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Presented by:

- **Samia BENZITA**
- **Ahmed Saadeddine BERTAL**

Thesis Title

Bearing Fault Detection and Classification Using Machine Learning Neural Networks – Application to Rotating Machines –

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Jury Committee:

Name	Grade	University	Role
Dr. Aissa AMEUR	Prof.	Univ. of Laghouat	President
Dr. Djamel eddine BOUGRINE	MCB	Univ. of Laghouat	Examiner
Dr. Saddam BENSAOUCHA	MCB	Univ. of Laghouat	Supervisor

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Dedication

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✎... *Samia BENZITA*

Univ. Amar TELIDJI, Laghaout

s.benzita.elt@lagh-univ.dz

25-Juin-2025

Dedication

To you **Allah** Almighty God, creator of heaven and earth. I thank You for giving me the will and especially the courage to carry out this work under good conditions.

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✎... *AHMED SAAD EDDINE BERTAL*
Univ. Amar TELIDJI, Laghaout
a.bertal.elt@lagh-univ.dz
20-juin-2025

Abstract

This thesis focuses on the application of artificial intelligence, particularly Multilayer Perceptron (MLP) neural networks, for the detection and diagnosis of bearing faults in rotating machinery. Bearings, as key components of industrial systems, require early fault detection to prevent costly failures and production downtime. Although traditional methods are effective, they remain limited by their reliance on human intervention and predefined failure modes. This research proposes an automated approach based on machine learning using vibration signals to detect and classify faults. Inputs to the MLP networks are extracted through statistical analysis of the signals, using parameters such as maximum, minimum, and median. Several network architectures are tested on datasets, including the Case Western Reserve University dataset. The results demonstrate that these methods improve diagnostic accuracy, opening promising prospects for predictive maintenance. Finally, the study examines the implications of the findings and suggests ways to enhance the performance and robustness of fault detection systems.
Keywords: rotating machines, bearing faults, fault detection, artificial intelligence, neural networks.

Résumé

Ce mémoire porte sur l'application de l'intelligence artificielle, notamment des réseaux de neurones MLP, pour la détection et le diagnostic des défauts de roulements dans les machines rotatives. Les roulements, composants clés des systèmes industriels, nécessitent une détection précoce afin d'éviter pannes coûteuses et interruptions de production. Bien que les méthodes classiques soient efficaces, elles restent limitées par leur dépendance à l'intervention humaine et aux modes de défaillance prédéfinis. Cette recherche propose une méthode automatisée basée sur l'apprentissage automatique à partir de signaux de vibration pour détecter et classer les défauts. Les entrées des réseaux MLP sont extraites par une analyse statistique des signaux, utilisant des paramètres comme le maximum, le minimum et la médiane. Plusieurs architectures de réseaux sont testées sur des jeux de données, dont celui de l'université Case Western Reserve. Les résultats montrent que ces méthodes améliorent la précision du diagnostic, ouvrant des perspectives prometteuses pour la maintenance prédictive. Enfin, l'étude analyse les implications des résultats et propose des pistes pour améliorer la performance et la robustesse des systèmes de détection.
Mots-clés : machines rotatives, défauts de roulements, détection, intelligence artificielle, réseaux de neurones.

ملخص

تركز هذه الرسالة على تطبيق الذكاء الاصطناعي، وبشكل خاص شبكات العصبونات متعددة الطبقات ، للكشف وتشخيص عيوب المحامل في الآلات الدوارة. تعتبر المحامل من المكونات الأساسية في الأنظمة الصناعية، وتتطلب كشفًا مبكرًا للأعطال لتجنب الأعطال المكلفة وتوقف الإنتاج. بالرغم من فعالية الطرق التقليدية، إلا أنها تبقى محدودة بسبب اعتمادها على التدخل البشري وأنماط الأعطال المحددة مسبقًا. تقترح هذه الدراسة نهجًا آليًا قائمًا على التعلم الآلي باستخدام إشارات الاهتزاز للكشف وتصنيف الأعطال. يتم استخراج مدخلات الشبكات العصبية من خلال تحليل إحصائي للإشارات باستخدام معايير مثل القيم العظمى، الصغرى، والوسيط. تم اختبار عدة هياكل شبكية على مجموعات بيانات، من بينها مجموعة بيانات جامعة ثس واسترن غسرڤ. تظهر النتائج أن هذه الطرق تحسن من دقة التشخيص، مما يفتح آفاقًا واعدة للصيانة التنبؤية. وأخيرًا، تناقش الدراسة تداعيات النتائج وتقترح سبلًا لتعزيز أداء وموثوقية أنظمة كشف الأعطال.

الكلمات المفتاحية: الآلات الدوارة، أعطال المحامل، الكشف عن الأعطال، الذكاء الاصطناعي، الشبكات العصبية.

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Abbreviation

Abbreviation	Definition
AI	Artificial Intelligence
ML	Machine Learning
ANN	Artificial Neural Network
MLPs	Multi-Layer Perceptrons
CNN	Convolutional Neural Network
LSTM	Long Short-Term Memory
FFT	Fast Fourier Transform
NNN	Narrow Neural Network
MNN	Medium Neural Network
WNN	Wide Neural Network
BNN	Bilayered Neural Network
TNN	Trilayered Neural Network
ONN	Optimizable Neural Network

General Introduction

General introduction

Rotating machines are a key part of contemporary industrial plants, including manufacturing plants, power plants, transportation networks, and automated manufacturing environments. The stable and continuous operation of the machines is crucial in order to gain system reliability, operational safety, and economic efficiency. Among all parts of rotating machinery, bearings assume the most crucial function, considering that they locate rotating shafts and enable free relative motion by reducing friction between moving parts. Though they are critical, bearings are susceptible to degradation due to prolonged mechanical stress,lubrication deficiency, misalignment, and exposure to contaminants [25, 26, 27]. These conditions induce progressive degradation and, eventually, failure in operation. Hidden faults in bearings may result in unplanned downtime, costly repair measures, and, in some cases, catastrophic machine failure. Therefore, the early detection of faults and bearing faults diagnosis is essential for maintaining the operational integrity and lifespan of rotating machines,the problem that we addressed in our research was the ineffectiveness of traditional diagnostic methods for bearing fault detection, which are non-flexible and not accurate enough to stably work under real industrial conditions. Traditional approaches were not able to provide timely and accurate fault diagnosis, particularly when dealing with non-stationary and compound vibration signals [1].

In our study, we avoided this issue by designing an intelligent predictive maintenance system based on advanced data-driven techniques. We combined high-level signal processing with machine learning techniques to build a robust real-time monitoring system capable of stably detecting mechanical failure.

Artificial neural networks, namely the Multilayer Perceptron (MLP) model, were employed due to their proven ability in pattern recognition and time-series analysis of vibration signals [25][27]

The primary objective of our study was to achieve early and reliable detection and classification of bearing faults of rotating equipment. Using MLP-based classification in conjunction with carefully obtained signal features, we significantly enhanced fault diagnosis reliability and accuracy with utmost contribution to more secure and efficient industrial operations.

In Chapter 1, the concept of rotating machines was introduced, with emphasis on their various types and fundamental structural components. Given that bearings constitute the central focus of this thesis, particular attention was paid to their construction and classification. Among the commonly encountered issues, mechanical stress was identified as a significant factor affecting bearing performance. Finally, a brief overview of fault detection techniques was presented, aiming to enhance operational reliability and prevent unexpected failures.

In Chapter 2, we explained the fundamental concepts of Machine Learning and Artificial Intelligence, outlining their history and principal areas of application. Special attention was dedicated to the three principal machine learning types:

supervised learning, reinforcement learning, and unsupervised learning, which were explained through their principles and applications. We also touched upon commonly used machine learning algorithms, with the emphasis on their application to industrial fields. This chapter gave the theoretical framework needed for understanding how smart systems can be used to analyze processes such as fault detection and classification in rotating machinery.

In Chapter 3, we delve into the application of Artificial Neural Networks (ANNs) for fault diagnosis in rotating machinery, with a particular focus on bearing defect detection and classification. We begin by introducing the basic structure and working principles of neural networks, emphasizing the architecture of Multilayer Perceptrons (MLPs). This chapter demonstrates how AI-based approaches, especially MLPs, can enhance predictive maintenance and operational reliability in industrial settings.

In Chapter 4, we shift our focus to the practical implementation and evaluation of the proposed Multilayer Perceptron (MLP) model for bearing fault diagnosis using vibration data. This chapter presents the detailed process of data preparation, feature extraction, and model training and testing on real industrial datasets. We analyze the performance of the MLP in terms of accuracy, reliability, and early fault detection capabilities. This chapter bridges the gap between theoretical concepts and practical applications, demonstrating the effectiveness of machine learning techniques in predictive maintenance of rotating machinery.

Together, the four chapters provide an end-to-end framework for understanding and addressing the problem of bearing fault diagnosis of rotating machinery. From the fundamentals of rotating machines and bearing faults, and moving on to artificial intelligence and neural network theory, the work arrives at the practical application of an MLP-based diagnosis system. This structured approach not only demonstrates the viability of intelligent systems in modern industrial maintenance but also demonstrates the potential of data analytics to improve reliability, reduce downtime, and increase operational effectiveness in real-world applications.

Chapter I

State of the Art on Rotating Machines, Their Defects and Detection

I.1 Introduction

Rotating machines have a pivotal role in modern industry, where they are used to effect a conversion from electrical energy to mechanical energy (motors) or mechanical energy to electrical energy (generators). Rotating machines such as induction motors, synchronous motors, and generators, among them find widespread applications in industrial automation, transportation, and power generation systems. Due to continuous operation and exposure to mechanical, electrical, and environmental stresses, rotating machines are vulnerable to various faults. Mechanical faults such as bearing defects, misalignment, and eccentricity, as well as electrical faults like stator winding failures and rotor bar cracks, are common. If undetected, these issues may cause serious breakdowns, downtime, and financial loss [25, 26, 27].

In this chapter, we provided a detailed overview of rotating machines, covering their classification into electrical and mechanical types, as well as their main structural components such as the stator, rotor, and bearings. We highlighted the critical role of bearings as the most failure-prone part of rotating machinery and discussed common mechanical and electrical faults that affect these machines. Furthermore, the chapter explored various fault detection and diagnosis techniques, ranging from traditional methods like vibration analysis to advanced signal processing and artificial intelligence approaches.

I.2 Rotating machines

Rotating machines include motors, turbines, and pumps. In various industries, electricity is used to convert energy into a critical function. The rotating machine works by continually rotating elements in different directions such as through a shaft (rather than a single vertical motion), through a rotor (rather than an inward rotation) or through an impeller. Electric engines take a form of mechanical movement, and convert electrical energy in the form of the movement of an electric motor or in the form of electricity from mechanical input. Others, such as turbines, pumps and compressors, are effective at the transfer of energy or fluid. Problems with these types of machines include bearing faults, misalignment, unbalance, electrical problems, etc. This lead to costlier and less efficient failure. Early fault detection helps to minimize downtime, downtime costs, and maintenance downtime. Traditional scheduled maintenance are increasingly replaced by real-time condition monitoring using advanced technologies such as vibration analysis, thermography, and ultrasonic testing. There are increasing applications of machine learning and neural networks in fault detection and classification, which contribute to predictive maintenance strategies for reliability and efficiency [25, 27]. Figure II.2 presents a rotating machine.

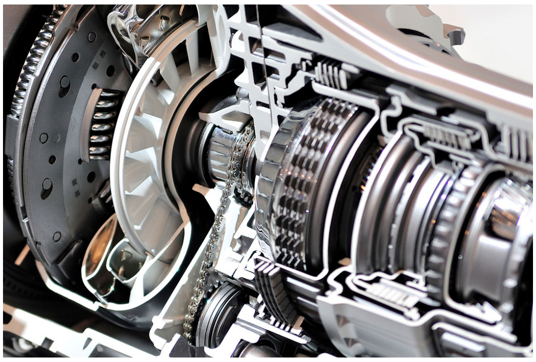


Figure I.1: Rotating Machinery [1].

Rotating machines are broadly classified on the basis of their function and operating principles. Below are the main types of rotating machine, categorized into electric machines and mechanical machines [25, 2]:

I.2.1 Electrical Rotating Machines

Electrical rotating machines convert electrical energy into mechanical energy (motors) or mechanical energy into electrical energy (generators)[25, 2] :

I.2.1.1 Electric Motors

Electric motors are used to drive mechanical loads in industrial, transportation, and domestic applications. They are classified based on their power source [25, 2]:

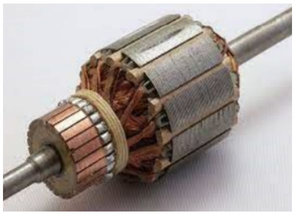
- **AC Motors**:
  - Induction Motors (Asynchronous Motors)
  - Synchronous Motors
- **DC Motors**:
  - Powered by direct current (DC), suitable for applications requiring variable speed control.

I.2.1.2 Electric Generators

Electric generators (In figure I.2) convert mechanical energy into electrical energy. They are mainly categorized as:

- **AC Generators (Alternators)**:
  - Commonly used in power generation stations.
  - Convert mechanical rotation into alternating current (AC) electricity.
- **DC Generators**:
  - Used in specialized applications such as control system power supplies.

Figure 1.2 below presents an illustrative representation of them.



(a) D.C. Generator

(b) A.C. Generator .

(c) D.C Motor.

(d) A.C. Motor

Figure I.2: Different Types of Electrical Machines[2].

I.2.2 Mechanical Rotating Machines

Mechanical rotating machines operate through the transmission of mechanical energy and are widely used in industrial processes. They can be categorized into the following types [28]:

- **Turbines**:
  - Examples include steam turbines, gas turbines, wind turbines, and hydraulic turbines.

- **Pumps and Compressors**:
  - Common types include centrifugal pumps and reciprocating compressors.
- **Gear Systems and Rotational Shafts**:
  - These are critical components in vehicles, industrial machinery, and power transmission systems.

Figure I.3 presents a diagram that provides a comparative overview of the different types of rotating machines.

