

T.R.
GEBZE TECHNICAL UNIVERSITY
GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCE

**DAMAGE DETECTION TURBOMACHINERY WITH MACHINE
LEARNING ALGORITHM**



AHMET DEVLET ÖZÇELİK

**A THESIS SUBMITTED FOR THE DEGREE OF MASTER OF
SCIENCE DEPARTMENT OF MECHANICAL ENGINEERING**

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ADVISOR: PROF. DR. AHMET SİNAN ÖKTEM

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T.C.
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FEN BİLİMLERİ ENSTİTÜSÜ

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AHMET DEVLET ÖZÇELİK
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DANIŞMAN: PROF. DR. AHMET SİNAN ÖKTEM

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2023



M.Sc. JURY APPROVAL FORM

A Thesis/Dissertation submitted by **Ahmet Devlet ÖZÇELİK**, whose thesis defense exam was made on 11/10/2023 by the jury formed with the 10/07/2023 date and 2023/38 numbered decision of the GTU Graduate School Of Natural And Applied Science, was accepted as a **MASTER of SCIENCE** thesis in the **Department of Mechanical Engineering Program**.

JURY

JURY MEMBERS

(THESIS ADVISOR) :Prof. Dr. Ahmet Sinan ÖKTEM

MEMBER :Dr. Öğr. Üyesi Recep ÖNLER

MEMBER :Dr. Öğr. Üyesi Ayhan KÜÇÜKMANİSA

APPROVAL

Gebze Technical University Graduate Administrative Board
...../...../..... date and/..... numbered decision.

SIGNATURE/MÜHÜR

ABSTRACT

In this study, machine learning techniques were used to identify possible failures of turbine engine components. In turbines some maintenance checks are performed at regular intervals using non-destructive testing methods and if no damage is found the parts are not replaced and the next inspection only expected at the next performance test or an unexpected event. This can have serious consequences when considering human error. During this period when Industry 4.0 is becoming a part of our lives, it is expected that maintenance activities will be performed using artificial intelligence.

In addition, we note that predictive maintenance or prognostic care has improved thanks to the development of artificial intelligence technology and the increasing power of computer solutions. To address this situation, a machine learning algorithm, which generally achieves an accuracy of 96% in determining the deteriorated components of turbomachines, has been developed with the classification technique. Thus, it is aimed to reduce human error and maintenance costs in turbomachinery maintenance, as well as to reduce downtime. With the Support Vector Machine algorithm, an accuracy rate of at least 93% and the highest 97% has been successfully achieved in the low-pressure compressor, high-pressure compressor, combustion chamber, high-pressure turbine, low-pressure turbine, which are the components of the gas turbine in the study.

Keywords: Turbomachinery, Machine Learning, Predictive Maintenance, Prognostic Maintenance, Damage Detection.

ÖZET

Bu çalışmada, turbomakinelerin parçalarındaki olası bozulmaları belirlemek için makine öğrenimi tekniklerini kullanılmıştır. Turbomakinelerde belirli aralıklarla tahribatsız muayene yöntemleri kullanılarak belirli bakım kontrolleri yapılır ve herhangi bir hasar bulunmaması halinde parçalar değiştirilmez ve bir sonraki bakım kontrolüne veya beklenmeyen bir olaya kadar bir sonraki muayene beklenmez. Bu durum insan hataları ele alındığında ölümcül sonuçlara sebep olabilir. Endüstri 4.0'ın hayatımıza entegre olduğu bu dönemde bakım işlemlerinin yapay zeka ile gerçekleştirileceği öngörülmüyor. Ayrıca gelişen yapay zeka teknolojileri ve bilgisayar çözüm gücünün artmasıyla öngörüselle bakım ya da prognostic bakımın da geliştiği görülmektedir.

Bu durum ele alınarak için turbomakinelerin bozulan bileşenlerini belirlemede genel olarak %96'lık bir doğruluk oranı elde eden bir makine öğrenimi algoritması classification tekniğiyle geliştirilmiştir. Böylece turbomakina bakımlarındaki insan hatasının ve bakım maliyetlerinin azaltılması ayrıca makinenin çalıştırılmadığı sürenin de düşürülmesi amaçlanmıştır. Support Vector Machine algoritması ile çalışmadaki gaz türbininin bileşenleri olan düşük basınç kompresörü, yüksek basınç kompresörü, yanma odası, yüksek basınç türbini, düşük basınç türbininde, en az %93 en yüksek %97'lik bir doğruluk oranı başarıyla elde edilmiştir.

Anahtar Kelimeler: Turbomakineler, Makine Öğrenmesi, Tahminsel Bakım, Prognostik Bakım, Hasar Tespiti.

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LIST OF SYMBOLS AND ABBREVIATIONS

AI	: Artificial Intelligence
ANN	: Artificial Neural Networks
CC	: Combustion Chamberw2q
CMA PSS	: Commercial Modular Aero-Propulsion System Simulation
DGCA	: Directorate General of Civil Aviation
DOE	: Design of Experiments
EASA	: European Union Aviation Safety Agency
FAA	: Federal Aviation Administration
HPC	: High Pressure Compressor
HPT	: High Pressure Turbine
IAEA	: The International Atomic Energy Agency
ICAO	: International Civil Aviation Organization
KNN	: K-Nearest Neighbor
lbm/s	: Pound Mass Per Second
LPC	: Low Pressure Compressor
LPT	: Low Pressure Turbine
LR	: Linear Regression
MEWMA	: Multivariate Exponentially Weighted Moving Average
NASA	: National Aeronautics and Space Administration
NDT	: Non-Destructive Testing
psia	: Pounds per Square Inch Absolute
°R	: Rankine
RUL	: Remaining Useful Life
SVM	: Support Vector Machine
TMF	: Thermomechanical Fatigue

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1.INTRODUCTION

Turbomachinery refers to a type of machine that transfers energy between a rotor and a fluid, and the history of these devices dates back to the Hellenistic period. The Greek mathematician and engineer Hero of Alexandria conceptualized the first turbine machine, the radial steam engine called "Aeolipile" in his book "Pneumatics Circa" in between 100 BC and 60 AD [Meher-Homji, 2000, Sawyer, 1945]. Although the Aeolipile was not in practical use at that time, turbines today play an important role in many industrial applications, including power generation, aviation, and oil and gas production. Modern turbine machines include components such as turbines, compressors, and pumps. Turbine is an apparatus that converts the energy of a moving fluid into mechanical energy. They are widely used in power generation, aviation and marine propulsion. Turbines can be classified into two types: jet turbines and impulse turbines. The former works based on the fluid reaction, while the latter works on the action of the liquid [Korpela, 2011].

Turbines are devices that convert the energy of a moving fluid into mechanical energy. They are widely used in power generation, aviation, and marine propulsion. Turbines can be categorized into two types: reaction turbines and impulse turbines. The former operates based on the reaction of the fluid, while the latter operates based on the impact of the fluid [Korpela, 2011].



Figure 1.1. Aeolipile Developed by Hero of Alexandria, 120 BC [Sawyer, 1945].

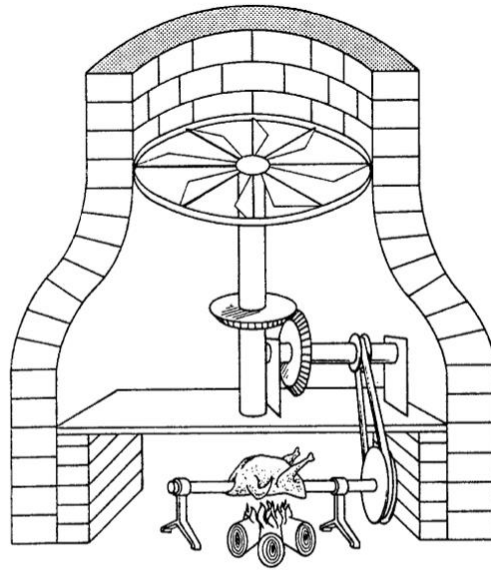


Figure 1.2. Chimney Jack Design by Leonardo Da Vinci, 1500 AD [Dhahri and Omri, 2013].

Compressors are devices that increase the pressure of a fluid. They are used in extensive industrial applications, including air conditioning, refrigeration, and gas transportation. There are several types of compressors, such as centrifugal, axial, and reciprocating compressors (Bansal, 2005).

The compressor is a device that increases the pressure of a fluid. They are used in many industrial applications including air conditioning, refrigeration and gas transportation. There are several types of compressors, such as centrifugal, axial and reciprocating compressors [Bansal, 2005]. The pump is a device that transfers fluid from one point to another. They are used in many industrial applications, including water supply, chemical processing, and oil and gas. Pumps can be classified into two types: positive displacement pumps and dynamic pumps. The former works by retaining a fixed amount of liquid and releasing it into the system, while the latter works by increasing the velocity of the fluid [Çengel and Michael, 2014].

In short, turbo machines are an important part of modern industrial processes. The various components of turbine machines, i.e. turbines, compressors and pumps, play an important role in many different industries around the world. Understanding the different types of turbine engines and their functions is essential for engineers and researchers working in the field [Fox et al., 2004].

Following are some general contributing factors of gas turbine damage:

- Erosion: Instead of adhering interior surfaces of a compressor, certain airborne particles can degrade and damage the interior surfaces. Aircraft engine parts are often damaged by erosion caused by solid particles. Both stationary and rotating aircraft wings can suffer material loss due to the impact of corrosive particles. This damage sometimes has a negative impact on the hot hardware hardware and the overall performance of the engine.

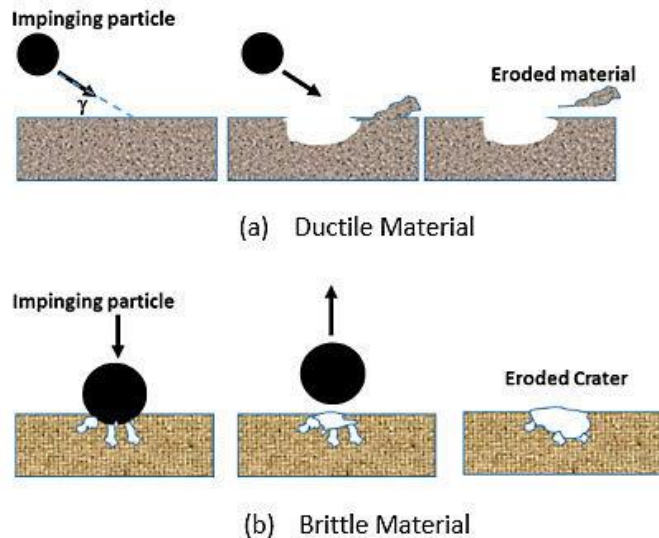


Figure 1.3. Erosion Mechanism a) Ductile Material 23b) Brittle Material [Ansys, 2017].

- Abrasion: The mechanical action of one surface rubbing against another, resulting in abrasion, a type of abrasion. The hardness and roughness of surfaces related to the presence of foreign particles, sliding speed and contact pressure between surfaces are just some of the causes. Surface damage, loss of material and changes in surface properties such as hardness and roughness can all be caused by abrasion [Hutchings and Shipway, 2020].

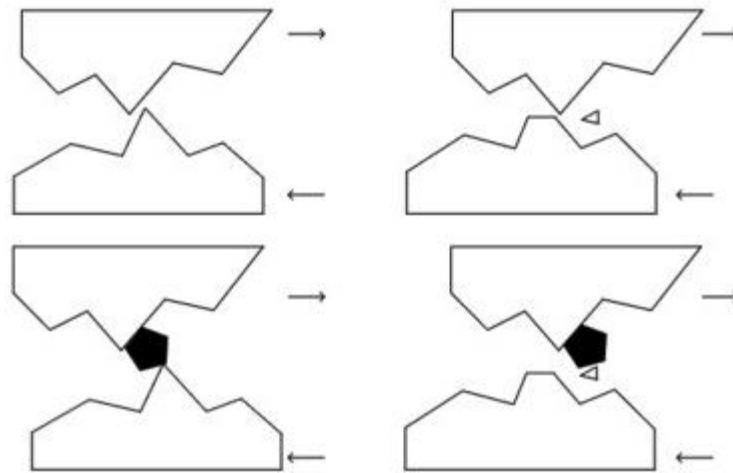


Figure 1.4. Abrasion Mechanism. Two and Three Body Abrasion. [Hutchings and Shipway, 2020].

- **Corrosion:** Sodium sulfate is produced during high-temperature combustion, which combines sulfur from the fuel with sodium chloride from the air. Sodium sulfate accelerates the oxidation (or sulfurization) attack of hot components after deposition ([Lai, 2007], [Rani, 2018]).

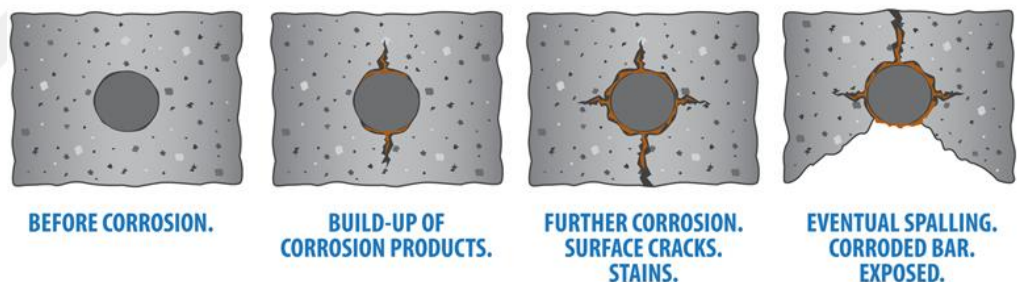


Figure 1.5. Corrosion on Steel [TUF-Bar, 2023].

- **Foreign Object Damage:** Gas turbines with open inlets can be severely damaged by objects entering the compressor [Nowell et al., 2003].
- **Fatigue:** Fatigue is a term used to describe the initiation and progression of cracks in materials due to cyclic stresses. Dynamic stress, vibration, impact or thermal load can all lead to fatigue [Schijve, 2003]. For turbine engines used in the aviation industry, fatigue is a significant risk. Undesirable results may occur if power or thrust is lost rapidly. Therefore, fatigue detection is crucial.

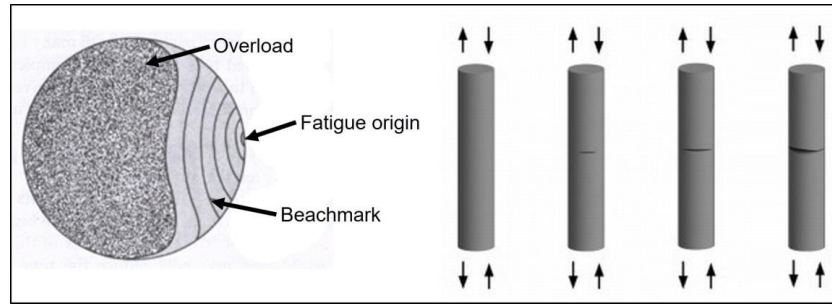


Figure 1.6. Fatigue Mechanism [Industrial Metallurgist, 2023].

