JMES The International Journal of
Mechanical Engineering and Sciences
https://iptek.its.ac.id/index.php/jmes
e-ISSN 2580-7471

Intelligent Fault Prediction in Diesel Engines: A Comparative Study of SVM and BPNN for Condition-Based Maintenance

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Received: 19 March 2025, Revised: 16 September 2025, Accepted: 2 October 2025

Abstract

This study investigates the use of Support Vector Machine (SVM) and Backpropagation Neural Network (BPNN) for predicting diesel engine health based on operational data that was relabeled using K-Means Clustering. Two SVM kernels, Radial Basis Function (RBF) and Sigmoid, were tested with various parameter settings. The results show that the SVM with a Sigmoid kernel achieved an accuracy of 94.06% but had lower sensitivity in identifying unhealthy engine conditions. In contrast, BPNN with a three-hidden-layer configuration (1-2-1 neurons) and the tansig activation function delivered superior performance, achieving an accuracy of 97.13%, MSE of 0.03, recall of 94%, precision of 100%, and an F1-score of 97%. These findings highlight that BPNN is more effective than SVM in capturing complex data patterns and more accurate in detecting unhealthy engine states. Moreover, dataset relabeling significantly improved prediction accuracy, from 72.3% to 97.13%, underscoring the critical role of data balance in modeling. Overall, the study confirms that BPNN with an optimized configuration provides a more reliable approach for diesel engine condition monitoring.

Keywords: Diesel Engine; Machine Health Prediction; Support Vector Machine; Backpropagation Neural Network; Condition-Based Maintenance; Artificial Intelligence

1. Introduction

Machine health plays a critical role in ensuring reliable operations across diverse sectors, including industry, automotive, maritime, and air transportation [1]. Unexpected machine disruptions or failures can lead to serious consequences, both in terms of operational efficiency and maintenance costs [2]. Therefore, effective maintenance strategies, such as Condition-Based Maintenance (CBM), are increasingly being implemented to detect and prevent potential machine failures before they occur [3]. CBM is a predictive maintenance approach that utilizes real-time data from sensors installed on machines to analyze their operational conditions. This method offers significant advantages over time-based and corrective maintenance, as it can reduce operational costs and extend machine lifespan. However, the main challenge in implementing CBM lies in accurately and efficiently processing large and complex sensor data [4, 5].

Several studies have investigated the application of CBM in machine maintenance. For example, [6] developed a machine learning–based CBM model for early anomaly detection in industrial machines, which improved failure prediction accuracy by up to 95%. In another study, [7] implemented a deep learning–based CBM model to identify degradation patterns in diesel engines used in heavy-duty vehicles, demonstrating a 30% increase in maintenance efficiency compared to traditional approaches.

In the context of predictive maintenance, various artificial intelligence methods have been applied, including Support Vector Machine (SVM) and Backpropagation Neural Network (BPNN). SVM is recognized for its capability to handle high-dimensional data and deliver strong classification performance, whereas BPNN is more effective in capturing complex patterns from machine sensor data. Nevertheless, both methods have notable limitations: SVM often requires considerable computational time when dealing with large datasets, while the performance of BPNN is highly dependent on initial parameter settings and remains vulnerable to overfitting.

Several previous studies have examined the application of SVM and BPNN in machine health prediction. For instance, [8] developed a predictive maintenance system for motor vehicles using SVM, achieving an accuracy of 92.92%. In another study, [9] applied an Optimized Backpropagation Neural Network (OBPNN) combined with the Fish Swarm Algorithm (FSA) to predict the health of marine diesel engines, reaching an accuracy of 99.05%. Similarly, [10] compared Logistic Regression, SVM, and K-

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Nearest Neighbors (KNN) for diesel engine maintenance, with SVM demonstrating the best performance at 93% accuracy.

Although previous studies have demonstrated the effectiveness of SVM and BPNN in predicting machine health, several research gaps remain to be addressed. First, the use of more advanced kernels in SVM, such as Radial Basis Function (RBF) and Sigmoid, has not been extensively investigated to improve accuracy on non-linear datasets. Second, parameter optimization in BPNN continues to pose challenges, particularly in mitigating overfitting and accelerating convergence.

This study contributes to the development of diesel engine health prediction by comparing a modified SVM approach with an optimized BPNN. Accordingly, it seeks to bridge the existing gap in the literature by investigating more accurate and efficient strategies for AI-based predictive maintenance.

2. Experimental/theoretical method

2.1. System Design

The system developed in this study is designed to assess the condition of diesel engines using Support Vector Machine (SVM) and Backpropagation Neural Network (BPNN) within the framework of Condition-Based Maintenance (CBM). The workflow of the proposed system comprises four main stages: dataset preparation, preprocessing, parameter mapping, model analysis, and evaluation. These stages are presented in Figure 1, which illustrates the overall workflow of the system model.

