IRJCS: International Research Journal of Computer Science
Volume 11, Issue 05, May 2024

ISSN: 2393-9842
https://www.irjcs.com/archives

Prediction of RUL of lubricating oil based on Deep Learning Technique

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Publication History
Manuscript Reference No: IRJCS/RS/Vol.11/Issue05/MYCS10098
Research Article | Open Access | Double-Blind Peer-Reviewed | Article ID: IRJCS/RS/Vol.11/Issue05/MYCS10098
Received: 12, April 2024 | Revised: 10, May 2024 | Accepted: 23 May 2024 | Published Online: 30, May 2024
http://www.irjcs.com/volumes/Vol11/iss-05/12.MYCS10098.pdf
Article Citation: Kajal,Kishan,Deepak(2024).Prediction of RUL of lubricating oil based on Deep Learning Technique. IRJCS: International Research Journal of Computer Science, Volume 11, Issue 05 of 2024 pages 504-511
doi:> https://doi.org/10.26562/irjcs.2024.v1105.12
BibTeX Kajal@2024Prediction

Abstract: This study uses condition monitoring (CM) to determine the lubricating oil's remaining usable life (RUL). First, Atomic emission spectroscopy (AES) was used to determine the lubricating oil's element makeup and content. Under use were quantitatively examined. The precision and efficacy of the RUL prediction model might be diminished in light of the wide range of oil data acquired using AES. A thorough it is recommended to screen oil data using a method for choosing parameters based on correlation analysis, lubricant degradation analysis, and information entropy. In order to address this issue. The lubricant's RUL prediction model was then developed using a support vector machine (SVM). It is shown that the SVM prediction model's efficacy and accuracy by contrasting the experimental findings with the prediction model's output data.

Keywords: information entropy, residual useful life, atomic emission spectrometry, and support vector machines

I. INTRODUCTION

An essential component of mechanical machinery is lubricating oil. It can lessen wear and friction prevent rust and corrosion, cool and clean components, and ensure the machine keeps working properly [1-3]. When the machine is running, the lubricating oil It gradually degrades, generating wear particles, water, contaminants, acid substances, etc., until it can no longer match the machine's requirements and has to be replaced [4–8]. Currently the suggested lubricating oil manufacturer's or the equipment manufacturer's service time or mileage determines how often to replenish lubricating oil. The majority of suggested values are often cautious, because replacing lubricating oil too soon wastes oil resources, which raises both the financial and environmental expenses [9]. Lubricating oil deterioration is accelerated and early lubricating oil failure results from poor mechanical equipment condition or poor working conditions. If you replace the lubricating oil too soon, the mechanical wear will get worse. raise the possibility of equipment damage and possibly even result in catastrophic mishaps [10,11]. As a result, the idea of condition-based maintenance (CBM) states that the schedule lubricating oil replacement should be determined by looking at the oil's real condition.CBM stands for condition-based maintenance. By using condition monitoring (CM) to gather machine data, it determines the optimal course of maintenance [12,13]. One crucial area of study in the realm of CBM is lubrication condition monitoring (LCM). It uses electrochemical, spectroscopic, and iron spectrum studies to track the condition of the lubricating oil. analysis, among other techniques, can serve as the foundation for lubricating oil change and machine maintenance. In order to prevent potentially catastrophic equipment failures, LCM is an active maintenance technique that is frequently utilized to identify and forecast the occurrence of early mechanical equipment failures [14–17]. LCM's primary function is to extract and evaluate important data (chemical and physical characteristics) from lubricants in order to produce output that will support choices. Mechanical equipment can have its lifespan increased by making wise maintenance decisions; nevertheless, unwise or biased maintenance choices will have a negative impact on the machinery [14]. As a result, decisions on maintenance should be based on data from the LCM in a timely, accurate, and trustworthy manner.

