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

Fadli Nurdin[1,*,a] **and Mohammad Khoirul Effendi**[1,b]
[1]Mechanical Engineering Department, Sepuluh Nopember Institute of Technology, Jalan Teknik Kimia, Surabaya, 60111, Indonesia
[*, a]fadli.nurdin01@gmail.com (Corresponding Author), [b]khoirul_effendi@me.its.ac.id

Abstract—**This study discusses the application of Support Vector Machine (SVM) and Backpropagation Neural Network (BPNN) in predicting diesel engine health based on operational data relabeled using K-Means Clustering. Two types of SVM kernels were tested, namely Radial Basis Function (RBF) and sigmoid, with various parameter combinations. The results indicate that SVM with sigmoid kernel achieved an accuracy of 94.06%, but it was less sensitive in detecting unhealthy engine conditions. In comparison, the BPNN method with a three-hidden-layer configuration (1-2-1 neurons) and tansig activation function showed superior performance with 97.13% accuracy, MSE of 0.03, recall of 94%, precision of 100%, and F1-score of 97%. These findings prove that BPNN outperforms SVM in capturing complex data patterns and is more accurate in detecting unhealthy engine conditions. Additionally, relabeling the dataset significantly improved predictive accuracy from 72.3% to 97.13%, highlighting the importance of balanced data in modeling. Overall, this study demonstrates that optimally configured BPNN is more effective in predicting diesel engine health than SVM, making it a more reliable approach for engine condition monitoring.**

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

I. Introduction

Engine health is a crucial factor in machine operations across various sectors, including industry, automotive, and maritime or aviation transportation. Unexpected failures can have severe consequences, impacting both operational efficiency and maintenance costs. Therefore, effective maintenance strategies such as Condition-Based Maintenance (CBM) are increasingly being adopted to detect and prevent potential failures before they occur [1]. CBM is a predictive maintenance approach that utilizes real-time sensor data installed on engines to analyze operational conditions. This method surpasses time-based or corrective maintenance by reducing operational costs and extending engine lifespan. However, a major challenge in CBM implementation lies in accurately and efficiently processing large and complex sensor data.

Previous studies have explored CBM applications in machine maintenance. For instance, [2] a study developed a machine-learning-based CBM model for early anomaly detection in industrial engines, achieving a failure prediction accuracy of up to 95%. Another research implemented [3] a deep learning-based CBM model to detect degradation patterns in heavy-duty diesel engines, demonstrating a 30% improvement in maintenance efficiency compared to traditional methods.

In the context of predictive maintenance, several artificial intelligence methods have been applied, including SVM and BPNN. SVM is known for its advantage in handling high-dimensional data and producing accurate classifications, while BPNN is more effective in recognizing complex patterns from machine sensor data. However, both methods have significant drawbacks: SVM often requires high computational time for large datasets, whereas BPNN's performance heavily depends on the initial parameter configuration and is prone to overfitting.

Several previous studies have explored the use of SVM and BPNN in machine health prediction. A predictive maintenance system for motor vehicles has been developed using Suppor Vector Machine, achieving an accuracy of 92.92%. An Optimized Backpropagation Neural Network (OBPNN) combined with the Fish Swarm Algorithm (FSA) was proposed to predict the health of marine diesel engines, resulting an accuracy of 99.05% [4]. In another study, Logistic Regression, SVM, and K-Nearest Neighbors (KNN) were compared for diesel engine fault detection, SVM performed best with 93% accuracy [5].

Although previous studies have demonstrated the effectiveness of SVM and BPNN in predicting machine health, several research gaps still need to be addressed. First, the use of more optimal kernels in SVM, such as RBF and sigmoid Kernel, has not been extensively explored to improve accuracy on non-linear datasets. Second, parameter optimization in BPNN remains a challenge, particularly in avoiding overfitting and accelerating convergence. This study contributes to the development of a diesel engine health prediction system by comparing a modified SVM approach with an optimized BPNN. Thus, this research aims to bridge the gap in the literature by exploring more accurate and efficient strategies for AI-based predictive maintenance.

II. Research Methodology

A. System Design

The system developed in this study is designed to analyze the condition of diesel engines using SVM and BPNN in Condition-Based Maintenance, as shown in Figure 1.

The flowchart illustrates the structured process of analyzing the health of a diesel engine using SVM and BPNN. It begins with the collection of operational data, followed by preprocessing steps to clean, normalize, and relabeling the data, ensuring its quality and consistency.

