

Proficiency of Physics Informed Machine Learning in Multi-component Fault Recognition of Rotational Machines under Different Speed Conditions

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ABSTRACT

Understanding the limitations of incorporating conventional machine learning synergy led to the inclusion of physics knowledge. This study presents the potency of physics-informed feature engineering for machine learning to enhance fault detection in gears, shafts, and bearings at three constant-speed running conditions. AI models such as Decision Tree (DT), Random Forest (RF), and Support Vector Machine-Radial Basis Function (SVM-RBF) are constructed to verify traditional statistical performance metric and physics-based signal descriptors. Additionally, time-frequency domain representation as spectrogram images is fed into the CNN-oriented ResNet-152 architecture to demonstrate the skillfulness of the model's ability. Based on the results obtained, RF is observed to be supreme with 98.42% upon applying physics-centric parameters when compared with statistical variables. To make an inference, further comparison of the best classification model's accuracy using physics expertise when accounted with ResNet image-based categorization, physics-grounded RF models have premier achievements. Thus, it is concluded that physical laws are expedient in offering exceptional outcomes for identifying various defects in complex industrial rotary machines in different operating modes.

Keywords: *Fault diagnosis, Physics-informed machine learning, CNN-based ResNet, Rotational machinery*

1. INTRODUCTION

With regard to reliable operations in rotational machines, effective fault diagnosis is perceived using AI techniques (R. Liu et al., 2018). The fault prediction of essential machine components such as bearings, gears, and shafts are distinctively performed by vibration analysis with the aid of AI-based condition monitoring (Y. Liu & Zhao, 2022). Undoubtedly, vibration signals are significantly proven in detecting the presence of component deformities in rotational machines (Praveen Kumar et al., 2024). A discovery of another perspective states that either a pure machine learning (ML) or pure physics-based method is inconvenient if there is a sparse dataset and a lack of mechanical failure knowledge. In this scenario, physics-informed machine learning (PIML) has evolved to address these issues and accurately predict faults (Deng et al., 2023). Though various existing deep learning (DL) techniques have gained optimal results, which are dependent on larger datasets, this fails to reproduce meaningful physics knowledge. This infused physics-informed concepts in the DL model for the open-accessible bearing dataset are used to attain reasonable diagnostic performance (Shen et al., 2021). Thus, the implication of physics concepts in these AI models strengthens the failure analysis in complex industrial systems.

The complexity in industrial environments, such as continuity of component degradation, the need for high maintenance, and changes in operational mode, enlarges and introduces challenges in identifying multi-component defects (Yang et al., 2022). In this concern, statistical features can be calculated for the divided samples of mechanical equipment's time-domain vibration signals to distinguish healthy and abnormal machine health status (Shukla et al.,

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2016). To increase the benefits of attaining the expedient solution in the aforementioned industrial plant issues, Xing et al. (Xing et al., 2020) have explained that the multi-component faults are detected effectively using Fast Iterative Filtering (FIF). This technique decomposes signals utilized from several components into intrinsic mode function (IMF) with the assistance of Fast Fourier Transform (FFT). A popularly known machine fault analysis, Time-Frequency representation (TFR) (Park et al., 2022), is utilized to extract valuable signal properties. Short-Time Fourier Transform (STFT) (Shi et al., 2016), Wavelet Transform (WT) (Park et al., 2019), Wigner-Ville Distribution, etc., serve to provide TFR. Zhang et al. (Zhang et al., 2021) have applied Wavelet Packet Transform (WPT) to the raw vibration signals of the wind-turbine gearbox and adopted improved residual network (ResNet) for TF feature extraction. This yields superior classification accuracy in recognizing five health states of bearings and four different faults in gears. Hertrampf et al. (Hertrampf & Oberst, 2024) have applied the integration of recurrence-based power spectra and machine learning to improve the identification of noise-contaminant non-linear signals by training its spectrogram images using ResNet-50. Thus, several elements' mechanical failures are revealed through statistical-based and TFR-based approaches in a concise manner by planning systematically. Especially, ResNet has evidently proved that TFR images via transform methods can assess the failures in rotary machines prudently.

Routinely discussed downfall in rotational machinery can be mitigated by inputting the signal's features into the developed ML models (Rameshkumar et al., 2024). The contribution of individual features is justified through the classification algorithm, and this proves the feature's efficacy (Parihar et al., 2024). For instance, statistical parameter values are extracted from vibration signals for the wind turbine blade, and further relevant attributes are selected to send as source input data into the decision tree to identify different faults in the blade which resulted in 91.67% accuracy (Joshuva. & Sugumaran., 2017). Tom et al. (Toma et al., 2020) have summarized that Decision Tree (DT) and Random Forest (RF) have gained 98% of fault classification accuracy by estimating statistical properties from motor current signals in bearings and selecting it using a Genetic Algorithm (GA). Kannan V. et al. (Kannan et al., 2023) have chosen DT, SVM, and Artificial Neural Network (ANN) for discriminating multi-variate problems using statistical metrics with linear and quadratic discriminant analysis. Nair et al. (Nair et al., 2024) have also adopted ML techniques such as SVM, DT and ANN in machining systems for machining process conditions. From the previously cited articles, classification achievement for the statistical-based derivations in categorizing multi-faults, DT, RF, and SVM models are involved. In this proposed research work, these three familiar models are utilized to check the proficiency of physics-based features in multicomponent fault recognition.