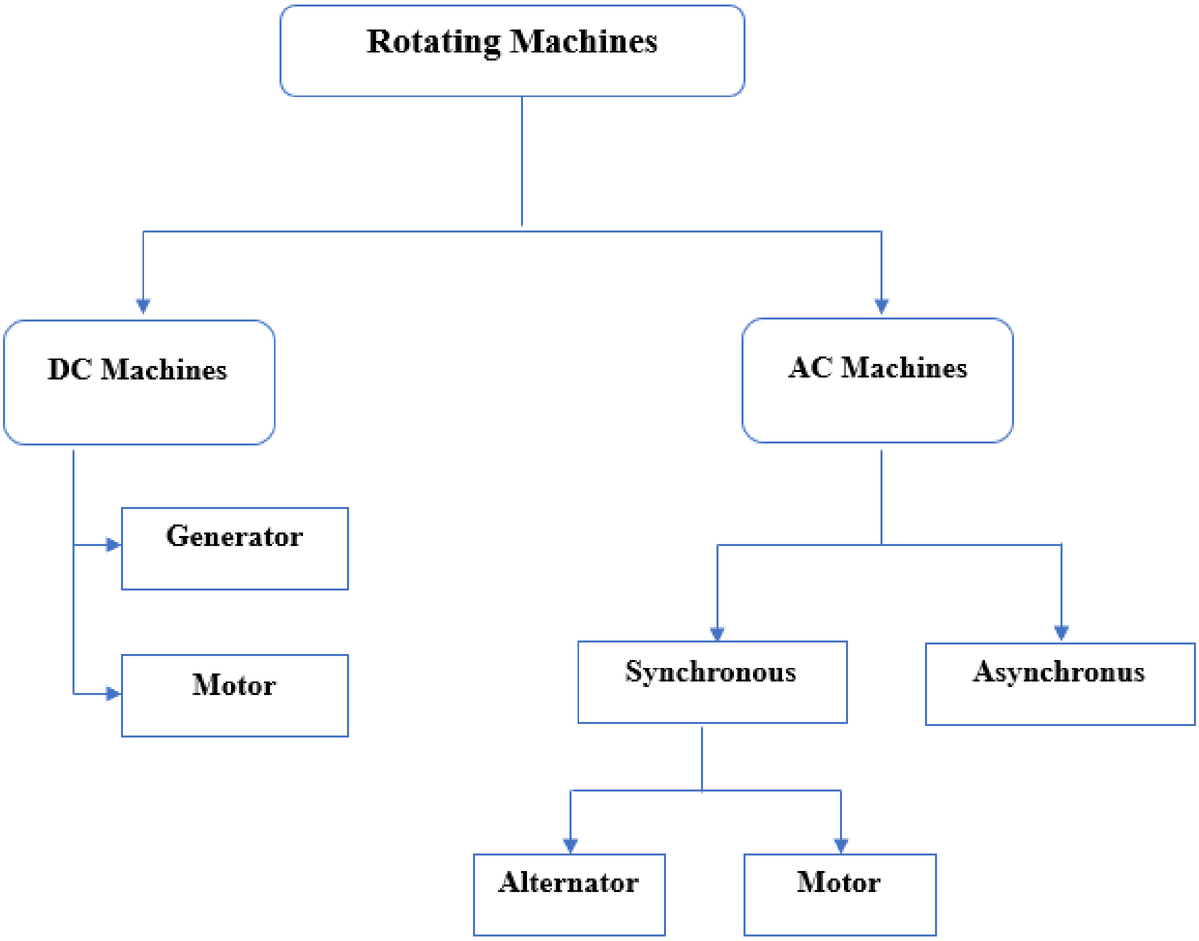


Figure I.3: Basic Machines Types [3].

I.3 Rotating Machine Construction and Structure

Rotating machines consist of two principal components: the stator and the rotor. The stator is the stationary part, typically fixed within the machine housing, while the rotor is mounted on a shaft and rotates within the stator. Bearings support the rotor and ensure smooth motion. In electric machines, the stator produces a magnetic field that drives the rotor, whereas in mechanical systems, the design of the bearings and structural components depends on the machine's specific function [29]:

I.3.1 Stator (Stationary Part)

As shown in Figure I.4, the stator surrounds the rotor and remains fixed. It is crucial in motors for generating the magnetic field that initiates rotor movement, and in generators, it interacts with the rotor to convert mechanical energy into electrical energy [29].

I.3.2 Rotor (Rotating Part)

Also illustrated in Figure I.4, the rotor rotates within the stator and is supported by bearings. In motors, it converts electrical energy into mechanical rotation, while in generators, it uses mechanical input to induce current in the stator windings [29].

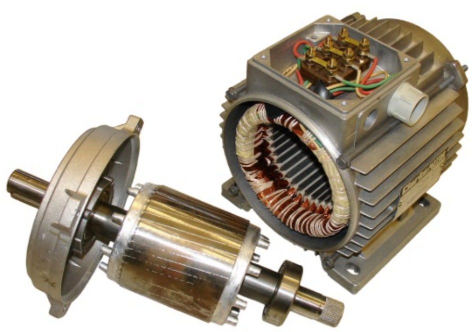


Figure I.4: Stator and Rotor [4].

I.3.3 Bearings

Bearings, illustrated in Figure I.5, are critical mechanical components designed to support the rotor and facilitate its smooth rotation. Positioned between the rotor shaft and the machine housing, they play a fundamental role in minimizing friction and wear between moving and stationary parts. By maintaining proper alignment and supporting the rotor's weight, bearings ensure reliable operation and extend the operational lifespan of rotating machines.

Several types of bearings are commonly used in industrial applications [30, 5]:

- **Ball Bearings:** Widely used in electric motors, these bearings support both radial and axial loads, offering low friction and high-speed performance.

- **Roller Bearings:** Suitable for applications involving heavy radial loads, they provide greater load capacity due to line contact between rolling elements and races.

- **Magnetic Bearings:** These advanced bearings use magnetic fields to levitate the rotor, thereby eliminating physical contact, reducing mechanical losses, and enabling virtually wear-free operation.

Figure I.5: bearings [5].

I.4 Common Faults in Rotating Machines

Rotating electrical machines are subject to a wide range of faults that can significantly impact their performance and operational reliability. These faults are generally classified into two main categories: electrical and mechanical faults [31, 32].

I.4.1 Electrical Faults

Electrical faults typically originate within the stator or rotor windings and include[31, 32].:

- **Stator winding faults**: Such as inter-turn short circuits, phase-to-phase faults, or phase-to-ground faults.

- **Broken rotor bars**: A frequent issue in squirrel-cage induction motors, leading to asymmetrical rotor currents and torque pulsations.

- **Insulation failures**: Resulting from thermal aging, voltage surges, or contamination, which may lead to electrical breakdown.

- **Phase imbalances**: Unequal voltage or current in the supply phases can cause overheating and reduced efficiency.

I.4.2 Mechanical Faults

Mechanical faults arise due to structural or dynamic issues within the rotating machine. Common types include[31, 32].:

- **Bearing defects**: Such as wear, pitting, or spalling, which generate vibration and noise, potentially leading to catastrophic failure.
- **Rotor imbalance**: Occurs when the mass distribution is uneven, causing excessive vibration and wear.
- **Shaft misalignment**: Misalignment between the motor and driven load can result in mechanical stress and premature failure of bearings or couplings.
- **Component looseness**: Includes loosened bolts, mounts, or other mechanical connections, often indicated by non-linear vibration behavior.
- **Mechanical resonance**: When the operating frequency coincides with a natural frequency of the system, potentially leading to excessive vibrations.
- **Gear-related faults**: In systems involving gears, defects such as tooth wear or misalignment may arise, leading to irregular torque transmission and vibration.

Failure to detect these faults in a timely manner can result in degraded machine performance, elevated energy consumption, unplanned operational downtimes, and significant maintenance costs. Consequently, early fault detection and accurate diagnosis are critical to maintaining the reliability, efficiency, and safety of rotating machinery.

I.5 Bearing Faults

Bearings play a crucial role in rotating machinery by minimizing friction between moving components, thereby enabling smooth operation. Studies show that bearings are the most common point of failure in these systems, more so than the stator and rotor, which typically have longer lifespans. Their vulnerability is attributed to factors such as inadequate lubrication, mechanical fatigue, misalignment, overloading, contamination, and electrical discharges—all of which contribute to their gradual deterioration. According to literature, bearing faults account for approximately 40–45% of rotating machine failures, followed by stator faults 30-37% and rotor faults (10%) [27, 30, 33].

Bearings are mechanical components that support loads while allowing rotational or linear motion with minimal friction and wear. They achieve this through rolling elements, such as balls or rollers, positioned between inner and outer rings. This design ensures low-resistance movement and reliable performance. Bearings are widely used in applications such as automotive systems, electric motors, turbines, and aerospace engineering [30, 34]. Common bearing faults include:

- Outer race defects
- Inner race defects
- Ball defects
- Cage defects

These faults can lead to increased vibration, noise, heat generation, and mechanical instability. If undetected, they may cause serious damage to the machinery, reduce operational efficiency, and lead to unexpected shutdowns or costly repairs. Detection techniques include vibration analysis (to identify fault-related frequencies), acoustic emission analysis (to detect high-frequency stress waves), and thermographic imaging (to monitor abnormal temperature rises). Figure I.6 illustrates the various types of bearing faults [30, 34].

Figure I.6: The bearing faults [6].

I.6 Fault Diagnosis in Rotating Machinery

Fault diagnosis refers to the systematic process of detecting, identifying, localizing, and assessing faults in dynamic systems through the analysis of data collected from various sensors and operational signals. In the context of rotating machinery, fault diagnosis plays a critical role in ensuring operational reliability, enhancing safety, and enabling predictive maintenance strategies. Diagnostic systems typically utilize different types of signals, including vibration, acoustic emissions, temperature, and electrical current [35, 36].

The main techniques used for fault detection and diagnosis can be grouped into three categories: traditional methods, signal processing techniques, and artificial intelligence-based approaches.

I.6.1 Traditional Diagnostic Methods

Traditional approaches rely on direct measurements and human interpretation to detect physical or operational anomalies. These include [35, 31]:

- **Vibration Analysis:** Detects faults such as misalignment, imbalance, and bearing defects through time and frequency-domain analysis.
- **Acoustic Emission:** Captures high-frequency stress waves generated by crack initiation or friction between components.
- **Thermography:** Utilizes infrared imaging to reveal abnormal heating patterns due to friction or electrical faults.
- **Oil Analysis:** Monitors lubricant quality and detects metallic wear particles indicative of gear or bearing wear.
- **Electrical Signature Analysis:** Analyzes electrical parameters to detect faults in windings, rotor bars, or power supply systems.

I.6.2 Signal Processing Techniques

Signal processing techniques enhance fault-related features and are essential for interpreting complex or non-stationary signals [31, 36]:

- **Fast Fourier Transform (FFT):** Provides frequency-domain analysis of periodic signals.
- **Wavelet Transform (WT):** Offers multi-resolution time-frequency analysis suitable for non-stationary and transient signals.

- **Envelope Analysis:** Effective for identifying repetitive impact events in defective bearings and gear systems.

- **Hilbert-Huang Transform (HHT):** A data-driven method suitable for nonlinear, non-stationary signal decomposition.

I.6.3 Machine Learning and Artificial Intelligence Techniques

Recent developments in AI have enabled data-driven fault detection models that improve accuracy, scalability, and adaptability [32, 36]:

- **Artificial Neural Networks (ANNs)** and **Multi-Layer Perceptrons (MLPs)** for supervised classification of fault types.
- **Support Vector Machines (SVMs)** for binary or multi-class classification with strong generalization performance.
- **Decision Trees** and **Random Forests** for interpretable model-based diagnostics.
- **Convolutional Neural Networks (CNNs)** for feature extraction from spectrograms or vibration images.
- **Autoencoders** for anomaly detection and unsupervised fault identification.
- **Deep Learning Techniques** for complex fault pattern recognition and high-dimensional data processing.

These techniques provide a comprehensive toolbox for efficient and accurate fault diagnosis, supporting condition-based maintenance and minimizing unplanned downtime.

I.7 Conclusion

This chapter provided a comprehensive overview of rotating machines, their main components, and the common mechanical and electrical faults they may encounter. Bearings were highlighted as the most failure-prone parts. We also reviewed traditional and modern fault detection techniques, emphasizing the growing role of artificial intelligence, especially neural networks, in enhancing fault diagnosis. In the following chapter, we will focus on the detailed analysis and application of the concepts introduced here, particularly the use of AI techniques for fault detection and classification in rotating machines.

Chapter II

Artificial Intelligence and Machine Learning Algorithms

II.1 Introduction

Artificial Intelligence (AI) has notably advanced industrial diagnostics, particularly in rotating machinery, where traditional maintenance methods are often insufficient to detect faults in critical components like bearings. AI-based, data-driven approaches—especially Machine Learning (ML) and Artificial Neural Networks (ANNs)—enable effective fault detection and classification by identifying patterns in signals such as vibration and sound. These techniques support predictive maintenance, lower operational costs, and improve machine reliability. This chapter provides a foundational overview of AI and ML, outlining their industrial applications, main learning categories (supervised, unsupervised, and reinforcement), and commonly used algorithms, serving as a basis for deeper exploration in subsequent chapters [37, 38].

II.2 Definition of Artificial Intelligence

AI is a dynamic field of computer science focused on enabling machines to perform tasks that typically require human intelligence, such as speech recognition, decision-making, problem-solving, and pattern recognition. AI systems improve performance through experience, often by leveraging ML algorithms that enable learning from data.

AI technologies are widely implemented in applications such as chatbots, recommendation systems, image recognition, and fraud detection. These tools are increasingly prevalent across sectors including finance, healthcare, manufacturing, education, and transportation, where they contribute to enhanced efficiency and accuracy.

While concerns about workforce displacement exist, the primary aim of AI is to assist humans by automating repetitive or routine tasks, allowing human workers to focus on more complex, creative, or strategic responsibilities. Consequently, AI represents a valuable asset for organizations seeking to boost productivity, drive innovation, and maintain competitiveness [37, 39, 40].

Figure II.1: Artificiel intelligence [23].

II.3 History of Artificial Intelligence

The evolution of artificial intelligence (AI) is a story that covers a number of decades and has drawn contributions from many different disciplines. It started in the 1940s when Warren McCulloch and Walter Pitts devised neural networks alongside Alan Turing's development of the Turing Test in 1950. It was really at the Dartmouth Conference of 1956 that the term "artificial intelligence" was first used. The initial AI research developed programs like the Logic Theorist and ELIZA that simulated conversation. The initial optimism subsequently gave rise to disappointment and cutbacks in funding, and the first AI winter set in during the 1970s. The scenario improved in the 1980s with the development of expert systems, but the second AI winter arrived in the late 1980s when the constraints of expert systems became evident. The 1990s saw a shift towards machine learning with IBM's Deep Blue defeating chess champion Garry Kasparov in 1997. The advent of deep learning in the 2000s led to breakthroughs like Alex Krizhevsky's convolutional neural network winning the ImageNet competition in 2012 and Google's AlphaGo defeating a Go champion in 2016. AI is today integrated into various industries, with applications in healthcare, finance, and natural language processing, while ethical concerns and the pursuit of artificial general intelligence (AGI) remain at the center of ongoing discussions on the future of AI [41, 40].

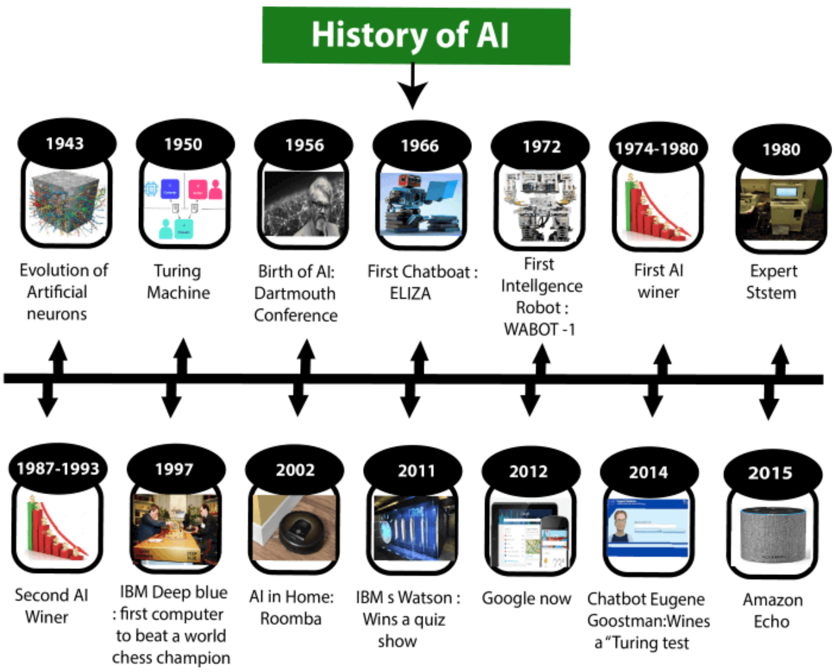


Figure II.2: History of artificial intelligence [7].