- Thermomechanical Fatigue: Due to the heat resistance of different component materials as well as the uneven temperature fields across the components, the hot parts of a gas turbine engine are always susceptible to failure through the damage process. Starting and stopping a gas turbine engine can induce a temperature redistribution in components, which can lead to failure due to thermomechanical fatigue [Salehnasab et al., 2021].
- Creep: Parts of a gas turbine operating at high temperatures will eventually deform due to the applied stress. Eventually, such deformity builds up and leads to a creep damage mechanism, leading to fracture. Blade creep reduction is a major cause of blade life reduction in primary gas turbines. These deformation and failure processes must be included in the design evaluation of components critical to high-temperature applications and engineering calculations that require knowledge of the fracture properties of magnets variables for the material of the structure under construction [Mazur et al., 2011].

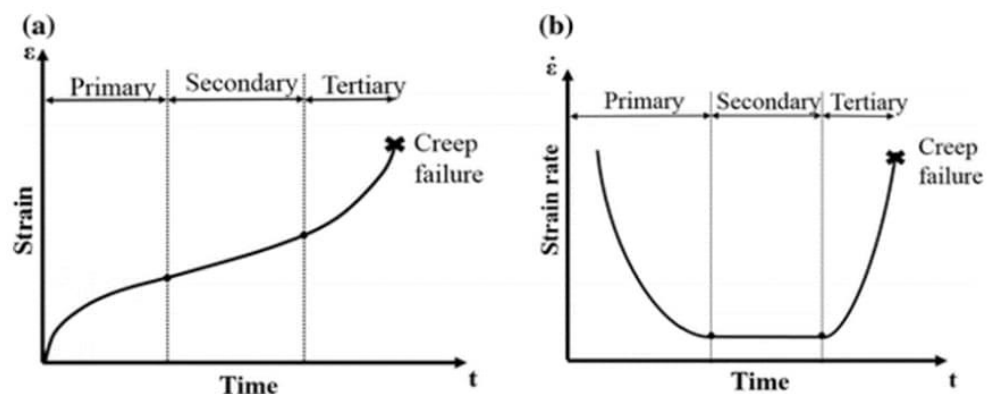


Figure 1.7. Strain vs. Time and Strain Rate (Creep Rate) vs. Time [Tran et. al., 2018].

1.1. Damage Detection on Turbomachinery

To detect turbine failure, non-destructive testing (NDT) is used. Non-destructive testing is used in many industries, including manufacturing, aerospace, energy, and more, to detect any anomalies, defects, or defects that could affect performance, safety or reliability of the system. There are several NDT methods, each with advantages and disadvantages. These methods are:

- **Ultrasonic Testing:** Uses high frequency sound waves to detect internal defects, cracks or discontinuities in materials. UT is commonly used in metallurgy, plastics and composites.
- **Radiographic Testing:** Use X-rays or gamma rays to create an image of the internal structure of a part or material. RT is commonly used in welding, casting and forging.
- **Magnetic Particle Inspection:** Uses magnetic fields and magnetic particles to detect surface and subsurface cracks, porosity or other discontinuities in ferromagnetic materials.
- **Liquid Penetrant Testing:** Use liquid dye or fluorescent penetrant applied to the surface of the material to detect cracks or surface defects.
- **Eddy Current Testing:** Uses a coil and high frequency alternating current to induce eddy currents in the material. The response of materials to eddy currents can reveal surface or near-surface defects.
- **Visual Inspection:** A simple but important technique that involves visual inspection of a part or material for surface defects or anomalies [Tarhan & Kurt, 2021].

1.2. Artificial Intelligence

Artificial intelligence (AI) is a field of computer science that focuses on the development of machines that can perform tasks that typically require human intelligence. AI has rapidly become an integral part of our daily lives, from personal assistants like Siri and Alexa to self-driving cars and advanced medical diagnoses.

AI refers to the ability of machines to perform cognitive tasks that would typically require human intelligence. These include processes like learning, reasoning,

perception, and decision-making. AI systems are designed to simulate human intelligence and adapt to changing circumstances [Russel and Norvig, 2016].

There are two main types of AI: narrow or weak, and general or strong. Narrow AI is designed to perform a specific task or set of tasks, such as recognizing speech or analyzing data. On the other hand, general AI is designed to perform any intellectual task that a human can, with the ability to reason, plan, learn, and adapt to new situations [Jordan and Mitchell, 2015]. Also, AI can be categorized as supervised and unsupervised as their learning types. A labeled dataset, in which each data point is connected to a predetermined goal value, is used to train the algorithm in supervised learning. Based on the patterns it discovers in the training data, the algorithm learns to estimate the target value for fresh, unforeseen data. Linear regression, decision trees, and neural networks are some common supervised learning techniques [Goodfellow et al., 2016].

The algorithm is trained on an unlabeled dataset, in contrast, meaning that the data points do not have any associated goal values; unsupervised learning is a subset of machine learning. Instead, without any prior understanding of what the data represents, the program finds patterns and structure within the data itself. The methods of clustering, anomaly detection, and dimensionality reduction are frequently used in unsupervised learning [Hastie et al., 2009].

Both supervised and unsupervised learning have advantages and disadvantages, and which method should be used depends on the issue and available data. Both supervised and unsupervised learning techniques and others have been shown below.

1.2.1. Regression

In a regression modeling scenario, a data set typically consists of a collection of dual input properties commonly referred to as x and the corresponding output values conventionally represented as y . The goal is to define a mathematical function that accurately models the relationship between the input variables and the related output values. This function is often represented as a mathematical equation or model that has the ability to produce accurate estimates for new, unobserved data.

The following basic principles and components are related to regression in the field of artificial intelligence: (AI).

There are various regression models widely used in statistical analysis. These models are used to study the relationship between a dependent variable and one or more independent variables.

- Linear regression assumes a linear relationship between input variables and connected variables. The goal is to identify the line that best matches, minimizing differences between expected values and observed values.
- Polynomial regression is a statistical technique that allows the modeling of non-linear relationships between variables by integrating higher order components, such as fourth or cubic terms into a linear equation.
- Support Vector Regression (SVR) is a regression technique that uses support vector machines to perform regression analysis. The goal is to identify a hyperplane that best places their databases and take into account a specific error margin.
- Decision tree regression is to divide the entrance area into different areas and assign a fixed value to each area.
- Random Forest Regression is a machine learning technique that uses a series of decision trees to increase the accuracy of predictions [Lu, 2010].

Parameter and hyperparameter concepts play crucial roles in various fields, including machine learning and optimization. Parameters refer to the intrinsic variables of a learned model. Parameters refer to factors in the regression equation that play an important role in determining the relationship between input properties and output. The parameters of the algorithm are modified iteratively during the training process to reduce errors in estimates. Hyperparameters refer to settings that can be modified in the pre-training process to regulate the behavior of the regression algorithm. Examples include parameters such as learning rate, editing intensity, number of iterations, and so on.

The metrics used for evaluation are:

- Mean Square Error (MSE) is a statistical measurement that calculates the average of the square differences between expected and observed values. The system imposes harsher penalties for larger mistakes.
- Root Mean Square Error (RMSE) is a mathematical metric derived from the average square error. (MSE). It is calculated by taking the square root of

the MSE and serves as a measurement of the amount of the average error size. Importantly, RMSE is expressed in the same units as the output variable, thus allowing for a more meaningful interpretation of the error size.

- Average absolute error (MAE) is a metric that calculates the average of the absolute differences between expected and actual values. The method shows a higher resistance to external views compared to the average square error (MSE).
- The R-squared (R^2) score is a statistical measurement of the amount of difference observed in dependent variables that can be explained or predicted by independent variables. The measurement scale for this variable ranges from 0 to 1, so larger values correspond to a more optimal level of correction [Lu, 2010].

1.2.2. Classification

The idea of classification holds an essential place, especially in the field of artificial intelligence (AI) and machine learning in the area of supervised learning. The resulting task involves the procedure for classifying or identifying a particular data point, taking into account its distinctive characteristics. The purpose of classification is to create a model that can distinguish patterns and relationships in a labeled database. This information is then used to categorize new, unobserved data points into pre-set classes or categories.

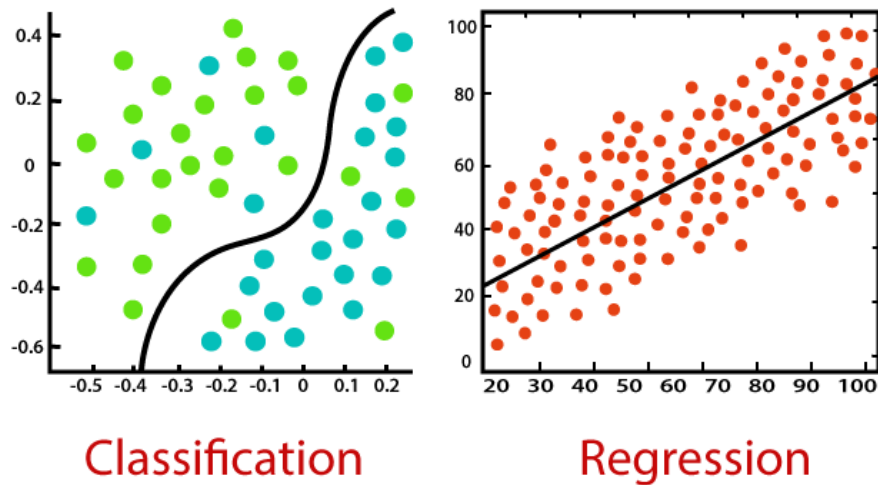


Figure 1.8. Classification vs Regression in Machine Learning [Jaavatpoint, 2023]The following section presents a list of classification methods and related parameters [Lu, 2010].

1.2.2.1.Support Vector Machines

Support Vector Machine (SVM) is a machine learning algorithm commonly used for classification and regression tasks. The kernel is responsible for identifying a specific type of map used to translate given data into a higher-dimensional field. The core functions we typically encounter include the varieties of linear, polynomial, and radial basic functions.

The adjustment parameter, marked as C , is required to balance the optimization of the margin with the minimization of classification errors. Reduced values of hyperparameter C produce a wider margin despite potentially providing some misclassifications. Rather, the elevated values of C prioritize correct classification, but can potentially bring a narrower margin.

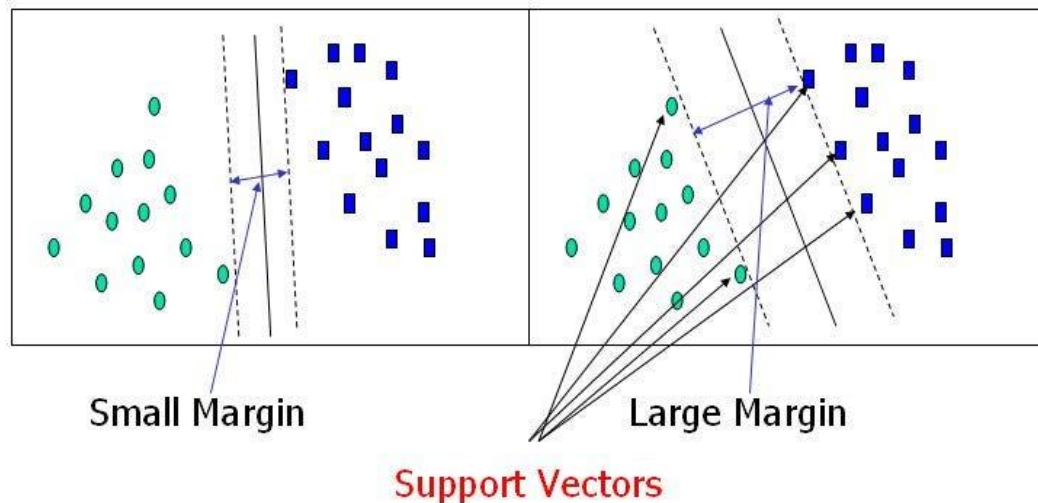


Figure 1.9. A Comparison of Different Types of Support Vectors [Towards Data Science, 2018].

The gamma parameter used in the Radial Basis Function (RBF) core affects the curvature and shape of the decision boundary. The decrease in gamma values is associated with greater flexibility in defining the boundary, whereas the increase in gamma value is linked to the creation of a more complex and striking limit [Lu, 2010].

1.2.2.2. Logistic Regression

Logistic regression is a statistical model used to estimate the probability of binary outcomes based on one or more independent variables. It is used in many areas, for example.

Parameter C, which is the opposite of the regulating force, plays a role in Support Vector Machines. (SVM). Manages the balance between correctly adjusting training data and reducing the risk of over-adjustment. Reducing the C value increases the adjustment effect and therefore reduces the risk of overfitting [Lu, 2010].

1.2.2.3. The Decision Tree

The decision tree is a common machine-learning algorithm used for both classification and regression tasks. It is a non-parametric controlled learning method and predicts by generating results.

The *max_depth* parameter is used to limit the depth of the decision tree, thus reducing the risk of excessive complexity and overfit [Lu, 2010].

The *min_samples_leaf* parameter is used to determine the minimum amount of sample that must be available to create a leaf node. This mechanism is used to alleviate the formation of nodes that do not have enough samples on the tree, thereby reducing the risk of overfitting [Lu, 2010].

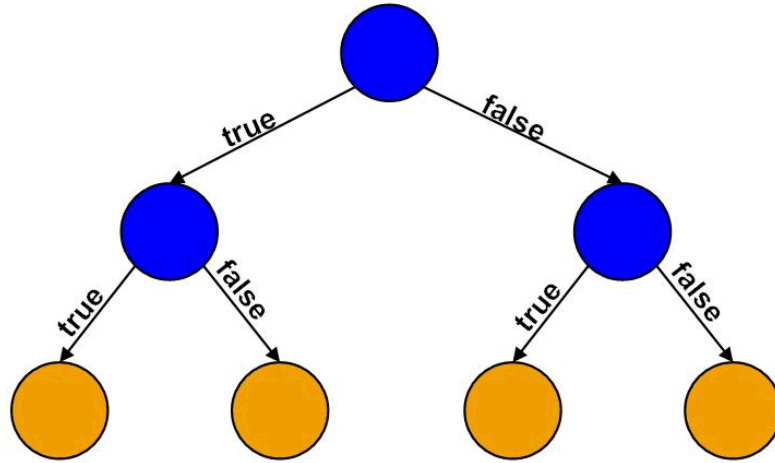


Figure 1.10. Decision Tree Expression [SAP, 2023].

1.2.2.4. The Random Forest

Random Forests, a popular ensemble learning method, inherits certain parameters including *max_depth* and *min_samples_leaf* from decision trees.

The “Tree Number” (*n_estimators*) parameter determines the number of individual decision trees in the forest. Increasing the number of trees has the potential to improve their generalization abilities but at the expense of increasing the calculation time [Lu, 2010].

