Fault Diagnosis of Fan Motors Using Multi-Domain Feature Extraction and Kolmogorov–Arnold Networks (KAN)

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***Abstract*—The evolution of industrial and robotic systems has revolutionized operations across sectors, including manufacturing, healthcare, and automation. However, the increasing complexity of these systems has heightened the need for robust fault detection mechanisms to ensure reliability, reduce downtime, and mitigate safety hazards. This study proposes a comprehensive framework for the fault diagnosis of fan motors, utilizing multi-domain feature extraction in conjunction with the Kolmogorov–Arnold Network (KAN). The approach incorporates time, frequency, and time–frequency domain analyses to derive a diverse set of statistical features from triaxial accelerometer data. A wrapper-based feature selection method, optimized using the KAN model, was employed to eliminate redundancy and enhance classification performance. The final KAN model, grounded in the Kolmogorov–Arnold superposition theorem, achieved a macro-averaged F_1-score of 95%, outperforming conventional classifiers such as Random Forest, MLP, CatBoost, and SVM. The findings demonstrate the efficacy and robustness of combining advanced signal processing with novel neural architectures for intelligent, predictive maintenance in industrial applications.**

Keywords—Fault Diagnosis, predictive maintenance, Feature Extraction, Kolmogorov-Arnold Networks

I. INTRODUCTION

Rotating machines have a very significant role in industrial applications. The most commonly used components of the common rotating machinery are the rolling element bearings, the gearbox box, and the planetary gearbox. The rotatory equipment works under harsh operating environments, and this has a tendency to create errors and generate malfunctioning components. The rotating machinery faults have the possibility to lower the performance of the machinery service in numerous ways, which include diminishing the quality of manufacturing, diminishing the manufacturing speed and safety of operations, and even causing the entire breakdown. The rotating machinery in modern industry develops with more critical requirements on maintenance, machinery dimension, automation, and precise performance. Another common fault diagnosis is that by applying proper signal processing algorithms, the nature of faults can be extracted based on the monitoring signals [1], [2]. Nevertheless, the drawback is the shortcoming of such classical methodology in automatic fault identification and locating the most crucial fault data in adaptive fault diagnosis.

A general fault diagnosis system is supposed to be operational in two tasks, namely fault detection and fault diagnosis. Fault detection: This will be aimed at finding out whether a fault was detected on the target machine. The data regarding the health monitoring of the target machine shall be collected and analyzed with the aim of determining whether there are any differences in comparison to the one that was gathered under normal conditions of the machinery. To increase the operational reliability of rotating machines, it is necessary to keep monitoring critical components. Typically, accelerometers are widely used for collecting vibration data from the target machine. Several signal processing procedures have been developed and applied in order to obtain fault information on the raw signal.

ML has revolutionized many fields by the ability to yield knowledge without constraining itself to specified rules but based on directly collected data. On fault detection, ML could be applied with large quantities of historical and real-time data to determine any patterns that would indicate a possible failure. This capability is for handling complex systems where the relationships between variables may not be apparent. Traditional ML techniques are still being applied across multiple settings due to the simplicity and interpretability present in each of them, as well as the data-learning capabilities the techniques already possess [3], [4].

The rest of the paper is described as follows. Section 2 gives a comprehensive related work regarding the status of fault detection and diagnosis of rotating machinery. Section 3 also introduces the theoretical background applied during the diagnosis of faults in rotating machinery. The proposed methodology is described in Section 4. Experimental results are shown in Section 5. Finally, the dissertation is concluded in section 6.

II. RELATED WORKS

A. Model-Based Approaches for Fault Detection

Model-based approaches for fault detection have gained significant traction in various engineering fields, particularly in control systems, chemical processes, and electrical networks. These methods leverage mathematical models to compare system measurements against expected behavior, thereby identifying discrepancies indicative of faults. This synthesis will explore traditional model-based approaches, highlighting their methodologies, advantages, and limitations. One of the foundational techniques in model-based fault detection is Principal Component Analysis

(PCA), which has been extensively utilized for monitoring multivariate processes.

