2025 IEEE Intelligent Vehicles Symposium (IV)
June 22-25, 2025. Cluj-Napoca, Romania

Machine Learning-Based Prognostic Approaches for Construction Equipment Powertrain Systems

Zafer Yiğit
Volvo Construction Equipment
Eskilstuna, Sweden
Mälardalen University
Västerås, Sweden
Email: zafer.yigit@volvo.com

Håkan Forsberg
Mälardalen University
Västerås, Sweden
Email:hakan.forsberg@mdu.se

Masoud Daneshtalab
Tallinn University of Technology
Tallinn, Estonia
Mälardalen University
Västerås, Sweden
Email: masoud.daneshtalab@mdu.se

***Abstract*—Construction equipment has important roles in industries such as construction and mining. Any downtime because of failures increase cost. Traditional diagnostic systems detect failures only after they occur, making it difficult to take precautions and prolonging repair times. This paper is the first to address the analysis of machine learning-powered Prognostic and Health Management (PHM) systems specifically for predicting failures in diesel engine air intake systems, focusing on two common issues: air leakage and Exhaust Gas Recirculation (EGR) blockage. This study compares various machine learning and deep learning models for anomaly detection and fault classification using real-world sensor data from controlled engine tests. The results demonstrate that ensemble and neural network-based machine learning methods, such as Random Forest, XGBoost, and LSTM, achieve highly successful predictions for anomaly detection and fault classification.**

***Index Terms*—Construction Equipment, Airpath, PHM, Machine Learning, Neural Networks.**

I. INTRODUCTION

Construction machines have complex structures composed of multiple different subsystems working together. These subsystems should work efficiently and smoothly to operate at high performance and in accordance with legal regulations. Identifying and resolving issues correctly and on time is crucial to maintain the optimal performance of these systems. Diagnostic functions, which are part of the powertrain application software, detect faults in machines and record Diagnostic Trouble Codes (DTCs) related to faults within J1939 standards [1], [2]. Data coming from Electronic Control Units (ECUs) are monitored and warnings are generated when a failure is detected. They cannot prevent bigger problems or long-term damage to the machine because they activate after the fault has occurred. In addition, DTC codes provide only general description about the failure so finding the failure and making a diagnosis can be hard and may take too much time. Detecting possible failures in advance and taking precautions provide longer life to the equipment, save costs, minimize environmental damage, and reduce machine downtime. As mentioned in many studies, Prognostic and Health Management (PHM) systems predict possible failures by continuously observing the functions and components of the system and ensure the necessary interventions are made on time [10], [11], [16].

This study has several key contributions. First, a comprehensive performance comparison has been made through studying literature on anomaly detection and failure prediction using machine learning models. Detecting anomalies and predicting faults are important parts of PHM in construction equipment powertrain systems. The study also focuses on two critical failure types in diesel engine airpath systems; air leakage and Exhaust Gas Recirculation (EGR) system clogging failures. We have selected these failures in our use-case, as they occur frequently in diesel engine air intake systems.

Finally, all data were gathered by performing controlled tests on a real engine. Real-world sensor data collected from diesel engine testing under controlled conditions simulates both normal operations and designed failure scenarios.

The second chapter of this research article describes PHM and applied methods in the literature for PHM systems powered by machine learning. In the third chapter, focus is on the analysis results of the data gathered from engine sensors about engine and air systems under different conditions. The same chapter also includes more information about performance and results of machine learning and deep learning methods applied for anomaly detection and failure classification. In chapter four, the results of the applied methods are compared, and future studies about the research are discussed.

This work is partially funded by the Swedish Knowledge Foundation within the RELIANT Research School. This study was co-funded by the European Union and Estonian Research Council via project TEM-TA138, the Swedish Innovation Agency VINNOVA project AutoDeep. The computations were enabled by resources provided by the National Academic Infrastructure for Supercomputing in Sweden (NAISS), partially funded by the Swedish Research Council through grant agreement no. 2022-06725

2025 IEEE Intelligent Vehicles Symposium (IV) | 979-8-3315-3803-3/25/$31.00 ©2025 IEEE | DOI: 10.1109/IV64158.2025.11097476

II. APPROACHES FOR PROGNOSTIC HEALTH MANAGEMENT SYSTEMS

The main purpose of PHM systems is to ensure long life for the construction machines, operational continuity and save maintenance costs. As an engineering system, PHM continuously monitors the health of machines and their subsystems using components such as data collection, data processing, anomaly detection, fault diagnosis, and prognosis. Through the outputs from these processes, PHM determines the health status of the machine and estimates its Remaining Useful Life (RUL)[11].

