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Comparative Analysis of Fault Classification Algorithms for Triplex Pumps

Abstract: - Maintenance strategies have undergone significant evolution during the last thirty years, leveraging advancements in digital twin modeling, sensor technology, communication, augmented reality, artificial intelligence, and predictive analytics. Fault detection and isolation (FDI) within complex systems like triplex pumps have emerged as critical components for effective maintenance planning. Thus, monitoring the triplex pump is crucial to managing faults and avoiding unscheduled maintenance. Feature extraction and selection are pivotal for optimizing fault diagnosis algorithms. This paper aims to present a comparison study of fault classification algorithms based on data collected from the simulation model of a triplex pump under different failure scenarios. The features are extracted from the pump's flow signal and grouped into four sets of features. The first set includes all the extracted features from the signal. These features are a combination of time domain and frequency domain features. The second set includes only the time domain features. The third set of features includes the frequency domain. The fourth set includes the peak magnitude in the power spectrum and the mean value of the flow signal, which are the features that rank highest in both the second and third sets based on Chi2 algorithms. Fourteen classification algorithms are trained, validated, and tested using four feature sets based on the simulation data. The simulation provides data for seven operation scenarios, including healthy conditions with free fault, three single failures, and three combined failures. The performance of the classification algorithms is evaluated using the recall, precision, accuracy, and the F1 score. The results indicate that the Weighted KNN and Bagged Trees Ensemble algorithms achieve perfect accuracy (100%) across all feature sets, indicating their robustness and effectiveness in classification tasks. However, some algorithms exhibit variable performance depending on the feature set used. For example, the Efficient Linear SVM algorithm shows a significant decrease in accuracy when utilizing the 14-feature set or 5 frequency-domain features compared to others, suggesting a potential mismatch for time-domain feature spaces. In addition, the performance metrics, including accuracy, precision, recall, and F1 score, across models showed a remarkable variation between them. Weighted KNN, Bagged Trees Ensemble, and Neural Network models were found to be exceptional, with all perfect scores indicating that they can accurately classify instances according to these metrics.

Keywords: Fault Detection, Features Domain, Classification Algorithms, Triplex pump

I. INTRODUCTION

The manufacturing sector has developed rapidly using recent automation, IoT, and digitalization technologies. Although these technologies have supported the vision of smart manufacturing and maintenance optimization, they have led to more new types of failures and increased maintenance costs [1]. For example, the authors in [2] estimated the machinery maintenance costs in discrete manufacturing to be a staggering $57.3 billion in 2016. This figure does not even include the additional costs due to unexpected breakdowns, estimated at $16.3 billion.

Maintenance strategies have evolved over the last three decades, benefiting from modelling, sensor technology, communication, artificial intelligence, and predictive analytics development [3], [4]. Maintenance strategies are divided into three main categories: reactive, preventive, and predictive [5]. In the reactive strategy, maintenance tasks are focused on repair after the breakdown. In the preventive strategy, maintenance tasks are based on scheduling activities in interval periods based on the timing of previous preventive tasks or asset usage. In the predictive strategy, maintenance tasks are based on the monitored data collected from the system's sensory data. These monitored data are analyzed continuously to detect abnormal conditions and forecast the remaining useful life (RUL) to plan maintenance tasks [4].

Fault detection and isolation (FDI) in complex systems can be broadly categorized into model-based and data-driven approaches [6]. Model-based approaches depend on a fundamental understanding of the physics of the process, such as model-based parameter estimation, parity relation, and fault tree methods [6]. Moreover, the data-driven approaches depend on available historical process data, such as support vector machine (SVM) and neural network (NN) methods. In addition, hybrid FDI approaches also exist by combining model-based approaches and data-driven approaches, such as NN and fuzzy logic methods [6]. Lately, there has been significant research interest in machine learning algorithms supported by the digitalization of the monitoring system, particularly in their application to FDI [7], [8]. Machine learning techniques fall into two main categories: supervised and unsupervised learning. Supervised learning involves the user providing data to train the computational model, while unsupervised learning allows the model to learn independently. However, there are huge challenges in implementing machine learning in the domain of FDI linked to the availability of the dataset covering various failures under different scenarios and operation conditions, the availability of labelled data for each failure mode, and the increasing

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complexity of the systems. Therefore, researchers moved toward implementing the concept of a digital twin to replicate the physical model of the system to generate more labelled datasets for the multiple faults [9].