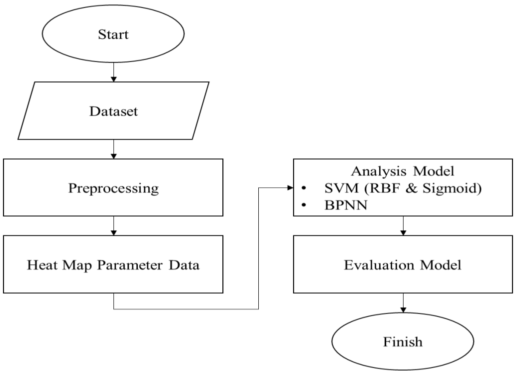

Figure 1. System Model Workflow

A heat map is then utilized to identify correlations between parameters, providing valuable insights into influential features that impact engine health. The prepared data is analyzed using SVM with RBF and sigmoid kernels, alongside BPNN, to predict engine health status. Model evaluation metrics such as accuracy, MSE, recall, and F1-score are employed to assess and compare the performance of both methods. The process concludes with drawing meaningful conclusions that can guide future research and practical applications, helping to maintain engine reliability and prevent potential failures.

B. Dataset

This study utilizes a dataset consisting of operational parameters of diesel engines, such as temperature, pressure, and vibration, as shown in Table 1. The data is divided into two parts: training data and testing data. SVM is used to classify engine conditions based on an optimal hyperplane, while BPNN employs a neural network architecture with a backpropagation algorithm to learn data patterns.

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

The dataset is obtained from a previous study, the papers titled [5] and [6] by D. Mohakul. The type of engine examined in this research is the MTU Series 1400 diesel engine. The dataset includes several operational parameters, namely engine speed (Engine RPM), lubricating oil pressure (Lub Oil Pressure) in bar, fuel pressure (Fuel Pressure) in bar, engine cooling system pressure (Coolant Pressure) in bar, lubricating oil temperature (Lub Oil Temperature) in degrees Celsius, and engine cooling system temperature (Coolant Temperature) in degrees Celsius. The data labels or output parameters used to determine engine conditions consist of two categories: healthy (1) and unhealthy (0). This dataset is utilized for training and testing the predictive models to evaluate the performance of SVM and BPNN in predicting diesel engine health.

C. *Preprocessing*

Data preprocessing aims to ensure that the data used in the analysis is clean, structured, and ready for processing by the algorithm [7]. The preprocessing stages include data cleaning to handle missing values using mean imputation and removing outliers with the Interquartile Range (IQR) method. Next, data normalization is performed using Min-Max Normalization to standardize feature scales, making them suitable for both the SVM and BPNN algorithms.

Relabeling engine condition data using the K-Means clustering method aims to improve data quality by distributing labels more representatively. This process includes 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.

After relabeling, the dataset is divided into three subsets: a training set (70%) for model training, a testing set (15%) for model performance evaluation, and a validation set (15%) to prevent overfitting. The dataset is randomly split to avoid bias in data distribution.

D. *Heat Map Parameter Data*

The analysis of the relationship between operational parameters and diesel engine health is conducted using Spearman correlation, visualized in a heat map, as shown in Figure 2 [8]. The correlation coefficient is calculated to measure the strength and direction of relationships between variables, with the results presented in a correlation matrix. The heat map colors indicate the intensity of the relationships, where positive values close to +1 signify a strong correlation, negative values close to -1 indicate a strong inverse correlation, and values near 0 suggest a weak relationship. This analysis helps identify the most influential parameters for predicting engine health, which can be utilized in optimizing condition-based maintenance models.