A. Approaches for PHM

PHM systems are classified under three categories. These are model-based approaches, data-driven approaches, and hybrid approaches combining the model-based and data-driven approaches [3]. Model-based approaches depend on the physics and mathematical models of the system to detect failures or create the degradation model to predict RUL [20]. The data-driven approach does not need the physical information of the system. It can learn the behavior and the logic of the system from measured sensor data, and it can be used for very complex systems that are difficult to model mathematically [10]. In hybrid models, these two approaches are used together to create more robust models [4].

B. Data Driven Approaches

Data-driven models use the data acquired from inputs and outputs of the system to check the health status of the system. These models try to predict the time and type of possible failures according to pre-trained models. Nowadays, data-driven PHM methodologies have been widely studied in the literature, especially based on machine learning and deep learning methods. A digital twin, a digital copy of the machine, can be combined with machine learning methods and used to detect possible failures in the machine. For example, Duarte, Viegas, & Santin [5] created a machine learning-based digital twin model to predict the pressure levels in the fuel injection system of a diesel engine and to understand system behavior and failures. Another example is a digital twin hierarchy designed and used to monitor the bearing and seal to detect failures of a pump used by industries [6].

1) Machine Learning Methods: Machine learning applications of PHM contain prediction of RUL, failure classification and anomaly detection under the different types of approaches like supervised, unsupervised and reinforcement machine learning methods.

The linear regression model is one method. It has been used in a digital twin to predict pressure levels in the fuel injection system [5] and to predict NOx emissions from industrial diesel engines [7]. Support vector machine (SVM) is another supervised learning method generally used in classification problems [8]. K-Nearest Neighbor (K-NN) is yet another method which uses nearest distances from similar values to make classifications or predictions [9]. Extreme gradient boosting (XGBoost) is also one of the popular approaches that performs high efficiency for regression and classification [7]. To detect and diagnose different type of failures in automotive electric machines, decision trees, linear discriminant, and SVMs can be used [8]. Some supervised machine learning models like K-NN, SVM, decision tree, and random forest are used to predict CO2 emissions level for automotive [9]. Linear regression method is proposed as a solution to predict the failure of clogging plural problems in exhaust gas recirculation (EGR) system [12]. It also present a way to update weights of the model derived from one machine to another machine with using online stochastic gradient descent approach. Yang, Chen, & Guan [19] use an AVL-Boost model to run simulations of diesel engine failures, and the fault diagnosis is performed by analyzing data from the simulations using the random forest model, the SVM model, and BP neural network algorithms.

2) Deep Learning Methods: Deep learning and its powerful tools, especially in overcoming complex problems in big data, makes these tools indispensable for research. Recurrent Neural Networks (RNNs) have the ability to keep the status of previous cells. Thus, they are suitable for applications using sequential time-based data [16]. Long-short term memory (LSTM) neural networks and Gated Recurrent units (GRU) which are types of RNNs also seem to be quite successful in applications used for time-based data. They can handle big multivariate sequential time-series data without dimensional reduction and detect different types of anomalies effectively [13]. These are also popular approaches for prediction of remaining useful life in industry [14]. Research in which these RNNs and other Neural networks like Convolutional neural networks (CNNs) methods are combined and used are becoming quite common. Han, Ellefsen, Li, Æsøy, & Zhang [15] use an LSTM network model which includes two LSTM layers, two feed-forward neural network (FNN) layers, and a dropout layer to prevent overfitting, to predict faults and RUL of engine components based on sensor data in marine diesel engines. Ellefsen, Li, Holmeset, & Zhang [17] use an LSTM-based variational autoencoder for anomaly detection in marine diesel engines and performance is compared with an autoencoder, an isolation forest-based detector, and a standard variational autoencoder. An analytical pipeline for PHM designed with Semi-supervised ML with Autoencoder (AE), XGBoost, and the SHAP (Shapley Additive exPlanations) method is proposed for anomaly detection failure detection and RUL estimation. Also, LSTM, CNN, and GRU models are used to comparison for performance. SHAP is an analyzing technique which uses the game theory to calculate each feature's contribution to the system for machine learning techniques [14]. Machine learning techniques based on genetic algorithms and generated synthetic data created by simulation models of a mobile harbor crane, have also been used for predicting failures [18].