Fault characteristic frequencies (FCF) (Hou et al., 2021) give detailed information on machine elements by valuating signals using FFT. This transforms time-domain to frequency-domain, where various FCFs can be achieved. In the fault diagnosis process, the variation in amplitude at a particular a fault characteristic frequency (FCF) indicates fault exists in the corresponding component. The FCF values depend on the geometry and rotational speed of the component, which are obtained from the physics-derived equation. Very few works are attempted to utilize these physics-based features to generate a prediction model in the bearing fault diagnosis. The physics-derived domains are combined with data-driven to generate adaptive solutions for fault diagnosis (Li et al., 2023). In general, FCFs are computed to detect component faults. Selecting sub-bands around these frequencies based on known physical characteristics of bearing faults ensures that features used for fault identification are grounded in the mechanical behavior of components (Shen et al., 2021). In the proposed work, the effectiveness of these physics-based features is extended to multi-component fault diagnosis and compared with data-driven features.

From the formerly stated review, it is concluded that physics-informed feature engineering for ML techniques is proficiently resolving the constraints faced if statistical attributes are individually fed into classifiers such as DT, RF, and SVM for fault prediction. To emphasize this subject area, Convolution Neural Network (CNN)-based ResNet, as debated in the earlier topics, is also accounted for in the comparison. To promote the novelty in this current investigation, the comparative analysis of time and frequency-domain signal aspects is taken into consideration for showcasing mechanics-informed machine learning. This is taken forward with the TFR images using STFT into ResNet for reaffirming the proficiency of physics-based fault classification in this research aspect.

Feature engineering is a primary step in machine learning that includes feature creation, transformation, and extraction for enhancing the model performance. In consideration of this point, the uniqueness and main contribution of the proposed work is to illuminate the physics knowledge in the input data by extracting the FCF information of multi-component rotational machines from the frequency-domain. This is implemented to inherit the need for physics-guided parameters for recognizing machine health. Further, the influence of the planned feature engineering (FE) strategy in enriching the fault identification rate through a well-suited prediction model is emphasized. In addition, this is empowered with the comparative results of the model for different classes.

The research work methodology is explained in Section 2. Experimental setup and procedure are elaborated in Section 3. Section 4 has transparently expounded the output of fault recognition using machine learning with the aid of traditional

and physics-grounded machine learning concepts. With this continuity, as a comparative methodology, image-focused CNN classification are elucidated in Section 5. Further, results of different domain knowledge themes are inferred in Section 6. Finally, the conclusions are drawn in Section 7.

2. METHODOLOGY OF PROPOSED WORK

The intended research work involves a well-planned structure of integrating different domain attributes, and it is referred to as physics-informed ML based on the signal characteristics. The flowchart of the application of physics-derived features for the ML model is clearly depicted in Figure 1, and further CNN-ResNet is leveraged using TFR images in Figure 2 for illuminating the excellence of the planned methodology. To begin with, vibration data are collected using an accelerometer under three different speeds during machinery operation. The collected signals are then subjected to a series of preprocessing steps to prepare them for feature extraction.

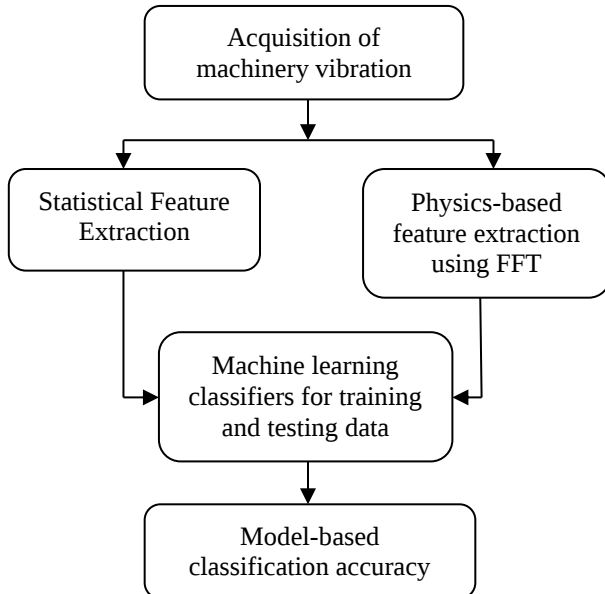


Figure 1. Flowchart of implementation of Physics-informed feature engineering for machine learning technique with the comparison of statistically-derived fault diagnosis.

In the feature extraction phase, statistical traits are derived from time-domain signals. These characteristics include mean, median, mode, minimum, maximum, sum, variance, standard deviation, skewness, and kurtosis. Simultaneously, the accrued signals are transformed from time to frequency domain using FFT. This conversion facilitates the extraction of amplitudes of fault frequencies such as Ball Spin Frequency (BSF), Ball Pass Frequency Outer Race (BPFO), Ball Pass Frequency Inner Race (BPFI), and Fundamental Train Frequency (FTF) along with shaft and gear fault frequency. The peak amplitude values at these FCF represent the physics-based information about the mechanical equipment's failure. These peak values, when paired with the

statistical characteristics, provide a rich dataset for training and testing the ML model classifiers.

In contrast to the above innovative methodology, implying CNN uplifts the noteworthiness of physics-based model classification in a transparent perception. Figure 2 exhibits the transformation of vibration signals to spectrogram images that represent the signals in the time-frequency domain. This is then further processed using ResNet architecture for image-based fault diagnosis.