Figure 1 illustrates the process for lubricating oil RUL prediction. The procedure for obtaining oil samples and using AES to determine the element composition of those samples is covered in Section2. Section3 outlines the procedure for using lubricant deterioration analysis, correlation analysis, and information entropy to screen oil data. In Section 4 the lubricating oil RUL prediction model is built using Support Vector Machines (SVM). To illustrate the suggested approach, the impacts the impacts of parameter selection on the SVM prediction model are contrasted in Section 5.Section 6 is where the conclusion is ultimately stated. One of the first and most useful methods for oil analysis used to diagnose mechanical equipment faults is oil spectrum analysis, which is also a key technique in the field of LCM [2,7,18–20]. It is possible to efficiently identify the content of the amount of oil pollution, the presence of additives, and the abrasive elements in the oil. Currently Among the most effective LCM methods is oil spectrum analysis technology.[7] identified the spectrum differences of automobile lubricants with different SAE Requirements using Raman spectroscopy.This allowed them to more precisely identify the kind of base oil and the SAE viscosity classes of the samples under examination at both low and high temperatures. Fourier transform infrared spectroscopy (FTIR), partial least squares, and In this work, atomic emission spectrometry (AES) was used to quantitatively analyze the element composition and content of the lubricating oil in use. based theory. Next, utilizing the information, a quantitative analysis of the CM data's information content is performed. entropy theory, and The proper quality index is chosen as the supporting data for the prediction model based on the association between the CM data and the lubricating oil degradation process. The lubricating oil RUL prediction model was constructed using a support vector machine (SVM) based on this information. Next, using the chosen quality index data, train and evaluate the SVM model. This paper suggests a thorough technique for choosing parameters based on correlation and information entropy.

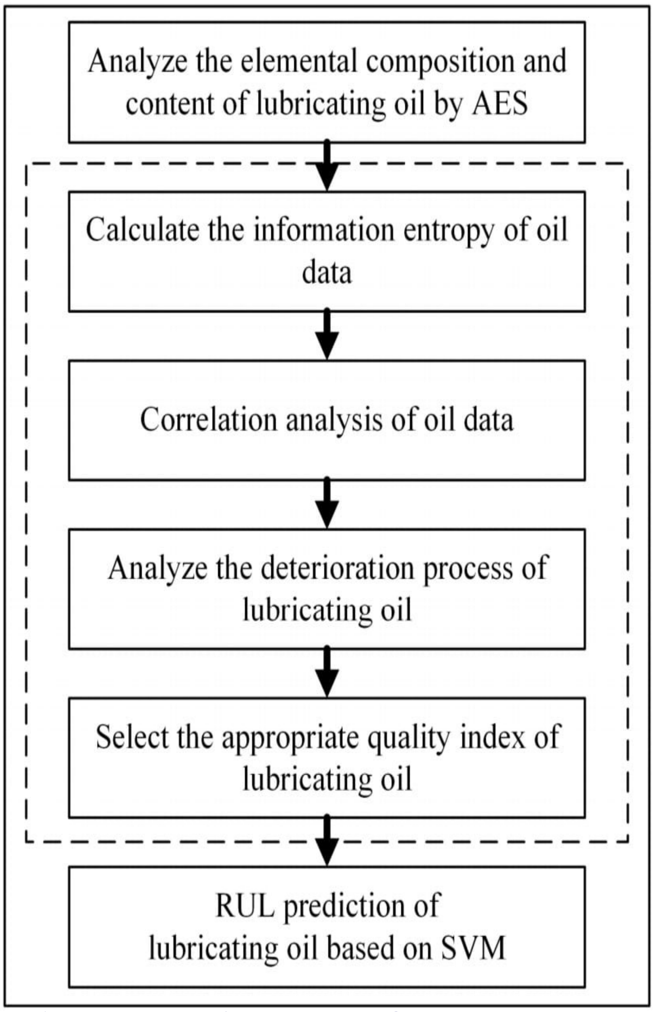

Figure1. Method for Lubricating Oil RUL Prediction

2. LITERATURE REVIEW

An analysis of the literature on estimating the Remaining Useful Life (RUL)of lubricating oil based on deep learning techniques would encompass various studies and methodologies. Introduction to RUL Prediction: Define RUL and its significance in maintenance and reliability engineering. Explain the importance of accurate RUL prediction for minimizing downtime, optimizing maintenance schedules, and reducing costs. Traditional Methods vs. Deep Learning: Discuss traditional methods like statistical modeling, machine learning (e.g., regression, classification), and physics-based models for RUL prediction. Highlight limitations such as reliance on expert knowledge, difficulty in handling complex systems, and challenges in capturing nonlinear degradation patterns.