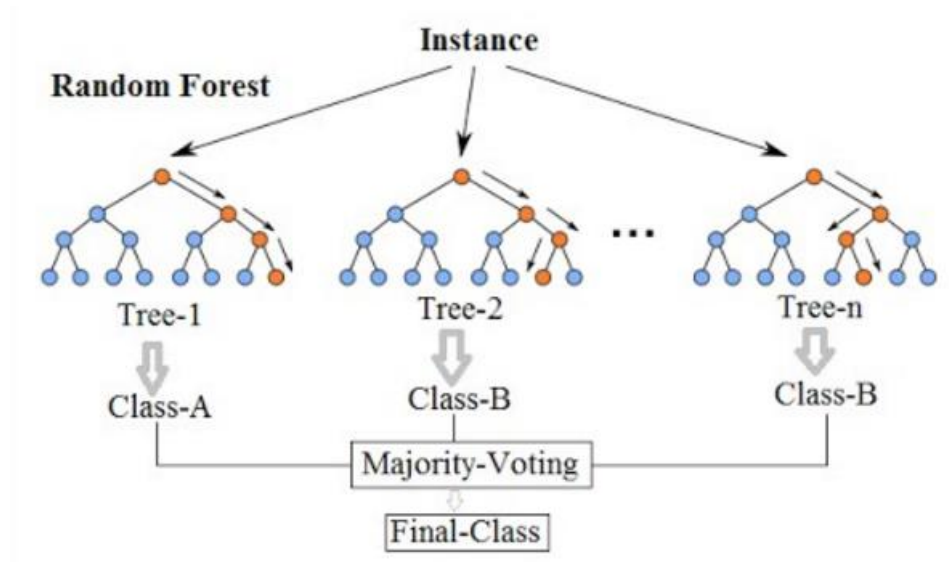


Figure 1.11. Random Forest Expression Simplified [Medium,2020].

1.2.2.5.K-Nearest Neighbors

The K-Nearest Neighbors (KNN) algorithm involves considering a certain number of nearest neighbors called $n_neighbours$ to make predictions. A greater numeric value leads to a smoother decision limit, while a smaller numerical value increases noise sensitivity [Lu, 2010].

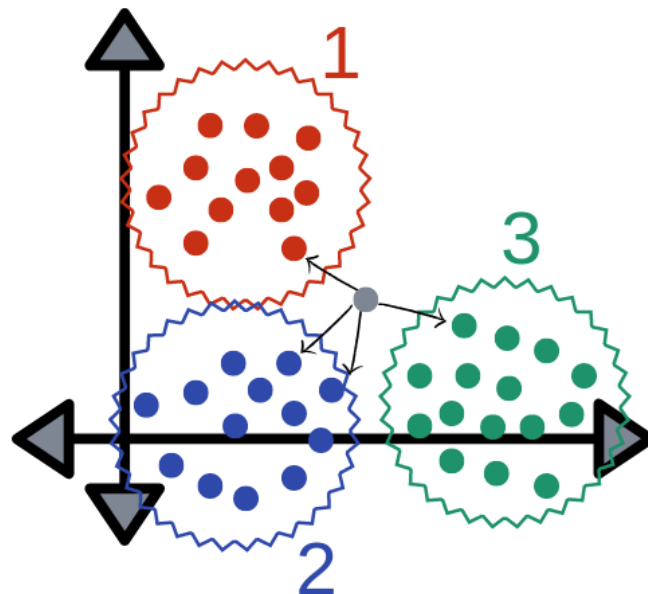


Figure 1.12. Schematic Representation of K-Nearest Neighbors [Machine Learning HD, 2021].

1.2.2.6. Naive Bayes

Naive Bayes do not have a significant number of adjustable parameters, but certain variations (such as Gaussian naive Bayes and Multinomial naive Bayes) may have certain parameters for data distribution assumptions [Lu, 2010].

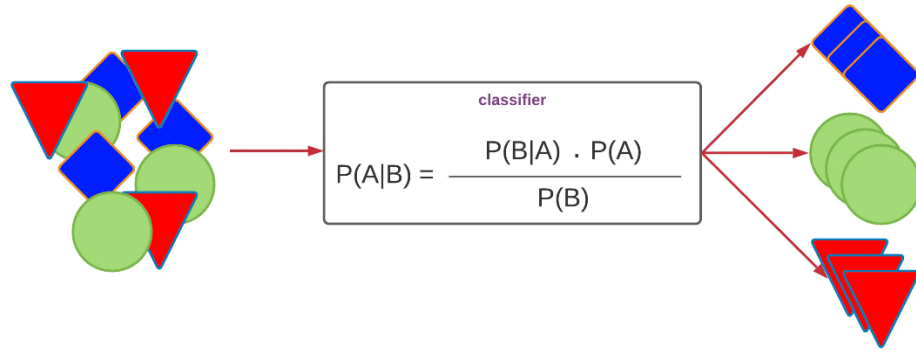


Figure 1.13. Schematic Representation of Naive Bayes [ML Archive, 2023].

1.2.2.6.1. Gaussian Naïve Bayes

The Gauss Naive Bayes algorithm assumes that the characteristics correspond to the Gauss (normal) distribution. This method is suitable for continuous numerical characteristics. This process involves calculating the average and standard deviation of each property for each class and is then used to estimate the probability of the class [Lu, 2010].

1.2.2.6.2. Multinomial Naive Bayes

The Multinomial naive Bayes algorithm is often used to process detailed data in the context of text classification tasks such as document classification and spam detection. This approach assumes multi-word distribution for properties, which typically reflect the number of words or keyword frequencies in documents. In this approach, each property is regarded as a separate number, such as the number of occurrences of a word in a particular class [Lu, 2010].

1.2.2.6.3. Bernoulli Naïve Bayes

An alternative approach that is suitable for text classification, especially for binary and categorical information, is the Bernoulli naive Bayes method. The assumption made in this context is that the characteristics are characterized by a dual nature, that is, they can be present or absent. Furthermore, it is assumed that the distribution of these properties follows a Bernoulli distribution. Text classification algorithms are commonly used in many applications such as sentiment analysis, document categorization, and spam filtering [Lu, 2010].

1.2.2.6.4. Complement Naive Bayes

The Complement Naive Bayes algorithm is a modified version of the Multinomial naive Bayes aimed at mitigating class imbalance. The probability estimates for the complementary of each class are used to mitigate the influence of the dominant class in the classification process [Lu, 2010].

1.2.2.6.5. Categorical Naive Bayes

Categorical naive Bayes is a classification algorithm developed specifically for their databases, including categorical variables with multiple levels or different values. This method is suitable for data sets that contain nominal or ordinal properties [Lu, 2010].

1.2.3. Clustering

Clustering is a technique used in the field of artificial intelligence (AI) and data analysis, and this process involves categorizing data points with comparable properties or characteristics into different groups. The purpose of classification is to identify the basic patterns or structures in the data without any prior knowledge about class labels or categories.

The k-means algorithm is a widely used grouping technique. The purpose of the k-means algorithm is to divide the database into k different sets, the k value is determined by the user. The procedure begins by randomly selecting the k starting set centroids and then assigning each data point to the closest centroid. Centroids are

then iteratively updated by calculating the average of the data points assigned to each set until convergence is achieved. The goal of the K-average algorithm is to minimize the number of squares within each cluster to create both compact and well-separated clusters [Hartigan & Wong, 1979]. This algorithm is characterized by its simplicity and efficiency; however, it requires predetermination of the number of sets.

The elbow method is a commonly used approach to determine the number of most suitable sets in the k-high classification. This process creates a piece that shows displays the within-cluster sum of squares (WCSS) in relation to the number of sets. The goal is to find a turning point called the “red” point, which represents the stage where further reduction in WCSS leads to falling returns. The suggested approach is to determine the optimum number of sets on the basis of the dressing point, which significantly increases the efficiency of clustering, avoiding excessive complexity [Tibshirani et al., 2001].

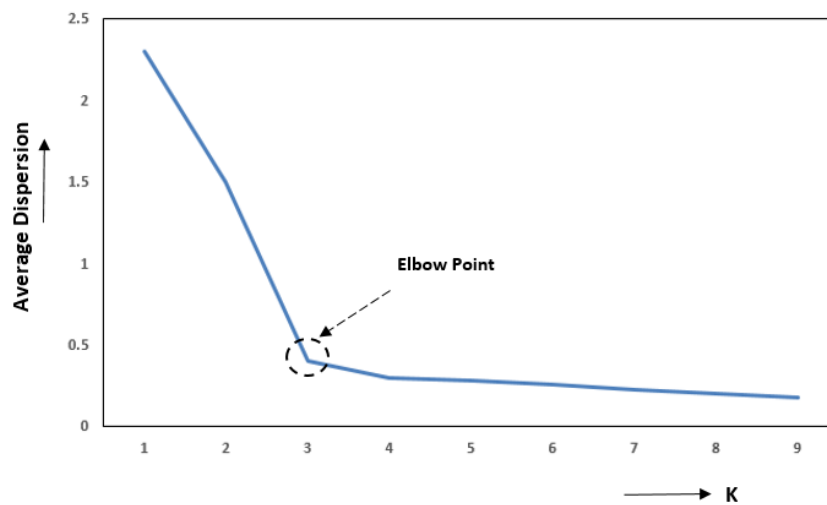


Figure 1.14. Elbow Method for Selection of Optimal "K" Clusters [O'Reilly, 2023].

DBSCAN (Density-Based Spatial Clustering of Applications with Noise) is another clustering technique that is commonly used [Chakraborty et al. 2011]. The DBSCAN algorithm is used to collect data points considering density and connectivity. Folders are high data point density fields separated by areas with lower density. This method starts by selecting a random data point and continues to expand the sets by establishing links to neighboring points that meet certain criteria related to density and distance. According to Chakraborty et al. [2011], the DBSCAN algorithm can

autonomously identify clusters in various shapes and successfully manage noise or exclusion. This method does not require the number of sets to be specified in advance.

In short, clustering is a technique used in the field of artificial intelligence and data analysis to categorize data points with similar qualities into consistent groups. K-means and DBSCAN are widely used grouping algorithms that can identify patterns and structures within a database. The elbow method is a valuable technique for determining the number of suitable sets in the context of k-means collection. The use of these techniques is extremely important in a wide range of applications, including customer segmentation, image identification, and abnormality detection.

1.2.4. Dimensionality Reduction

Dimensionality reduction in A.I. involves the procedure of reducing the number of variables or properties that enter a database and storing the most important data. The use of this technique is used to alleviate the difficulties associated with the curse of dimensions, optimize computing efficiency, and increase the interpretability and effectiveness of machine learning models.

There are various methods for reducing size, each characterized by different approaches and basic assumptions. Principal Component Analysis (PCA) is a method commonly used in dimensionality reduction. PCA is a statistical technique used to identify aspects representing the highest amount of variation in a database. The data is then projected onto a lower-dimensional subfield defined by these policy components. This study aims to identify a new collection of independent variables called core components, which can create the highest possible differential ratio in the original database. [Tenenbaum et al., 2000].

Another methodology that may be used is t-distributed Stochastic Neighbor Embedding (t-SNE). t-SNE is a non-linear approach to reducing data sizes to preserve the local structure of data points in a lower dimensional field. The algorithm creates a probability distribution for pairs of data points in a high-dimensional field, but also a distribution that corresponds to pairs of representations in their own lower dimensions. The difference between the two distributions is then minimized to determine a lower dimensional representation that effectively represents the local

structure of the data. [Alejandro et al., 2022]. The t-SNE algorithm is often used to visually represent large-scale datasets in a two- or three-dimensional field.

Additional techniques for size reduction are Linear Discriminant Analysis (LDA), which attempts to define a linear combination of characteristics that optimize differentiation between classes [Lu, 2010], and automatic coders are neural networks that gain the ability to reconfigure input data from a representative compressed into a bottleneck layer [Hinton & Salakhutdinov, 2006]. Automatic encoders can record nonlinear correlations, which makes them valuable for tasks such as unsupervised learning.

When using size reduction approaches, certain features must be considered. In the context of PCA, it is possible to specify the desired number of principal components to be created or the percentage of differences to be explained.. The confusion parameter in t-SNE is responsible for regulating the compromise between preserving the local and global structure. The choice of parameters has the potential to affect the effectiveness of size reduction results and requires the need to adjust experiments and parameters to desired results.

1.2.5. Ensemble Methods

All methods in the field of artificial intelligence are related to the approach of combining a large number of models or classmates to improve the performance of predicting and enhance the adaptability of the learning system. Ensemble approaches are based on the principle that combining predictions from multiple models provides better accuracy and generalization compared to the performance of any single model [Rokach, 2009]. Ensemble methods include various parameters and strategies. Several ensemble approaches used regularly include:

Bagging, also known as Bootstrap Aggregating, is an entire strategy in which the training data of many models is trained according to different bootstrap examples. Training for each model is carried out separately, and the final estimate is obtained using the average of the estimates or votes made by all models [Breiman, 1996]. The use of bagging techniques has been found to effectively alleviate the problem of over-assembly and thus increase the stability and accuracy of the ensemble model.

Boosting is a widespread ensemble strategy that follows a series of training approaches to develop weak models and then build a strong model by combining their predictions. Subsequent models in this approach prioritize situations that were wrongly classified by previous models, which leads to an improvement in overall performance [Dietterich, 2000]. The AdaBoost algorithm, introduced by Dietterich in 2000, is a widely recognized reinforcement technique that assigns weights to training samples to emphasize challenging situations.

The random forest algorithm is a popular ensemble technique that blends a large number of decision trees. Each tree in the training process involves being trained on a subset of randomly selected characteristics. The final estimate is then obtained by combining the estimates of all trees using the average or the vote. The random forest algorithm is famous for its ability to effectively manage multidimensional datasets and deliver reliable estimates [Shahhosseini et al., 2021].

Stacking is a methodological approach that involves combining predictions from many models by training a meta-model related to the outputs generated by the base models. The first models generate predictions based on training data and are then used as input features for the meta-model. [Lu et al., 2015]. The compression technique can use the individual capabilities of more than one model, which leads to an increase in overall performance.

1.2.6. Neural Networks

Neural networks, also known as artificial neuronal networks (ANNs), are computational models inspired by the structure and functioning of biological neural networks in the human brain. Artificial intelligence (AI) and machine learning are core components, they can learn complex patterns and make predictions or decisions based on input data. Each has different types of neural networks with its own architecture and characteristics. Some commonly used types are described below.

Feedforwards neural networks (FNN) are the simplest and most basic type of neural network. They consist of an input layer, one or more hidden layers, and an output layer. Information flows in one direction from the input layer to the hidden output layer, without any feedback link [Lu & O'Donnell, 2020]. Feedforward neural

networks are widely used for tasks such as classification, regression, and pattern recognition.

Repeated neural networks (RNN) are designed to process sequential or time series data. They have feedback connections that allow information to flow through cycles so that the network can capture time dependencies and contexts. RNNs have memory capabilities and are suitable for tasks such as speech recognition, language modeling, and emotion analysis. [Cao et al., 2017].

Convolutional neural networks (CNN) are primarily used for image and video analysis. It is designed to automatically learn the hierarchical representations of visual data with convulsive layers, aggregation layers, and fully connected layers. CNN has achieved significant successes in tasks such as image classification, object perception, and image production [Kim et al., 2018].

Each type of these nerve network has its own unique characteristics and applications. Feedforward neural networks are versatile and are widely used for various tasks. RNNs are suitable for serial data analysis, and CNNs are excellent for image and video processing tasks. The choice of neural network type depends on a specific problem and the nature of the data.

In neural networks, layers refer to different levels or calculation stages within the network. Each layer consists of a series of interconnected nodes that perform calculations in input data, also known as neurons or units. Layers are arranged in order, and information is transferred from the input layer to the output layer via one or more hidden layers.

