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Long-Short Term Memory And Gradient Boosting Model For Hydraulic System Predictive Maintenance

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ABSTRACT

A hydraulic system, a drive technology that uses a fluid to create force, is used in a wide range of industrial settings, as well as buildings, construction equipment, and vehicles. Well-planned predictive maintenance is considered the most efficient maintenance strategy to maintain the performance of the system. While data-driven approaches such as machine learning approaches are providing increasingly effective solutions in this domain, determining which method is fit, robust, and provides the most accurate detection has remained a challenge. This research proposes two Long-Short Term Memory (LSTM) models to predict the condition of each feature over time and various supervised algorithms to predict predicts the type of fault and the time fault that occur based on the condition of the features over time. The result shows the LSTM model which only considering one feature in the model provides higher accuracy than the model with all features. In predicting the fault, Gradient Boosting Classifier has the best performance among other models, including Logistic Regression, K-Nearest Neighbor, Support Vector Machine, Gaussian Naïve Bayes and the other ensemble models (extreme gradient boosting, random forest classifier, AdaBoost Classifier, extra tree classifier).

Keywords: *Deep Learning, Long-Short Term Memory, Gradient Boosting, Predictive Maintenance, Hydraulic System*

1. INTRODUCTION

A hydraulic system, a drive technology that uses a fluid to create force, is used in a wide range of industrial settings, as well as buildings, construction equipment, and vehicles. A well-maintained hydraulic system is critical for keeping equipment running efficiently today and in the future. Preventing breakdowns through regular maintenance is far more productive than dealing with the downtime and increased costs associated with hydraulic system failures. The industry implements preventive maintenance instead of reactive maintenance which repair or replace breakdown equipment to reduce the downtime due to equipment breakdown [1], [2]. Preventive maintenance regularly inspecting and performing maintenance on machinery, regardless of whether the equipment needed maintenance either based on time or usage. However, research[3], [4] found that only 18% of asset failures had a pattern that increased with use or age. It appears to follow that preventive maintenance alone will not prevent the remaining 82 percent of asset failures, and a more advanced approach is required. Predictive maintenance, which involves monitoring the performance and condition of equipment during normal operation to predict the future failure point of a machine component, is one of the new types of maintenance that may gain increasing attention. So that the component, based on a plan, can be replaced just before it fails[1].

Condition monitoring, which is defined as the continuous monitoring of machines during process conditions to ensure the optimal use of machines, is required for predictive maintenance to exist. Data on usage history is an important indicator of equipment condition, as well as maintenance and service history. Historical data should be collected far enough in the past to accurately reflect the deterioration processes of the machines. Other static details about the machine/system, such as data about a machine's features, mechanical properties, typical usage behavior, and environmental operating conditions, are also useful. Data can be derived from various sources such as sensors, business data from ERP, and production data[1].

Data-driven methods have been widely used in the manufacturing, power plant, mining, and oil and gas industry[5]–[9]. Aided by growing hardware capabilities, cloud-based solutions, and newly introduced state-of-the-art algorithms machine learning approaches have been demonstrated to provide increasingly effective solutions in this domain. Machine learning can extract useful information from vast amounts of data that would be far too large for any human engineer to handle all at once and predict data [1].

Considering the potential of machine learning in making prediction based on historical data, this research proposes supervised machine learning approaches to predicts when the next maintenance should be performed, and the component(s) that should be maintained in the next maintenance cycle.

Former research successfully identify the features to a specific fault and classify fault condition and the grade of severity[10]–[12]. This research utilizes the result from the prior result to predict the time for next maintenance what which item that should be maintained in a hydraulic system using a machine learning approach.

2. RESEARCH METHODOLOGY

This research follows activities as shown in Figure 1, which consist of design, data collection, data preprocessing, modelling, then validation and testing.

Figure 1. Research Activities

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Detail activities is shown in Figure 2. Several decisions are made during design such as, selecting features that will be included in the model and target components that will be predicted by the model, algorithm for training and validation. Once the features and targets are selected, raw data related to those features and targets are collected. Data are divided into three groups; training, validation, and testing.