III. PHM APPROACH FOR DIESEL ENGINE AIR SYSTEMS

The air system plays a fundamental role for the combustion quality, output power, fuel efficiency, and emission levels of the diesel engine. Engine application software has diagnostic functions for air systems, but a prognostic approach is necessary and important to detect faults earlier, also to keep the system performance at maximum and to prevent the downtime of the construction equipment. For this reason, in this article, anomaly detection and fault classification models powered by machine and deep learning methods are created with real sensor data. The fault classification framework enables the identification of various types and extensions of anomalies, such as different levels of EGR clogging.

A. Data Acquisition

Data is collected from a diesel engine test rig under constant ambient conditions at sea level. The data is then cleaned and filtered based on the engine's speed and torque values. Faulty parts were used for different classes of air system failures in the tests. Normal state and failure state data were collected by running different types of test cycles such as part load cycle and non-road transient cycle (NRTC). The total data set included 436746 samples of 51 tests, 14 tests are normal state data, and others are different types of faulty data. Three different data sets were prepared for training and nine different data sets were prepared to test the models depending on different types of failure. Two of three training data sets only included normal state engine condition data to train the models for anomaly detection. The third data set includes mixed (normal and faulty state) engine conditions and was only used to train the models for failure classification.

B. Anomaly Detection

Air leakage is a common and important failure type for diesel engines. The correct amount of boost is crucial for diesel engines because it affects combustion, performance, and efficiency. When there is a leak on the boost line, boost pressure will decrease and the necessary air inside the cylinder of engine for combustion is lost. This loss can result in issues such as reduced power output and higher fuel consumption. Air leakage can be detected by diagnostic functions based on boost pressure value shown in Fig.1. A damaged pipe was used instead of the existing elastic pipe on the airpath to simulate the air leak scenario, see Fig.2a. The 3-way valve shown in Fig.2b was installed in the airpath and a 1 cm diameter opening was left to simulate high boost leakage.

Another common failure is the blockage in the Exhaust Gas Recirculation (EGR) systems. Exhaust gas including largely CO_2, water vapor, and soot has higher heat than air. While the hot exhaust gas is passing through the EGR valve and EGR cooler, it gets cooler and condenses. Wet soot can cause the EGR valve and cooler clogged and prevent the passage of exhaust gas. EGR clogging is usually one of the hardest problems to diagnose until the last stage. Using some plates with different sizes of cuts shown in Fig.3, the EGR gas outlet in the engine was blocked and data was collected for different types of clogging scenarios from the engine. Machine and deep learning approaches can be used to detect these anomalies.

Data sets were cleaned and filtered according to the input parameters. Models are trained to predict boost pressure sensor

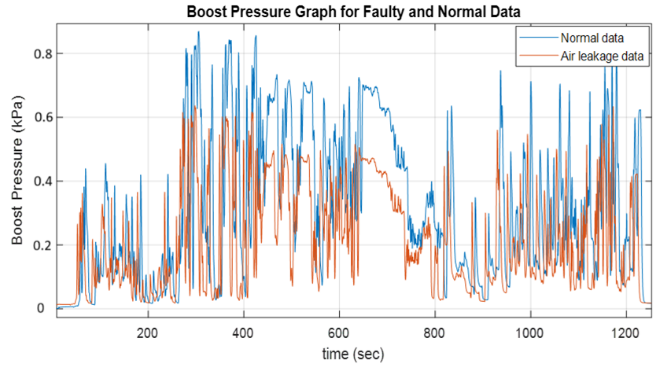


Fig. 1. Boost Pressure Sensor Value for Normal and Faulty State Engine Condition.