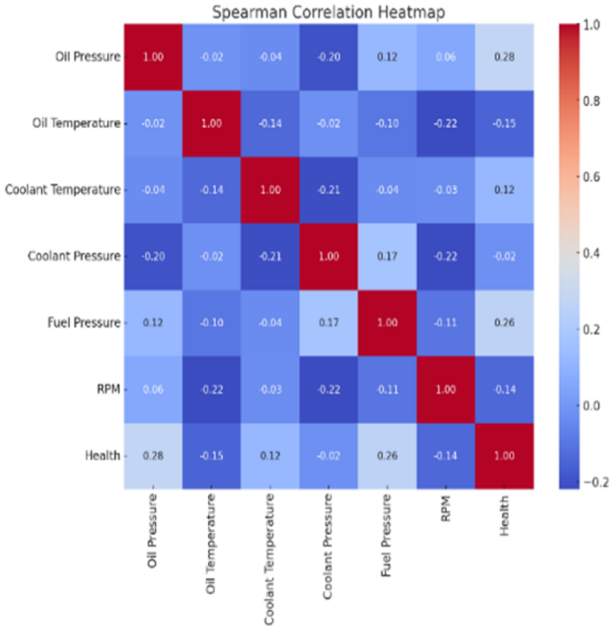

Figure 2. Heat Map of Machine Parameter Correlation

E. *Analysis Model*

Deviance-based Analysis of Variance (ANOVA) in Logistic Regression is used to evaluate the significance of differences between groups in a dataset with a binary response variable. This test compares the full logistic regression model with a reduced model using the Likelihood Ratio Test (LRT), where a p-value < 0.05 indicates that a variable significantly affects the health condition of the diesel engine. The analysis is conducted in three stages: Deviance ANOVA testing to identify significant variables, post-ANOVA analysis with odds ratio to measure the impact of parameters, and model validation through goodness-of-fit testing and data independence assessment. This approach provides deeper insights into the factors influencing engine conditions and enhances the predictive accuracy of SVM- and BPNN-based models.

F. *Support Vector Machine*

The Support Vector Machine modeling in this study utilizes two types of kernels [9], namely RBF and sigmoid, each of which has advantages in handling non-linear patterns in diesel engine health data.

1. RBF Kernel

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

$$K(x_{i,}x_{j)} = \exp(-\lambda\,.\,(||x_i - x_j||^2) \quad (1)$$

where λ (gamma) controls the model's sensitivity to data differences. A high gamma value makes the model overly sensitive (overfitting), while a low gamma value makes the model less flexible (underfitting). The parameters C and gamma are optimized using Grid Search to achieve the best performance.

2. Sigmoid Kernel

The sigmoid kernel resembles the activation function of an artificial neural network and is used to capture non-linear relationships. Its formula is:

$$K\ (x_{i,}, x_{j)} = \tanh\ (\gamma.\left(x_i, x_j\right) + c) \quad (2)$$

where gamma determines the slope of the function, and parameters C shifts the curve to adjust data separation. This kernel is suitable for datasets that resemble artificial neural network (ANN) patterns but is more sensitive to parameter selection.

G. Backpropagation Neural Network (BPNN)

The Backpropagation Neural Network (BPNN) model is used to predict engine health conditions [10] based on operational parameters, including engine speed, oil pressure, engine temperature, coolant pressure, coolant temperature, and fuel pressure. The network architecture consists of three main layers: the input layer, hidden layer, and output layer. The input layer receives operational parameters as input data, while the hidden layer processes and captures non-linear relationships within the data. The number of hidden layers varies between one and three, with each hidden layer containing between one and three neurons. The output layer generates the final prediction of the engine condition, classified as either healthy or unhealthy.

In BPNN modeling, various activation functions are used, playing an important role in determining the output of each neuron based on the received input. These activation functions introduce non-linearity into the network, allowing the model to learn complex patterns in the data. Some commonly used activation functions include sigmoid, which is suitable for binary outputs as it produces values between 0 and 1; ReLU (Rectified Linear Unit), which accelerates convergence and addresses the vanishing gradient problem; and Tanh, which keeps output values within the range of -1 to 1, making it more stable compared to the sigmoid function.

For the training process, the Levenberg-Marquardt (trainlm) algorithm is used, which is an optimization method based on gradient descent combined with Newton's method, as illustrated in Figure 3.

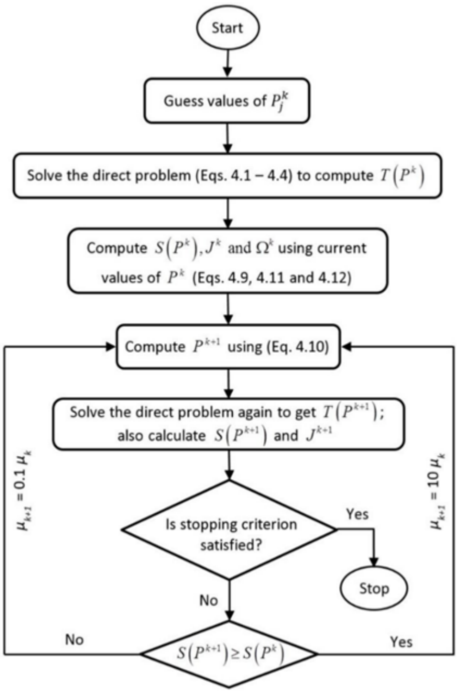

Figure 3. Levenberg-Marquardt Algorithm Flowchart

This algorithm is chosen because it accelerates the convergence process and is more efficient than conventional optimization methods in handling non-linear models like BPNN. With this approach, the model can adapt more quickly to the data and improve accuracy in predicting engine health conditions.