II.4 Applications of Artificial Intelligence

AI has become a transformative force across numerous sectors, offering innovative solutions that enhance performance, efficiency, and decision-making processes. Its integration into various domains has led to automation, improved accuracy, and data-driven insights. Some notable applications of AI in key industries are [42, 8]:

1. **Healthcare:** AI is widely used for medical diagnostics, personalized treatment planning, drug discovery, and patient risk assessment.

2. **Finance:** It supports fraud detection, algorithmic trading, and route optimization for financial logistics and services.

3. **Education:** Applications include adaptive learning platforms, automated grading systems, and AI-powered tutoring for personalized academic support.

4. **Transportation:** AI powers autonomous vehicles and intelligent traffic management systems for congestion reduction and route planning.

5. **Robotics:** In manufacturing, AI enhances robotic precision, enables safe human-robot collaboration, and automates complex or hazardous tasks.

6. **Industry:** AI facilitates predictive maintenance, ensures quality control, and streamlines supply chain and logistics operations.

7. **Automotive:** AI contributes to self-driving technologies, predictive vehicle maintenance, and the development of in-car virtual assistants.

Figure II.3 illustrates the ten most prominent applications of AI projected for the year 2025.

Figure II.3: The top 10 AI applications in 2025 [8].

II.5 Definition of Machine Learning

Machine Learning (ML) is a core branch of Artificial Intelligence (AI) that enables machines to learn from data without explicit programming. AI aims to replicate human capabilities such as language understanding, reasoning, perception, and decision-making. While AI can be implemented through various approaches, neural-based methods currently dominate due to their adaptability and capacity for data-driven learning.

ML typically requires large datasets for training and optimization, raising important concerns about data privacy and security. One of its significant industrial applications is predictive maintenance, where ML algorithms analyze equipment performance data to forecast failures and prevent unexpected downtimes. This proactive strategy enhances operational efficiency, improves safety, and reduces maintenance costs. The increasing ease of data collection and storage has further accelerated the development and deployment of ML-based solutions in recent years [43, 9, 10].

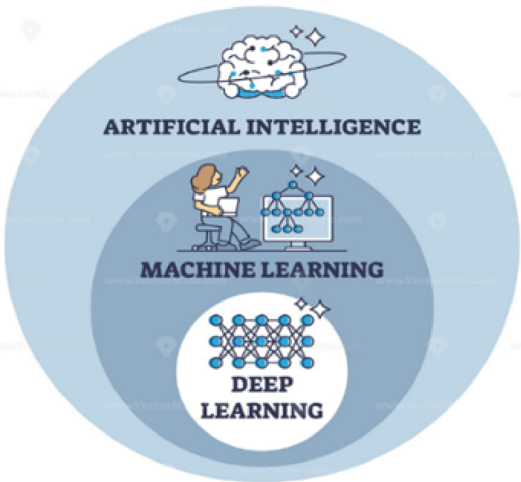


Figure II.4: Abstract Technology Machine authorized Learning Artificial [9].

II.5.1 Approaches to Machine Learning

There are three main approaches in machine learning: supervised learning, unsupervised learning, and reinforcement learning, each utilizing distinct methods, as illustrated in Figure II.5

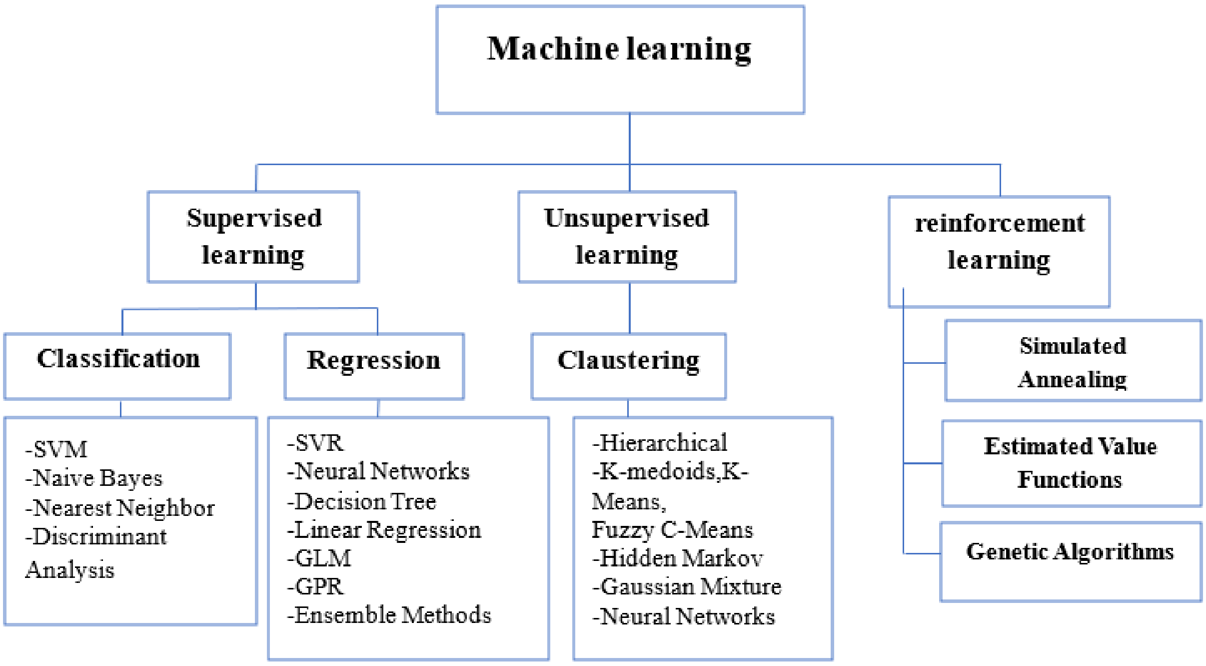
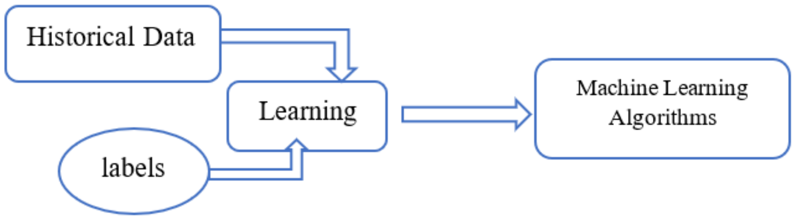


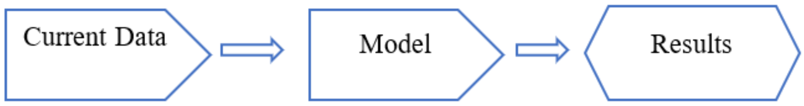
Figure II.5: Classifications within Machine Learning Techniques[10] .

II.5.1.1 Supervised Learning

Supervised learning involves training an algorithm on labeled data, where each input is paired with a known output. This process enables the model to learn mappings for future predictions. It primarily uses classification to group data based on features, serving domains such as healthcare, finance, and digital applications—for example, distinguishing spam from legitimate emails. Regression is also employed to predict continuous variables. Effective training requires high-quality, representative data and domain expertise, as the model's accuracy depends on the relevance of the training set. Poor data selection or limited generalization can result in significant prediction errors. Therefore, careful data curation and regular model updates are essential to maintain performance [10, 44, 45].



Supervised Machine Learning – Step 1.



Supervised Machine Learning – Step 2.

Figure II.6: Supervised Machine Learning Steps[11].

Supervised machine learning can be divided into two main types:

– **Classification** The output variable is a category (spam vs not spam).

– **Regression** The output variable is a specific numerical value (predicting house prices) [46].

II.5.1.2 Unsupervised Learning

Unlike supervised learning, unsupervised learning is based on input data without predefined labels or known outputs. The main goal of this technique is to uncover hidden patterns, relationships, or structures within the data. One of the most common techniques in unsupervised learning is clustering, which helps identify similarities between data points and group them into clusters. This method is widely used for segmentation tasks, such as customer classification, fraud detection, and market research. Unsupervised learning is particularly useful for knowledge discovery from raw data. However, it is often more challenging to implement compared to supervised learning, as it requires extensive data preprocessing to make the information useful for analysis [10, 47].

These methods enable better understanding of hidden patterns in datasets and have applications in market segmentation, anomaly detection, recommendation systems, and fraud detection [11].

Table II.1 presents a comparison between supervised and unsupervised learning.

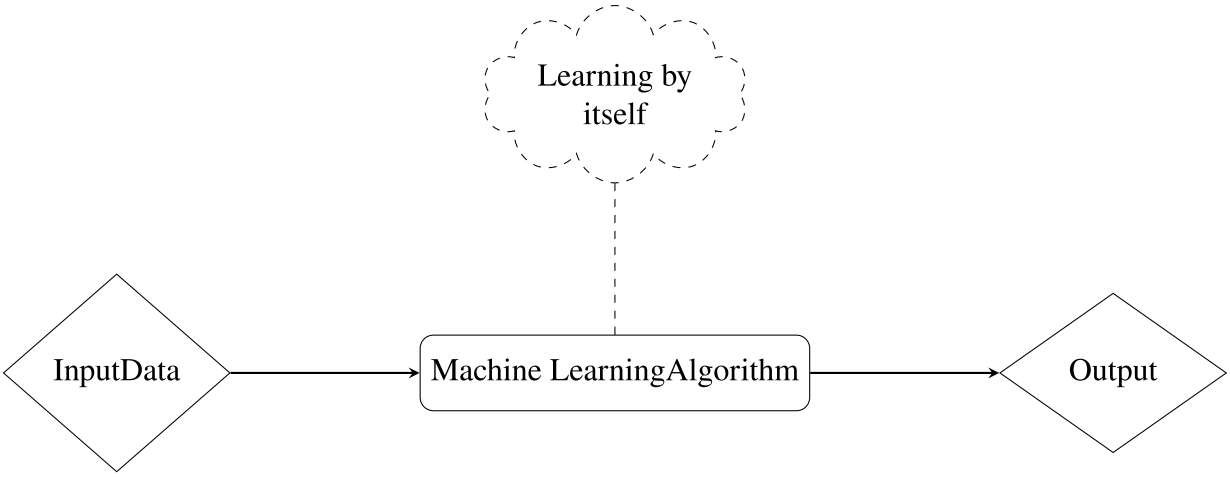


Figure II.7: Unsupervised Machine Learning [11].

Table II.1: Comparison between Supervised and Unsupervised Learning [48].

Criteria	Supervised Learning	Unsupervised Learning
Input Data	Known input data with corresponding labels	Unlabeled input data without predefined outputs
Computational Complexity	Generally more complex due to the training process	Typically less complex
Application Domains	Used for classification and regression tasks	Applied in clustering and association rule mining
Accuracy	High accuracy when trained with quality data	Moderate accuracy, depends on the data structure

II.5.1.3 Reinforcement learning

Reinforcement learning is an approach in which an agent interacts with its environment to maximize a long-term reward. The model learns to make decisions based on its state and the rewards received. Common applications include gaming, robotics, and trajectory planning [44]:.

II.6 Machine Learning Algorithms

Machine learning encompasses a variety of algorithms designed to analyze data, identify patterns, and make informed decisions with minimal human intervention. Among the most widely used algorithms are Support Vector Machines (SVM), Linear Regression, Decision Trees, K-Nearest Neighbors (KNN), and Artificial Neural Networks (ANN). Each of these techniques offers distinct advantages depending on the nature of the problem, data characteristics, and application context [9].

II.6.1 Support Vector Machines (SVM)

SVM are preferred for handling high-dimensional data and are relatively simple to implement. Performance depends on selecting suitable hyperparameters, particularly the regularization method and kernel, based on the data structure and problem type (Figure II.8).

A linear kernel is typically used for linearly separable classification tasks, while a Gaussian (RBF) kernel is suited for non-linear problems. SVM is a binary classification algorithm, like logistic regression, but focuses on achieving the cleanest separation between classes. It partitions data based on the "maximum margin" principle—the largest possible distance between the separating hyperplane and the nearest data points from each class—earning it the name Large Margin Classifier[49, 12].

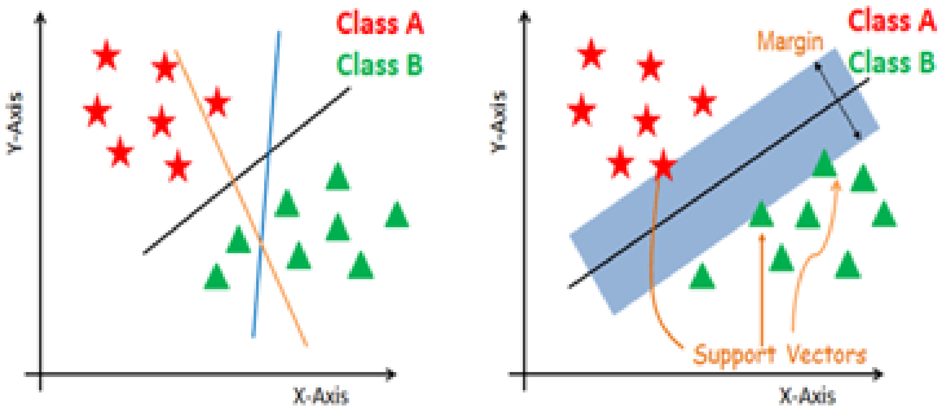


Figure II.8: Support Vector Machine (SVM)[12].

II.6.2 Linear Regression

Linear regression is a fundamental statistical method used to model the relationship between a dependent variable and one or more independent variables by fitting a straight line to the data (Figure II.9)[13].

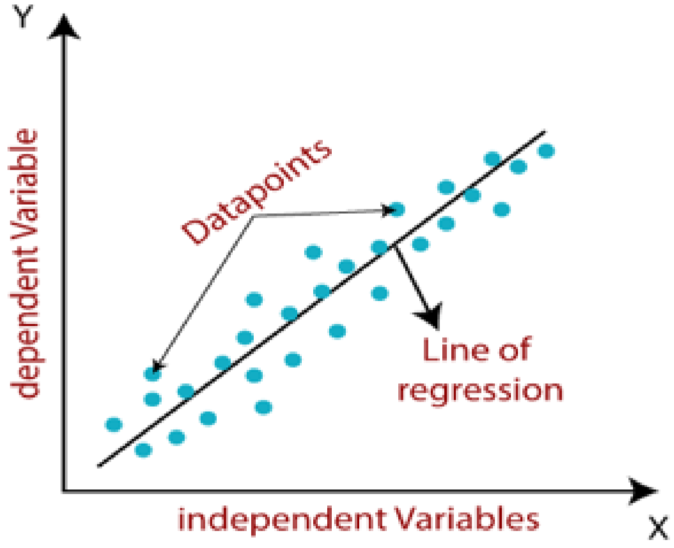


Figure II.9: Simple Linear Regression Model [13].

II.6.3 Decision Tree

A decision tree, as shown in Figure II.10, is a flowchart-like model that makes predictions based on a series of feature-based decisions. It recursively splits the data into branches until reaching a decision node [14].

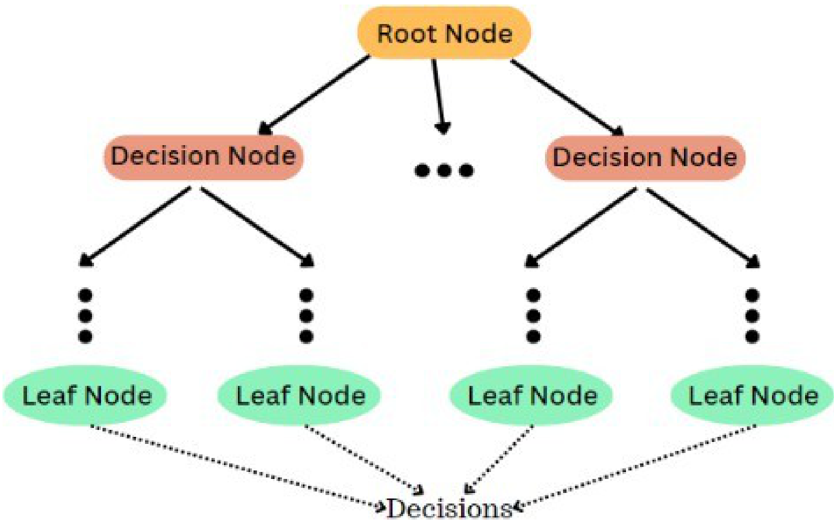


Figure II.10: Example Illustration of a Decision Tree[14].

