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# Wind Turbine Blades Fault Diagnosis based on Vibration Signals Utilizing Convolutional Neural Network

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**Abstract**— Wind energy is a key contributor to renewable energy production, with wind turbines playing a critical role in its generation. However, the operational efficiency of wind turbines is often compromised by blade faults, leading to reduced performance, expensive maintenance, and potential safety hazards. Traditional methods of diagnosing faults in wind turbine blades are limited in both accuracy and efficiency. This study proposes a novel fault diagnosis approach using Convolutional Neural Networks (CNNs), a powerful deep learning technique for data analysis. The dataset comprises four sets of vibration signals representing both healthy and faulty wind turbine blades, covering fault conditions such as blade cracks, surface degradation, imbalance, and blade twist. Our proposed CNN-based method aims to accurately detect and classify these faults, enabling proactive maintenance and improving the overall reliability and efficiency of wind energy systems.

**Keywords**— *Wind Turbine; Fault Diagnosis; Vibration signals; Convolution Neural Networks.*

## I. INTRODUCTION

Wind energy has emerged as a prominent and sustainable source of renewable energy, playing a crucial role in contributing to climate change and reducing reliance on fossil fuels. Wind turbines, the cornerstone of harnessing wind power, are instrumental in converting wind energy into electricity [1]. However, the operational efficiency of wind turbines is susceptible to various challenges, notably blade faults, which can significantly impede performance, escalate maintenance costs, and enhance safety [2].

As the demand for clean energy sources intensifies, the development and maintenance of wind energy systems become paramount. However, ensuring the optimal performance and longevity of wind turbines pose significant challenges, particularly in the realm of fault detection and diagnosis [3].

This scientific article delves into the crucial domain of fault detection and diagnosis in wind turbines, focusing specifically on the analysis of vibration signals for condition monitoring. Fault diagnosis and prognosis are crucial for wind turbine

maintenance, but traditional methods struggle with complex systems and limited data. Recent advancements in machine learning and artificial intelligence have spurred interest in utilizing these technologies for fault diagnosis in wind turbines [4].

For instance, in [5] Li et al. (2019) address limitations of traditional feature-based rolling bearing fault diagnosis by proposing a method using a Back-Propagation Neural Network (BPNN) for multiscale local feature learning. This approach aims to automatically extract informative features from raw vibration signals at different scales, improving fault classification accuracy and reducing reliance on manual feature selection.

Several Studies have investigated the efficacy of Artificial Neural Networks (ANN), Deep Neural Network (DNN), Stacked AutoEncoder (SAE)[6], Multi-Layer Perceptrons (MLP) [7,8], Support Vector Machines (SVM) and Long Short-Term Memory (LSTM) networks in addressing the challenges of fault diagnosis in wind turbine[9,10].

In study [11] introduced a hybrid method for Remaining Useful Life (RUL) prediction in wind turbine systems. Recognizing limitations of individual methods like statistics and machine learning (ML), they advocate for a combined approach. This hybrid method likely involves feature extraction from sensor data, employing ML algorithms for prediction, and potentially incorporating data fusion from various sources.

In [12] the authors proposes an wind turbine condition monitoring method using Long Short-Term Memory (LSTM) algorithms. LSTMs, known for capturing long-term dependencies in data sequences, analyze historical sensor readings from the turbine. By comparing predicted future readings with actual sensor data, the method identifies deviations (residual signal) that could indicate developing defects.

In [13] Nguyen et al. (2021) propose a method for bearing fault diagnosis using a Multi-Branch Deep Neural Network (MB-DNN). This approach addresses limitations of traditional feature extraction and single-architecture DNNs.

The MB-DNN utilizes multiple branches with different architectures to capture a wider range of features from vibration signals. Future research can enhance this approach by incorporating additional data sources and exploring deep learning for real-time wind turbine fault management.

In this study, we propose a novel approach to fault diagnosis in wind turbine blades utilizing Convolutional Neural Network (CNN). CNNs represent a powerful class of deep learning algorithms well-suited for data analysis tasks, particularly pattern detection [14]. By leveraging CNNs, we aim to overcome the shortcomings of traditional fault diagnosis methods and enhance the accuracy and efficiency of identifying blade faults in wind turbines.

The organization of this paper is outlined as follows: the subsequent section provides detailed insights into the methodology employed to develop this approach, Section 3 outlines the findings and initiates discussion, and lastly, the concluding section offers a summary of the paper.

