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Fault Prognosis from Telemetry Data Using Multivariate Regression

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Dedication

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Praise be to God who enabled me to reach this day. I dedicate this humble work to my mother and father because they were the reason for my success. I also express my gratitude to my brothers and sisters, as well as all my friends at the master's level, especially Kafi Mohammed Anes and those who persevered with me.

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Abstract

Predictive maintenance has changed the traditional principles of old maintenance systems and its technologies include vibration measuring devices and thermal imaging cameras. They have a significant impact on achieving high quality levels, improving the working performance of equipment in industrial facilities, increasing production efficiency and reducing the costs incurred by these facilities for the maintenance of their equipment, especially with the beginning of the Fourth Industrial revolution and the emergence of the Internet of Things concepts, have contributed to the development of the technology of this new approach of maintenance. Failure prediction can be achieved with the application of artificial intelligence tools to examine data and discover patterns that indicate that a problem or failure will occur in the future. These predictions rely on the examination of past and current data to make reliable predictions about when and where failures might occur. In our research, we used telemetry systems to collect information quickly and reliably in order to predict machine failures. This study addresses the importance of artificial intelligence for predictive maintenance by providing a comprehensive overview of modern maintenance techniques and methods.

Keywords: Telemetry, Machine Learning, Deep Neural Networks.

Resumé

La maintenance prédictive a modifié les principes traditionnels des anciens systèmes de maintenance et ses technologies incluent des appareils de mesure des vibrations et des caméras thermiques. Elles ont un impact significatif sur l'atteinte de niveaux de qualité élevés, l'amélioration des performances de travail des équipements dans les installations industrielles, l'augmentation de l'efficacité de la production et réduire les coûts supportés par ces installations pour la maintenance de leurs équipements, notamment avec le début de la Révolution Quatrième Industrielle et l'émergence des concepts de l'Internet des Objets, ont contribué à développer la technologie de cette nouvelle approche de maintenance. La prédiction des pannes est l'application d'outils d'intelligence artificielle pour examiner les données et découvrir des modèles indiquant qu'un problème ou une panne se produira dans le futur. Ces prévisions s'appuient sur l'examen des données passées et actuelles pour faire des prévisions fiables sur le moment et le lieu où les pannes pourraient survenir. Dans nos recherches, nous avons utilisé des systèmes de télémétrie pour collecter des informations de manière rapide et fiable. Cette étude aborde l'importance de l'intelligence artificielle pour la maintenance prédictive en fournissant un aperçu complet des techniques et méthodes de maintenance modernes**.**

Mots clés : Télémétrie, Machine Learning, Réseaux de Neurones Profonds.

الملخص

لقد غيرت الصيانة التنبؤية المبادئ التقليدية لأنظمة الصيانة القديمة، وشملت تقنياتها أجهزة قياس الاهتزاز والكاميرات الحرارية التي لها أثر كبير في الوصول إلى مستويات عالية من الجودة، وتعزيز أداء عمل المعدات في المنشآت الصناعية، وزيادة كفاءة الإنتاج، وتقليل التكاليف التي تكبدتها هذه المنشآت في صيانة معداتها خاصة مع بداية الثورة وقد ساعدت المنطقة الصناعية الرابعة وظهور مفاهيم إنترنت الأشياء في تطوير تكنولوجيا هذا النهج الجديد للصيانة التنبؤ بالفشل هو تطبيق أدوات الذكاء الاصطناعي لفحص البيانات واكتشاف الأنماط التي تشير إلى حدوث مشكلة أو فشل في المستقبل. تعتمد هذه التوقعات على فحص البيانات السابقة والحالية لعمل تنبؤات موثوقة حول متى وأين قد تحدث حالات الفشل. في بحثنا، استخدمنا أنظمة القياس عن بعد لجمع المعلومات بسرعة وبشكل موثوق. تتناول هذه الدراسة أهمية الذكاء الاصطناعي للصيانة التنبؤية من خلال تقديم نظرة شاملة لتقنيات وطرق الصيانة الحديثة .

الكلمات المفتاحية: القياس عن بعد، ، التعلم الالي، الشبكات العصبية العميقة.

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List of Abbreviations

ACM: Availability centered maintenance

AGM: Age-based maintenance

AI: artificial intelligence

ANN: Artificial Neural Networks

BBM: Block-Based Maintenance

BCM: Business Centered Maintenance

BSI: British Standards Institute

CBM: Condition-Based Maintenance

CIM: Constant Interval Maintenance

DOM: Design-Out Maintenance

DRM: Deferred Reactive Maintenance

FBM: Failure-Based Maintenance

FTM: Fixed Time Maintenance

IBM: Inspection-Based Maintenance

LBM: Life-Based Maintenance

ML: Machine Learning

OTF: Operate To Failure

PPM: Planned Preventive Maintenance

RBM: Risk-Based Maintenance

RCM: Reliability-Centered Maintenance

RF: Radio Frequency

IRM: Immediate Reactive Maintenance

RUL: Remaining Useful Life

SCADA: Supervisory Control And Data Acquisition

SSL: Semisupervised Learning

SL: Supervised Learning

SRM: Scheduled Reactive Maintenance

SVM: Support Vector Machines

TBM: Time-Based Maintenance

PM: Productive Maintenance

TPM: Total Productive Maintenance

UBM: Use-Based Maintenance

UL: Unsupervised learning

General Introduction

Predictive maintenance is one of the latest innovations in equipment and infrastructure maintenance and relies heavily on modern technology to improve efficiency and reduce costs. In this context, artificial intelligence (AI) plays a pivotal role, especially when combined with telemetry devices.

Artificial intelligence, through its advanced technologies such as machine learning and big data analysis, enables the processing of huge amounts of data collected via telemetry devices. These devices, such as Internet-connected sensors and gadgets, constantly monitor equipment status and operating conditions, sending real-time data to analysis systems.

When AI analyzes this data, potential malfunctions can be predicted before they occur. This proactive approach to maintenance is known as predictive maintenance, and it enhances operational efficiency and reduces unplanned downtime. Instead of relying on fixed maintenance schedules or waiting until breakdowns occur, predictive maintenance allows for advanced planning and timely intervention, contributing to improved overall performance and increased equipment life.

Moreover, predictive maintenance contributes to improved resource allocation. By knowing in advance which equipment needs maintenance, companies can organize technical teams' work schedules and store spare parts more efficiently, reducing waste and improving resource use.

Integrating AI with telemetry is a paradigm shift in the field of predictive maintenance. This integration helps enhance operational efficiency, reduce costs, and improve reliability and overall equipment performance. As technology develops, this approach is expected to become more widespread and integrated, contributing to significant improvements in various industries. This thesis is organized as follows:

In the first chapter, we provided general information about the telemetry system. Then, in the second chapter, the definition of artificial intelligence and the classification of machine learning were presented. Then, in the third chapter, the results were detailed in the analysis and discussion of the experiments studied. Finally, the conclusion section summarizes the results of our work

Chapter I: INDUSTRIAL TELEMETRY

1.1. Introduction

In this first chapter, we will aim to provide a general overview of the field of telemetry. We will start by defining telemetry, and telemetry industrial. Then we will address the question, "What is the telemetry system?" Listing contemporary applications of industrial telemetry. So, it is used extensively in the field of oil and gas.

1.2. TELEMETRY

The science of telemetry is the collection of data at a far-off place and sending it to a handy place for analysis. One can do telemetry using optical, mechanical, hydraulic, electric, etc. techniques. For short distances, the mechanical techniques—pneumatic or hydraulic—produce respectable performance and are applied in settings with high electromagnetic.

Interference, and circumstances such as explosive places, when using electrical signals are prohibited for security reasons. More recently, the measurement of wide bandwidth and excellent immunity to noise and interference is made possible by the employment of optical fiber systems. Other suggested telemetry systems, based on infrared radiation, capacitive or magnetic coupling, and acoustics, are seldom used. The main advantage of electric-based telemetry over mechanical methods is that the distance between the measurement and the analysis sites can be practically unlimited and it can be easily updated in previously existing infrastructures. Wire telemetry and wireless (or radio) telemetry are two more classifications for electric telemetry techniques based on the transmission channel.

The restricted bandwidth and transmission speed of wire telemetry are its drawbacks. It is employed, nevertheless, when the transmission wires can make use of the current infrastructure, like in the majority of electric power lines that double as wire telemetry carriers. As wireless telemetry needs a last radio frequency (RF) stage, it is more complicated than wire telemetry. Its ability to send data over greater distances makes it frequently employed despite its complexity; as such, it is used in applications where the measurement region is not generally accessible [1].

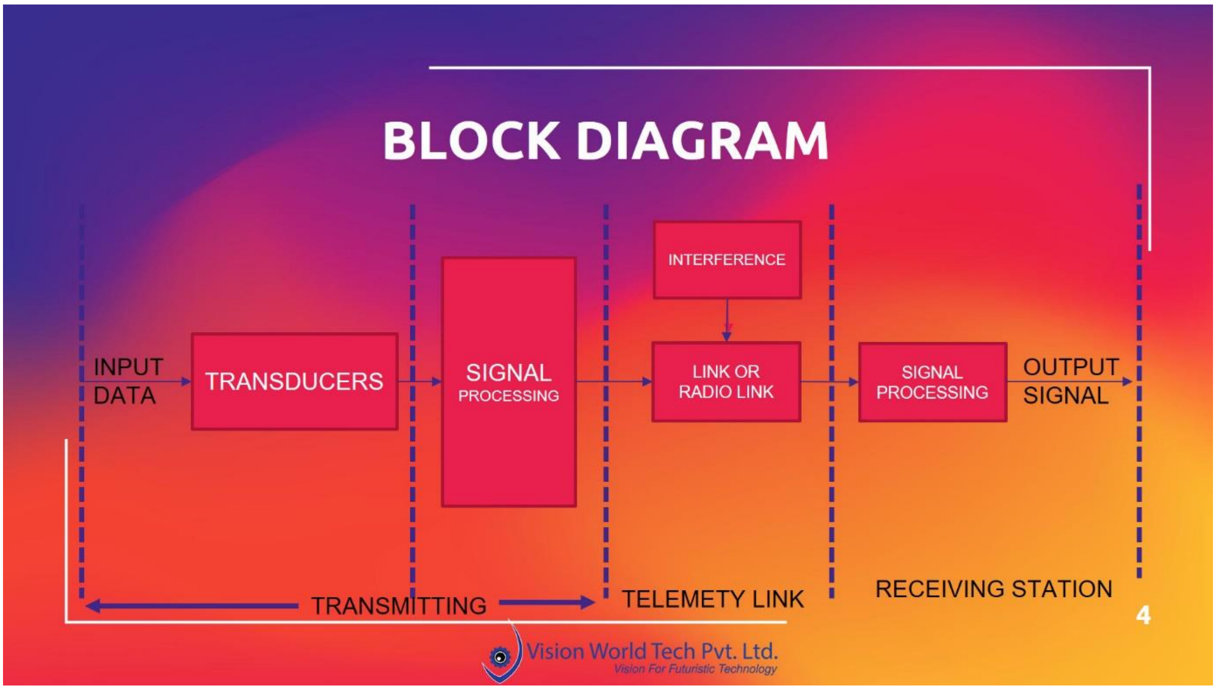

Figure 1.1: Block diagram for a telemetry system.

This is a general diagram for understanding the system. So, the Block Diagram consists of three pieces .

Transmitting : It comprises of all the input units, which comprise sensors (flow meter, level sensors, proximity sensors, etc.) [2].

Telemetry Link: At this level, any data received may take the form of a pulse, current, or voltage process. We perceive this as a converter explanation since the signal is converted into machine code [2].

The transformed signal is then transferred to the dedicated destination via wire (landline) or wireless systems (radio frequency-based) [2].

Receiving Station: This is the receiving end, where all data is collected and processed. In this region, users can check the data [2].

1.2.1Telemetry System Definition

A telemetry system's objective is to gather data from an inaccessible or remote location and transmit it to a location where it can be analyzed. Telemetry systems are typically employed in the testing of moving objects, including automobiles, airplanes, and missiles. A unique kind of communication system are telemetry system. Supervisory control and data acquisition refers to the usage of the telemetry system for both control and data collecting.[3]

A telemetry system typically includes a transducer as an input device, a transmission channel such as cable lines or radio waves, signal processing equipment, and devices for recording or displaying telemetry

1.2.2 Data Collection System

Devices including computers, transducers, filters, accelerometers, signal conditioners, and thermocouples are all part of the data collection system. Numerous physical parameters need to be measured and transformed into an electrical signal, including temperatures, vibrations, pressures, forces, and humidity. It is necessary to condition, amplify, and combine the electrical signal or message with other signals before attaching it to the carrier and sending it to the intended destination. The data collection system's job is to gather information from the sensor system, prepare the signals, and provide the multiplexing subsystem with access to them. The system may also contain computer data, which needs to be managed. It is possible to modulate the computer data onto a subcarrier [3].

1.2.3 Modern industrial applications to use telemetry

- Petroleum Sectors.
- The Utility Power Sector.
- Railroad Transportation.
- Producing.
- Municipal Water Supplies.
- Fire-Life-Safety Systems.
- Transportation Systems with Intelligence [3].

1.3- Industrial Telemetry

In industrial settings, telemetry is utilized for both control and monitoring. In contemporary industrial telemetry systems, where these two roles are typically combined, the system is referred to as supervisory control and data acquisition (SCADA). Industrial telemetry has a 200-year history, and significant historical moments such as the Industrial Revolution, World War II, and the advancement of computer technology have influenced the technology employed in this field. Industrial telemetry design engineers now have access to a wide range of office and field tools, almost as many as the applications they support [3].

1.3.1 History of Industrial Telemetry

Industrial telemetry has its roots in steam-driven applications, James Watt specifically improved Thomas Newcomen's steam engine by adding several monitoring and control mechanisms, like the well-known fly-ball governor and the mercury pressure gauge. The Industrial Revolution was aided by the development of commercial high-pressure steam gauges, such as the Bourdon tube pressure gauge, in the middle of the 1800s [4]. In a similar vein, Westinghouse's hydraulic servos eventually took the place of fly-ball governors in large engines [5]. This was the early days of telemetry. With the creation of their Eight Wheeler, the Baldwin Locomotive Works of Philadelphia, Pennsylvania, started producing useful railroad locomotives in the United States in 1845 [6]. At the end of the nineteenth century, the Industrial Revolution was coming to an end, but improvements in industrial process monitoring and control were just getting started. The industrial revolution was fueled by basic mechanical and hydraulic devices, but by the end of the 19th century, new sensors that used air to measure flow, level, or pressure indirectly were being developed.