II.6.4 K-Nearest Neighbors (KNN)

KNN, as illustrated in Figure II.11, is a simple yet effective classification algorithm that assigns a label to a new data point based on the majority class of its k-nearest neighbors [14].

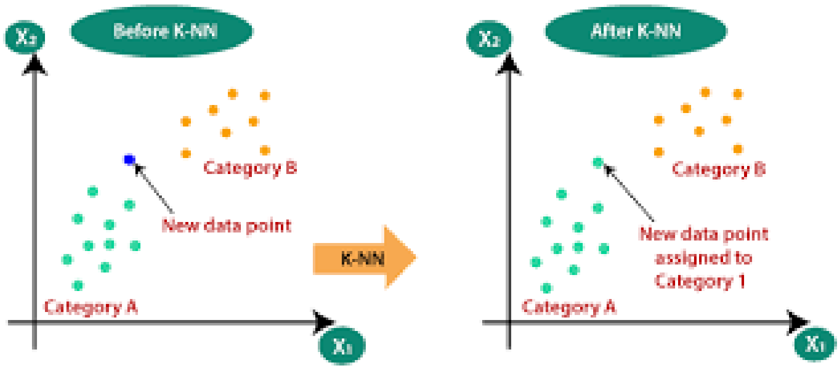


Figure II.11: K-Nearest Neighbors (k-NN)[14].

II.6.5 Random Forest

Random Forest (Figure II.12) is an ensemble learning method that combines multiple decision trees to enhance accuracy and reduce overfitting. It is widely used for both classification and regression tasks [50].

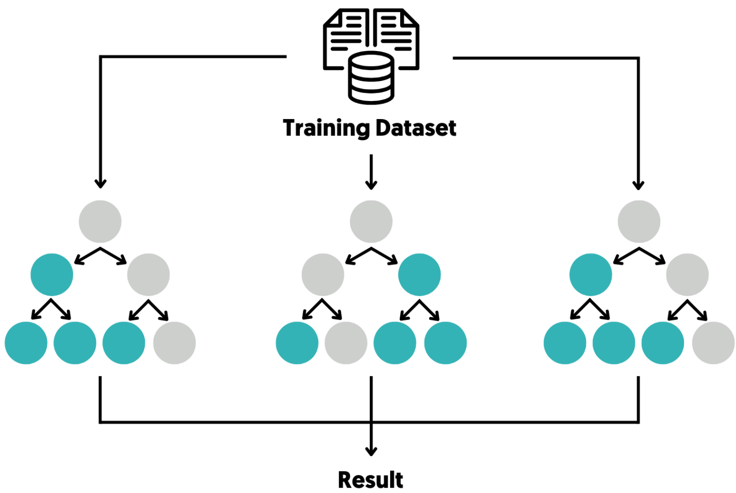


Figure II.12: The Random Forest Algorithm [15].

II.6.6 Artificial Neural Networks (ANN)

Artificial Neural Networks (ANNs), depicted in Figure II.13, are computational models inspired by biological neurons in the human brain. They consist of layers of interconnected nodes (neurons) and are utilized in machine learning and deep learning to recognize patterns, classify data, and make predictions. This is particularly relevant to our study, as ANNs play a crucial role in analyzing complex data and enhancing decision-making processes across various domains, including predictive maintenance, image recognition, and natural language processing [17, 16].

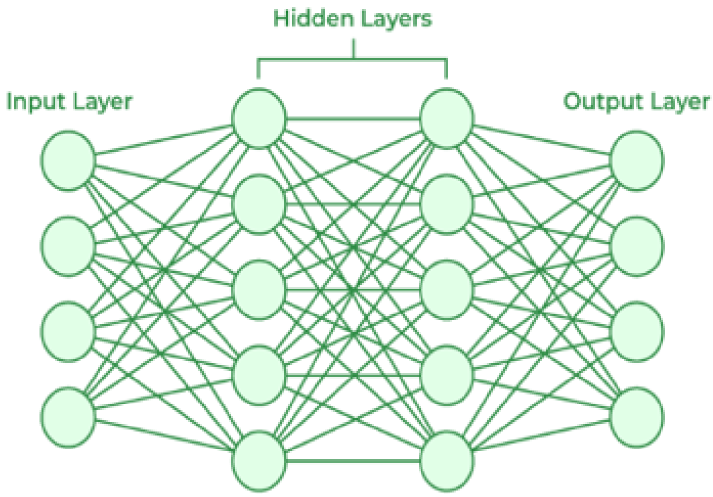


Figure II.13: Neural Networks Architecture [16].

II.7 Conclusion

This chapter provided a foundational overview of Artificial Intelligence, with an emphasis on Machine Learning and its core methodologies. We explored key supervised and unsupervised learning algorithms, highlighting their principles and relevance in the context of industrial diagnostics.

Among these techniques, Artificial Neural Networks (ANNs) stand out for their capacity to model complex and non-linear data relationships, making them particularly effective for fault detection and classification tasks.

The chapter serves as a basis for the next discussion, which will delve deeper into neural network architectures—specifically Multilayer Perceptrons (MLPs)—and their practical application in diagnosing faults in rotating electrical machines.

Chapter III

Principles and Structural Components of Artificial Neural Networks

III.1 Introduction

Artificial Neural Networks (ANNs) are computational models inspired by the structure and functioning of the human brain. They possess the ability to learn from data and recognize complex patterns, making them particularly effective for machine condition monitoring and fault diagnosis [16]. In the context of predictive maintenance, ANNs have shown considerable success in identifying faults where early detection of anomalies is essential to prevent unexpected failures.

This chapter focuses on the principles of ANNs and presents their architecture and key components.

III.2 Artificial Neural Networks (ANNs)

ANNs are machine learning models inspired by the structure and function of the human brain. ANNs consist of nodes or neurons connected together in layers: an input layer, one or more hidden layers, and an output layer. Each connection between nodes has an associated weight, which is optimized during training with optimization techniques such as backpropagation. ANNs are capable of learning complex nonlinear mappings between inputs and outputs and have proved to be very effective in classification, regression, and pattern recognition applications. ANNs, in industrial processes, especially in fault diagnosis of rotating machinery, can learn automatically to extract useful features from raw signal data and make correct predictions without the need for explicit physical models [17, 16].

This brings us to our main topic: the use of artificial neural networks (ANNs). Inspired by the human brain, ANNs are made up of interconnected nodes (neurons) that process and transmit information. They play a key role in modern AI, powering technologies like voice assistants and self-driving cars. Their ability to learn complex patterns makes them ideal for detecting and classifying faults in rotating machinery, which is the focus of our work[16, 51].

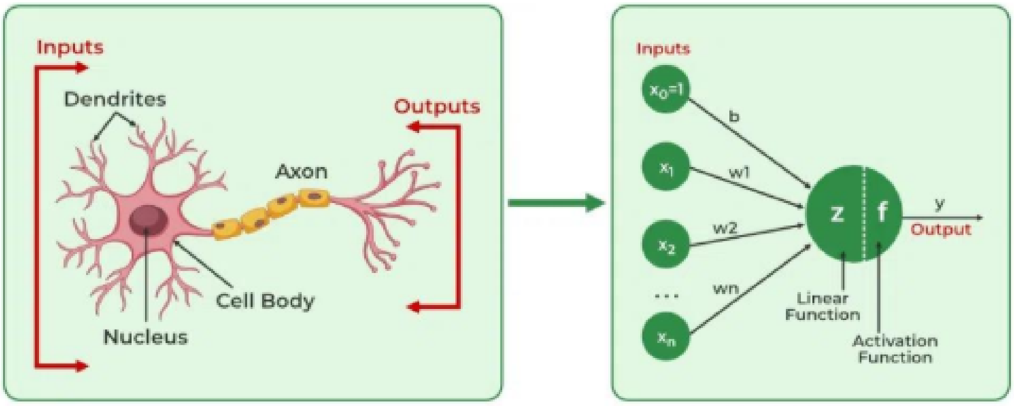


Figure III.1: Biological neurons to Artificial neurons [16].

III.2.1 Biological Neurons vs Artificial Neurons

ANNs are inspired by the way biological neurons work in the human brain. However, while they share some similarities, their functioning is fundamentally different.

Biological neurons work with electrical and chemical signals, while artificial neurons process numerical data using mathematical functions. ANNs are trainable models that learn by adjusting weights, while biological neurons adapt through synaptic plasticity. (Table III.1) presents a comparison between biological and artificial neurons, highlighting their structural and functional differences [17]:

Table III.1: Comparison Between Biological and Artificial Neurons [17].

Biological Neuron	**Artificial Neuron**
Dendrites: Receive signals from other neurons.	Inputs: Receive input data.
Cell Nucleus (Soma): Processes information and decides whether to activate the neuron.	Nodes: Computational units that transform inputs.
Synapses: Connections between neurons, transmitting signals chemically or electrically.	Weights: Numerical values that determine the strength of connections.
Axon: Transmits the signal to other neurons.	Output: Final result after processing inputs.

III.3 Main Components of an Artificial Neural Network

An ANN is a network made up of connected artificial neurons that work together to process information in layers. Each neuron takes inputs and does some math to find patterns (Figure III.2).

- **Neurons (Nodes)**: Basic computation units.
- **Layers** : Input, hidden, and output layers.
- **Weights & Biases** : Modify input impact for learning.
- **Activation Functions** : Enable learning of complex relationships[17, 16].

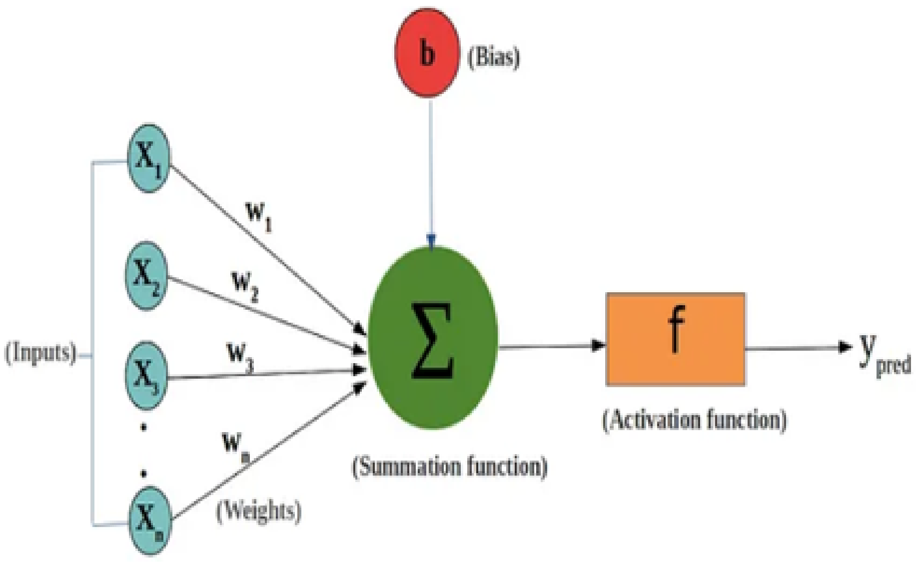


Figure III.2: Artificial Neuron: Inputs, Weights, Bias, Activation Function[17].

III.3.1 Neurons and Perceptrons

The basic computational unit in a neural network is the neuron. It receives inputs, processes them, and produces an output. Neurons act as decision-makers, determining whether to pass signals to the next layer. Neural networks consist of layers of neurons, typically fully connected, with hidden layers often containing more neurons to capture complex patterns. The perceptron, the simplest form of an artificial neuron, is used in single-layer networks and is limited to linearly separable problems [16, 51].

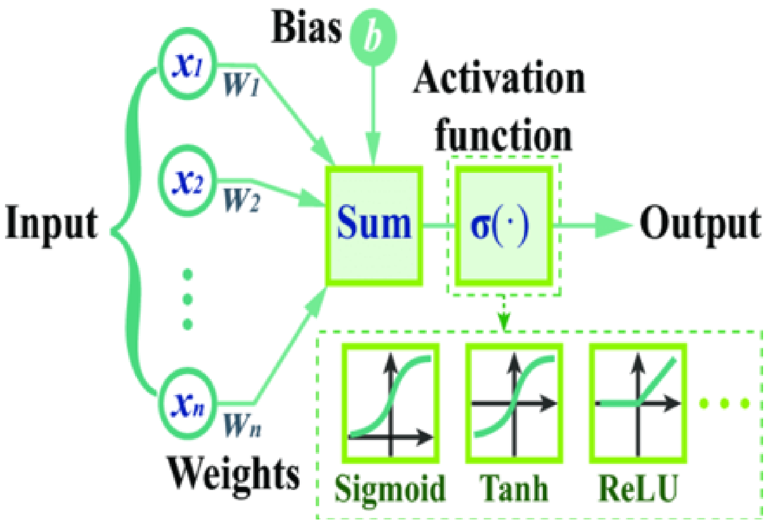


Figure III.3: Basic Architecture of an Artificial Neuron with Activation Functions [17].

III.3.2 Weights

In a neural network, weights decide how strong the connections are between neurons. Each connection has a weight that affects how much one neuron's output impacts another neuron's input. Positive weights boost the signal, making it more likely for the next neuron to fire, while negative weights reduce it. The bigger the absolute value of a weight, the stronger its effect. When training the network, these weights get adjusted to cut down errors and enhance its skill in making accurate predictions or classifications based on the input [17, 16].

III.3.3 Bias

Bias is a parameter in a neuron that acts like a constant input, helping to adjust the neuron's activation threshold. It shifts the activation function to the left or right, influencing how easily the neuron is triggered.

- Positive bias $\Rightarrow$ Easier activation.
- Negative bias $\Rightarrow$ Harder activation[17, 16].

III.3.4 Activation Functions

Activation functions determine neuron activation based on the weighted sum and bias. They introduce non-linearity into the model. As shown in Figure III.4.