## II. METHODOLOGY

This section outlines our methodology for diagnosing faults in wind turbine blades. Analyzing vibration signals generated by wind turbines under various operational conditions and compute a single metric, known as the wind turbine blade condition index, which acts as an indicator of the turbine's overall health. To assess the effectiveness of signal characteristics in fault diagnosis, we employ a ranking process. The proposed approach begins with data preprocessing to enhance dataset quality. Then, CNNs are utilized for feature extraction and optimizing model parameters and architecture, thereby ensuring accurate fault classification [15]. Fig. 1 illustrates the flowchart of the proposed methodology, which encompasses the following steps:

1. Feature extraction: statistical features are utilized to capture essential characteristics from raw vibration data [16].
2. Feature selection: The features are chosen from the extracted features using distinct ranking techniques [17].
3. Feature ranking: The extracted features are ranked using the ReliefF algorithm [18].
4. Fault classification: The CNN classifier is employed for fault classification.

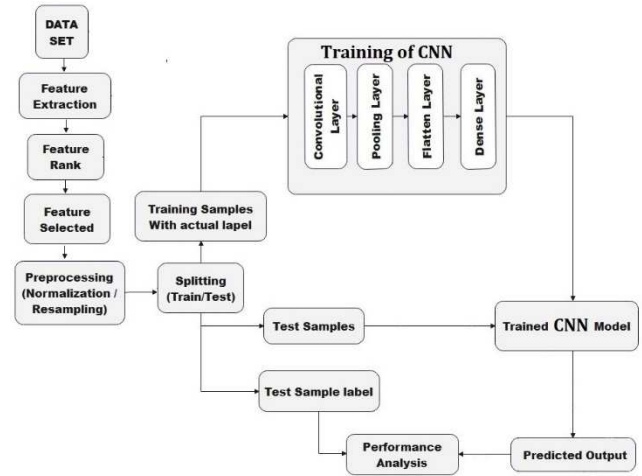


Fig. 1. Proposed *fault diagnosis architecture*.

### 1.1 Wind turbine blade state:

The data used in this research are obtained from [19]. The study considers various health conditions of wind turbine blades while assuming all other components are functioning properly. Fig. 2 illustrates the different failure scenarios simulated on the blade. Vibration signals are recorded accordingly. The scenarios simulated on the blade include:

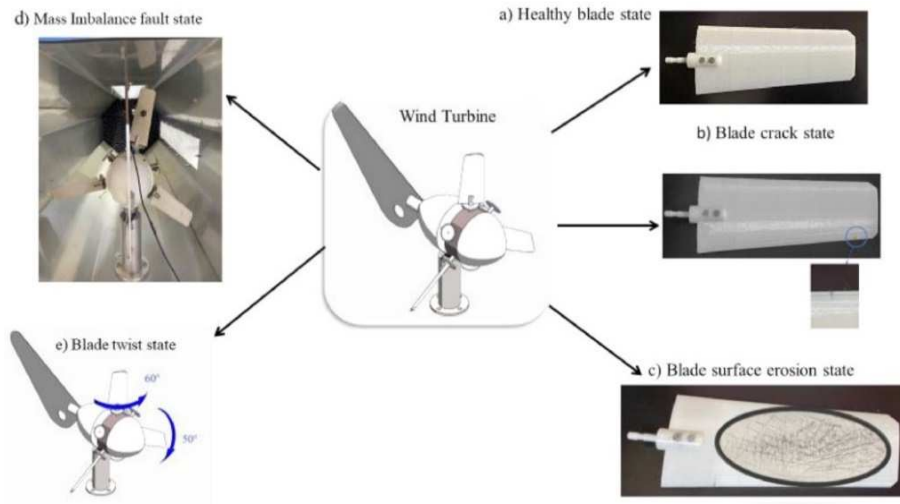


Fig. 2. The fault simulated in this research

- State 1: The blade is healthy without any defects, operating at a blade angle of  $60^\circ$ . Fig.(2.a).
- State 2: A blade crack occurs due to damage from foreign objects during operation. Fig.(2.eb).
- State 3: Blade erosion caused by high-velocity wind erosion, simulated by degrading the flawless surface using sandpaper. Fig.(2.c).
- State 4: Mass imbalance in the blade is simulated by adding a mass at a specific distance from the root. Fig.(2.d).
- State 5: blade angle anomalies (twisted blade), resulting from extreme wind loads and asymmetric wind directions, potentially leading to surface damage and abnormal blade angles over time. Fig.(2.e).

### 1.2 Dataset Description:

The dataset was created by Ogaili et al, in 2023. It comprises three sets of vibration data from turbines in normal operating conditions and three sets from turbines experiencing issues, encompass blade cracks, surface degradation, twist and blade imbalance. The data was collected at a sampling rate of 1 kHz, with 500 samples recorded per channel.