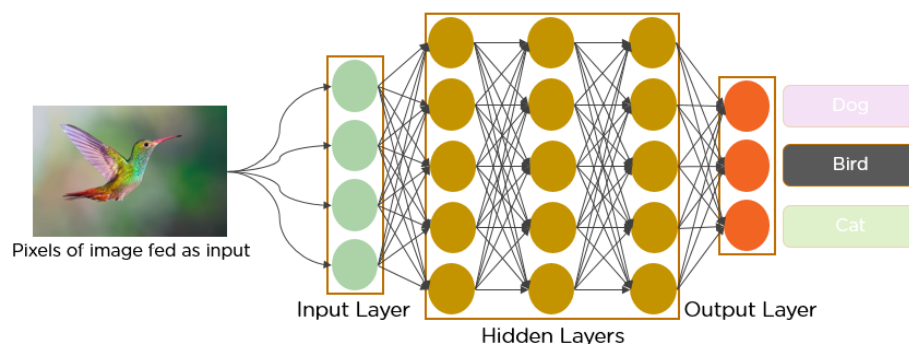


Figure 1.15. Neural Networks and Hidden Layers [Analytics Vidhya, 2023].

The parameters of neural networks include various components that define the architecture and behavior of the network. Some important parameters are given below.

- The number of layers in a nerve network indicates the depth of the network. The input layer includes one or more hidden layers and the output layer. The choice of the number of layers depends on the complexity of the problem and the amount of data available.
- The number of neurons in each layer determines the capacity and representative power of the network. The network is an important parameter that affects the ability to learn complex patterns. The number of neurons is usually determined through experiments and adjustments.
- Activation functions bring non-linearity to the network and determine the output of each neuron. Common activation functions include the sigmoid function, ReLU (Rectified Linear Unit), and tanh. (hyperbolic tangent). The selection of the activation function depends on the problem and the desired network characteristics.
- Learning Speed controls the learning speed of the step size that sets the weights of the network during the training process. It determines how quickly the network will merge for the optimal solution. A high learning rate can cause the network to exceed the optimal solution, while a low learning rate may cause a slow merger.
- Regulation Techniques are used to prevent network overload and improve generalization capacity. Common editing techniques include L1 and L2 editing, drop-out, and group normalization. These techniques bring restrictions or modifications to the parameters of the network to reduce overload.

It is important to note that certain parameters and values depend on the problem, the data set, and the architecture of the neural network. Experiments and adjustments are often required to find optimal values for these parameters.

In a neural network, different layers make certain calculations and play different roles in the overall functioning of the network. Here are some layers commonly used in neural networks:

1. **Input Layer:** The input layer is the starting layer of the network that holds the input data. Represents the properties or properties of the input data and transfers them to the subsequent layers for processing.
2. **The hidden layers** are the middle layers between the input and output layers. They make calculations in their input data and extract related characteristics. The number of hidden layers and the number of neurons in each layer can vary depending on the complexity of the problem.
3. **Convolutional layers** are often used in convolutional neural networks (CNNs) to process data such as networks, such as images. They apply convolutions to input data using learnable filters or cores to extract local patterns and properties.
4. **Pooling Layer:** Pooling layers are often used in convoluted layers on CNN. They sample property maps obtained from convulsive layers by summarizing or combining information in local regions. Collective collection operations include max collection and average collection [Szegedy et al., 2015].
5. **Flatting layer:** A flatting layer is used to convert multidimensional data, such as feature maps from convulsive layers, into a single-dimensional vector. It makes input data fully compatible with connected layers [Zeiler & Fergus, 2014].
6. **Fully Connected Layer:** Fully connected layers, also known as the dense layer, connect every neuron of the existing layer to each neuron located in the next layer. They play an important role in learning complex relationships and making final estimates or classifications [He et al., 2016].
7. **Output Layer:** The output layer is the last layer of the grid to produce the desired output or prediction. The number of neurons in the output layer depends on a specific task such as binary classification, multi-class classification, or regression [He et al., 2016].

1.2.7. Transfer Learning

The concept of transfer learning in the field of artificial intelligence refers to the use of knowledge or models obtained from a particular job or field and the method of using them in a different but similar activity or field. Transfer learning is a technique

that allows a model to use the information obtained from previous learning samples, instead of starting the learning process from scratch [Yang, 2009].

The parameters associated with transfer learning depend on the approach and framework used. Some commonly used parameters are:

1. Pre-trained Model: The pre-trained model includes the concept of a model trained in a critical database or in a closely related task. Transfer serves as the initial stage of application learning. The choice of the pre-trained model depends on the degree of similarity between the resource and target tasks or fields. [Pan & Yang, 2010].
2. Fine-tuning: Fine-tuning refers to the process of changing the parameters of a pre-trained model to optimize its performance on a specific task [Yang, 2009]. This feature allows the model to dynamically adjust its performance and specialize according to the unique characteristics and requirements of a particular task. According to Yang [2009], the degree and scope of fine adjustment depend on the presence of the recorded data and the complexity of the objective work.
3. Feature Extraction: The use of a pre-trained model as a feature extractor is a transfer learning technique. The layers of the pre-trained model are fixed and only the output features are used as an entry for a new model or classifier. This methodology has proven to be advantageous in scenarios that indicate that the intended target is low in the recorded data. [Malleesh et al., 2021].
4. Domain Adaptation: Domain adaptation strategies are designed to reduce the gap between source and target areas by matching their distribution. This process involves changing the parameters of the model to reduce the distribution difference between the source and the target data [Zhu et al., 2020]. The use of domain adaptation provides an advantage in scenarios where the source and target fields have different characteristics.
5. Task-Specific Layers: The fifth component of the system architecture. Task-specific layers are additional layers that are integrated into a pre-trained model to customize for a specific target task. Layers are usually initiated randomly and then trained using labeled data specific to the target task. The amount and structure of task-specific layers depend on the complexity of the planned work [Yang, 2009].

1.2.8. Reinforcement Learning

Reinforcement Learning (RL) is a learning framework in the field of artificial intelligence (AI) where an independent agency has the ability to make a range of decisions in an environment in order to maximize a collective reward signal. The agent interacts with the environment, carries out actions, and receives feedback in the form of rewards or penalties. Through the learning process, it aims to improve decision-making policy over time to optimize agent performance.

Strengthening learning includes different features and components that are fundamental to its work.

1. State: refers to existing regulation or environmental observation. Informing agents about existing circumstances helps in the decision-making process.
2. Action: Actions are the various choices an agency can make to interact with its surroundings. The agent decides on its actions based on its policies, which can be described as a function that maps situations to matching actions.
3. Reward: In the context of Agent-environment interactions, rewards can be defined as feedback signals received by the agent after an action has been carried out. Indicators are used to assess the attractiveness or effectiveness of the agency's actions and guide the learning process.
4. Policy: refers to the framework that defines an agency's strategy or behavior, and determines how it will make decisions taking into account the situations it sees. The thought phenomenon has the potential to show either deterministic or stochastic behavior.
5. Value function: A value function is a calculation tool used to capture the expected total reward or value associated with being in a particular situation or performing a particular action. The use of this tool makes it easier for the agent to evaluate and match various activities or situations.
6. Exploration-Exploitation Tradeoff: The Reinforcement Learning (RL) field includes a core trade known as exploration and expenditure trade. The term "drug" refers to the agency's active investigation of the environment to explore new behaviors and situations. In return, "exploitation" means that the agency uses its existing information to optimize rewards.

7. Discount Factor: Discount factor is a metric that measures the relative importance of future rewards about direct earnings. Effectively manages the compromise between quick benefits and future benefits.

8. Q-Learning: Q-learning is a popular RL algorithm that learns the values of state-action pairs iteratively. It uses a Q-table or Q-function to estimate the expected cumulative reward for each state-action pair [Mnih et al., 2015].

1.2.9. Natural Language Processing

The field of Artificial Intelligence (AI) includes the study and development of algorithms and methodologies that help computers understand, analyze, and produce human language (NLP). The main purpose of the method is to establish a connection between human language and machine understanding. This connection facilitates the development of various applications including language translation, emotional analysis, text summary, and question answers.

The choice of parameters in NLP depends on a specific business or practice. There are several common factors and approaches used in the field of NLP.

1. Tokenization refers to the procedure of splitting the text into detailed pieces or tokens that may contain words or sub-words. The initial stage of NLP is an important technique that facilitates the subsequent examination and manipulation of text data.

2. Part-of-Speech (POS): POS labeling is a process that involves assigning grammar tags to individual words within a sentence, thus categorizing them into speech pieces such as words, dictionaries, adjectives, and so on. Studying the syntax structure of words helps to understand.

3. Named Entity Recognition (NER): The process of identifying and categorizing assets named within a specific text. These assets may include but are not limited to, personal names, corporate names, and locations. The process helps in extracting organized data from texts that do not have a pre-defined structure.

4. Sentiment Analysis: The purpose of the analysis of emotions is to determine whether the emotion or opinion transmitted in a text composition is good, negative, or neutral. Using this tool is useful for understanding the feelings of the public, analyzing customer feedback, and monitoring social media activities.

5. Word embeddings refer to compact vector representations of words that effectively capture both semantic and contextual information. Methods such as Word2Vec, GloVe, and FastText are then used to create word embeddings used as input features for a series of NLP applications.

6. Language Models: Language models are statistical models that obtain the probability distribution of the string of words within a given language. These models are applied to a variety of tasks such as language production, speech recognition, and machine translation.

7. Neural Networks: Neural networks, especially recurrent neural networks (RNNs) are widely used in the field of NLP. The ability to acquire complex patterns and relationships in text materials enables various tasks such as machine translation, text production, and language understanding [Liu and Zhang, 2018, Castañón, 2019].

There are some problems with AI. One of them is overfitting. When a machine learning model predicts outcomes accurately for training data but not for new data, this undesired tendency is known as overfitting. Data scientists train machine learning models on known data sets before using them to make predictions. The algorithm then tries to forecast results for fresh data sets based on this knowledge. An overfit model cannot perform effectively for all sorts of incoming data and might provide erroneous predictions. Testing machine learning models on larger datasets with thorough representations of potential input data values and kinds is the best way to identify overfit models. To check for overfitting, a portion of the training data is typically utilized as test data. Overfitting is evident when the testing data have a high error rate. One of the testing techniques that is applied in real life is cross-validation. With this technique, data scientists divide the training set into folds or equally sized sample sets [Zhang et al., 2022].

AI has a wide range of applications in various industries. Some of the most significant ones include healthcare (for analyzing medical data, identifying diseases, and developing personalized treatment plans), finance (for fraud detection, risk assessment, and automated investment management), transportation (for self-driving cars, traffic management systems, and logistics optimization), manufacturing (for quality control, predictive maintenance, and supply chain optimization), and retail

(for personalized marketing, customer service, and inventory management) [Russel and Norvig, 2016].

1.3. Where Mechanical Engineering and AI Intersect

AI is used in mechanical engineering to create intelligent systems that can learn, reason, and make decisions. The integration of AI in mechanical engineering has led to the development of smart systems that can perform tasks that are beyond the capabilities of traditional mechanical systems [Ramadge and Wonham, 1987]. These tasks (not all) can be summarized as follows:

1. Robotics: AI is used in robotics to create intelligent systems that can perform tasks autonomously. These robots can perform tasks that are dangerous or difficult for humans to perform.
2. Predictive Maintenance: AI is used in predictive maintenance to monitor the performance of mechanical systems and predict when maintenance is required. This reduces downtime and increases the lifespan of the system.
3. Design Optimization: AI is used in design optimization to create better designs that are more efficient and cost-effective. This reduces the cost of production and increases the reliability of the system.
4. Intelligent Control: AI is used in intelligent control to create control systems that can learn and adapt to changing conditions. This increases the efficiency and reliability of the system [Huang et al., 2006].

The interaction of artificial intelligence and mechanical engineering has many benefits. For instance, AI improves efficiency by leading to the development of systems that are more competent and reliable, and these systems lead to a reduction in the cost of production and increased profitability. In addition, AI led to the development of systems that are safer for humans to operate, along with robots that can perform dangerous tasks, reducing the risk of injury to human operators, and overall improving safety. AI collaboration with mechanical engineering also reduces downtime, which leads to increased productivity and profitability. Moreover, the use of AI in design optimization improves product quality, so customer satisfaction and profitability increase [Patel et al., 2020].

Predictive maintenance is a type of maintenance that uses data analysis and machine learning algorithms to predict equipment failure before it occurs. By analyzing historical data on equipment performance, predictive maintenance algorithms can detect patterns and trends that signal impending equipment failure. This allows maintenance teams to act before equipment fails, reducing downtime and maintenance costs.

Traditionally, maintenance has been performed on a reactive or preventative basis. Reactive maintenance involves fixing equipment after it fails, while preventative maintenance involves performing maintenance on a regular schedule, regardless of the equipment's actual condition. Both approaches have limitations. Reactive maintenance is costly and can result in long periods of downtime, while preventative maintenance can be wasteful and lead to unnecessary maintenance costs (Moubray, 1997).

Predictive maintenance offers a more efficient and effective way to manage maintenance. By analyzing data on equipment performance, maintenance teams can identify when equipment is likely to fail and act before it does. This can reduce downtime and maintenance costs while also extending the life of equipment [Ersöz et al., 2022]. One of the key benefits of predictive maintenance is that it allows maintenance teams to schedule maintenance activities at a time that is convenient and least disruptive to operations. By predicting when equipment will fail, maintenance teams can plan maintenance activities around scheduled downtime, rather than being forced to shut down equipment unexpectedly. To implement predictive maintenance, organizations need to collect and analyze data on equipment performance. This requires a combination of hardware and software tools. Sensors can be installed on equipment to collect data on factors such as temperature, vibration, and power consumption. This data can then be fed into machine learning algorithms that analyze the data and identify patterns and trends [Compare et al., 2020].

There are several types of predictive maintenance algorithms, including rule-based algorithms and machine learning algorithms. Rule-based algorithms use a set of predetermined rules to identify when equipment is likely to fail. Machine learning algorithms, on the other hand, use data to learn and adapt over time, improving their accuracy with each new data point [Lee et al., 2013]. To be effective, predictive

maintenance algorithms need to be continuously trained and refined. This requires ongoing data collection and analysis to ensure that the algorithms are up-to-date and accurate. Over time, predictive maintenance algorithms can become more accurate and effective, allowing organizations to reduce downtime and maintenance costs while improving equipment reliability [Coanda et al., 2020].

As previously said, turbomachines are a crucial component of many industrial processes, including the generating of electricity, the production of oil and gas, the processing of chemicals, and many others. These devices are used to transform fluid (gaseous or liquid) energy into mechanical energy, which is subsequently utilized to power various pieces of machinery. Turbomachines can, however, result in catastrophic mishaps if they are not properly maintained.

There have been numerous incidents where poorly maintained turbomachines have caused accidents, resulting in significant damage to equipment, injuries to personnel, and even loss of life. A few examples of accidents caused by turbomachines are:

- Piper Alpha Disaster: On July 6, 1988, a gas leak occurred on the Piper Alpha oil rig in the North Sea. The gas leak was caused by a gas turbine that was not properly maintained. The gas ignited, causing a massive explosion that resulted in the loss of 167 lives and the destruction of the entire platform [Reid, 2020].
- United Airlines Flight 232: In 1989, United Airlines Flight 232 experienced a catastrophic failure of its tail-mounted engine, which was caused by the disintegration of the engine's fan disk due to a previously undetected metallurgical defect. The engine was a General Electric CF6-6, which had been in service for 18 years and had accumulated more than 37,000 cycles. The accident resulted in the loss of the aircraft, with 111 fatalities and 185 injuries (National Transportation Safety Board, 1989).

The incidents mentioned above demonstrate the importance of proper maintenance of turbomachines. Regular maintenance and inspections can help prevent accidents and ensure the safe and efficient operation of turbomachines. It's crucial to follow manufacturer guidelines and industry standards for the maintenance and repair of these machines.