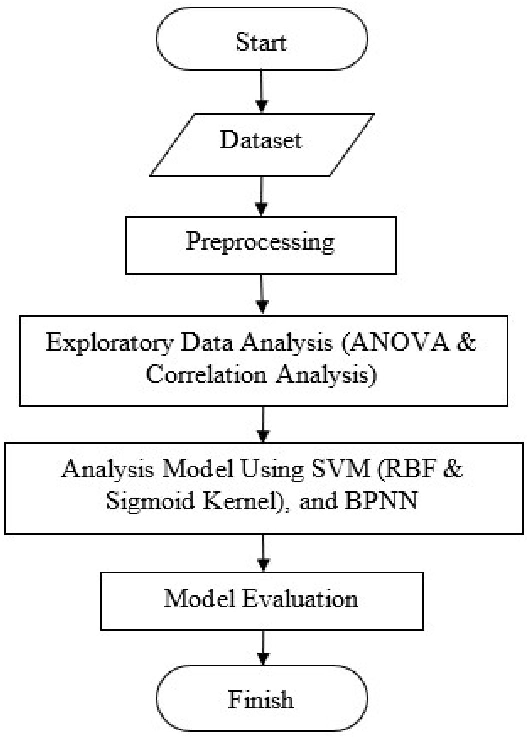

Figure 1. System Model Workflow

2.2. Dataset & Engine Data Acquisition

This study employs a dataset comprising diesel engine operational parameters, including temperature, pressure, and vibration. The dataset is divided into two subsets: training data and testing data. SVM is used to classify engine conditions based on the optimal hyperplane, while BPNN applies a neural network architecture with a backpropagation algorithm to learn the underlying data patterns.

The dataset used in this study is sourced from papers [11] and [10] by D. Mohakul (2023). The engine examined in this research is the MTU Series 1400 diesel engine. The dataset comprises several operational parameters, including engine speed (Engine RPM), lubricating oil pressure (Lub Oil Pressure) in bar, fuel pressure (Fuel Pressure) in bar, cooling system pressure (Coolant Pressure) in bar, lubricating oil temperature (Lub Oil Temperature) in degrees Celsius, and cooling system temperature (Coolant Temperature) in degrees Celsius.

The output label used to determine engine condition consists of two categories: healthy (1) and unhealthy (0). This dataset is employed for training and testing predictive models to evaluate the performance of SVM and BPNN in diesel engine health prediction. The detailed structure of the dataset used in this study is presented in Table 1, while the data acquisition process is illustrated in Figure 2.

2.3. Data Preprocessing

Data preprocessing ensures that the dataset used in the analysis is clean, structured, and ready for algorithmic processing [12]. The preprocessing steps include data cleaning to address missing values through mean imputation and the removal of outliers using the Interquartile Range (IQR) method. Subsequently, data normalization is applied using Min-Max Normalization to standardize feature scales, ensuring compatibility with both SVM and BPNN algorithms.

Re-labeling of engine condition data using the K-Means clustering method is carried out to improve data quality by distributing labels more representatively. This process involves re-normalization, determining the number of clusters (K = 2), applying the K-Means algorithm, and validating the clustering results using the Silhouette Score and prediction accuracy. Following re-labeling, the dataset is divided into three subsets: a training set (70%) for model training, a testing set (15%) for performance evaluation, and a validation set (15%) to prevent overfitting. The dataset is randomly split to minimize bias in data distribution.

Table 1. Dataset

No	Engine rpm	Lub oil pressure	Fuel pressure	Coolant pressure	Lub oil temp	Coolant temp	Engine Condition
1	520	2.96	6.55	1.06	77.75	79.65	1
2	1221	3.99	6.68	2.21	76.40	75.67	0
3	729	3.85	10.19	2.36	77.92	71.67	1
4	845	4.88	3.64	3.53	76.30	70.50	0
5	824	3.74	7.63	1.30	77.07	85.14	0
6	1230	3.43	10.84	1.83	77.41	85.92	0
7	538	4.26	7.69	2.08	80.18	81.18	1
8	1187	2.59	6.89	1.83	78.10	84.97	1
9	609	3.75	10.09	3.00	77.28	75.58	1
10	606	2.27	5.49	1.91	75.17	77.73	1
...	...	...	...	...	...	...	...
165	1286	5.12	3.83	3.25	77.37	71.86	1
166	524	3.22	8.19	1.86	79.28	68.36	1
167	980	3.53	9.05	1.02	76.80	80.01	0
168	571	3.56	7.63	2.68	76.32	69.89	1
169	541	3.11	6.36	1.72	76.65	86.09	1
170	422	2.80	9.51	1.31	77.18	71.52	1
171	430	2.20	5.47	3.32	77.59	77.07	1
172	801	4.84	5.80	1.12	80.36	84.06	1
173	588	2.28	6.52	1.87	75.68	73.38	0
174	709	2.04	5.20	2.55	75.93	80.22	1