During data pre-processing, datasets which have different distribution range should be normalized to reach convergence[13]. Normalized datasets are then transformed into a 3-D array format before it becomes an input for the machine learning model.

This research uses two different models; the forecasting model predicts the condition of each features over time, and the classification model predicts the type of fault and the time fault occur based on the condition of the features over time.

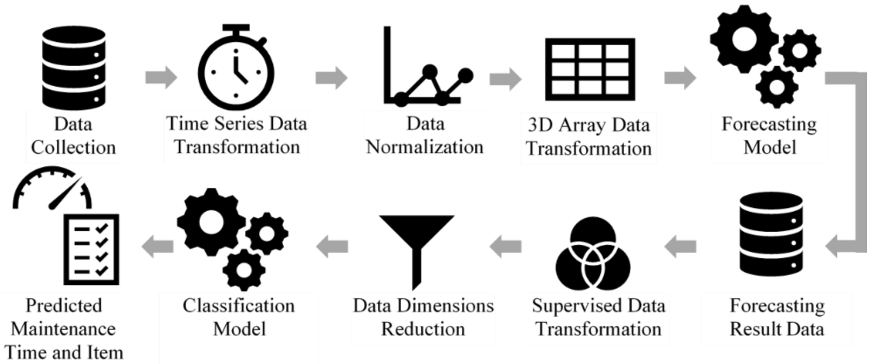

Figure 2. Training, Validation and Testing Steps

The forecasting model uses Long-Short Term Memory, an artificial recurrent neural network (RNN) architecture[14], which resolves the vanishing gradient problem of RNN. This model is selected because it uses mainly sequential processing over time. This research uses two approaches to forecast maintenance time; the first approach considers all selected features in one model, and the second approach creates a forecast model for each feature.

Data resulted from the forecasting model is transformed into supervised data; then, data dimension reduction is performed before using the dataset as an input for the classification model. Dimension reduction reduces several features into one feature by calculating the average data points from those features. Supervised algorithm requires balanced representations of all the classes contained in a dataset to perform effectively[15]. This research uses over-sampling and ensemble[16], [17] to improve the model accuracy related to class-imbalanced data.

For classification model, this research compares several algorithms such as; logistic regression, K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Gaussian Naïve Bayes, decision tree, and several ensemble models (extreme gradient boosting, gradient boosting classifier, random forest classifier, AdaBoost Classifier, extra tree classifier). Validation for classification model will not use validation data. Instead, this research uses k-fold cross-validation using all datasets (training, validation, and testing).

During the training, both forecasting and classification model is run using training data, and hyperparameter tuning are performed to improve the accuracy of the model. The most optimized model is then validated and tested using validation and testing datasets during the validation and testing stage.

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3. RESULT AND ANALYSIS

This research uses 17 features to predict when maintenance should perform in the five fault categories. The selected features represent temperature, pressure, volume flow, motor power, vibration, cooling efficiency, cooling power, and efficiency factor. Each fault category has several classes as shown in Table 1. Table 1 also shows the number of instances for every fault class.

The dataset is derived from a public data set[1], which is the result of a hydraulic test rig experiment. The test rig is made up of a primary working circuit and a secondary cooling-filtration circuit that are linked by an oil tank. The system cycles through constant load cycles (duration 60 seconds). It quantifies the condition of four hydraulic components while measuring process values such as pressures, volume flows, and temperatures (cooler, valve, pump, and accumulator).

Table 1. Dataset for each Fault Class

Fault Categories	Fault Classes	Total Instances
Cooler	Close to Failure	732
	Reduced Efficiency	732
	Full Efficiency	741
Valve	Close to Total Failure	360
	Severe Lag	360
	Small Lag	360
	Optimal switching	1125
Internal Pump	Severe Leakage	492
	Weak Leakage	492
	No Leakage	1221
Hydraulic Accumulator	Close to Total Failure	808
	Severely Reduced Pressure	399
	Slightly Reduced Pressure	399
	Optimal Pressure	599
Stable Flag	Not stable yet	756
	Stable	1449

Data are divided into three groups for the forecasting model; training (86639 data points), validation (21660 data points), and test (24000 data points). The result from the forecasting model becomes an input dataset for the classification model. Eighty percent of the dataset is used as the training dataset, while the remaining 20 percent dataset is used for testing dataset. All dataset is used to validate the classification model.