Introduce deep learning as a promising alternative due to its ability to automatically learn in tricate patterns from raw data. Deep Learning Techniques: Review various deep learning architectures used for RUL prediction, Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, and hybrid models. Explain how these architectures handle time series data, feature extraction, and sequence modeling, which are crucial for RUL prediction tasks. Data Sources and Preprocessing: Describe common data sources for RUL prediction, such as sensor measurements, operating conditions, and historical maintenance records. Discuss preprocessing steps like data normalization, feature selection, and handling missing values to prepare the data for deep learning models. Case Studies and Experiments: Summarize key studies that have applied deep learning to predict RUL of lubricating oil or similar equipment. Compare experimental setups, including dataset sizes, feature engineering strategies, hyper parameter tuning, and evaluation measures (such as Root Mean Square Error and Mean Absolute Error). Performance Evaluation and Challenges: Analyze the performance of deep learning models in terms of prediction accuracy, reliability, and robustness across different operating conditions. Identify challenges such as limited labeled data, transferability to new equipment, model interpretability, and integration with existing maintenance systems. Future Directions and Innovations: Propose future research directions, such as incorporating domain knowledge into deep learning models, exploring ensemble techniques, and leveraging edge computing for real-time RUL prediction. Discuss potential innovations in data collection (e.g., IoT sensors), model explainability, and collaboration between academia and industry for practical deployment.

3. METHADOLOGY

Predicting the lubricating oil's Remaining Useful Life (RUL) using deep learning involves several steps and methodologies. Here's a general approach to consider:

Data Collection and Preprocessing: Gather historical data on lubricating oil usage, including operating conditions (temperature, pressure, speed), maintenance records, and failure instances. Clean the data by managing noise, outliers, and missing values. To guarantee consistency and enhance the model's performance, scale, or normalize the information.

Features of Engineering: Take pertinent characteristics out of the data. that are indicative of oil degradation and equipment health. This can include features like temperature variations, vibration patterns, chemical composition changes, etc. Use domain knowledge or expert advice to select informative features that can capture the degradation patterns effectively. Dataset splitting is the process of dividing a dataset into training, validation, and test sets. The test set evaluates the model's performance on unseen data, the training set is used to train the model, and the validation set helps to tweak hyperparameters and prevent over fitting.

Model Choice: Select a deep learning model architecture that makes sense. for RUL prediction. Common choices include Convolutional neural networks (CNNs), Long Short-Term Memory (LSTM) networks, or a hybrid of the two (e.g., CNN-LSTM).Take into account the model's complexity and the volume of data that is accessible. ,and computational resources when selecting the architecture.

Model Training: Train the chosen model using the training dataset. Optimize hyperparameters include batch size, learning rate, and regularization methods (such dropout) to improve training performance. Monitor training progress using metrics like loss function values and validation scores to ensure the model is learning effectively.

Model Evaluation: Using the validation set, evaluate the trained model to determine how well it generalizes and make any required adjustments. To measure how well the model predicts RUL, use evaluation metrics such as R- squared (R2), Root Mean Squared Error (RMSE),and Mean Absolute Error (MAE).

Fore casting and Implementation: Utilize the learned model to anticipate the RUL. of new lubricating oil samples or equipment instances. Deploy the model into production systems for real-time or periodic RUL predictions, integrating it with data acquisition and monitoring systems as needed.

Constant Monitoring and Model Updates: Keep an eye on the model's functionality throughout time, and retrain or update it from time to time with fresh data. To maintain its accuracy and reliability in corporate feedback from maintenance records and actual failure instances to improve the model's predictive capabilities and adapt to changing operating conditions.