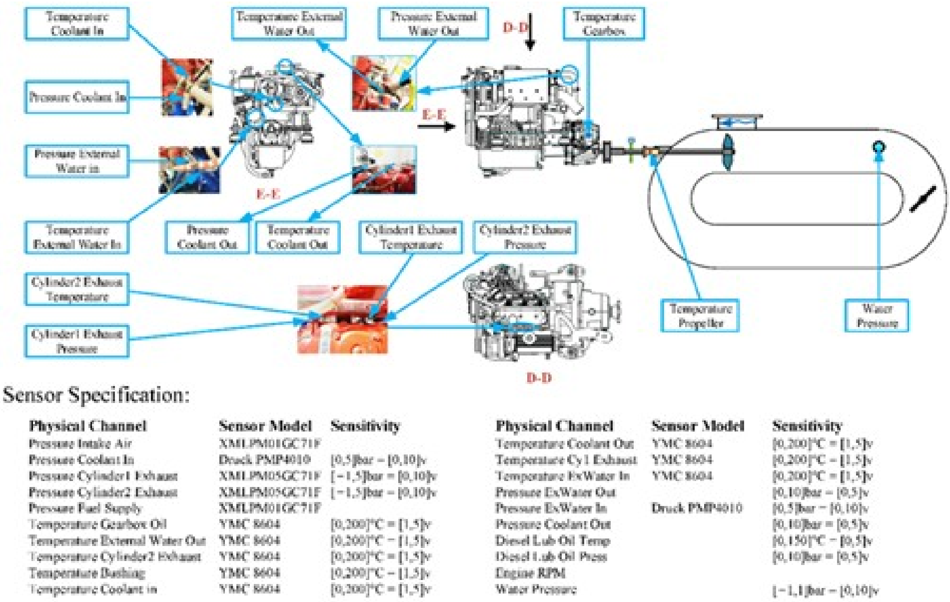

Figure 2. Diesel Engine Operation Data Acquisition Scheme [13]

2.4. Analysis of Engine Operational Parameter Relationships

The relationship between operational parameters and diesel engine health is analyzed using Spearman correlation [14], with the results visualized in a heatmap as illustrated in Figure 3. The correlation coefficient is calculated to measure both the strength and direction of the relationships between variables, and the outcomes are presented in a correlation matrix. The colors in the heatmap represent the intensity of these relationships: positive values close to +1 indicate a strong correlation, negative values close to –1 indicate a strong inverse correlation, and values near 0 represent weak relationships. This analysis helps identify the most influential parameters for predicting engine health, thereby supporting the optimization of condition-based maintenance models.

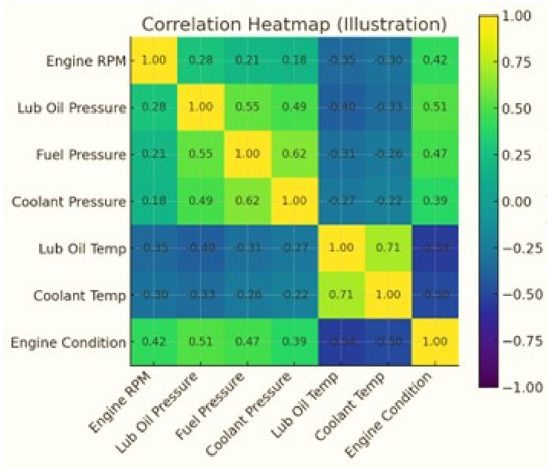

Figure 3. Diesel Engine Operation Data Acquisition Scheme

2.5. Model Analysis

In Logistic Regression, Deviance-based Analysis of Variance (ANOVA) is applied to examine whether group differences are statistically significant in a binary response dataset [15]. The method relies on the Likelihood Ratio Test (LRT), which contrasts the full model against a reduced model; a p-value < 0.05 indicates that specific variables have a significant effect on the diesel engine's health condition.

The analysis is conducted in three stages: (1) ANOVA Deviance test to identify significant variables, (2) post-ANOVA analysis using odds ratios to measure the influence of each parameter, and (3) model validation through goodness-of-fit tests and data independence checks. This process provides insights into the factors affecting engine health and supports the development of accurate predictive models using SVM and BPNN.

2.6. Support Vector Machine

The Support Vector Machine (SVM) modeling in this study applies two types of kernels [16]: Radial Basis Function (RBF) and Sigmoid, each offering advantages in handling non-linear patterns in diesel engine health data. The kernel function, which transforms data non-linearity into a higher-dimensional space, is illustrated in Figure 4.

a. Radial Basis Function (RBF) Kernel

The RBF kernel enables the separation of non-linear data by mapping it into a higher-dimensional space. Its formula is;

$$K(x_i, x_j) = \exp\exp(-\lambda.(|x_i - x_j|^2)) \qquad (1)$$

Where λ (lambda) controls the model's sensitivity to data variations. A high gamma value makes the model too sensitive (overfitting), while a low value makes the model less flexible (underfitting). The parameters C and gamma are optimized using Grid Search for the best results.

b. Sigmoid Kernel

The Sigmoid kernel resembles the activation function of artificial neural networks and is used to capture non-linear relationships. The formula is:

$$K(x_i, x_j) = \tanh\tanh(\gamma.(x_i, x_j) + c) \qquad (2)$$

where gamma determines the slope of the function, and c shifts the curve to adjust data separation. This kernel is suitable for datasets that resemble ANN patterns but is more sensitive to parameter selection.

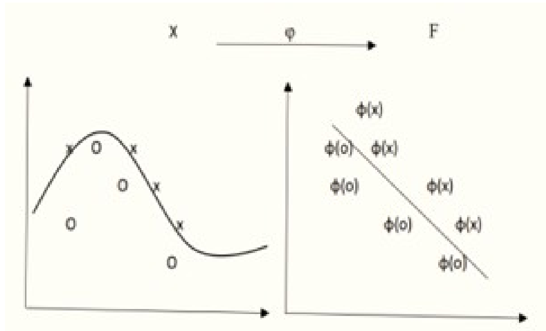

Figure 4. Kernel Transforms Non-Linear Problems into Linear Problems in a New Space (Ritonga & Purwaningsih, 2018).