2.LITERATURE SURVEY

With the start of the twenty-first century, Industry 4.0 started to enter all around the world. As mentioned in the introduction section, the intersection of artificial intelligence and engineering fields was inevitable. Therefore, in this section, a literature review was conducted in which artificial intelligence and turbomachines were studied together and the remaining useful life in gas turbines. In addition, articles using artificial intelligence in the energy sector were also examined.

Saxena and Simon [2008] published results that discusses the modeling of damage propagation within the components of aviation gas turbine engines. To achieve this goal, response surfaces for all sensors are developed using a thermo-dynamical simulation model for the engine. These response surfaces are determined based on changes in the flow and efficiency of the modules that are of interest. A randomly selected starting deterioration set point was used to initiate an exponential rate of change for flow and efficiency loss in each data set. The rate of change in the flow and efficiency indicates an unidentified problem that progressively deteriorates. The rates of change of the faults were subject to an upper threshold limitation, while the remaining values were selected randomly. The propagation of damage was allowed to continue until a certain failure condition was met. The concept of a health index was established to represent the lowest value among many operational margins that are concurrently present at a certain moment in time. The failure condition is met when the health index reaches a value of zero. The model generated a time series (cycles) of sensed data that are often obtained from gas turbine engines in airplanes. The data that was created was utilized as challenge data for the Prognostics and Health Management (PHM) data competition held at PHM'08.

In their 2016 publication titled "NARX Time Series Model for Remaining Useful Life Estimation of Gas Turbine Engines," Bektas and Jones provided a prognostic model for gas turbine applications. This framework uses a data-driven approach by adapting current methods of nonlinear autoregressive neural networks with external input. The Nonlinear autoregressive exogenous inputs (NARX) model depends on the transformation of open and closed loop modes in order to predict multistep exponential development patterns using recorded historical data. The model, that is

used in Bektas and Jones’s study, gets trained first on a dataset to acquire knowledge about the operation of the engine. A separate subset of data is then used to make predictions regarding the future amount of wear. The utilization of the proposed methodology demonstrates that the NARX model is capable of efficiently detecting the unknown Remaining Useful Life (RUL) and accurately predicting the exponential degradation level of the system across several time steps.

“Wind Turbine Blade Damage Detection Using Supervised Machine Learning Algorithms” by Regan et al. [2017] proposes a method for detecting damage to wind turbine blades using supervised machine learning algorithms using data that is provided from acoustic waves that are generated because of the movement of the blades. The study begins by noting that damage to wind turbine blades can result in decreased power output, increased maintenance costs, and potential safety hazards. Therefore, early detection of damage is crucial. The authors collected data on various wind turbine blade conditions, including undamaged blades and blades with different types of damage. They then trained three supervised machine learning algorithms (k-nearest neighbors, support vector machine, and random forests) on this data to detect damage and evaluated the performance of each algorithm using metrics such as accuracy, precision, recall, and F1 score. They found that the random forest algorithm outperformed the other two algorithms in terms of accuracy, achieving an accuracy of 98.4%. The authors also tested the algorithm on a new set of data to evaluate its real-world performance. In short, this research demonstrates that supervised machine learning algorithms can be effective in detecting damage to wind turbine blades and suggests that this method could be incorporated into a wind turbine monitoring system to provide early detection of damage, thereby reducing maintenance costs and improving safety.

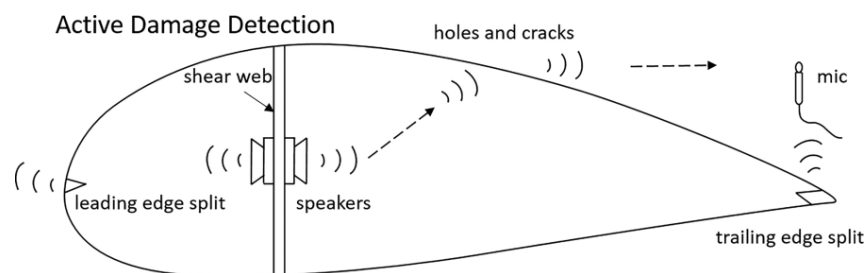


Figure 2.1. Schematic Drawing of Active Damage Detection [Regan et al., 2017].

Ghalandari et al. [2019] propose a hybrid machine-learning approach to optimize the aeromechanical performance of the first-row compressor blades. The study notes that the first-row compressor blades are critical components in gas turbine engines and that their aeromechanical performance is influenced by a range of design parameters. The authors first use a design of experiments (DOE) technique to generate a set of sample points in the design space. They then use an artificial neural network (ANN) to predict the aeromechanical performance of the blades at each sample point. The authors also use a genetic algorithm (GA) to optimize the design parameters of the blades based on the ANN predictions and evaluated the performance of the hybrid machine learning model by comparing it to a baseline model that used only the DOE technique. They found that the hybrid model outperformed the baseline model in terms of accuracy and efficiency, reducing the number of required simulations by 71%. The optimized design parameters showed a 20% improvement in the aeromechanical performance of the blades. Overall, this study demonstrates the effectiveness of a hybrid machine-learning approach for optimizing the aeromechanical performance of first-row compressor blades. The authors suggest that this approach could be used to optimize the design of other critical components in gas turbine engines, thereby reducing development costs and improving performance.

The major aim of the study, “Prognosis of Gas Turbine Remaining Useful Life Using Particle Filter Approach” by Ahsan et al. [2019], is to construct a hybrid model, combining the particle filter and Z-test, in order to predict the remaining useful life of a gas turbine. The case problem for this study is related to the NASA benchmark turbofan engine. The main results gained from the study are as follows:

- The utilization of the particle filter and Z-test approach has shown promising capabilities in terms of predicting the remaining useful life. These results are supported by the numerical figures of 559.9 and 21.6, which represent the score and MAPE (Mean Absolute Percentage Error), respectively. However, it has been shown that the existence of noise in measurements has an impact on the accuracy of predictions. Hence, the utilization of Wavelet or other de-noising mechanisms may potentially improve performance.

- The Z-test is an accurate technique to evaluate the initial stage of the particle filter. Therefore, the ability to correctly predict remaining useful life values was improved. As emphasized in the discussion section of the study, the particle filter method demonstrates good parameter estimation when a noticeable degradation or defect is recognized, rather than depending only on the initial trend when no problem has been observed. Therefore, the suggested methodology is more suitable for real-world applications since it effectively captures the significant variations in sensory signals following a fault occurrence.

The Z-test was utilized to determine the optimal starting point for the particle filter model. The authors stated that further research is needed to look into the potential application of the same methodology in identifying other transition points that may occur subsequent to gas turbine compressor wash or system repair. Additional topics that may be of significance include: (i) examining methods to minimize the computational time associated with using a large number of particles in particle filter models; (ii) studying the application of multiple sensor data in predicting remaining useful life; and (iii) integrating particle filter methodology with other approaches, such as multiple regression and computational intelligence [Ahsan et al., 2019].

Another study by Zagorowska et al. [2020] proposed a method for detecting and predicting performance degradation in offshore turbomachinery using adaptive machine-learning techniques. The authors note that performance degradation in offshore turbines can result in reduced power output, increased maintenance costs, and safety hazards. Therefore, early detection and prediction of performance degradation is crucial. Researchers first collect data on the operational and environmental conditions of offshore turbines, including rotor speed, power output, wind speed, and temperature. They found that the algorithm was able to detect and predict performance degradation with high accuracy, while also adapting to changes in the operational and environmental conditions of the turbines. Overall, this research demonstrates the effectiveness of an adaptive machine-learning approach for detecting and predicting performance degradation in offshore turbomachinery. The authors suggest that this method could be incorporated into a monitoring system for offshore turbines, providing early detection and prediction of performance degradation, thereby reducing maintenance costs, and improving safety.

The paper titled “Predicting Power Plant Equipment Life Using Machine Learning” by Gascon et al. [2020] proposed a method for predicting the remaining useful life (RUL) of power plant equipment using machine learning techniques. The study notes that predicting the RUL of equipment is crucial for maintenance planning and decision-making in the power plant industry. The authors first collected data on various operating conditions of the equipment, such as temperature, pressure, and vibration, and collect data on maintenance activities and equipment failures. They then used this data to train several machine-learning models, including logistic regression, decision trees, and random forests, to predict the RUL of the equipment, and evaluated the performance of each model using metrics such as mean absolute error and root mean squared error. They found that the random forest model outperformed the other models in terms of accuracy, achieving a mean absolute error of 5.5% and a root mean squared error of 7.7%. The researchers also tested the random forest model on a new set of data to evaluate its real-world performance and found that the model was able to predict the RUL of the equipment with high accuracy in this new set of data as well. In short, the paper demonstrates the effectiveness of machine learning models in predicting the RUL of power plant equipment and suggests that this method could be incorporated into a predictive maintenance system for power plants, allowing for more efficient maintenance planning and decision-making.

The study conducted by Rengasamy et al. [2020] showed the improvement of Remaining Useful Life (RUL) estimates for gas turbine engines by the utilization of deep learning models using asymmetrical loss functions. These functions operate by introducing a tendency towards early predictions, with the primary goals of optimizing cognitive bias modification (CBM) and ensuring safety. The objective of employing asymmetrical loss functions is to enhance the Remaining Useful Life (RUL) score, while keeping the deep learning architectures unchanged. The deep learning models underwent testing using both symmetrical loss functions, namely mean square error (MSE) and mean absolute error (MAE), as well as asymmetrical loss functions, including Mean Square Logarithmic Error-Mean Square Error (MSLE-MSE), Linear-Mean Square Error (LIN-MSE), Linear-Linear (LIN-LIN), and Quadratic-Quadratic (QUAD-QUAD). The results of the experiment showed enhancements in the Remaining Useful Life (RUL) metric on the CMAPSS dataset

through the utilization of three distinct deep learning architectures, namely Deep Neural Network (DNN), 1D Convolutional Neural Network (CNN1D), and Bidirectional Long Short-Term Memory (Bi-LSTM). These advantages were shown when an asymmetrical loss function was used. The authors also demonstrated that the advantages of asymmetrical loss functions over symmetrical loss functions are not universal, and that the identification of the most appropriate asymmetrical loss functions requires optimization and experimentation.

The study “Aircraft Engine Run-to-Failure Dataset under Real Flight Conditions for Prognostics and Diagnostics” by Chao et al. [2021] describes a dataset of aircraft engine run-to-failure data collected under real flight conditions for use in prognostics and diagnostics of aircraft engines. The authors note that real-world failure data is necessary for the development and evaluation of prognostic and diagnostic models. The dataset was collected from a commercial aircraft engine and includes sensor data on various engine operating conditions such as temperature, vibration, and pressure. The dataset also includes maintenance records and failure data. The authors use the dataset to demonstrate the effectiveness of prognostic models for predicting the remaining useful life (RUL) of aircraft engines. They apply various machine learning models, including linear regression, support vector regression, and neural networks, to predict the RUL of the engine based on sensor data, and evaluate the performance of each model using metrics such as root mean squared error and mean absolute percentage error. They found that the neural network model outperformed the other models in terms of accuracy, achieving a mean absolute percentage error of 4.8%. The paper demonstrates the use of the dataset for diagnostic purposes, identifying the root cause of engine failures using failure data and sensor data from the dataset, also provides a valuable dataset for the development and evaluation of prognostic and diagnostic models for aircraft engines. The authors suggest that this dataset could be used to improve the safety and efficiency of aircraft operations through more accurate prediction and diagnosis of engine failures [Chao, Kulkarni, Goebel, & Fink, 2021].

3.METHODOLOGY

A detailed literature review and research show that there isn't a proper attempt on this subject and the companies reject the share their datasets, the dataset was acquired from NASA's Prognostics Data Repository (2021), which was previously analyzed by Chao et al.'s study (2021). Figure 4 provides a diagram of the engine and the CMAPSS model's station numbers.

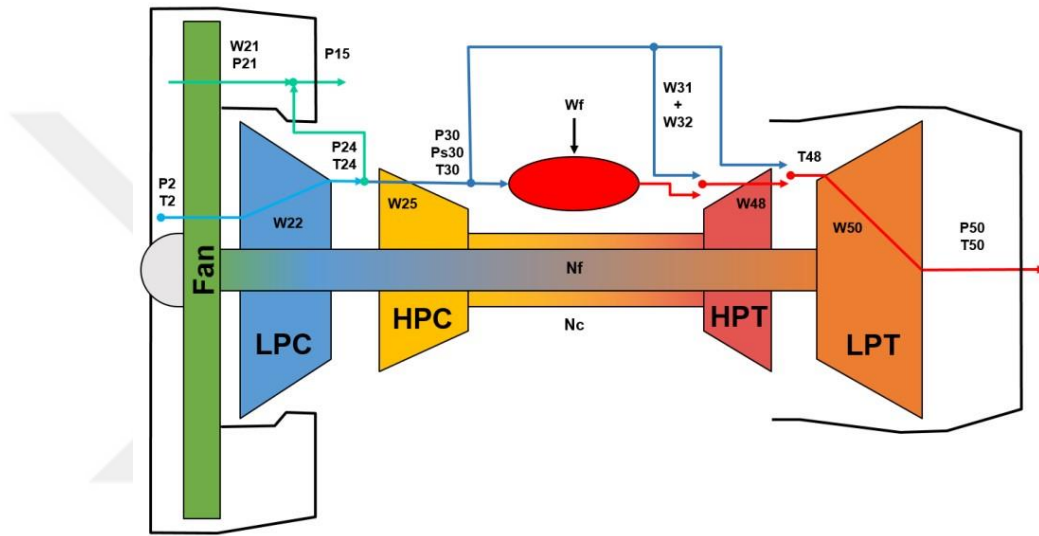


Figure 3.1. Schematic Representation of the CMAPSS Model [Chao et al., 2021].

The names, descriptions, and units of each input variable in the dataset are listed in Tables 3.1-3.4. In the CMAPSS model, the variable symbol corresponds to the internal variable name. The model documentation is used to generate the descriptions and units [Chao et al., 2021].

Table 3.1. Sensor Measurements and Their Units from Real Flight Conditions [Chao et al., 2021].

<i>Symbol</i>	<i>Description</i>	<i>Units</i>
<i>Wf</i>	Fuel flow	pps
<i>Nf</i>	Physical fan speed	rpm
<i>Nc</i>	Physical core speed	rpm
<i>T24</i>	Total temperature at LPC outlet	°R
<i>T30</i>	Total temperature at HPC outlet	°R
<i>T48</i>	Total temperature at HPT outlet	°R
<i>T50</i>	Total temperature at LPT outlet	°R
<i>P15</i>	Total pressure in bypass-duct	psia
<i>P2</i>	Total pressure at fan inlet	psia
<i>P21</i>	Total pressure at fan outlet	psia
<i>P24</i>	Total pressure at LPC outlet	psia
<i>Ps30</i>	Static pressure at HPC outlet	psia
<i>P40</i>	Total pressure at combustion chamber outlet	psia
<i>P50</i>	Total pressure at LPT outlet	psia

Table 3.2. Sensor Measurements and Units from CMAPSS [Chao et al., 2021].