Data processing consist of time-series transformation, normalization, and 3-D array transformation. Training data is transformed into a time series based on the 60-second cycle. The

[1] https://archive.ics.uci.edu/ml/datasets/Condition+monitoring+of+hydraulic+systems

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transformation result is shown in Figure 3(a). Because the range of data for each feature is different, data are normalized using Min-Max Scaler utilizing MinMaxScaler function from sklearn library. The normalization result is drawn in Figure 3(b). The LSTM model requires input in 3D-array, so the normalization results in Figure 3(b) is transformed into 3D-array. The 3D array dimension represents the number of samples, the number of timesteps, and the number of features.

(a)

		Features								
seconds	cycle	CP	CE	EPS1	FS1	FS2	PS1	PS2	PS3	PS4
0	0	2.184	47.202	2411.6	8.990	10.179	151.47	125.500	2.305	0.0
1	0	2.184	47.273	2411.6	0.770	10.174	151.45	125.390	2.305	0.0
2	0	2.184	47.250	2411.6	0.641	10.151	151.52	125.400	2.336	0.0
3	0	2.185	47.332	2411.6	0.006	10.149	151.27	125.030	2.578	0.0
4	0	2.178	47.213	2411.6	0.000	10.172	150.80	124.050	2.977	0.0
5	0	2.188	47.372	2411.6	0.000	10.176	150.69	123.180	3.234	0.0
6	0	2.177	47.273	2411.6	0.001	10.169	153.89	104.010	2.414	0.0

(b)

TS1	TS2	TS3	TS4	PS1	PS2	PS3
0.013646	0.013646	0.013646	0.013646	0.206882	0.186170	0.973019
0.060357	0.060357	0.060357	0.060357	0.204134	0.182048	0.960137
0.113658	0.113658	0.113658	0.113658	0.194123	0.174836	0.956747
0.157856	0.157856	0.157856	0.157856	0.187870	0.171377	0.935069
0.198806	0.198806	0.198806	0.198806	0.180522	0.166470	0.914895
0.236686	0.236686	0.236686	0.236686	0.177378	0.164861	0.906931
0.272292	0.272292	0.272292	0.272292	0.167682	0.157091	0.885645

Figure 3. Data Pre-processing Result (a) time-series transform (b) normalization

Normalized data then becomes the input for the forecasting model. Forecasting uses two approaches, considering one feature and considering all features. Both approached use the same model, which consists of 3 layers; the first layer has 256 nodes, the second layer is the dropout layer with dropout ration 0.2, the third layer is the output layer, which consists of 17 nodes. The model uses the sigmoid activation function, Adam algorithm as an optimizer, and Mean Square Error loss function. The batch size is 32, and the epoch is 100, with early stopping. Figure 4 shows that the all-features approach has a higher loss than the one-feature approach. Figure 5 depicts the prediction of the condition of several features over time, and it shows that the one-feature approach has higher accuracy than the all-feature approach. The result shows that the one-feature approach has a better result in terms of loss and accuracy compares to the all-features approach.

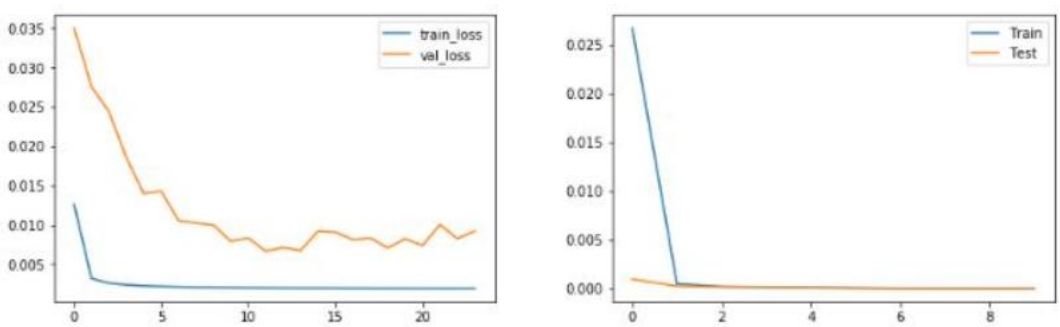

Figure 4. LSTM Loss (left) all features (right) one feature.