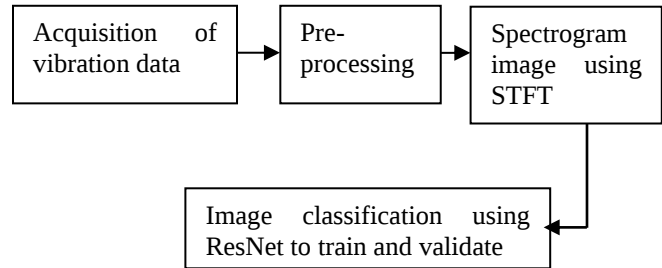


Figure 2. Time-frequency representation image classification using ResNet model

The interpretability of the significance of ML classification using physics-dependent features is deliberately explained through fault diagnostic accuracy by comparing it with the robust CNN model to ensure the safeguarded machine functions under various conditions.

3. EXPERIMENTAL SET-UP AND PROCEDURE

This sections describes the experimental arrangement to run the machine as per the operational settings. For 16 mixed defect combinations of bearings, gears, and shaft, vibration signals are acquired using accelerometer. Machine fault simulator with vibration sensor and other several critical components are enlisted in this experimental set up as shown in Fig 3.

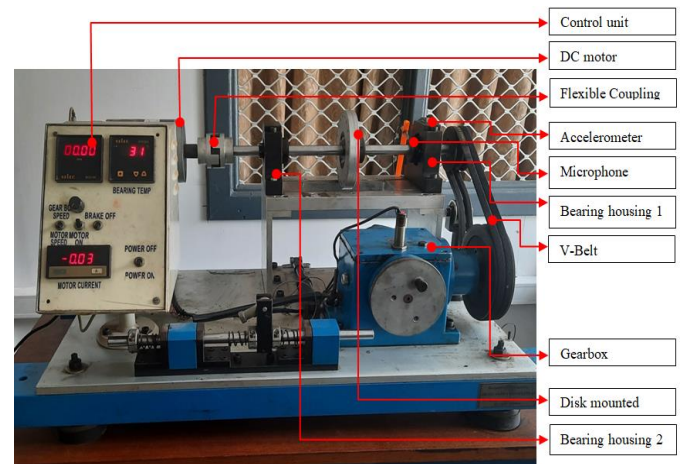


Figure 3. Fault Simulator Setup

The overall procedure begins with the rotational machinery running at a constant speed condition of 500, 750, and 1000

rpm to acquire vibration signals at the sampling rate of 8192 Hz for 100 seconds. This extensive dataset of different fault conditions is then divided into one hundred segments, with each segment containing 8192 data points. Relevant signal characteristics retrieval from each of the signal segments is executed.

The primary components considered for labeling include shaft, bearing, and gear-pinion configurations.

In each of the components, different health states are as listed below:

- a) Good gears (GG) and Faulty gears (FG)
- b) Bearings with normal (GB), Inner Race Fault (IRFB), Outer Race Fault (ORFB) and combined inner race with outer race faults (BOTHFB) as four bearing health status
- c) Shaft are of balanced (BS) and unbalanced state (UNBS)

The equipment health is portrayed in Figure 4, and it is combined in a varied mixture that is collectively totaled as sixteen fault conditions.



Figure 4. (a)



Figure 4. (b)



Figure 4. (c)

Figure 4. Different fault states of (a) Gears (b) Bearings and (c) shaft

Following this, well-suited signal behaviours are ascertained from the sensor-accumulated data in different domains and debated in the following sections to enlighten the vital objective of the investigative problem. This can be expressed differently as domain-centric features, which are retrieved from the signals acquired via sensors and fed into the ML and CNN classifiers for focusing on the impact of physics-centric parameters.

4. MACHINE LEARNING BASED FAULT DIAGNOSIS

The theory of machine learning centralizes the diagnostic model learning of correlation between features and system health states. This enhances the fault diagnostic accuracy by adaptive learning through experience without requiring manual expert knowledge (Lei et al., 2020). By utilizing this algorithm, domain-focused statistical features are fed to SVM, RF, and DT to verify the model performance as well as the efficacy of input features. Moreover, conceptual PIML technique is majorly given attention to prove its primacy over data-driven ML concepts.

4.1. Statistical feature-based ML classification

Statistical features (SF) of time series represent the underlying details of original data, thereby rendering reliable classification results (Ge & Ge, 2016). Therefore, the following attributes are quantified for sourcing into the persistently noted ML classifier models.

- 1) **Mean** is the most common measure of central tendency, which indicates the sum of all the values in a dataset divided by the number of values.

$$Mean = \frac{\sum f_x}{N} \quad (1)$$

- 2) **Median** is a measure of central tendency that is less affected by outliers and is termed median. It is a mid-value in a dataset that is sorted in ascending order.

$$Median = L_m + \left(\frac{\frac{n}{2} - F}{f_m} \right) i \quad (2)$$

- 3) **Mode** is the frequently appearing value in datapoints. In the case of signal processing, this is denoted as the most common amplitude or frequency component.

$$Mode = L + h \frac{(f_m - f_1)}{(f_m - f_1) + (f_m - f_2)} \quad (3)$$

- 4) **Sum** is defined as the total values of the dataset that signify the overall magnitude or energy of the signal.
- 5) **Maximum** is the highest value, which indicates peaks or extreme values in the signal.
- 6) **Minimum** is the lowest value indicating the troughs or lowest points in the signal.
- 7) **Variance** is the square of the standard deviation. It quantifies the amount of variation or dispersion in the dataset.

$$Variance = \frac{\sum x^2 - (\sum x)^2}{n(n-1)} \quad (4)$$

- 8) **Standard deviation** measures the dispersion or spread of the values around the mean. A low standard deviation implies that the values are close to the mean, while a high standard deviation means values are more spread out.