4. MATERIALS AND METHODS

An essential tool for testing and confirming the operation of the engine and any associated parts is the engine bench test, which may replicate various operating environments. A standard diesel engine is chosen as the research subject in this work, and the dependability Bench testing is used to replicate a 200-hour test conducted in harsh circumstances. Every ten working hours, gather oil samples, and make sure the location and sampling technique are constant. Exx on Mobil produces Diesel requires a certain type of oil, SAE15W-40. Engines. The manufacturer has set a maximum service life of 7500 kilometers, or 6 months. Table 1 displays the attributes of the chosen engine.

AES Measurements The Spectro Oil Q100 Rotary Disc Electron de Atomic Emission Spectrometer (RDE-AES), made by Spectro Scientific, is the oil monitoring instrument utilized in this study. Its primary responsibility is to identify wear metals, impurities, and additives in lubricants and hydraulic fluids. Samples of oil are delivered to an arc that is very hot. Via RED-AES. Created by rotating the disc electrode between the rod. When a hot arc is excited, certain elements in the oil samples produce distinct spectra. Using an optical device to identify the characteristic spectra will reveal the content of various components. The RED-AES main structure is displayed. We discovered that lubricating oil included 17 different components (such as Fe, Al, and Cu). using RDE-AES. Each and every measurement was done at room temperature. We tested each oil sample three times in order to increase test accuracy, and we used the average value as the test's ultimate outcome. A few statistics about engine oil spectrum.

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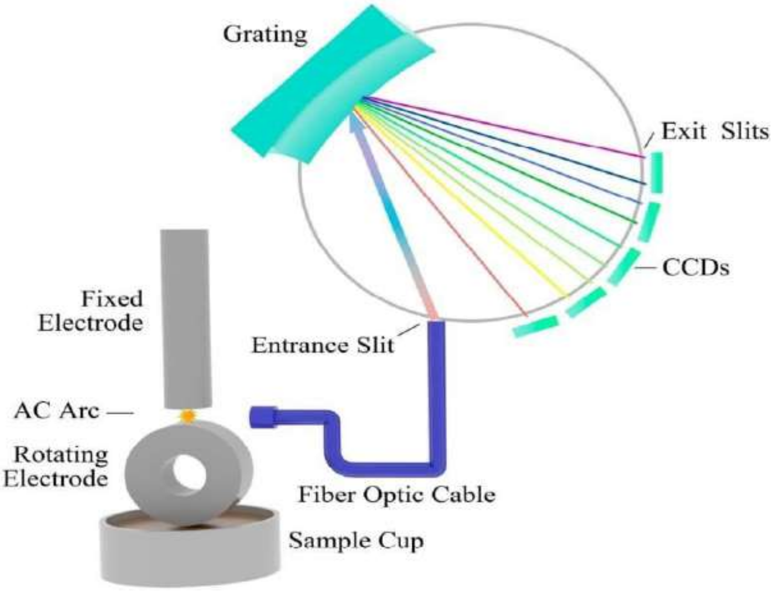

Figure-2 The RED-AES Primary Structure

INFORMATION ENTROPY

Information entropy is a useful technique for selecting attributes since it is a theory that may measure the information content of variables [25–27]. In their study of attribute selection in decision information systems with heterogeneous data The terms conditional information entropy, joint information entropy, and mutual information entropy were first introduced by Li et al. [26].Sun et al.'s study [27] looked at the process of classifying gene expression data using uncertainty metrics based on neighborhood entropy. The goal of this work was to assess the information content of each element in the oil spectrum data using information entropy in order to provide the groundwork for the extraction of distinguishing indexes.

The information entropy formula is as follows:

$$H(X)=-n \sum i=1 P(Xi)\log[P(Xi)]$$

The information entropic value of the five elements — Al,V,B,Ba, and Mo in Figure3 demonstrates The oil spectrum data is less than 2.5bits. It demonstrates that these five factors do not substantially alter when engine lubricant is used, making the munable to accurately represent the engine oil degradation procedure.