- **Sigmoid Function:** Sigmoid function produces an S-shaped curve that is used to map input values to one of numeric values between 0 and 1. A common use is in the output layer for binary classification problems, giving the probabilities. Yet, it suffers from vanishing gradient problem where gradients get so small to be ineffective in deep networks.

$$\sigma(x) = \frac{1}{1 + e^{-x}} \tag{2.2}$$

- **ReLU (Rectified Linear Unit):** ReLU outputs the input if positive, otherwise zero. It is popular in hidden layers for its efficiency and its role in mitigating the vanishing gradient problem. However, it may suffer from the "dying ReLU" issue, where neurons become inactive by outputting zero for all inputs.

$$\mathrm{ReLU}(x) = \max(0, x) \tag{2.3}$$

- **Tanh (Hyperbolic Tangent):** The tanh function, similar to sigmoid function maps the data into range -1 to 1. It is the one mostly you will see used in hidden layers, because it zero- centers the output which helps with the gradient during the training. Although tanh is generally better than sigmoid (especially in deep net) it can have the same vanishing gradient problem [17, 51, 52].

$$\tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{2.4}$$

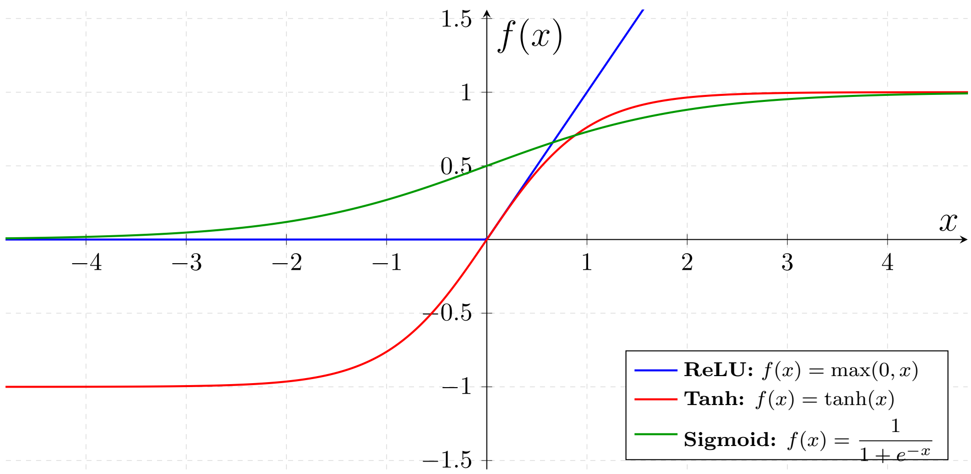


Figure III.4: Fonctions d'activation : ReLU, Tanh, Sigmoid

III.4 The Training Process in Artificial Neural Networks

ANNs learn by adjusting their **weights and biases** to **minimize prediction error**. This learning process consists of the following steps[15, 17]:

1. **Forward Propagation**
   - Inputs pass through the network.
   - Each neuron applies **weighted sums and activation functions.**
   - The output is generated.
2. **Loss Calculation**
   - The difference between the predicted and actual output is measured using **a loss function**, such as Mean Squared Error or Cross-Entropy Loss.
3. **Backpropagation**
   - The error is **propagated backward** through the network.
   - Weights are updated using **gradient descent** to improve accuracy.
4. **Optimization**
   - Algorithms like **Stochastic Gradient Descent (SGD), Adam, and RMSprop** are used to enhance learning efficiency.

III.5 Types of Artificial Neural Networks

There are several types of Artificial Neural Networks (ANNs), each suited to different tasks and data types[15, 17]:

- **Feedforward Neural Networks (FNN)**
  - Information flows in one direction (Input → Hidden → Output).
  - Commonly used for basic classification and regression tasks.
- **Convolutional Neural Networks (CNN)**
  - Specialized for image recognition tasks.
  - Utilizes convolutional layers to detect features in images.
- **Recurrent Neural Networks (RNN)**
  - Designed to handle sequential data (like :speech, time series).
  - Maintains hidden states to process information over time.
- **Multi-Layer Perceptrons (MLPs)**
  - MLPs process features and classify various fault types.
- **Long Short-Term Memory (LSTM)**
  - A specialized type of RNN that addresses short-term memory limitations.
  - Widely used in speech recognition, natural language processing (NLP), and financial forecasting.
- **Generative Adversarial Networks (GANs)**
  - Used to generate new data, such as deepfake images and AI-generated art.
  - Comprises two components: a Generator and a Discriminator.

III.6 Applications of Artificial Neural Networks

Artificial Neural Networks (ANNs) are widely used across various industries, including [17]:

- **Computer Vision:** Facial recognition, object detection.
- **Natural Language Processing (NLP):** Chatbots, text summarization.
- **Speech Recognition:** Google Assistant, Siri, Alexa.
- **Healthcare:** Disease diagnosis, drug discovery.
- **Predictive Maintenance:** Detecting faults in machines, bearing failure prediction [47].

III.6.1 Application of ANNs in Predictive Maintenance

ANN play a significant role in predictive maintenance by enabling the early detection and classification of mechanical faults. Their ability to process complex sensor data makes them well-suited for monitoring the condition of rotating machinery. Specifically, ANNs can:

- Analyze vibration data acquired from sensor systems.
- Identify anomalies in rotating equipment, including bearings and electric motors.
- Classify various types of faults, such as outer race, inner race, and ball defects.
- Forecast potential failures in advance, thereby minimizing unexpected downtime and improving system reliability[43].

III.6.2 Neural Networks for Fault Diagnosis

In contemporary industrial environments, rotating machinery such as motors, pumps, and turbines operates under demanding conditions that often lead to mechanical faults, particularly in bearings. These faults can result in unexpected failures, costly downtime, and safety risks.

Fault diagnosis has progressed from manual inspections and rule-based systems to data-driven approaches. Artificial Neural Networks (ANNs) have proven effective due to their ability to model complex, non-linear relationships and process large volumes of sensor data [25, 35, 51].

III.7 Advantages of AI-Based Diagnostic Systems

The integration of AI and ANNs in fault diagnosis offers several key advantages[51, 52]:

- **Automation:** Reduces the need for manual inspection or expert intervention.
- **Early Detection:** Identifies faults before they lead to machine failure.
- **Accuracy:** Achieves high performance even with complex and noisy data.
- **Adaptability:** Can learn from new data and adjust to changing conditions.
- **Real-Time Monitoring:** Enables continuous health monitoring and decision-making.

III.8 Conclusion

This chapter provided an overview of Artificial Neural Networks (ANNs), highlighting their foundational principles, architecture, and key components. As computational models inspired by the human brain, ANNs are capable of learning complex patterns from data, making them a powerful tool across various applications.

The following chapters will illustrate how these models can be applied to machine condition monitoring and fault diagnosis, with a particular focus on bearing fault detection.

Chapter IV

Bearing Fault Classification Results Using Neural Networks

IV.1 Introduction

This chapter explores the application of neural networks for detecting and classifying bearing faults in rotating machinery, focusing on vibration signal analysis. It begins with an overview of the exact dataset used, followed by detailed steps of data preprocessing and signal segmentation to prepare the data for analysis. Next, feature extraction techniques are presented to capture the most relevant information from the vibration signals. The chapter then explains the design and training of artificial neural network models, specifically the Multilayer Perceptron (MLP), for fault detection and classification. All the steps were implemented using MATLAB, which provided powerful tools for signal processing and neural network modeling. Finally, results from the model evaluation are discussed.

Methodology of Appling ANN in bearing fault detection

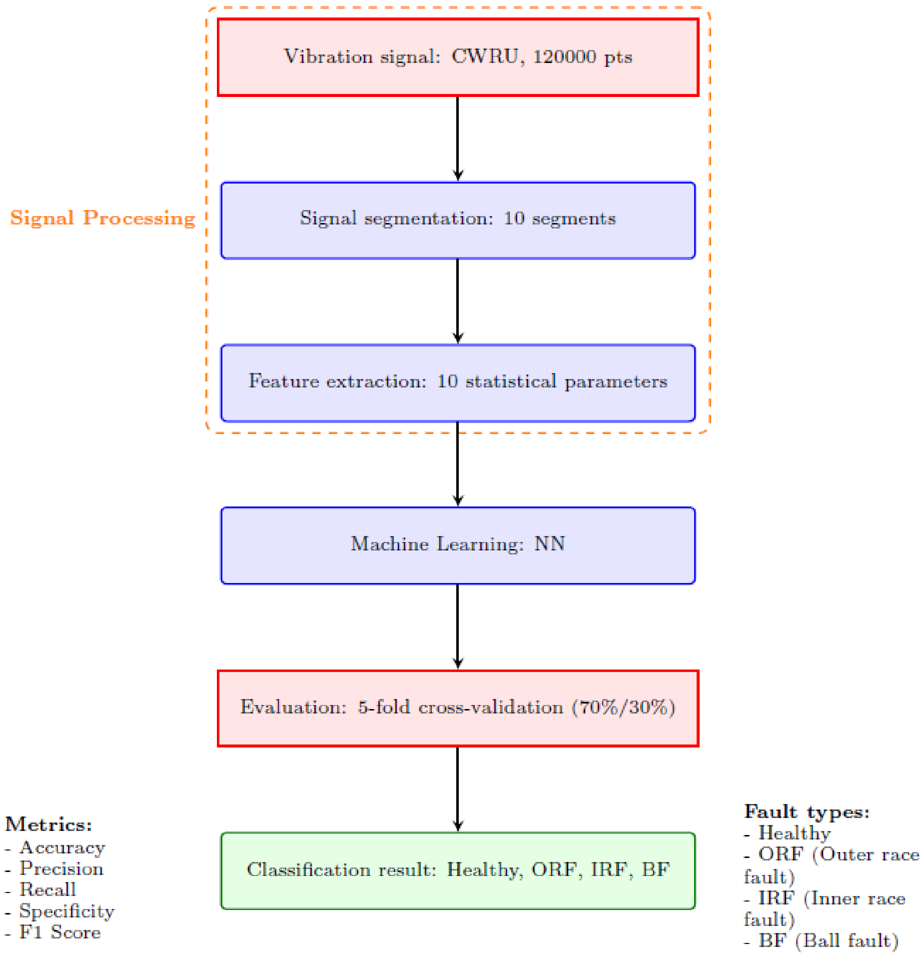


Figure IV.1: Workflow of the Proposed ANN-Based Fault Detection Approach.

IV.2 Overview of the CWRU Dataset for Bearing Fault Detection

The data used in this study comes from the Case Western Reserve University Bearing Data Center (CWRU). We used this dataset because it is widely known and one of the most commonly used benchmarks in bearing fault diagnosis research. It includes vibration signals collected under both normal and faulty bearing conditions, with four fault types: healthy, inner race fault, outer race fault, and ball fault, as shown in the figure IV.2.

The experiments were conducted using a 2 hp Reliance Electric motor, where faults were intentionally introduced into the bearings using electro-discharge machining (EDM). Fault sizes ranged from 0.007 to 0.028 inches. Acceleration data was recorded using accelerometers placed near and far from the bearings, under motor loads from 0 to 3 horsepower and speeds between 1720 and 1797 RPM. These signals are crucial for training and validating machine learning models, particularly the Multi-Layer Perceptron (MLP), to accurately detect and classify bearing faults[21].

The data is publicly available on the website at the following address:

https://engineering.case.edu/bearingdatacenter/welcome.

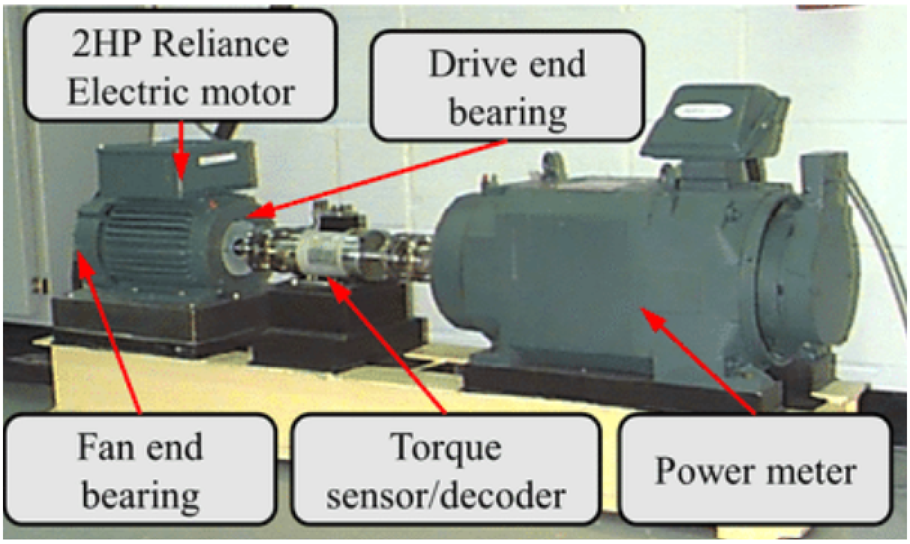


Figure IV.2: Test bench of Case Western Reserve University (CWRU)[18].

Table IV.1 presents operating conditions and fault types of CWRU dataset.

Figure IV.3: Basic Bearing Components [19].

Table IV.1: CWRU Bearing Dataset Parameters [21].

Fault Type	Fault Size (in)	Load (hp)	Speed (RPM)	Data Format
No Fault (Healthy)	0	0	1720–1797	.mat
Outer Race Fault	0.007, 0.014, 0.021	0, 1, 2, 3	1720–1797	.mat
Inner Race Fault	0.007, 0.014, 0.021, 0.028	0, 1, 2, 3	1720–1797	.mat
Ball Fault	0.007, 0.014, 0.021, 0.028	0, 1, 2, 3	1720–1797	.mat

Figure IV.3 illustrates the basic components of a bearing, complementing the fault types and operating conditions summarized in Table IV.1.

IV.3 Data Processing

In order to provide a comprehensive analysis, each of the four cases will be examined individually, here are the following four cases:

IV.3.1 First Case-Bearing Healthy

The first condition analyzed in this study is the healthy bearing condition, which corresponds to the motor operating under no load (0 horsepower). This condition is represented by four vibration signals recorded at the Drive End (DE) of the motor.

In this case, each of the four signals was divided into 10 equal sub-signals, resulting in a total of 40 sub-signals used for further analysis and feature extraction. The (X097_DE_time) signal was selected as a representative sample of the healthy state. This plot displays the complete raw signal in its raw, unsegmented, and unfeature-extracted form to provide an immediate sense of its overall behavior in the time domain. All of these sub-signals were labeled with the output class 0, indicating the healthy condition. Below, an illustration shows the original signals before the segmentation process IV.4.

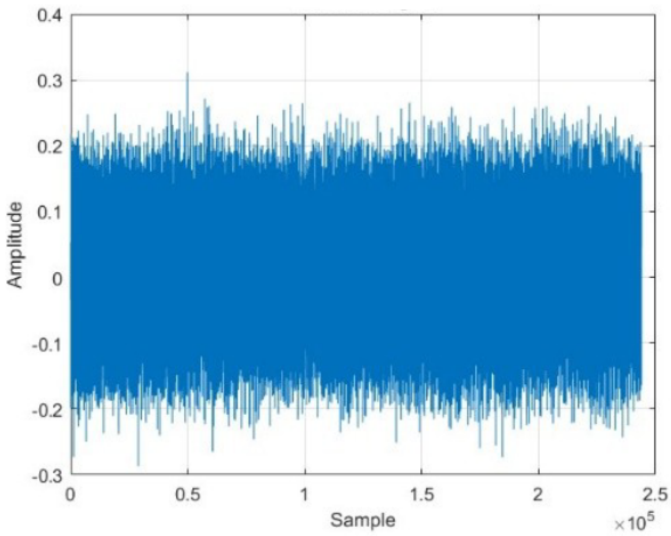


Figure IV.4: Vibration Signal for healthy bearing.

- **Duration:** The signal contains approximately 240,000 samples, as shown on the x-axis (Sample = one data point from the signal).
- **Amplitude:** The amplitude oscillates within the range of approximately -0.3 m/s^2 to $+0.3$ m/s^2 , indicating a relatively stable vibration pattern, which is typical for a healthy bearing.

IV.3.2 Second Case- Outer Race Fault

The second condition analyzed in this study corresponds to the outer race fault condition, where damage occurs on the outer race of the bearing. This fault was simulated by introducing defects of varying sizes, ranging from 0.007 inches to 0.021 inches in diameter. For this condition, 12 vibration signals were recorded at the Drive End (DE) of the motor.

Each of these 12 signals was divided into 10 equal sub-signals, resulting in a total of 120 sub-signals used for further analysis and feature extraction. The `X200_DE_time` signal was selected as a representative sample of the outer race fault condition. This plot displays the raw signal in its original, unsegmented, and unfeature-extracted form, offering a clear visual representation of the signal behavior in the time domain. All of these sub-signals were labeled with the output class **1**, indicating the presence of an outer race fault. An illustration showing the original signals before the segmentation process is provided in Figure IV.5.