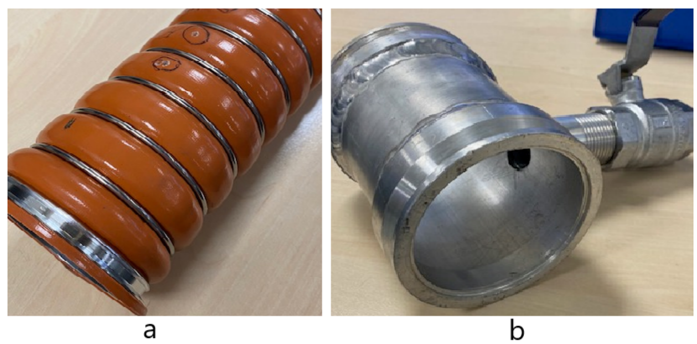


Fig. 2. (a) Punctured Air Hose, (b) 3-way Valve having 1 cm diameter outport

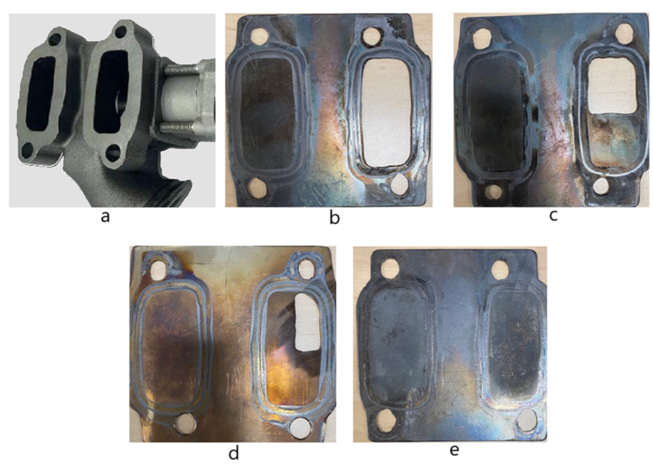


Fig. 3. Engine EGR and plates with different sizes of cuts used for blocking scenario. (a) EGR, (b) %50-60 blocked EGR plate, (c) %75-80 blocked EGR plate, (d) %85-90 blocked EGR plate, (e) Fully blocked EGR plate

and EGR differential pressure sensor values separately. Test datasets are used on the trained models for validation purposes and some performance metrics are calculated for comparison of the models. All models trained by normal state engine condition datasets for two sensor predictions takes approximately 13.5 hours to run. The system used for training consists of an Intel(R) Core (TM) Ultra 7 165H 3.80 GHz, with 64 GB memory on a Windows 64 bit Operating System.

12 different models and some of their variations were trained for anomaly detection for air leakage and EGR clogging failures. We trained and analyzed the performance using regression functions and tools in MATLAB R2021b for the following models: linear regression (lasso and ridge regularization approaches), two different (SVM) models having second order polynomial and gaussian kernels, decision trees, and two ensemble models (Random Forest and XGBoost). Hyperparameters were optimized for each model separately. In addition, feedforward neural network (FFNN), convolutional 1D neural network (CNN1D), residual convolutional neural network (ResNet1D), and long-term memory (LSTM) models were trained. Their performance were then analyzed using the PyTorch machine learning library. Hyperparameters such as learning rate, sliding window size, epoch number, etc. of neural network models with different types of structures were run separately and optimized. Parameters and structures were selected according to the performance of the minimum error and maximum accuracy. The sliding window technique, which is a method for dividing and iterating sequence of time series data, is one of the common methods in the literature and is generally preferred to increase the accuracy performance [21], [22]. Time windows were created to increase the accuracy of CNN1D, ResNet1D, and LSTM models. Size of sliding windows were determined depend on the maximum accuracy of the models.

Models were trained to detect anomalies with different training data and input-output parameters about the air leakage and EGR clogging separately. Table I shows the results (inference time for training and test, error values and anomaly percentages) for air leakage anomaly detection.

1) Performance Tools for Anomaly Detection Regression Models:
Each model was tested using test data having different engine conditions. First, both training and testing inference times were measured on the CPU. Additionally, mean absolute error (MAE) and anomaly percentage metrics were calculated and used to measure the accuracy of the models' performance.

Training Inference Time (s): This is the time spent on training the model. Hyperparameter optimization is not included in this time.

Test Inference Time (s): This is the time spent on testing the model with test data.

