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Research Article

Fault Detection from Horizontal Shaft Centrifugal Pump Fan Sound Analysis Using Artificial Intelligence

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***Abstract*—Axial misalignment, over-forced and wear of the components that constitute the machine is changed in the sound. It is of critical importance to implement early fault diagnosis and predictive maintenance planning in order to prevent errors caused by machines that break down or fail during operation. In this study, data comprising 15 one-dimensional sequences and 15 two-dimensional images from MFCCs (Mel-Frequency Cepstral Coefficients) for each sound were utilized in CNN (Convolutional Neural Networks). Furthermore, the data used in ML (Machine Learning) models were created by extracting 28 features from various audio characteristics such as amplitude-time, mel-spectrogram, MFCCs, ZCRs (Zero Crossing Rates), and RMS (Root Mean Square) energy. SVM (Support Vector Machine), KNN (K-Nearest Neighbours) and EL (Ensemble Learning), which combines SVM, KNN and RF (Random Forest) models, were utilized. The results indicated that the accuracy rates varied between 93.09% and 99.59%. The EL model exhibited the highest accuracy, correctly predicting all 99 sounds for faulty, 248 sounds out of 249 sounds for slightly faulty and 143 sounds out of 144 sounds for intact. The results indicate that it is possible to diagnose faults in centrifugal pumps and preventing errors. Consequently, economic savings will be achieved by reducing the losses caused by faulty parts and energy loss caused by the decrease in the efficiency of the system when it operates incorrectly will be prevented.**

*Index **Terms***—**Artificial Intelligence, Classification models, Centrifugal pump fan, Early fault diagnosis, Predictive maintenance**

I. INTRODUCTION

CENTRIFUGAL PUMPS, which are rotary machines, are employed in a multitude of industrial applications, including wastewater treatment, agriculture, paper and pulp, the food industry, the oil and gas industry, and numerous other fields. Centrifugal pumps are one of the most prevalent types of machinery utilized in industrial settings for the pumping and transportation of a diverse array of liquids, including water, oil, and chemicals [1]. The horizontal shaft centrifugal pump is a versatile device employed in a multitude of settings, including irrigation systems and industrial applications [2-3]. It is an effective means of transferring and pressurizing water [4].

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Horizontal shaft pumps are available in a range of configurations and features, making them suitable for a diverse array of applications. The horizontal shaft pump is a type of pump that moves water horizontally and controls the direction of water flow [5]. They are designed for different flow rates and pressure requirements. The two most commonly used models of these pumps are the multi-stage and monoblock (mono-stage). They are a highly effective way to control the movement of water and direct it. They are employed in agricultural irrigation systems to ensure accurate distribution of water [1, 6]. Due to pump failure, the performance of the system may decrease and reliability may decrease [7]. Therefore, it is necessary to monitor whether the pump is operating properly or not.

Fan and bearings are the most affected parts of pumps due to deformation of slurry particles, corrosion caused by reactive chemicals and improper lubrication [8]. Diagnosing the failures of these parts at an early stage can be beneficial to minimize the failures without causing large costs [9]. In an Industry 4.0 environment, maintenance must do much more than prevent the downtime of individual assets. The implementation of predictive maintenance can increase the uptime of a system by 10-20%, while simultaneously reducing the overall maintenance costs by 5-10% and the time required for maintenance planning by 20-50%. Furthermore, due to the increased interconnectivity and the new opportunities to collect process and analyze information, predictive maintenance can be a very powerful strategy [10]. The sounds emitted by machines during operation are indicative of the machine's operational state. The sound characteristics of a machine are determined by the sounds emitted by its components during a given operational cycle. Any changes in the machine's health will alter this characteristic, indicating the nature of any disruptions or faults occurring during the machine's operational cycle. Sound signals transferred to a computer environment with digital sound recording can be analyzed using sound analysis software. By examining the amplitude changes of these signals on the time axis, it is possible to determine the acoustic profile that machines draw in both malfunction and normal operating conditions [11]. The utilization of sensing technology in production processes has become pervasive. The most pivotal aspects of this technology are the acquisition and analysis of data. From these analyses, it is possible to identify the factors that affect working time and productivity [12-13]. By evaluating predictive maintenance applications using ML (Machine Learning) methods, production losses due to shutdowns in the production phase can be prevented [14].The failure of machine fans used in the industrial sector causes critical economic losses in production [15]. Gong et al. [16] were said that the fan, which is the rotating element of these machines, should be inspected before it fails.