2.7. Backpropagation Neural Network (BPNN)

The Backpropagation Neural Network (BPNN) is employed to predict machine health conditions [17] using operational parameters, including engine speed, oil pressure, fuel pressure, coolant pressure, oil temperature, and coolant temperature. The network architecture comprises three main layers: input, hidden, and output. The input layer receives operational parameters, while the hidden layer captures non-linear relationships in the data. The hidden layer configuration varies from one to three layers, each containing one to three neurons. The output layer produces binary predictions of machine condition: healthy or unhealthy. The overall BPNN structure and its algorithmic process are illustrated in Figure 5.

In BPNN modeling, activation functions play a pivotal role in determining each neuron's output based on its input. By introducing non-linearity into the network, these functions enable the model to capture complex patterns within the data. Commonly employed activation functions include the sigmoid function, which is suitable for binary classification tasks as it produces outputs between 0 and 1; the Rectified Linear Unit (ReLU), which enhances convergence speed and alleviates the vanishing gradient problem; and the hyperbolic tangent (Tansig), which constrains outputs within the range of –1 to 1, providing greater stability compared to the sigmoid function.

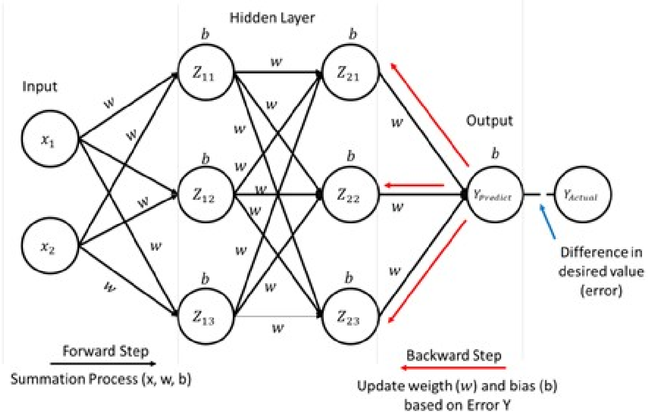

Figure 5. Backpropagation Algorithmic Scheme

For the training process, the Levenberg–Marquardt (trainlm) algorithm is employed. This optimization method integrates gradient descent with Newton's method and is selected for its capability to accelerate convergence and improve efficiency compared to conventional optimization approaches in handling non-linear models such as BPNN. By enabling faster adaptation to data, this method enhances the accuracy of predicting machine health conditions.

2.8. Model Evaluation

The Confusion Matrix is an evaluation technique that visually represents the performance of a classification model by comparing predicted outcomes with actual values [18]. It consists of four key categories: True Positive (TP), when an unhealthy machine is correctly identified as unhealthy; True Negative (TN), when a healthy machine is correctly identified as healthy; False Positive (FP), when a healthy machine is incorrectly classified as unhealthy; and False Negative (FN), when an unhealthy machine is incorrectly classified as healthy.

By analyzing the Confusion Matrix, it is possible to determine whether the model tends to overlook truly unhealthy machines (high FN) or frequently misclassify healthy machines as unhealthy (high FP), which could result in unnecessary maintenance costs. Moreover, the Confusion Matrix provides the basis for calculating other evaluation metrics such as Accuracy, Precision, Recall, and F1-score, which offer a more comprehensive assessment of the model's effectiveness in classifying machine conditions. Several performance evaluation equations can be derived from the Confusion Matrix to quantify these metrics.

1. **Accuracy**

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{3}$$

Accuracy measures how often the model makes correct predictions across the entire dataset.

2. **Precision**

$$\text{Precision} = \frac{TP}{TP + FP} \tag{4}$$

Precision measures the proportion of positive predictions that are actually positive, which is crucial for avoiding false positives.

3. **Recall (Sensitivity)**

$$\text{Sensitivity} = \frac{TP}{TP + FN} \tag{5}$$

Recall indicates the model's ability to capture all actual positive cases.

4. **F1-Score**

$$F_1\text{-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{6}$$

F1-score is the harmonic mean of precision and recall, used to balance the trade-off between them.

3. Results and Discussion

This study analyzes the operational data of the MTU Series 4000 marine diesel engine, covering key parameters such as engine speed (RPM), oil pressure and temperature, fuel pressure, and coolant system temperature. The Support Vector Machine (SVM) model is applied using Radial Basis Function (RBF) and Sigmoid kernels, while the Backpropagation Neural Network (BPNN) is implemented with variations in the number of hidden layers and neurons per hidden layer. The performance of these models is then evaluated and compared with previous research conducted by D. Mohakul (2023), which utilized SVM with Linear and Polynomial kernels, along with other approaches.

During the data preprocessing stage, cleaning and transformation processes were carried out to ensure dataset quality before analysis. These processes included checking for missing values and outliers to prevent data imperfections that could reduce model accuracy. The missing values check aimed to detect any data loss due to input errors or format inconsistencies. Analysis results indicated that the dataset contained no missing values, eliminating the need for imputation techniques. Subsequently, outlier identification was performed to detect extreme values that could affect modeling. The distribution analysis revealed that the dataset was not normally distributed, as shown in Figure 6, necessitating further handling steps.

