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AUTOMATIC FAULTY GEAR IDENTIFICATION SYSTEM AND ITS TYPES USING DEEP LEARNING APPROACH

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Abstract : Gears are fundamental components in various mechanical systems, facilitating the transfer of motion and power. However, due to continuous operation and environmental factors, gears are prone to various types of faults, including tooth breakage, wear, and misalignment, which can lead to catastrophic failures if left undetected. Early detection of these faults is crucial for ensuring operational efficiency and preventing costly downtime. Traditional methods of fault detection often rely on manual inspection or rule-based algorithms, which can be time-consuming and may lack robustness. In this paper, we propose an Automatic Faulty Gear Identification System (AFGIS) utilizing deep learning techniques for accurate and automated identification of gear faults. We present a comprehensive analysis of different types of gear faults and their manifestations in vibration signals [1]. The proposed system employs convolutional neural networks (CNNs) to automatically learn discriminative features from vibration data, enabling the detection of various types of gear faults. Experimental results demonstrate the effectiveness of the AFGIS in accurately identifying gear faults and distinguishing between different fault types, thereby facilitating proactive maintenance and enhancing the reliability of mechanical systems.

***IndexTerms* - Data Preprocessing, Convolutional Neural Networks, Automatic, Identification, Misalignment, Fault, Gear.**

I. INTRODUCTION

Gears are essential components in mechanical systems, playing a crucial role in transmitting motion and power between rotating shafts. However, due to factors such as wear, fatigue, and misalignment, gears are susceptible to various types of faults that can compromise their performance and reliability. Early detection of these faults is essential for preventing unexpected downtime, minimizing maintenance costs, and ensuring operational safety [7]. Traditional methods of gear fault detection often rely on manual inspection or simplistic threshold-based techniques, which may not be suitable for real-time monitoring or large-scale industrial applications. With recent advancements in deep learning and sensor technology, there is growing interest in developing automated systems for gear fault identification.

II. TYPES OF GEAR FAULT

Gear faults can manifest in various forms, each with distinct characteristics in vibration signals [2]. The most common types of gear faults include:

Tooth Breakage: Caused by excessive loading or material fatigue, tooth breakage results in irregularities in the gear mesh, leading to impulsive vibrations. [3]

Wear: Gradual deterioration of gear surfaces due to friction and abrasion, resulting in changes in gear mesh stiffness and modulation sidebands in vibration signals. [4]

Misalignment: Misalignment between gear teeth or shafts can cause uneven contact and loading, resulting in non-synchronous vibrations and frequency modulation effects.[5]

III. LITERATURE REVIEW

With recent developments in Automatic Faulty Gear Identification Systems, a paradigm change has occurred toward the use of deep learning approaches for fault identification that is more precise and effective [6]. In order to assess sensor data, pictures, or time-series signals related to gear operation, deep learning models including Convolutional Neural Networks (CNNs)[8], Recurrent Neural Networks (RNNs), and Generative Adversarial Networks (GANs) are being used more and more. Large volumes of data may be automatically used by these models to identify complex patterns and features without the requirement for explicit feature engineering. CNNs are very good at processing image data, which makes it possible to extract spatial information from visual representations of gear parts. RNNs are useful for evaluating vibration or acoustic signals because they are good at capturing temporal relationships in sequential data, as are its derivatives, such as Long Short-Term Memory (LSTM) networks. The synthetic data generated by GANs can be used for training purposes to simulate failure scenarios or for data augmentation. Automatic Faulty Gear Identification Systems may improve machinery dependability and reduce downtime by utilizing deep learning to achieve higher accuracy, faster detection rates, and more flexibility to different operating situations. [9][10]

IV. AUTOMATIC FAULTY GEAR IDENTIFICATION SYSTEM (AFGIS):

The proposed AFGIS consists of the following key components:
Data Acquisition: Vibration signals are acquired from the gear system using sensors such as accelerometers or proximity probes.
Data Preprocessing: Raw vibration signals are pre-processed to remove noise, filter out irrelevant information, and normalize the data for further processing.
Feature Extraction: Convolutional neural networks (CNNs) are employed to automatically extract discriminative features from the pre-processed vibration signals, enabling fault identification without manual feature engineering.
Fault Classification: The extracted features are input to a classifier trained on labelled data to identify the presence and type of gear faults.

