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Comparative Study on Deep Learning Models for Bearing Fault Diagnosis

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***Abstract*—Fault diagnosing of bearings generally depends upon vibrating signals and a group of features will be derived for classifying the faults. A particular feature portrays only a single characteristic of vibration signals. As a result, a lot of works merge more than a single feature to enhance the performances of fault diagnosing. This work mostly aims on proposing a new Bearing Fault Diagnosis model, where, "Empirical Wavelet Transform (EWT), Empirical Mode Decomposition (EMD) and Wavelet Transform (WT) based features" are extracted at first. Further, these extracted features are classified via Quantum Neural Network (QNN), where the weights are tuned optimally by Whale with Modified Update Evaluation (WMUE). At the end, the supreme performance of the adopted model is proven by comparing different deep learning models.**

***Index Terms*— Fault diagnosis; EWT feature; WT feature; QNN classifier; WOA Model.**

Nomenclature

Abbreviation	Description
ALIFD	Adaptive Local Iterative Filtering Decomposition
AM	Amplitude Modulation
CWSS	Continuous Wavelet Scale Spectrum
CWRU	Case Western Reserve University
CNN	Convolutional Neural Network
DCNN	Deep CNN
DA	Dragonfly Algorithm
DBN	Deep Belief Network
EWT	Empirical Wavelet Transform
EDM	Electro-Discharge Machining
EMD	Empirical Mode Decomposition
IMFs	Intrinsic Mode Functions
FrHT	Fractional Hilbert Transform
FM	Frequency Modulation
FDR	False Discovery Rate

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FNR	False Negative Rate
FPR	False Positive Rate
GWO	Grey Wolf Optimization
LSTM	Long Short Term Memory
MSE	Mean Square Error
MCP	Multistage Centrifugal Pump
MBO	Monarch Butterfly Optimization
MFO	Moth Flame Optimization
MCC	Matthews Correlation Coefficient
MIFBs	Most Impulsive Frequency Bands
NPV	Net Predictive Value
PSO	Particle Swarm Optimization
QNN	Quantum Neural Network
RNN	Recurrent NN
STFT	Short-Time Fourier Transform
SVM	Support Vector Machine
TKEO	Teager–Kaiser Energy Operator
WOA	Whale Optimization
WMUE	Whale with Modified Update Evaluation
WT	Wavelet Transform

I. INTRODUCTION

Rotating machinery is a significant tool in the manufacturing and could be seen in most industrialized sectors. Scrutinizing of the machinery is a essential function for ensuring the usual function of the manufacture line [1] [2]. The major failure in rotating machineries are owing to rolling bearing and therefore, the analysis of bearing errors is significant in maintenance and attracted the consideration of a lot of analysts [3] [4] [5]. There are constantly the non-stationary and nonlinear features and combined with various multifaceted FM and AM signals in vibrated signals of rolling element bearing while there were limited errors in those bearing [6] [7].

For extracting the features in rolling bearing fault vibration waveform, currently, the time frequency study depending upon signal decomposition is extensively deployed [8] [9]. But it is essential for the investigation techniques to be stable, adaptive and local, time frequency study for non-stationary and nonlinear signals is extremely demanding. Widespread time frequency studies techniques consist of the WT, EMD, STFT etc [10] [7].

Even though the above said techniques are effectual and easier to executed, those have various limits. STFT is much appropriate for stationary or periodic linear system, and it could not deal with nonlinear signals or non-stationary systems [11] [12]. WT is moreover a linear examination tool and require being pre-determined basis operations, while it is not modeled to be information adaptive. EMD acts as a non-stationary and nonlinear signal study technique that do not require to be pre-determined basis operations and include the adaptability and completeness orthogonality and, consequently it is extensively deployed in error analysis of rolling bearings [13] [14]. However this technique also has limits, such as mode integration, partial envelope and conclusion effects [15][7].

The contribution is listed below:

- Presents a new fault diagnosis model, where the QNN weights are optimized via WMUE model.

Here, Section II reviews the conventional works on this topic. Section III proposed bearing fault diagnosis approach. Section IV elucidates extraction of WT, EWT and EMD features. Section V delineates WMUE based QNN optimization. The results and conclusion are in Section VI and VII.