<i>Symbol</i>	<i>Description</i>	<i>Units</i>
<i>T40</i>	Total temp. at burner outlet	°R
<i>P30</i>	Total pressure at HPC outlet	psia
<i>P45</i>	Total pressure at HPT outlet	psia
<i>W21</i>	Fan flow	pps
<i>W22</i>	Flow out of LPC	lbm/s
<i>W25</i>	Flow into HPC	lbm/s
<i>W31</i>	HPT coolant bleed	lbm/s
<i>W32</i>	HPT coolant bleed	lbm/s
<i>W48</i>	Flow out of HPT	lbm/s
<i>W50</i>	Flow out of LPT	lbm/s
<i>phi</i>	Ratio of fuel flow to Ps30	pps/psi

Table 3.3. Auxiliary Data of CMAPSS [Chao et al., 2021].

<i>Symbol</i>	<i>Description</i>	<i>Units</i>
<i>UNIT</i>	Unit Number	-
<i>CYCLE</i>	Flight cycle number	-
<i>FC</i>	Flight class	-
<i>HS</i>	Health state	-

Data that is used in this study has no damage or maintenance data but only a remaining useful life. Because of this case, damage data has been generated with relations that are gathered from Aust et al.'s study (2019). Table 4 shows these relations.

Table 3.4. Damage Relations Gathered from Aust et al.'s Study.

	<i>rpm</i>	<i>Temp.</i>	<i>Pre.</i>	<i>Flow</i>	<i>phi</i>
<i>Fatigue</i>	+	+	-	-	-
<i>Creep</i>	-	+	-	-	-
<i>Erosion</i>	-	+	+	+	-
<i>Abrasion</i>	-	-	-	+	-
<i>TMF</i>	-	+	+	-	+
<i>Corrosion</i>	-	+	-	-	+

In Table 5 which damage mechanisms occurred in components. To avoid overfitting, LPT damage mechanisms have been restricted to fatigue and creep.

Table 3.5. Damage Types for Components.

	<i>Fatigue</i>	<i>Creep</i>	<i>Erosion</i>	<i>Abrasion</i>	<i>TMF</i>	<i>Corrosion</i>
<i>LPC</i>	+	+	+	+	-	-
<i>HPC</i>	+	+	+	+	-	-
<i>CC</i>	+	+	+	-	+	+
<i>HPT</i>	+	+	+	-	+	+
<i>LPT</i>	+	+	-	-	-	-

For the study, all flight cases have been merged. Due to the large number of data, the computational power of the computer that was used for the study was not enough. Since that, a data reduction algorithm has been created. After the data reduction algorithm started data was reduced from sixty-nine million columns to ninety-nine columns. The flow chart of the data reduction algorithm has been given below in Figure 3.2.

At the flow chart, incoming data is CMAPSS output which is RUL. As can be seen in the flowchart whenever incoming data is zero, which is when gas turbine RUL equals zero, the algorithm finds minimum, maximum, mean, most occurring and how many times occurs most occurring data. After finding these variables, data have been compared with each other to generate damages. If the most occurring data is bigger than the mean data, and the difference between maximum data and mean data is bigger than the difference between mean data and minimum data; it is assumed that damage has occurred. With this approach, damage data has been generated. After the generation of damage data, data has been separated for each component's damage mechanism to lower computational time.

For the study, classification and convolutional neural network techniques have been chosen. The results of these two techniques have been compared in the Result section. Also, to check overfitting cross-validation has been done for two techniques.

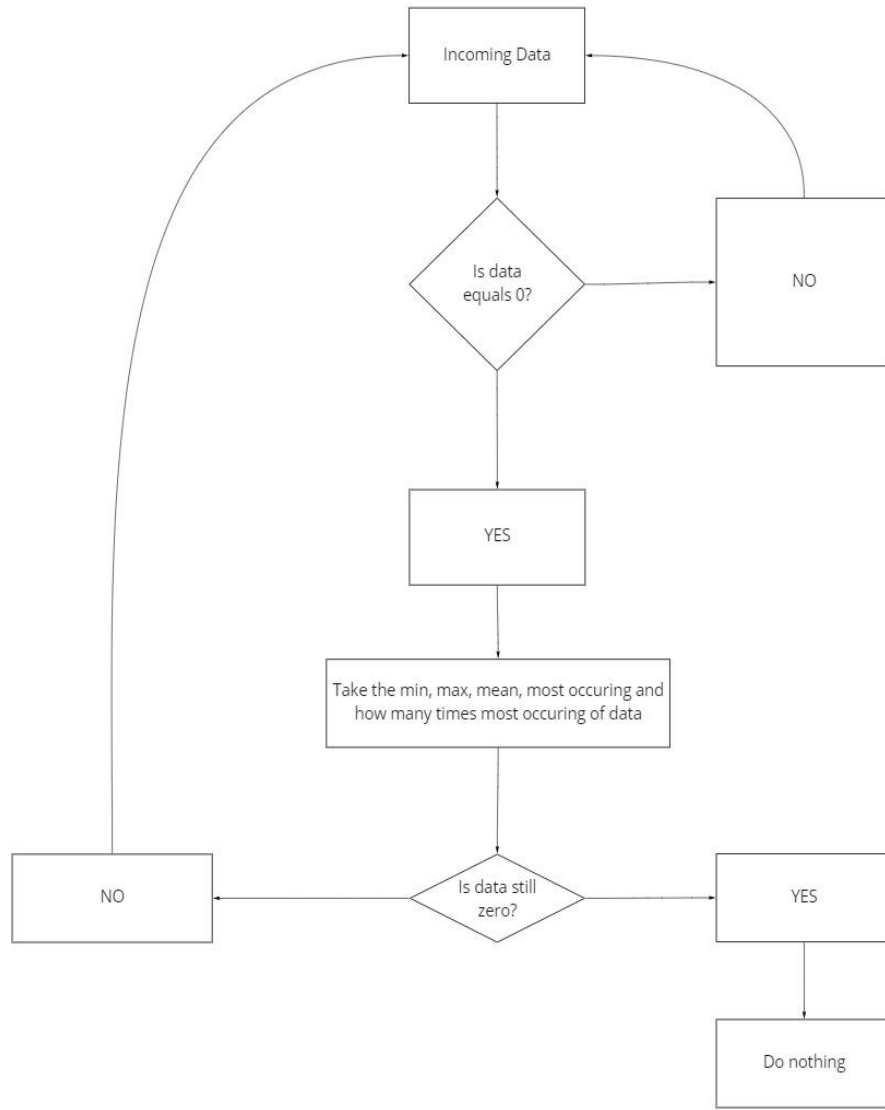


Figure 3.2. Flow Chart of Data Reduction Algorithm.

4.RESULTS

As above mentioned in the “Methodology” section; once the data processing stage is complete, classification and convolutional neural network techniques were selected as the Machine Learning algorithm due to their quick solution and ability to leverage computer power. Each damage for each component was individually inputted into the algorithm. 80% of the dataset was used for training the algorithm, while the remaining 20% was used for testing.

4.1. Classification

The metrics of each classification technique remained the same. For logistic regression; C equals 1. For k-nearest neighbor, neighbor number or n_neighbors equals 2, the distance metric is Minkowski and the power parameter for Minkowski is 2. For the support vector machine, the kernel metric is taken linear, and the same metric is taken rbf for Kernel SVM. The classifier has been chosen as Gaussian for naïve Bayes. The criterion is entropy for Decision Tree and Random Forest. And lastly, n_estimators equal to 10 for Random Forest.

Tables 4.1-4.5 which are shown below show the accuracy scores of each component’s damage mechanism. The cross-validation fold is 2 and the metrics for each technique have been kept the same.

Table 4.1. Accuracy Scores of LPC.

	<i>Fatigue</i>	<i>Erosion</i>	<i>Creep</i>	<i>Abrasion</i>
<i>LR</i>	0.95	0.96	1	0.98
<i>KNN</i>	0.91	0.97	0.77	0.99
<i>SVM</i>	0.85	0.95	1	0.98
<i>Kernel SVM</i>	0.71	0.94	0.71	0.99
<i>Naive Bayes</i>	0.86	0.86	1	0.99
<i>Decision Tree</i>	0.91	0.98	1	0.97
<i>Random Forest</i>	0.88	0.98	1	0.97

As can be seen from Table 4.1, the models' performance varies depending on which measures are used. For instance, the models consistently achieve high scores in Erosion, ranging from 0.94 to 0.98. On the other side, models had lower Creep ratings, with Kernel SVM having the lowest at 0.71. Some models perform well across the measures, such as Decision Tree and Random Forest, both of which receive the highest possible score of 1 for Creep and Abrasion. Other models, including Naive Bayes and SVM, have varied rankings across various measures.

Table 4.2. Accuracy Scores of HPC.

	<i>Fatigue</i>	<i>Erosion</i>	<i>Creep</i>	<i>Abrasion</i>
<i>LR</i>	0.94	0.98	0.90	0.98
<i>KNN</i>	0.91	0.94	0.93	0.96
<i>SVM</i>	0.94	0.97	0.97	0.98
<i>Kernel SVM</i>	0.67	0.88	0.83	0.94
<i>Naive Bayes</i>	0.88	0.90	0.85	0.94
<i>Decision Tree</i>	0.83	0.95	0.86	0.94
<i>Random Forest</i>	0.89	0.93	0.99	0.94

In Table 4.2, it can easily be seen that Random Forest typically outperforms other models in a variety of measures, frequently scoring at or near the top. SVM performs well across most measures as well.

Table 4.3. Accuracy Scores of Burner.

	<i>T.M.F.</i>	<i>Fatigue</i>	<i>Erosion</i>	<i>Creep</i>	<i>Corrosion</i>
<i>LR</i>	0.93	0.97	0.93	0.99	0.93
<i>KNN</i>	0.92	0.97	0.92	0.87	0.78
<i>SVM</i>	0.93	0.97	0.93	1	0.93
<i>Kernel SVM</i>	0.78	0.72	0.78	0.72	0.93
<i>Naive Bayes</i>	0.94	0.92	0.94	1	0.96
<i>Decision Tree</i>	0.94	0.96	0.94	1	0.95
<i>Random Forest</i>	0.94	0.92	0.94	1	0.95

Table 4.3 shows that Models from the SVM, LR, and Decision Tree families continue to excel. Additionally, displaying consistent performance across the measures are Naive Bayes and Random Forest.

Table 4.4. Accuracy Scores of HPT.

	<i>T.M.F.</i>	<i>Fatigue</i>	<i>Erosion</i>	<i>Creep</i>	<i>Corrosion</i>
<i>LR</i>	0.88	0.97	0.93	0.90	0.91
<i>KNN</i>	0.75	0.93	0.97	0.94	0.83
<i>SVM</i>	0.85	0.93	0.93	0.96	0.92
<i>Kernel SVM</i>	0.60	0.52	0.82	0.83	0.73
<i>Naive Bayes</i>	0.78	0.90	0.97	0.67	0.95
<i>Decision Tree</i>	0.81	0.90	0.96	1	0.96
<i>Random Forest</i>	0.86	0.91	0.92	1	0.93

According to Table 4.4, LR stands out as one of the better performers, scoring highly in the T.M.F., Fatigue, Erosion, and Corrosion categories. In some measures, SVM and Random Forest also perform favorably.

Table 4.5. Accuracy Scores of LPT.

	<i>Fatigue</i>	<i>Creep</i>
<i>LR</i>	0.91	0.96
<i>KNN</i>	0.84	0.96
<i>SVM</i>	0.93	0.96
<i>Kernel SVM</i>	0.79	0.96
<i>Naive Bayes</i>	0.89	0.98
<i>Decision Tree</i>	0.92	1
<i>Random Forest</i>	0.92	0.98

In Table 4.5, in terms of fatigue, SVM has the best score of 0.93, followed closely by LR, Decision Tree, and Random Forest, all of which receive 0.92. Apart from the Decision Tree, which receives a perfect score of 1, all models have the same Creep

score of 0.96. This shows that the Creep measure consistently yields good results for all models.

SVM, LR, Decision Tree, and Random Forest regularly stand up as high performers across a variety of measures, according to the data from tables 6-10. These models have strong generalization ability and may be trusted to do the tasks at hand. While Naive Bayes and KNN also demonstrate competitive performance in some criteria, their results may vary considerably between workloads.

4.2. Convolutional Neural Network

For the Convolutional Neural Network, 6 layers have been created. The loss function has been chosen as binary cross-entropy, and the optimizer is Adam.

Table 4.6 below shows the accuracy scores of each component's damage mechanism. The cross-validation fold is 2 and the metrics for each technique have been kept the same.

Table 4.6. Accuracy Scores of CNN.

	<i>TMF</i>	<i>Fatigue</i>	<i>Erosion</i>	<i>Creep</i>	<i>Corrosion</i>	<i>Abrasion</i>
<i>LPC</i>	-	0.67	0.94	0.71	-	0.76
<i>HPC</i>	-	0.67	0.79	0.83	-	0.75
<i>CC</i>	0.83	0.46	0.78	0.72	0.93	-
<i>HPT</i>	0.48	0.45	0.82	0.83	0.49	-
<i>LPT</i>	-	0.78	-	0.96	-	-

According to Table 4.6, CNN performs admirably on LPC in terms of abrasion, fatigue, and erosion. The performance in Fatigue and Abrasion on HPC is average. In terms of erosion, creep, and corrosion, CNN works on CC admirably. Except for creep, HPT's ratings are often lower, however, creep is the only statistic it excels in.

4.3. Clustering

4.3.1. Low Pressure Compressor

In all damage mechanisms for the clustering method used in the Low Pressure Compressor; the elbow method showed that three different clusters should be created for the damage mechanism. Clusters created for creep are not included in this section because the algorithm did not give the desired results.

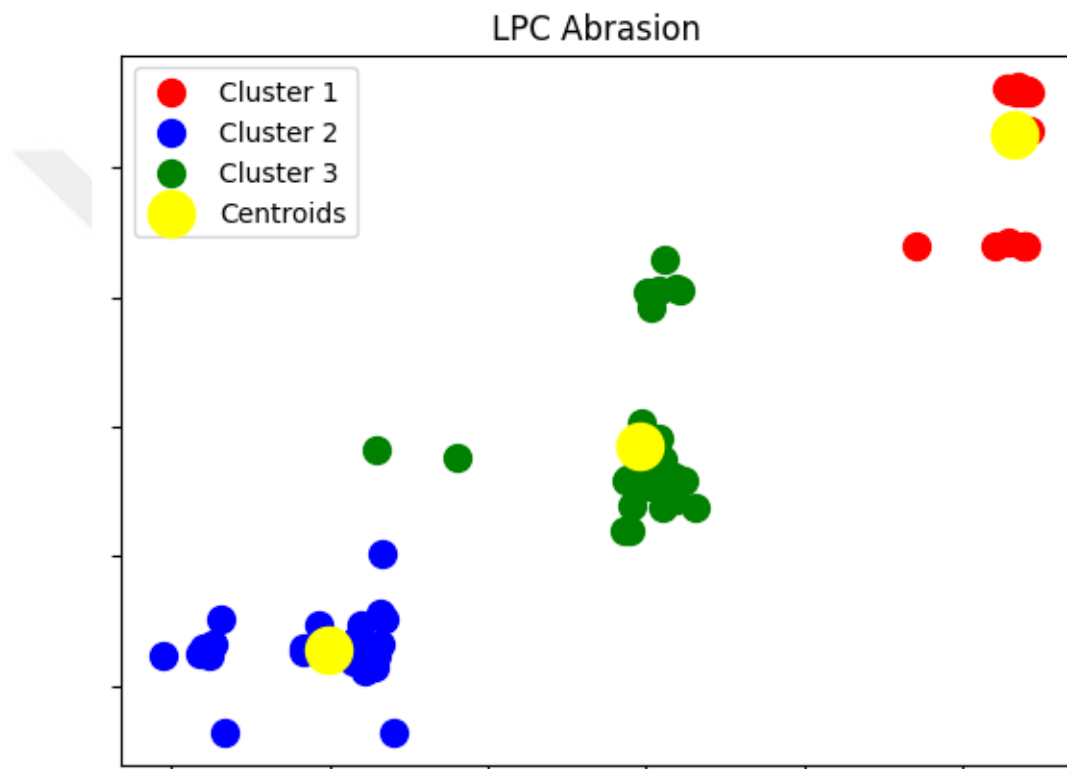


Figure 4.1. Clusters for LPC Abrasion.