$$Standard\ Deviation = \sqrt{\frac{\sum x^2 - (\sum x)^2}{n(n-1)}} \quad (5)$$

- 9) **Skewness** measures the asymmetry of the probability distribution of a real-valued random variable about its mean. Positive skewness indicates that the right tail of the distribution is longer or fatter than the left tail, while negative skewness indicates the opposite.

$$Skewness = \frac{n}{(n-1)} \sum \left(\frac{x_i - \bar{x}}{s} \right)^3 \quad (6)$$

- 10) **Kurtosis** measures the tailedness of the probability distribution of a real-valued random variable. High kurtosis indicates that the distribution has a sharper peak and heavier tails than a normal distribution, while low kurtosis indicates the opposite.

$$Kurtosis = \left\{ \frac{n(n+1)}{(n-1)(n-2)(n-3)} \sum \left(\frac{x_i - \bar{x}}{s} \right)^4 \right\} - \frac{3(n-1)^2}{(n-2)(n-3)} \quad (7)$$

The above attributes are chosen to provide a detailed summary of data's distribution and variability to disclose the important properties that are associated with normal and fault modes of mechanical elements. In most of the research, these input parameters are fed to ML models such as DT, RF, and SVM that result in optimal end results. Thus, to prove the efficacy of the proposed research, the above-mentioned metrics and algorithms are chosen for further evaluation.

4.1.1. Verification of ML classifiers using Statistical Features

In this section, the exploitation of SF into recurrently pointed DT, RF, and SVM models is evaluated to recognize which of the models outperforms in fault classification. With the ten-fold cross-validation method for training and testing, better differentiation between multiple fault states is explicitly seen. Maleki et al. (Maleki et al., 2020) have clearly stated that the aim of cross-validation is to yield impartial estimation for better reproducibility and minimum generalization error.

Having k-fold cross-validation, the model can be trained and tested k times, which eventually reduces the performance measure's variance and improves model reliability. So, 10-fold cross-validation is carried out in the current work to verify the model evaluation.

The intuitive structure, interpretability, and decision-making of DT make them the best choice in yielding higher labeling precision. Popular algorithms such as Iterative Dichotomiser 3 (ID3) and C4.5, which apply different splitting criteria, are favorable for building DT to determine the optimal way to partition data (Abolhosseini et al., 2024). An important metric, information gain (IG), is measured to select the best attribute in the ID3 algorithm. Pruning improves the model's generalization ability by reducing the redundant tree sections. But without pruning, ID3 results in ineffective data handling. So C4.5, an improved version of ID3, uses gain ratio to handle missing values, overfitting, and reducing bias in multivariate attributes (Sun & Hu, 2017). The root node denotes higher-ranked features in the tree structure. In the research study, based on the above key considerations, the DT model opted to affirm its capability in harnessing statistics-derived parameters as input data with 16 labeled responses at different operating speed modes. The mean classification accuracy of 3 constant speeds has evidenced the model's efficiency in categorizing faults using SF as expressed in Table 1.

Classification accuracy (%) at each speed			Mean classification accuracy (%)
500 rpm	750 rpm	1000 rpm	89.27
89.0625	89.375	89.375	

Table 1. Fault identification accuracy of DT model at three speed states

Random Forest is an ensemble learning technique of decision trees that is used for classification as well as regression tasks (Vakharia et al., 2016). Each tree makes a binary decision, and the model response is predicted by the voting committee. This improves the model's generalization and robustness by employing the combined decision-making of multiple trees. From Table 2, this is proved by the input of SF into the RF algorithm through mean fault classification results.

Classification accuracy (%) at each speed			Mean classification accuracy (%)
500 rpm	750 rpm	1000 rpm	92.875
91.125	94.0625	93.4375	

Table 2. Fault identification accuracy of RF model at three speed modes

Support vector machine is most popular among other algorithms, where it is also employed for classification and regression applications (Y. Liu et al., 2019) as the same as

RF. The main concern in this technique is to find the hyperplane and maximize the margin for error reduction to separate binary classes (Peng et al., 2021). In the case of non-linear data separation, higher-dimensional mapping (Martínez-Morales et al., 2018) is enabled with a kernel function to solve multi-class problems (Y. Liu et al., 2019). Radial Basis Function (RBF) is chosen for the result endorsement in the SVM model using habitually addressed data-driven features.

Gaussian-RBF kernel function is expressed as

$$K(x_i - x_j) = \exp\left(-\frac{\|x_i - x_j\|^2}{2\sigma^2}\right)$$

where x_i, x_j reveals input feature vectors

$\|\cdot\|$ is a Euclidean norm, and σ conveys free parameter for determining dispersion of support vectors (Martínez-Morales et al., 2018).

Accuracy (%) at each speed			Mean classification accuracy (%)
500 rpm	750 rpm	1000 rpm	83.33
86.88	84.06	79.06	

Table 3. Fault grouping analysis results of SVM-RBF under three speed scenarios

As validated results obtained using DT and RF in Tables 1 and 2, the acclaimed SVM is also endorsed to show its computational ability in discerning varied machine operational states as illustrated in Table 3. As inferred from Tables 1, 2, and 3, the mean fault detection accuracy of RF is 92.875%, which is superior to DT and SVM.

Although SVM is effective in classifying multiple classes using RBF, its performance declines when statistical features of vibration signals are used as input. This shortcoming motivated efforts to enhance the results of standard classification algorithms by integrating physical principles, emphasizing the importance of the key objective discussed in the next section.

