Modern industry relies heavily on machines that must operate reliably over long periods. Unexpected machine failures lead to costly downtime, production losses, and sometimes even pose risks to human safety or the environment. To prevent such issues, engineers increasingly turn to predictive maintenance systems – solutions designed to detect signs of wear or malfunction before the machine actually breaks down. This allows for better planning of maintenance tasks, reduces unexpected outages, and lowers operational costs.

One of the most effective and widely used diagnostic methods is vibration analysis. Sensors mounted on the machine's casing "listen" to its operation by recording vibrations, which are then processed by computer algorithms. This analysis can reveal subtle anomalies that are otherwise invisible. However, today's algorithms are typically trained on very "clean" laboratory data, free from disturbances, temperature shifts, or variable workloads. In real-world production environments, such ideal conditions rarely exist – machines operate at different speeds, sensors degrade over time, and background noise from nearby equipment can distort the signals.

This project aims to develop a new generation of diagnostic algorithms that will be:

- more resistant to disturbances and changes in operating conditions,

- easier to deploy across different machines and industrial setups,

- more transparent and understandable for engineers.

To achieve this, a hybrid vibration analysis system that combines traditional condition indicators (e.g. frequencies specific to bearing faults) with raw vibration signals will be designed. This system will be capable of learning from the data and adapting itself to new environments – such as different machines or operating regimes – without the need for manual configuration. This type of learning and adjustment is known as domain adaptation in computer science.

Furthermore, to address situations where real-life fault data is scarce – such as for rare but dangerous failures like shaft cracks – artificial intelligence will be used to generate realistic training data. The algorithm responsible for this task will follow physical constraints, such as those related to rotational frequencies or mechanical resonance, to ensure that the synthetic data is not only mathematically valid but also physically meaningful.

The proposed solution will be tested on both well-known datasets (e.g. NASA's bearing data) and on a custom-built experimental test rig. This platform will allow controlled fault injection, variable load settings, and real-time signal analysis, closely simulating real industrial scenarios.

The project outcomes – datasets, algorithms, and diagnostic tools – will be made publicly available as open-source software. This will enable other researchers and engineers to use, validate, and extend the work. Additionally, I hope that through accessible documentation and educational materials, the project will contribute to the popularisation of AI applications in industry and inspire young scientists to pursue research in this important field.