H. Evaluation Model

The Confusion Matrix is an evaluation method that provides a visual representation of the classification model's performance by comparing prediction results with actual values [11]. This matrix consists of four main categories: True Positive (TP), when an unhealthy engine is correctly predicted as unhealthy; True Negative (TN), when a healthy engine is predicted as healthy; False Positive (FP), when a healthy engine is incorrectly classified as unhealthy; and False Negative (FN), when an unhealthy engine is instead predicted as healthy.

By analyzing the confusion matrix, it can be determined whether the model tends to overlook truly

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unhealthy engines (high FN) or too often classifies healthy engines as unhealthy (high FP), which can lead to unnecessary maintenance costs. Additionally, the confusion matrix serves as the basis for calculating other evaluation metrics such as Accuracy, Precision, Recall, and F1-score to assess the model's effectiveness in accurately classifying engine conditions.

Some equations that can be derived from the confusion matrix are:

1. Accuracy

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (3)$$

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

2. Precision

$$Precision = \frac{TP}{TP+FP} \quad (4)$$

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

3. Recall (Sensitivities)

$$Recall = \frac{TP}{TP+FN} \quad (5)$$

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

4. F1-Score

$$f1 - Score = 2x\frac{Precision \times Recall}{Precision + Recall} \quad (6)$$

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

By using the confusion matrix and the above metrics, the model's performance in classifying engine health conditions can be analyzed comprehensively.

III. Results and Discussion

This study analyzes the operational data of MTU Series 4000 marine diesel engines, encompassing key parameters such as engine speed, oil pressure and temperature, fuel pressure, and coolant system temperature. The SVM model is implemented using the RBF and sigmoid kernels, requiring approximately 364 seconds (6 minutes) of training time, while BPNN is applied with variations in the number of hidden layers and neurons per hidden layer, with a training time of 322 seconds (5 minutes). The performance of these models is then evaluated and compared with previous research conducted by D. Mohakul [6], which utilized SVM with Linear and Polynomial kernels, along with several other approaches.

At the data preprocessing stage, cleaning and transformation are performed to ensure dataset quality before analysis. This process includes checking for missing values and outliers to prevent data imperfections that could reduce model accuracy.

The missing values check aims to detect missing data due to input errors or format inconsistencies. The analysis results indicate that the dataset does not contain missing values, eliminating the need for imputation techniques. Next, outlier identification is conducted to detect extreme values that may affect modeling. The distribution analysis shows that the dataset is not normally distributed, as illustrated in Figure 4, necessitating further handling steps.

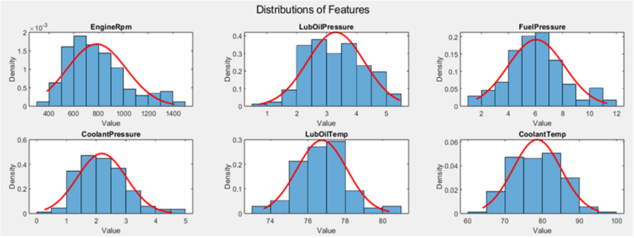

Figure 4. Histogram of Data Distribution on Dataset

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 non-normally distributed data and provides a clear representation of the acceptable value range within the dataset.

IQR is calculated as the difference between the first quartile (Q1) and the third quartile (Q3), which represent the 25th and 75th percentiles of the data, respectively. Data points falling outside the lower or upper bounds are considered outliers, with the calculations as follows:

$$IQR = Q3 - Q1$$

Lower Bound = Q1 - (1.5 x IQR)
Upper Bound = Q3 + (1.5 x IQR)

Based on this formula, the outlier detection results for each feature in the dataset are visualized in Figure 5, which presents a summary graph of outliers along with an outlier box plot.

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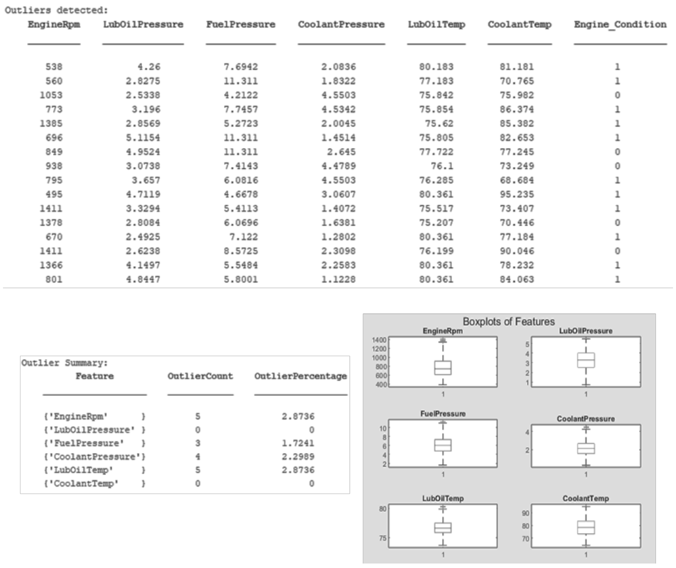