In the present era, companies that prioritize periodic maintenance employ their accumulated experience and statistical methods to ascertain the probability of breakdowns occurring outside of their scheduled times. The periodic preventive maintenance technique employed by contemporary companies renders breakdowns likely to occur between the periods calculated using statistical methods or based on experience. Consequently, predictive maintenance techniques are utilized in conjunction with traditional maintenance activities to detect failures before they occur. The advent of predictive maintenance represents one of the most significant developments in the field of industrial maintenance, offering a reliable and high-quality solution to the challenges faced by modern companies [17-18]. This study aims to elucidate the distinction between periodic preventive maintenance and predictive maintenance and to propose a mixed maintenance model for the subject company. Furthermore, the utilization of vibration analysis, a predictive maintenance technique, enables the acquisition of general information regarding the vibration characteristics of faults. Additionally, the application of predictive maintenance to equipment utilized in the water distribution sector has led to the identification of potential faults with varying characteristics. This has resulted in the formulation of a maintenance management organization. The technical specifications of the equipment and the vibration measurement points were determined, and a vibration measurement plan for this system was prepared. Vibration measurements were taken at these points during the specified period and analyzed. The vibration behavior of characteristic faults was investigated, and the data obtained were compared with existing standards [19-20].

The growth of artificial intelligence has been exponential in recent years, coinciding with the emergence of new technological advances. Artificial intelligence technologies such as neural networks, fuzzy logic, genetic algorithms, ML, and DL (Deep Learning) are becoming increasingly popular in many fields, including agriculture, medicine, healthcare, speech recognition, robotics, and disease detection. In the regression and classification, a variety of ML models is used to process data of varying sizes. ANN (Artificial neural networks), RF (Random Forest), SVM (Support Vector Machine) and KNN (K-Nearest Neighbours) are frequently employed [21-23].

Sound-based classifications are a common practice in the field of health, particularly in the analysis of heartbeats, respiratory sounds, chewing sounds, asthma wheezes, and stethoscope lung sounds. Additionally, sound classification can be applied to animal sounds, including those of birds, pigs, fish, and bees, as well as sounds emitted by both living and non-living objects in the environment and internal sounds of vehicles [24-26].

Images and curves, such as spectrograms, mel-spectrograms, MFCCs (Mel-Frequency Cepstral Coefficients), log-mel spectrograms, ZCRs (Zero Crossing Rates), and RMS (Root Mean Square), have been used to extract features from sound data. In recent research, CNN (Convolutional Neural Networks)-based models are utilized to extract features. The VGGish and bottleneck Deep CNN models are extracted features from spectrogram images through 1D and 2D convolutional layers and maxpooling layers. Furthermore, features are extracted from values such as Wave and STFT (Short Time Fourier Transform), LQMP (Local Quintet Magnitude Pattern), Spectral Integrated, Shannon Entropy, Logarithmic Energy Entropy, and Spectrogram Based Spectral Entropy [27-29].

In the study on engine misfire, it was predicted that the success rate would be 94% by analyzing sounds recorded near the cylinder block and exhaust pipe. This was achieved using the SVM classifier [30]. By analyzing the sounds obtained with microphones placed around the asynchronous motor, both the fault status of the motor and the type of fault were classified. The classification of faults was successful in nearly 100% of cases by training the features extracted by wavelet transform with the LVQ (Learning Vector Quantization) algorithm [31]. A deep CNN network was employed to distinguish between impulse and non-impulse military sounds. The optimal classification prediction for machine gun, wind, thunder, explosion, vehicle and aircraft sounds was made for machine gun, with a 97.43% success rate [32]. In order to classify vehicle interior sound, images were obtained using mel-spectrograms and subsequently trained with 1D CNN and LSTM (Long Short-Term Memory) models. The classification training achieved a 94.9% success rate, while the prediction of tests achieved a 97.5% success rate [33]. A method for the diagnosis of mechanical faults in GIS (gas-insulated switchgear) has been developed. This involves the classification of input sounds in order to diagnose faults. The features obtained by using MFCCs attributes of the recorded sounds are classified using the SVM. The success of the prediction is increased above 95% by changing the signal-to-noise ratio [34]. Classification was also performed by analyzing the sounds emitted by moving tracked and wheeled vehicles. The classification results obtained by processing the sounds recorded from real experiments with PSD (power spectral density estimation) and LPC (linear prediction coding) were compared with standard methods such as KNN and SVM [35].

II. MATERIAL and METHODS

The objective of this study is to diagnose faults in horizontal shaft centrifugal pump fan, which is shown in Figure 1, through the analysis of fan sounds. The external sounds of the pump fan were recorded on a weekly basis over a five-month period, from 1 September 2023 to 5 January 2024. The recordings were made for six pumps. The pumps have a power of 90 and 132 kW, respectively, and are 2 and 3-stage units comprising three pumps. One of these pumps serves as a spare unit and feeds two separate tanks with a capacity of four and six tons, respectively. The pumps are located at the city drinking water pumping station in the Bismil District of the Diyarbakır Province. A microphone was placed close to the outer part of the fan housing of the pumps located indoors to record the sound. In this study, 489 faulty, 1247 slightly faulty and 724 intact horizontal shaft centrifugal pump fan sounds were used. The 80% of sounds were selected as training data, while the remaining 20% were selected as test data. The test data, comprising 99 faulty, 249 slightly faulty, and 144 intact sounds, were employed in the predictions.