Additionally, the pneumatic diaphragm-actuated valve created in 1890, allowed for monitoring and control process automation by using air as the connecting medium [5]. These sensors and actuators were linked together directly and were collocated with the processing equipment. These pneumatic systems monitored parameters and then performed rudimentary control loop functions using on-off or proportional control in an automated process. The invention of the pneumatic transmitter in 1938.

The Foxboro Corporation meant that the process engineer could be located in a centralized control room [5]. The 3 to 15 pound-per-square-inch (psi) transmitter signal became the standard in the United States and created a robust means of relaying a transducer’s state, while also demonstrating whether a fault condition existed. In the event of a leak, a value of 0 psi is detected as a fault condition since it is out of range. The use of pneumatic control and monitoring increased slowly through the first few decades of the twentieth century, peaking in the 50s and 60s when the 3 to 15 psi standard gained wide acceptance [7]. Because of its relative simplicity, inherent safety in flammable environments, and passive electrical classification, this type of mechanical instrumentation is still in use and available in the marketplace [3].

1.3.2 Industrial Communications Equipment

- Devices for Measuring Temperature.
- Devices for Measuring Gas and Fluid Flow.
- Tools for Measuring Fluid Levels.
- Other Measuring Devices.
- Control Output Devices.
- Devices for Field Control [3].

1.4 Conclusions

Design engineers can better understand the rationale for the use of various telemetry devices in certain applications by knowing the history of industrial telemetry technology. Many different devices connect to the applications, some of which are specially designed to complete a given duty. The office and control sides of industrial telemetry applications have been completely transformed by computers, which has had a significant impact on this sector.

What remains is to discuss how these various devices interconnect. Several prominent and well-established communications techniques complete the remote control and monitoring system. New techniques as well as techniques borrowed from other industries are also contributing to the industrial telemetry landscape of the twenty-first century.

Chapter II: Machine learning and Maintenance strategies

2.1. Introduction

Artificial intelligence (AI) technologies are playing an increasingly important role in maintenance, helping to improve efficiency, reduce costs, and enhance performance through multiple applications. These applications include predictive analysis, preventive maintenance, self-analysis of systems, and learning from historical data.

This is done by collecting and analyzing data to predict equipment failure and detect malfunctions before they occur. Through this chapter, we study the most important algorithms used and the role and importance of maintenance.

2.2. Artificial Intelligence

Artificial intelligence (AI) is a branch of computer science that develops and manages systems that can collect measurements and behave in human-like ways. It involves skills like comprehension, reasoning, problem solving, and perception [8].

- **Learning**: In artificial intelligence, learning refers to machines' ability to autonomously improve their performance based on experience or historical data.
- **Reasoning** : AI systems can make judgments and solve issues by applying logic and reasoning.
- **Perception** : AI systems can use sensors, cameras, and other input devices to collect information about their surroundings.
- **Decision making :** AI systems can execute based on data and algorithms, frequently without human participation.
- The ideal feature of AI is its ability to rationalize and execute actions that have the best likelihood of reaching the objective [8].

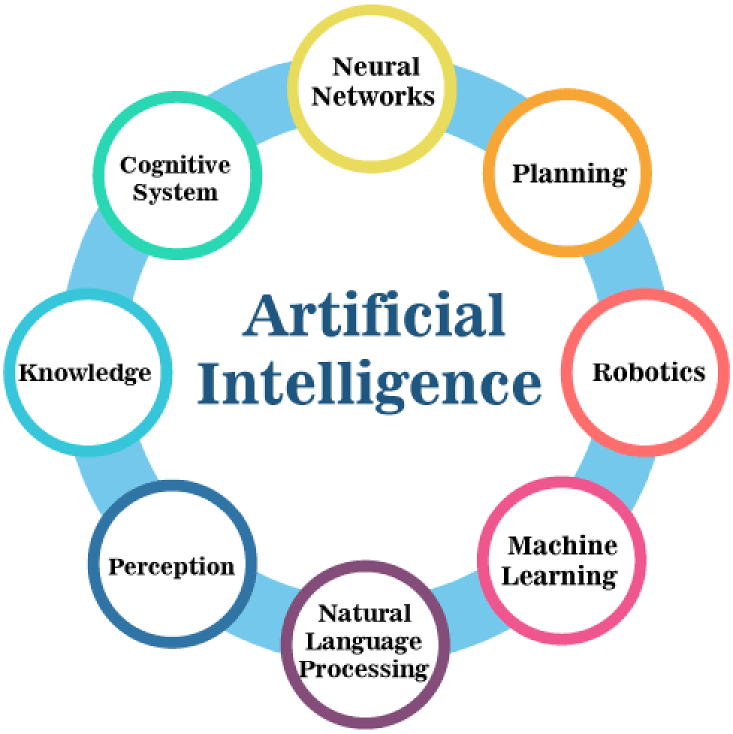

Figure 2.1: diagram depicting various components of (AI).

2.3. Machine Learning (ML)

2.3.1 What Is Machine Learning (ML)

Machine learning is an area of artificial intelligence. Machine learning algorithms make it easier for computers to make decisions without requiring explicit coding. Following the receipt of historical data, these algorithms predict future events. This makes them faster and more effective than alternative methods that require hand-coding rules. The recommendation system is one common use case. Other common uses include fraud detection, business procedures, spam, malware risks, and predictive maintenance [9].

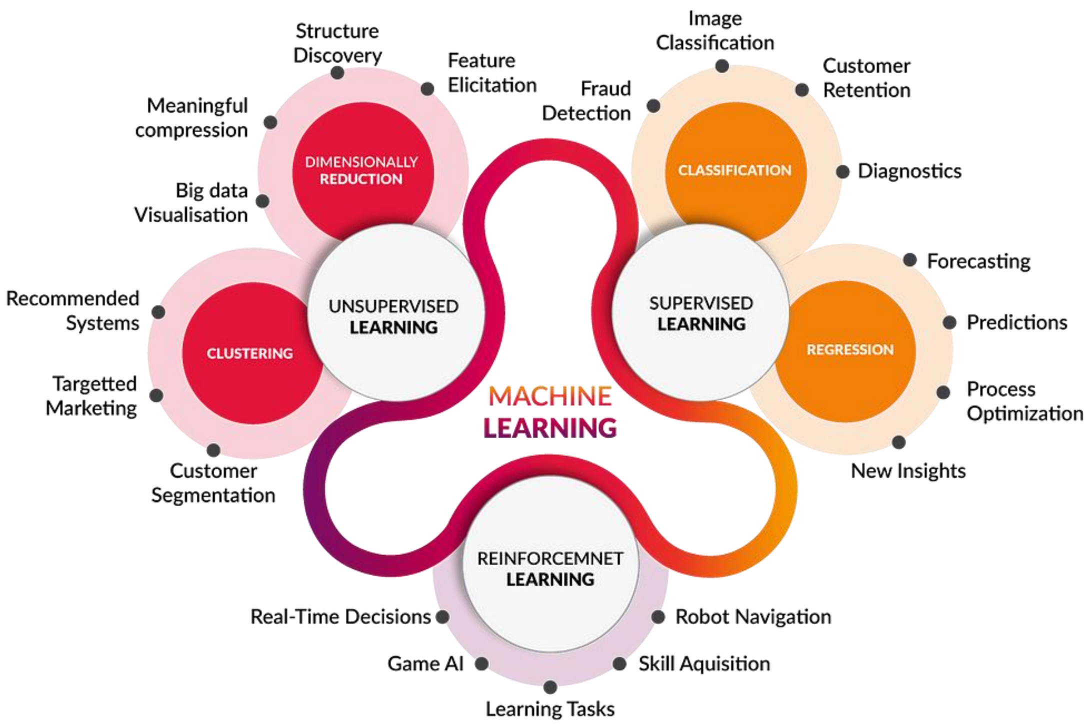

Figure 2.2: machine-learning applications.

2.3.2 Elements of Machine Learning

2.3.2.1 Algorithms:

Simply defined, an algorithm is a scientific or logical program that converts a data collection into a model. Various methods can be used, depending on the type of problem that the model is attempting to address, the resources available, and the nature of the data.

Machine learning algorithms employ computer methods to "learn" information directly from data, rather than using a preconceived equation as a model [10].

2.3.2.2 Models:

In machine learning, a model is a mathematical representation of real-world events. An ML model is trained to recognize specific patterns by running it through a set of data with applicable algorithms. Once trained, a model can make predictions [10].

2.3.2.3 Feature Extraction:

Usually termed Parameters or Variables, it is a field. A data field describes a trait or feature of a specific object in a database [10].

Datasets can contain several features. If the characteristics in the dataset are similar or vary significantly, the observations contained in the dataset are likely to cause an ML model to suffer from overfitting [10].

Overfitting occurs when a model learns the detail and noise in training data to the point where it hurts the model's performance with new data. To solve this problem, the amount of features in the datasets must be regularized using feature extraction techniques. Feature extraction reduces the number of features in a data set by producing new features from existing features.

2.3.2.4 Training:

Training methods enable ML models to discover patterns and make decisions. There are several approaches to accomplishing this, including supervised learning, unsupervised learning, reinforcement learning, and so on [10].

2.3.3 The Uses of machine learning

• Problems for which existing solutions require many hand-tuning or long lists of rules: one Machine Learning algorithm can often simplify code and perform better.

• Complex problems for which there is no good solution at all using a traditional approach: the best Machine Learning techniques can find a solution.

• Fluctuating environments: a Machine Learning system can adapt to new data.

• Getting insights about complex problems and large amounts of data [11].

2.3.4 Types of Machine Learning Systems

There are four types; each type depends on the type of supervision they need during the learning process.

- Supervised learning.
- Unsupervised learning.
- Semi-supervised learning.
- Reinforcement learning [11].

2.3.4.1 Supervised learning (Sl):

Supervised learning is a category of machine learning that uses labeled datasets to train algorithms to predict outcomes and recognize patterns [11].

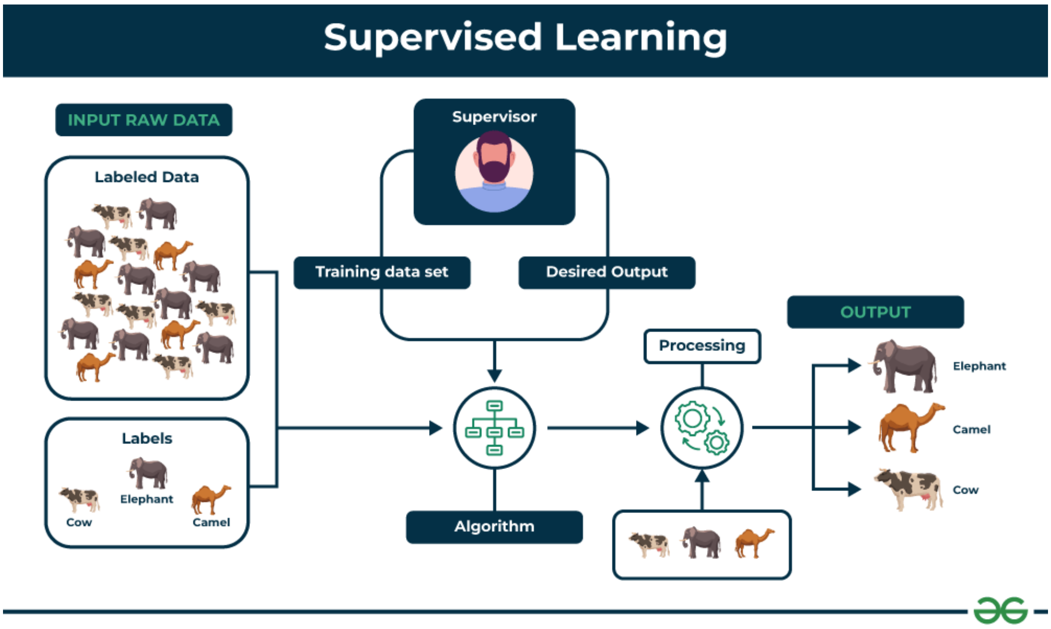

Figure 2.3: Supervised learning.

Figure [2.3] is an example of machine learning where the outputs are known in advance: elephant, camel, and cow, the machine learns through examples and solutions.

In supervised learning, training data is made up of input features (also known as independent variables) and their matching output labels. The purpose is to discover a match or association between input attributes and output labels, allowing the algorithm to make predictions or excisions on that new data. Supervised training algorithms are divided into two main categories: classification and regression.

2.3.4.1.1.Regression :

Regression techniques are employed when the output variable is either continuous or numerical. Algorithmic learning is a method that adapts a function or curve from training data to predict fresh input values. Examples of regression jobs include estimating a home's price based on factors such as size, location, and number of bedrooms, as well as estimating sales volume based on advertising spend.[12]

a – Linear Regression

A regression problem involves studying changes in the average value of a variable (random) when another variable or multiple other variables take on different fixed values. The first variable is called the dependent variable or the explained variable, while the other variables are referred to as "independent variables" or explanatory variables. When there is only one explanatory variable, it is called simple regression. When there are at least two explanatory variables, it is referred to as multiple regression.

To formally write a simple regression model, Y represents the dependent variable, X represents the explanatory variable, and E(Y/X=x) denotes the mean value of Y when the variable X is fixed at x. To describe the changes that may occur in the variable Y as the variable X takes on different values, we establish:

$$E\,(Y / X = x) = f(x,\beta) \qquad (1)$$

When f is an arbitrary function depending on the unknown parameter β, known as the regression function, and assumes a linear form of the parameter β, it is referred to as linear regression:

The most basic regression model is f(x,β) = β0 + β1x, where β0 and β1 are unknown parameters.

In this case, we explain

$$E\,(Y/X=x) = \beta_0 + \beta_1 x \qquad (2)$$

A simple linear model

The expression (2) is not commonly used because, in reality, we do not observe E(Y|X=x) Then we can write the linear, first-order model:

$$y = \beta_0 + \beta_1 x + \varepsilon \qquad (3)$$

y, x, and ε are vectors. ε represents an unobservable random error. Error 1' assumes a zero mean (E(ε) = 0) and an unknown variance (Var(ε) = σ2). The parameters β0, β1, and σ2 are unknown.

b – Multiple Linear Regression

We examine the regression issue in cases where the response variable relies on several explanatory variables, known as a multiple linear regression model. This model expands on simple linear regression in two key aspects. It permits the mean function E(y) to be linked to multiple explanatory variables and display non-linear forms.[12]

The linear model:

Let y be the dependent variable, which is linearly connected to k independent variables X_1, X_2, X_k:

through the parameters β_1, β_2, β_k

$$E\,(Y / X_1 = x_1, \ldots\ldots, X_k = x_k) = \beta_0 + \beta_1 x_1 + \ldots + \beta_1 x_1 + \beta_k x_k + \varepsilon \qquad (4)$$

This is identified as a multiple linear regression model. The parameters (β_1, β_2, β_k) are the regression coefficients for (X_1, X_2, X_k), and (ε) is the random error component that represents the difference between the observed and fitted linear relationships. There could be a variety of explanations for this difference, such as the combined influence of variables that are not included in the model, random elements that cannot be accounted for in the model, and so on.

