905	8.3153	1.995
150	0.1144s	0.4957	6.1745	1.447
200	0.1608s	0.4261	6.1503	1.265

Inference – It can be seen from Figure 6 and Figure 8 that the model accuracy and recall are not that high. However, from Figure 7, the precision is quite high with percentages reaching as high as 100. However, it must be noted that precision also has the highest standard deviation among all the three metrics as seen from Table V.

Choice of Activation Function – Relu

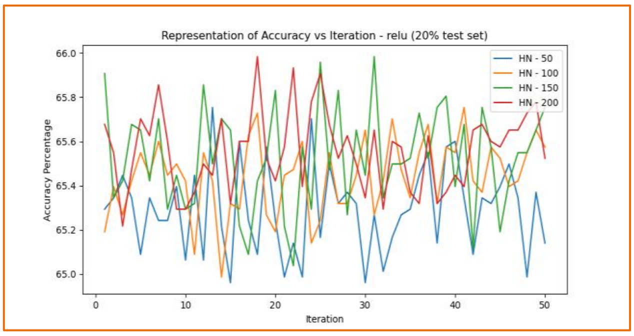

Figure 9 – Accuracy for the ELM Relu Activation Function.

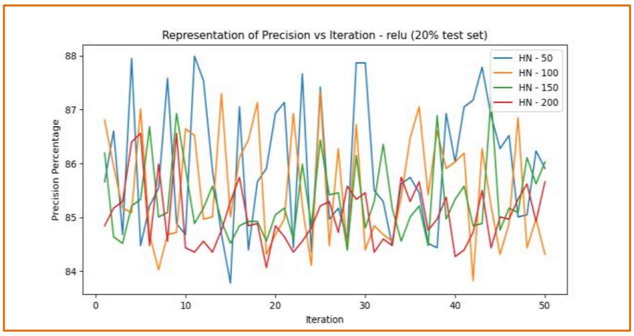

Figure 10 – Precision for the ELM Relu Activation Function.

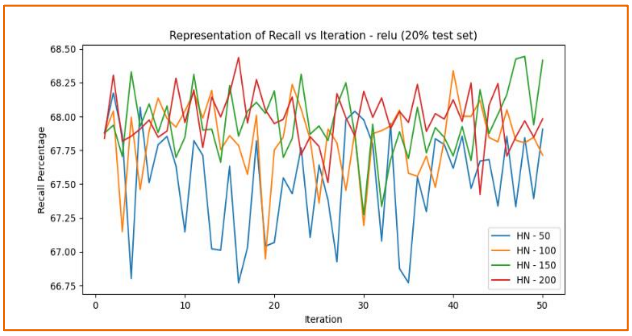

Figure 11 – Recall for the ELM Relu Activation Function.

Table VI

Number of Hidden Neurons	μ(Training Time Per Iteration)	σ of Model Accuracy	σ of Model Precision	σ of Model Recall
50	0.030s	0.239	1.170	0.398
100	0.052s	0.212	0.781	0.238
150	0.157s	0.223	0.737	0.273
200	0.107s	0.202	0.570	0.174

Inference – It can be seen from Figures 9 and 11 that while the accuracy and recall rates are not that high the precision is quite high touching nearly 90. Also, the standard deviations of the metrics are not very significant as seen from Table VI.

Choice of Activation Function – sine

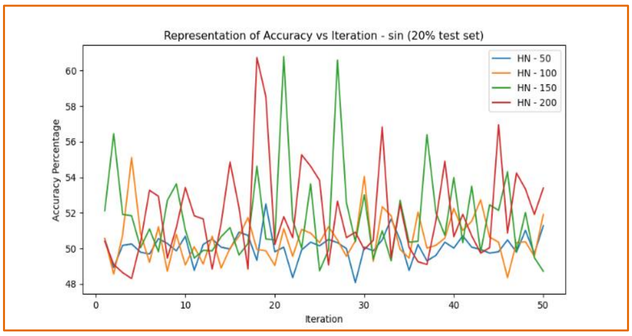

Figure 12 – Accuracy for the ELM sine Activation Function

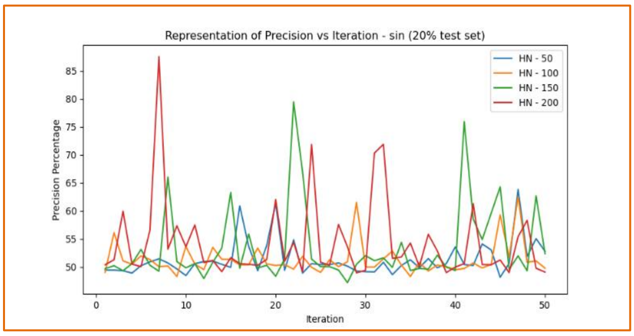

Figure 13 - Precision for the ELM Sine Activation Function.