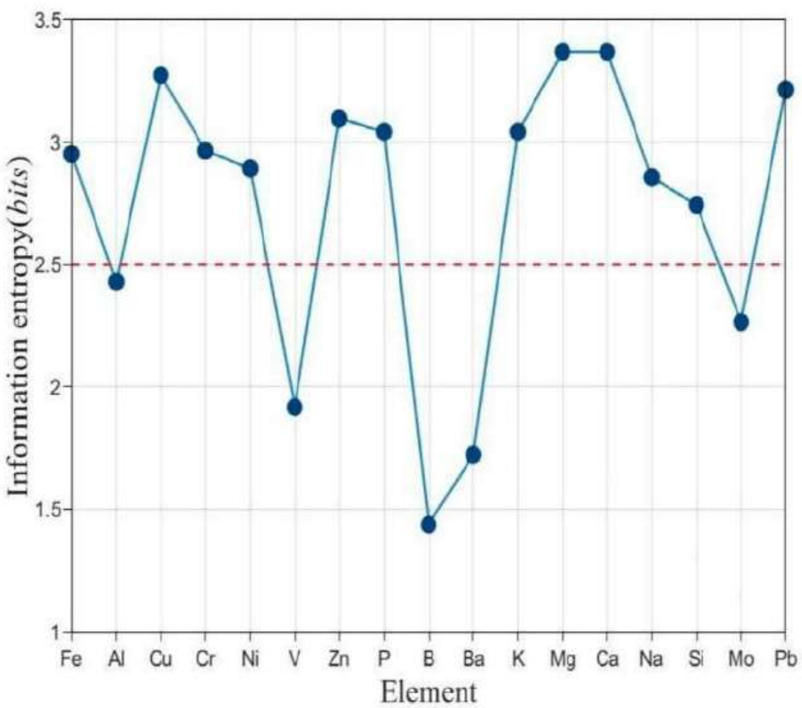

Figure-3 each element's information entropy in the oil spectral data

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5. Lubricating Oil RUL Prediction Using SVM

5.1 Principle of SVM

Support vector machine (SVM), a fundamental technique in supervised learning, is mostly used to determine the best possible outcome for data categorization., thanks to the widespread usage of neural network technology [29, 30]. SVM, a generalized linear classifier, fully takes structural risk reduction and empirical risk into account. then divides the linearly separable data samples using the optimal classification surface approach [31, 32]. Numerous lines can discriminate between two different sorts of points in the classification of two- dimensional space, as illustrated in Figure 6. Which border represents the best decision? It goes without saying that the distance is as great as it can be situated between the nearest point and the decision border. The maximum interval method is this one. The location nearest to the boundary of the choice is referred to as the support vector.

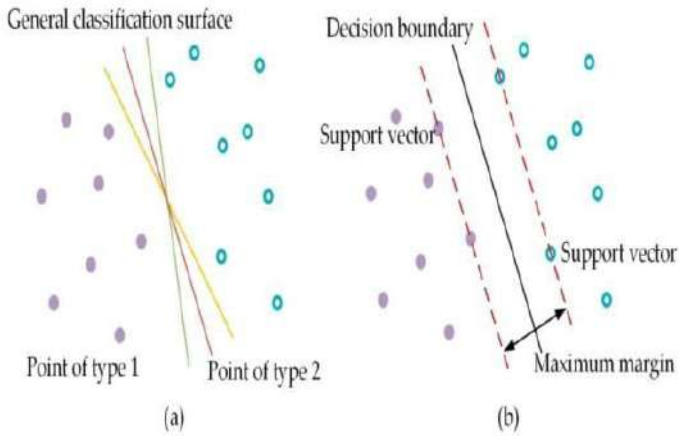

Figure 4. The SVM principle. Diagrams for general and optimal classification surfaces are shown in (a) and (b) Respectively.