### 1.3 Convolutional Neural Network algorithm

This section provides an extensive explanation of the proposed method for detecting and classifying faults. Researchers have introduced various methods for normalizing data, as well as for training, validating, and testing neural networks [20]. The flowchart given in Fig. 3 showcases a comprehensive illustration of the development convolutional neural networks algorithm.

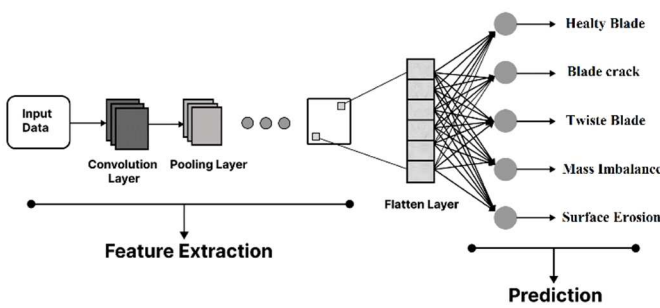


Fig. 3. The flowchart of the approach.

The CNN architecture designed for fault classification in wind turbine blades undergoes preprocessing steps involving normalization and resampling before progressing through a convolution filter [21]. The output layer, consisting of five nodes, is engaged for classification. These nodes correspond to distinct fault occurrences: Healthy and faultless, Crack fault,

Surface erosion fault, Imbalance and Blade twist fault. offering a comprehensive classification framework for fault analysis.

## III. RESULTS AND DISCUSSION

This section presents a comparative analysis is conducted based on standard ML evaluation metrics, including precision, recall, fl-score and accuracy [22]. These metrics provide a comprehensive understanding of the algorithm performance in classifying faults across multiple classes, allowing for a quantitative analysis of its effectiveness.

The dataset was randomly divided into two portions: a training set, which consisted 80% of the data, and a testing set, which contained 20%. The segmentation facilitates a comprehensive evaluation of the algorithm's performance on novel data, typically represented by the testing dataset.

Following the completion of training, the algorithm was tested with fresh data to forecast and classify faults in the wind turbine blades. The results depicted in Fig. 4 illustrates the training and validation accuracy of our suggested CNN-driven model. which shows that the model will predict well for unseen data.



Fig. 4. Training and validation accuracy.

The performance of the algorithm was evaluated based on its ability to classify faults in wind turbine blades. To assess this, the fault classifications generated by the algorithm were analyzed using a confusion matrix, which provides an overview of a model's performance on fresh data, typically the test data. As depicted in Fig. 5. The predictions are represented on the x-axis, while the actual class labels are represented on the y-axis.

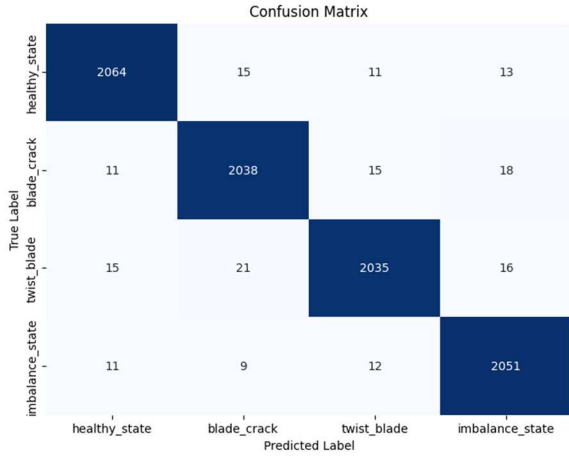


Fig. 5. The confusion matrix.

The confusion matrix summarizes the classification performance of a model across different classes. The model accurately classified all instances. However, there were misclassifications observed. Our model achieved accuracies of 98.7% for Healthy State, 97.8% for Blade Crack, 97.5% for Twist Blade, and 98.5% for Imbalance State. The overall testing accuracy of the model was 98.10%.

TABLE I. TESTING RESULTS

Wind Speed	1.3 m/s	3.3 m/s	5.3 m/s	Average
<b>Precision</b>	98.3%	98.3%	98.6%	98.4%
<b>Recall</b>	97.89%	98%	98.1%	98.1%
<b>F1-score</b>	98.1%	98.3%	98.3%	98.2%
<b>Accuracy</b>	97.7%	98.14%	98.86%	98.2%

Table I provides the testing results of the model across three different tests speed, along with their average values. The model demonstrates consistently high performance across all evaluation metrics. Precision average 98.4%, recall 98.1%, f1-score achieved 98.3%, and accuracy achieved 98.86%. These results indicate the model's robustness and reliability in fault detection within Wind turbine blades.