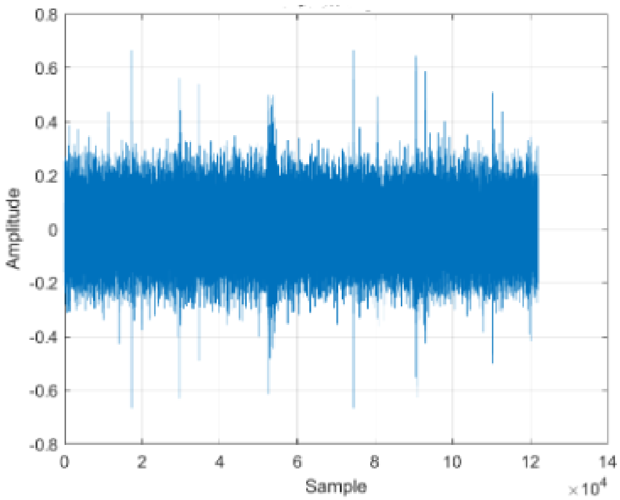


Figure IV.5: Vibration Signal for Outer Race Fault.

- **Duration:** The signal consists of approximately 125,000 samples, as represented on the x-axis.
- **Amplitude:** The amplitude varies between -0.7 m/s^2 and $+0.7$ m/s^2 , indicating the presence of high-energy impacts. This range, along with observable irregular peaks, is characteristic of an outer race fault in rolling element bearings.

IV.3.3 Third Case-Inner Race Fault

The third condition analyzed in this study corresponds to the inner race fault condition, where the damage is located on the inner race of the bearing. This fault type is considered one of the most critical due to its impact on the rotation of the shaft and load transmission. The fault was simulated by introducing defects of varying sizes on the inner race surface, ranging from 0.007 inches to 0.028 inches in diameter. For this condition, 16 vibration signals were recorded at the Drive End (DE) of the motor.

Each of these 16 signals was divided into 10 equal sub-signals, resulting in a total of 160 sub- signals used for further analysis and feature extraction. One of these signals, such as (X169_DE_time), can be selected as a representative sample to visualize the raw signal behavior in the time domain under the inner race fault condition. All sub-signals extracted from these recordings were labeled with the output class 2, indicating the presence of an inner race fault. Below, an illustration shows the original signals before the segmentation process Figure IV.6.

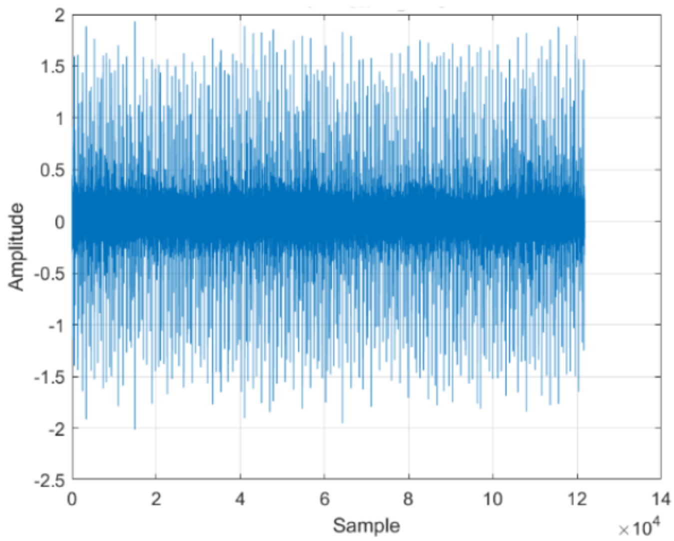


Figure IV.6: Vibration Signal for Inner Race fault.

- **Duration:** The signal consists of approximately 125,000 samples, as represented on the x-axis.
- **Amplitude:** The amplitude varies between $-2\ m/s^2$ and $+2\ m/s^2$, indicating the presence of high-energy impacts. This range, along with observable irregular peaks, is characteristic of an outer race fault in rolling element bearings.

IV.3.3.1 Fourth Case-Ball Fault

The fourth condition analyzed in this study corresponds to a ball fault, where the damage is located on the rolling element (ball) of the bearing. Although less common than inner or outer race faults, ball faults can still have a significant impact on machine performance due to their influence on the dynamic behavior of the bearing. This fault type was simulated by introducing localized defects of varying diameters ranging from 0.007 inches to 0.028 inches on the surface of the ball elements. For this condition, 16 vibration signals were acquired at the Drive End (DE) of the motor. Each signal was divided into 10 equal-length sub-signals, resulting in a total of 160 sub-signals for further processing and feature extraction. One example, such as `X120_DE_time`, may be visualized to observe the time-domain characteristics of the signal under a ball fault condition. All sub-signals generated from this case were labeled with the output class **3**, indicating the presence of a ball fault.

An illustration showing the original signals before the segmentation process is provided in Figure IV.7.

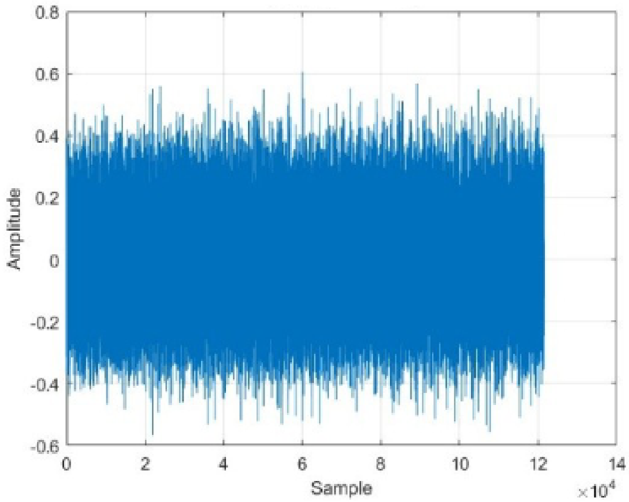


Figure IV.7: Vibration Signal for Ball fault.

- **Duration:** The signal spans approximately 125000 samples, as shown on the x-axis. This provides sufficient resolution to capture the dynamic behavior of the system under test.
- **Amplitude:** The amplitude ranges between -0.6 m/s^2 and 0.6 m/s^2 , indicating moderate vibration intensity.

IV.3.4 Signal Segmentation

As previously mentioned, our work focuses on the study of bearings and the detection of whether a fault is present or not. Specifically, we aim to perform classifications of bearing conditions into four possible categories: **normal**, **inner race fault**, **outer race fault**, and **ball fault**.

In order to enhance the dataset size and avoid overfitting during model training, we divided each original signal provided on the website into 10 equal sub-signals. This segmentation process was applied solely to increase the volume of training data, enabling the neural networks to generalize better.

An illustration showing how the original signal was divided into 10 equal sub-signals during the segmentation process is provided in Figure IV.8.

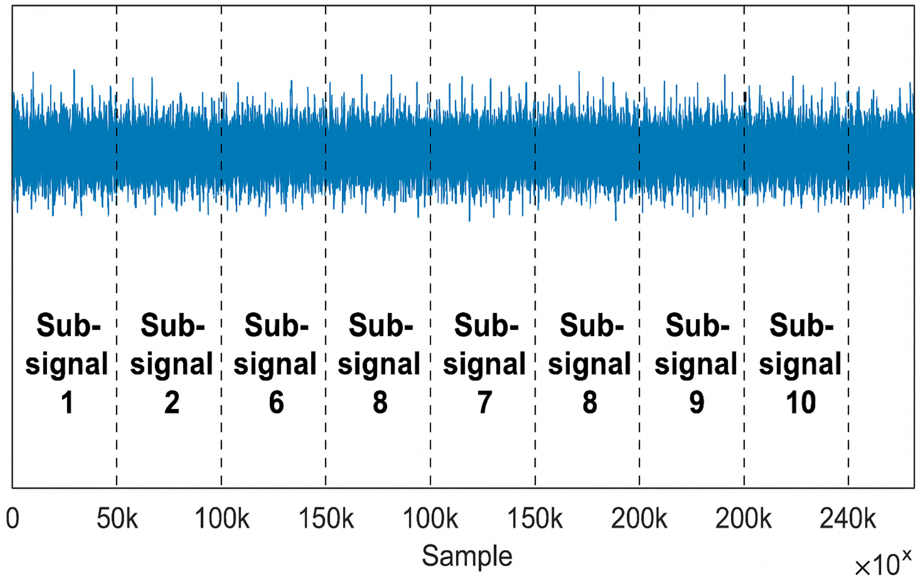


Figure IV.8: Division of the Raw Signal into 10 Sub-Segments.

IV.4 Features Extraction

Features are measurable and meaningful attributes extracted from raw data that capture important patterns or behaviors in a system. They transform complex signals into simplified representations that can be effectively used by machine learning algorithms for tasks such as classification, prediction, and anomaly detection. Features can be broadly categorized into statistical features that describe the distribution and variability of the signal, frequency domain features extracted via Fourier transform, and time frequency features like wavelet coefficients that capture both temporal and spectral information. Additionally, shape-based and cepstral features are used to characterize signal patterns and improve classification performance. In bearing fault diagnosis, raw vibration signals are complex and high-dimensional, so extracting meaningful features is essential. Feature extraction converts these signals into numerical descriptors that machine learning models can easily interpret and use [22, 53, 54].

IV.4.1 Statistical Features

Statistical features are numerical measures that describe essential properties of time-domain signals, such as amplitude, variability, impulsiveness, and energy content. These features provide valuable insights into the signal's behavior by quantifying characteristics like central tendency, spread, asymmetry, and peakedness.In fault diagnosis, a carefully selected set of statistical features commonly including mean, root mean square (RMS), standard deviation, kurtosis, and crest factor is often used due to their proven effectiveness and computational simplicity. By extracting these features, it becomes possible to reduce complex raw vibration signals into meaningful numerical descriptors that balance the depth of analysis with processing efficiency.This balance is crucial for accurately assessing the condition of rotating machinery and enhancing the performance of fault detection and classification algorithms, as these features serve as clear indicators of potential defects and their severity [22, 53].

The ten features we selected are :

Table IV.2: Extracted Statistical Features and Their Mathematical Expressions [22].

Feature Name	**Symbol**	**Description**	**Formula**
Minimum	$\min(x)$	Smallest value in the signal	$\min\{x_1, x_2, \ldots, x_N\}$
Maximum	$\max(x)$	Largest value in the signal	$\max\{x_1, x_2, \ldots, x_N\}$
Mean	μ	Arithmetic average of the signal	$\mu = \frac{1}{N}\sum_{i=1}^{N} x_i$
Median	Med	Middle value when the signal is sorted	**Step 1: Sort the signal:** $x_{\text{sorted}} = \text{sort}(x_1, x_2, \ldots, x_N)$ **Step 2: Compute median:** If N is odd: Median $= x_{\text{sorted}}\left(\frac{N+1}{2}\right)$ If N is even: Median $= \frac{1}{2}\left[x_{\text{sorted}}\left(\frac{N}{2}\right) + x_{\text{sorted}}\left(\frac{N}{2}+1\right)\right]$
Root Mean Square	RMS	Indicates the energy or power content of the signal	$\text{RMS} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2}$
Standard Deviation	σ	Measures signal spread around the mean	$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2}$
Kurtosis	kur	Measures sharpness/peakedness of the signal	$\text{kur} = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{x_i-\mu}{\sigma}\right)^4$
Peak Value	Peak	Maximum absolute value in the signal	$\max\left(\lvert x_i\rvert\right)$
Crest Factor	CF	Ratio of peak value to the RMS	$\text{CF} = \frac{\text{Peak}}{\text{RMS}}$
Impulse Factor	IF	Ratio of the peak value to the mean of absolute values	$\text{IF} = \frac{\text{Peak}}{\frac{1}{N}\sum_{i=1}^{N}\lvert x_i\rvert}$

In our study, the raw signals were divided into 480 sub-signals (40 healthy + 120 outer race fault + 160 inner race fault + 160 ball fault). This segmentation was carried out to facilitate the extraction of meaningful statistical and time-domain features from each sub-segment.For each sub-signal, the same ten distinctive features were computed based on their strong relevance to fault detection and classification. As a result, a feature matrix of size 480×10 was constructed, where each row corresponds to a sub-signal and each column represents one of the selected features.This structured representation enables the efficient application of intelligent diagnostic models. These extracted features will serve as input to artificial neural networks (ANNs), which will be used to detect and classify bearing faults with high accuracy.

IV.5 Neural Network Implementation Using MATLAB

This study employs Artificial Neural Networks (ANNs) to solve a classification problem. The implementation relies on the **Classification Learner** app in **MATLAB 2023**, which offers a user-friendly environment for training, validating, and testing machine learning models without the need for extensive coding.

The dataset follows a 70%–30% split: 70% for training and 30% for testing. The training portion allows the model to learn patterns and relationships within the data, while the testing portion evaluates the model's ability to generalize to new, unseen inputs. To further ensure model reliability and reduce overfitting, the process includes 5-fold cross-validation.

The neural network uses **ten statistical input features**, as shown in Figure IV.9.

MATLAB automatically configures the internal architecture of the ANN, including the number of hidden layers, neurons per layer, and activation functions. Although manual tuning remains possible and flexible, this study uses the default automatic optimization to ensure consistency and ease of replication.

The output layer classifies inputs into four distinct categories labeled (0), (1), (2), and (3), corresponding to the predefined classes in the dataset.

All operations—data loading, training, validation, testing, and performance evaluation—take place within the MATLAB Classification Learner App. This tool provides several predefined ANN configurations and includes a model optimization stage to help select the best-performing network.

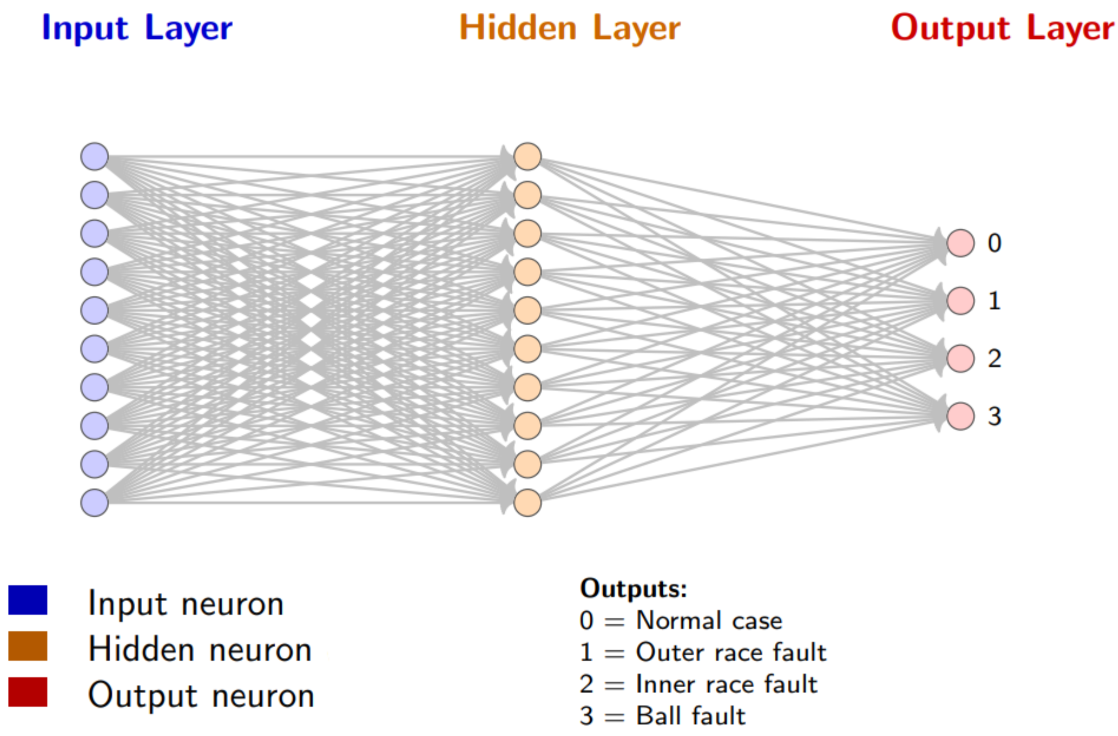


Figure IV.9: Neural Network Model for Bearing Fault Diagnosis.