II. LITERATURE REVIEW

A. Related works

In 2020, Zhang *et al*. [16] proposed a fault diagnosing technique depending upon CNN for the weaker vibration waveform of casing under rolling fault bearing excitation. Initially, the processing technique of vibration waveform was analysed. During analysis and comparison, it was said that fault characters of rolling bearing were more simply articulated by CWSS, and an improved identification rate was attained. In conclusion, the experimentation was done with an “aero engine rotor tester with a casing”, and the technique depending upon WSS and CNN was utilized for analysis.

In 2020, Attoui *et al*. [17] made an effectual analysis concerning the rolling element bearing faults and proposed new produced features, which could sustain the substantial connotation of derived vibration signal, whilst recognizing its association to damages in rolling bearing. For this principle, MIFBs of calculated vibrating signals for a lot of bearing situations were proposed with 33 feature constraints. By means of a wrapper method, these constraints were decreased till a group of them were found enhancing the effectiveness of the analytic scheme.
In 2019, Zhao *et al*. [7] united TKEO with ALIFD for fault diagnosis on rolling element bearing. This experimentation provided access to bear test data for defective bearing, and acceleration information was computed at positions close to bearings. The resultants has shown that this technique can be deployed for precisely take out dissimilar frequency elements of fault vibration bearing signals and make a diagnosis on fault positions.
In 2018, Abdel kader *et al*. [5] proposed an improvement of rolling bearing fault analysis depending upon development of EMD denoising technique. This technique was done for extracting the constructive faulty signal for using the recognition indicators like envelope spectrum and kurtosis. Initially, EMD was deployed to vibration signals for obtaining a sequence of tasks termed as IMFs. Subsequently, a scheme depending upon energy content of every mode was presented for determining the trip point that allowed electing the pertinent modes. Lastly, the spectral envelope and kurtosis study were examined for earlier localization and detection of fault location.
In 2018, Jahagirdar *et al.* [18] explored the appliance of FrHT for diagnosing bearing faults. Although current publication portrayed the usage of FrHT and showed that kurtosis varied considerably. Here, the usage of PSO was proposed for maximizing the kurtosis and obtain a improved FrHT performance for diagnosing bearing faults. Simulated resultants showed enhancement of kurtosis over other transforms. Bearing error sizes of 21, 14 and 7mil were more distinguishable by means of adopted technique over conservative models.

III. Proposed Bearing Fault Diagnosis Approach

The developed fault diagnosing model covers 2 principal phases namely: **"**Feature extraction and Classification". At first, the features like WT $\left(fe_{WT}\right)$, EMD $\left(fe_{EMD}\right)$ as well as EWT $\left(fe_{EWT}\right)$ are derived from data. These derived features are then classified via optimized QNN. Further, the weights of QNN are optimized via WMUE model that aids in identifying the faults in an exact manner. Fig. 1 demonstrates the portrait of presented model.

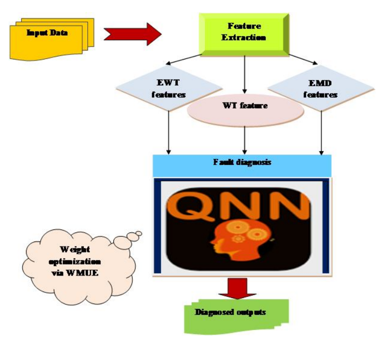


Fig 1. Architecture of proposed model

IV. Extraction Of WT, EWT and EMD Features

At first, features like WT, EMD and EWT features are derived.

A. EMD features

EMD [19] is an adaptive time-space analysis method suitable for processing series that are non-stationary and non-linear. It decomposes a multifaceted signal to a group of IMFs devoid of the knowledge from higher to lower frequency by means of shifting procedure. It is calculated as in Eq. (1). Here, $c_i(t)$ signifies i^{th} IMP and $r_n(t)$ signifies residual signal $s(t)$.

$$fe_{EMD} = s(t) = \sum_{i=1}^{n} c_i(t) + r_n(t) \tag{1}$$

IMF satisfies 2 states.

(a) The count of zero crossing and extrema is equal or could differ by 1 in dataset.

(b) "The mean value of moving envelop is defined by local maxima and envelop defined by local minima are zero at any point".

The derived EMD features are represented as fe_{EMD} .