#### 1.4 Comparative study

This section conducts a comparative study between our approach and recent models in the field of fault detection within wind turbine blades using ML techniques such as kNN as detailed in Table II. To evaluate how effective our suggested research is compared to previous studies, we compiled the table, outlining the identified fault types, the employed

algorithms, and the accuracy of each method. Our method exhibits significantly superior testing accuracy when compared to these algorithms.

TABLE II. RESULTS OF THE COMPARATIVE STUDY

Classifier	Faults	Accuracy
MLP [6]	Crack near the root fault, Blade tip and mid-span crack	94.75%
kNN [22]	Crack near the root fault, Blade tip and mid-span crack	97 %
<b>Our method</b>	<b>blade crack, surface degradation, imbalance and twist blade</b>	<b>98.2 %</b>

Table II compares the performance of different classifiers in fault detection within wind turbine blades. MLP achieved 94.75% accuracy in identifying Crack near the root fault, Blade tip and mid-span crack faults, while kNN achieved 97%. Notably, our method demonstrated the highest accuracy among all classifiers, at 98.86%, in identifying blade crack, surface degradation, imbalance and twist blade faults. These results highlight the potential of our approach to significantly enhance fault detection accuracy in wind turbines blade, thereby improving their reliability and efficiency.

#### IV. CONCLUSION

In summary, this study explores the application of Convolutional Neural Networks for diagnosing faults in wind turbine blade using vibration data. By analyzing a comprehensive dataset encompassing various fault conditions, including blade cracks, surface degradation, and imbalance, the study demonstrates the CNN ability to accurately detect and classify these faults. This approach offers advantages over traditional methods, enabling proactive maintenance strategies that enhance wind turbine reliability and efficiency. The successful implementation of CNNs suggests promising avenues for future research in improving renewable energy infrastructure through advanced fault diagnosis techniques.

