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Gear Fault Detection with InceptionResNetV2 Transfer Learning

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ABSTRACT

This study addresses the critical need for reliable gearbox fault detection in industrial machinery, aiming to enhance operational efficiency and reduce downtime. The research explores the application of deep learning techniques, specifically focusing on the InceptionResNetV2 transfer learning model, for analysing vibration signals using Constant Q Transform (CQT) spectrograms. CQT's adaptive resolution and noise robustness make it superior for capturing time-varying frequency content in non-stationary signals, such as those from gearboxes. The custom dataset, derived from SpectraQuest's Gearbox Fault Diagnostics Simulator, includes labeled CQT spectrograms of healthy and faulty gearboxes, preprocessed and augmented for model training. The InceptionResNetV2 architecture, combining Inception modules and residual connections, effectively captures multiscale features, achieving 98.04% accuracy in fault classification. Evaluation metrics, including precision, recall, and F1 score, confirm the model's robustness. Comparative analysis with other methods highlights its superiority in handling limited data and noisy conditions. This work demonstrates the viability of transfer learning-based fault detection systems for industrial applications, offering a template for predictive maintenance solutions. Future improvements will focus on multi-modal fusion and explainable AI techniques for enhanced interpretability.

Keywords: *Gearbox Fault Detection; Deep Learning; Constant Q Transform (CQT); Transfer Learning; Vibration Analysis.*

1.0 Introduction

The field of machinery fault diagnosis is critical for ensuring the reliable and efficient operation of industrial equipment (Neupane *et al.*, 2024).

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Gearboxes, as essential components in many mechanical systems, are particularly susceptible to faults that can lead to significant downtime, economic losses, and safety hazards (Liu *et al.*, 2016). Traditional methods of condition monitoring, which rely on manual feature extraction and statistical analysis of signals, often struggle to cope with the complexity and variability of modern machinery (Kumar *et al.*, 2018). These methods may be limited in their ability to distinguish between different fault types and locations, and they may not be robust when operating under time-varying conditions (Wang *et al.*, 2019). Therefore, there is a need for more intelligent and automated techniques for gearbox fault diagnosis. In recent years, deep learning (DL) has emerged as a promising approach for addressing these challenges. DL models, such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Autoencoders (AEs), can automatically learn complex features directly from raw data, thus reducing the need for manual feature engineering and expert knowledge (Liu *et al.*, 2018).

These techniques have shown excellent performance in various domains, including image recognition and speech recognition. They are also well-suited for analyzing time series data, allowing for the capture of temporal patterns present in vibration or acoustic signals generated by faulty gearboxes (Liu *et al.*, 2016). The capacity of deep learning models to extract complex, high-level features and improve classification performance has led to their increasing application in mechanical fault diagnosis (Neupane et al, 2024). Among the various DL techniques, Stacked Autoencoders (SAEs) have demonstrated effectiveness in extracting meaningful features from data (Liu *et al.*, 2018). SAEs are a type of neural network that can learn compressed representations of input data. By stacking multiple autoencoders, the network can learn hierarchical feature representations, capturing more complex patterns within the data.

These features can then be used to train a classifier to identify different fault types. Furthermore, techniques like dropout and ReLU activation can be used to improve the performance and reduce overfitting in SAE networks (Liu *et al.*, 2018). Another area of interest is the use of time-frequency analysis methods, such as the Short-Time Fourier Transform (STFT) and the Stockwell Transform (ST), which allow for the representation of signals in both the time and frequency domains (Stockwell *et al.*, 1996). These methods are particularly useful in fault diagnosis where the frequency components of a signal can change over time, or where the signal is non-stationary. By combining timefrequency analysis with deep learning models, it is possible to develop robust fault diagnosis systems that are invariant to changes in load and rotational speed (Wang *et al.*, 2019).