Fig. 1. Front view of three-stage horizontal shaft centrifugal pump

Figure 2 is shown the faulty and intact images of an fan in the first stage, which corresponds to the suction port of a three-stage horizontal shaft centrifugal pump.

(a) (b)

Fig. 2. Centrifugal pump fan a) intact fan and b) faulty fan

A. Recording and Analyzing of sounds

In Figure 3, two groups of pumps, each consisting of three pumps, were monitored at weekly intervals using an Olympus sound recorder. All pumps were stopped, and only the pump to be monitored was operated first for 20 seconds, then for 60 seconds. The sound recordings were saved in the "monitoring sounds" folder on the computer, organized chronologically by date. The sound files were generated using the Avidemux software program.

Fig. 3. Cross-sectional picture of the centrifugal pump under listening

Subsequently, the sounds were categorized into three classes: faulty, slightly faulty and intact. The sound of the pump is analyzed by an expert who has worked for 16 years as a master in the maintenance and repair of pumps, according to the extent of the change in the sound caused by the particles (sand, gravel, etc.) in the water as a result of the erosion of the suction vanes of the pump's fan. The defects in the form of tingling in the vanes of the fan are classified as slightly faulty, the defects in the form of broken vanes of the fan are classified as faulty and the state after the installation of the zero fan is classified as intact. In order to process the sounds in the computer environment and to use them in classification models by extracting features, the sounds in each folder were cut into four-second segments. The Anaconda Navigator interface was used in the creation, segmentation and reproduction of sound data. Python code created in the Spyder programme in the interface was used. The Librosa library was employed for the loading, processing and feature extraction. The Librosa library, developed by software engineers utilizing Python code, is an open-source, free library used for the loading and execution of sound and music files in a variety of sound formats, as well as for the development of fundamental and advanced features related to sound and music processing. The library facilitates the utilization of its functions in a number of domains, including the creation of images of sound and music files, the generation of data to be employed in classification and regression models, and the extraction of features.

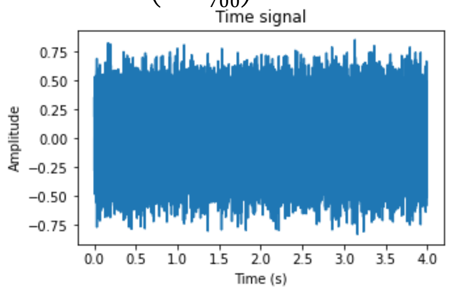
B. Extracting Features

Feature extraction is a crucial aspect of the processing of sound signals. It decomposes sound signals into three categories of features: temporal, spectral and prosodic [36]. Sound signals are composed of numerous features, which are extracted and used to define a vector in the feature space in classification systems. Temporal features, or amplitude fluctuations over time, are initially obtained directly from the first sound without data. They are comprised of various types of features, including ZCRs, amplitude-based features, and power-based features. These features are generally used alongside spectral features to process sound signals [37]. The ZCRs of a sound frame are defined as the number of times the sound signal crosses zero per unit time, or alternatively, as the number of changes in the sign of the sound signal (Eq. 1) [36]. The MFCCs employ bandwidths analogous to the manner in which the human ear functions. They perform a Fourier Transform on the sound samples and project the spectral powers obtained to the Mel scale, subsequently calculating the logs comprising these values at Mel frequencies (Eq. 3). Thereafter, utilizing these frequencies as a signal, MFCCs are generated by passing them through a discrete cosine transform [38]. The RMS Energy is a method of measuring the energy in a signal. It is calculated by taking the square root of the sum of the squares of the amplitude (Eq. 2). RMS Energy is the root-mean-square of all samples in the frame. It is also an indicator of loudness, but is less sensitive to outliers. The extraction of RMS Energy is mostly used for sound segmentation and music classification [39]. Graphs of feature extraction methods such as amplitude-time, Mel-spectrogram, MFCCs, ZCRs and RMS Energy are shown in the Figure 4.