B. EWT features

EWT [19] aims to decompose a signal on wavelet tight frames. It attains adaptive wavelet to extract and identify AM-FM factors. Here, the chief plan is to gain the signal modes with a proper wavelet filter bank. It is calculated as in Eq. (2).

$$U_f^E(n,t) = \langle f, \psi_n \rangle = \int f(\tau)\overline{\psi_n(\tau - t)}d\tau \quad (2)$$

The approximate coefficient $U_f^E(o,t)$ is calculated as in Eq. (3).

$$U_f^E(o,t) = \langle f, \phi_1 \rangle = \int f(\tau)\overline{\phi_1(\tau - t)}d\tau \quad (3)$$

The reconstructed signal and empirical modes are shown as in Eq. (4).

$$f(t) = U_f^E(o,t) * \phi(t) = \langle f, \phi_1 \rangle + \sum_{n=1}^{N} U_f^E(n,t) * \psi_n(t) \quad (4)$$

$$f_o(t) = U_f^E(o,t) * \phi(t) \quad (5)$$

$$fe_{EWT} = f_k(t) = U_f^E(k,t) * \psi_k(t) \quad (6)$$

The derived EWT features are represented as fe_{EWT} .

C. WT features

"A WT [19] is the decomposition of a signal into a set of basic functions consisting of contractions, expansions, and translations of a mother function called the wavelet". For deriving frequency factors, it deploys mother wavelets. It is calculated as in Eq. (7), wherein, x signifies compound conjugate sign and ψ signifies function randomly chosen by abiding certain rules.

$$fe_{WT} = C(p,q) = \int_{-\infty}^{+\infty} c(x)\psi^*_{(p,q)}(x)dx \quad (7)$$

The derived WT features are represented as fe_{WT} .

Accordingly, these EMD, WT and EWT features jointly denoted by fe $\left(fe = fe_{EMD} + fe_{WT} + fe_{EWT}\right)$ is provided as input to optimized QNN for classification.

V. WMUE Based QNN Optimization For Bearing Fault Diagnosis

A. Optimized QNN

The QNN has 3 significant layers [20]: "inputs, 1 hidden units, & output layer, respectively and a multi-level activation function is deployed rather than the normal activation function". The sigmoid function is agitated with the quantum variation is obtainable in all multi-level functions that is represented as N_s and for quantum level r , the quantum period is represented as φ^r . In scientific, the sigmoid function is portrayed as in Eq. (8). The QNN weight is indicated by W .

$$sgm(out) = \frac{1}{N_s}\sum_{r=1}^{N_s}\left(\frac{1}{1+\exp(-out \pm \varphi^r)}\right) \quad (8)$$

The QNN is the perfect decision maker, and it tells about presence / absence of attacker. The detecting error of QNN is portrayed for lower MSE, which results in maximal accuracy.

B. Solution Encoding

The weights of QNN W are optimally tuned via a new WMUE scheme. The solution given as input to WMUE method is exposed in Fig. 2, in which, u stand for entire weight count. Furthermore, the objective Obj is shown in Eq. (9), in which Acc denote accuracy.

$$Obj = \frac{1}{Loss} = Max(Acc) \tag{9}$$

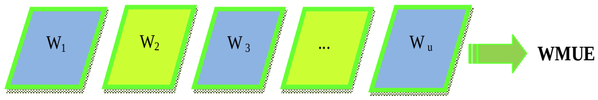


Fig 2. Solution encoding

Due to certain limits of WOA, a new WMUE model is developed here [21] [22]. Generally, self-enhancement is better in conservative optimization models.

The whales find their victim position and surround them. Meantime, the other whales update their location for improved search as shown in Eq. (10) and (11), here t → present iteration, and S^* → position vectors of necessary solutions, $|\ |$ → absolute value, S →location vector, and '·' → "element-by-element multiplication".

$$\vec{P} = \left|\vec{E}.\vec{S}^*(t) - \vec{S}(t)\right| \tag{10}$$

$$\vec{S}(t+1) = \vec{S}^*(t) - \vec{J}.\vec{P} \tag{11}$$

The coefficients J and A are calculated as in Eq. (12) and Eq. (13), wherein, $\vec{r}$ → arbitrary vector in [0, 1] and $\vec{y}$ → random integer amid 2 to 0.

$$\vec{J} = 2y.\vec{r} - \vec{y} \tag{12}$$

$$\vec{A} = 2.\vec{r} \tag{13}$$

$$\vec{y} = 2 - 2\log\left((e-1)\frac{t}{ma(t)} + 1\right) \tag{14}$$

Exploitation phase: This procedure is exposed in Eq. (15), wherein, $P^{\vec{'}} = \left|\vec{S}^*(t) - \vec{S}(t)\right|$ → distance amid whale and prey, l → arbitrary integer, b → "shape of logarithmic spiral" and $ma(t)$ → higher iteration.