Example:

A person's income and education are related. It is predicted that a better level of education leads to a higher income. A simple linear regression model can be written as follows:

$$\text{income} = \beta_0 + \beta_1 \text{ education} + \varepsilon$$

Not that β_1 indicates the change in income per unit change in education, and β_0 reflects the income when education is zero because it is believed that even an illiterate individual can earn some money. Furthermore, this approach ignores the fact that most people earn more money as they get older, regardless of their degree level. So β_1 will overestimate education's marginal impact. If age and education are positively associated, the regression model will attribute all observed increases in income to an increase in education. So a better model:

$$\text{income} = \beta_0 + \beta_1 \text{ education} + \beta_2 \text{ age} + \varepsilon$$

Income often rises more slowly in later earning years than in earlier years. To address this situation, we may extend the model to:

$$\text{income} = \beta_0 + \beta_1 \text{ education} + \beta_2 \text{ age} + \beta_3 \text{ age}^2 + \varepsilon$$

This is how we approach regression modeling in situations from life. Before selecting how many, why, and how to select dependent and independent variables, one must analyze the experimental condition and phenomenon [12].

- **Model set up**

Let an experiment be conducted n times, and the data is obtained as follows:

Table 2.1: Data from a multiple linear regression

Observation number	Response y	Explanatory variables X_1	X_2	X_k
1	y_1	X_{11}	X_{12}	X_{1K}
2	y_2	X_{21}	X_{22}	X_{2K}
..	..	..	..	..
n	y_n	X_{n1}	X_{n2}	X_{nk}

Assuming that the model is:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_k x_k + \varepsilon \tag{5}$$

Through the table, we extract the equations:

$$y = \beta_0 + \beta_1 x_{11} + \beta_2 x_{12} + \beta_k x_{1k} + \varepsilon_1$$

$$y = \beta_0 + \beta_1 x_{21} + \beta_2 x_{22} + \beta_k x_{2k} + \varepsilon_2$$

..

..

..

$$y = \beta_0 + \beta_1 x_{n1} + \beta_2 x_{n2} + \beta_k x_{nk} + \varepsilon_n$$

The n equations can be expressed as:

$$\begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{pmatrix} = \begin{pmatrix} 1 & x_{11} & x_{12} & \cdots & x_{1k} \\ 1 & x_{21} & x_{22} & \cdots & x_{2k} \\ \vdots & \vdots & \vdots & \cdot & \vdots \\ 1 & x_{n1} & x_{n2} & \cdots & x_{nk} \end{pmatrix} \begin{pmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_k \end{pmatrix} + \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{pmatrix}$$

or

$$y = X\beta + \varepsilon$$

In general, the model with k explanatory variables can be stated as: $y = X\beta + \varepsilon$

where $y = (y_1, y_2, y_3,)$ is a $n \times 1$ vector of n observation on study variable,

$$X = \begin{pmatrix} X_{11} & X_{12} & \cdots & X_{1k} \\ X_{21} & X_{22} & \cdots & X_{2k} \\ \vdots & \vdots & \ddots & \vdots \\ X_{n1} & X_{n2} & \cdots & X_{nk} \end{pmatrix}$$

is a $n \times k$ matrix of n observations on each of the k explanatory variables.

$\beta = (\beta_1, \beta_2, \beta_3)$ vector of regression coefficients.

$\varepsilon = (\varepsilon_1, \varepsilon_2, \varepsilon_3)$ vector of random error components or disturbance term.

2.3.4.1.2 Classifications:

When the output variable is conclusive or belongs to a certain category or categories, classification algorithms are employed. Using training examples, the algorithm learns to categorize input data into specified classes or categories. Classification actions include discovering unsolicited emails, identifying photos, and assessing attitudes [13-14].

Supervised learning has a variety of applications, including sentiment analysis, fraud detection, and stock price prediction. Supervised learning algorithms may make accurate predictions and decisions using labeled data, making them a useful tool in a variety of industries.

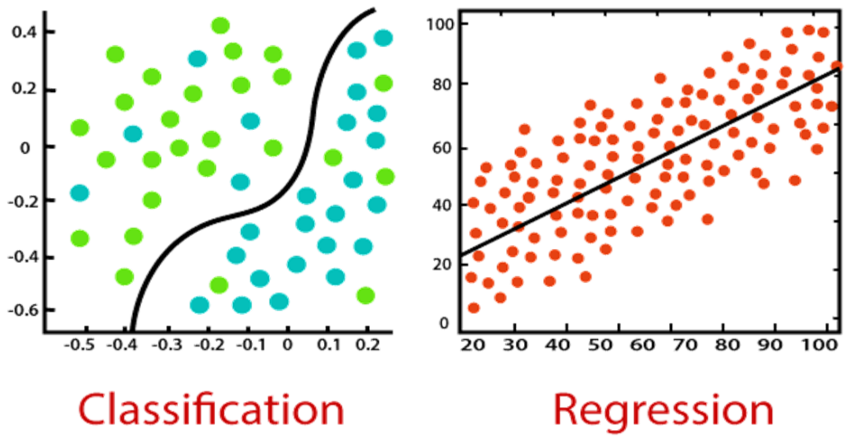

Figure 2.4: Regression et Classification in machine Learning.

– The most important algorithms of Classification:

- k-Nearest Neighbors.
- Linear L Classifiers.
- Logistic Regression.
- Support Vector Machines (SVMs).
- Decision Trees and Random Forests.
- Neural networks [11].

2.3.4.2 Unsupervised learning

In unsupervised learning, as one might guess, the training data is unlabeled (Figure2.5). The system tries to learn without a teacher [11].

2.3.4.3 Semisupervised learning

Semi-supervised learning, where training data contain a few marked examples in which there are a large number of classified evidence and a few disaggregated data, and a large number of unnamed examples. The semi-supervised learning model is intended to make effective use of all available data, not disaggregated data as in supervised learning [11].

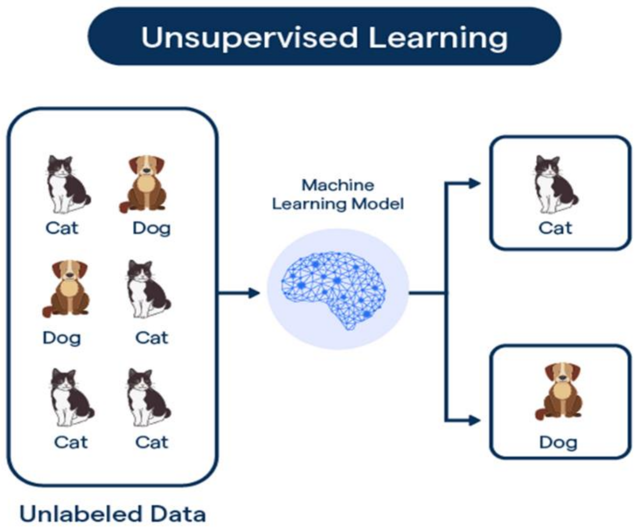

Figure 2.5: An unlabeled training set for unsupervised learning.

2.3.4.4 Reinforcement Learning

Reinforcement learning is a machine learning paradigm where an agent learns to make decisions by interacting with an environment. It learns through trial and error, receiving feedback in the form of rewards or penalties for its actions, with the goal of maximizing cumulative reward over time. It's widely used in areas like robotics, gaming, and autonomous vehicles [11].

2.3.5 Main Challenges of Machine Learning

- Insufficieity of Training Data.
- Nonrepresentative Training Data.
- Poor-Quality Data.
- Irrelevant Features.
- Overfitting the Training Data.
- Underfitting the Training Data.
- Testing and Validating [11].

2.4. Deep learning

Deep learning is a branch of automated learning that uses neural networks with many layers to automatically create copies of unregulated inputs. By allowing networks to learn complex models and connections directly from data, it reduces the need for manual job engineering. Deep learning has made great progress in seeing the computer, the form shows -- the content of artificial intelligence, the treatment of the natural language, and other areas, changing processes such as image classification, language translation, and speech recognition. Its success is linked to its ability to capture hierarchical and abstract references, which are facilitated by access to large data sets and powerful computational capabilities. Deep learning continues to drive innovation in many industries [15-16].

Deep learning is one of the most important areas of artificial intelligence [15-16].

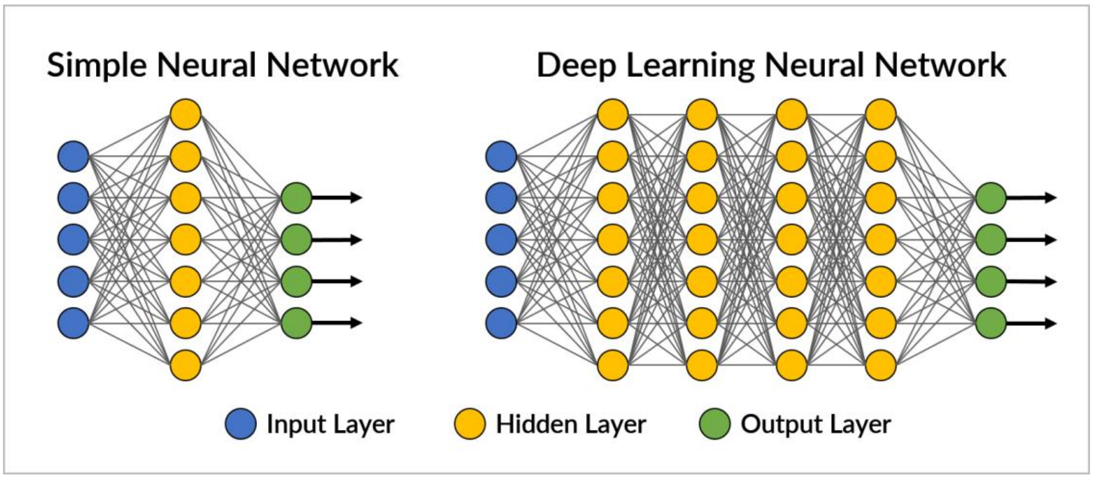

Figure 2.6: Deep learning.

Convolutional neural networks (CNs), recurrent neural networks (RNNs), and transformers are three common deep learning designs for image analysis, sequential data processing, and natural language interpretation. Deep learning frameworks such as TensorFlow and PyTorch provide tools and resources for creating and training deep neural networks. Deep learning's rapid expansion and utilization in a variety of fields can be ascribed to increased access to big data sets, the development of powerful computing hardware, and the enhancement of deep learning algorithms. It continues to set the bar for AI research and drive advancement in numerous areas [17].

2.4.1 Artificial Neural Networks

2.4.1.1 A brief history of neural networks

The history is important because for about two decades, the future of neural networks was undefined. McCulloch and Pitts (1943) are widely regarded as the creators of the first neural network. They merged several simple processing units, which could result in an overall boost in computational capability. They proposed numerous concepts, such as a neuron has a threshold level, and when that level is reached, the neuron fires. It remains the core way that ANNs operate. The McCulloch and Pitts network has a fixed set of weights.

In the 1950s and 1960s, numerous scholars (Block, Minsky, Papert, and Rosenblatt) worked on perceptrons. The neural network model could be proven to converge to the correct weights, so solving the problem. The perceptron's weight adjustment (learning algorithm) proved to be more potent than Hebb's learning principles. The perceptron sparked widespread excitement. It was proposed to develop programs that could think.

Minsky and Papert (1969) demonstrated that perceptrons could not learn functions that are not linearly separable. Neural network research decreased from the 1970s to the mid-1980s because the perceptron could not learn certain critical functions. In 1985-86, neural networks recovered their relevance. Parker and LeCun created a learning approach for multi-layer networks called backpropagation, which could solve problems that were not linearly separable [18].

2.4.1.2 Definition of Artificial Neural Networks

Let's start with a working definition of what a "neural network" is, and then go on to some basic definitional explanations of some of the concepts that are important to understand. A neural network is a network of interconnected basic processing units, or nodes, with functionality largely derived from animal neurons. The interunit connection strengths, or weights, that the network acquires through adaptation to, or learning from, a set of training patterns, store its processing power [19].

2.4.1.3 Neural Network structure

2.4.1.3.1 The Biological Neural System

The human brain is made up of many neuronal cells that process information, over a billion in total. Each cell operates as a basic processor. The brain's skills are only conceivable due to the vast interaction between all cells and their concurrent processing [20].

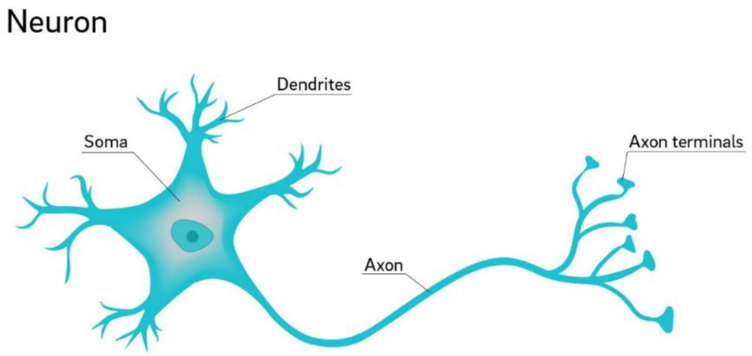

Figure 2.7: Biological Neuron.

- **Dendrites:** are branching fibers that originate from the cell body or soma.
- **Soma or cell body:** A neuron's structure, including the nucleus, supports chemical processing and neurotransmitter generation [20].
- **Axon:** is a singular fiber that transmits information from the soma to synaptic locations on other neurons (dendrites and somas), muscles, or glands [20].
- **Axon Terminal :** Neurons have a little knob at the end of their axons that release chemicals known as neurotransmitters [20].

2.4.1.3.2 Components of an Artificial Neuron

An Artificial Neural Network (ANN) is a mathematical model that tries to simulate the structure and functionalities of biological neural networks. The basic building block of every artificial neural network is the artificial neuron, that is, a simple mathematical model (function). Such a model has three simple sets of rules: multiplication, summation, and activation. At the entrance of the artificial neuron, the inputs are weighted which means that every input value is multiplied with individual weight. In the middle section of the artificial neuron is the sum function that sums all weighted inputs and bias. At the exit of the artificial neuron, the sum of previously weighted inputs and bias passes through the activation function which is also called the transfer function [19].