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## REFERENCES

- [1] T. Ackermann, "Wind energy technology and current status: a review," *Renewable and Sustainable Energy Reviews*, vol. 4, no. 4. Elsevier BV, pp. 315–374, Dec. 2000. doi: 10.1016/s1364-0321(00)00004-6.
- [2] H. Li, H. Diaz, and C. Guedes Soares, "A developed failure mode and effect analysis for floating offshore wind turbine support structures," *Renewable Energy*, vol. 164. Elsevier BV, pp. 133–145, Feb. 2021. doi: 10.1016/j.renene.2020.09.033.
- [3] K. Kong, K. Dyer, C. Payne, I. Hamerton, and P. M. Weaver, "Progress and Trends in Damage Detection Methods, Maintenance, and Data-driven Monitoring of Wind Turbine Blades – A Review," *Renewable Energy Focus*, vol. 44. Elsevier BV, pp. 390–412, Mar. 2023. doi: 10.1016/j.ref.2022.08.005.
- [4] X. Hang, X. Zhu, X. Gao, Y. Wang, and L. Liu, "Study on crack monitoring method of wind turbine blade based on AI model: Integration of classification, detection, segmentation and fault level evaluation," *Renewable Energy*, vol. 224. Elsevier BV, p. 120152, Apr. 2024. doi: 10.1016/j.renene.2024.120152.
- [5] J. Li, X. Yao, X. Wang, Q. Yu, and Y. Zhang, "Multiscale local features learning based on BP neural network for rolling bearing intelligent fault diagnosis," *Measurement*, vol. 153. Elsevier BV, p. 107419, Mar. 2020. doi: 10.1016/j.measurement.2019.107419.
- [6] M. Bougoffa, S. Benmoussa, M. Djeziri, and T. Contaret, "Stacked AutoEncoder based diagnosis applied on a Solar Photovoltaic System," *IFAC-PapersOnLine*, vol. 58, no. 4. Elsevier BV, pp. 384–389, 2024. doi: 10.1016/j.ifacol.2024.07.248.
- [7] A. Joshua and V. Sugumaran, "Crack Detection and Localization on Wind Turbine Blade Using Machine Learning Algorithms: A Data Mining Approach," *Structural Durability & Health Monitoring*, vol. 13, no. 2. Computers, Materials and Continua (Tech Science Press), pp. 181–203, 2019. doi: 10.32604/sdhm.2019.00287.
- [8] B. Mouaad, B. Samir and D. Mohand, "Dynamic Modeling for Fault Diagnosis in PV Systems Utilizing AI Techniques Based on Multilayer Perceptron (MLP)," 2024 ASU International Conference in Emerging Technologies for Sustainability and Intelligent Systems (ICETISIS), Manama, Bahrain, 2024, pp. 1032-1036, doi: 10.1109/ICETISIS61505.2024.10459490
- [9] E. Y.-K. Ng and J. T. Lim, "Machine Learning on Fault Diagnosis in Wind Turbines," *Fluids*, vol. 7, no. 12. MDPI AG, p. 371, Dec. 02, 2022. doi: 10.3390/fluids7120371.
- [10] P. W. Khan and Y.-C. Byun, "A Review of machine learning techniques for wind turbine's fault detection, diagnosis, and prognosis," *International Journal of Green Energy*, vol. 21, no. 4. Informa UK Limited, pp. 771–786, May 29, 2023. doi: 10.1080/15435075.2023.2217901.
- [11] M. A. Djeziri, S. Benmoussa, and R. Sanchez, "Hybrid method for remaining useful life prediction in wind turbine systems," *Renewable Energy*, vol. 116. Elsevier BV, pp. 173–187, Feb. 2018. doi: 10.1016/j.renene.2017.05.020.
- [12] P. Qian, X. Tian, J. Kanfoud, J. Lee, and T.-H. Gan, "A Novel Condition Monitoring Method of Wind Turbines Based on Long Short-Term Memory Neural Network," *Energies*, vol. 12, no. 18. MDPI AG, p. 3411, Sep. 04, 2019. doi: 10.3390/en12183411.
- [13] V.-C. Nguyen, D.-T. Hoang, X.-T. Tran, M. Van, and H.-J. Kang, "A Bearing Fault Diagnosis Method Using Multi-Branch Deep Neural Network," *Machines*, vol. 9, no. 12. MDPI AG, p. 345, Dec. 09, 2021. doi: 10.3390/machines9120345.
- [14] X. Wang, D. Mao, and X. Li, "Bearing fault diagnosis based on vibro-acoustic data fusion and 1D-CNN network," *Measurement*, vol. 173. Elsevier BV, p. 108518, Mar. 2021. doi: 10.1016/j.measurement.2020.108518.
- [15] J. Zhang, G. Cosma, and J. Watkins, "Image Enhanced Mask R-CNN: A Deep Learning Pipeline with New Evaluation Measures for Wind Turbine Blade Defect Detection and Classification," *Journal of Imaging*, vol. 7, no. 3. MDPI AG, p. 46, Mar. 04, 2021. doi: 10.3390/jimaging7030046.
- [16] R. Zebari, A. Abdulazeez, D. Zeebaree, D. Zebari, and J. Saeed, "A Comprehensive Review of Dimensionality Reduction Techniques for Feature Selection and Feature Extraction," *Journal of Applied Science and Technology Trends*, vol. 1, no. 1. Interdisciplinary Publishing Academia, pp. 56–70, May 15, 2020. doi: 10.38094/jastt1224.
- [17] J. Cai, J. Luo, S. Wang, and S. Yang, "Feature selection in machine learning: A new perspective," *Neurocomputing*, vol. 300. Elsevier BV, pp. 70–79, Jul. 2018. doi: 10.1016/j.neucom.2017.11.077.
- [18] R. J. Urbanowicz, M. Meeker, W. La Cava, R. S. Olson, and J. H. Moore, "Relief-based feature selection: Introduction and review," *Journal of Biomedical Informatics*, vol. 85. Elsevier BV, pp. 189–203, Sep. 2018. doi: 10.1016/j.jbi.2018.07.014.
- [19] A. A. F. Ogaili, A. Abdulhady Jaber, and M. N. Hamzah, "Wind turbine blades fault diagnosis based on vibration dataset analysis," *Data in Brief*, vol. 49. Elsevier BV, p. 109414, Aug. 2023. doi: 10.1016/j.dib.2023.109414.
- [20] S. Yang et al., "A 2DCNN-RF Model for Offshore Wind Turbine High-Speed Bearing-Fault Diagnosis under Noisy Environment," *Energies*, vol. 15, no. 9. MDPI AG, p. 3340, May 04, 2022. doi: 10.3390/en15093340.
- [21] Y. Sun, Q. Zhou, L. Sun, L. Sun, J. Kang, and H. Li, "CNN-LSTM-AM: A power prediction model for offshore wind turbines," *Ocean Engineering*, vol. 301. Elsevier BV, p. 117598, Jun. 2024. doi: 10.1016/j.oceaneng.2024.117598.
- [22] A. A. F. Ogaili, A. A. Jaber, and M. N. Hamzah, "A methodological approach for detecting multiple faults in wind turbine blades based on vibration signals and machine learning," *Curved and Layered Structures*, vol. 10, no. 1. Walter de Gruyter GmbH, Jan. 01, 2023. doi: 10.1515/cls-2022-0214.