Mean Absolute Error (MAE): It measures the average value of the difference between predictions and true values [23], see Equation 1.

Anomaly Percentage: Anomaly percentage shows how much deviation from the true values occurs in the predictions of models. It is calculated based on Z-score, see Equation 3, and error distribution [24], [25], see Equation 4. A threshold value is defined for Z-score and the percentage of anomaly is calculated according to values which exceeds the threshold. The predictions and error distributions of the LSTM model on 50% clogged EGR test data are shown in Fig.4 and Fig.5. In a normal distributed data set, 99% of the data falls within the -3 to +3 sigma range. The outer part of this region can be described as an outlier so that threshold value is selected as Z greater than 3 for this detection sample.

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^{n} |y_{\text{true}} - y_{\text{pred}}| \tag{1}$$

$$\text{Error} = |y_{\text{true}} - y_{\text{pred}}| \tag{2}$$

$$Zscore = \frac{\text{Error} - \mu}{\sigma} \tag{3}$$

$$\text{Anomaly Percentage} = \left(\frac{\text{Number of Anomalies}}{\text{Number of Total Samples}} \right) \times 100 \tag{4}$$

where μ is the mean value of the error value of the normal state engine condition training data. σ is the standard deviation of the error value of normal state engine condition training data. The error is the difference between the prediction and the true value in test data. The number of anomalies gives the number of samples exceed the threshold value.

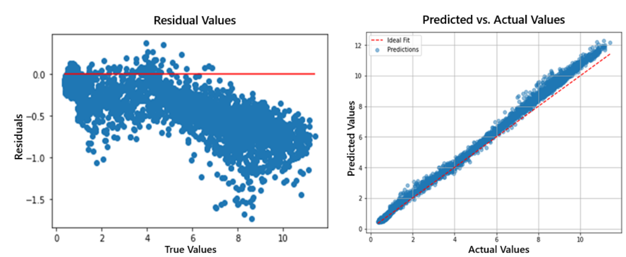


Fig. 4. LSTM Model Predictions on %50 Clogged EGR Engine Condition

C. Failure Classification

Two new datasets were created by taking equal numbers of samples from the datasets having different engine conditions and characteristics. These new data sets were filtered, cleaned, and classified under certain engine speed and torque conditions. Mitigation strategies to solve problems such as class imbalance, biasing to major class, and overfitting were implemented. Equalization of the number of samples was not done on the test data. Failure types are shown in Table II.

We trained and analyzed the performance using classification methods and tools in MATLAB R2021b for the following models: SVM, decision trees, and ensemble models (Random Forest and XGBoost). In addition, FFNN, CNN1D, ResNet1D, and LSTM models were trained and analyzed using the PyTorch machine learning library.

TABLE I
AIR LEAKAGE ENGINE CONDITION REGRESSION METHODS RESULTS FOR ANOMALIES

Machine Learning Approach	Training Time (s)	Test_Data1 (Normal Condition) Test Time(s)	MAE	Anomaly %	Test_Data2 (Normal Condition) Test Time(s)	MAE	Anomaly %	Test_Data3 (Low Air Leak Condition) Test Time(s)	MAE	Anomaly %	Test_Data4 (Visible Air Leak Condition) Test Time(s)	MAE	Anomaly %
Linear Regression	0.55	0.0228	3.0747	1.64	0.0139	5.9809	8.35	0.0108	3.743	0.13	0.0199	13.8368	54.11
Lasso	0.11	0.0121	3.9556	1.43	0.0071	8.0852	17.37	0.0070	7.9820	0.13	0.0106	15.9600	52.13
Ridge	0.16	0.0120	3.0459	1.66	0.0063	6.0064	8.78	0.0076	3.8649	0.13	0.0114	13.8622	54.01
SVM (Second Order)	25.03	0.044354	2.1377	0.16	0.0190	3.0568	2.05	0.0256	1.0705	0.04	0.0150	13.1750	90.07
SVM (Gaussian)	5.38	0.28452	2.3738	0.81	0.1025	3.7564	8.99	0.2072	12.7444	80.85	0.2139	12.5580	74.51
Decision Tree	19.09	0.9250	0.7828	4.06	0.0059	3.0098	23.35	0.0075	7.7733	73.12	0.0155	12.9546	91.98
Random Forest	23.68	0.461827	0.5515	3.77	0.3391	2.3314	26.96	0.4046	8.7624	97.87	0.4138	14.7856	99.64
XGBoost	3.87	0.061999	0.5615	4.17	0.1200	1.8552	26.61	0.0180	8.4197	96.5813	0.0247	11.9253	99.4
FFNN	578.31	0.01338	0.8693	1.75	0.0044	2.2242	14.44	0.0096	3.2827	38.58	0.0090	12.8902	92.73
CNN-1D	284.95	1.35	0.8047	1.43	0.7	1.7351	16.37	0.15	3.9549	97.14	0.16	11.8804	98.75
ResNet1D	15697.9	8.39	3.0033	0.46	2.93	3.5287	11.47	5.17	4.0123	95.09	6.33	29.6680	98.79
LSTM	15886.7	75.37	1.2980	1.57	8.09	1.8331	7.78	20.56	6.2790	87.1	24.89	13.2504	91.98