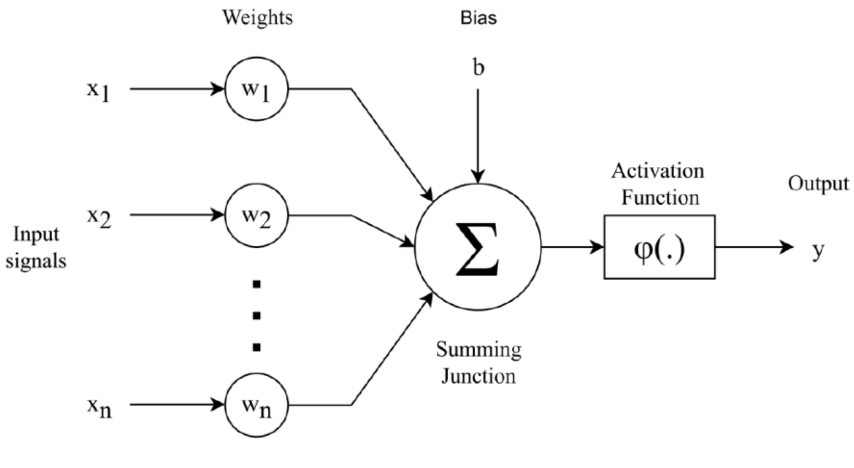

Figure 2.8: Nonlinear model of a neuron

2.4.1.3.3 Mathematical Model of Neuron:

It is hard to reproduce the different characteristics of a biological neuron accurately in a modern computer, thus we must make numerous appropriate simplifications. In contemporary research on neural networks, the neuron is the most important information-processing unit [20].

The collection $\{x1,2,\ldots,xn\}$ represents many input signals, similar to the external electrical impulses collected by dendrites in a biological neuron. Weights $\{w1,w2,\ldots,wn\}$ are applied to synaptic connections on the artificial neuron to calculate the importance of each xi input from the neuronal input by multiplying it by the corresponding synaptic weight wi.

- Input signals $\{x1,2,\ldots,xn\}$ are external signals or samples that reflect the values assumed by a certain application's variables. Input signals are typically standardized to improve the performance of learning algorithms.
- Synaptic weights $\{w1,w2,\ldots,wn\}$ are the values used to weigh each of the input variables, allowing the assessment of their relevance to the neuron's functionality.
- Linear aggregator (Σ) collects all input signals weighted by the synaptic weights and generates an activation voltage [21].
- Activation threshold or bias (b) is a variable used to determine the suitable threshold that the result produced by the linear aggregator should have to create a trigger value toward the neuron output [t].
- Activation potential (u) The difference between the linear aggregator and the activation threshold produces this result. If $u \geq$ b, the neuron produces an excitatory potential, otherwise it is inhibitory. [t]
- Activation function (φ) The functional image assumes that the purpose is to limit the neuron output to a suitable range of values. [21]
- The output signal (y) represents the final value produced by the neuron given a certain set of input signals. It can also be used as input for other progressively coupled neurons.[21]

❖ **Activation Functions:**

Every neuron has an activation function and a threshold value. The threshold value is the lowest value that an input must have to activate the neuron. The activation function is used, and the output is sent to the next neuron(s) in the network.

An activation function limits the neuron's output to values between 0 and 1, or -1 and +1. In most cases, each neuron in a network uses the same activation function $[\varphi]$. Different activation functions have been tested, but only a few have found practical use. The figure shows four popular choices: the step, sign, linear, and sigmoid functions. [22]

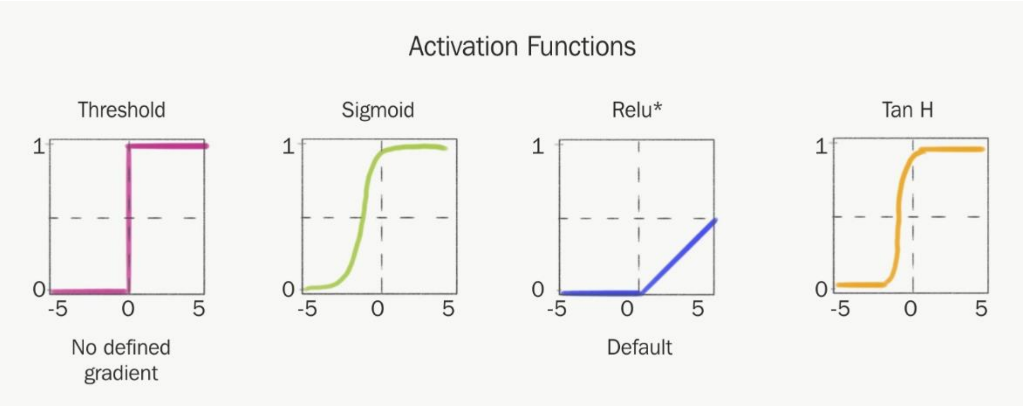

Figure 2.9: Activation functions of a neuron.

The step and sign activation functions, sometimes known as hard limit functions, are frequently utilized in decision-making neurons for categorization and pattern recognition. The sigmoid function converts the input, which can have any value between plus and negative infinity, into a sensible value in the range of 0 to 1. This function is used by neurons in back-propagation networks. The linear activation function produces an output equal to the neuron-weighted input [22].

❖ **Training Processes and Properties of Learning**

One of the most important aspects of artificial neural networks is their ability to learn from samples that represent a system's behavior. As a result, once the network understands the relationship between input and output, it can generalize solutions, which means it can generate output that is close to the expected (or desired) output for any given input values. There are two learning modes: supervised and unsupervised. The supervised learning mode sends input-output data combinations to the network. As a result, the connection weights and node biases, which are originally randomly distributed, alter their values to create output that is as close as possible to the real output; that is, the learning method (recursive algorithm) strives to minimize the present mistakes of all processing parts. With each succeeding cycle, the overall network error between the desired and actual outputs will decrease. Finally, the result is a minimized error between the network and actual output (or intended network accuracy), as well as the internal network structure, which depicts the overall input-output dependency [22].

2.4.1.4 Architecture of a Typical Artificial Neural Network

An Artificial Neural Network (ANN) is a system for processing data. comprising a large number of simple highly interconnected processing systems as artificial neurons in a network topology that can be represented by a directed graph G. an ordered two-tuple (V, E), consists of a set V of vertices and a set E of edges

- The vertices might be representing neurons (input/output), and
- The edges could represent synaptic links, as shown by the weights attached [23]

2.4.1.4.1 Single Layer Feed-forward Network

The Single Layer Feed-forward Network contains a single layer of weights. The synaptic linkages containing weights connect every input to every output, but not in the opposite direction. This is a feed-forward network. Each neuron node calculates the total of the weights and inputs, and if the value is greater than a certain threshold (usually 0), the neuron fires and takes the active value (typically 1); otherwise, it takes the deactivated value (commonly -1). [23].

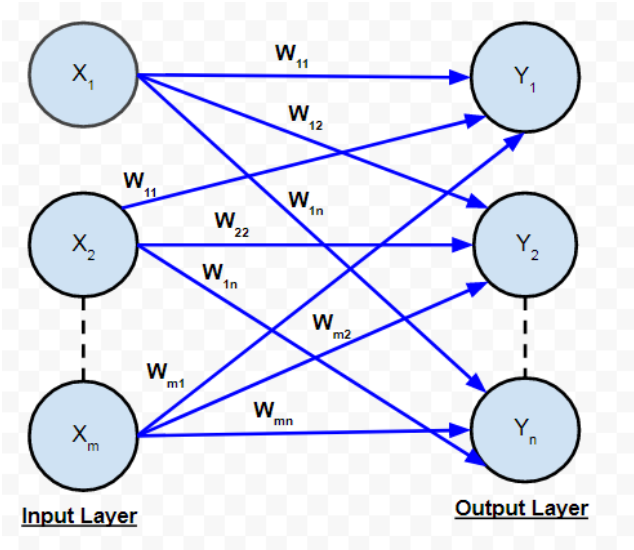

Figure 2.10: Single Layer Feed-forward Network.

2.4.1.4.2 Multi Layer Feed-forward Network

As the name implies, it is made up of numerous layers. In addition to the input and output layers, the architecture of this type of network includes one or more intermediate levels known as hidden layers. Hidden neurons are the computational units that comprise the hidden layer. [23].

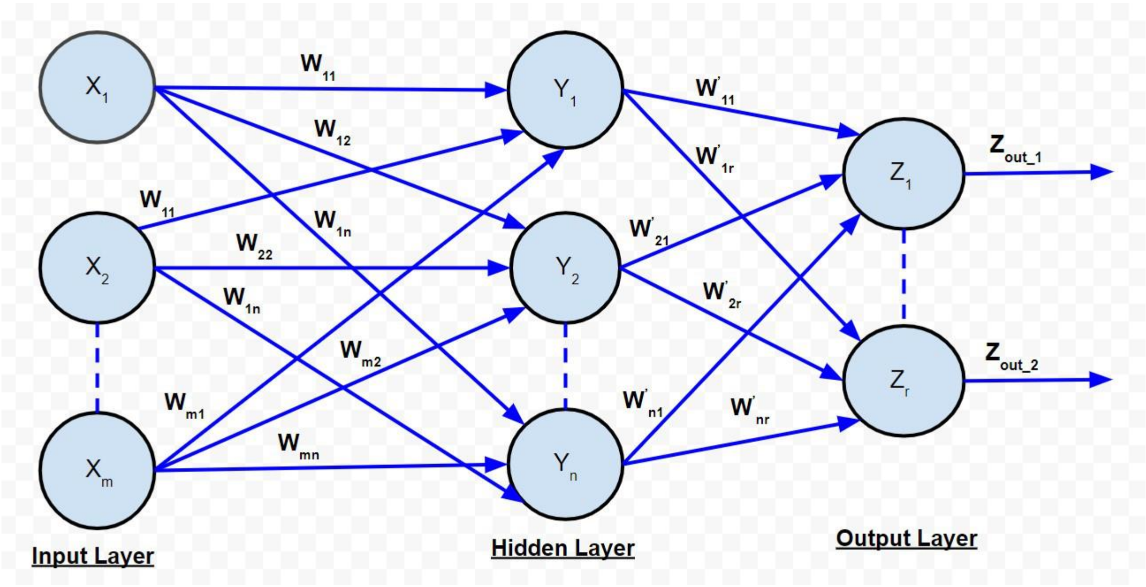

Figure 2.11: Multilayer feed-forward network in (ℓ – m – n) configuration.

- The hidden layer performs preliminary processing before sending the input to the output layer.
- The input layer neurons connect to the hidden layer neurons; the weights on the connections correspond to input-hidden layer weights.
- The hidden layer neurons and their weights are identified as output-hidden layer weights.
- A multi-layer feed-forward network with ℓ input neurons, m1 neurons in the first concealed layers, m2 neurons in the second hidden layers, and n output neurons in the output layers is denoted as (ℓ - m1 - m2 - n).
- The picture above shows a multilayer feed-forward network with the configuration (ℓ - m - n) [23].

2.4.1.4.3 Recurrent Networks

Recurrent networks are not the same as feed-forward architecture. A recurrent network contains at least one feedback loop

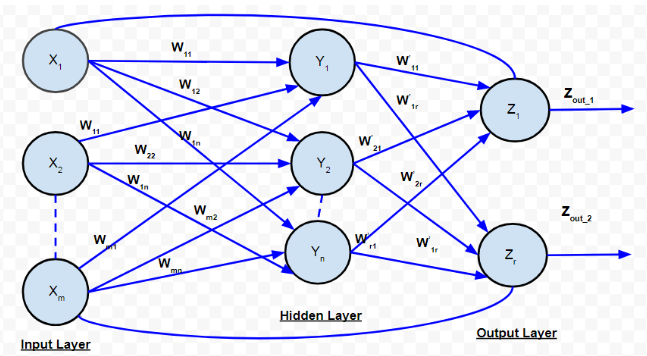

Figure 2.12: Recurrent Neural Network.

2.5. Maintenance

2.5-1 Definition

Maintenance is defined as a set of all technical, administrative, and organizational procedures, during the life cycle of the facility, meant to preserve it or bring it back to a condition where it can carry out the necessary task [24].

Over the years, the concept and process of maintenance have evolved significantly, over time, the notion and execution of maintenance have undergone substantial evolution. Initially, simple tasks done individually to address machine or instrument failures have transformed into a complex system tightly woven into broader production processes.

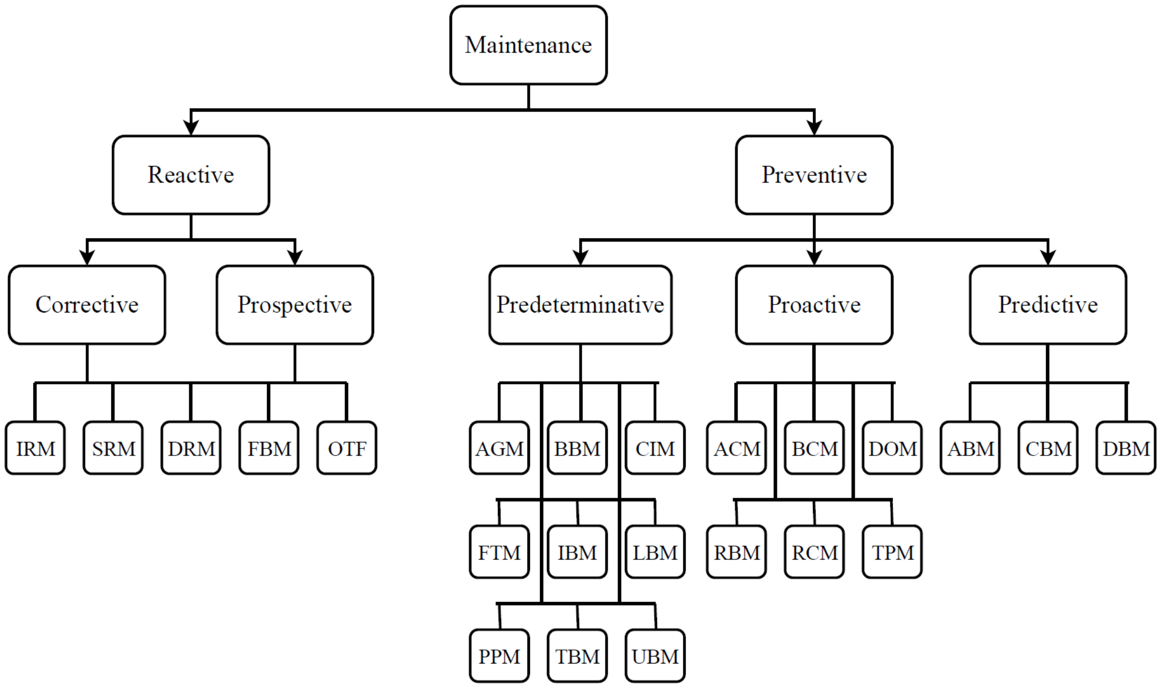

Figure 2.13: Taxonomy of Maintenance adopted.