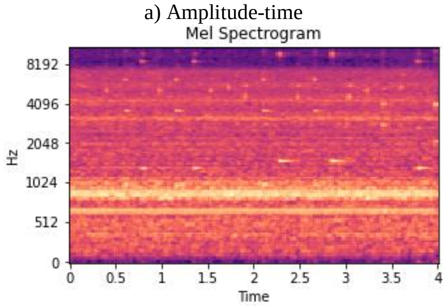
$$ZCR = \frac{1}{2N}\sum_{n=1}^{N}|sign(x[n]) - sign(x[n-1])| \quad (1)$$

$$RMS = \sqrt{\frac{1}{N}\sum_{n=1}^{N}|x(n)|^2} \quad (2)$$

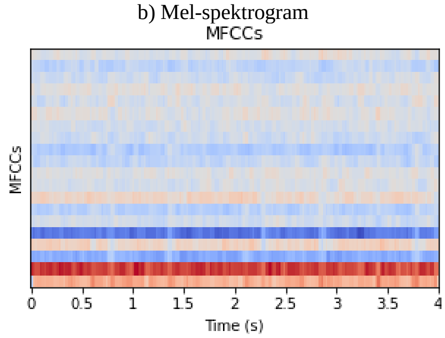
$$Mel(f) = 2595 \log\left(1 + \frac{f}{700}\right) \quad (3)$$



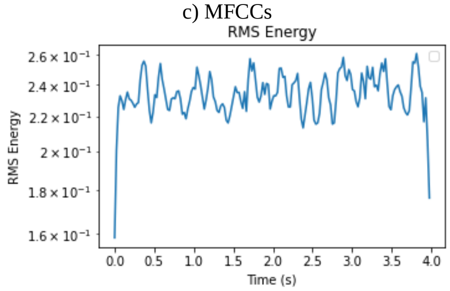
a) Amplitude-time



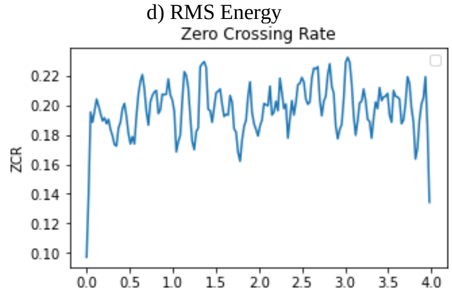
b) Mel-spektrogram



c) MFCCs



d) RMS Energy



e) ZCRs

Fig. 4. Feature extraction methods a) Amplitude-time, b) Mel-spectrogram, c) MFCCs, d) RMS Energy, and e) ZCRs

C. Classification models

1) *1D CNN model*

The success of CNN architectures in training two-dimensional images on large data sets and the abundance of data obtained from images have led to the proposal of a 1D CNN architecture for the analysis of single-index matrices formed by sound and vibration signals. The efficacy of a 1D CNN architecture adapted to run on patient-specific ECG (electrocardiogram) signals has been demonstrated. The results were obtained in a shorter time, given the limited data, limited capacity of the computers used in the training, and the datasets formed by the signals. In addition to ECG signal processing, it has been used in structural health applications and structural damage diagnosis. Furthermore, 1D CNN architectures consisting of deep networks were used to detect, localize, and measure bearing failures in high-power motor failure systems [40].

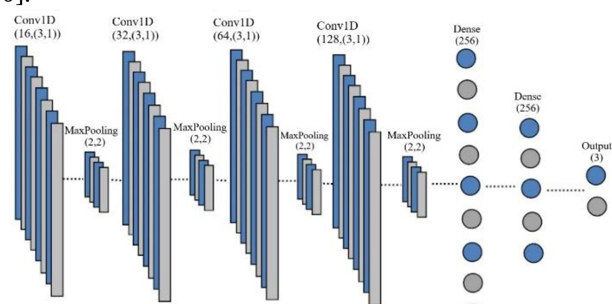


Fig. 5.1D CNN example diagram [41]

The CNN is to create a convolution data layer based on the attributes of an image or sound, reduce the size by maximum pooling, identify the largest intensity values without losing any data, create a single-column flattened layer, and then pass it to the FC (fully connected) layer and display it in the dropout layer. The 1D CNN model, which employs fewer parameters in one-dimensional data modelling and training, such as sound, comprises convolution layers, maxpooling and dropout steps. In this study, the sound data sequence consisting of 15 features from each sound signal was utilized. The filters with a size of 3x1 were employed in the convolution layer. In the convolution layers, 16, 32, 64 and 128 filters were used, respectively. This was achieved by employing the Conv1 layer in the Keras library. In order to prevent overfitting during training, a dropout value of 0.5 was selected. An example diagram of a 1D CNN is shown in Figure 5.

2) 2D CNN model

The 2D CNN model used in image classification is a multilayer neural network model comprising a convolution layer, a pooling layer and a FC layer. The convolution layers generate N feature maps by processing the output data obtained by convolving an input image comprising N filters, each consisting of small weighted matrices, through the non-linear ReLU activation function.