$$\vec{S}(it+1) = \vec{P}'.e^{bl}.Cos(2\pi l) + \vec{S}^*(t) \tag{15}$$

$$\vec{S}(it+1) = w(t) * \vec{P}'.e^{bl}.Cos(2\pi l) + \vec{S}^*(t) \tag{16}$$

$$w(t) = 2\cos\left(\frac{\pi}{2} \times \frac{t}{ma(t)}\right) - 1 \tag{17}$$

Eq. (38) shows the spiral position of whales as per arbitrary numeral p.

$$S(t+1) = \begin{cases} S^*(t) - J.P & if\ \ p < 0.5 \\ \vec{P}'.e^{bl}.Cos(2\pi l) + \vec{S}^*(t) & if\ \ p > 0.5 \end{cases}$$

Exploration phase: It is modelled as in Eq. (27) and (28), wherein, $\vec{S}_{rand}$ → random whale chosen from current populace.

$$\vec{P} = \left|\vec{A}.\vec{S}_{rand} - \vec{S}\right| \tag{27}$$

$$\vec{S}(it+1) = \vec{S}_{rand} - \vec{J}.\vec{P} \tag{28}$$

VI. Results and Discussions

A. Simulation procedure

The deployed model to find fault in bearings using WMUE was done in "MATLAB". The dataset was gathered from "CWRU and MCP were denoted as dataset 1 and 2 respectively" in description part. The deployed model of adopted technique was proven over SVM, DBN, DCNN, LSTM and RNN. Furthermore, the LRs were varied from 60, 70, 80 and 90.

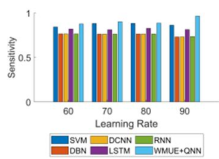
"Dataset description:

Case Western Reserve University: This website provides access to ball bearing test data for normal and faulty bearings. Experiments were conducted using a 2 hp Reliance Electric motor, and acceleration data was measured at locations near to and remote from the motor bearings. Faults ranging from 0.007 inches in diameter to 0.040 inches in diameter were introduced separately at the inner raceway, rolling element (i.e. ball) and outer raceway.

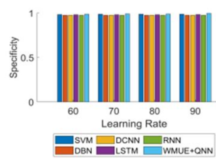
Multistage Centrifugal Pump: The impressive new CR 255 is now available, completing the CR range and continuing to move limits with a flow range up to 320m3/h. After the last big addition of the CR 185 and CR 215 pumps – with a flow range capacity up to 240 m3/h and 280m3/h respectively – we continue to push the boundaries with this strong addition to the world's most modular pump range.

B. Performance Analysis

The performances of WMUE scheme for finding faults in bearings is evaluated over SVM, DBN, DCNN, LSTM and RNN for several metrics. The adopted WMUE technique demonstrated improved outcomes for positive metrics like specificity and precision over SVM, DBN, DCNN, LSTM and RNN models. Further, the employed WMUE model attains greatest precision at 90^{th} LR in Fig 3(d) for dataset 1. Also, the deployed WMUE method holds greatest sensitivity at 90^{th} LR over SVM, DBN, DCNN, LSTM and RNN as shown in Fig. 3(a). Likewise, the specificity of WMUE system as exposed in Fig. 3(b) obtains enhanced values; nonetheless, the existing models like SVM, DBN, DCNN, LSTM and RNN enclosed lesser values at 90^{th} LR for dataset 1. Thereby, the development of WMUE scheme is obtained resourcefully for finding faults in bearings due to the incorporated improvements.



(a)



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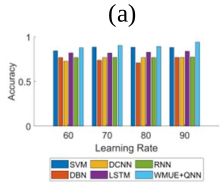

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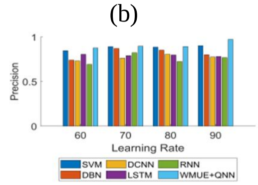
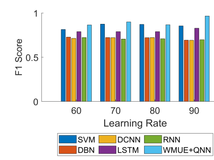
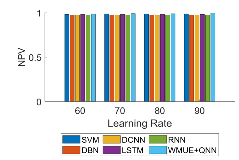


(d)

Fig 3. Performance of WMUE + QNN over others for (a) sensitivity (b) specificity (c) accuracy (d) precision for dataset 1



(a)