The figure below illustrates the bathtub curve, depicting the correlation between machine failures and time

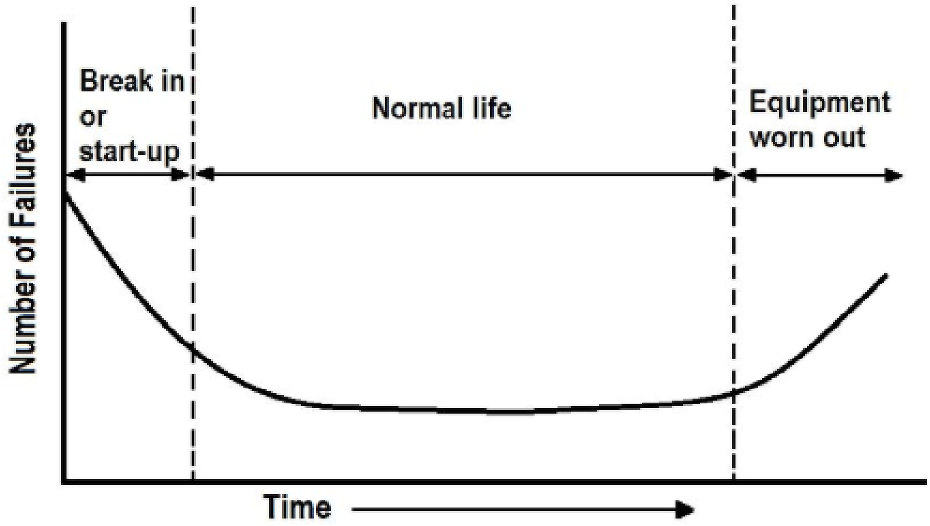

Figure 2.14: Bathtub curve.

The curve can be divided into three time zones, depending on the type of machine.

- **Start up**: This period begins when the machine is first put into operation, during which it is put into service. During this period, high failure rates are observed initially, gradually decreasing as familiarity with the new machine grows. The causes of failure during this period usually stem from defects in the machine's manufacturing itself or issues with its installation and operation due to insufficient knowledge in assembling its parts and performing initial operational procedures [24].
- **Normal life:** During this phase, the machine demonstrates a minimal failure rate and remains stable, representing the peak investment period for its capabilities within its intended operational lifespan. Random occurrences define the various causes of failures at this juncture, including external environmental factors or inadvertent errors made by technicians operating the machine. It's important to note that inadequate maintenance programs can also impact this period significantly, such as overlooking minor faults, thereby diminishing the machine's operational lifespan [24].
- **Equipment warn out** : During this phase, commonly known as the aging phase, witnesses a progressive rise in failure rates until the machine experiences complete malfunction and breakdown. One of the primary reasons for failures during this period is the machine nearing the end of its operational lifespan due to various gradual factors like stress, wear and tear, friction, and the buildup of unresolved faults from earlier stages. It entails uncovering the underlying causes behind these faults and often only attempting to mitigate their resulting consequences [24].

2.5.2 Maintenance Technologies Overview

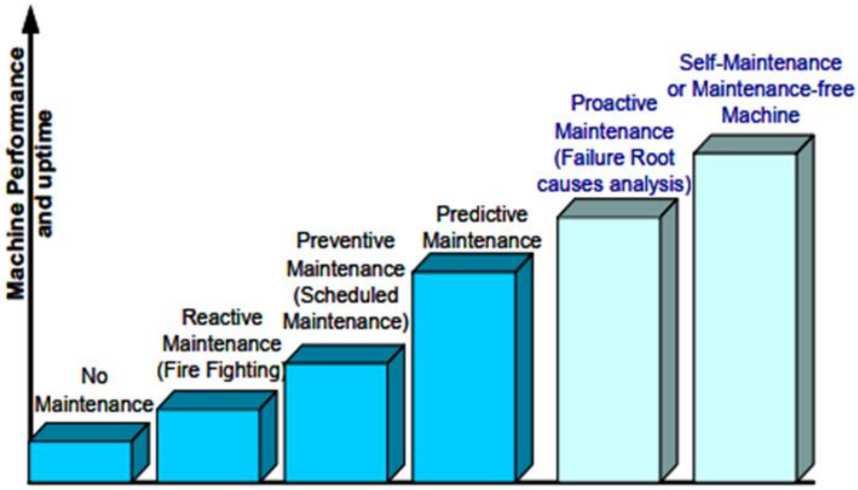

Figure 2.15: The development of maintenance technologies

2.5.4 Maintenance strategies

Maintenance encompasses all tasks required to keep an asset in high-functioning condition. The operations are often carried out according to a specific maintenance strategy. Maintenance strategies may have emerged together with the development of production systems [25].

In the early days, maintenance relied primarily on corrective maintenance. In more recent times, maintenance became a full-scale activity, rather than a sub-function of the overall production operation. Maintenance methods have been carefully developed from preventive maintenance (PM) including condition-based maintenance (CBM) and time-based maintenance (TBM) to design-out maintenance (DOM) and overall productive maintenance (TPM) [25].

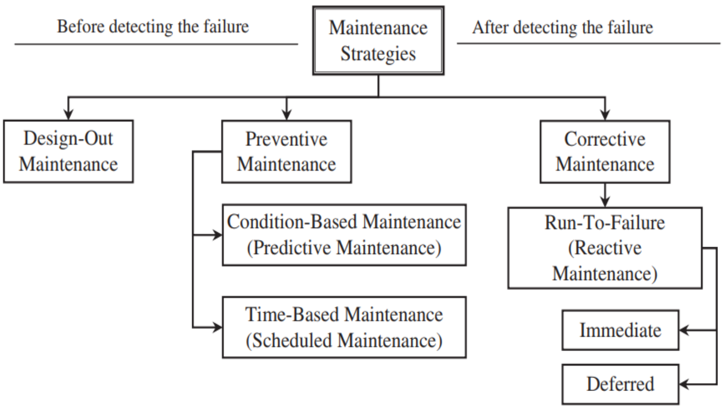

Figure 2.16: Types of maintenance strategies.

2.5.5 Importance Maintenance:

The various advantages that maintenance strategies offer facilities particularly industrial facilities where production lines, with their diverse human and mechanical components, are thought to be the primary hub for assessing the level of profit generated by the production process—make maintenance increasingly important

Companies that have prioritized maintenance as one of their key production pillars have been able to achieve economic benefits by [26]:

- The ability to keep machinery breakdown levels within their minimum thresholds, thereby prolonging the operational lifespan of the machines, results in reduced expenditure on replacing failed equipment prematurely due to the lack of an early maintenance strategy.
- Maintaining production stability protects the business from severe losses that could arise from orders not being fulfilled by customers because of production process interruptions brought on by recurrent faults.
- Maintenance saves the company money by reducing overtime costs and bringing in expensive outside expertise, in addition to saving money on spare part costs and machine replacement. This is especially true during times when it is inappropriate for machines to break down, such as on holidays and outside of regular business hours.
- Providing personnel with a comfortable and conducive work environment within the organization increases their productivity. Because there are constant cooling and heating systems accessible at work and few machine faults, machine operators become more productive.

2.5.6 Types of Maintenance

The evolution of multiple concepts and schools for maintenance and their types has been greatly influenced by maintenance's ability to stay up with technological advancements over time to satisfy the industrial needs of each generation.

- In the European Standard of EN 13306.
- In Germany there is a specific standard, called DIN 31051.
- In the USA for the US Department of Energy (US DOE).

In the corresponding figure, preventive maintenance was divided into two categories according to the European standard [27].

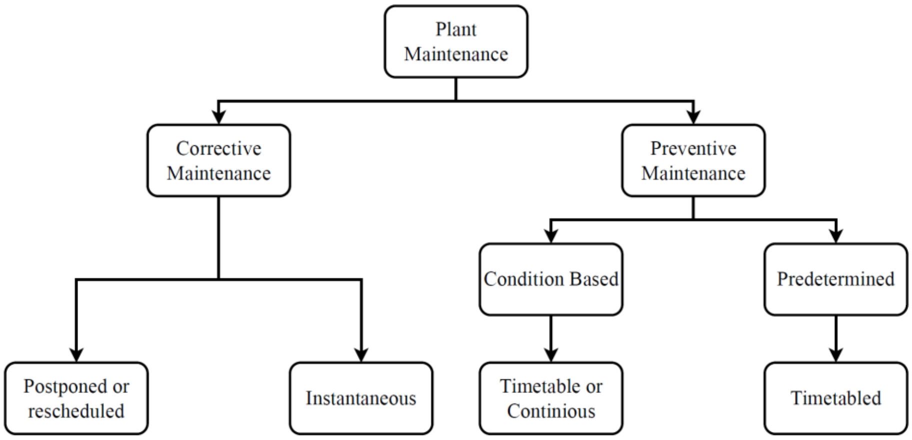

Figure 2.17 Maintenance Types by CEN (2001) .

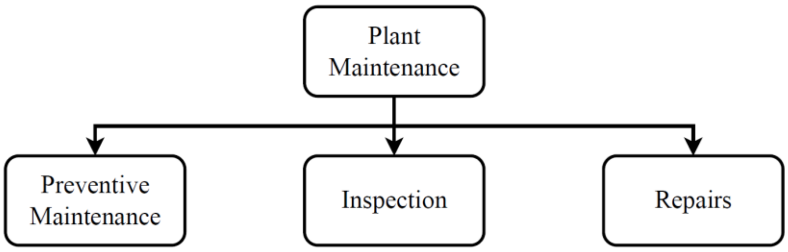

Figure:2.18 Types of Maintenance by DIN (2003) .

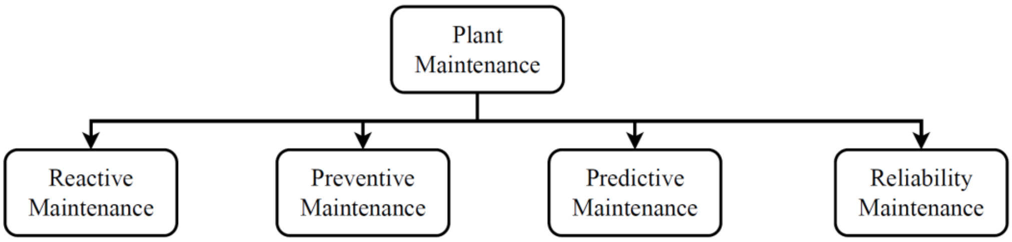

Figure 2.19: Maintenance Types by US DOE (2004).

Maintenance is classified accordingly into a variety of species some of the followings are mentioned:

2.5.6.1 Corrective Maintenance

Corrective maintenance is carried out following the discovery of a defect, meaning that an intervention is only carried out if a machine malfunctions. It is also known as reactive maintenance as a result.

It is the least costly method of implementation and easier to use, and the expenses associated with spare parts only if necessary.The costs mentioned above, however, are associated with machine downtime, which is frequently inevitable when a problem occurs. Consequently, this results in a stop to production and a general decrease in efficiency. Adding to the difficulty of planning interventions is the fact that a problem could happen at any point throughout an activity. Last but not least, the corrective method mandates that all of the primary component spare parts, or at the very least, those essential to manufacturing, be kept in stock at all times [24].

2.5.6.2 Preventive Maintenance

It integrates every maintenance operation performed on a set schedule or by standards to lower the risk that the entity will fail or degrade [24].

This method is motivated by the large cost savings that a planned intervention allows, as opposed to the reactive situation. According to an analysis of maintenance costs, the expense is roughly one-third that of corrective intervention [24]. Diagnostics and replacements are thus scheduled based on time constraints, to intervene before the malfunction occurs. Time intervals are derived from historical data, determining the average duration of the usable life of all components subjected to degradation. However, preventative maintenance is also subject to significant concerns because the average life of the components is only a statistical indicator and does not provide any guarantee. Indeed, instances in which components are replaced in good shape and still operating are feasible, creating a waste of resources, and cases in which corrective maintenance happens because components fail well before their projected lifespan.

2.5.6.3 Predictive Maintenance

Predictive maintenance (or prognostics) is essential in any engineering system to avoid system failure, especially for complex systems. With recent advancements in pervasive computing, prognostics may now be simply incorporated into any device or system. When smart machines are connected and remotely monitored, and as their data is modeled and continuously evaluated using advanced embedded technologies. It is possible to progress from simple "predictive maintenance" to intelligent "prognostics," which is the process of determining which components of a machine are likely to break and when, and then automatically triggering servicing and ordering spare parts [25].

It is the primary subject of this study, which will be discussed in depth in the following sections. However, we can describe it as maintenance that is based on predictions produced from repeated examination of the machine's condition and then evaluated to assess its degree of performance.

Predictive maintenance is broken into four components based on the technology used to read the data :

- **Vibrational Analysis** : It uses vibration sensors put on rotary motors to detect unbalance and corrosion.

- **Sonic Analysis**: It is particularly useful for detecting a lack of lubrication in the machine, which causes it to make sounds noticeable to the human ear.
- **Ultrasonic Analysis:** It is utilized for electrical and mechanical devices to recognize stress sounds and unheard touch with the ear using ultrasonic technology.
- **Infrared Analysis :** It reads the thermal image of electrical equipment, cooling, and air systems.[28]

2.5.6.3.1 Fault Prognosis

❖ **Prognostic Definition**:

There is no comprehensive definition of the term Prognosis, we will list below some suggested definitions [29]:

- Prognosis is a method that predicts future degradation and the system's remaining usable life (RUL) based on available degradation data
- ISO 13381-1, prognosis is defined as a prediction of the time to failure and danger associated with one or more existing and future failure modes.
- The prognosis targets to predict future failures or degradations and estimate the RUL of in-service systems utilizing failure datasets.
- Prognosis is the process of predicting the future validity of a product by checking the extent of derivation or degradation of the product from its predicted normal operating conditions. This is a prediction of their future state using current and past state conditions.

The first definition was chosen as a key definition for our prognostic task.