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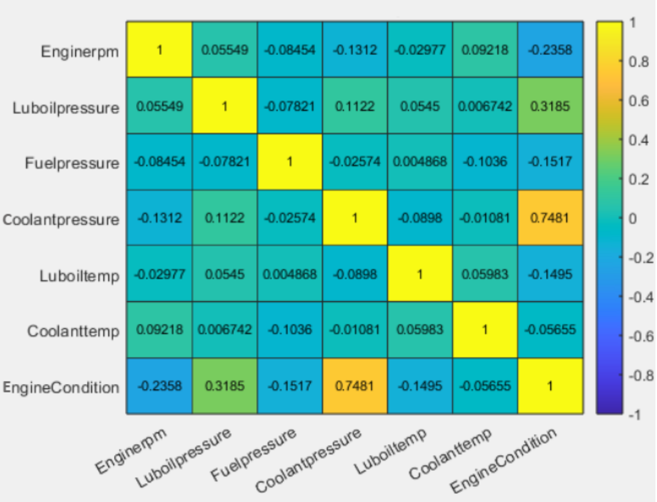
Outliers detected:
    EngineRpm    LubOilPressure    FuelPressure    CoolantPressure    LubOilTemp    CoolantTemp    Engine_Condition
    _________    ______________    ____________    _______________    __________    ___________    ________________

       538             4.26           7.6942           2.0836          80.183         81.181              1
       560           2.8275           11.311           1.8322          77.183         70.765              1
      1053           2.5338           4.2122           4.5503          75.842         75.982              0
       773            3.196           7.7457           4.5342          75.854         86.374              1
      1385           2.8569           5.2723           2.0045           75.62         85.382              1
       696           5.1154           11.311           1.4514          75.805         82.653              1
       849           4.9524           11.311            2.645          77.722         77.245              0
       938           3.0738           7.4143           4.4789            76.1         73.249              0
       795            3.657           6.0816           4.5503          76.285         68.684              1
       495           4.7119           4.6678           3.0607          80.361         95.235              1
      1411           3.3294           5.4113           1.4072          75.517         73.407              1
      1378           2.8084           6.0696           1.6381          75.207         70.446              0
       670           2.4925            7.122           1.2802          80.361         77.184              1
      1411           2.6238           8.5725           2.3098          76.199         90.046              0
      1366           4.1497           5.5484           2.2583          80.361         78.232              1
       801           4.8447           5.8001           1.1228          80.361         84.063              1
```

```
Outlier Summary:
          Feature          OutlierCount    OutlierPercentage
    ___________________    ____________    _________________