In Figure 4.1, results in cluster 2 may be observed as no damage, and results in cluster 1 may be observed as damaged. Cluster 3 is interpreted as a possibility of damage.

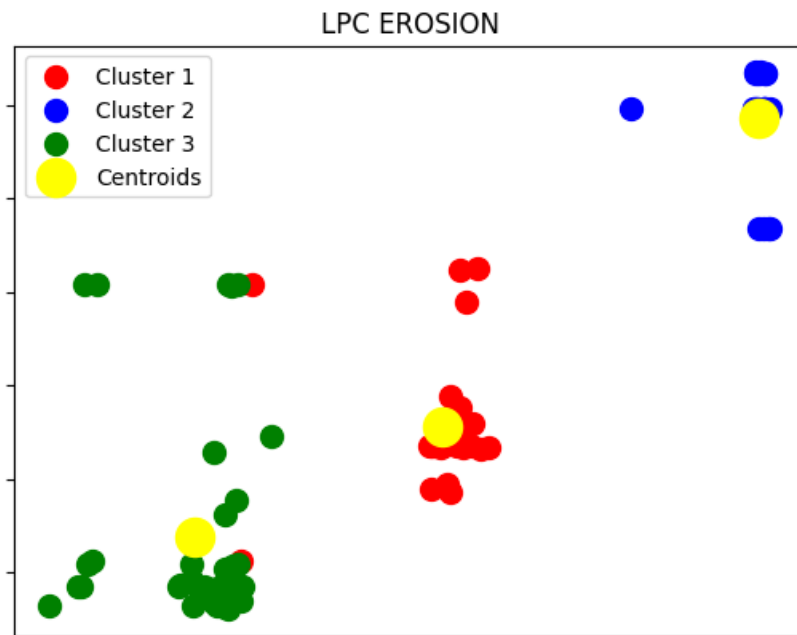


Figure 4.2. Clusters for LPC Erosion.

In Figure 4.2, results in cluster 3 may be observed as no damage, and results in cluster 2 may be observed as damaged. Cluster 1 is interpreted as a possibility of damage.

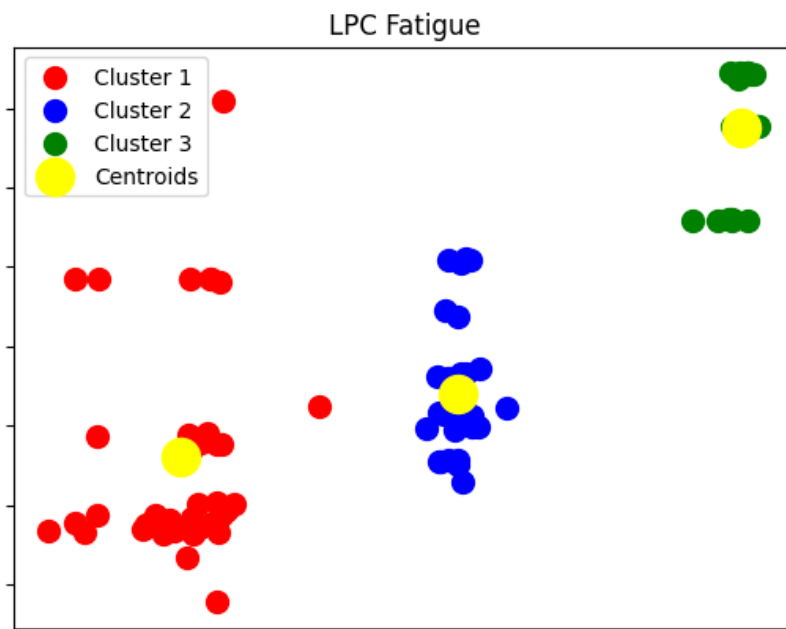


Figure 4.3. Clusters for LPC Fatigue.

In Figure 4.3, results in cluster 1 may be observed as no damage, and results in cluster 3 may be observed as damaged. Cluster 2 is interpreted as a possibility of damage.

4.3.2. High Pressure Compressor

In all damage mechanisms for the clustering method used in the High Pressure Compressor; the elbow method showed that three different clusters should be created for the damage mechanism. Clusters created for creep are not included in this section because the algorithm did not give the desired results.

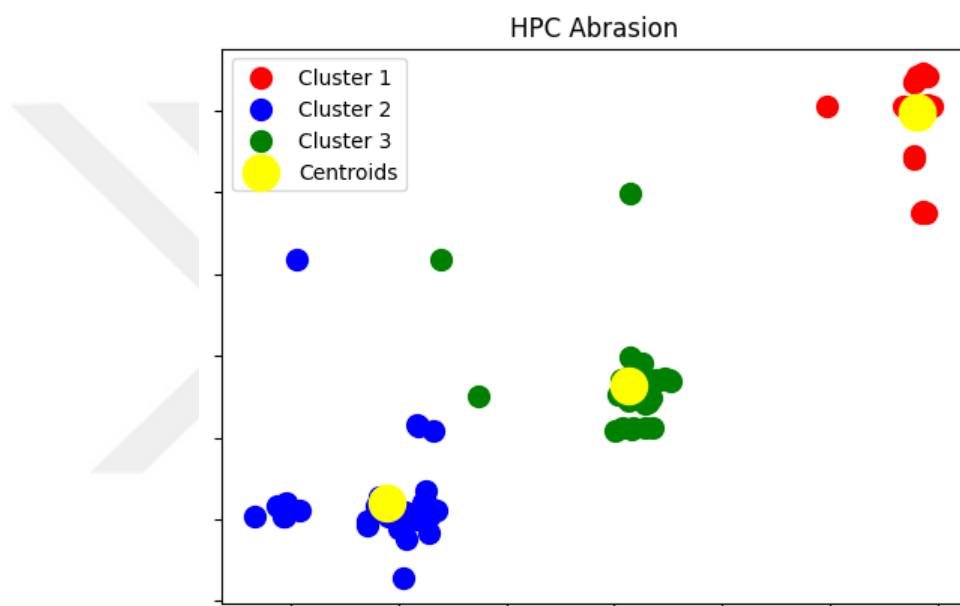


Figure 4.4. Clusters for HPC Abrasion.

In Figure 4.5, results in cluster 2 may be observed as no damage, and results in cluster 1 may be observed as damaged. Cluster 3 is interpreted as a possibility of damage.

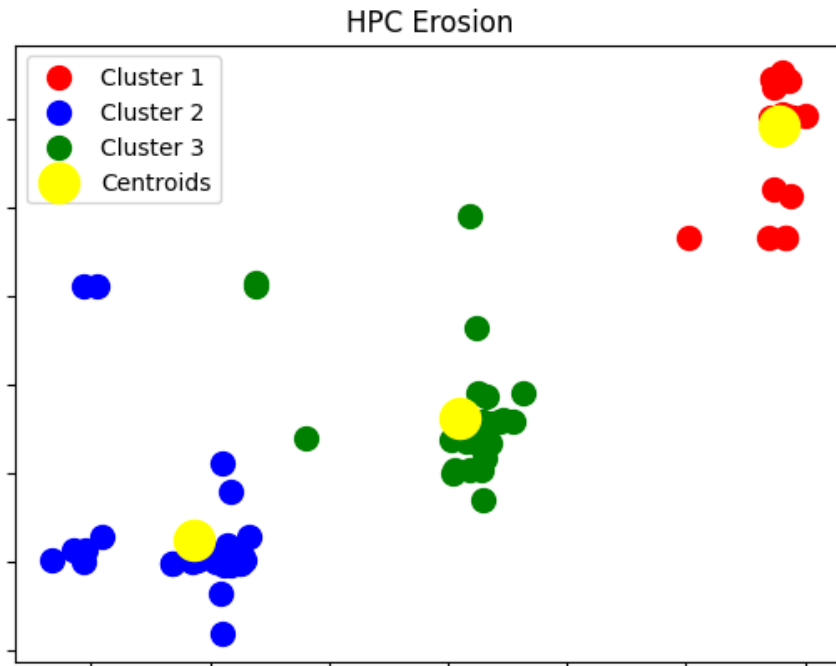


Figure 4.5. Clusters for HPC Erosion.

In Figure 4.5, results in cluster 2 may be observed as no damage, and results in cluster 1 may be observed as damaged. Cluster 3 is interpreted as a possibility of damage.

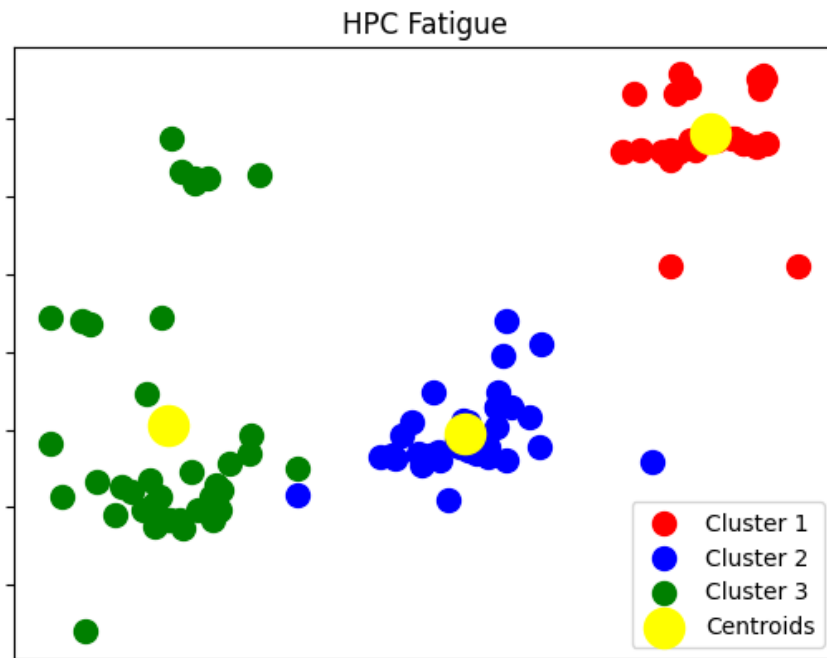


Figure 4.6. Clusters for HPC Fatigue.

In Figure 4.6, results in cluster 3 may be observed as no damage, and results in cluster 1 may be observed as damaged. Cluster 2 is interpreted as a possibility of damage.

4.3.3. Burner

In all damage mechanisms for the clustering method used in burner; the elbow method showed that three different clusters should be created for the damage mechanism, except for corrosion which are clusters numbers are 2.

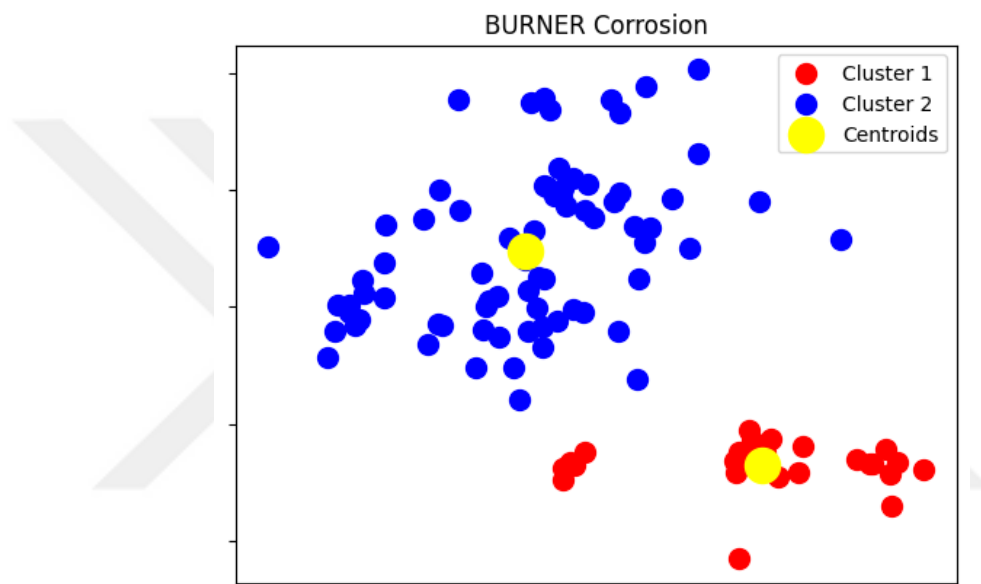


Figure 4.7. Clusters for Burner Corrosion.

In Figure 4.7., results in cluster 2 may be observed as no damage, and results in cluster 1 may be observed as damaged.

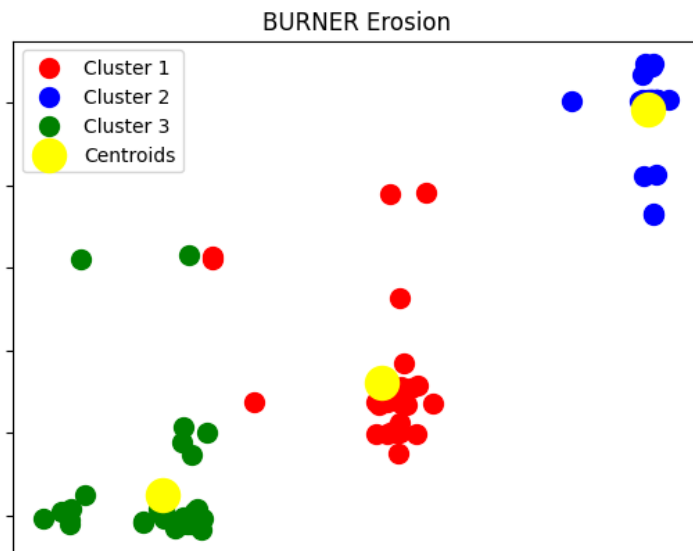


Figure 4.8. Clusters for Burner Erosion.

In Figure 4.8, results in cluster 3 could be observed as no damage, and results in cluster 2 could be observed as damaged. Cluster 1 is interpreted as a possibility of damage.