This study explores the application of deep learning techniques for gearbox fault diagnosis. It covers the use of CQT analysis for feature extraction, the integration of time-frequency analysis with deep learning, and the use of the Xception transfer learning model for fault detection (Bliznyuk *et al.*, 2014). Additionally, it discusses the use of spherical coordinates to improve the consistency of results from vibration signals and the development of a tacholess method for diagnosing faults when rotational speed is not constant (Mohammed & Rantatalo, 2020). The study also highlights the importance of transfer learning and the need for robust feature extraction methods that can improve the accuracy and reliability of fault diagnosis in complex industrial environments (Hakim *et al.*, 2023). By presenting a comprehensive overview of existing research, this paper serves as a valuable resource for researchers and engineers working in the field of machinery fault diagnosis.

2.0 Literature Review

Gear fault prediction is critical for ensuring the reliability and safety of mechanical systems. This literature review covers various techniques employed for this purpose, including deep learning, signal processing, and active learning, while highlighting their methodologies and limitations.

2.1 Deep Learning-based methods

Deep learning has revolutionized fault diagnosis by automating feature extraction and classification. The MF-DRCN model introduces a Multireceptive Field Denoising (MFD) block to improve feature extraction and an Adaptive Feature Integration (AFI) module for effective feature integration, achieving high diagnostic accuracy even under strong noise conditions (Xu *et al.*, 2022). However, the performance of MF-DRCN may vary across different industrial contexts. Transfer learning has been effectively used to address the issue of limited data availability. The MWSAN model uses a Multiscale Domain Adversarial Network (MDAN) and a weight selection mechanism based on maximum likelihood estimation and Gaussian mixture model for partial domain adaptation (Quan *et al.*, 2022). While effective in discriminating between shared and outlier classes, its focus is primarily on planetary gearbox fault diagnosis, suggesting the need for further exploration for other types of mechanical systems.

Similarly, another study combines Variational Mode Decomposition (VMD) for feature extraction and a fine-tuned VGG16 model for classification, achieving a high accuracy of 99.98% (Li *et al.*, 2022). This method is robust to noise and computationally efficient, but its results are limited to specific datasets. The ECA-CN model improves fault detection accuracy for compound faults using an Efficient Channel Attention (ECA) mechanism within a Capsule Network (CN) (Zhang *et al.*, 2023). It enhances feature selection and provides a robust, noise-resistant diagnosis system. However, it is only tested on one dataset, requiring further validation in real-world industry settings.

FaultFormer uses self-supervised pretraining with transformers, addressing data scarcity and improving adaptability to new fault classes and datasets (Zhou & Farimani, 2024). It employs different tokenization strategies (Constant, CNN, Fourier) and data augmentation to enhance the model's performance. However, the model requires large unlabeled datasets for effective pretraining and lacks interpretability. A fusion model using LSTM and CNN significantly improves fault detection accuracy, demonstrating the benefits of combining spatial and temporal features, using Continuous Wavelet Transform (CWT) for feature extraction, with an F1-score of 1.0 (Ghanbari *et al.*, 2023). This shows the model's superior precision and recall. However, it is tested on a specific dataset and may be computationally complex for real-time deployment. The FWR50 model, which uses Continuous Wavelet Transform (CWT) with transfer learning, is effective for fault classification with only 10% training data (Nguyen *et al.*, 2024). However, it requires further validation on different gear types.

2.2 Signal processing-based methods

Signal processing techniques are crucial for extracting relevant features from raw vibration data. A study introduces a novel rotational frequency search algorithm and a self referencing frequency identification method using PI and SI indices for automated fault diagnosis (Xu *et al.*, 2022). The anti-interference framework reduces false positives; however, it has only been tested on a bogie gearbox, requiring additional validation for other machinery. Similarly, FBSE-EWT improves frequency resolution and classification accuracy, particularly when used with the Random Forest classifier, demonstrating an 84% classification accuracy (Ramteke, *et al.*, 2023). However, the dataset size is limited, and its performance may vary under different conditions.

Another approach, GES2N, provides a generalized objective function for optimizing filter design under time-varying speed conditions by improving fault signature enhancement (Schmidt *et al.*, 2025). However, it requires careful parameter tuning and is primarily tested on gear faults.