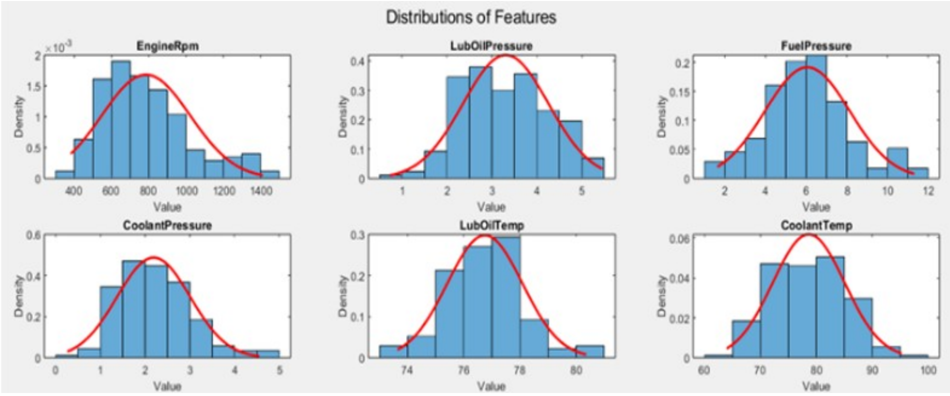

Figure 6. Histogram of Feature Data Distribution in the Dataset.

Since the data distribution is not normal, the Interquartile Range (IQR) method is used to detect outliers. This method is chosen because it is effective in identifying extreme values in data that do not follow a normal distribution and provides a clear representation of the reasonable value range within the dataset. IQR is calculated as the difference between the first quartile (Q1) and the third quartile (Q3), which represent 25% and 75% of the data, respectively. Data points that fall outside the lower or upper bounds are considered outliers, calculated as follows:

$$IQR = Q3 - Q1 \tag{7}$$

$$\text{Lower Bound} = Q_1 - (1.5 \times \text{IQR}) \tag{8}$$

$$\text{Upper Bound} = Q_3 + (1.5 \times \text{IQR}) \tag{9}$$

Based on this formula, the results of outlier detection for each feature in the dataset are visualized in Figure 7, which presents an outlier summary graph along with a box plot of the outliers.

Feature	Outlier Count	Outlier Percentage
Engine_rpm	5	2.87%
Lub_oil_pressure	0	0.00%
Fuel_pressure	3	1.72%
Coolant_pressure	4	2.30%
Lub_oil_temp	5	2.87%
Coolant_temp	0	0.00%

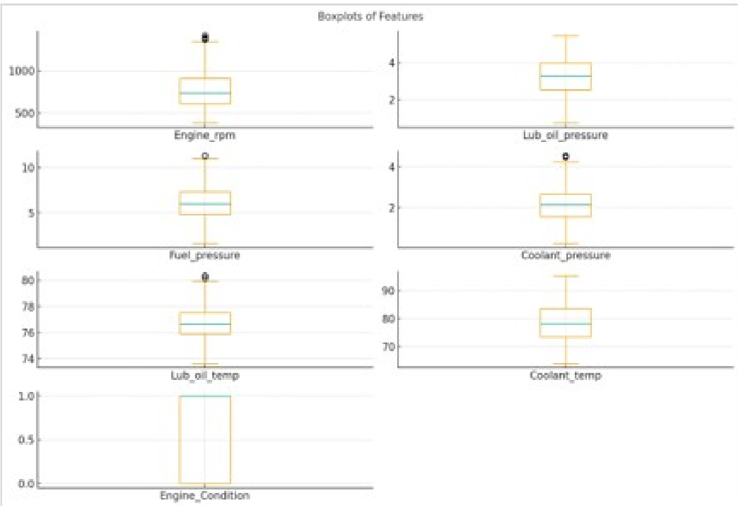

Figure 7. Histogram of Feature Data Distribution in the Dataset.

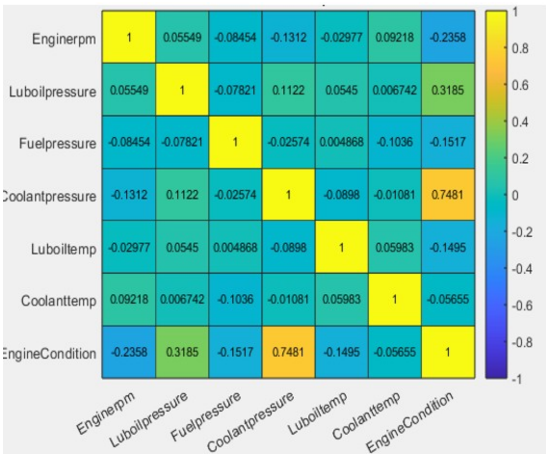

Figure 8. Heatmap of Correlation Between Engine Parameter Features

In addition, an analysis was conducted to examine the relationship between various operational parameters of the engine and its health condition, represented by the Engine Condition variable (healthy or unhealthy). The analysis was performed on the dataset after the relabeling process using the Spearman correlation method to assess the relationships between variables. The correlation results are visualized in a heatmap in Figure 8.