A triplex pump, which employs three plungers or pistons for fluid displacement and has high efficiency and reliability, is commonly used in high-pressure applications such as oil and gas drilling [10]. Therefore, monitoring the triplex pump is crucial to managing faults and avoiding unscheduled maintenance tasks. Monitoring the parameters of the triplex pumps, such as the vibration signals from the fluid end valve box, the pump output pressure, and output flow, helps minimize the degradation and wear of the system and reduces the cost of maintenance. A hybrid model combining wavelet transformation, fuzzy logic and neuro-networks has been developed for the fault diagnosis problem of a triplex pump [10]. The acceleration at the fluid end and the dynamic end have been measured as an indicator of the fault. Then, the power spectrum, cepstrum and the probability destiny function have been extracted from the acceleration as features for fault detection. The results revealed the possibility of classifying the failure characteristics into different scales using wavelet transformation. [11] have developed a neural network algorithm for fault diagnosis using the fused signal of the acoustic emission (AE) signal and the vibration acceleration signal. The features for the diagnosis algorithm have been extracted using wavelet packet signal processing. The findings indicate that the wavelet packet signal processing method adeptly extracts the frequency band energy eigenvalues from the signals, enhancing fault diagnosis accuracy. Furthermore, the integration of multi-sensor information significantly improves this accuracy.

To address the challenge of data availability for FDI, a digital twin model of the triplex pump has been built to emulate the dynamic behavior of the system [12], [13]. The digital twin model simulated three pump failures at different levels of severity and generated seven fault scenarios. The generated data from the digital twin model has been used to train the FDI algorithms, evaluate their performance, and compare them with state-of-the-art algorithms. Xia et al. [13] developed a novel sparse de-noising auto-encoder (NSDAE) model with a Wish activation function. The performance of the developed model has been tested using the raw data of output flow and compared with six algorithms: stacked SDAEs, LeNet-5 CNN, Gaussian DBN, stacked LSTM, and stacked GR, SVM, RF, and ELM. The comparisons were based on the raw data, 9-time domain features, 5-frequency domain features, and combined time-frequency domain features. The results show that the proposed NSDAE model outperformed the performance of the other methods. The authors in [12] enhanced the digital twin model in [13]and developed a stacked novel denoising autoencoder (NDAE) solution with Mish activation function and compared it with SVM, stacked SDAE and LeNet-5 CNN. The study shows that NDAE performance outperformed the other methods. However, constructing the digital twin model of the pump was the major challenge in implementing this method. Moreover, Zayed et al. [14] have developed a digital twin model for the triplex pump model and its transmission system using various optimization techniques combined with machine learning techniques for fault diagnosis. They tested three fault diagnosis techniques, namely: K-nearest neighbors (KNN), decision tree (CART), and random forest (RF). The extracted features from the raw data have been selected for classification training using the flower pollination optimization algorithm. Their findings revealed that the performance of the classification algorithm without optimization algorithm is lower than that of the classification algorithms with optimization. Also, the results revealed that employing the combined flower pollination optimization algorithm with CART yielded an accuracy of 96.8% while utilizing the same optimization algorithm with RF resulted in an accuracy of 85.7%, both deemed acceptable. Besides, [15] has developed a digital twin on the triplex pump and generated data for different working conditions. He also developed a deep adaptive adversarial network (DAAN) method and compared it with a hybrid distance-guided adversarial network (HDAN) and distance-guided domain adversarial network (DGDAN). The results show DAAN experimental results show that the proposed method is more accurate than HDAN and DGDAN methods. Also, the results show that using the principal component analysis (PCA) for feature selection has improved the accuracy of the DAAN method. Moreover, [9] has developed a combined machine learning technique with a genetic algorithm solution using the digital twin of a triplex pump to automate the fault diagnosis solution. The proposed solution has been benchmarked against conventional machine learning techniques such as logistic Regression, Naïve Bayes, and Support Vector Machine. The results indicate that the SVM has the highest detection accuracy of 93% compared with the other techniques. combined framework and the combined SVM algorithm with the genetic algorithm also have the highest of 95% compared with the other methods. Furthermore, [16] developed a digital twin model of a triplex pump using both hybrid physics-based and data-driven models. Also, it implemented adversarial network and long-and short-term memory techniques for extracting deep features and time-series features, respectively. The diagnosis algorithm has reached 89.28% accuracy after continuous model updates.