2.3 Active learning methods

Active learning focuses on reducing annotation efforts. A study using a Bayesian uncertainty estimation framework to reduce manual annotation effort in vision-based gear defect detection demonstrated that it reduces annotation effort by 6x while maintaining accuracy (Liao & De Geest, 2024). While this approach is beneficial for reducing data needs, class imbalance and annotation inconsistencies remain.While each method provides unique insights, there are some common drawbacks. Deep learning models often require large amounts of labeled data, though transfer learning and self supervised methods are addressing this. Furthermore, deep learning models can be computationally intensive and lack interpretability, making them difficult to deploy in real-time.

Signal processing techniques need manual feature engineering and might not capture complex nonlinearities in the data. Active learning methods still require some initial labeled data and may suffer from annotation bias or class imbalance. Many studies use specific datasets, which limits the generalizability of the models for varied industrial settings. Deep learning provides powerful tools for automatic feature extraction and classification, while signal processing techniques provide valuable methods for extracting interpretable features from data. Hence, we focus on combining the strengths of these approaches by applying CQT on the signals and then applying the Xception transfer learning mechanism to build robust, efficient, and adaptable fault diagnosis systems for a wide range.

3.0 Dataset and Preprocessing

The Gear Box Detection dataset includes vibration data recorded using SpectraQuest's Gearbox Fault Diagnostics Simulator (Figure 1). Four vibration sensors captured data under varying loads, ranging from 0% to 90% in 10% increments. The dataset consists of 20 files—10 for a healthy gearbox and 10 for a broken-tooth condition. By applying CQT, a custom dataset comprising labeled images of healthy and faulty gearboxes was created and partitioned into training (70%), validation (15%), and test (15%) sets. Images were standardized to a 128×128×3 resolution and normalized using Inception specific preprocessing. To enhance model generalization, data augmentation techniques were applied during training, including random horizontal flips (±20◦ rotation), contrast variation (10%), and horizontal flipping to simulate real-world operational variances.

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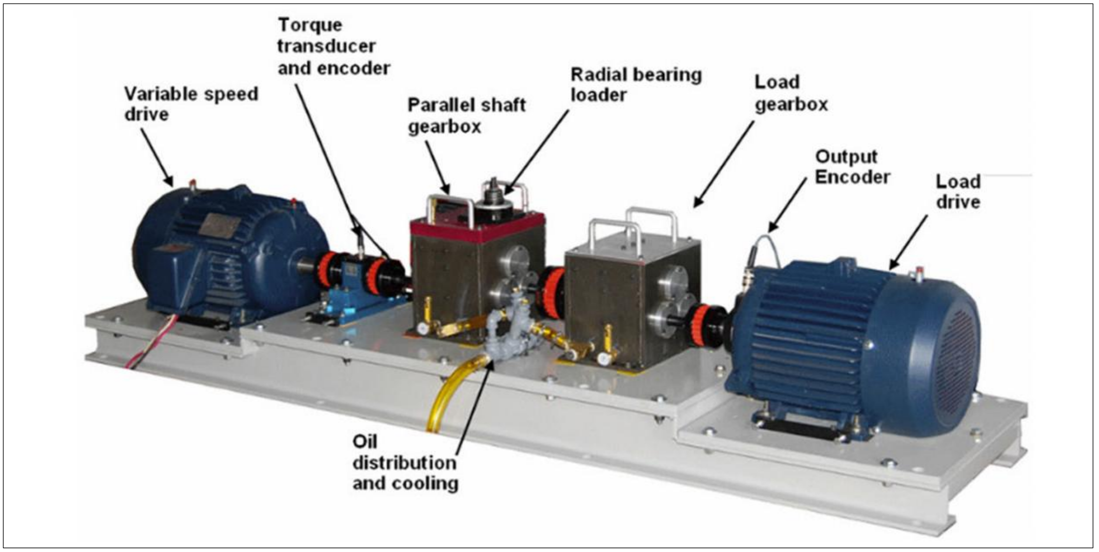
Figure 1: Illustrates the Gearbox Prognostics Simulator (GPS) by SpectraQuest, used for Machinery Health Monitoring