❖ **Remaining Useful Life**

The remaining useful life (RUL) is the amount of time that a component or system can continue to work. RUL prediction helps customers to extend the system's useful life while reducing risk [31.41]. Engineers and practitioners in the PHM field use the term RUL interchangeably with other expressions such as fatigue in the mechanical sector, fracture propagation speed in theoretical modeling, and wear rate for machine components.

Figure 2.21. depicts the prognostic process, which includes the principles described previously. Normal, degraded, and critical operational states are identified. Other key factors are also discussed, such as the system's current cycle, threshold, and end-of-life (EoL).

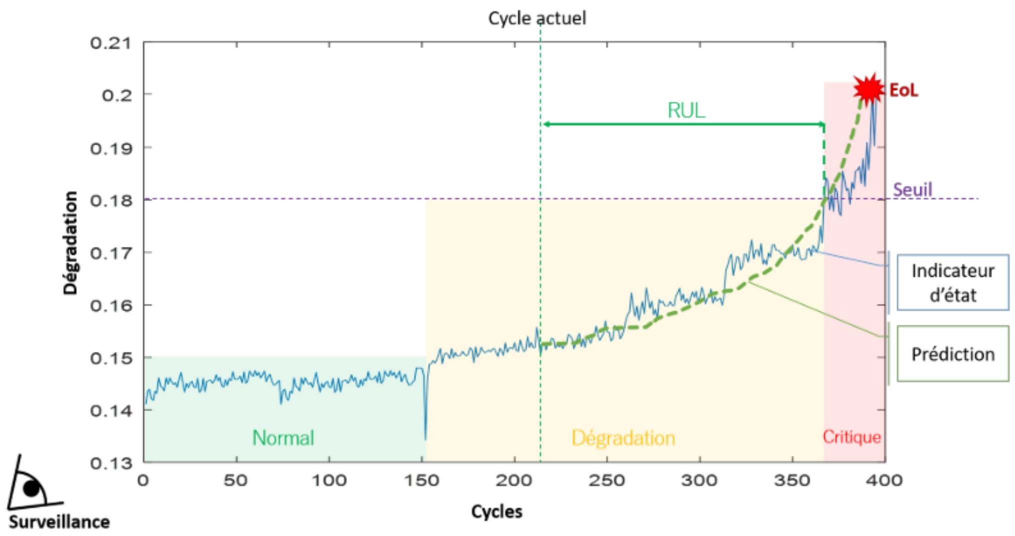

Figure 2.20: Illustration de différents concepts de pronostic.

2.6. Conclusion:

Artificial intelligence provides a paradigm leap in maintenance, increasing efficiency, and reliability, and lowering costs. As technology advances, the current focus is on using sophisticated "machine learning" approaches to assess system states and discover failure causes. As a result, prediction swings towards pattern recognition. In predictive systems, the prediction algorithm is critical for deducing the mathematical function.

Chapter III: FAULT PROGNOSIS FROM TELEMETRY SIGNALS

3.1 Introduction

This chapter is devoted to presenting and discussing experimental results obtained by training machine learning models for prediction and using four important models in learning. Failure prediction based on a site database kaggel.

3.2 Case Study

Telemetry is the process of collecting data from remote sources and transferring it to a central place for processing and analysis. In the oil and gas industry, telemetry is used to monitor a wide range of important variables such as pressure, temperature, flow rate, fluid levels, and equipment condition across oil fields and pipelines, to improve efficiency. Telemetry allows companies to monitor operations. Continuously improving operational efficiency by identifying areas needing improvement and reducing costs by monitoring equipment remotely, the need for field visits and unnecessary maintenance can be reduced.

Machine learning plays a vital role in improving predictive maintenance and predicting equipment failure. This technology contributes to increasing operational efficiency, reducing costs, and improving safety through early detection of faults, reducing costs, and analyzing big data.

- **Dataset Description**:
  - **Name:** Predictive Useful Life based into telemetry.
  - **Source: https://www.kaggle.com.**
- The dataset has telemetry Reading and identifying errors, maintenance, and failure:
  - The telemetry was set to 24 hours, with the original data read out every hour.
  - Voltage, telemetry, pressure, and vibration are measured.
  - The errors are identified by an error or not, and this error can create maintenance that can lead to failure identification.
- **Data size:** (20868 line for training & 7190 line for testing, 36 column).
- **File type:** CSV.
- **Column description:** Sensor Mearuements.

Table 3.1: Target and description

Target	Description
RUL	Remaining Useful Life in cycles by failure and machine

Table 3.2: features and description

Features	Description
machineID	Machine ID, reads from 100 machines
Datetime	Date of telemetry
time_in_cycles	Cycle reading
voltmean_24h	Volt telemetry average of the last 24h
rotatemean_24h	Rotate telemetry average of the last 24h
pressuremean_24h	Pressure telemetry average of the last 24h
vibrationmean_24h	Vibration telemetry average of the last 24h
voltsd_24h	Volt telemetry standard deviation of the last 24h
rotatesd_24h	Rotate telemetry standard deviation of the last 24h
pressuresd_24h	Pressure telemetry standard deviation of the last 24h
vibrationsd_24h	Vibration telemetry standard deviation of the last 24h
voltmean_5d	Volt telemetry average of the last 5 days
rotatemean_5d	Rotate telemetry average of the last 5 days
pressuremean_5d	Pressure telemetry average of the last 5 days
vibrationmean_5d	Vibration telemetry average of the last 5 days
voltsd_5d	Volt telemetry standard deviation of the last 5 days
rotatesd_5d	Rotate telemetry standard deviation of the last 5 days
pressuresd_5d	Pressure telemetry standard deviation of the last 5 days
vibrationsd_5d	Vibration telemetry standard deviation of the last 5 days
Error 1,2,3,4	Error identification 1,2,3,4
Comp 1,2,3,4	Component 1,2,3,4 maintenance cycle
Model	Machine model
Age	Machine age
RUWeek	Time in weeks for failure
Failure	Component identification that failed
Failed	Failed or not

Understanding the dataset is critical in any project since it serves as the foundation for selecting and applying the relevant algorithms to the problem. In this study, we have an industrial dataset that attempts to tackle the problem of detecting machine failure, and we have different readings of the attributes of the machines that can assist in determining the failure and the change of a failure to prepare or avoid it before it occurs.

3.3 Software & Experimentations

3.3.1. Software

Python is the most used open-source programming language among computer scientists. This language has emerged as an expert in infrastructure management, data analysis, and software development. The fundamental advantage of Python is that it allows developers to focus on what they are doing rather than how they are doing it. Python speeds up coding by removing the tight limits of previous languages. Furthermore, it remains beginner-friendly, requiring only a small-time commitment to get started [43].

- **Pandas** pandas is a Python library that provides quick, adaptive, and expressive data structures designed to make it easier to work with "relational" or "labeled" data. Its goal is to be the key high-level component for performing realistic, real-world data analysis in Python. Furthermore, it aims to be the most powerful and adaptable open-source tool for data analysis and manipulation in any language. It is making tremendous progress in achieving this goal [44].
- **Tensorflow:** TensorFlow is an open-source framework created by Google researchers to support machine learning, deep learning, and other statistical and predictive analytics workloads. It, like other platforms, is intended to simplify the process of designing and implementing advanced analytics applications for data scientists, statisticians, and predictive modelers [45].
- **Keras:** Keras is an advanced library designed for neural network operations, built on top of TensorFlow, Theano, and other recent releases. It streamlines numerous specific tasks and significantly minimizes repetitive code. Nonetheless, it might not be ideal for handling certain complex tasks [46].
- **Colab**: Colab is a hosted Jupyter Notebook service requiring no setup and offers free computing resources such as GPUs and TPUs. Colab is particularly well-suited for machine learning, data science, and teaching [47].

3.3.2 . Experimentation :

Proposed approach

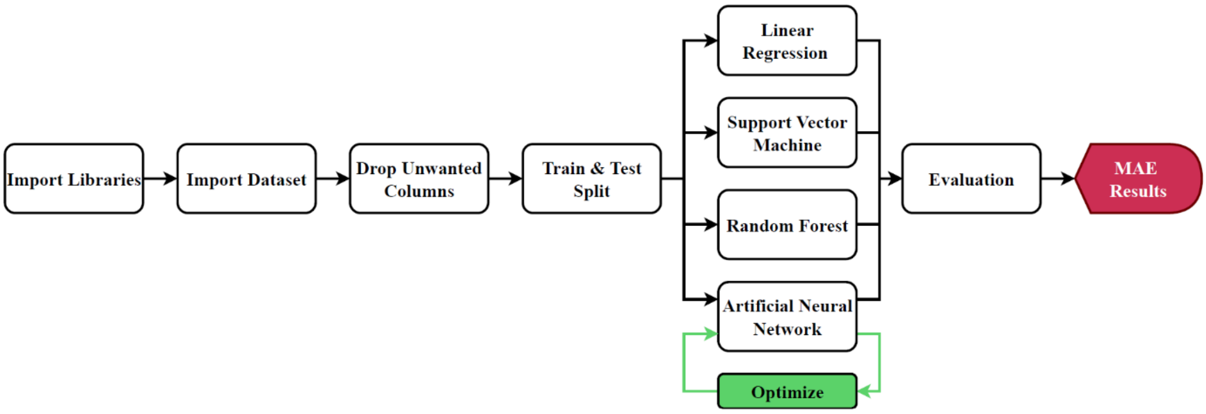

Figure 3.1: The Proposed Approach.

The figure depicts a process for developing and optimizing machine learning models to evaluate their performance using the Mean Absolute Error (MAE). Here's a step-by-step explanation for each component.

- **Import Libraries:** The method begins with importing the essential libraries. These could contain libraries for data processing (such as pandas), machine learning (such as scikit-learn), and other task-specific libraries**.**
- **Import Dataset**: The following step is to load the dataset into the environment. This dataset will be used to train and validate and test the models.
- **Drop Unwanted Columns:** After importing the dataset, any extraneous columns that do not help to model training or may degrade performance are eliminated**.** In our case study these column variables can be like the model of the machine, Machine ID, Date and Time, …etc. These columns usually have zero variance or misleading informations that either do not effect or harm the training process. Figure 3.2 showcase an example of the measurements collected from machine 71 used to predict the target variable represented in Figure 3.3 which is the RUL of machine 71.
- **Train & Test Split**: The dataset is then divided into training and test sets. The training set is used to develop the models, and the testing set is used to assess their performance
- **Model Training:** Multiple models are trained using the training dataset. The diagram mentions the following models:

- Linear Regression (LR).
- Support Vector Machine (SVM).
- Random Forest (RF).

- Artificial Neural Network (ANN).
  - **Evaluation:** Following training, the models are evaluated on the testing set. The Mean Absolute Error (MAE) is the performance metric used for evaluation, and it estimates the average magnitude of mistakes in a series of predictions without taking into account direction.
  - **MAE Results:** The MAE the results are compiled to compare the performances of various models.

The process enables the systematic training, evaluation, and optimization of various machine learning models to determine which one minimizes the mean absolute error (MAE) in predictions

Additionally, we will show some machine samples: we have picked two machine with long RUL, medium RUL, and short RUL.

❖ Evaluation Metrics

The MAE is used as an evaluation metric as it provides a more comprehensive measure of the prediction error.

$$MAE = |y - \hat{y}|$$

Where:

y: is the real value to be predicted.

$\hat{y}$: is the predicted value.

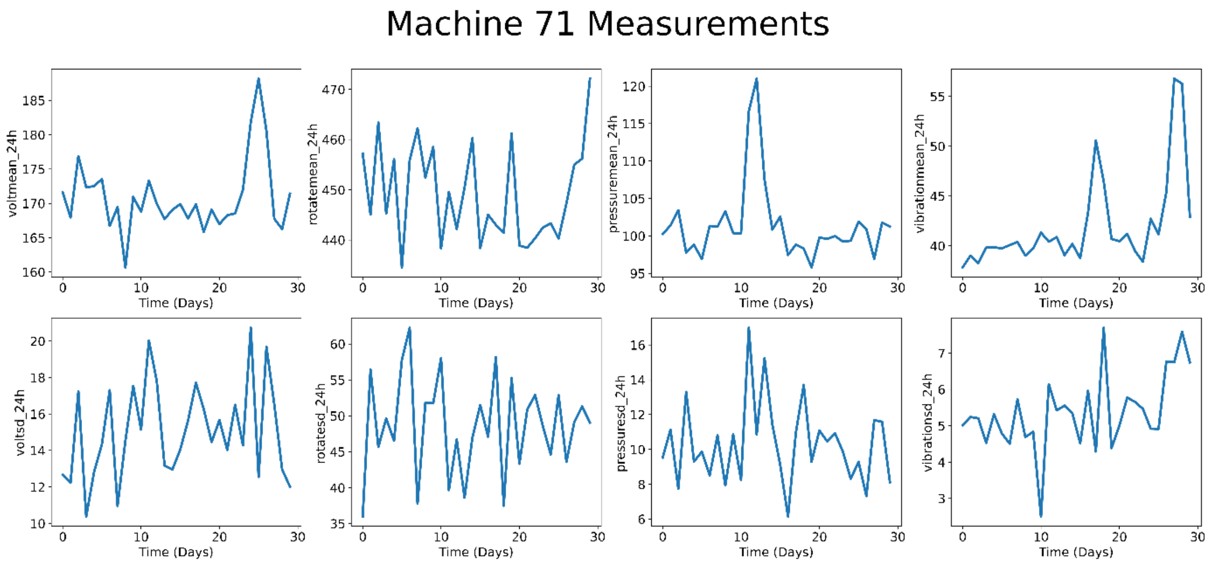

Figure 3.2: The Measurements Collected from Machine 71.

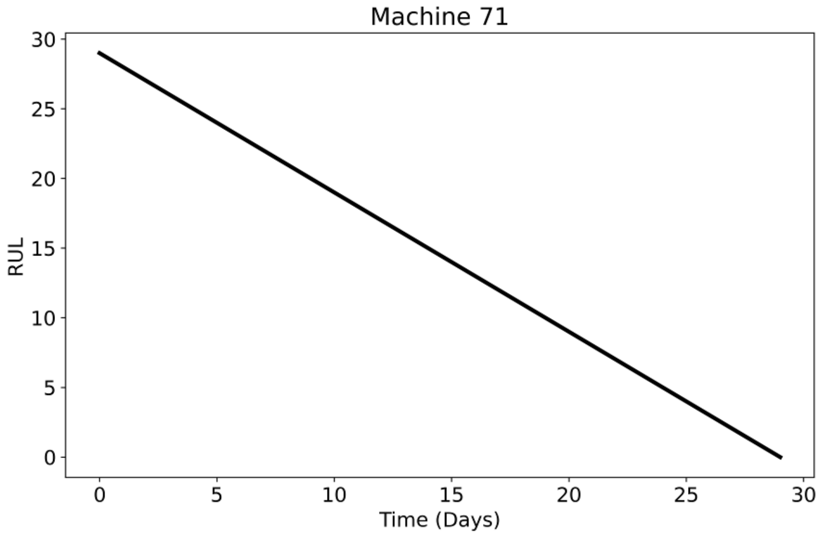

Figure 3.3: RUL of Machine 71.