Feature extraction and selection are pivotal for optimizing fault diagnosis algorithms. Feature extraction encompasses the process of extracting pertinent characteristics from gathered data. These extracted features may manifest in various domains, such as time, frequency, and time-frequency. Feature selection entails identifying the most consistent, non-redundant, and pertinent features for incorporation into fault diagnosis development. Based on the literature, researchers used different features to train and test the fault diagnosis algorithms of the triplex pumps. Table 1 summarizes the domain of features used with the FD algorithms implemented.

Table I shows that extracted features from different domains were used as input to their classifiers, which vary from conventional to advanced machine learning methods. The accuracy of FD ranged from 63% (Stacked LSTM with raw data, [13]) to 93% (GA-SVM with time-frequency features, [9] depending on the selected features and FD algorithms.

TABLE I. Review of algorithms with different feature types

Features	Diagnosis method	References
Raw data	Stacked NSDAE, Stacked SDAE1 (Swish with CS, Stacked SDAE2 (ReLU with CN), LeNet-5 CNN, Gaussian DBN, Stacked LSTM, Stacked GRU	[13]
	LeNet-5 CNN	(12]
Frequency Domain	Support Vector Machine (SVM), Random Forest (RF), Learning Machine (ELM)	[13]
	A combined method based on wavelet transformation, fuzzy logic, and neuro-networks	[10]
Time Domain	Support Vector Machine (SVM), Random Forest (RF), Learning Machine (ELM)	[12], [13]
	Support Vector Machine (SVM)	[12], [13]
Time-Frequency Domain	Support Vector Machine (SVM), Random Forest (RF), Extreme Learning Machine (ELM)	[13]
	k-nearest neighbor (KNN), Decision tree classifier (CART), Random forest classifier (RF), k-nearest neighbor (KNN) with FS–FPA optimization, Decision tree classifier (CART) with FS–FPA optimization, Random forest classifier (RF) with FS–FPA optimization	[14]
	logistic Regression (LR), Naïve Bayes(NB), Support Vector Machine (SVM), GA-LR, GA-NB, GA-SVM	[9]

This paper uses simulated data generated from the triplex pump's model to compare the performance of different classification algorithms based on different features from the time-domain, frequency-domain, and time-frequency features. After implementing the algorithms, their performance will be evaluated using metrics like the confusion matrix, accuracy of detection, precision, recall, F1 score, and ROC curve to compare the algorithms.

II. Case Study: Triplex Pump

This section briefly presents the modelling of the triplex pump and its failure modes, the selected sets of features for the machine learning algorithms, and the performance evaluation of algorithms.

A. *Triplex Pump Model*

The triplex pump system is emulated in MATLAB Simscape, as shown in Fig 1. The simulated system represents a virtual system based on the physical asset. The simulated model acts as a dataset generator, containing all fault conditions, such as leaks, blockages, and bearing faults.