For a discrete vibration signal x(n), the CQT at frequency bin k and time index n is defined as:

$$X[k,n] = \sum_{m=0}^{N_k-1} x[n-m] \cdot w_k[m] \cdot e^{-j2\pi f_k m/f_s} \quad ...1$$

where: center frequency f_s is geometrically spaced:

$$f_k = f_{min} \cdot 2^{k/b} \quad ...2$$

The window length N_k adapts inversely with f_k:

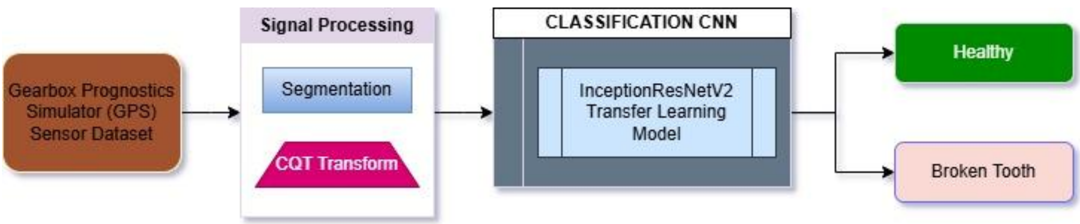
$$N_k = Q \cdot \frac{f_s}{f_k} \quad ...3$$

and the window function w_k is tapered and normalized. This structure ensures high frequency resolution at low frequencies and high time resolution at high frequencies, isolating meshing frequencies and transient impacts effectively. CQT's logarithmic scaling aligns with harmonic gearbox vibrations, enabling clear separation of meshing components and their modulations, while reduced spectral leakage improves fault detection accuracy. Computational efficiency via FFT-based optimizations supports real-time monitoring. Studies highlight CQT's superiority in diagnosing bearing defects and gear wear, where STFT and WT fail to resolve closely spaced harmonics.For non-stationary vibration signals, CQT's adaptive resolution,geometric frequency spacing, and noise robustness make it indispensable, positioning it as the preferred tool for gearbox diagnostics despite the continued utility of STFT and WT.

4.0 InceptionResNetV2 Transfer Learning Model

InceptionResNetV2 is a hybrid deep learning model that combines the strengths of the Inception architecture andresidual connections (ResNet), making it particularly well suited for analyzing CQT spectrograms,which are 2D time-frequency representations of vibration signals. This model offers several advantages for CQT spectrogram analysis, including its ability to capture complex patterns, robustness to noise, and scalability, making it ideal for industrial applications such as gearbox fault diagnosis (Figure 2). Compared to models like VGG or standard Inception, InceptionResNetV2 provides a more sophisticated feature extraction mechanism. One of its key strengths lies in the combination of Inception modules and residual connections, which allows the model to capture both fine-grained and high-level features in CQT spectrograms, critical for identifying subtle fault patterns in gearbox vibration signals.The Inception modules use parallel convolutional layers with different kernel sizes (e.g., 1 × 1, 3 × 3, 5 × 5), enabling multi-scale feature extraction.

Figure 2: Proposed InceptionResNetV2 Transfer Learning Model



This capability is particularly useful for analyzing CQT spectrograms, where transient events (e.g., gear tooth impacts) and steady-state patterns (e.g., harmonic frequencies) need to be detected.Additionally, the residual connections in InceptionResNetV2 enhance robustness to noise by preserving important features through skip connections, ensuring reliable feature extraction even in noisy conditions, which is common in vibration signals from gearboxes due to environmental factors or sensor inaccuracies. Another significant advantage of InceptionResNetV2 is its transfer learning capabilities. Pre-trained on large datasets like ImageNet, the model can be fine-tuned for specific tasks, such as analyzing CQT spectrograms, significantly reducing the need for large labeled datasets, which are often scarce in industrial applications.