4.2. Physics-Informed Feature Engineering for ML classification

The imperative physics knowledge is the fundamental of the ML technique followed by physics-validated metrics, which

Component fault frequencies	Frequency in Hz		
	500 rpm	750 rpm	1000 rpm
FTF	3.3	5	6.6
BSF	19.2	28.9	38.6
BPFO	29.6	44.6	59.6
BPFI	45.1	67.9	90.7
SHAFT	8.33	12.5	16.7
GEAR	4.16	6.25	8.33
PINION	5.833	8.75	11.66
GEAR MESH	145.6	218.75	291.55

Table 4. Defect frequencies of machinery components at each speed

spotlights the system failure processes and quantifies algebraic and governing equations from physics law. Thus, by establishing a physics-guided evaluation model requiring prior knowledge, it offers an advantageous effect in identifying complex system health in condition monitoring (Deng et al., 2023). This prompts us to decide which of the component's characteristic frequencies are assessed.

Bearing Fault Characteristics Frequency (FCF) is formulated in accord with shaft speed (rpm) with the specifications such as ball/roller diameter (d) in mm, number of balls (N_b), bearing pitch diameter (D_m), contact angle (θ) in degrees as listed in the equations below:

$$\text{Ball pass frequency outer (BPFO)} = \text{RPM} \frac{N_b}{2} \left(1 + \frac{d}{D_m} \cos \theta\right)$$

$$\text{Ball Pass Frequency Inner (BPFI)} = \text{RPM} \frac{N_b}{2} \left(1 - \frac{d}{D_m} \cos \theta\right)$$

$$\text{Ball Spin Frequency (BSF)} = \text{RPM} \frac{D_m}{d} \left[1 - \left(\frac{d}{D_m} \cos \theta\right)^2\right]$$

$$\text{Fundamental Train Frequency (FTF)} = \text{PM} \frac{1}{2} \left[1 - \frac{d}{D_m} \cos \theta\right]$$

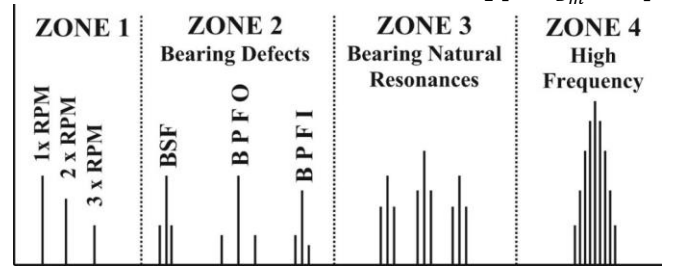


Figure 5. Bearing fault characteristic frequencies in frequency zone 2 of spectrum plot (Attoui et al., 2017)

This is realizable by transforming raw time-domain to frequency-domain representation, where it gives a detailed description of fault existence. These faulty bearing elements are revealed in zone 2, which contains bearing fault characteristic frequencies (Attoui et al., 2017). In this context, fault presence in bearings is deliberately depicted as shown in Figure 5.

In addition to bearings, the calculations for shaft, gear, pinions, and gear mesh frequencies derived from FFT at 500, 750, and 1000 RPM are enumerated in Table 4. Considering these FCFs of vibration signals, the features with labels are provided as an input to the ML models. The results will be detailed in the following subsection.

4.2.1. Verification of ML technique using physics-rooted features

An inspection of model potentiality is clearly rendered in this section by incorporating physics-guided attributes and validating the impact of the proposed approach. Machine learning classifier models using SF, as discussed in the

previous section, show slightly lower performance in DT and SVM compared to RF. To empower the model effect, physics-grounded parameters are valued in this context. The exceptional results are obtained for all the strategized models, as witnessed in Table 5.

It is distinctly reconfirmed that RF is performing way better than other models, achieving an accuracy of 98.42%. Notably, DT and SVM-RBF also show significant improvement, reaching accuracies above 94% compared to the results using SF. At 1000 rpm, the RF model attains an exemplary result of 99.69%. To closely analyze the individual fault classes, the confusion matrices of these 3 ML models using physics-based features are generated at this speed, as shown in Tables 6, 7, and 8.

Model	Frequency in Hz			Mean classification accuracy (%)
	500 rpm	750 rpm	1000 rpm	
DT	93.125	93.125	96.5625	94.27
RF	96.8125	98.75	99.6875	98.42
SVM-RBF	95.62	97.19	90.94	94.58

Table 5. Fault identification accuracy using physics-oriented features at three different speed modes

True Class	FGBSBOTHFB	100															
	FGBSGB		92.3														
	FGBSIRFB			92.3													
	FGBSORFB				100			19									
	FGUNSBOTHFB					77.1											
	FGUNBSGB		7.7				100										
	FGUNBSIRFB			7.7				100									
	FGUNBSORFB					22.9			91								
	GGBSBOTHFB									100							
	GGBSGB										100						
	GGBSIRFB											100					
	GGBSORFB												100				
	GGUNSBOTHFB													100			7.7
	GGUNBSGB														100		
	GGUNBSIRFB															100	
	GGUNBSORFB																92.33
PPV		100	92.3	92.3	100	77.1	100	100	91	100	100	100	100	100	100	100	92.3
FDR			7.7	7.7		22.9			19								7.7
		FGBSBOTHFB	FGBSGB	FGBSIRFB	FGBSORFB	FGUNSBOTHFB	FGUNBSGB	FGUNBSIRFB	FGUNBSORFB	GGBSBOTHFB	GGBSGB	GGBSIRFB	GGBSORFB	GGUNSBOTHFB	GGUNBSGB	GGUNBSIRFB	GGUNBSORFB
		Predicted Class															