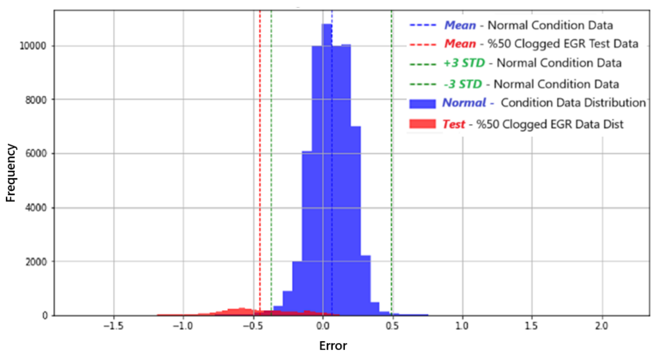


Fig. 5. LSTM model Prediction Error Distribution

TABLE II
FAILURE CLASSES FOR AIR SYSTEM

Engine Condition	Fault Type	Class
Normal	No Fault	0
Air Leakage	Low Air Leakage	1
Air Leakage	Visible Air Leakage	2
Clogged EGR	%50 -60 Clogged EGR	3
Clogged EGR	%75 -80 Clogged EGR	4
Clogged EGR	Fully Clogged EGR	5

1) Performance Tools for Failure Classification Models: Precision, recall, F1 scores, and accuracy were calculated besides training and testing times. Accuracy and F1 scores for each trained model are listed in Table III. Confusion matrix for worst and best performance is given as shown in Fig.6.

Precision:shows how many predicted values that were correct among all incorrectly and correctly detected values.

Recall (also called sensitivity):is also named as sensitivity is the metric that shows how many results predicted as positive, which should have been predicted as positive.

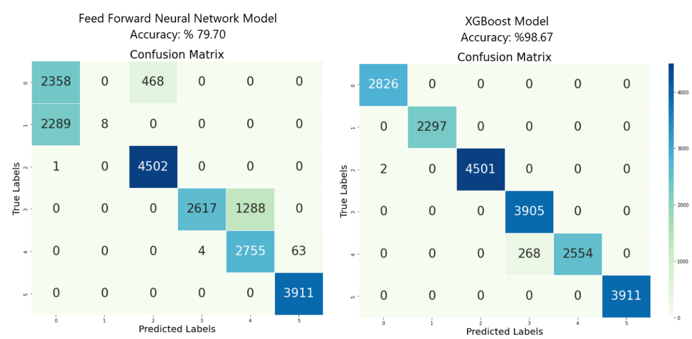
F1 Score: That value shows us the harmonic mean of the precision and recall values.

Accuracy: The accuracy, see Equation 5, is calculated by the ratio between the data predicted correctly in the model and the total data set.