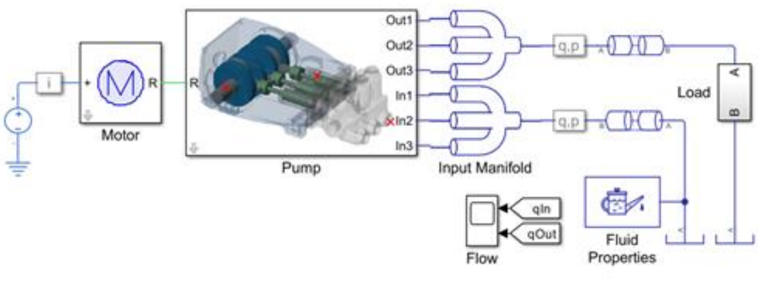

Fig. 1 Model of a triplex pump [14]

B. Failures Scenarios

This study collects the output flow data from the simulation flow rate sensor for seven operation scenarios, including healthy conditions with free fault, three single failures, and three combined failures. The details of the failure scenarios are shown in Table II. The simulation duration for each run is 2 seconds. and only the signals from 0.8 seconds to 2 seconds are selected to exclude the initial transient stage.

TABLE III. Failure modes of the triplex pump

Failure Mode	Class label
Health	0
Seal Leak	1
Blocked inlet	2
Seal Leak and Blocked inlet	3
Bearing wear	4
Bearing wear and Seal Leak	5
Bearing wear and Blocked inlet	6
Bearing wear, Blocked inlet and Seal Leak	7

C. Feature Extraction and Selection

The features are extracted from the pump's flow signal and split into four sets of features. The first set includes all the extracted features from the signal. These features are a combination of time domain and frequency domain features. The second set includes only the time domain feature, with 9 features in our paper. The third set of features includes the frequency domain, which has 5 features in our paper. The features from both the second and third sets have been ranked using Chi2 algorithms. The results show that the frequency of the peak magnitude in the power spectrum and the mean value of the flow signal are the highest-ranked features in their sets. Therefore, we selected them for the fourth set. The features of each set are shown in Table III.

TABLE IIIII. Sets of selected features

14 features (all)	9 Time-domain	5 frequency-domain	2 Time-Frequency
fPeak	qMean	fPeak	fPeak
pLow	qVar	pLow	qMean
pMid	qSkewness	pMid	
pHigh	qKurtosis	pHigh	
pKurtosis	qPeak2Peak	pKurtosis	
qMean	qCrest		
qVar	qRMS		
qSkewness	qMAD		
qKurtosis	qCSRange		
qPeak2Peak			
qCrest			
qRMS			
qMAD			
qCSRange			

D. Classification Algorithms

In this paper, 14 classification algorithms have been deployed and tested. These algorithms are Decision Tree, Linear Discriminant, Gaussian Naive Bayes, Kernel Naive Bayes, Kernel Naive Bayes, Linear SVM, Efficient Linear SVM, Cubic KNN, Weighted KNN, SVM Kernel, Logistic Regression Kernel, Boosted Tress Ensemble, Bagged Trees Ensemble, RUSBoosted Ensemble and Neural Network. More details about the classification algorithms can be found in [7], [8], [17], [18], [19], [20], [21], [22], [23]. The classification algorithms are trained, validated, and tested using four feature sets listed in Table III.

E. Performance Evaluation of Algorithms

Recall, precision, accuracy, and the F1 score are the four essential metrics frequently used in model evaluation and comparison [24]. We selected them to evaluate our suggested models' effectiveness and influence on classification. It is important to emphasize that higher accuracy, precision, recall, and F1 scores correspond to better outcomes. Table IV summarizes the equations for calculating the four used metrics in this paper.

TABLE IVV. Evaluation metrics

Accuracy = $\frac{TP+TN}{TP+TN+FP+FN}$	Precision = $\frac{TP}{TP+FP}$
Recall = $\frac{TP}{TP+FN}$	F1 score = $2 \times \frac{Precision \times Recall}{Precision + Recall}$
TP: True Positive	FN: False Positive
TN: True Negative	FN: False Negative

III. Results And Discussion

This section presents the comparison results of classification algorithms.