    {'EngineRpm'      }          5               2.8736
    {'LubOilPressure' }          0                    0
    {'FuelPressure'   }          3               1.7241
    {'CoolantPressure'}          4               2.2989
    {'LubOilTemp'     }          5               2.8736
    {'CoolantTemp'    }          0                    0
```

Figure 5. Summary Outlier Detected and Box Plot Data Outlier



	Enginerpm	Luboilpressure	Fuelpressure	Coolantpressure	Luboiltemp	Coolanttemp	EngineCondition
Enginerpm	1	0.05549	-0.08454	-0.1312	-0.02977	0.09218	-0.2358
Luboilpressure	0.05549	1	-0.07821	0.1122	0.0545	0.006742	0.3185
Fuelpressure	-0.08454	-0.07821	1	-0.02574	0.004868	-0.1036	-0.1517
Coolantpressure	-0.1312	0.1122	-0.02574	1	-0.0898	-0.01081	0.7481
Luboiltemp	-0.02977	0.0545	0.004868	-0.0898	1	0.05983	-0.1495
Coolanttemp	0.09218	0.006742	-0.1036	-0.01081	0.05983	1	-0.05655
EngineCondition	-0.2358	0.3185	-0.1517	0.7481	-0.1495	-0.05655	1

Figure 6. Heatmap of Correlation Between Machine Parameter Features

Next, an analysis is conducted to examine the relationship between various engine operational parameters and engine health status, represented by the variable Engine Condition (healthy or unhealthy). The analysis is performed on the dataset after the relabeling process using the Spearman correlation method to assess relationships between variables. The correlation results are visualized in a heatmap in Figure 6, providing a clear representation of the associations between diesel engine operational features and their health conditions.

The correlation analysis indicates that several diesel engine operational parameters have a significant relationship 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 a study by found that component wear rises by 25% at RPM >1500. Therefore, maintaining RPM within the optimal range (1500-1800 RPM) is crucial to reducing degradation.

Lub Oil Pressure (r = 0.3185) shows a weak positive correlation with engine condition. Stable pressure (4-6 bar) ensures optimal lubrication, while low pressure (<2 bar) increases wear by up to 18%. However, high pressure (>7 bar) may indicate system blockage. Therefore, regular inspections, including viscosity testing, are essential.

Fuel Pressure (r = -0.1517) exhibits a weak negative correlation, suggesting that excessive fuel pressure (>2200 bar) increases injector wear by up to 12%, while low pressure accelerates carbon deposit formation. Optimal pressure (4-10 bar) should be monitored using an AI-based diagnostic system.

Coolant Pressure (r = 0.7481) has a strong positive correlation, indicating that stable pressure (1-2 bar) prevents overheating. A 30% pressure drop can increase coolant temperature by up to 15°C, accelerating component wear by 20%. Therefore, monitoring coolant pressure is crucial.

Lub Oil Temp (r = -0.1495) indicates that high lubricant temperature (>100°C) causes a viscosity reduction of up to 40%, increasing the risk of bearing and piston failure. The use of high-quality lubricants and sensor-based temperature monitoring is recommended.

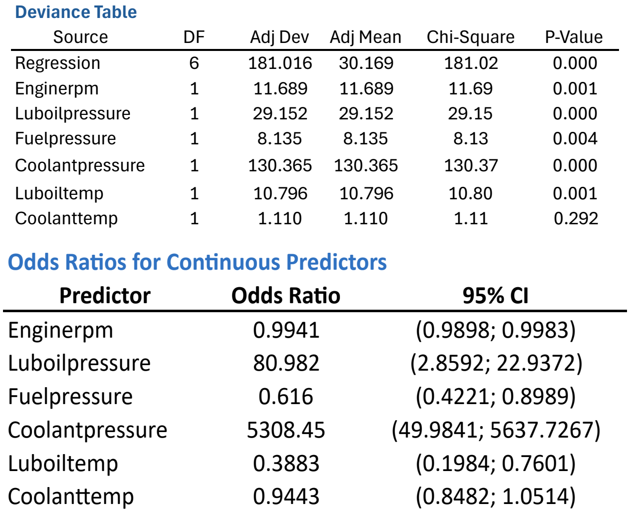
Coolant Temp (r = -0.0565) has a minor impact but should still be considered, as a temperature increase above 100°C can lead to thermal distortion and cylinder head failure [8].

Overall, engine RPM, oil pressure, and cooling pressure have the greatest impact on engine condition. In the Condition-Based Maintenance (CBM) concept, maintenance based on operational data is more effective than schedule-based maintenance. Therefore, oil pressure and cooling pressure are the most relevant parameters in the predictive model for the MTU Series 4000 diesel engine condition.

Following this, the Deviance ANOVA test, also known as the Likelihood Ratio Test (LRT), is used in logistic regression analysis to evaluate the influence of predictor variables on the probability of an event, such as diesel engine health status. The test results, as presented in Table 2, compare the full model, which includes all predictor variables, with the reduced model, which only includes the most significant variables.

Table 2. ANOVA Deviance Test Result

Model	Deviance	DF	p-value
Full Model	181.06	6	0
Reduction Model	179.905	5	0
LRT	-1.111		
Chi-Square (df=1)	3.841		



Deviance Table

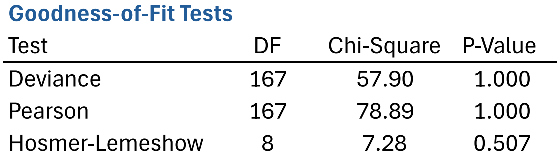
Source	DF	Adj Dev	Adj Mean	Chi-Square	P-Value
Regression	6	181.016	30.169	181.02	0.000
Enginerpm	1	11.689	11.689	11.69	0.001
Luboilpressure	1	29.152	29.152	29.15	0.000
Fuelpressure	1	8.135	8.135	8.13	0.004
Coolantpressure	1	130.365	130.365	130.37	0.000
Luboiltemp	1	10.796	10.796	10.80	0.001
Coolanttemp	1	1.110	1.110	1.11	0.292

Odds Ratios for Continuous Predictors