B. Data-Driven Approaches for Fault Detection

Machine learning (ML) and artificial intelligence (AI) are powerful methods of fault detection that have been offered by data-driven methods of fault detection as alternatives to traditional model-based techniques of fault detection, as it allow analyzing complex systems.

Machine learning methods have demonstrated considerable potential in the application of rotating machinery. Lei et al. [5] during a thorough review of intelligent fault diagnosis, showed the flexibility of the ML methods to obtain the fault diagnostic knowledge based on the collected data to improve the reliability of the fault detection systems. Rafi et al. (2024) [6] proposed a hybrid ANN-SVM model for power transmission line fault detection that achieved an impressive 98.43% accuracy by combining current and voltage signal features. In Industry 4.0 contexts, SVMs have been integrated with Naïve Bayes and Decision Trees to classify faults from IoT sensor data (Perumal & Meenakshi, 2023) [7], while Jawalkar et al. (2023) [8] demonstrated its effectiveness in automotive control systems by integrating SVM with ANN and DNNs to achieve accuracy levels approaching 99%. In power systems, Vivek et al. (2024) [9] applied RF alongside SMOTE to resolve class imbalances in electrical fault data, enhancing model accuracy. ANN-based analytical models may be better at identifying nonlinear correlations, such as the one in the task of fault detection by thermal images of power systems (Alwagait & Khan, 2023) [10], which was accessed using Levenberg-Marquardt optimization and Bayesian regularization to find abnormal heat areas accurately.

III. Theoretical Background

A. Feature Extraction

A feature is a characteristic of a signal that is unique to a particular class of signals. The extraction of informative features from preprocessed signals is an important basis for solving any kind of signal classification problem [11].

1) Fast Fourier Transform (FFT)

The frequency-based signals are beneficial for analyzing signal data over time-based signals. When a Fourier transform (FT) is applied, the signal is decomposed into complex exponential parameters, called frequency components. The FT can be mathematically written as the following [12]:

$$X(f) = \int_{-\infty}^{\infty} x(t)\, e^{-j2\pi ft} dt \tag{1}$$

$$x(t) = \int_{-\infty}^{\infty} X(f)\, e^{j2\pi ft} dt \tag{2}$$

Where x denotes the signal in the time domain, X denotes the signal in the frequency domain, t stands for time, and f stands for frequency. The FT of $x(t)$ is given by Equation (1), and the inverse FT of $X(f)$ is given by Equation (2).

It is observed that the above equations are not discrete and hence cannot be applied using a digital computer. For the purpose of numerical computation, the FT of the signal $x(t)$ with discrete sample values is represented as $x(n)$. For discrete time series $x(n)$, the discrete Fourier transform (DFT) is given by Equation 3:

$$X[k] = \sum_{n=0}^{N-1} x[n] e^{-j(\frac{2\pi}{N})kn}, (k = 0,1,2, \ldots N-1) \tag{3}$$

And its inverse transformation is given by [75]:

$$x[n] = \frac{1}{N}\sum_{k=0}^{N-1} X[k]\, e^{j(\frac{2\pi}{N})kn}\ (n = 0,1,2..N-1) \tag{4}$$

The computation of the DFT may be simplified by making use of a more efficient transformation technique called the Fast Fourier Transform (FFT). The problem of finding an N-point DFT is reduced by this technique to that of finding many smaller-sized DFTs. To implement FFT, the input waveform must have a number of samples equal to an integer power of 2 (i.e., 2^n). This constraint may seem to be limiting; however, FFT can be implemented to any kind of input by applying a zero-padding technique, which refers to adding zeros at the end of the waveform to make the number of samples equal to integer power of 2.

2) Discrete Wavelet Transform (DWT)

While FFT-based features offer advantages over time-domain features, they completely lose time information, making it impossible to determine when events occur in the signal. This limitation is especially critical for non-stationary signals. To address this, time-frequency analysis using wavelet transform (WT) is employed. WT uses variable-sized windows—longer for low-frequency components and shorter for high-frequency ones—allowing it to capture both time and frequency characteristics effectively [13].