The data resulted from LSTM model using one feature approach then becomes input for the classification model, because it has better accuracy and loss result. The dataset is transformed into supervised data by adding target values. The supervised transformation is followed by data dimension reduction. Features with more than one data point are reduced to one data point by calculating the mean of that data points.

The cross-validation in classification utilizes GridSearchCV from sklearn. GridSearchCV searches for the most optimum hyperparameter in the model among the defined list of initial parameters. To avoid overfitting, it uses five-folds cross-validation metrics. The optimum hyperparameters resulted from GridSearchCV are Max depth: 5, sub-samples: 0.5, max features: 17, n-estimators: 180.

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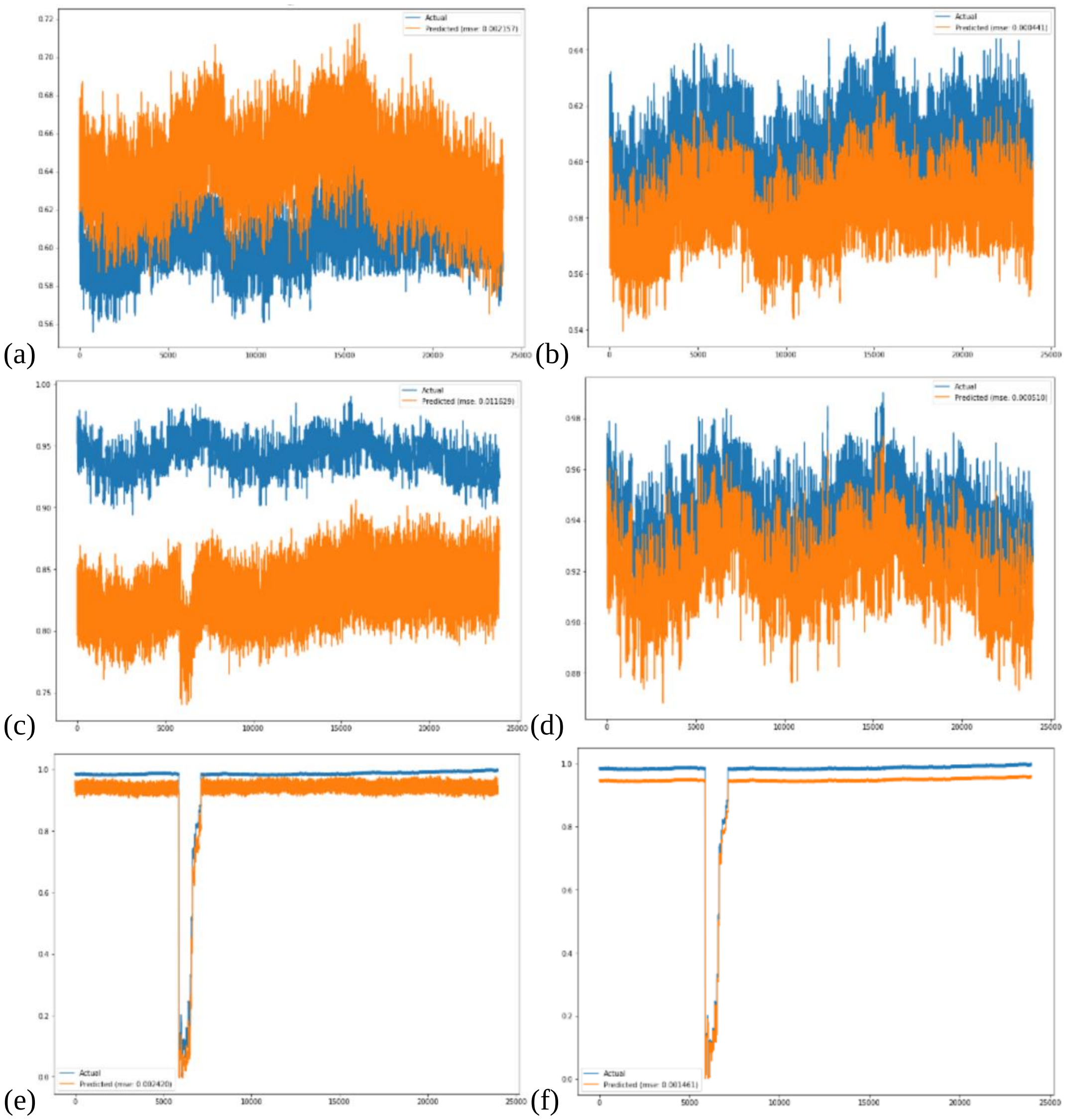

