Abstract (English)

The increasing reliance on vehicles for personal and commercial purposes underscores the critical need for efficient fault diagnosis systems to ensure reliability, reduce emissions, and maintain mechanical integrity. Among these faults, engine misfires and rotating element bearing faults present significant challenges present significant challenges due to their impact on performance, fuel efficiency, and environmental compliance. This thesis addresses these challenges by developing an advanced diagnostic framework that combines low-cost, high-performance MEMS accelerometers, state-of-the-art digital signal processing (DSP) techniques, and artificial intelligence (AI) models.

The ADXL1002 capacitive MEMS accelerometer was employed as the primary sensing device for its exceptional sensitivity, wide bandwidth, and cost-effectiveness. It was integrated with the BeagleBone Black controller, enabling real-time acquisition and processing of vibration signals from vehicle engines under varying operational conditions, including different RPMs, load levels, and induced misfire scenarios. Additionally, datasets of rotating element bearing vibrations from existing literature were incorporated to complement the analysis and broaden the diagnostic framework. A rigorous calibration process ensured precise and reliable measurements. The system generated a high-quality dataset of vibration signals, which forms the basis for subsequent analysis.

To extract meaningful diagnostic information from these complex and noisy signals, advanced DSP techniques were employed. These included Empirical Mode Decomposition (EMD) to isolate intrinsic mode functions, Spectral Kurtosis (SK) for transient signal analysis, and Short-Time Fourier Transform (STFT) for time-frequency representation. These methods effectively highlighted fault-specific patterns, enabling accurate identification of misfire-related characteristics. The findings were further validated using rolling bearing datasets, ensuring the robustness and generalizability of the approach.

The integration of AI into the diagnostic framework significantly enhanced fault detection capabilities. Convolutional Neural Networks (CNNs) and hybrid models combining Deep CNNs with Long Short-Term Memory (LSTM) units were developed. These models analyzed one-dimensional (1D) time-series data and two-dimensional (2D) image representations of vibration signals. The CNNs captured spatial features in the 2D domain, while the hybrid DCNN-LSTM models effectively leveraged temporal dependencies in the 1D domain. This dual approach yielded superior diagnostic accuracy and robustness across diverse operating conditions, demonstrating the potential of AI-driven systems in real-world applications.

This research makes several noteworthy contributions: the development of a reliable real-time vibration acquisition module, the creation of a novel engine vibration dataset, the application of advanced DSP techniques for fault feature extraction, and the implementation of AI models tailored for misfire diagnosis. The methodologies proposed extend beyond automotive applications, with potential implications for fault diagnosis in industrial machinery, aerospace systems, and renewable energy technologies. By integrating low-cost sensing technologies with advanced analysis methods, this work aligns with sustainable and scalable maintenance practices, setting a benchmark for future innovations in condition monitoring and predictive maintenance.

Keywords: Engine misfire diagnosis, vibration analysis, ADXL1002 accelerometer, BeagleBone Black, digital signal processing (DSP), artificial intelligence (AI), Convolutional Neural Networks (CNN), DCNN-LSTM hybrid models, Empirical Mode Decomposition (EMD), Spectral Kurtosis (SK), Short-Time Fourier Transform (STFT), condition monitoring, predictive maintenance.