This makes InceptionResNetV2 highly effective for tasks like gearbox fault diagnosis, where labeled data may be limited. Furthermore, the model achieves state-of-the-art performance with a relatively efficient architecture, balancing computational efficiency and feature extraction capability. Its architecture includes a Stem Block that down samples the input CQT spectrogram and extracts low-level features crucial for capturing transient events in vibration signals, such s gear tooth impacts or bearing defects. Inception-ResNet Modules combine multi-scale feature extraction with residual connections, ensuring smooth gradient flow and preventing vanishing gradients. Reduction Blocks downsample feature maps, reducing computational complexity while preserving important features, which is particularly useful for processing large CQT spectrograms.

Finally, Global Average Pooling and Fully Connected Layers aggregate high-level features and perform classification or regression tasks, with global average pooling reducing the dimensionality of feature maps to make the model more efficient. InceptionResNetV2 has been successfully applied in various industrial tasks, particularly in vibration signal analysis for gearbox fault diagnosis.

Table 1: Performance Comparison of Various Fault Detection Methods

Literature & Year	Accuracy (%)
Dutta *et al.*, 2024 (GearFaultNet-1D CNN)	94.06
Ahmed *et al.*, 2023(Autoencoder-based Model)	91.00
Proposed Method, 2025 (ResNet-EfficientNetV2-based Model)	**98.04**

It has been used to diagnose faults such as gear tooth cracks, misalignments, and bearing defects, leveraging its ability to capture multi-scale features to identify subtle fault patterns in CQT spectrograms. Additionally, it has been applied to condition monitoring of rotating machinery, including gearboxes and motors, demonstrating robustness to noise and the ability to capture complex patterns, making it suitable for real-world industrial environments. The model's pre-trained weights have been fine-tuned for various industrial tasks, including defect detection and fault diagnosis, highlighting its versatility for analyzing vibration signals in data-limited scenarios.

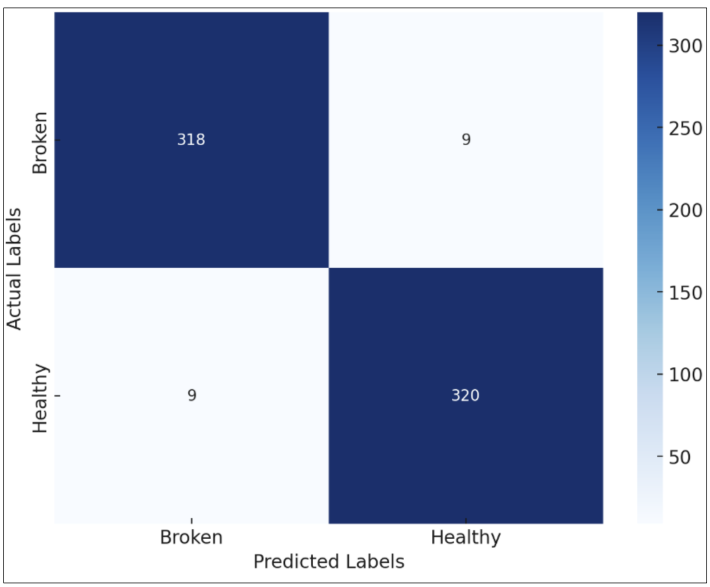
Overall, InceptionResNetV2 is a powerful and versatile model for analyzing CQT spectrograms, offering advantages such as multi-scale feature extraction, robustness to noise, and transfer learning capabilities. Its hybrid architecture, combining Inception modules and residual connections, makes it particularly effective for capturing the complex patterns present in gearbox vibration signals. Its proven success in industrial applications, such as gearbox fault diagnosis and condition monitoring, further validates its effectiveness for vibration signal analysis.leveraging InceptionResNetV2, researchers and engineers can achieve high accuracy and robustness in analyzing vibration signals, even in noisy and data-limited environments.

5.0 Results and discussions

The use of Adam optimizer, sparse categorical cross-entropy loss, confusion matrices, ROC analysis, specificity, and AUC is crucial for analyzing CQT spectrograms derived from gearbox vibration signals in industrial fault diagnosis. The Adam optimizer, with its adaptive learning rate and efficient convergence properties, is highly effective for training deep learning modelson complex datasets like CQT spectrograms, enabling faster convergence and higher accuracy in classifying gearbox faults. Sparse categorical cross-entropy loss is computationally efficientfor multi-class classification tasks, such as distinguishing between normal conditions, gear tooth cracks, and bearing defects, ensuring the model learns to differentiate fault typeseffectively.