Correlation analysis indicates that several operational parameters of the diesel engine significantly correlate with Engine Condition. The negative correlation of Engine RPM (r = -0.2358) suggests that high RPM accelerates component wear due to increased friction and temperature. According to Heywood (2018), operating above 75% capacity increases cylinder friction by up to 40%, while Zhang et al. (2019) reported a 25% rise in component wear at RPM >1500. Therefore, maintaining RPM within the optimal range (1500-1800 RPM) is crucial to reducing degradation. Lubricating Oil Pressure (r = 0.3185) shows a weak positive correlation with engine condition. Stable pressure (4-6 bar) ensures optimal lubrication, whereas low pressure (<2 bar) increases wear by up to 18% (Kumar et al., 2015). However, high pressure (>7 bar) may indicate system blockage. Regular inspections, including viscosity testing, are necessary. Fuel Pressure (r = -0.1517) exhibits a weak negative correlation, indicating that excessive fuel pressure (>2200 bar) increases injector wear by 12% (Chen et al., 2018), while low pressure accelerates carbon deposits. Maintaining optimal pressure (4-10 bar) should be monitored using AI-based diagnostic systems. Coolant Pressure (r = 0.7481) has a strong positive correlation, suggesting that stable pressure (1-2 bar) prevents overheating. A 30% pressure drop can increase coolant temperature by 15°C, accelerating component damage by 20% (Singh et al., 2017). Thus, monitoring coolant pressure is crucial. Lubrication Oil Temperature (r = -0.1495) indicates that high lubricant temperature (>100°C) reduces viscosity by up to 40% (Wang et al., 2016), increasing the risk of bearing and piston failure. The use of high-quality lubricants and sensor-based temperature monitoring is recommended. Coolant Temperature (r = -0.0565) has a minor impact but remains important, as an increase above 100°C can lead to thermal distortion and cylinder head failure (Guo et al., 2019). Overall, engine RPM, oil pressure, and coolant pressure have the most significant impact on engine condition. Thus, oil pressure and cooling pressure are the most relevant parameters in predicting the condition of MTU Series 4000 diesel engines.

The effect of engine operating parameters on the average engine condition (Engine Condition) is shown in Figure 9: Main Effects Plot. This graph uses data grouping (binning) to reduce data irregularity due to continuous parameter value variations, facilitating analysis of each parameter's effect on engine condition.

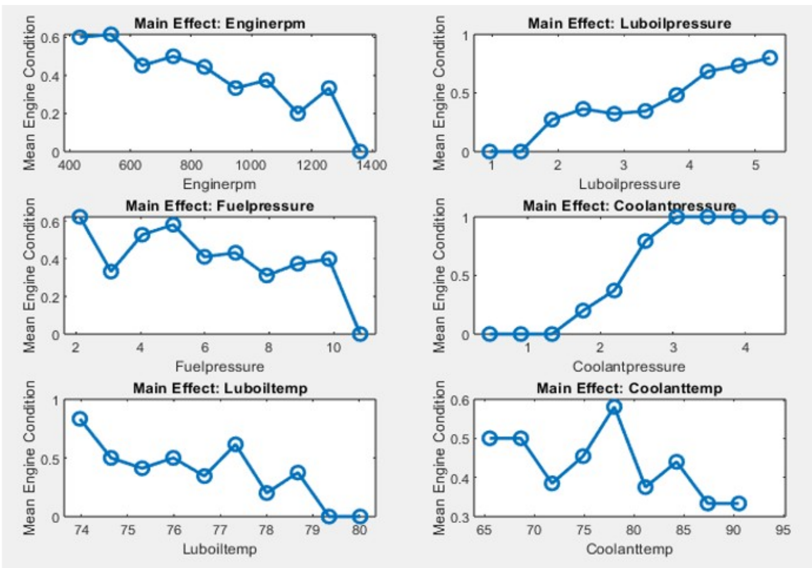

Figure 9. Main Effect Plot Engine Operating Parameters

Table 2. Result of ANOVA test Deviance

Model	Deviance	DF	p-value
Full Model	181.06	6	0.0000
Reduction Model	179.905	5	0.0000
LRT	-1.111		
Chi-Square (df = 1)	3.841		

The Main Effects Plot results show that each operating parameter has an effect on engine condition, especially oil pressure and coolant pressure. Overall, parameter values within the optimal range tend to produce healthy engine conditions, while extreme values (too low or too high) increase the risk of engine damage. These findings support the importance of real-time parameter monitoring in diagnosing and predicting diesel engine health.

Following this, a Deviance ANOVA (Likelihood Ratio Test, LRT) was applied in a logistic regression analysis, was used in logistic regression analysis to evaluate the impact of predictor variables on the probability of an event, such as engine health status. In this context, the analysis compared a full model that included all predictor variables with a reduced model containing only the most significant variables. The results of the Deviance ANOVA are summarized in Table 2. The LRT results showed a significant difference between the full and reduced models, indicating that the additional predictor variables in the full model contribute meaningfully to predicting engine health. Therefore, the full model is considered more appropriate for further analysis.