3.4. Results & Discussion

3.4.1 Results

a. Linear Regression

When we applied the Linear Regression model to the entire dataset for testing, this is depicted in Figure 3.4.

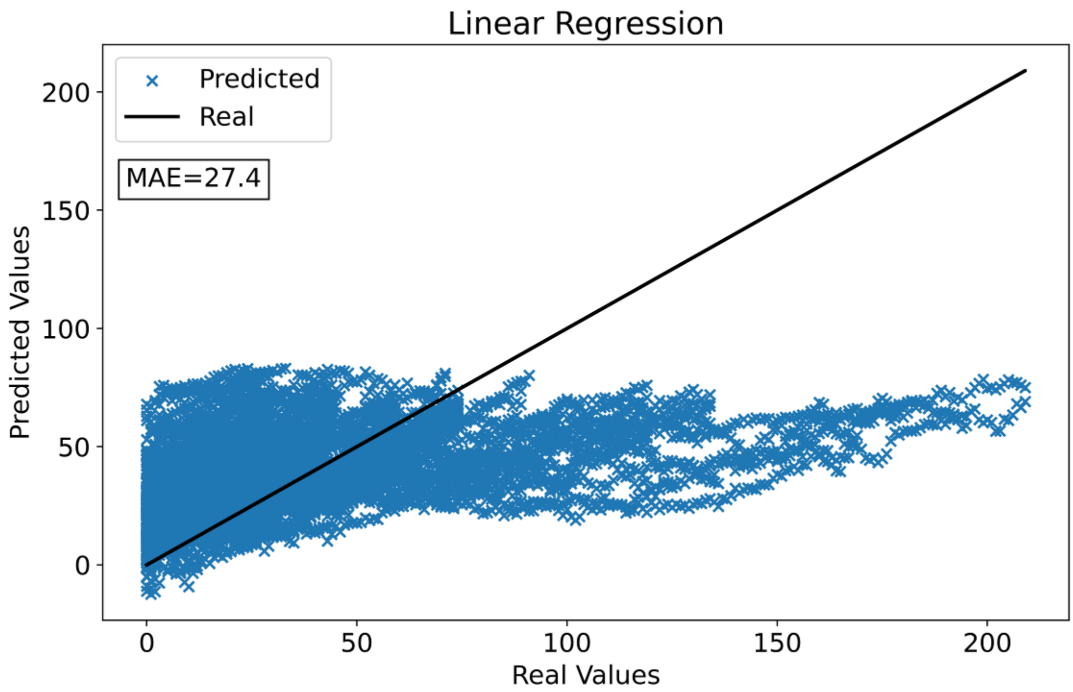

Figure 3.4: predicted and target values of the dataset for Linear Model

- **MAE :**

The "MAE=27.4" indicates that the mean absolute error of the model is 27.4. This means that, on average, the predictions differ from the actual values by 27.4 days.

Performance of a linear regression model on predicting the Remaining Useful Life (RUL) of several machines. Each subplot represents a different machine, comparing the real RUL against the predicted RUL, along with the Mean Absolute Error (MAE) for each machine.

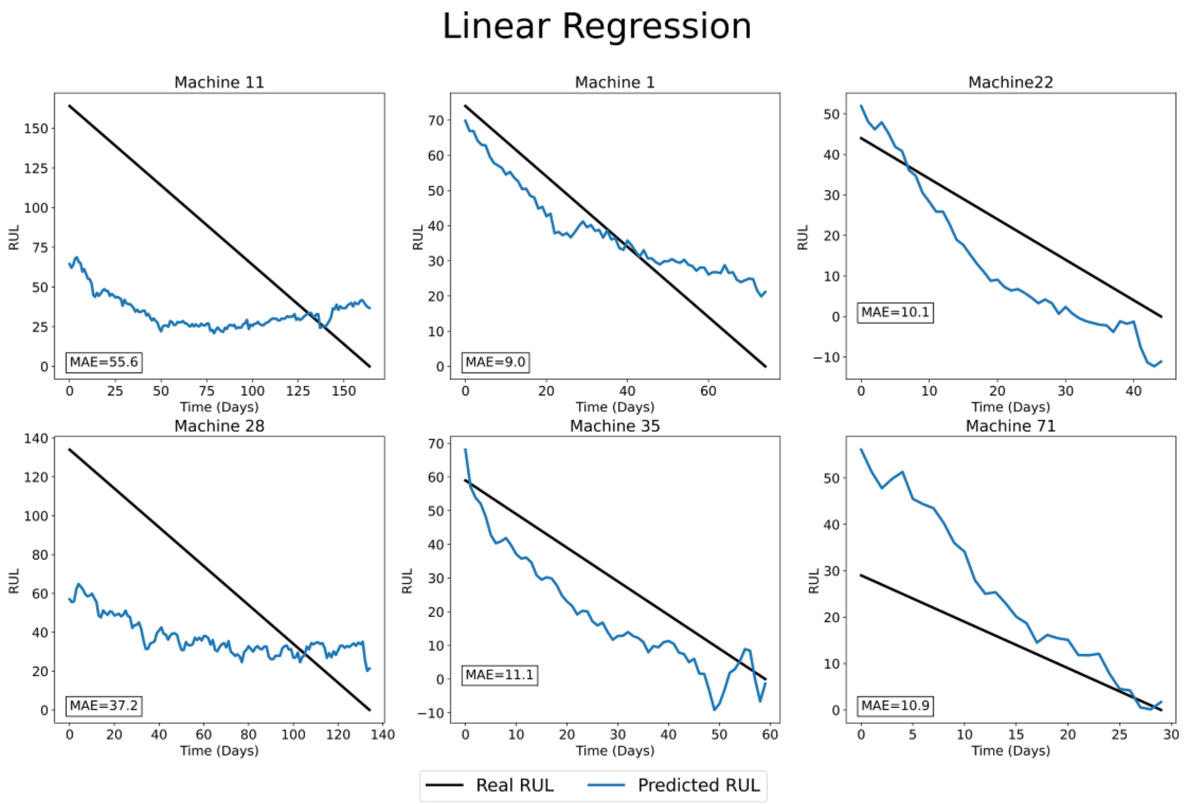

Figure 3.5 :predicted and target values of the dataset for Linear Model (Application on 6 machines).

Table 3.3: Summary of the Performance for Each Machine

	The MAE	The Predicted RUL (blue line)
Machine 11	Is 55.6, indicating a significant average prediction error.	Fluctuates considerably compared to the real RUL (black line).
Machine 1	Is 9.0, which is relatively low, indicating good prediction accuracy.	Closely follows a declining trend, which the linear model approximates well.
Machine 22	Is 10.1, suggesting reasonable prediction accuracy	declines sharply and the linear model captures this trend moderately well.

Machine 28	is 37.2, indicating a substantial prediction error.	demonstrates a slow decline with minor fluctuations, which the linear model cannot fully predict.
Machine 35	is 11.1, indicating moderate prediction accuracy.	declines steadily, and the linear model captures the general trend but misses some nuances.
Machine 71	is 10.9, suggesting reasonable prediction accuracy.	shows a steep decline initially, which the linear model captures fairly well.

b. Support Vector Machine Regression

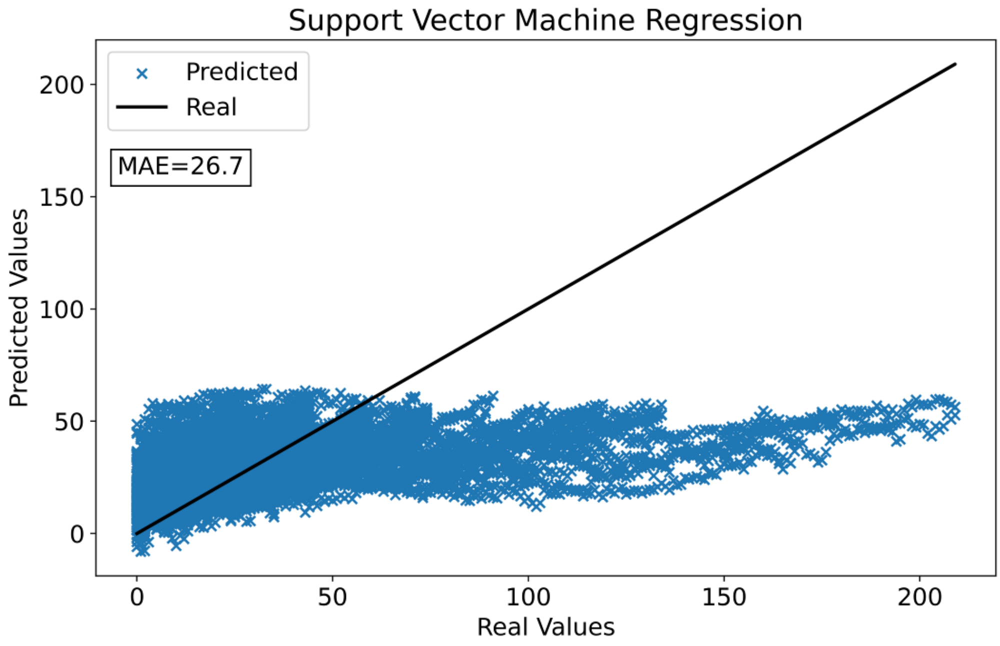

Figure 3.6: predicted and target values of the dataset for SVR

performance of a Support Vector Regression (SVR) model in predicting real values. The black line represents perfect real values (where the predicted value would be exactly equal to the real value), and the blue dots represent the values predicted by the SVR model.

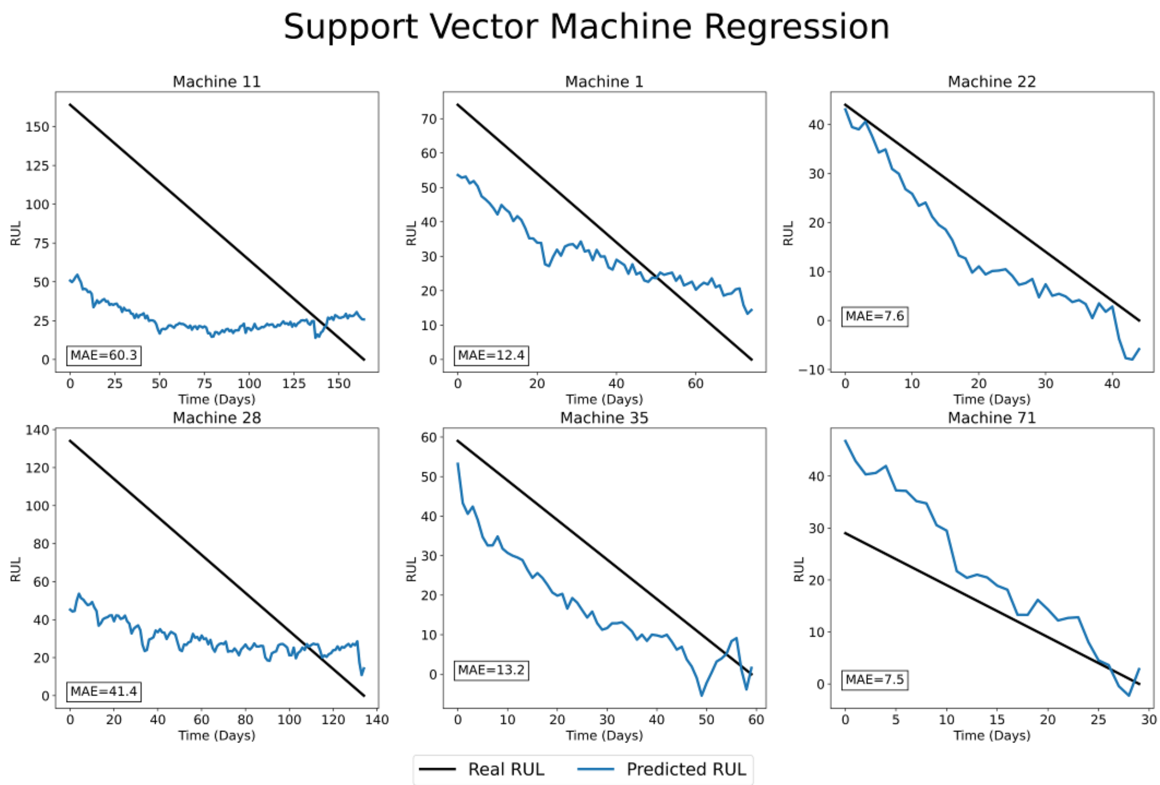

Figure 3.7: predicted and target values of the dataset for SVM (Application on 6 machines)

The results of a Support Vector Machine (SVM) regression were used to forecast the remaining useful life (RUL) of various devices. Each subplot depicts the performance of a given machine, comparing the actual RUL (black line) to the anticipated RUL (blue line) over time. The Mean Absolute Error (MAE) of each machine's forecast is also shown.

Overall, the SVM regression performs well for certain machines (e.g, Machine 22, Machine 71), but not so well for others (e.g., Machine 11, Machine 28) with high MAE. This shows that the model's performance differs greatly between machines.

Table 3.4: Summary of the Performance for each Machine.