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}} \times 100 \quad (5)$$

TABLE III
PERFORMANCE COMPARISON FOR CLASSIFICATION MODELS

Models	Training Time	Test Time	Accuracy (%)	F1-Score
SVM	64.82	0.17	87.67	84.11
Decision Tree	21.9	0.59	95.11	94.95
Random Forest	33.52	0.02	90.69	85.85
XGBoost	0.33	0.01	98.67	98.6
FFNN	553.98	0.20	79.70	69.75
CNN1D	3070.01	1.1	85.14	83.16
ResNet1D	3713.14	3.32	83.13	75.83
LSTM	22362.46	0.01	95.01	94.66



Class	Precision	Recall	F1-Score
0	50.73	83.44	63.10
1	100.00	0.35	0.69
2	90.58	99.98	95.05
3	99.85	67.02	80.20
4	68.14	97.63	80.26
5	98.41	100.00	99.20

Class	Precision	Recall	F1-Score
0	99.93	100.00	99.96
1	100.00	100.00	100.00
2	100.00	99.96	99.98
3	93.58	100.00	96.98
4	100.00	90.50	95.01
5	100.00	100.00	100.00

Fig. 6. Worst and Best Performance Results on Confusion Matrix for Classification Models.

IV. CONCLUSION AND FUTURE WORK

In this article we performed a comprehensive study about PHM on diesel engine air intake systems of construction equipment. The main idea is to develop a PHM that successfully predicts anomalies and takes necessary precautions in situations where existing diagnostic systems are insufficient and late. The study shows that some machine learning models, particularly ensemble models and neural network based models, give successful results, especially in cases where there is a fault or anomaly in the air intake system of the diesel engine. However, it is very difficult to measure.

In this research study two different use cases were selected from the construction machine diesel engine air intake system.

The different machine learning models were trained with engine data collected from a diesel engine test rig. Their performance on anomaly detection and failure classification were then compared. The performance of the machine learning models was compared according to their training and test speeds, as well as the accuracy of their predictions.

A. Performance Results for Anomaly Detection

All models were trained with normal state condition data, and they were tested with normal and faulty state condition dataset. While good predictions and low anomaly percentages are expected from models tested with the data set under normal state conditions, higher error predictions and increased anomaly percentages are expected when faced with data types with faulty conditions. Linear regression models could be trained and tested quickly due to their simple structure. Their predictions were successful for normal state condition data, but they failed to predict distinguishing results when they were tested with faulty condition data. SVM approaches could not make robust and accurate predictions on data sets of faulty conditions. XGBoost is successful in terms of speed training and test performance and especially in its distinguishing predictions on faulty datasets. The unexpected prediction errors of XGBoost, decision trees, and random forest approaches in test data, indicate that these models are too dependent on the training data. They have different engine speed and torque characteristics from the training data but have expected normal condition states. Although the training time of deep neural networks is extremely long, LSTM and ResNet approaches generally showed better performance in tests.

B. Accuracy Performance for Failure Classification

The data set with normal and different faulty state conditions was used for fault classification. To prevent the models from being biased towards any class during training, the data was filtered and distributed equally based on classes. Therefore, the training data was quite limited and especially neural networks were difficult to learn due to limited data. Decision tree and XGBoost stand out with their testing and training time as well as their accurate predictions. In addition, LSTM had very accurate predictions among the other neural network approaches.

In the future, more accurate models can be created by combining models that give successful results according to the study, or more robust predictive functions can be designed by ensuring that different models confirm each other. In addition, synthetic data can be generated using digital twin structures of the diesel engine to train these models more successfully.

References

[1] M. R. Stepper, S. R. Butler, G. G. Zhu, "On-Board Diagnostics, A Heavy Duty Perspective," SAE Technical Paper Series, 951947, 1995.

[2] "Application Layer - Diagnostics," SAE Recommended Practices J1939-73, SAE INTERNATIONAL, 2026.

[3] S. Hagmeyer, P. Zeiler, "A Comparative Study on Methods for Fusing Data-Driven and Physics-Based Models for Hybrid Remaining useful Life Prediction of Air Filters," IEEE Access, 2023.

[4] H. Saito, D. Kanzaki, K. Yonekura, "Applications of machine learning in surge prediction for vehicle turbochargers," Machine Learning with Applications 16, 100560, 2024.

[5] E. P. Duarte, E. K. Viegas, A. O. Santin, "A Machine Learning-Based Digital Twin Model for Pressure Prediction in the Fuel Injection System," 48th Annual Conference of the IEEE Industrial Electronics Society, IECON2022, 2022.