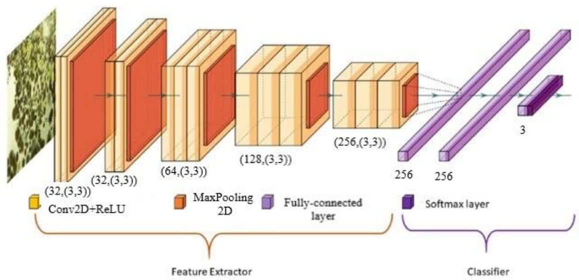


Fig. 6. 2D CNN architecture [42]

The feature maps, which contain superfluous information, are transformed into compact matrices by calculating the mean or maximum value in the mean pooling or maximum pooling layer. In the generation of these processes, the dropout value is employed to prevent rote learning. According to the dropout value, a subset of the data is eliminated. In order to smooth the final data, a full link layer is used, and classification is performed by passing through neural networks [43]. The 2D CNN is employed for the training of images and videos. The modelling and training of more complex data with more parameters can be performed [17]. In this study, three classes of sound files were uploaded and processed using the Librosa library. From the sound signals in the library, 15 feature maps consisting of MFCCs images were generated. The MFCCs images were used as input data for a 2D CNN architecture. The sound files were processed and classified in the CNN model comprising Conv2D, Maxpooling2D, with the ReLU selected as the activation function and 'same' selected for padding. In this 2D CNN model, 16x3x3 filters and 2x2 maximum pooling processes were used in a single step for the convolutional process. In the subsequent stages, the data underwent a series of transformations following the application of 32, 64 and 128 filters and pooling operations, respectively. These were then subjected to a process of FC and passed through a neural network comprising 128 neural networks. Classification was performed using the softmax function. Subsequently, 20% of the data was designated as the test set, while the remaining 80% constituted the training set. Figure 6 illustrates an example diagram of the 2D CNN.

3) KNN model

KNN is a simple yet effective non-parametric supervised ML algorithm that can be employed in both classification and regression prediction analysis. For the data to be classified, a neighborhood of this data is formed by taking k nearest neighbors. Its functionality is solely dependent on the definition of the number of nearest neighbors. However, for optimal classification performance, the appropriate k value should be selected. In order for the algorithm to be successful, it is necessary to train it according to the suitability of the k value. The k value with the best success percentage should then be selected. The KNN algorithm has been successfully used in pattern recognition, data mining, intrusion detection, big data processing and medical imaging data [44-45].

4) SVM model

The SVM model, which is accepted in the supervised learning category, is distinct from clustering algorithms. It is one of the most effective methods among techniques such as outlier classification, prediction and detection [46-47]. SVM undergoes two training and one testing process in the classification of data sets. This method demonstrates superior performance compared to previous classification methods and reduces the operational classification risk. The method is presented by providing a statistical model as one of the most well-known methods for categorization, utilizing a linear combination of kernel performance and running support vectors on a set of training data in prediction models. The SVM method is based on the construction of support vector planes in space, which can optimize the separation of different data sets. This method has been employed in numerous engineering fields, particularly mechanical and civil engineering. In comparison to other methods, it is relatively straightforward to use and performs well in high-dimensional data [46].

5) EL model

EL (Ensemble Learning) methods represent the most advanced solutions in many ML problems as shown in the Figure 7. They constitute classification and prediction models that combine predictions by training more than one model and work as a single model. In supervised learning applications, EL models gather stimuli under a single roof by combining them as decision makers. Stimuli, also defined as the basic learning element, is a model that takes a group of labelled class instances as input data and generalizes the instances [38].

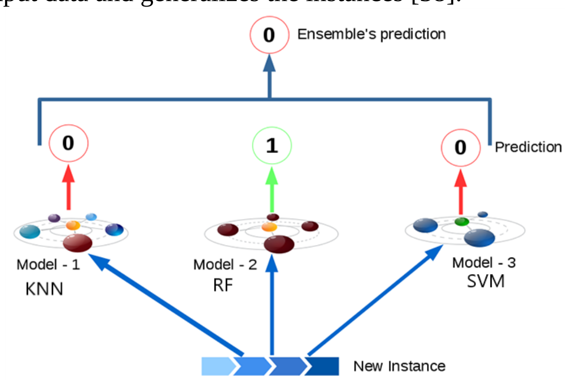


Fig. 7. Ensemble (voting) learning model [48]

An EL model can combine ML models of any type. Its fundamental principle is that it combines multiple models and improves the overall prediction performance over that of a single model by reducing errors [49]. In addition to the methods examined above, the ensemble model obtained by running a few of them together has started to be used. In this study, we use RF, KNN and SVM together for classification. A different path is created with new samples brought together. With this repetition, the samples are increased. The predictions are then made accordingly.

D. Classification metrics

Metrics such as accuracy, precision, recall, and F1 score are used to evaluate the performance in multiple classifications. This scores are calculated according to Equation 4-7.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{4}$$

$$Precision = \frac{TP}{TP+FP} \quad (5)$$

$$Recall = \frac{TP}{TP+FN} \quad (6)$$

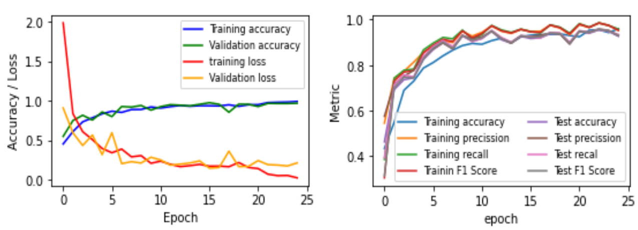
$$F1 = 2\frac{Precision*Recall}{Precision+Recal} \quad (7)$$

Where TP is the number of true positives, TN is the number of true negatives, FP is the number of false positives and FN is the number of false negatives [50].