Table 6. Confusion matrix of DT algorithm under 1000 rpm

Table 7 clearly shows that RF achieves the best results for all machine health conditions in the speed operational mode at 1000 rpm, regardless of overall accuracy. Therefore, this prediction table is used for result comparison. Though SVM-RBF has furnished a good classification accuracy of 90.94%, the positive prediction value (PPV) for FGBSBOTHFB, FGUNBSIRFB, FGUNBSORFB, GGBSBOTHFB,

GGBSGB, and GGUNSBOTHFB is below 90% as featured in Table 8. Among these six fault states, GGUNSBOTHFB representing a combined health state of an unbalanced shaft with both an inner race and an outer race faulty bearing, along with a good gear has the lowest PPV at 77.95%. This expresses the issue of class imbalance, indicating the model's difficulty in generalizing specific fault states effectively. The

lowest PPV value in DT confusion matrix is 77.1% for the fault state ‘fault gear unbalanced shaft both inner race and outer fault bearing’ (FGUNBSBOTHFB), as noticed in Table 6. However, in the case of SVM-RBF and RF, this fault state is correctly classified with 97.5%, and 91.35%, as stated in

Table 7 and Table 8, respectively. This intricate observation further revalidates the effectiveness of RF, which leverages physics-centric feature engineering, over other ML algorithms.

True Class	FGBSBOTHFB	100														
	FGBSGB		100													
	FGBSIRFB			100												
	FGBSORFB				100											
	FGUNBSBOTHFB					97.5										
	FGUNBSGB						100									
	FGUNBSIRFB							100								
	FGUNBSORFB					2.5			100							
	GGBSBOTHFB									100						
	GGBSGB										100					
	GGBSIRFB											100				
	GGBSORFB												100			
	GGUNBSBOTHFB													100		2.5
	GGUNBSGB														100	
	GGUNBSIRFB															100
	GGUNBSORFB															97.5
PPV	100	100	100	100	97.5	100	100	100	100	100	100	100	100	100	100	97.5
FDR					2.5											2.5
	FGBSBOTHFB	FGBSGB	FGBSIRFB	FGBSORFB	FGUNBSBOTHFB	FGUNBSGB	FGUNBSIRFB	FGUNBSORFB	GGBSBOTHFB	GGBSGB	GGBSIRFB	GGBSORFB	GGUNBSBOTHFB	GGUNBSGB	GGUNBSIRFB	GGUNBSORFB
	Predicted Class															

Table 7. Confusion matrix of RF algorithm under 1000 rpm

True Class	FGBSBOTHFB	87.4			2.5	2.4			2.3								
	FGBSGB	3.4	95.25				6.55										
	FGBSIRFB			100				10									
	FGBSORFB	2.4			91.45	1.45			2.3								
	FGUNBSBOTHFB	3.4			2.5	91.35		4.55	4.75								
	FGUNBSGB		4.75		3.55	2.4	90.45		3.5								
	FGUNBSIRFB							85.45									
	FGUNBSORFB	3.4				2.4	3		88.3								
	GGBSBOTHFB									81.05				10.55			5.05
	GGBSGB										81						
	GGBSIRFB										4.2	100					
	GGBSORFB										8.3		100				
	GGUNBSBOTHF									11.1				77.95			
	GGUNBSGB										2.3				100		
	GGUNBSIRFB										4.2					92.65	
	GGUNBSORFB									9.95					11.5		94.95
PPV	87.4	95.25	100	91.45	91.35	90.45	85.45	88.3	78.95	81	100	100	77.95	100	92.65	94.95	
FDR	12.6	4.75		8.55	8.65	9.55	14.55	11.7	21.05	19			22.05		7.35	5.05	
	FGBSBOTHFB	FGBSGB	FGBSIRFB	FGBSORFB	FGUNBSBOTHFB	FGUNBSGB	FGUNBSIRFB	FGUNBSORFB	GGBSBOTHFB	GGBSGB	GGBSIRFB	GGBSORFB	GGUNBSBOTHFB	GGUNBSGB	GGUNBSIRFB	GGUNBSORFB	
	Predicted Class																

Table 8. Confusion matrix of SVM-RBF algorithm under 1000 rpm

This can be intriguing to corroborate the essence of entailing the physics-driven perspective by evaluating it against other noted strategies, image-based classification using powerful CNN architecture.

5. TIME-FREQUENCY REPRESENTATION IMAGE-BASED FAULT DIAGNOSIS USING CNN

In this study, raw time-domain vibration signals are transformed to TFR using STFT and fed into a wisely chosen CNN structure. But initially, systematically segmented vibration data with 8192 Hz for each second are formulated using this transform method. Further labeling 100 spectrogram images and giving whole 16-class image folders into the ResNet architecture, it organizes the diverse fault conditions. This can be illustrated for a good gear balanced shaft good bearing (GGBSGB) at 500 rpm in Figure 6.

The primary reason for choosing ResNet is because of its residual learning ability using residual blocks. These blocks allow the network to bypass one or more layers using shortcut connections, which helps in mitigating the vanishing gradient problem. This improvement enables the training of much deeper networks, up to 152 layers, without the degradation issues that typically arise in very deep architectures. As a

result, ResNet can learn more complex features and hierarchical representations, leading to better performance on tasks like image classification and object detection. This ResNet-152 performance is appreciated for improved generalization capabilities, making ResNet more robust to overfitting and better suited for handling diverse datasets.