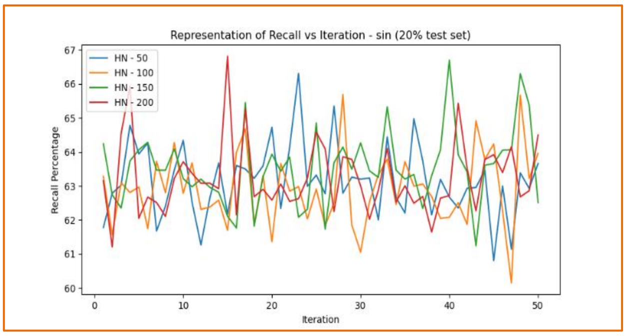

Figure 14 - Recall for the ELM Sine Activation Function.

Table VII

Number of Hidden Neurons	μ(Training Time Per Iteration)	σ of Model Accuracy	σ of Model Precision	σ of Model Recall
50	0.03s	1.682	4.474	1.0658
100	0.05s	2.817	8.173	1.254
150	0.076s	2.397	8.256	0.974
200	0.103s	2.183	6.300	1.537

Inference – It can be seen the training time is very low from Table VII. However, from the figures 12 – 14 it is evident that the precision, accuracy and recall rates have dropped implying that sin is not such a good fit to the data.

SUMMARY / CONCLUSION

While accuracy is relatively low for this dataset, depending on the models the precision and recalls are higher. However, it must be emphasized that recall is the most important factor for deciding the model for this example, as higher the recall rate, lower is the number of false negatives. This directly translates to the lower number of actual faulty engines being wrongly classified as good quality engines.

In accordance with this, random forests, with its high recall rate and low training time is the best model for this task. Future work in this area would revolve around development of application that would embed one or more of these models to assist the driver in estimating the engine quality.

POTENTIAL APPLICATIONS OF THE MODEL

In this section, we briefly list with some diagrams, potential use cases of this machine learning approach to the classification of engine health.

a. Engine Health Monitoring System

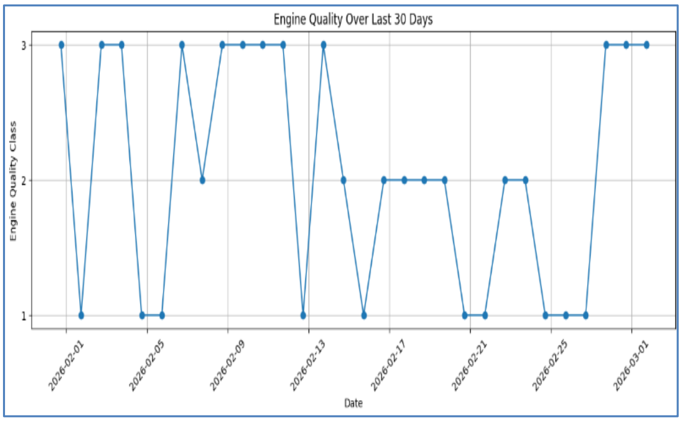

Figure 15 – Representative Image of dashboard in car / app showing engine health for the last month.

b. Personalized Recommendations

We can combine this engine's health to other factors such as environment and terrain, driver behaviors for suggesting optimized driving profiles/paths.

c. Predictive Maintenance

Mobile application(s) alerting consumers to book service early enough to ensure sustained engine performance.

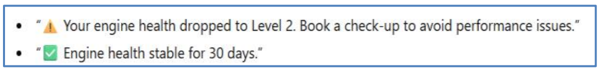

Figure 16 – Representative image showing one of the two instructions for car owners depending on engine state

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DEFINITIONS / ABBREVIATIONS

ELM	Extreme Learning Machines
SVM	Support Vector Machines
LR	Logistic Regression

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