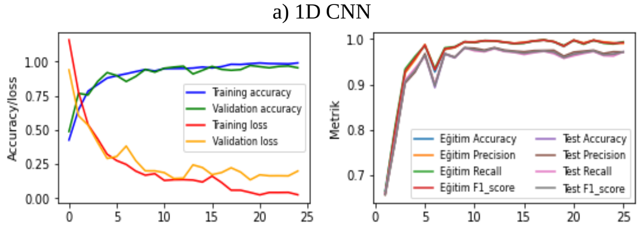
III. RESULTS AND DISCUSSION

A. Fitting the models using DL

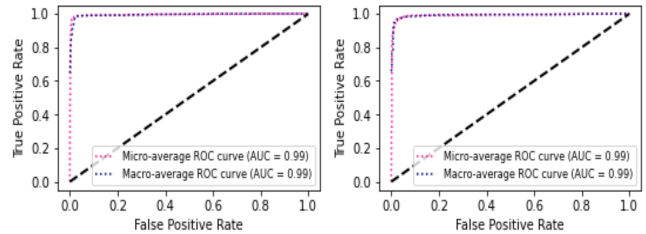
In the 1D CNN training process, the training procedure includes 15 features derived from the MFCC images obtained from each audio file. In the 2D CNN training process, 15 feature images derived from the MFCC images obtained from each audio file were used in the training. 1D CNN and 2D CNN models were trained using 25 epochs. Figure 8a presents the training success of the 1D CNN model, as well as the loss values at the end of each cycle, the accuracy success and loss values of the test data. Similarly, the accuracy score, precision score, recall score and f1 score values of the training obtained at the end of each cycle and the accuracy score, precision score, recall score and f1 score values of the test data are also shown. The training success, training loss values, test data accuracy success and loss values obtained as a result of the training of the 2D CNN model at the end of each cycle are presented in Figure 8b. Similarly, the accuracy score, precision score, recall score and F1 score values of the training data and the accuracy score, precision score and F1 score values of the test data obtained at the end of each cycle are shown. The ROC curves of the 1D CNN and 2D CNN classification models are shown in Figures 8c and 8d, respectively. Upon examining the results presented in the graphs, it is observed that the accuracy, loss, and scores have not significantly changed in the training cycles beyond the 5th epoch. In both cases, the training success rate and the success rate of the tests exceeded 90%.



a) 1D CNN



b) 2D CNN



c) 1D CNN d) 2D CNN

Fig. 8. a) Result of training and validation for the 1D CNN, b) result of training and validation for the 2D CNN c) ROC (Receiver Operating Characteristic) curve for the 1D CNN, d) ROC curve for the 2D CNN

As shown in the Figure 9, classification was conducted using two DL models and three ML models. The classification accuracy rates for the test data were 93.09% for 1D CNN, 94.72% for 2D CNN in the DL, 98.32% for SVM, 98.98% for KNN and 99.59% for EL in the ML models. The results indicate that ML models achieved a higher success rate than DL models. The success rate of EL models is enhanced by the combination of multiple ML model predictions [49]. In this study, the success values of RF, SVM and KNN were combined to generate a high success rate.

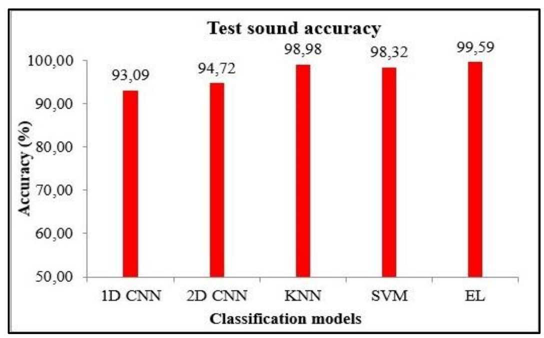


Fig. 9. Test data accuracy

The outcomes of the metrics utilized in the classification training of 1D CNN, 2D CNN, SVM, KNN and EL models are presented in Table 1. These outcomes indicate that the KNN and EL models achieved the highest success rate, while the 1D CNN metrics exhibited the lowest success rate. In the KNN and EL models, the values were found to be close to 100%.