[6] M.Toothman, B. Braun, S. J. Bury, J. Moyne, D. M. Tilbury, Y. Ye, K. Bart, "A digital twin framework for prognostics and health management," Computers in Industry 150, 103948, 2023.

[7] D. Balakrishnan, P. Sharma, F. Shaik, A. R. Lakshmipathi, "AI-based Prognostic Analysis of NOx Emission from Industrial Diesel Engine for Feedback Control System," 1st International Conference on Optimization Techniques for Learning (ICOTL), 2023.

[8] A. Salah, O. A. Mohareb and H. Reuss, "Fault Diagnosis for Automotive Electric Machines Based on a Combined Machine Learning and Parameter Estimation Method," International Conference on Control, Automation and Diagnosis (ICCAD), 2023.

[9] S. Kangralkar, R. Khanai, "Machine Learning Application for Automotive Emission Prediction," 6th International Conference for Convergence in Technology (I2CT), 2021.

[10] D. Bhat, S. Muench, M. Roellig, "Application of machine learning algorithms in prognostics and health monitoring of electronic systems: A review," e-Prime - Advances in Electrical Engineering, Electronics and Energy, 100166, 2023.

[11] K. T. P. Nguyen, K. Medjaher, D. T. Tran, "A review of artificial intelligence methods for engineering prognostics and health management with implementation guidelines," Artificial Intelligence Review, 56:3659–3709, 2023.

[12] M.Kumar, J.Cramsky, W. Löwe, P.O. Danielsson, "A prediction model for exhaust gas regeneration (EGR) clogging using offline and online machine learning," Commercial Vehicle Technology. ICVTS 2022. Proceedings. Springer Vieweg, Wiesbaden, 2022.

[13] A. Nanduri, L. Sherry, "Anomaly Detection In Aircraft Data Using Recurrent Neural Networks (RNN)," Center for Air Transportation Systems Research (CATSR), 2016.

[14] M. L. H. Souza, C. A. Costa , G. O. Ramos , "A machine-learning based data-oriented pipeline for Prognosis and Health Management Systems," Computers in Industry 148, 103903, 2023.

[15] P. Han, A. L. Ellefsen, G. Li, V. Æsøy, H. Zhang, "Fault Prognostics Using LSTM Networks: Application to Marine Diesel Engine," IEEE Sensors Journal, VOL.21, NO.22, 2021.

[16] M. A. El-Brawany, D. A. Ibrahim, H. K. Elminir, H. M. Elattar, E.A. Ramadan, "Artificial intelligence-based data-driven prognostics in industry: A survey," Computers and Industrial Engineering, 109605, 2023.

[17] P., A. L. Ellefsen, G. Li, F. T. Holmeset, H. Zhang, "Fault Detection With LSTM-Based Variational Autoencoder for Maritime Components," IEEE Sensors Journal, Vol.21, No.19, 2021.

[18] M. Burger, C. A. Boer, E. Straub, Y. A. Saanen, "Predictive Maintenance Powered By Machine Learning And Simulation," Winter Simulation Conference (WSC), 2022.

[19] M. Yang, H. Chen, C. Guan, "Research on diesel engine fault diagnosis method based on machine learning," 4th International Conference on Frontiers Technology of Information and Computer (ICFTIC), 2022.

[20] O. Lindgärde, R. Prytz, "On-Board Model Based Diagnosis Based on an Off-Board Engine Simulation Model," SAE Technical Papers, April 2014.

[21] R. Chandra, S. Goyal, R. Gupta, "Evaluation of deep learning models for multi-step ahead time series prediction," IEEE Access, 3085085, 2021.

[22] M. H. M. Noor, S. Y. Tan, M. N. Ab Wahab, "Deep Temporal Conv-LSTM for Activity Recognition," Springer Nature, 2022.

[23] G. James, D. Witten, T. Hastie, R. Tibshirani, "An Introduction to Statistical Learning," Springer, 2013.

[24] Timothy C. Urdan, "Statistics in Plain English," Lawrence Erlbaum Association, Publishers, 2001.

[25] A. S. Yaro, F. Maly, P. Prazak , K. Malý, "Outlier Detection Performance of a Modified Z-Score Method in Time-Series RSS Observation With Hybrid Scale Estimators," IEEEAccess, 2024.