Predictor	Odds Ratio	95% CI
Enginerpm	0.9941	(0.9898; 0.9983)
Luboilpressure	80.982	(2.8592; 22.9372)
Fuelpressure	0.616	(0.4221; 0.8989)
Coolantpressure	5308.45	(49.9841; 5637.7267)
Luboiltemp	0.3883	(0.1984; 0.7601)
Coolanttemp	0.9443	(0.8482; 1.0514)

Figure 7. Deviance Table and Odds Ratios for Continuous Predictors

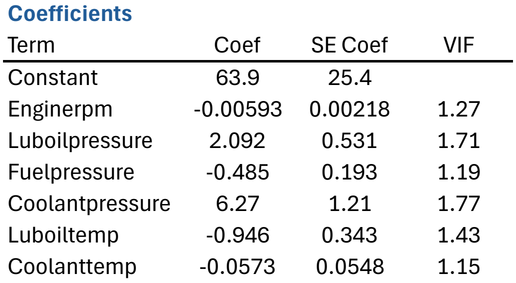
The LRT results indicate a significant difference between the full and reduced models, suggesting that the additional predictor variables in the full model contribute meaningfully to predicting engine health conditions. Additionally, Figure 7 presents the deviance table and odds ratios for continuous predictors, while Figure 8 shows the Goodness-of-Fit test results to assess model adequacy. Furthermore, Figure 9 illustrates the coefficient values of engine operation parameters in the logistic regression model. Based on these analyses, the full model is considered more appropriate for further analysis.



Goodness-of-Fit Tests

Test	DF	Chi-Square	P-Value
Deviance	167	57.90	1.000
Pearson	167	78.89	1.000
Hosmer-Lemeshow	8	7.28	0.507

Figure 8. Goodness Of Fit Tests Model



Coefficients

Term	Coef	SE Coef	VIF
Constant	63.9	25.4	
Enginerpm	-0.00593	0.00218	1.27
Luboilpressure	2.092	0.531	1.71
Fuelpressure	-0.485	0.193	1.19
Coolantpressure	6.27	1.21	1.77
Luboiltemp	-0.946	0.343	1.43
Coolanttemp	-0.0573	0.0548	1.15

Figure 9. Coefficient Parameter Engine Operation Parameters

This study applies the SVM method to predict diesel engine health based on relabeled operational data. SVM was chosen for its ability to generalize complex data effectively.

Two types of kernels were used: RBF and sigmoid, with nine parameter combinations for each to determine the best model. The prediction results are presented in Tables 3 and 4, which include evaluation metrics such as average accuracy, Mean Squared Error (MSE), precision, recall, and F1-score during the training, validation, and testing phases.

The sigmoid kernel varied parameters including 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 model was obtained with C = 10 and γ = 1, achieving 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.

Table 3. Evaluation Metrics for SVM Model Performance with sigmoid Kernel

Kernel Variation	Parameter C			Model Performance				
	C	c	γ	Avg Accuracy (%)	Avg MSE	Avg Precision	Avg Recall	Avg F1-Score
Sigmoid 1	0.1	-1	0.01	53.66	0.46	0	0. 00	0
Sigmoid 2	1	0	0.01	82.54	0.17	1	0.63	0.77
Sigmoid 3	10	1	0.01	92.52	0.07	0.99	0.84	0.91
Sigmoid 4	0.1	-1	0.1	58.91	0.41	0	0.12	0
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	0.8	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	0.8	0.73	0.76

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

Kernel Variation	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	0. 00	0
RBF 2	0.1	-	0.1	53.66	0.46	0	0. 00	0
RBF 3	0.1	-	1	53.66	0.46	0	0. 00	0
RBF 4	1	-	0.01	67.95	0.32	0	0.33	0
RBF 5	1	-	0.1	67.95	0.32	0	0.33	0
RBF 6	1	-	1	84.97	0.15	0.95	0.71	0.8
RBF 7	10	-	0.01	67.95	0.32	0	0.33	0
RBF 8	10	-	0.1	67.95	0.32	0	0.33	0
RBF 9	10	-	1	86.01	0.14	0.92	0.77	0.83

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

The best parameter combination for the sigmoid kernel ($C = 1, c = 0, \gamma = 0.1$) provides an optimal balance 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%, which is lower than sigmoid. Despite its good generalization capability, its performance is lower due to:

1. Overfitting Parameter: The optimal combination ($C = 10$, $\gamma = 1$) increases model complexity, leading to overfitting and reducing generalization.
2. Data Characteristics: The RBF kernel is better suited for local data patterns, whereas this dataset exhibits more globally nonlinear patterns.

This evaluation confirms that the sigmoid kernel is more effective in capturing complex patterns within this dataset, whereas the RBF kernel is better suited for local data distributions. Therefore, kernel selection should be aligned with the characteristics of the data used.

Table 5. Evaluation Metrics for BPNN Prediction Model

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: [12 1] Activations: tansig, tansig, tansig OutputFcn: tansig	97.13	0.03	1	0.94	0.97

The next method is the BPNN, which is applied to predict diesel engine health using various artificial neural network configurations. The parameters varied 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 learning algorithm used is Levenberg-Marquardt (trainlm).