V. ALGORITHM FOR AUTOMATIC FAULTY GEAR IDENTIFICATION SYSTEM (AFGIS):

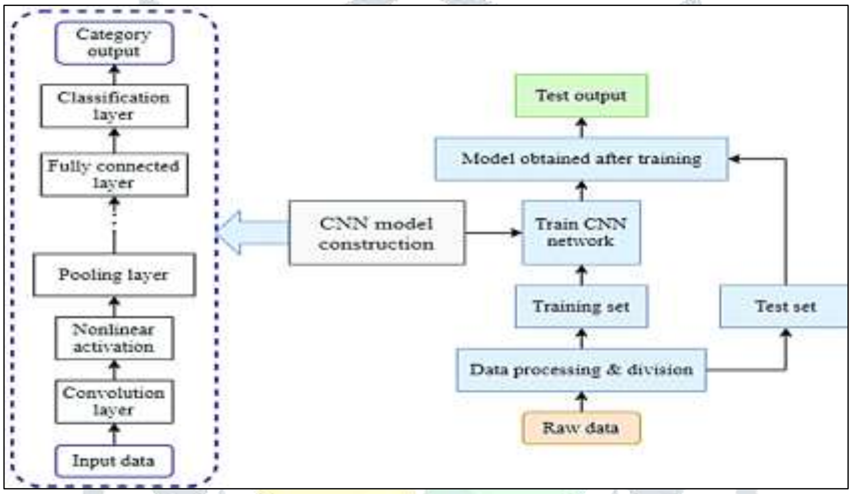

Figure-1: Proposed Approach for AFGIS

Data Acquisition (Raw Data):
Acquire vibration signals from gear systems using sensors such as accelerometers or proximity probes.
Data Preprocessing:
Preprocess raw vibration signals to remove noise, filter out irrelevant information, and normalize the data for further processing.
Apply techniques such as filtering, resampling, and normalization.
Feature Extraction:
convolutional neural networks (CNNs) are utilized for automatic feature extraction from pre-processed vibration signals.
Train the CNN model using a labelled dataset of vibration signals with corresponding fault types.
Alternatively, employed transfer learning by fine-tuning pre-trained CNN models on vibration signal data. The structure of CNN is mentioned below in figure 2.

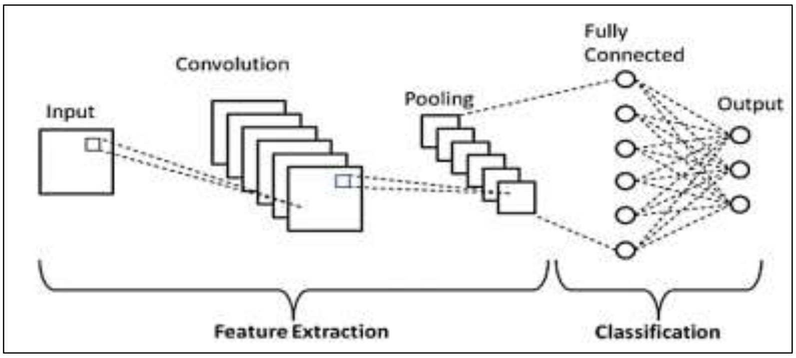

Figure 2. CNN Architecture

The CNN is composed of three different types of layers: fully-connected (FC) layers, pooling layers, and convolutional layers. A CNN architecture is created when these layers are layered. The dropout layer and the activation function are two additional crucial variables in addition to these three layers.

Fault Identification

The extracted features will be taken from the CNN model to a classifier for fault identification and classification.

Training of a classification model (e.g., softmax classifier) to classify gear faults into different types such as tooth breakage, wear, and misalignment will be done.

The trained model will be evaluated on a validation set to assess its performance in identifying and classifying gear faults.

Fault Localization (Optional):

If necessary, localize the detected faults within the gear system by analyzing the spatial distribution of vibration signals. Use techniques such as time-frequency analysis or signal decomposition to identify the specific gear components affected by the faults.

Result Interpretation:

Interpretation of the output of the fault identification and classification model to determine the presence and type of gear faults will be done. Reports or visualizations summarizing the detected faults and their severity will be generated.