TABLE V. Algorithms accuracy with different sets of features

	14 Features	9 TD Features	5 FD Features	2 Features
Model Type	**Accuracy %**			
Decision Tree	93.3	86.7	85.8	89.4
Linear Discriminant	96.7	93.9	80.0	75.0
Gaussien Naive Bayes	84.2	84.2	73.1	68.6
Kernel Naive Bayes	90.3	86.7	86.1	79.4
Linear SVM	92.5	94.7	79.4	72.2
Efficient Linear SVM	64.7	47.2	69.7	54.7
Cubic KNN	83.1	86.9	74.4	82.8
Weighted KNN	100.0	100.0	100.0	100.0
SVM Kernel	99.2	99.4	91.4	86.1
Logistic Regression Kernel	94.4	93.6	84.2	85.0
Bossted Tress Ensemble	98.9	94.2	94.4	91.1
Bagged Trees Ensemble	100.0	100.0	100.0	100.0
RUSBoosted Ensemble	96.1	94.2	93.3	89.7
Neural Network	100.0	98.9	83.3	81.4

Table V presents the results of various machine learning algorithms trained on different sets of features: one with 14 features, another with 9 Time-Domain (TD) features, a third with 9 Frequency-Domain (FD) features, and the last set containing only 2 time-frequency domain features. Each algorithm's accuracy percentage is provided across these feature sets, offering insights into their effectiveness across diverse feature dimensions. Across all feature sets, certain algorithms consistently outperform others in terms of accuracy. Notably, the Weighted KNN and Bagged Trees Ensemble algorithms achieve perfect accuracy (100%) across all feature sets, indicating their robustness and effectiveness in classification tasks. This suggests their suitability for the dataset and its feature representations. Linear Discriminant (LD) and Neural Network algorithms also demonstrate strong performance across most feature sets, with accuracy percentages exceeding 90% in many cases. LD's ability to identify linear combinations of features that effectively separate different classes highlights its efficacy, while Neural Networks excel in detecting complex patterns within the data. However, some algorithms exhibit variable performance depending on the feature set used. For example, the Efficient Linear SVM algorithm shows a significant decrease in accuracy when utilizing the 14-feature set or 5 frequency-domain features compared to others, suggesting a potential mismatch for time-domain feature spaces. Similarly, Gaussian Naive Bayes and Kernel Naive Bayes algorithms display reduced accuracy with fewer features, indicating their dependence on richer feature representations for optimal performance. In summary, all machine learning algorithms have higher accuracy in the case of a set with 14 features compared with the other feature sets. Therefore, further performance analysis will be considered for the set of 14 features in Table VI.

Table VI presents the performance metrics of different machine learning models trained on a data set composed of 14 features. It shows each model's accuracy, precision, recall and F1 score, thus providing a complete visualization of their classification efficiency. Performance metrics across models showed a remarkable variation between them. Weighted KNN, Bagged Trees Ensemble and Neural Network models were found to be exceptional with all perfect scores, including accuracy, precision, recall and F1 score, indicating that they can accurately classify instances according to these metrics. The above models are robust and reliable on this dataset, suggesting their suitability for this type of classification task. Similarly, LD and SVM Kernel have high performance across all metrics with at least 0.90 accuracy, precision recall and F1 score LD makes linear combinations out of features while the ability of SVM Kernel to handle non-linear decision boundaries explains why they are effective in classification problems. However, some algorithms, such as Gaussian Naive Bayes and Efficient Linear SVM, didn't perform as well across all areas in relation to other models listed in the table.