Confusion matrices provide a detailed breakdown of predictions, highlighting true positives, false positives, and other metrics to evaluate class-wise performance, which iscritical for understanding model strengths and weaknesses in identifying fault types. ROC analysis evaluates model performance across classification thresholds by plotting the true positive rate against the false positive rate, offering threshold independent insights and enabling comparisons between models, especially in imbalanced datasets. Specificity ensures the model reliably identifies normal conditions, minimizing false alarms in industrial settings.

Figure 3: Confusion Matrix of Proposed Model



Finally, AUC, the area under theROC curve, summarizes overall model performance with a single scalar value, providing a robust metric for evaluating fault diagnosis models in scenarios with class imbalance. In Figure 3, Confusion matrix metrics reveal strong performance with 318 true positives, 320 true negatives, 9 false positives, and 9 false negatives, yielding an accuracy of 98.04% (Table 1), precision of 97.06%, recall of 97.04%, and an F1 score of 95.04%. Specificity is calculated at 97.27%, ensuring reliable identification of normal conditions, while ROC analysis and AUC provide threshold-independent evaluations, particularly valuable for imbalanced datasets. Together, these tools ensure reliable fault diagnosis and enhance the practical applicability of deep learning models in analyzing gearbox vibration signals.

These metrics are essential for evaluating the performance of fault diagnosis models, particularly in scenarios where class imbalance is prevalent. By leveraging these tools and metrics,researchers and engineers can develop robust and reliable models for analyzing gearbox vibration signals using CQT spectrograms. Various fault detection methods have been explored for machinery, with notable advancements in deep learning, signal processing, and transfer learning techniques.

One approach,using Deep Neural Networks (DNN) for gear defect detection, achieved 95.5% accuracy, offering real-time diagnosis in low performance settings, but with limitations in classifying new defect types. Autoencoder-based models, particularly a 6-layer model for anomaly detection in industrial machines, demonstrated high precision (98%) and recall (83%), proving effective for gearbox fault detection. GearFaultNet, a lightweight 1D Convolutional Neural Network (CNN), achieved 94.06% accuracy in distinguishing gearbox conditions but was limited to binary classification. LECA-EfficientNetV2, which utilizes a lightweight channel attention mechanism, set a new standard with 99.38% accuracy on bearing and 99.75% on gear samples,optimizing diagnosis time and robustness, especially for small sample sizes. LECA-EfficientNetV2 also outperformed other attention mechanisms, such as SE-EfficientNetV2 and ECA-EfficientNetV2, in both accuracy and diagnosis time.

Additionally, transfer learning tasks demonstrated its superior feature learning ability, reaching 99.63% accuracy in fault diagnosis under varying conditions. When compared to models like ResNet50 and MobileNetV3-L, LECA-EfficientNetV2 showed the highest accuracy and shortest diagnosis time. Traditional algorithms, including Support Vector Machines (SVM) and Artificial Neural Networks (ANN), were mentioned but lacked detailed performance metrics. CNNs, in various forms (1D-CNN, 2D-CNN, and hybrid), continue to be highly effective for fault diagnosis, with attention mechanisms frequently enhancing performance by focusing on relevant features in data.

6.0 Conclusions

This work demonstrates the viability of ResNet- EfficientNetV2 transfer learning-based fault detection for industrial systems, achieving 98.04% accuracy with rigorous evaluation. The pipeline's modular design permits adaptation to other rotating machinery systems, offering a template for predictive maintenance solutions. By reducing unplanned downtime through early fault identification, the framework holds significant potential for cost reduction in manufacturing and energy sectors. The system, while effective for visible faults, requires future improvements in multi-modal fusion for subsurface defect detection, few-shot learning to handle rare fault categories, and explainable AI techniques like Grad-CAM or attention mechanisms for enhanced interpretability in maintenance. Future efforts will focus on real-time deployment and multi-modal data integration for comprehensive health monitoring.

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