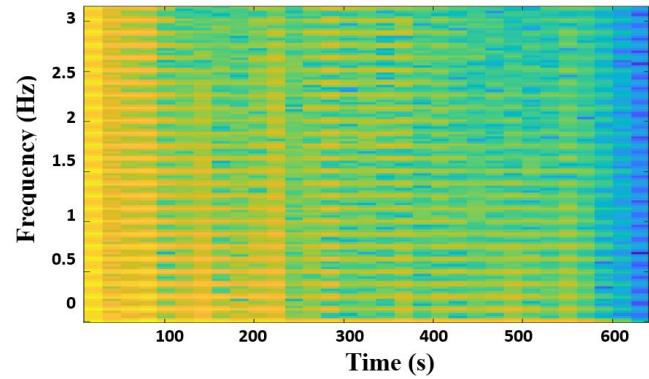


Figure 6. Spectrogram image of GGBSGB at speed of 500 rpm
The validation accuracy for vibration data at different speed using ResNet are observed in Table 9.

Frequency in Hz			Mean classification accuracy (%)
500 rpm	750 rpm	1000 rpm	
91.46	86.88	87.5	88.61

Table 9. Fault identification accuracy of ResNet under three speed condition

True Class	FGBSBOTHFB	84.88														
	FGBSGB		92.73				6.26									
	FGBSIRFB			100												
	FGBSORFB				94.45											
	FGUNBSBOTHFB				5.55	100	4.70	18.92								
	FGUNBSGB						74.78	18.85								
	FGUNBSIRFB						14.25	62.23								
	FGUNBSORFB	15.12	7.27						100							
	GGBSBOTHFB									100						7.24
	GGBSGB										100					
	GGBSIRFB											90.83				
	GGBSORFB												100		27.52	
	GGUNBSBOTHFB													77		32
	GGUNBSGB											9.17			90	
	GGUNBSIRFB														10	72.48
	GGUNBSORFB													23		60.76
PPV	84.88	92.73	100	94.45	100	74.78	62.23	100	100	100	90.83	100	77	90	72.48	60.76
FDR	15.12	7.27		5.55		25.22	37.77				9.17		23	10	27.52	39.24
	FGBSBOTHFB	FGBSGB	FGBSIRFB	FGBSORFB	FGUNBSBOTHFB	FGUNBSGB	FGUNBSIRFB	FGUNBSORFB	GGBSBOTHFB	GGBSGB	GGBSIRFB	GGBSORFB	GGUNBSBOTHFB	GGUNBSGB	GGUNBSIRFB	GGUNBSORFB
	Predicted Class															

Table 10. Confusion matrix of CNN-ResNet under 1000 rpm

Compared with the other two speed conditions, fault recognition accuracy at 500 rpm is estimated to be 91.46% using CNN-ResNet. But overall accuracy is determined with 88.61% fault identification, which is reasonable.

The outstanding results of RF at a consistently referred speed rate of 1000 rpm are factored in comparison with other feasible algorithms. In this view, the contingency matrix of ResNet is robustly analyzed for the same operating condition to concisely examine each health state, which is exhibited in Table 10.

Across all the domain-reliant features and image-dependent differentiating the multi-class fault modes, comparative scrutinization is required to check the dominance of the PIML technique. Thus, this is presented concisely in the following section.

6. RESULTS AND DISCUSSION

From the previous sections, results of each domain-centric feature and image-focused anomaly classification are discussed to highlight the significance of the ML approach in accordance with physical knowledge. The inclusion of domain knowledge markedly improved the performance of all classifiers. Specifically, the physics-enabled ML models are recognized as having a higher mean classification accuracy of all three classifiers than the diagnostic result of utilizing statistics-constrained machine learning, as illustrated in Figure 7.

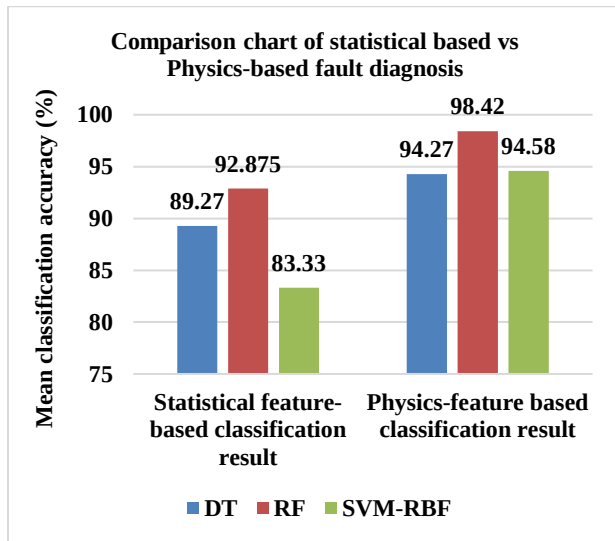


Figure 7. Comparison of Fault identification accuracy using statistical and physics-based features

Indeed, the best classifying model is found to be RF, which seems to be superior to other models in terms of both the features. Remarkably, this model has drastically accomplished 98.42% when physics-driven features are deployed as input attributes. Also, SVM-RBF has earned 94.58% better prediction ability when physical knowledge is

included, which is slightly higher than DT. This seems to be rapid improvement in classification accuracy when compared with the data-driven statistical features. In this aspect, the physics-integrated ML basis is substantially agreed to be influential.