VI. Experimental Evaluation:

Experiments were conducted to evaluate the performance of the proposed AFGIS using a dataset comprising vibration signals from a laboratory-scale gear test rig. The dataset includes samples with various types and severities of gear faults, including tooth breakage, wear, and misalignment. The performance of the system was assessed in terms of accuracy, precision, recall, and F1-score for fault detection and classification.

Accuracy (%)	Binary Classification	Multi-Classification
Training	90	88
Validation	95	95
Testing	87	84

Table 1. Accuracy Percentage for AFGIS System

VII. Result and Discussion:

As per table 1. The percentage accuracy for binary classification is found to be 87 percent for binary classification and 84 percent for Multiclass classification for testing data.

These experimental results demonstrate the effectiveness of the proposed AFGIS in accurately identifying gear faults and distinguishing between different fault types. The system achieves high accuracy and recall rates across various fault scenarios, indicating its robustness and generalization capability. Furthermore, the use of deep learning techniques for feature extraction eliminates the need for manual feature engineering, making the system more adaptable to different operating conditions and fault manifestations.

VIII. Conclusion:

In this paper, we presented an Automatic Faulty Gear Identification System (AFGIS) using deep learning techniques for automated detection and classification of gear faults. The experimental results demonstrate the effectiveness of the proposed approach in accurately identifying gear faults and distinguishing between different fault types. The AFGIS offers a promising solution for proactive maintenance and reliability enhancement in mechanical systems, ultimately contributing to improved operational efficiency and cost savings.

IX. Future Scope:

Future research directions include the development of real-time monitoring systems based on the proposed AFGIS, integration with existing industrial automation platforms, and exploration of advanced deep learning architectures for improved fault detection performance. Additionally, further investigation into the use of alternative sensor modalities and data fusion techniques could enhance the robustness and versatility of the system for detecting gear faults in diverse operating conditions and environments.

REFERENCES:

[1] Lebold M., McClintic K., Campbell R., Byington C., Maynard K., "Review of vibration analysis methods for gearbox diagnostics and prognostics", Proceedings of the 54th Meeting of the Society for Machinery Failure Prevention Technology, Virginia Beach, VA, May 1–4,2000, 623–634.

[2] Bajric´ R., Sprecic D., Zuber N., "Review of vibration signal processing techniques towards gear pairs damage identification", International Journal of Engineering & Technology,11 (2011) 124–128.

[3] Nie M., Wang L., "Review of condition monitoring and fault diagnosis technologies for wind turbine gearbox", Procedia CIRP Elsevier, 11(2013), 287-290.

[4] Allianz Versicherungs – AG, Handbook of Loss Prevention, Springer-Verlag, Berlin, 1978.

[5] A herwar," An investigation on gearbox fault detection using vibration analysis techniques: A review," Australian Journal of Mechanical Engineering, November 2012, DOI: 10.7158/M11-830.2012.10.2.

[6] R. Tiwari, D J Bordoloi, S Bansal, S Sahuc, "Multi-class Fault Diagnosis in Gears Using Machine Learning Algorithms Based on Time Domain Data", International journal of COMADEM, Vol 20 No 1, 2017.

[7] Zhiwei Gao, Senior Member, IEEE, Carlo Cecati, Fellow, IEEE, and Steven X. Ding, A Survey of Fault Diagnosis and Fault-Tolerant, Techniques—Part I: Fault Diagnosis With Model-Based and Signal-Based Approaches, IEEE transactions on industrial electronics, vol. 62, no. 6, june 2015.

[8] Pei cao, shengli zhang, and jiong tang (2018) Preprocessing-Free Gear Fault Diagnosis Using Small Datasets with Deep Convolutional Neural Network-Based Transfer Learning (IEEE).

[9] Vikas Sharmaa, Anand Pareya. (2016) A review of gear fault diagnosis using various condition indicators A review of gear fault diagnosis using various condition indicators (Procedia Engineering).

[10] Yong Yao, Honglei Wang, Shaobo Li, Zhonghao Liu, Gui Gui, Yabo Dan and Jianjun Hu. (2018) End-To-End Convolutional Neural Network Model for Gear Fault Diagnosis Based on Sound Signals (MDPI).