TABLE I
CLASSIFICATION METRIC RESULTS

Model	Class	Accuracy (%)	Precision (%)	Recall (%)	F1 (%)
	faulty		96	94	95
1 D CNN	S. faulty	93.09	93	94	94
	intact		92	90	91
	faulty		93	95	95
2 D CNN	S. faulty	94.71	95	95	95
	intact		96	92	94
	faulty		99	99	99
KNN	S. faulty	98,98	99	99	99
	intact		99	99	99
	faulty		97	99	98
SVM	S. faulty	98.32	98	98	98
	intact		99	99	99
	faulty		99	100	99
EL	S.faulty	99.59	100	100	100
	intact		100	99	100

In the field of fault diagnosis for centrifugal pumps, studies have demonstrated the successful prediction of faults caused by the operating conditions of the fan or fan using vibration signals. In the study by Dong et al. [51], a novel fault diagnosis method based on IPSO (Improved Particle Swarm Optimization)-based VMD (Variational Mode Decomposition) and RVM (Relevance Vector Machine) was proposed, where the rotor's vibration displacement signals were obtained using a sensor. This method achieved a fault detection accuracy of 97.87%. Similarly, Sakthivel et al. [1] classified the data obtained from vibration signals using the Decision Tree model and achieved 99.60% accuracy. Kumar and Kumar [8] analyzed vibration signals using SVM, genetic algorithms, and automatic signal processing techniques, reaching an accuracy rate of 96.66%. Xiao et al. [53] achieved accuracy rates of 97.7% with the SVM-ReliefF method and 98.3% with the ANN-Xgboost method for fault detection using vibration signals. Obaidi [54] diagnosed cavitation faults using an acoustic-based system with RMS energy and frequency values. Additionally, Ebrahimi and Javidan [55] achieved 96.67% accuracy with the SVM-Radial Basis Function (RBF) model by utilizing SVM and discrete wavelet transform (DWT). Finally, Karagiovanidis et al. [56] achieved 100% accuracy in classifying cavitation faults using vibration signals obtained from accelerometers and sound signals recorded through Classification Tree, KNN, and SVM models. In this study, high classification accuracy of 99.66% was obtained in ML algorithms such as KNN and EL by using features extracted from the sounds of the centrifugal pump fan. These studies demonstrate that sound and vibration signals can be used with high accuracy in the early diagnosis of fan, bearing, and cavitation faults in centrifugal pumps. Particularly, near 100% accuracy rates provide a significant contribution to the classification of centrifugal pump fan faults.

B. Predicting the sounds

The confusion matrix presents the predictions made using test data for classification. The diagonal elements represent true predictions for each class, while other values indicate misclassifications. The classification labels are defined as follows: faulty (1), slightly faulty (2), and intact (3). Based on the results shown in Figure 10, for the 1D CNN model, the prediction accuracy for sounds classified as faulty was found to be 96.15%, for slightly faulty sounds 96.73%, and for intact sounds 97.97%. In the 2D CNN model, the prediction accuracy for faulty sounds was 90.38%, for slightly faulty sounds 97.14%, and for intact sounds 97.46%. In the SVM model, the accuracy for faulty sounds was 98.72%, for slightly faulty sounds 97.55%, and for intact sounds 98.98%. For the KNN model, the prediction accuracy for faulty sounds was 100%, for slightly faulty sounds 98.78%, and for intact sounds 100%. Lastly, in the EL model, the accuracy for faulty sounds was 100%, for slightly faulty sounds 98.78%, and for intact sounds 100%. According to these results, the KNN and EL models achieved the highest prediction accuracy.

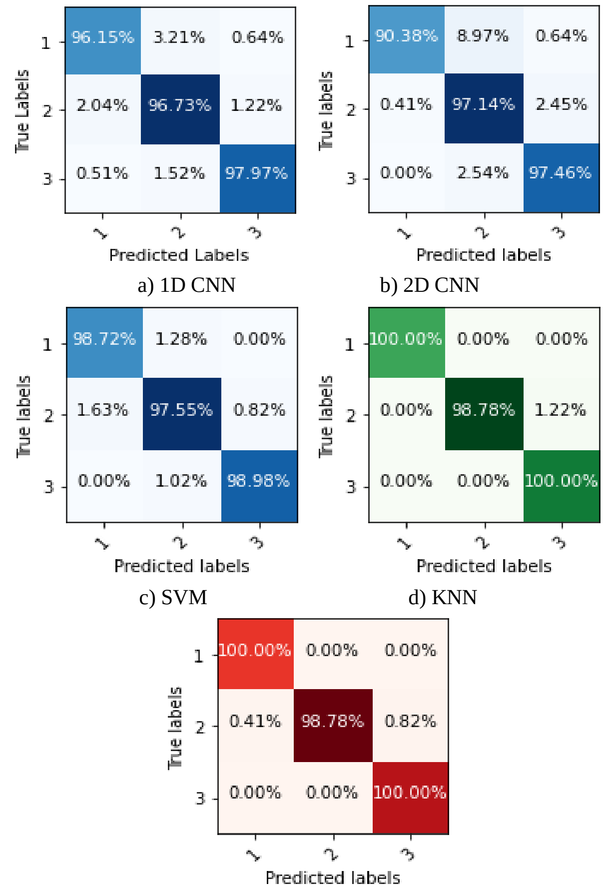


Fig. 10. The sounds prediction and confusion matrix a) 1D CNN, b) 2D CNN, c) SVM, d) KNN and e) EL