Figure 5. LSTM Accuracy (a)Cooling Power-all features (b)Cooling power-one feature (c)Cooling Efficiency-all features (d)Cooling Efficiency-one feature (e)Pressure-all features (f)Pressure-one feature.

All model shows an excellent performance in predicting the targets shown in Figure 6, except when predicting the valve condition and hydraulic accumulator shown in Figure 7(a). From the results drawn in Figure 6, we can see those ensemble algorithms have a better performance than simple algorithms such as Logistic Regression, SVM, and Gaussian Naive Bayes. However, the ensemble algorithms cross-validation does not have a promising result. It can be seen from the relatively low result for test precision and test recall. The weak result of test precision and recall indicate overfitting in the training model.

Considering the imbalanced data identified before, oversampling utilizing sklearn random oversampling is used to tackle the overfitting result. The algorithm generates new samples for under-represented classes by randomly sampling with replacement of the currently available samples. The balanced dataset gives a significant improvement, as shown in Figure 7(b).

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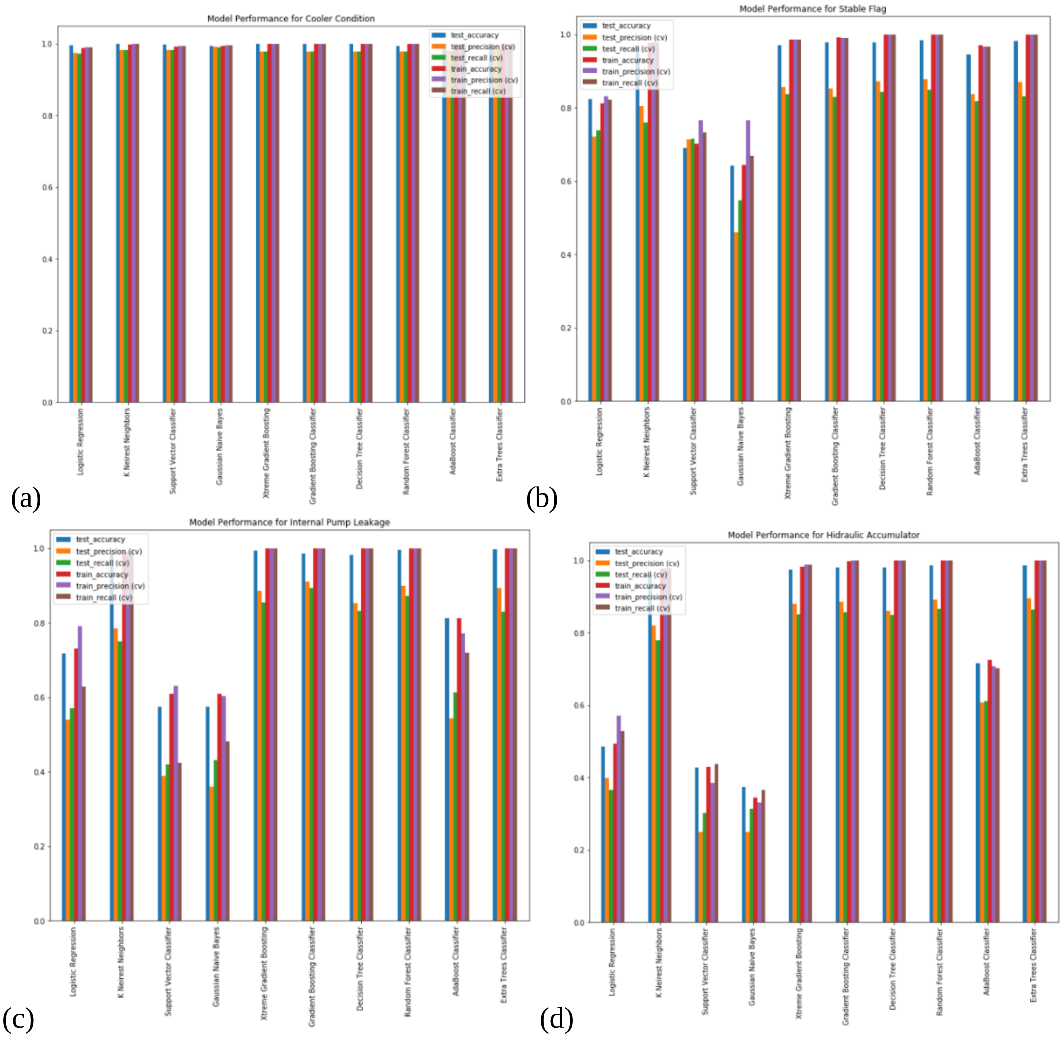