In the Fourier analysis of a signal, the signal is fragmented into sine waves of various frequencies. Whereas the signal is decomposed into scaled and shifted versions in the wavelet analysis. The wavelet can be defined as a waveform of limited duration with a mean of zero, while in Fourier analysis, the sinusoids extend from minus infinity to plus infinity, hence, do not have limited duration. Therefore, the sinusoids tend to be predictable and smooth, while wavelets are asymmetric and irregular. In a continuous time scenario, the WT is given by Equation (5):

$$WT_x^{\psi}(\tau, s) = \psi_x^{\psi}(\tau, s) = \frac{1}{\sqrt{|s|}}\int x(t)\psi^{*}(\frac{t-\tau}{s})\, dt \tag{5}$$

Where is the transformed signal, which is a function of two variables, τ and s. τ represents the translation parameter, s represents the scale parameter, and $\Psi(t)$ is the function to be transformed or the mother wavelet. In signal analysis, the wavelet analysis, specifically the Discrete Wavelet transform (DWT) has been used widely to obtain the WT of a discrete time signal. The DWT is derived from the idea of finding the wavelet coefficients at only a subset of positions and scales.

B. Feature Selection

The dimension reduction is often necessary in process modelling and analysis, especially when performing complex manufacturing processes that involve a significant number of process parameters, where the aim is to eliminate the meaningless features, and to enhance speed. There are two ways to reduce the dimension of data: feature selection and feature extraction [2], [4]. In feature selection, a subset of the original features is selected and the rest are discarded, while in feature extraction, new features are obtained by combining original features or projecting the original data onto a new feature space. After the dimension of data is reduced to an acceptable level, prediction models could be built using various modelling frameworks.

C. Kolmogorov-Arnold Network (KAN)

The Kolmogorov-Arnold Network (KAN) model offers a novel approach to neural network architecture, drawing heavily on fundamental theorems in approximation theory, particularly the Kolmogorov-Arnold superposition theorem. This theorem, a cornerstone of KAN's theoretical underpinnings, states that any continuous multivariate function can be represented as a superposition of continuous functions of a single variable and the addition operation. More formally, for a continuous function $f: [0,1]^n \rightarrow R$,it can be written as:

$$f(x_1, \ldots, x_n) = \sum_{q=0}^{2n} \Phi_q(\sum_{p=1}^{n} \phi_q, p^{(x_p)}) \quad (6)$$

Where $\Phi_q, p^{:[0,1]} \rightarrow R \ and \ \Phi_q: R \rightarrow R$

This theorem provides a theoretical guarantee for the expressive power of KANs, suggesting that even complex, high-dimensional relationships can be decomposed into simpler, univariate transformations and sums. Unlike traditional Multi-Layer Perceptrons (MLPs), which use fixed activation functions after linear transformations, KANs implement learnable, univariate activation functions on the edges of their network.

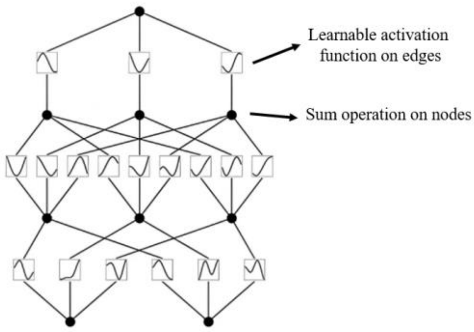

Figure 1. The Kolmogorov-Arnold Network structure *[14]*

The architecture of a KAN can be seen as a direct instantiation of this theorem. Instead of stacked layers of matrix multiplications followed by non-linearities, KANs represent each connection between neurons with a learnable, one-dimensional function. For instance, in a simple two-layer KAN, the output of a neuron is not just a weighted sum passed through an activation function, but rather a sum of learned univariate functions applied to the inputs. This inherent functional flexibility allows KANs to adapt their non-linearities specifically to the data, potentially leading to more accurate and interpretable models compared to models relying on pre-defined activation functions like ReLU or sigmoid. The learnable nature of these basis functions, often implemented as splines or other flexible function approximators, is a key theoretical differentiator that contributes to KANs' expressive capabilities.