Significance evaluation is evaluated as follows: if LRT > chi-square, variable reduction is not significant; if LRT $\leq$ chi-square, it is significant. The ANOVA results obtained show LRT = -1.111, which is smaller than chi square 3.841. Thus, the variable reduction in the reduction model is not significant, and the full model is better. The full model yielded a P-value < 0.05, which indicates that there is at least one variable that has a significant impact on the health of the diesel engine.

Table 3. Evaluation Metrics for SVM Model Prediction Performance with Sigmoid Kernel

Kernel Function	Parameter			Model Performance				
	C	c	y	Avg. Accuracy (%)	Avg. MSE	Avg. Precision	Avg. Recall	Avg. F1 Score
Sigmoid 1	0.1	-1	0.01	53.66	0.46	0.00	0.00	0.00
Sigmoid 2	1	0	0.01	82.54	0.17	1.00	0.63	0.77
Sigmoid 3	10	1	0.01	95.52	0.07	0.99	0.84	0.91
Sigmoid 4	0.1	-1	0.1	58.91	0.41	0.00	0.12	0.00
Sigmoid 5	1	0	0.1	94.07	0.06	0.99	0.88	0.93
Sigmoid 6	10	1	0.1	84.43	0.16	0.85	0.80	0.82
Sigmoid 7	0.1	-1	1	87.42	0.13	0.96	0.76	0.85
Sigmoid 8	1	0	1	78.28	0.22	0.80	0.73	0.76
Sigmoid 9	10	1	1	73.53	0.26	0.76	0.64	0.69

Table 4. Evaluation Metrics for SVM Model Prediction Performance with RBF Kernel

Kernel Function	Parameter			Model Performance				
	C	c	y	Avg. Accuracy (%)	Avg. MSE	Avg. Precision	Avg. Recall	Avg. F1 Score
RBF 1	0.1	-	0.01	53.66	0.46	0.00	0.00	0.00
RBF 2	0.1	-	0.1	53.66	0.46	0.00	0.00	0.00
RBF 3	0.1	-	1	53.66	0.46	0.00	0.00	0.00
RBF 4	1	-	0.01	67.95	0.32	0.00	0.33	0.00
RBF 5	1	-	0.1	67.95	0.32	0.00	0.33	0.00
RBF 6	1	-	1	84.97	0.15	0.95	0.71	0.80
RBF 7	10	-	0.01	67.95	0.32	0.00	0.33	0.00
RBF 8	10	-	0.1	67.95	0.32	0.00	0.33	0.00
RBF 9	10	-	1	86.01	0.14	0.92	0.77	0.83

This study applies the Support Vector Machine (SVM) to predict diesel engine health based on relabeled operational data. SVM was chosen for its ability to generalize complex data. Two types of kernels were used: Radial Basis Function (RBF) and Sigmoid, with nine parameter combinations each to determine the best model. The prediction results are presented in Tables 3 and 4, including evaluation metrics such as average accuracy, Mean Squared Error (MSE), precision, recall, and F1-score during the training, validation, and testing phases.

In the Sigmoid kernel, the varied parameters include Box Constraint (C), constant (c), and gamma (γ) with combinations of C = 0.1, 1, 10, c = -1, 0, 1, and γ = 0.01, 0.1, 1. The best results were achieved with C = 1, c = 0, and γ = 0.1, yielding an average accuracy of 94.07%, MSE of 0.06, recall of 0.88, precision of 0.99, and an F1-Score of 0.93. Meanwhile, for the RBF kernel, the varied parameters were Box Constraint (C) and gamma (γ), with combinations of C = 0.1, 1, 10 and γ = 0.01, 0.1, 1. The best-performing model was obtained with C = 10 and γ = 1, resulting in an average accuracy of 86.01%, MSE of 0.14, recall of 0.77, precision of 0.92, and an F1-Score of 0.83.

Based on the results, the SVM model with the Sigmoid kernel demonstrated superior performance compared to the RBF kernel, achieving the highest prediction accuracy of 94.07%. Its ability to effectively handle complex distributions allows the model to capture nonlinear patterns that are difficult for other kernels to identify. Additionally, the dataset's characteristics, which likely involve variable interactions and a non-homogeneous distribution, support the superiority of the Sigmoid kernel.

The optimal parameter combination for the Sigmoid kernel (C = 1, c = 0, γ = 0.1) provides a balanced trade-off between bias and variance. A lower C value prevents overfitting, while a small γ ensures the model is not overly sensitive to noise, making it ideal for this dataset. On the other hand, the RBF kernel achieved a maximum accuracy of 86.01%, lower than the Sigmoid kernel. Despite its good generalization capabilities, its performance was lower due to:

- **Overfitting Parameters:** The optimal combination ($C = 10$, $\gamma = 1$) increased model complexity, leading to overfitting and reduced generalization.
- **Data Characteristics:** The RBF kernel is better suited for local data patterns, whereas this dataset exhibits more global nonlinear patterns.