Figure 6. Algorithm Performance (a) Cooler (b) Stable Flag (c) Pump (d) Accumulator

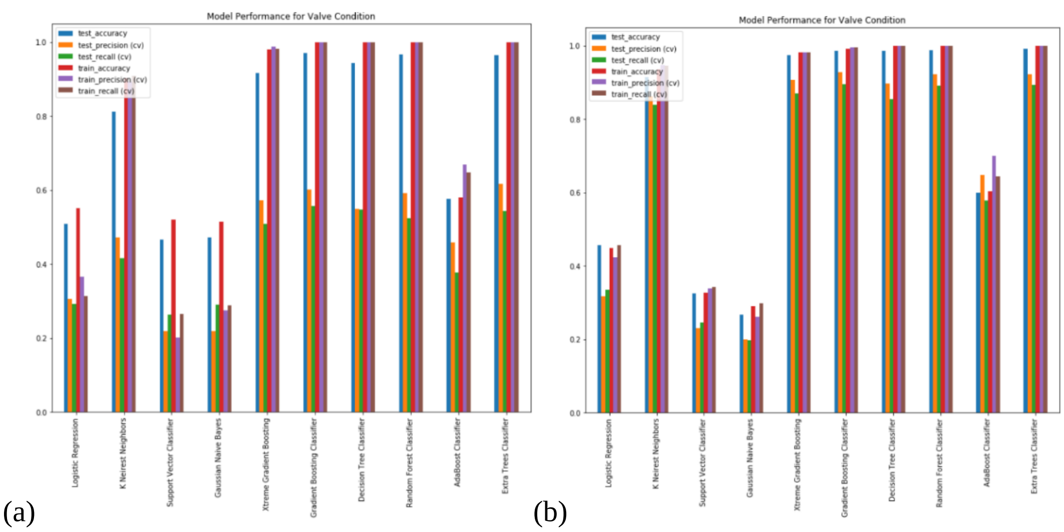

Figure 7. Valve Condition (a)Overfit Prediction (b) Prediction after Oversampling

4. CONCLUSION

The simulation results show that the forecasting model that only considers one feature has a better performance than the model that uses all features. However, the single feature model is challenging to maintain, and it requires a long time to find the fittest LSTM model for each feature. The resampling approach provides a better result than the ensemble in this training data set. In performing classification, ensemble algorithms have better performance compared to the other models. Several potential improvements for further research are observing the correlation between features and targets or the significant features for a specific target and uses feature engineering to determine the group of data based on its time or cycle and the dependency among the groups as well as the target condition at that time or cycle. For example, to predict valve condition, the most significant feature is pressure, and the pressure at cycle 1000 -1500 is affected by the pressure at cycle 200-700.

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