TABLE VI. Evaluation metrics of algorithms

Model Type	14 Features			
	Accuracy	Precision	Recall	F1 Score
Decision Tree	0.93	0.89	0.91	0.90
Linear Discriminant	0.97	0.96	0.96	0.96
Gaussien Naive Bayes	0.84	0.76	0.77	0.76
Kernel Naive Bayes	0.90	0.86	0.87	0.96
Linear SVM	0.93	0.89	0.90	0.90
Efficient Linear SVM	0.65	0.45	0.57	0.50
Cubic KNN	0.83	0.74	0.75	0.74
Weighted KNN	1.00	1.00	1.00	1.00
SVM Kernel	0.99	0.97	0.97	0.97
Logistic Regression Kernel	0.94	0.91	0.94	0.92
Bossted Tress Ensemble	0.99	0.98	0.99	0.99
Bagged Trees Ensemble	1.00	1.00	1.00	1.00
RUSBoosted Ensemble	0.96	0.95	0.94	0.94
Neural Network	1.00	1.00	1.00	1.00

The confusion matrix and the s the receiver operating characteristic (ROC) curve of the tested linear SVM model and NN model using the four sets of features are shown in Figs. 2-5. The predicted and actual labels of the state are plotted on the horizontal and vertical axes, respectively, in a confusion matrix. The primary diagonal numbers indicate the diagnostic accuracy of each state, whereas other numbers represent misdiagnosis rates. For example, Fig 2 represents a comprehensive overview of the model's classification performance by showing a confusion matrix for the SVM model with a set of 14 features. According to the confusion matrix, classes with labels 0, 1, 2 and 5 have perfect classification accuracy because all instances have been correctly classified. However, classes having labels such as class 3, class 4, class 6 and class 7 exhibit varying degrees of misclassification. In addition, a class with label 3 exhibits significant confusion, with a portion misclassified as a class with labels 1, 6, and 7. This misclassification refers to potential similarities or overlaps between these classes. Similarly, a class with label 6 shows misclassification with classes 2 and 4, possibly due to the similarities or overlaps in the features between these classes. The presented results in Figs. 2-5 show that the performance of the tested linear SVM model and NN model using a set of 14 features are more accurate in classifying the data into the right failure class than using the other sets of features.