This evaluation confirms that the Sigmoid kernel is more effective in capturing complex patterns within this dataset, while the RBF kernel is more suitable for localized data distributions. Therefore, kernel selection should be tailored to the dataset characteristics. The next method applied is Backpropagation Neural Network (BPNN) to predict diesel engine health using various artificial neural network configurations. The varied parameters include the number of hidden layers (1–3), the number of neurons per hidden layer (1–3), and activation functions such as logsig, tansig, purelin, softmax, satlin, satlins, hardlim, hardlims, and poslin. The training algorithm used is Levenberg-Marquardt (trainlm). Prediction results are summarized in Table 5, which presents the best network configuration based on the number of hidden layers. Model evaluation is conducted using average accuracy, MSE, precision, recall, and F1-score across training, validation, and testing stages.

Based on Table 5, the experimental results indicate that the best configuration is achieved with a neural network containing three hidden layers. The optimal structure consists of one neuron in the first hidden layer, two neurons in the second hidden layer, and one neuron in the third hidden layer, using the "tansig" activation function. This configuration yields an average accuracy of 97.13%, MSE of 0.03, recall of 0.94, precision of 1, and an F1-Score of 0.97. The addition of a third hidden layer enhances the model's ability to capture more complex patterns without causing overfitting, whereas a single hidden layer is insufficient to capture nonlinear relationships in the data. Additionally, the tansig activation function demonstrates the best performance due to its flexibility in handling nonlinear data. Its use in both the hidden layer and output layer proves effective in enhancing model accuracy, aligning with findings from previous studies.

Table 5. Evaluation Metrics of BPNN Model Prediction

Network Configuration	Avg. Accuracy (%)	Avg. MSE	Avg. Precision	Avg. Recall	Avg. F1 Score
Layer: 1, Neurons: 1, Activations: tansig, OutputFcn: tansig	97.13	0.03	1.00	0.94	0.97
Layer: 2, Neurons: [1 2], Activations: [tansig tansig], OutputFcn: tansig	97.13	0.03	1.00	0.94	0.97
Layer: 3, Neurons: [1 2 1], Activations: [tansig tansig tansig], OutputFcn: tansig	97.13	0.03	1.00	0.94	0.97

Table 6. Comparison of SVM and BPNN Prediction Results with Related Studies

Model	Accuracy	Precision	Recall	F1-Score	Source
SVM (Sigmoid)	94	99	88	93	Propose Method
SVM (RBF)	86	92	77	83	
BPNN	97	100	94	97	
Logistic Regression	89	88	87	88	D. Mohakul 2023
SVM (Linear)	89	88	87	88	
SVM (Polynomial)	88	87	84	86	
KNN	89	88	87	87	
Naïve Bayes	83	82	79	80	
Decision Tree	74	72	67	68	

By comparing accuracy, MSE, recall, precision, and F1-score with prior studies, the performance improvements achieved can be assessed, along with the key factors contributing to the model's enhancement. The comparison of prediction performance between the proposed method and related studies is presented in Table 6.

Based on the table above, the BPNN method in this study demonstrated the best performance, achieving 97% accuracy, 100% precision, 94% recall, and a 97% F1-score. Additionally, the SVM method with the sigmoid kernel also outperformed the SVM model from Mohakul's (2023) study, particularly in terms of accuracy—94% compared to 89% for the Linear SVM. This difference indicates that the approach used in this study is more optimal for predicting diesel engine health conditions. This advantage can be attributed to a more suitable model configuration, such as the use of the sigmoid kernel, which is better at handling nonlinear patterns, as well as more effective parameter optimization.

4. Conclusions

This study evaluates the performance of SVM and BPNN in predicting diesel engine health. SVM with a Sigmoid kernel achieved 94.06% accuracy but was less sensitive in detecting unhealthy conditions, while BPNN with a three-hidden-layer (1-2-1) tansig configuration outperformed SVM with 97.13% accuracy, demonstrating superior ability to capture complex patterns. Dataset relabeling using K-Means also improved BPNN accuracy significantly, from 72.3% to 97.13%, highlighting the importance of data balance. Overall, BPNN with optimal configuration and well-processed data proved to be the most reliable method for diesel engine health prediction.

Beyond experimental validation, the model offers practical implications for real-world maintenance. Integrated into a condition-based maintenance (CBM) framework, SVM and BPNN predictions can support early detection of engine degradation, enabling proactive scheduling, reducing unplanned breakdowns, and optimizing spare parts management. In marine applications, this is especially valuable for ship diesel engines operating under varying loads and harsh conditions. By monitoring parameters such as oil pressure, coolant temperature, and fuel system behavior, the model can provide early warnings before failures occur at sea, allowing maintenance during port calls and improving fleet reliability, efficiency, and regulatory compliance.

Future research should explore advanced methods such as Gradient Boosting, XGBoost, alternative ANN architectures, and ensemble learning to further improve predictive performance. Expanding datasets with broader operational conditions and diverse engine types will also enhance generalizability and reliability across various contexts.

Acknowledgement

The author expresses gratitude to Institut Teknologi Sepuluh Nopember (ITS), Surabaya, and the ITS Department of Mechanical Engineering for their support in providing facilities and academic guidance throughout this research. Appreciation is extended to Dr. Mohammad Khoirul Effendi for his valuable mentorship and insights, as well as to fellow laboratory members for their technical assistance and constructive discussions. The author also thanks those who contributed to providing the dataset and references that formed the foundation of this analysis. Finally, heartfelt gratitude is extended to family and friends for their moral support throughout the research process.

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