The prediction results are summarized in Table 5, which presents the best network configuration combinations based on the number of hidden layers. Model evaluation is performed 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 network consisting of three hidden layers. The optimal structure includes one neuron in the first hidden layer, two neurons in the second hidden layer, and one neuron in the third hidden layer, utilizing the "tansig" activation function. This configuration yields an average accuracy of 97.13%, an MSE of 0.03, a recall of 0.94, a precision of 1.00, and an F1-score of 0.97.

Further analysis shows that the BPNN model with the optimal configuration can predict diesel engine health with high accuracy. The high accuracy and low MSE values indicate that the model's predictions closely align with actual data.

The best configuration with three hidden layers (1 neuron in the first hidden layer, 2 neurons in the second hidden layer, and 1 neuron in the third hidden layer) and the tansig activation function provides an optimal balance between model complexity and generalization. The addition of a third hidden layer helps capture more complex patterns without causing overfitting, whereas a single hidden layer is less capable of identifying nonlinear relationships within the data.

Additionally, the tansig activation function demonstrated the best performance due to its flexibility in handling nonlinear data. Its use in both the hidden layer and output layer proved effective in improving model accuracy, aligning with findings from various previous studies.

A comparison with previous research was conducted to evaluate the advantages and validity of the model used in this study. By comparing accuracy, MSE, recall, precision, and F1-score with past studies, as shown in Table 6, the extent of performance improvements achieved and the factors contributing to model enhancement can be identified.

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	Proposed 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	

Based on the table above, the BPNN method in this study demonstrated the best performance with an accuracy of 97%, precision of 100%, recall of 94%, and an F1-score of 97%. Additionally, the SVM method with the sigmoid kernel also outperformed the SVM model in Mohakul's study, particularly in terms of accuracy, achieving 94% compared to 89% for the Linear SVM. This difference indicates that the approach used in this study is more optimal for predicting the health condition of diesel engines. This advantage can be attributed to the selection of a model configuration better suited to the data characteristics, such as using the BPNN and SVM sigmoid kernel, as well as more efficient parameter optimization. However, deploying these models in real diesel engine monitoring systems for CBM presents several challenges. These include the need for consistent and high-quality real-time sensor data, the scalability of the model across various engine types, and the integration of predictive outputs with actual maintenance decision-making processes. Additionally, the computational complexity of SVM may lead to delays in real-time monitoring, while BPNN may require continuous parameter tuning to adapt to changing operational conditions. Addressing these deployment challenges is crucial for practical CBM implementation to ensure reliable and cost-effective engine health monitoring.

IV. Conclusion

This study evaluates SVM and BPNN in predicting diesel engine health. SVM with a sigmoid kernel achieved 94.06% accuracy but it was less sensitive in detecting unhealthy conditions. BPNN, with a three-hidden-layer configuration (1-2-1 neurons) and the tansig activation function, outperformed SVM with an accuracy of 97.13%, demonstrating superior capability in capturing complex patterns and detecting unhealthy engine conditions.

Comparison with previous methods confirms that BPNN is more accurate and consistent than SVM and earlier models. Additionally, relabeling the dataset using K-Means improved BPNN accuracy from 72.3% to 97.13%, proving the importance of data balance in modeling. Overall, BPNN with an optimal configuration and well-processed data is the best method for predicting diesel engine health.

Future research can explore other machine learning methods such as Gradient Boosting, XGBoost, or different types of ANN, which may further enhance prediction accuracy. Additionally, ensemble learning approaches could be considered to combine the strengths of multiple methods for more accurate predictions. Using a larger and more diverse dataset is also crucial for future studies. By incorporating data from various operational conditions and diesel engine types, models can better generalize data patterns, thereby improving reliability and prediction accuracy across different usage scenarios.

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