$$KAN(x) = (\Phi_{L-1} \circ \Phi_{L-2} \circ \ldots \circ \Phi_1 \circ \Phi_0)x \quad (7)$$

$$MLP(x) = (W_{L-1} \circ \ \sigma \circ W_{L-2} \circ \ \sigma \circ \ldots \circ (W_1 \circ \sigma \circ W_0)x \quad (8)$$

Where σ: non-linear activation function, $\circ$: linear weight parameter

Furthermore, the theoretical appeal of KANs extends to their potential for interpretability. By explicitly learning the underlying univariate functions, it may be possible to analyze and understand the contribution of individual input features to the final output more directly. This contrasts with the "black box" nature often associated with deep neural networks, where the complex interplay of weights and fixed activation functions makes direct interpretation challenging. While still an active area of research, the theoretical framework of KANs suggests a path towards more transparent and explainable AI models, where the learned functions can reveal underlying relationships and dependencies within the data in a more intuitive manner.

IV. RESEARCH METHODOLOGY

The presented framework illustrates a comprehensive pipeline for data-driven analysis using a Kolmogorov-Arnold Network (KAN) model. It starts with the pre-processing phase where the input data is normalized and standardized to bring consistency and better the performance of the model. Subsequently, the feature extraction stage extracts features in three domains (the time domain, the frequency domain through Fast Fourier Transform (FFT), and the time-frequency domain through Discrete Wavelet Transform (DWT)). Such features are then analyzed further using a feature selection algorithm that is based on a model-based feature selection, where the feature set is fine tuned by comparing subsets in terms of the performance in the model. The chosen features are input into a Kolmogorov-Arnold Network, which is highly nonlinear with state of ability at approximating multivariate functions. Finally, the framework concludes with a performance evaluation stage to assess the model's predictive accuracy and generalization capability.

A. Dataset overview

The Cooling Fan Motor Dataset consists of raw vibration signals recorded in the time domain along three perpendicular axes—x, y, and z—capturing accelerometer outputs. As detailed in Table 2, the dataset includes five main attributes. Of these, the first two—motor speed (pctid) and operational mode (wconfid)—were combined to generate a composite used for fault classification tasks. The vibration data was initially introduced in [15], where the experimental setup involved simulating fan motor behavior. This procedure yielded a total of 153,000 data points. The dataset is publicly accessible and was sourced from [16], where it is curated to promote reproducibility and facilitate further research in the fields of fault detection and condition-based monitoring.

Table 1. The description of the fan cooling dataset

Variable Name	Feature Type	Description
wconfid	Integer	1 - normal configuration 2 - perpendicular configuration 3 - opposite configuration
pctid	Integer	Cooler Fan RPM Speed Percentage ID
x	Continuous	x value of the accelerometer
y	Continuous	y value of the accelerometer
z	Continuous	z value of the accelerometer

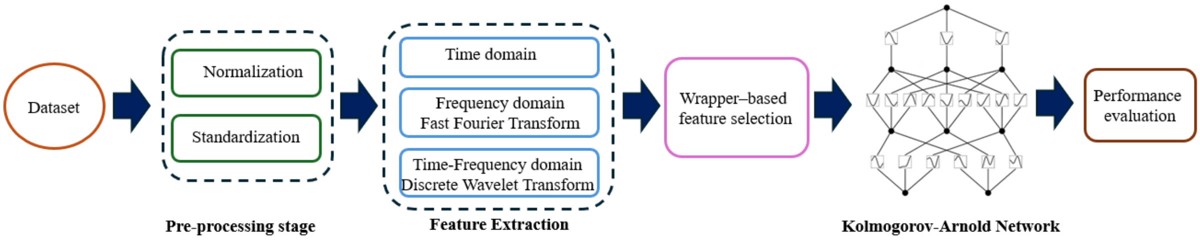

Figure 2. The proposed framework

B. Data-preprocessing

First, we normalized the raw accelerometer data using min-max scaling on each independent axis. This process rescales all values to a range between 0 and 1. This normalization is crucial because it eliminates the impact of varying absolute signal amplitudes, ensuring that all features contribute equally regardless of their original scale. It also significantly improves the numerical stability of machine learning models and helps them converge faster during training. The formula for this normalization is:

$$\boldsymbol{Normalize\ signal} = \frac{\boldsymbol{a_i - a_{minimum}}}{\boldsymbol{a_{maximum} - a_{minimum}}} \quad (9)$$

where X is the original accelerometer value, Xmin is the minimum value in that signal, and Xmax is the maximum value.

A multi-labeling strategy was developed based on two key parameters: rotational speed (pctid) and working condition (wconfid). Speed was grouped into three ranges—Low (20–45%), Medium (50–75%), and High (80–100%)—and combined with three condition labels (1, 2, 3), forming nine composite classes. Samples outside these ranges were excluded to ensure label quality.

To enrich the feature set, we calculated the standard deviation of normalized signals for each of the nine state combinations along the x, y, and z axes, generating three new features: std_x, std_y, and std_z. These capture vibration variability under different conditions and help distinguish between fault types.

C. Proposed system

1) Multi-domain Feature Extraction

To enable effective fault diagnosis of fan motors, a comprehensive feature extraction approach was employed that spans three signal domains: time, frequency, and time-frequency. The raw sensor data—collected along three axes (x, y, z)—was segmented into fixed-size windows, within which multiple statistical features were extracted

a) Time–domain

In the time domain, key descriptors such as mean, standard deviation, root mean square (RMS), skewness, kurtosis, crest factor, shape factor, entropy, and peak-to-peak value were calculated to capture the signal's statistical and dynamic behavior

b) Frequency Domain

For the frequency domain, Fast Fourier Transform (FFT) was applied to each segment, from which features like spectral mean, spectral standard deviation, spectral skewness, spectral kurtosis, spectral entropy, and harmonic power components were derived, effectively quantifying the spectral content

c) Time–Frequency Domain

In the time-frequency domain, a discrete wavelet transform (DWT) with Daubechies wavelets (db4) was used to decompose the signals into multiple resolution levels. From the resulting wavelet coefficients, statistical features such as mean, standard deviation, RMS, entropy, and energy were extracted at each level to capture transient and localized information.

2) Feature selection method

To select the most relevant features while preserving classification accuracy, a model-based feature selection method was applied using the Kolmogorov–Arnold Network (KAN). This approach embeds feature selection into training by using KAN's regularization to evaluate feature importance across combinations of lambda (sparsity control) and threshold (pruning). For each setting, the model is trained, pruned, and retained on the reduced set, and evaluated using weighted F_1-score. A Pareto optimization step identifies the best trade-offs between performance and feature count. The key parameters used in this process are listed in Table 2.

Table 2. Configuration Parameters for Feature Selection

Parameter	Value
lambda range	[0.001, 0.1]
threshold range	[0.01, 0.02, 0.05]
grid_size, grid_eps	5, 0.2
k	3
optim	"LBFGS"
epochs	80
data_split	(70, 15, 15)

3) Kolmogorov-Arnold Networks (KAN)

The final classification model used the Kolmogorov–Arnold Network (KAN), with input and output sizes matching the number of selected features and the nine fault classes, respectively. The model was configured with k = 3 for interpolation and seed = 42 for reproducibility. Training employed the L-BFGS optimizer for 80 steps with cross-entropy loss, suitable for multi-class tasks. Regularization was disabled (λ = 0.0) to retain all selected features. Custom accuracy metrics were used to monitor training and testing performance. The model configuration is shown in Table 3.