The MATLAB Classification Learner App provides six neural network model configurations: five with predefined architectures and one that is automatically optimized. These models include:

1. Narrow Neural Network (NNN);
2. Medium Neural Network (MNN);
3. Wide Neural Network (WNN);
4. Bilayered Neural Network (BNN);
5. Trilayered Neural Network (TNN);
6. Optimizable Neural Network (ONN).

The predefined architectures allow users to explore various network complexities, while the Optimizable Neural Network enables automatic tuning of both the structure and hyperparameters using optimization techniques such as Bayesian optimization or cross-validation.

Each configuration is designed to address different levels of problem complexity and data availability, making it easier to select a suitable model based on the specific requirements of the classification task. The table IV.3 below summarizes the characteristics and typical use cases of each model[24, 23].

Table IV.3: Summary of Common Artificial Neural Network (ANN) Models and Their Use Cases [23].

Model	**Definition**	**Use Case**
NNN	Few neurons per hidden layer	Less complicated problems or when data are limited
MNN	A mix between narrow and wide networks, with a fair number of neurons per layer	General applications where a trade-off between performance and computational cost is acceptable
WNN	A network with large numbers of neurons per hidden layer	Complex problems with large datasets
BNN	Two hidden layers (plus input and output layers)	Problems of moderate difficulty where a small amount of extra depth is helpful
TNN	A three-hidden-layer network	Complex problems such as signal processing, image recognition, etc.
ONN	A network whose architecture or hyperparameters can be optimized automatically (using cross-validation, Bayesian optimization)	Automatically optimize model performance with minimal human intervention

Hyperparameters

Hyperparameters are the pre-defined configuration parameters that govern the learning process of a machine learning model and are set prior to training. In neural networks, hyperparameters define the structure and behavior of the model, including:

- The number of hidden layers and neurons per layer
- The type of activation function (ReLU, sigmoid, tanh)
- The maximum number of training iterations (epochs)
- Whether input data is standardized
- The learning rate and regularization strength

These parameters significantly influence the model's ability to learn and generalize. For instance, regularization helps to prevent overfitting by penalizing overly complex models[24, 23].

Table IV.4: Key Hyperparameters in Neural Networks[24].

Learning Rate	Controls how fast the model learns.
Batch Size	Number of samples used per training step.
Number of Layers & Neurons	Define the model's structure.
Activation Function	Adds non-linearity (example: ReLU, Sigmoid).
Regularization	Helps reduce overfitting (example: L2,Dropout).
Loss Function	Measures prediction error.

Hyperparameters play a crucial role in controlling how a machine learning model learns from data. Choosing appropriate values for these parameters can significantly enhance performance, while poor choices may result in underfitting, overfitting, or unstable training dynamics.

IV.6 Performance Evaluation Metrics

To assess the effectiveness of the trained classification models, several essential performance metrics are employed. These include the **confusion matrix**, **accuracy**, **total cost**, **recall**, **precision**, and the **F1-score**. Together, these metrics offer a comprehensive evaluation framework that captures various

IV.6.1 Confusion Matrix

A confusion matrix is a summary table that shows the number of correct and incorrect predictions made by the classification model, organized by actual versus predicted classes. It provides insight into the types of errors the model makes.
In classification problems, performance is often evaluated using a **confusion matrix**, which provides a summary of prediction results on a classification task. Figure IV.10 illustrates a typical structure of a confusion matrix[20].

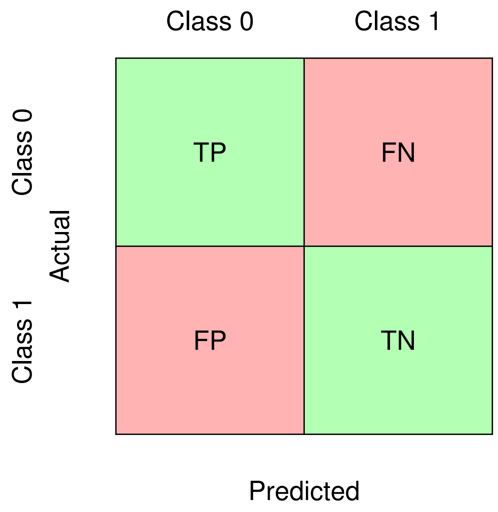


Figure IV.10: confusion matrix[20].

For clarity, we define the following terms [20]:

- **TP (True Positives)** – Correctly predicted positive instances.
- **FP (False Positives)** – Incorrectly predicted as positive.
- **TN (True Negatives)** – Correctly predicted negative instances.
- **FN (False Negatives)** – Incorrectly predicted as negative.

IV.6.2 Accuracy

Accuracy is the percentage of correct predictions over the total number of cases. It tells us how often the model is correct [20].

$$\textbf{Accuracy} = \frac{\text{True Positives} + \text{True Negatives}}{\text{True Positives} + \text{True Negatives} + \text{False Positives} + \text{False Negatives}}$$

IV.6.3 Total Cost

A custom measure that combines false positives and false negatives, often weighted based on their importance. It is used in scenarios where different types of errors have varying consequences (For examples, medical or financial systems) [20].

IV.6.4 Recall

Recall measures the model's ability to correctly identify all relevant (positive) instances.

$$\textbf{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

Out of all actual positive cases, how many did the model correctly detect?

Example: If there are 100 faulty bearings and your model correctly identifies 90 of them, the recall is 90%[20].

IV.6.5 Precision

Precision is the proportion of predicted positive cases that are actually positive[20].

$$\textbf{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

IV.6.6 F1 Score

The F1 Score is the harmonic mean of precision and recall. It balances the two metrics into a single value.

$$\textbf{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

F1 Score gives a better measure than accuracy when dealing with imbalanced data by combining both recall and precision[20].

IV.7 Classification Results of ANN Models for Bearing Fault Detection

Table IV.5 presents the classification accuracy and total cost for various **ANN architectures** during both training and testing phases.

Table IV.5: Classification Accuracy and Total Cost of ANN Models

Model	Training Accuracy	Training Cost	Testing Accuracy	Testing Cost
NNN	94.3%	19	96.5%	5
MNN	95.8%	14	94.4%	8
WNN	94.3%	19	95.8%	6
BNN	95.8%	14	96.5%	5
TNN	93.8%	21	97.9%	3
ONN	97.6%	8	98.6%	2

Table IV.6 provides the **Recall**, **Precision**, and **F1-Score** for each ANN model during training and testing phases.

Table IV.6: Performance Evaluation of ANN Models Based on Recall, Precision, and F1-Score

Model	Training Metrics			Testing Metrics		
	Recall	Precision	F1-Score	Recall	Precision	F1-Score
NNN	0.95	0.95	0.95	0.99	0.98	0.97
MNN	0.95	0.96	0.96	0.94	0.96	0.95
WNN	0.94	0.93	0.94	0.96	0.97	0.96
BNN	0.95	0.96	0.96	0.97	0.96	0.96
TNN	0.94	0.92	0.93	0.98	0.99	0.98
ONN	0.97	0.98	0.97	0.99	0.99	0.99

Table IV.7 outlines the architectural configurations and hyperparameters used in each ANN model.

Table IV.7: Hyperparameter Settings of ANN Models

Model	No. of Layers	Layer 1	Layer 2	Layer 3	Activation Function	Iterations
NNN	1	10	–	–	ReLU	1000
MNN	1	25	–	–	ReLU	1000
WNN	1	100	–	–	ReLU	1000
BNN	2	10	10	–	ReLU	1000
TNN	3	10	10	10	ReLU	1000
ONN	1	12	–	–	Sigmoid	1000

Figure IV.11 presents a combined and comprehensive visualization of confusion matrices summarizing the training and testing performance across all ANN architectures.

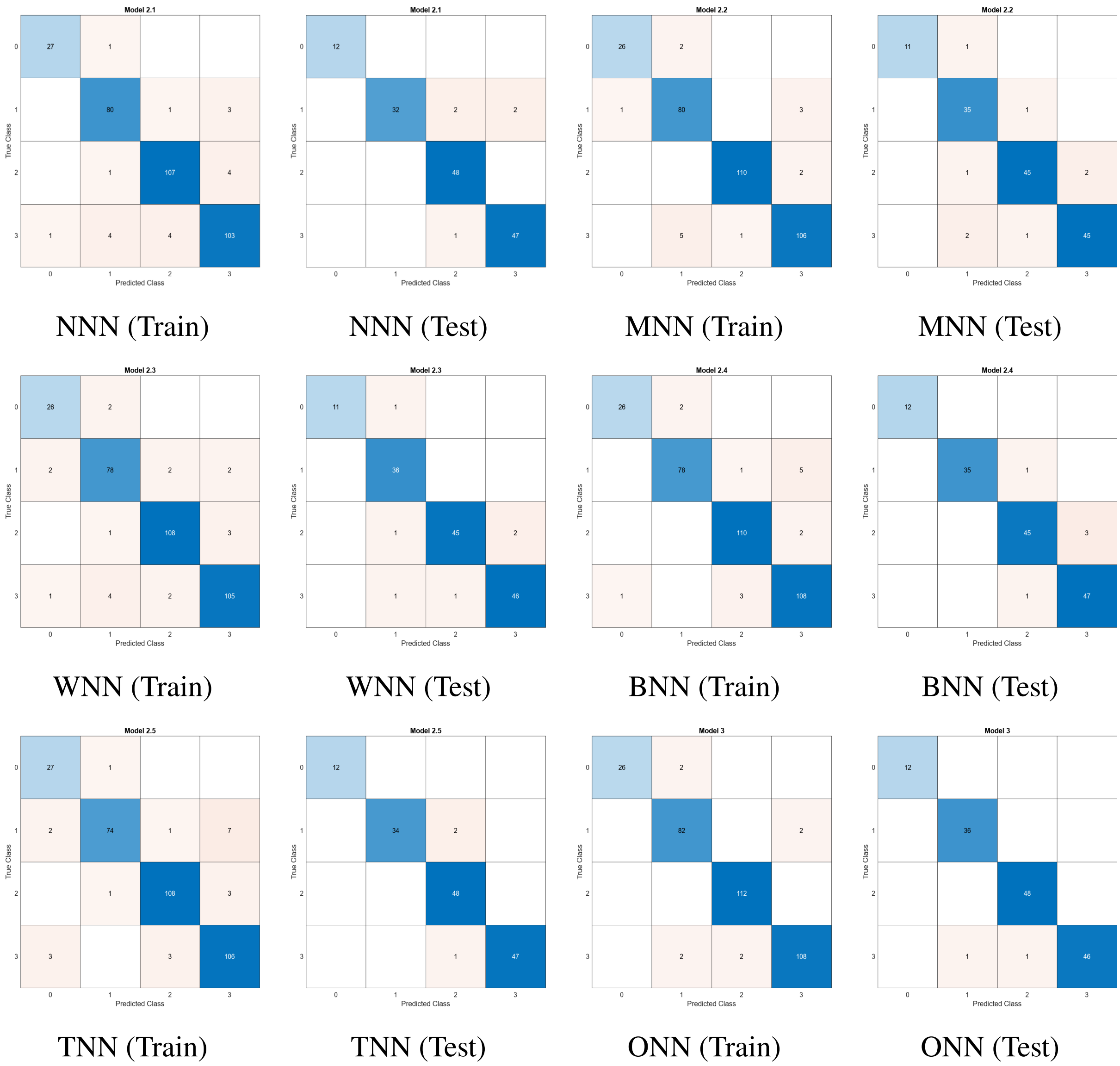
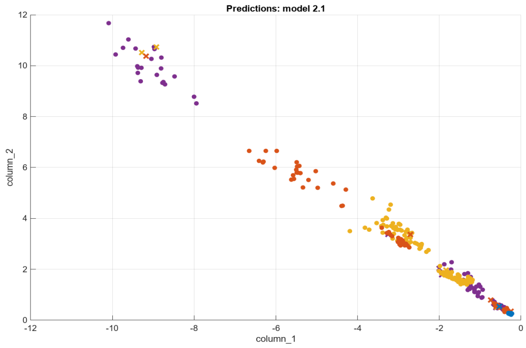
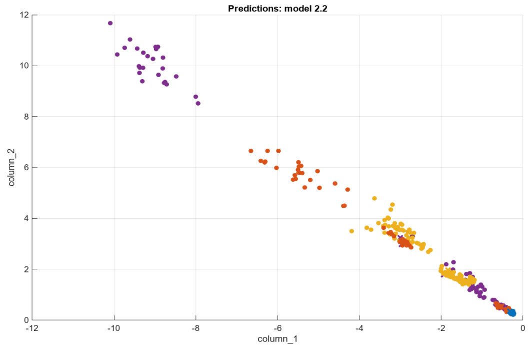


Figure IV.11: Confusion matrices of ANN models.

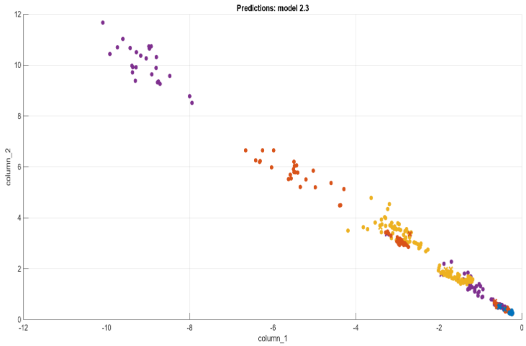
Figure IV.12 presents the combined scatter plots of the training phase for all ANN models.



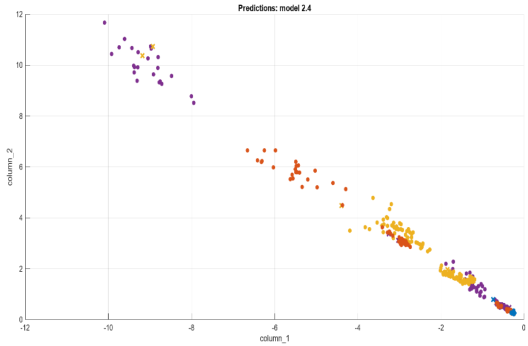
NNN



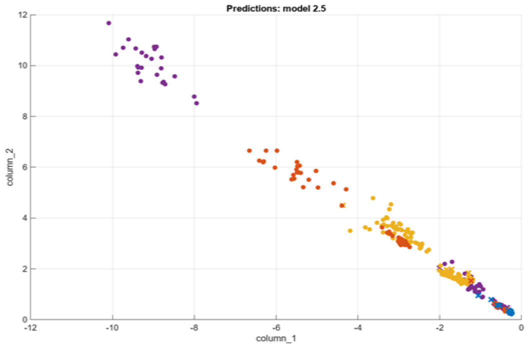
MNN



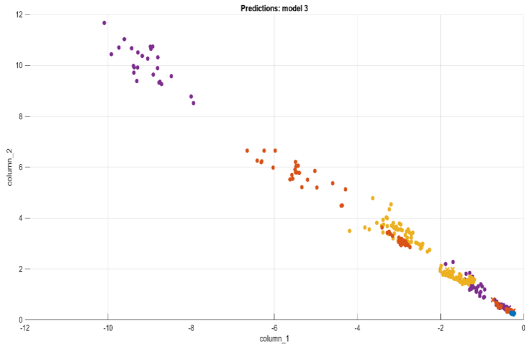
WNN



BNN



TNN



ONN

Figure IV.12: Scatter plots of all ANN models during the training phase.