Figure 11 presents the graph illustrating the accuracy of the models in predicting the test data. Upon examination of the values in this graph, it can be observed that the 1D CNN model predicted 93 sounds true and 6 sounds false in the faulty class. In contrast, the 2D CNN model predicted 96 sounds true and 3 sounds false. The SVM model, on the other hand, predicted 96 sounds true and 3 sounds false. The KNN model true predicted 98 sounds and false predicted 1 sound. The EL model predicted all sounds true. Similarly, the classification results for each model in terms of 'slightly faulty' and 'intact' can also be provided. Consequently, the EL model demonstrated the most accurate predictions, while the 1D CNN model exhibited the least accurate predictions.

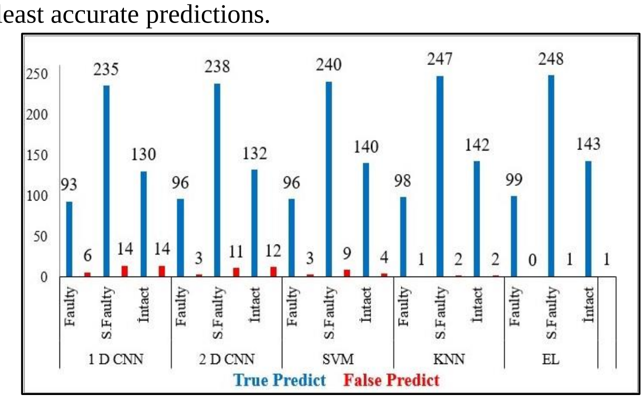


Fig. 11. True and false predicts for the test data

It is of great importance to be able to diagnose faults at an early stage in order to prevent the negative consequences that can result from the breakage, deterioration or frictional looseness of the parts of rotating machines. In the field of predictive maintenance and early fault diagnosis of machines, the initial approach involved analyzing the changes in the vibrations of the machine components because of faults. Recently, however, the advent of artificial intelligence tools has enabled the determination of failure status from the sounds caused by rotating objects or mechanical movements, as a result of mechanical movements. Consequently, studies investigating the potential fault of the sound change in the machines, the necessity for maintenance according to the failure status, and the efficacy of the sound change itself have become increasingly pertinent. As the performance of the classification models continues to improve with the rapid development of these models, the use of multiple learning and deep networks, the success rates approach 100%. In this study, the success rate of the 1D CNN model was low, whereas the success rate and prediction values of the EL model were high. In the literature, the detection of faults occurring in the moving parts of centrifugal pump or as a result of cavitation or the classification of fault are carried out by processing the signals received from acoustic, vibration, noise and sound sensors [6, 55-56]. Various ML models, including SVM, ANN and CNN, are employed. The success rates vary between 95% and 100%, while in this study, the EL model achieved a success rate of 99.59%, making the best predictions. Moreover, this study stands out due to the literature on the analysis of sounds, the extraction of images and features from sounds, and the utilization of these in classification models. Based on the sounds emitted from the fan of a centrifugal pump, the failure status of the fan can be determined. If the fan is less fault, it can be replaced preventing major errors.

IV.CONCLUSION

The continued use of fault parts can result in energy losses occurring in machines that are operating with low efficiency, as well as economic losses. The sounds emitted by the fan used in the centrifugal pump were categorized as faulty, slightly faulty and intact. To determine the condition of the fans used in the pumps supplying drinking water, a period of four to five months was dedicated to listening and recording the sounds emitted by the fans. The sounds were processed in a computer environment and used as data in classification models. During the training process, 15 feature sequences and 15 feature images from MFCCs images were used in DL models. In contrast, 28 features were extracted from amplitude-time, Mel-spectrogram, MFCCs, ZCRs and RMS Energy features to be used in ML models. The results of the training indicated that the accuracy rate was 93.09% in the 1D CNN model, 94.72% in the 2D CNN model, 98.32% in the SVM model, 98.98% in the KNN model and 99.59% in the EL model. The EL model demonstrated an accuracy of 100% in predicting all sounds correctly for faulty fans, while only one sound was incorrectly predicted for slightly faulty and intact fans. These results indicate that the use of KNN and EL models will facilitate the early diagnosis of faults and the prevention of major damage to devices. Especially in pumping stations where more than one horizontal shaft centrifugal pump works, production and cost loss can be minimized by using sound sensors to be connected to the computer by leaving certain intervals and sound isolation.

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