	The MAE	The real RUL (blue line)
Machine 11	60.3	significantly deviates from the real RUL.
Machine 1	12.4	The prediction closely follows the real RUL with minor deviations
Machine 22	7.6	The prediction closely aligns with the real RUL
Machine 28	41.4	The prediction deviates significantly from the real RUL.
Machine 35	13.2	The prediction closely follows the real RUL.
Machine 71	7.5.	The prediction closely aligns with the real RUL.

c. Random Forest Regressor

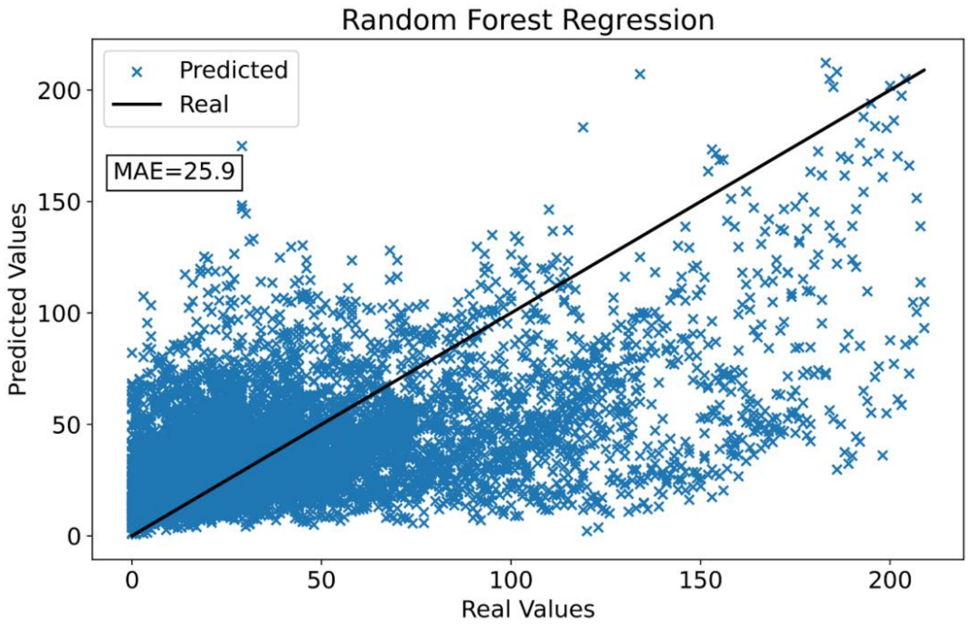

Figure 3.8: predicted and target values of the dataset for RF

The Random Forest model performs consistently across the whole dataset, as evidenced by the single scatter plot. In contrast, the SVM performance differed dramatically among different machines.

- **Model Performance Consistency**: The Random Forest model performs consistently across the whole dataset, as evidenced by the single scatter plot. In contrast, the SVM performance differed dramatically among different machines.

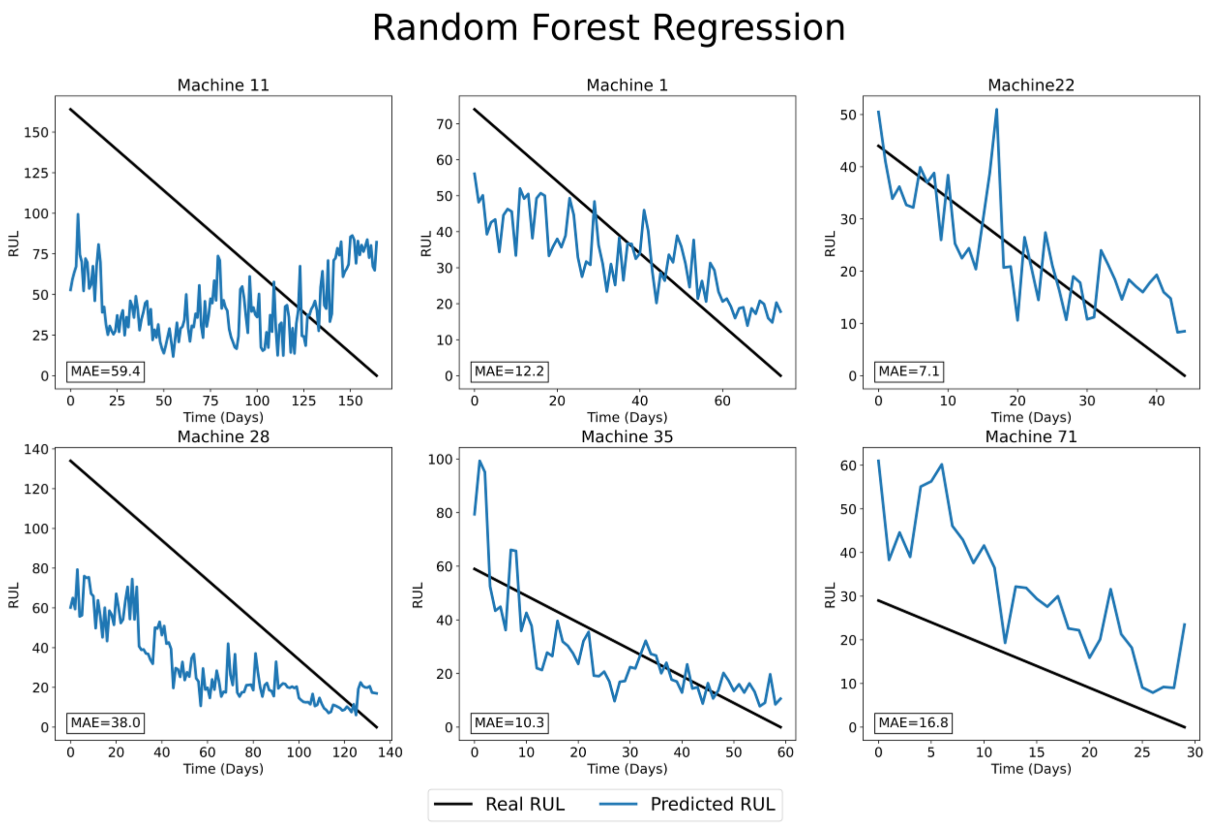

Figure 3.9: predicted and target values of the dataset for RF (Application on 6 machines).

the results of a Random Forest Regression model for predicting the Remaining Useful Life (RUL) of different machines, similar to the SVM regression results. Each subplot represents the performance for a specific machine, comparing the real RUL (black line) to the predicted RUL (blue line) over time, along with the Mean Absolute Error (MAE) for each machine's prediction.

Table 3.5 summary of the performance for each machine

	The MAE	The real RUL (blue line)
Machine 11	59.4	The prediction significantly deviates from the real RUL.
Machine 1	12.2	The prediction closely follows the real RUL with minor deviations
Machine 22	7.1	The prediction closely aligns with the real RUL
Machine 28	38.0	The prediction deviates significantly from the real RUL.
Machine 35	10.3	The prediction closely follows the real RUL with some deviations.
Machine 71	16.8	The prediction moderately aligns with the real RUL but shows noticeable deviations

In summary, the Random Forest Regression has a modest MAE and delivers a general prediction accuracy across all data points, whereas the Support Vector Machine Regression performs inconsistently, succeeding in some circumstances but failing in others. Each model has strengths and challenges based on the specific application and data characteristics.

d. Artificial Neuron Network

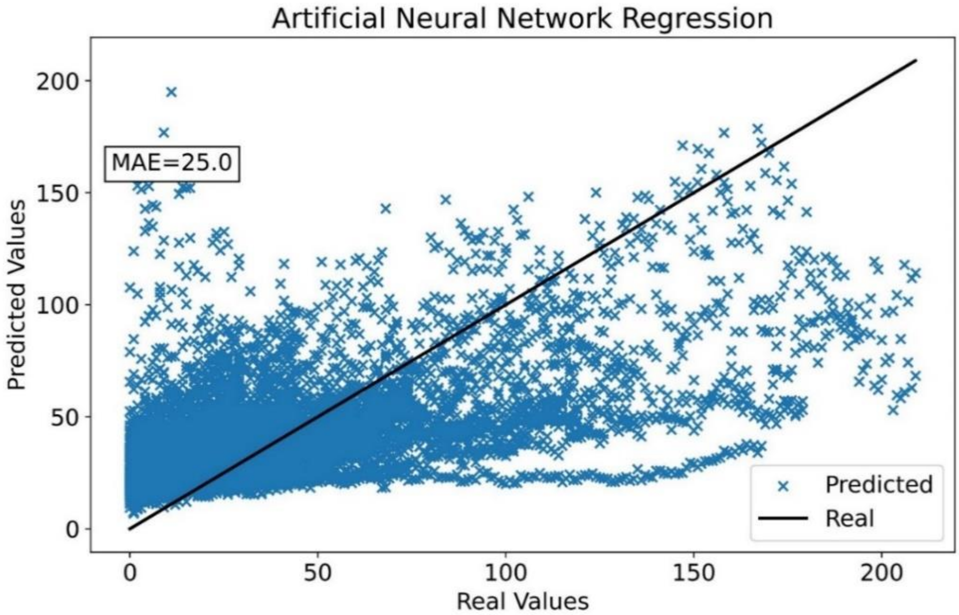

Figure 3.10: predicted and target values of the dataset for ANN

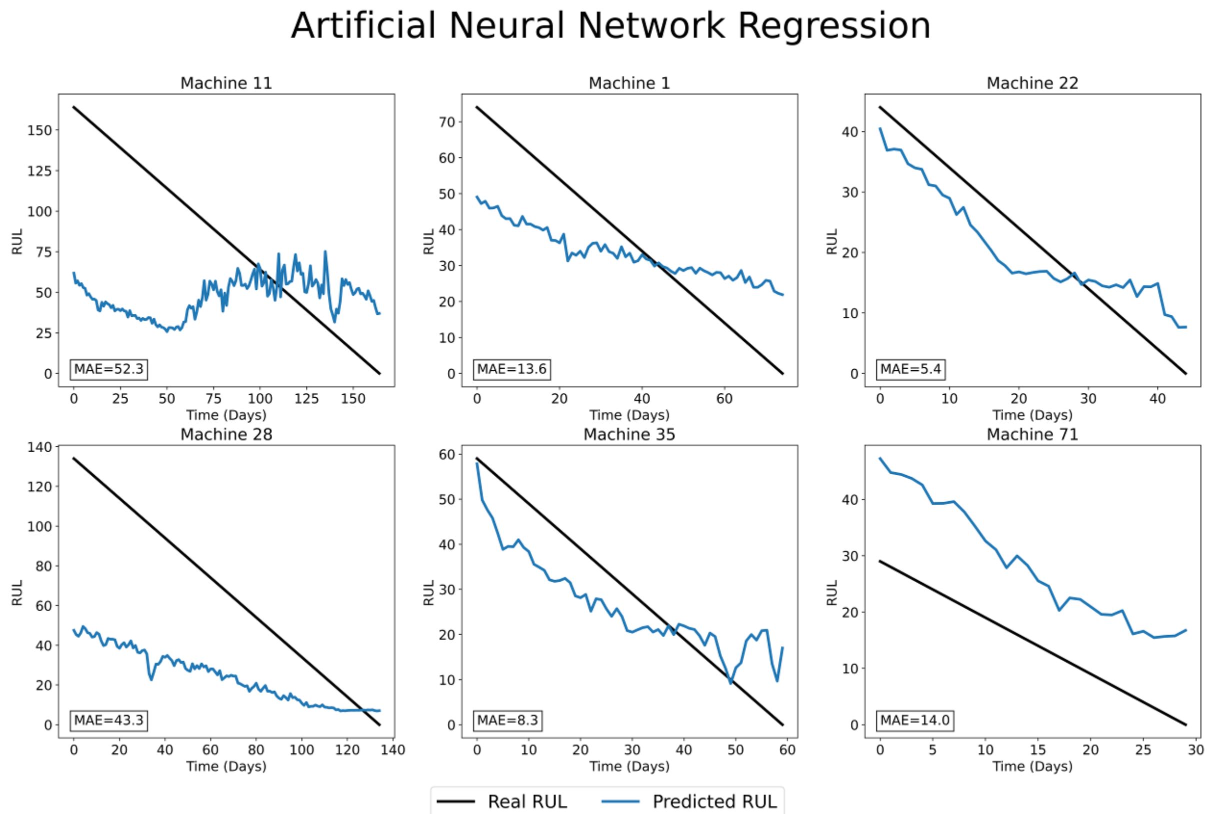

Figure 3.11: predicted and target values of the dataset for ANN (Application on 6 machines)

e. Results Summary

Table 3.6: Summary of the Experimentation Results.

	Linear Regression	**SVMR**	**Random Forest**	**ANN**
Machine 11	55.5	60.3	59.4	**52.3**
Machine 28	**37.2**	41.4	38.0	43.3
Machine 1	**9.0**	12.4	12.2	13.6
Machine 35	11.1	13.2	10.3	**8.3**
Machine 22	10.1	7.6	7.1	**5.4**
Machine 71	10.9	**7.5**	16.8	14.0
All 100 Machines	27.4	26.7	25.9	**25.0**

3.5 Discussion

In this study, we used regression models to predict machine failure and remaining life. In the machine learning models, where we selected the six machines to which we applied the above models, we can see that the linear regression classifier gave us a failure definition of 55.5 days when the machine is long and 9.0 days when the machine is short. It failed at 59.4 days when the machine life was long and 7.1 days when the machine life was short. The supporting machine regression identified failure at 60.3 days when the machine life was long and 7.5 days when the machine life was short. ANN gave us a failure determination of 52.3 days when The machine had a long life and 5.4 days when the machine had a short life.The explanation for the failure to produce accurate results is good results for the various models used, for several reasons, including:

Random forests require large memory and high processing capabilities, especially when the number of trees and the number of features is large and the number of data is small

Sensitivity to Noise, A support vector machine can be sensitive to noise and outliers in the data. The presence of inaccurate data or outliers can negatively affect the overall performance of the model.

Artificial neural networks are characterized by high speed of operation, flexibility, and the ability to deal with inaccurate data, and they can formulate models even in the presence of complex relationships between variables. As a result, the ANN is kept as the final prediction model because it has the best accuracy.

3.6. Conclusion

multivariable regression models are a powerful tool for analyzing data and predicting future trends. Although there are some challenges, the significant benefits it provides make it an attractive option in many areas. As developments in data analysis and machine learning continue, the effectiveness and uses of regression models are expected to increase in the future.

General Conclusion

In conclusion, the use of artificial intelligence and multiple linear regression technology to study predictive failure and determine life by sending information remotely represents an advanced step towards improving operational efficiency and reducing costs in various industries. This approach combines the power of statistical analysis with the advanced capabilities of artificial intelligence, enabling companies to predict disruptions before they occur and take proactive actions to ensure that operations continue smoothly and efficiently.

Regression model predictions are very popular because companies often rely on time when they need to predict and prevent certain failures. Time series models predict future events using a time component and historical data. Machine learning predictive maintenance is about evaluating the possibility of future events based on past failures. Using time series models, a data science team can analyze sequences of events in different time periods. They estimate historical data and identify temporal patterns to make accurate and timely forecasts.

Because predictive maintenance is proactive, it enhances preventive maintenance by providing continuous insights into the actual condition of equipment. Instead of relying on the expected condition of equipment based on a historical baseline. With predictive maintenance, corrective maintenance is only performed when it needs to be done, thus avoiding unnecessary maintenance costs and machine downtime.

Although the error rate is acceptable, there is an urgent need to improve these results and we can enhance these results by collecting more accurate and quality data.

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