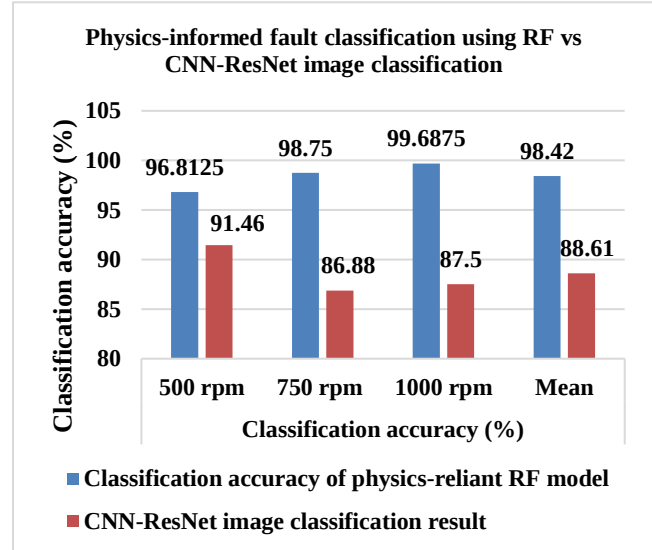


Figure 8. Comparative review of physics-embedded RF algorithm vs CNN-reliant ResNet image categorization results

In other comparative cases, physics-involved fault classification using RF techniques vs. CNN-based ResNet image classifier results are envisioned in Figure 8. This is clearly outspoken that the physics-assisted RF algorithm excels at different constant speed rates. The overall mean accuracy of physics-dependent RF is admirably domineering when judged with the results of CNN-ResNet.

To spotlight the essentiality of inheriting physical knowledge to classify multiple faults, minor misclassification results of the RF model are taken into account for reaffirmation. In this regard, two classes, such as FGUNBSBOTHFB and good gear with an unbalanced shaft and outer race faulty bearing (GGUNBSORFB) health state, are found to be yielding a PPV of 97.5%, where the remaining fault states have scored 100%. Thus, the values of FGUNBSBOTHFB and GGUNBSORFB in RF are compared against DT, SVM-RBF, and CNN-ResNet as spotted in Table 11.

Model	Positive predicted value (PPV)%	
	FGUNBSBOTHFB	GGUNBSORFB
RF	97.5	97.5
DT	77.1	92.3
SVM-RBF	91.35	94.95
CNN-ResNet	100	60.76

Table 11. Comparison of RF with DT, SVM-RBF and CNN-ResNet based on two specific fault class.

Though PPV of ResNet for FGUNBSBOTHFB attains 100%, it yields poor results for GGUNBSORFB. But with further comparison of these two classes for other models, RF is recognized to be producing remarkable results with 97.5%. Balanced consistency across classes is highly indicative in the physics-involved RF model, which combines predictions from multiple decision trees. This ML technique captures feature nuances that DT or SVM-RBF might miss. CNN-ResNet's performance disparity is due to overfitting issues and potential data imbalance.

Thus, the conceptual physics-rooted predictive model is reliably acknowledged by comparatively analyzing it with data-derived statistical concepts and image-focused CNN perception. This re-establishment of well-planned research work upholds its standardization in entailing physics for elevating the model's performance to discern multi-component faults of rotational machines.

7. CONCLUSION

The core research of diagnosing the multi-fault classes of rotational machinery under three different speed operating scenarios is successfully attained by unveiling the exceptional effect of the physics-informed model concept. This is featured in a succinct path, where statistically enabled derivative models are considered to prove the benchmarking quality of physics-involved ML models. In addition, the efficiency of CNN-enabled ResNet using TFR image datasets is assessed against this ideal technique.

In this cognition, primarily, data-derived statistical aspects are evaluated for the models such as DT, RF, and SVM-RBF, where RF models are discovered to be higher ranked with 92.875% accuracy. Further, the involvement of physics-oriented features in these ML algorithms is also verified, which delivers promising output for all the classifiers. Here again, RF is remarkably effective, rendering an accuracy of 98.42%, a result higher than DT and SVM-RBF. To ensure the capability of this physics-validated feature engineering for machine learning, the TFR image-based CNN ResNet classifier is opted to validate the end results. This again reaffirms that physics-guided metrics in ML concepts are feasibly top-scoring in all aspects. Rigorous inspection of each health state of rotational machinery reveals how well a model categorizes. In this aspect, RF at 1000 rpm is regarded to be outranked, and its supremacy is conveyed through the prediction matrix compared with SVM-RBF and DT.

Besides the overview of all the quantitative results, chart-based comparison and contrast fosters a profound understanding of the novel approach. Thus, differentiating multi-component fault classes using statistical descriptors and physical law-augmented learning is taken into account for emphasizing the model as well as domain-based implications. In this context, the satisfactory result of the physics-driven RF model makes it superior to the traditional ML process. This is taken forward with the analysis of the

image classifier, ResNet of CNN, which is found to be less effective than physics-involved model classification. Further, FGUNBSBOTHFB and GGUNBSORFB of exceptional RF model's performance for the constant speed rate of 1000 rpm are keenly observed to be slightly misclassified. When this is compared with ResNet-152 in accordance with the contingency table, the superiority of physics-modeled attributes for fault discernment using RF is evident.

In various research outlooks, the proficiency of planned research work in the physics domain of knowledge is admirably proven. Thus, the prediction of multi-component defects is factored into this mechanics-guided AI scenario and successfully verified under three running conditions of constant speeds in a rotational machine. Future studies can be explored in this subject area in complex environmental settings such as varying speed and load in complex industrial machines.

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