Most problems in the real world are non linear, even though SVM is a linear classifier Kernel technique (KMs): KMs increase the dimension of the properties of the data. To the point where a hyperplane may split the data, are introduced by SVM to address the non-linear classification problem. Figure5 illustrates the fundamental idea of KMs.

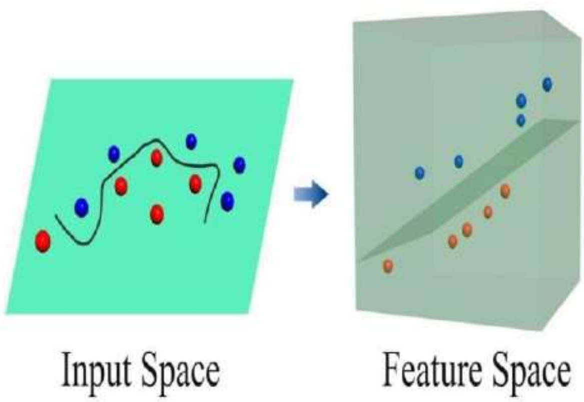

Figure 5: The fundamental idea behind KMs.

Some often used kernel functions are the Laplace kernel function, the radial basis kernel function (RBF), the polynomial kernel function, etc. The popular RBF is chosen as the kernel function in this study, and its expression The input space's eigen vectors are represented by the variables x and x in Equation (5); The parameter |1x-x112; represents the action, while the freeparameter is the square Euclidean distance between two eigenvectors.

5.2. RUL Prediction Model for Lubricating Oil

We created an SVM model using MATLAB software based on the aforementioned hypothesis, which allowed us to forecast the lubricating oil RUL. The kernel's SVM mode functionality I was chosen to be RBF. To confirm how oil data selection affects oil RUL prediction, data from both the pre- and post-The SVM input variables were the parameter screening phases. Because the amount of measured oil was limited, the interpolation approach was employed to increase the data set and normalize all the data. In order to enhance SVM performance. Lubricating oil was separated into three states based on how long it was used, and the collection of data has labels. Half of the data were utilized for training, while the other 30% were used for analysis. The SVM model was then trained using the training data. Finally, the obtained SVM model was used for testing and prediction. Figure 8 shows The procedure for creating the RUL prediction model for lubricating oil. To assess the SVM model's performance The SVM model's test and prediction results were visually shown in an intuitive manner.

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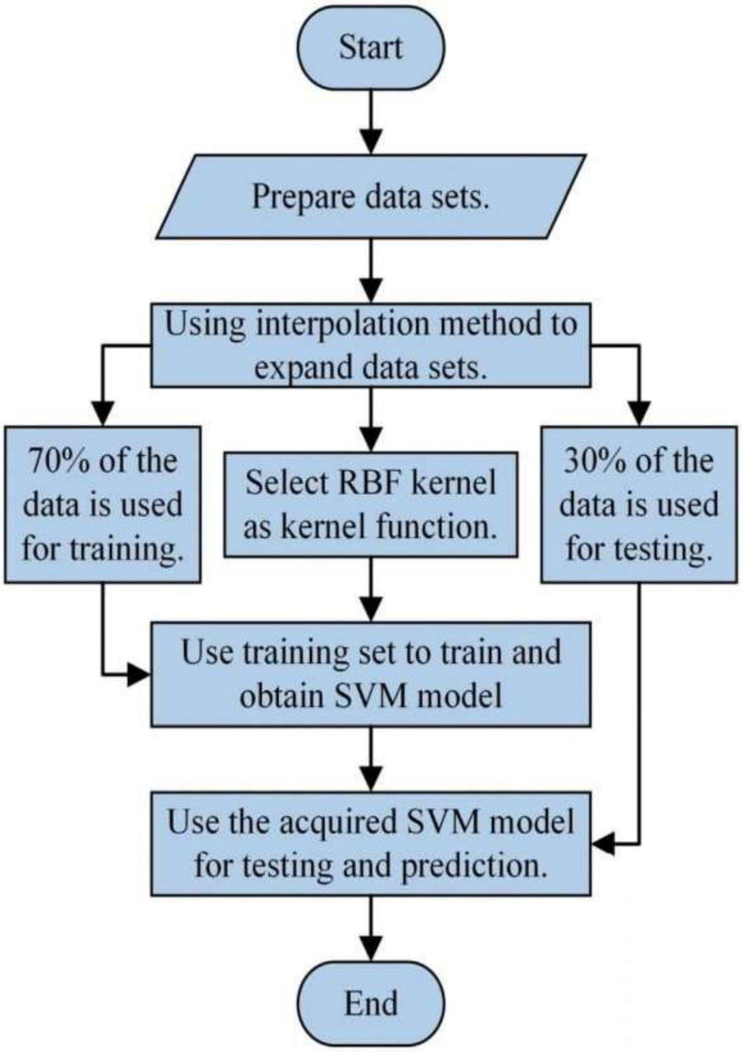