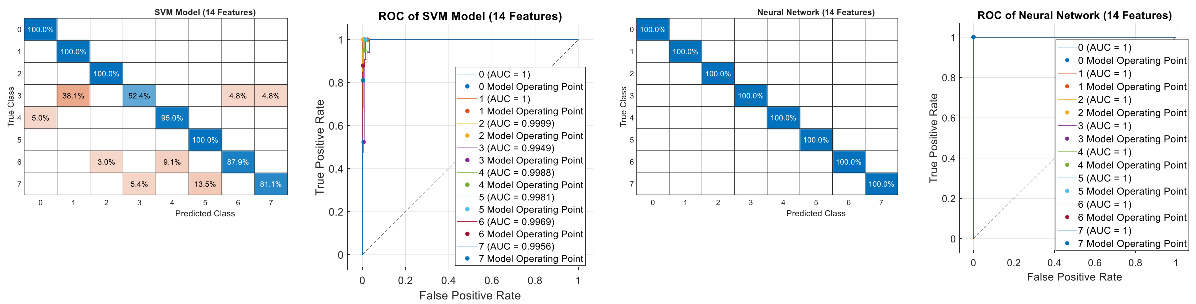

Fig. 2 Performance evaluation of SVM model and NN with 14 features

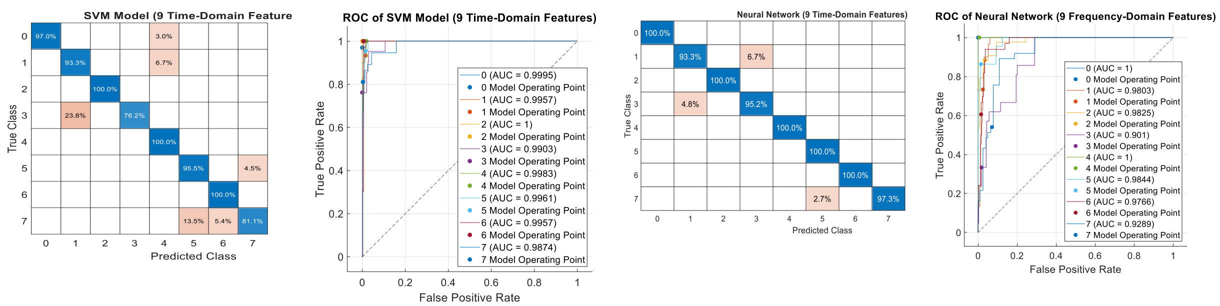

Fig. 3 Performance evaluation of SVM model and NN with 9 features

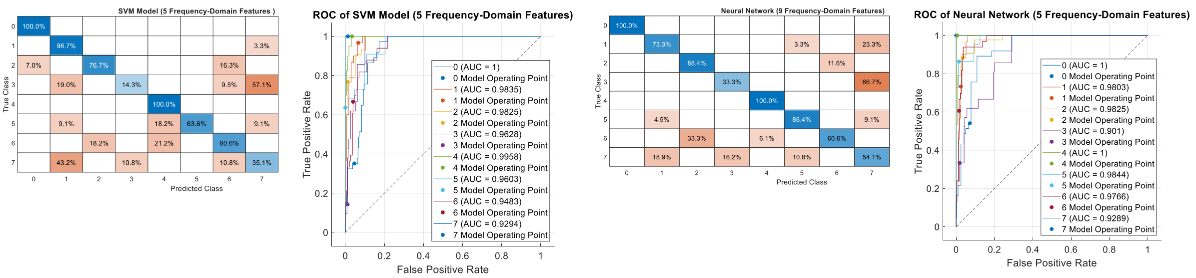

Fig. 4 Performance evaluation of the SVM model and NN with 5 features

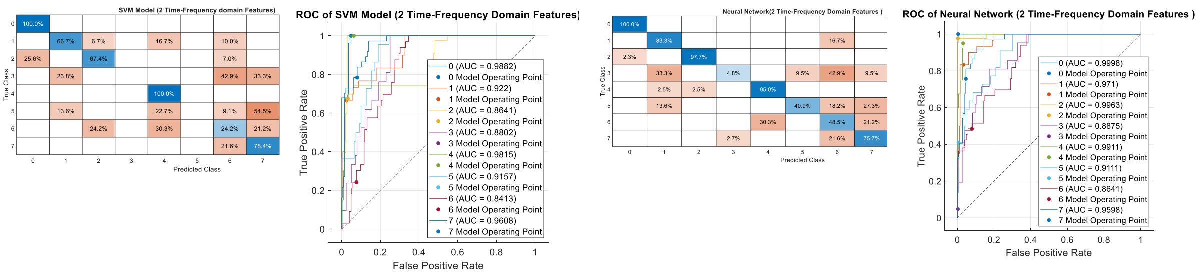

Fig. 5 Performance evaluation of the SVM model and NN with 2 features

IV. Conclusions

The papers discussed the optimization of fault diagnosis algorithms by focusing on feature extraction and selection as the key factors that needed to be addressed, and the paper also provided a better understanding of the comparative study of fault classification algorithms using the data collected from the simulation model of triplex pump. From the flow signal of the pump, some features were extracted and categorized into four sets that contained features in both the time-domain and frequency-domain categories. Fourteen classification algorithms were trained, validated, and tested using the four feature sets. As evident, the Weighted KNN and Bagged Trees Ensemble algorithms are proven to be the least sensitive to noise and have very good AUC. In addition, the result shows that both algorithms' accuracy is perfect, which is 100% for all the feature sets used. Nevertheless, the fluctuation in the rates of particular algorithms, such as SVM algorithms, when using different features clearly proves that further research should be focused on selecting specific algorithms appropriate to particular features of the dataset. Furthermore, while comparing the performance measures, the study shows that implementing and utilizing performance metrics reveals how techniques such as Weighted KNN, Bagged Trees Ensemble, and Neural Network exhibit higher performance in classifying instances using accuracy, precision, recall, and F1 score. Thus, the implementation of such high-performance classification algorithms can play a valuable role in improving fault detection and maintenance techniques related to complex systems like triplex pumps, which are part of the overall section of industrial maintenance.

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