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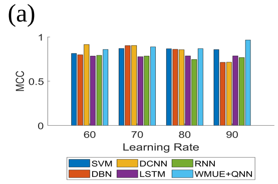
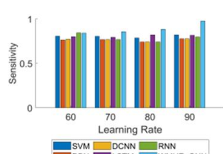
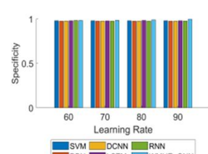


(c)

Fig 5. Performance of WMUE + QNN over others for (a) F1-score (b) NPV (c) MCC for dataset 1



(a)



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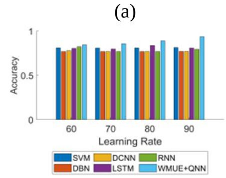

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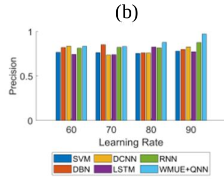
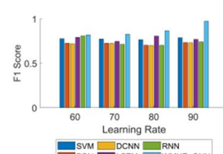
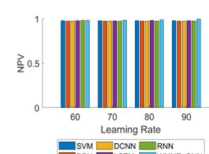


(d)

Fig 4. Performance of WMUE + QNN over others for (a) sensitivity (b) specificity (c) accuracy (d) precision for dataset 2



(a)



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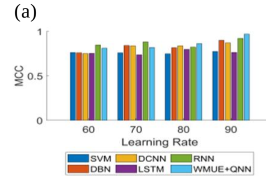
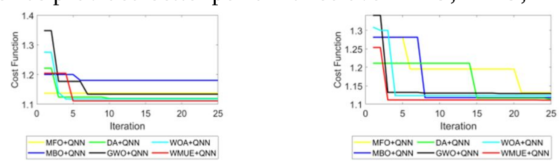


(c)

Fig 6. Performance of WMUE + QNN over others for (a) F1-score (b) NPV (c) MCC for dataset 2

C. Convergence Analysis

The cost analysis for developed WMUE + QNN model over MFO, MBO, DA, GWO and WOA is given by Fig. 9 for wide-ranging iterations. The investigation is made for dataset 1 and 2 as shown in Fig. 7(a) and 7(b) correspondingly. From the examination, the offered model has exposed minimal cost values for varied iteration over other schemes, thus ensure the improved performances of WMUE + QNN model. Chiefly, from Fig. 7 (a), a negligible cost of 1.12 is obtained by WMUE + QNN method for dataset 1 & 2, which is much enhanced over MFO, MBO, DA, GWO and WOA models at 5 - 25th iteration. As a result, from the assessment, it is obvious that WMUE + QNN scheme has provided better performance over MFO, MBO, DA, GWO and WOA schemes.



(a) (b)

Fig 7. Convergence analysis attained by WMUE + QNN over others for dataset (a) 1 and (b) 2

D. Analysis on Features

The examination on deployed WMUE + QNN method over adopted WMUE + QNN scheme without optimization and adopted WMUE + QNN scheme without features is shown in Table I. From Table I, the accuracy of WMUE + QNN is high over adopted WMUE + QNN scheme without optimization and adopted WMUE + QNN scheme without features. Subsequent to WMUE + QNN scheme, adopted WMUE + QNN scheme without features has achieved good outcomes over adopted WMUE + QNN scheme without features.

TABLE I. PERFORMANCE ANALYSIS ON VARIED FEATURES

	WMUE + QNN	Without optimization	Without features
Specificity	0.99688	0.98788	0.98285
Accuracy	0.9362	0.89	0.845
FPR	0.003115	0.012119	0.017147
Sensitivity	0.97586	0.88363	0.83955
NPV	0.99688	0.98788	0.98285
F1-Score	0.97237	0.86631	0.81761
Precision	0.97295	0.87869	0.83456
FNR	0.024138	0.11637	0.16045
MCC	0.97052	0.86326	0.81259
FDR	0.027051	0.12131	0.16544

VII. CONCLUSION

This work developed a novel bearing fault diagnosis model, where, “EWT, EMD and WT based features” were extracted at first. Further, these extracted features were classified via QNN, where the weights were tuned optimally by WMUE. Chiefly, a negligible cost of 1.12 was obtained by WMUE + QNN method for dataset 1 & 2, which was much enhanced over MFO, MBO, DA, GWO and WOA models at 5 - 25th iteration. Similarly, the adopted WMUE method attains a lower FPR of 0.003 over SVM, DBN, DCNN, LSTM and RNN at 90th LR for dataset 1. Thus, the effectiveness of WMUE scheme was proven over other schemes.

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