Figure-6 The lubricating oil RUL prediction model establishment process.

6. RESULTS AND DISCUSSIONS

In order to evaluate the SVM model's performance, the training data were shown. Prior to parameter filtering, the prediction results are displayed in Figure9. The prediction results after parameter screening are shown in Figure 10. While the training set's accuracy is 92.8571%, the test set's accuracy is 93.5484%. The test set's accuracy is 96.7742%, where as the training set's accuracy is 94.2857%. It is evident that the relevant output and the experimental data differ somewhat from one another. Comparatively speaking, following screening parameters, the precision of the test and training sets was higher than it was previously. The fore mentioned analysis shows that Prediction accuracy has increased using the SVM-based RUL prediction model. Been improved after filtering parameters. Additionally, the volume of input data is significantly decreased during parameter filtering, which may enhance the SVM model's training effectiveness. The findings demonstrate the effectiveness of the comprehensive parameter selection strategy put out in this work, which is founded on the lubricant degradation process, information entropy, and correlation analysis.

Figure 7. Confusion matrix prior to filtering parameters

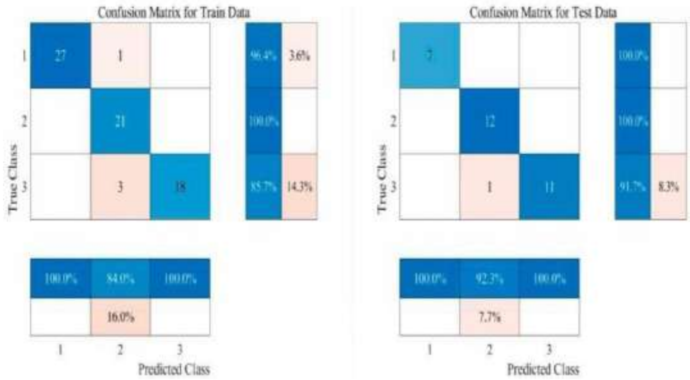

Figure-8 prediction outcomes upon filtering of parameters

7. CONCLUSION

This study investigates the lubricant RUL prediction using CM data. Initially, the utilized lubricants' mass fractions of 17 different components were determined by using RDE-AES to extract the spectrum data of the lubricants. First, a thorough parameter selection approach was presented in this work. After a thorough examination of the deterioration process, correlation, and information entropy of Using 17- dimensional spectral data, 12 components from the oil data were selected as lubricant RUL prediction quality indicators. Following that, an SVM model was created to forecast the lubricant's RUL. The three different types of lubricant states were employed as the output variables, and the input variables were the 17-dimensional oil data before parameter screening and the 12-dimensional oil data after parameter screening. The difference between the experiment and the related results demonstrated a notable improvement in the SVM model's accuracy following parameter filtering. Additionally, after parameter filtering, the SVM model's training efficiency increased and the quantity of input data decreased. Thus, it was possible to implement the entire a method for choosing parameters based on correlation analysis, lubricant degrading process, and information entropy. Compared to parameter selection based on experience, the study's recommended strategy is more generalizable and practical.

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