Table 3. KAN Model configuration

Parameter	Value
Width	[input_dim, output_dim]
k	3
seed	42
device	'cuda' or 'cpu'
opt	"LBFGS"
steps	80
loss_fn	CrossEntropyLoss()
lamb	0.0

V. RESULTS

A. *Analysis result of multi-domain feature extraction and feature selection method*

Table 4 lists all features extracted from vibration signals along the x, y, and z axes, grouped into time-domain, frequency-domain, and time-frequency (wavelet) categories. Time-domain features capture statistical traits like mean, standard deviation, skewness, and kurtosis. Frequency-domain features, obtained via FFT, describe spectral properties such as energy distribution and harmonic content. Time-frequency features are derived using discrete wavelet transform across four levels (0–3), offering localized time and frequency insights. Each axis yields 36 features (9 time-domain, 7 frequency-domain, 20 wavelet), totaling 108 features overall. This multi-domain feature set provides a rich representation of signal behavior, enhancing fault detection and classification performance.

Table 4. List of extracted features

Axis	Time-Domain Features	Frequency-Domain Features	Time-Frequency Domain Features (Wavelet Levels 0–3)
x	mean, std, rms, skewness, kurtosis, crest_factor, shape_factor, entropy, peak_to_peak	spectral_mean, spectral_std, spectral_skewness, spectral_kurtosis, spectral_entropy, fundamental_power, harmonic_power	wavelet_0/1/2/3: mean, std, rms, entropy, energy
y			
z			

Figure 3 shows two heatmaps illustrating how the regularization parameter λ (lambda) and threshold τ (tau) affect model performance and feature count. The left heatmap shows that the highest F_1-scores occur when λ is moderate (around 0.01–0.05) and τ is low (around 0.01). The right heatmap indicates that fewer features are retained as both λ and τ increase. These visualizations highlight the trade-off between performance and model simplicity, helping identify optimal regions that balance high accuracy with a reduced number of features.

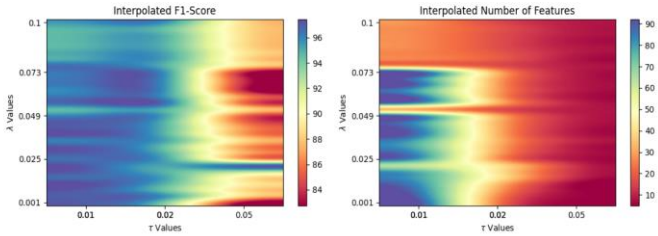

Figure 3. Heatmaps of Interpolated F_1-Score and Number of Selected Features Across λ–τ Grid

The optimal feature selection retained 82 out of 108 features, resulting in a high F_1-score of 95%. This selection was guided by two key parameters: λ = 0.011 (from the range [0.001, 0.1]) to promote sparsity, and τ = 0.010 (from {0.01, 0.02, 0.05}) to filter out low-importance features. This compact feature subset maintained strong classification performance, highlighting the effectiveness of the Pareto-based multi-objective selection strategy.

Figure 4 illustrates the trade-off between classification performance and model complexity by plotting the F_1-score against the number of retained features. Each point represents a different feature subset evaluated during the feature selection process. Orange points indicate solutions on the Pareto front, where no other solution achieves both a higher F_1-score and fewer features simultaneously. Purple points represent non-optimal configurations.

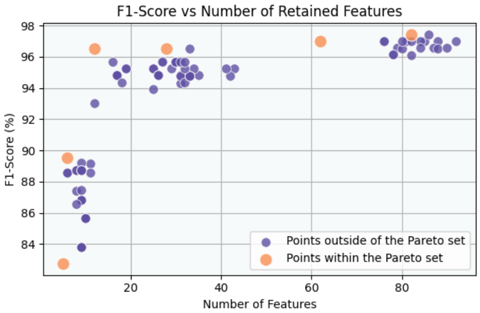

Figure 4. Trade-off Between Model Accuracy and Feature Count in Feature Selection Process

B. *Analysis result of Kolmogorov-Arnold Network (KAN)*

The final KAN model evaluation (Table 5, Figure 5) yields a macro-averaged F_1-score of 95%, with class F1-scores ranging from 87% to 100%. Classes 0-5, 8, and 9 achieve near-perfect precision and recall (96%-100%), while classes 6 and 7 show lower F_1-Scores (87%-88%). The confusion matrix confirms high accuracy, with minor overlaps between similar classes. Using 82 of 108 features, the model proves effective for fault diagnosis, with potential refinement for classes 6 and 7.