Figure IV.13 presents the combined ROC curves of all ANN models. The curves represent both the training and testing phases for each neural network model.

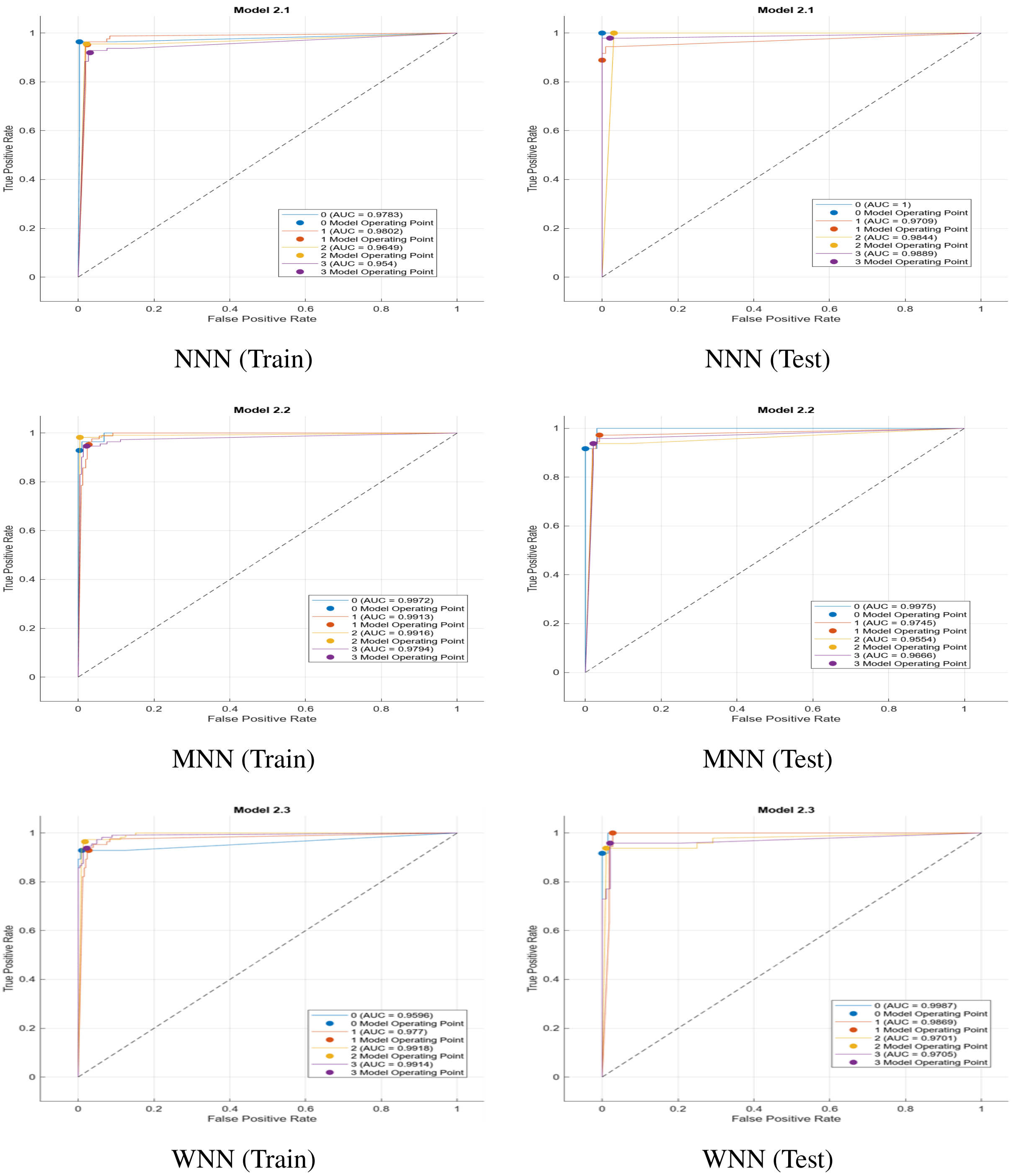


Figure IV.13: ROC Curve of NNN, MNN and WNN Models

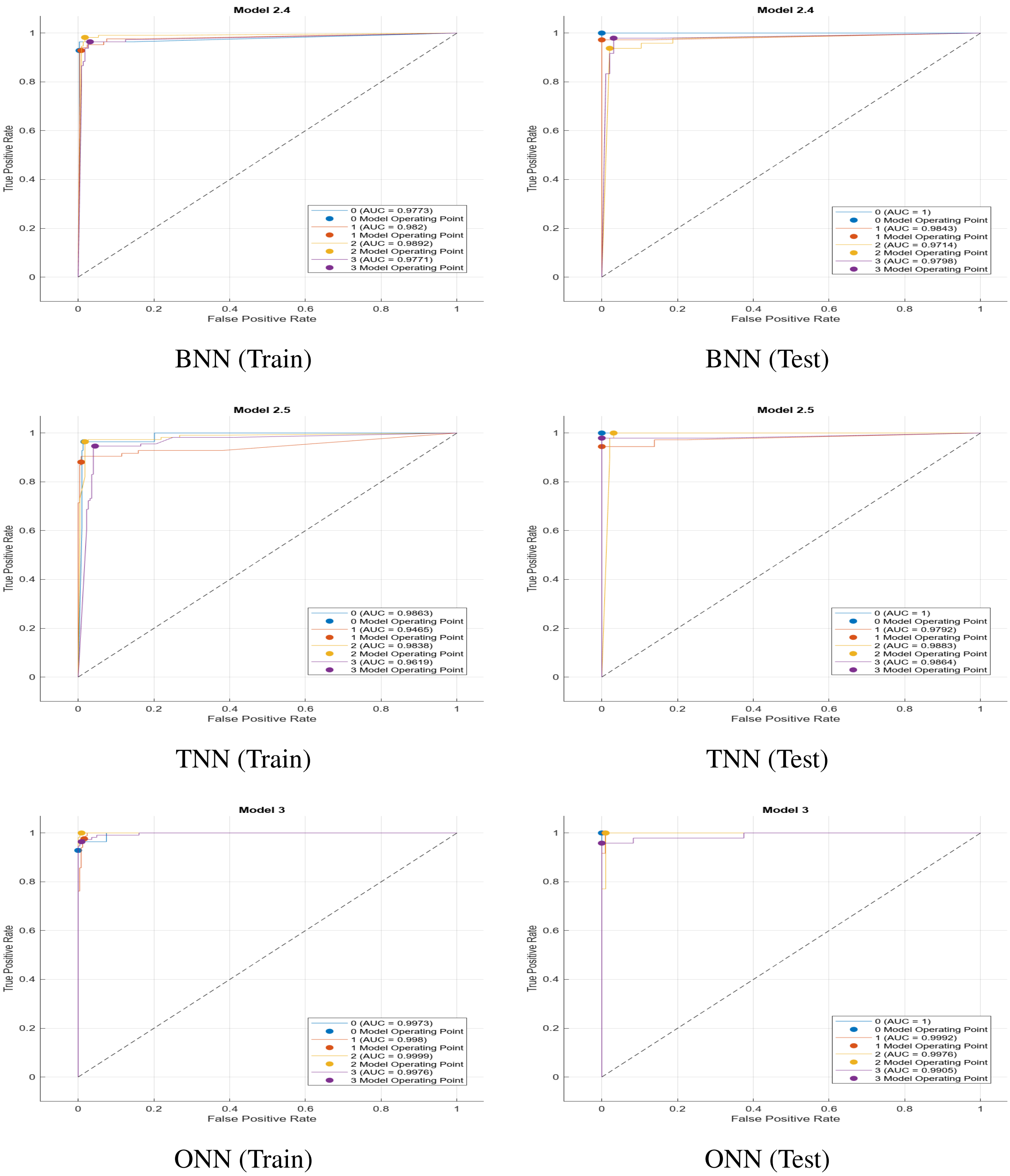


Figure IV.13: ROC Curve of BNN, TNN and ONN Models

Figure IV.14 illustrates how the optimizer efficiently fine-tuned the network parameters to reduce errors on the training dataset. This consistent reduction in classification error signifies improved accuracy and robustness, confirming the effectiveness of the adopted optimization strategy without leading to overfitting.

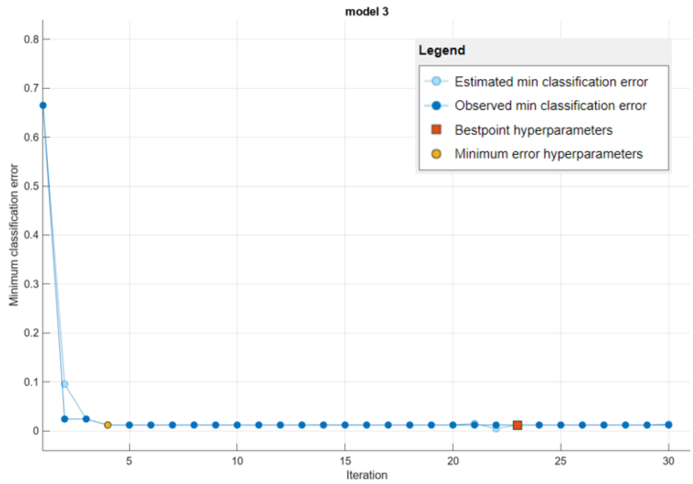


Figure IV.14: Evolution of the Minimum Classification Error During Model Optimization.

IV.8 Discussion of Results

Performance of ANN Models (Tab. IV.5, Tab. IV.6)

The **ONN** achieved the highest accuracy (97.6% for training and 98.6% for testing) with the lowest classification cost, establishing it as the best-performing model overall. In contrast, the **TNN** exhibited the weakest training performance (93.8%) and the highest cost, indicating signs of underfitting. The **BNN** and **MNN** models provided a balanced trade-off between accuracy and cost, whereas **NNN** and **WNN** showed moderate performance.

All models attained **F1-scores** above 0.90, with the **Optimizable Neural Network (ONN)** showing the most consistent and robust classification results.

As shown in Table IV.7, the Narrow, Medium, and Wide models each consist of a single hidden layer with increasing size; however, the performance improvements remain limited. The Bilayered and Trilayered models incorporate additional hidden layers to capture more complex patterns, but their performance does not surpass that of the simpler ONN. Notably, the ONN—comprising only a single hidden layer with 12 neurons and using a Sigmoid activation function—outperforms more complex models, demonstrating that well-tuned, lightweight architectures can yield superior results. All models were trained under the same iteration limit (1000), ensuring a fair comparison.

Confusion Matrix (Fig.IV.11)

The confusion matrix analysis revealed that the **NNN** showed moderate training performance with notable misclassifications. The **MNN** performed slightly better, offering improved generalization. The **WNN** yielded good testing performance but showed signs of overfitting during training. The **BNN** delivered consistent results across both training and testing phases. Despite its increased depth, the **TNN** underperformed during training but generalized relatively well in the testing phase. The best overall results were obtained using the **ONN**, confirming that optimized, simpler architectures can outperform deeper yet less refined models.

Scatter Plots (Fig.IV.12)

The scatter plots revealed clear differences in class separability among the models. The **ONN** exhibited the most distinct separation, with well-clustered fault classes, reflecting its high classification capability. The **BNN** and **TNN** demonstrated moderate separation with some degree of class overlap. In contrast, the **NNN**, **MNN**, and **WNN** showed more scattered and overlapping points—especially during training—indicating lower discriminative performance. Overall, the visual patterns observed in the scatter plots are consistent with the quantitative evaluation metrics, reinforcing the advantage of optimized architectures for clear class discrimination.

ROC Curves (Fig.IV.13))

Analysis of the ROC curves for each neural network model further highlighted their classification capabilities. The **ONN** delivered the most favorable results, with a curve closely approaching the top-left corner—indicative of high sensitivity and a low false positive rate.

The **BNN** and **TNN** also demonstrated strong performance, with curves reflecting a reasonable balance between true positive and false positive rates. In contrast, the **NNN**, **MNN**, and **WNN** showed ROC curves that deviated more from the ideal, suggesting reduced classification performance and increased risk of misclassification at certain thresholds. These results align well with previous evaluation metrics and further validate the effectiveness of optimized architectures in achieving superior fault classification in rotating machinery.

The results clearly demonstrate that the **ONN**, as the optimized model, achieves the highest classification accuracy while maintaining the lowest computational cost. This optimization not only enhances generalization and robustness but also significantly reduces training time and resource consumption. These findings highlight the effectiveness of targeted optimization in improving diagnostic performance, showing that well-tuned, lightweight models can be both efficient and highly accurate for fault classification in rotating machinery.

IV.9 Conclusion

This chapter demonstrated the effective use of artificial neural networks, especially the Multilayer Perceptron, for bearing fault detection using vibration signals. After describing the dataset and preprocessing steps, several neural network models were trained and evaluated. The optimizable neural network showed the best performance, proving that careful tuning can outperform more complex architectures. Overall, neural networks offer a reliable solution for accurate and early fault diagnosis, supporting predictive maintenance in rotating machinery.
The **Optimizable Neural Network** is a relatively simple architecture that leverages automatic hyperparameter tuning to identify the optimal configuration—such as the number of neurons, learning rate, and activation function. This optimization enables the network to achieve high accuracy while maintaining low complexity, resulting in fast and efficient learning without overfitting or poor generalization. In the context of fault diagnosis, particularly for bearing defects, this model accurately distinguishes between fault types by adapting to data characteristics and minimizing classification errors.

General Conclusion

General Conclusion

This thesis explored the application of artificial neural networks (ANNs) for bearing fault detection in rotating machinery, aiming to enhance diagnostic accuracy and efficiency through data-driven methodologies.

Chapter one introduced the fundamentals of rotating machines, the most common fault types, and traditional fault detection techniques. Chapter two provided an overview of artificial intelligence and machine learning approaches, emphasizing their growing role in predictive maintenance. The third chapter detailed the architecture and learning mechanisms of ANNs, underlining their capability for effective fault classification. Chapter four presented a comprehensive experimental study using the CWRU benchmark dataset, covering data preprocessing, model training, and evaluation procedures.

A comparative analysis was conducted between predefined ANN models and those optimized through hyperparameter tuning. Parameters such as the number of hidden layers, neurons per layer, learning rate, and activation functions were systematically adjusted. The results demonstrated that carefully optimizing these parameters significantly improved classification performance, outperforming baseline architectures with fixed configurations. This finding confirms that intelligent design and tuning of the ANN architecture is more beneficial than merely increasing its depth or complexity.

The optimized ANN models achieved a favorable trade-off between classification accuracy and computational efficiency. Performance metrics—including accuracy, recall, precision, and F1 score—validated the reliability and robustness of the proposed approach.

In conclusion, ANNs have proven to be effective tools for early detection of bearing faults, thereby supporting predictive maintenance strategies and reducing unplanned machine downtime.

Further studies could explore the incorporation of deep learning architectures to enhance the scalability and industrial relevance of these diagnostic solutions.

Acknowledgement of Resources

Sincere thanks are extended to **Case Western Reserve University (CWRU)** for providing the bearing fault dataset, which served as a fundamental resource for the experimental analysis conducted in this work. The dataset is publicly available at:

https://engineering.case.edu/bearingdatacenter.

Appreciation is also expressed to **MathWorks®** for the advanced capabilities of the *Machine Learning Toolbox* in **MATLAB**, which enabled the implementation and assessment of the diagnostic models. More information is available at:

https://www.mathworks.com/products/machine-learning.html.

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