Table 5. KAN Model Evaluation

Class	Precision (%)	Recall (%)	F_1 score (%)
0	100	93	96
1	100	100	100
2	100	100	100
3	100	81	90
4	96	100	98
5	100	95	98
6	81	93	87
7	81	96	88
8	100	91	95
Macro avg (%)	**95**	**94**	**95**

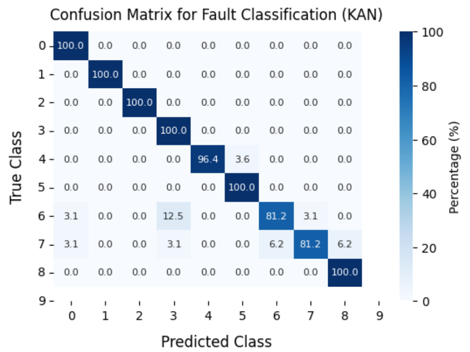

Figure 5. Confusion matrix using the KAN model

C. *Sensitivity analysis*

Table 6 presents a comparative performance analysis of the proposed model against several baseline classifiers, including Random Forest, MLP, CatBoost, and SVM. The results show that our proposed model outperforms all other methods across all evaluation metrics. It achieves the highest accuracy (95%), precision (95%), recall (94%), and F_1-score (95%), indicating strong and balanced classification performance. While RF shows competitive precision (95%) and recall (92%), its F_1-score (91%) remains lower than the proposed model. Other classifiers, such as MLP and SVM, perform significantly worse, particularly in recall and F_1-score, highlighting their limitations in capturing subtle fault patterns. These results confirm the robustness and sensitivity of the proposed method in distinguishing fault conditions.

Table 6. The performance comparison

Classifiers	Accuracy (%)	Precision (%)	Recall (%)	F_1 score (%)
Random Forest	92	95	92	91
MLP	84	83	84	83
Catboost	88	89	88	88
SVM	84	89	84	82
Our proposed model	**95**	**95**	**94**	**95**

Table 7 provides a comparative overview of recent studies in the field of fault diagnosis, highlighting the faults considered, feature extraction methods, classification models used, and resulting performance. Among the reviewed works, various approaches have been applied to different fault types such as cooler fans, rolling bearings, and power systems.

Table 7. Comparison of Recent Fault Diagnosis Methods

Model	Model	Performance
Khaled Akkad [17]	Normalized Standard deviation - Random Forest/Decision Tree	Accuracy: 95.56%
Sikder et al.[18]	Morlet Wavelet Transform – ANN/SVM	ANN: 72.9% CNN:90.3
Rafi et al. [6]	Hybrid ANN-SVM	Accuracy: 98.43%
Perumal & Meenak-shi, 2023 [7]	Logistic Regression for feature selection - SVM/Naïve Bayes/Decision Tree	Accuracy: over 90%
Vivek et al., 2024 [9]	SMOTE for handling imbalance - Decision Tree/Random Forest	Decision Tree: 88.95% Random Forest: 83.49%
Proposed Model	FFT/DWT - Model-based Feature selection - Kolmogorov	**Accuracy: 95%**

VI. CONCLUSION

This research presents a reliable and interpretable framework for diagnosing faults in cooling fan motors, integrating multi-domain signal feature extraction with the Kolmogorov–Arnold Network (KAN). By combining time, frequency, and time–frequency domain features, the model effectively captures comprehensive diagnostic information from raw vibration signals. A KAN-based wrapper feature selection technique successfully reduced the feature space while preserving high classification accuracy. The final model attained an F_1-score of 95% with only 82 features and outperformed several baseline models—including Random Forest, MLP, CatBoost, and SVM—across all key evaluation metrics. These results underscore the potential of KANs for modelling complex fault patterns with high accuracy and improved interpretability. Future work may explore further enhancements to the model's architecture and its applicability to broader and noisier industrial datasets.

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