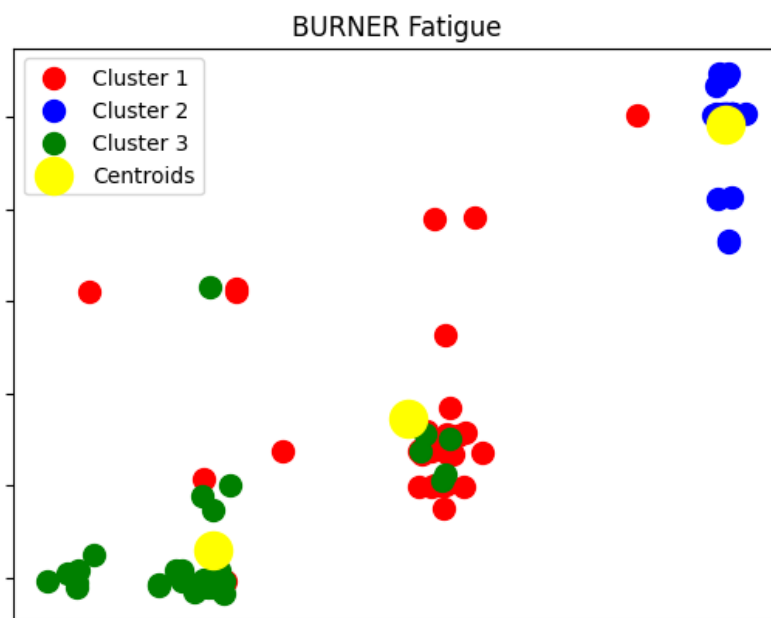


Figure 4.9. Clusters for Burner Fatigue.

In Figure 4.9, results in cluster 3 may be observed as no damage, and results in cluster 2 may be observed as damaged. Cluster 1 is interpreted as a possibility of damage.

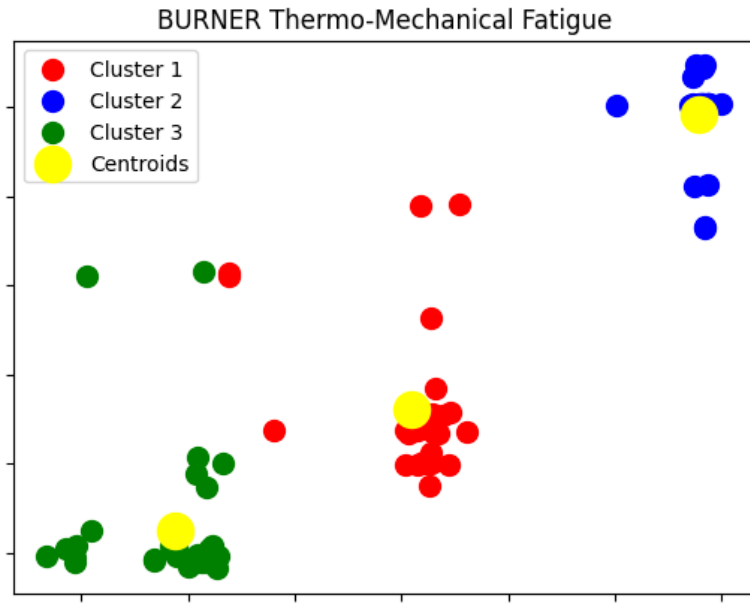


Figure 4.10. Burner Thermo-Mechanical Fatigue.

In Figure 4.10, results in cluster 3 may be observed as no damage, and results in cluster 2 may be observed as damaged. Cluster 1 is interpreted as a possibility of damage.

4.3.4. High Pressure Turbine

In all damage mechanisms for the clustering method used in the High Pressure Turbine; the elbow method showed that two different clusters should be created for all the damage mechanisms. Clusters created for creep are not included in this section because the algorithm did not give the desired results.

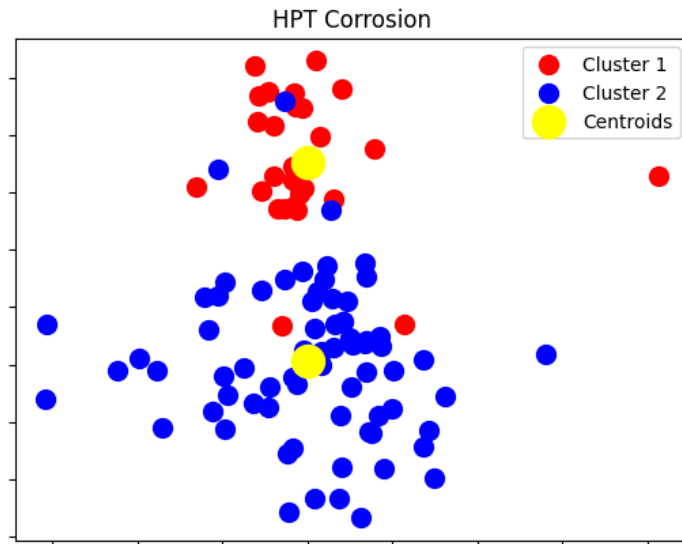


Figure 4.11. Clusters for HPT Corrosion.

In Figure 4.11, results in cluster 2 may be observed as no damage, and results in cluster 1 may be observed as damaged.

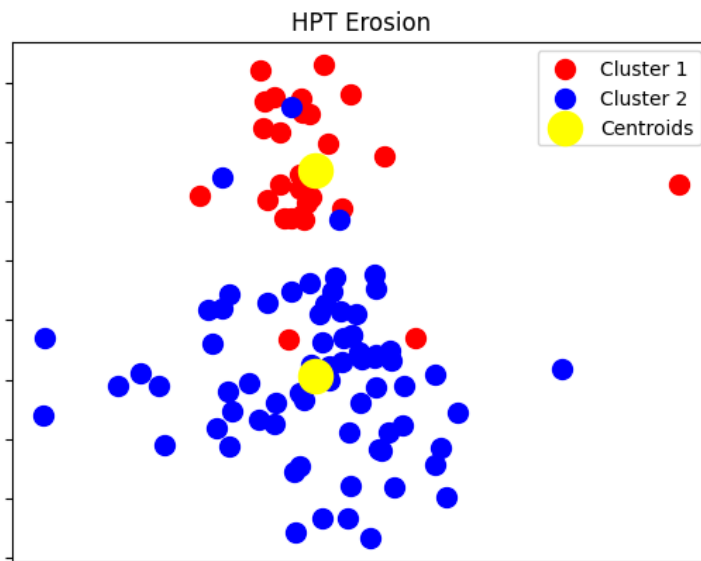


Figure 4.12. Clusters for HPT Erosion.

In Figure 4.12, results in cluster 2 may be observed as no damage, and results in cluster 1 may be observed as damaged.

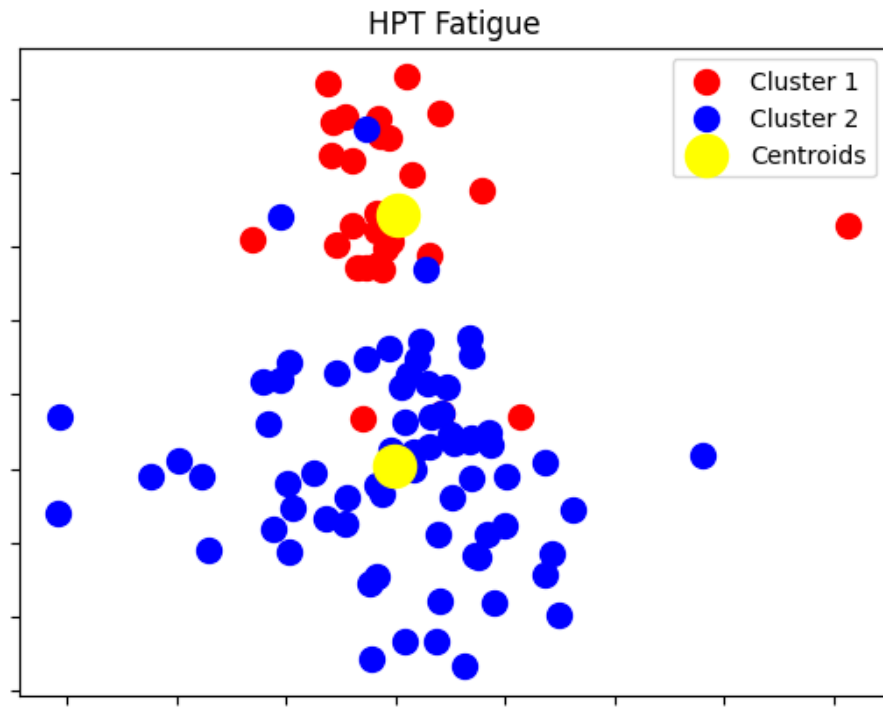


Figure 4.13. Clusters for HPT Fatigue.

In Figure 4.13, results in cluster 2 may be observed as no damage, and results in cluster 1 may be observed as damaged.

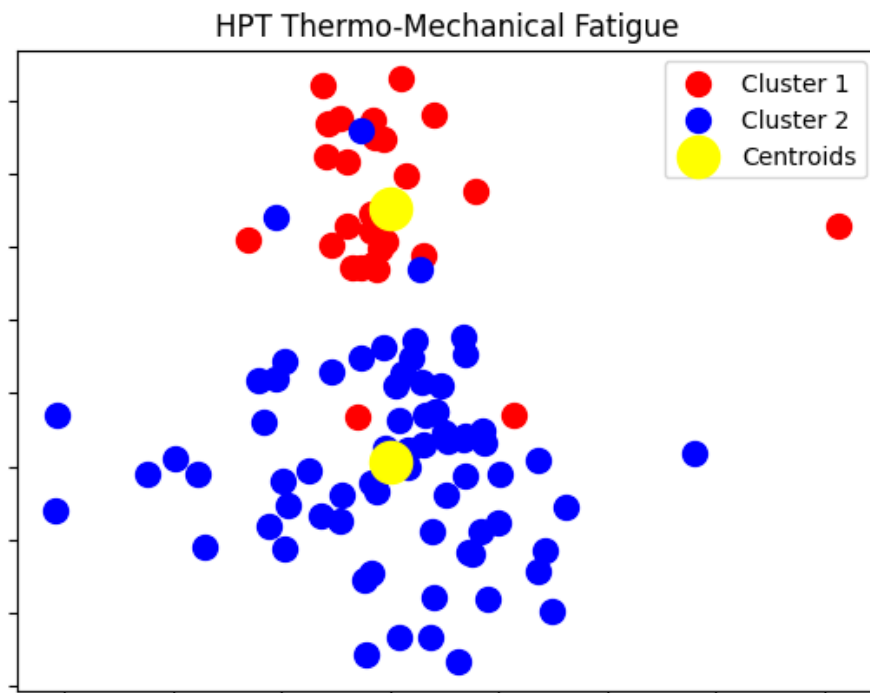


Figure 4.14. Clusters for HPT Thermo-Mechanical Fatigue.

In Figure 4.14, results in cluster 2 may be observed as no damage, and results in cluster 1 may be observed as damaged.

4.3.5. Low Pressure Turbine

In all damage mechanisms for the clustering method used in Low Pressure Turbine, the elbow method showed that three different clusters should be created for the fatigue's damage mechanism. Clusters created for creep are not included in this section because the algorithm did not give the desired results.

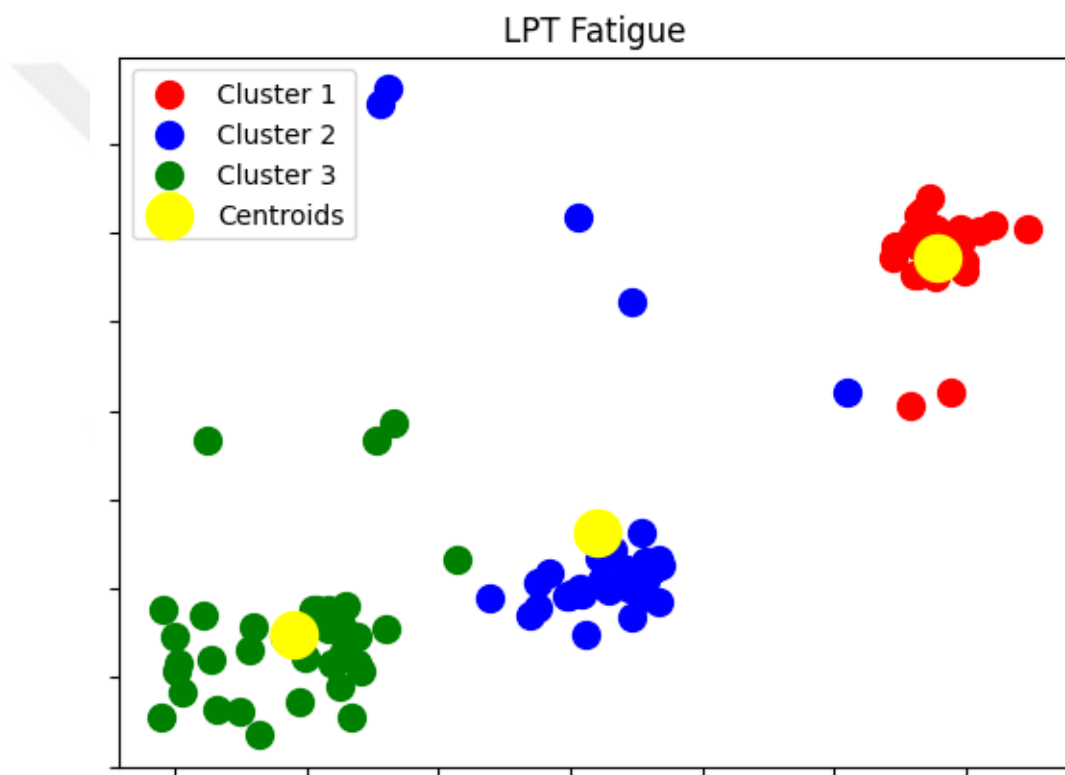


Figure 4.15. Clusters for LPT Fatigue.

In Figure 4.15, results in cluster 3 may be observed as no damage, and results in cluster 1 may be observed as damaged. Cluster 2 is interpreted as a possibility of damage.

CONCLUSION

The current work was conducted and demonstrated the potential of machine learning algorithms in detecting deterioration in turbomachine parts with a high degree of accuracy. In the Classification technique; SVM, LR, Decision Tree, and Random Forest methods were found to have the best accuracy overall. This is a significant development as traditional damage control procedures can be time-consuming and may miss undetected damage which may pose risks in the future. With the development of machine learning algorithms, it has been shown that a high level of accuracy can be achieved which can ultimately help to improve the safety and reliability of turbomachines. In addition, the Clustering Method was used in rule-based class labeling analysis and showed similarity in damage mechanisms. Although there are outliers in this analysis, this similarity is very important for future studies. It is also thought that outliers cause errors in other artificial intelligence methods. Working with real damage data will yield results for higher accuracy.

This development in machine learning algorithms is particularly relevant in the aviation industry, where safety is the top priority. Although the results of the study suggest high accuracy rates, there is still a concern that a false positive error may result in catastrophic consequences. It is believed that the lack of access to real data may contribute to this type of error. However, further research and development in this area will lead to improvements in the algorithm and reduce the costs and time required for maintenance periods, particularly in the aviation industry.

Despite these challenges, the energy sector is expected to benefit from this development in machine learning algorithms. With the ability to accurately detect damage and deterioration in gas turbines, the algorithm may reduce the time needed for damage detection during maintenance work, allowing businesses to resume operations sooner. This will potentially increase their profit margins by reducing the downtime and revenue loss associated with more extended maintenance periods.

This study can also start ethical problems. Both energy and aviation sector leaders would like to use this study even though the accuracy is not 100%. Because of the accuracy scores, some false positive scores can be generated, and this situation can lead to catastrophic results, such as hundreds of human lives if not thousands.

Overall, the study provides evidence that machine learning algorithms have great potential in the field of turbomachines. Further research and development may lead to even more effective methods for detecting damage and deterioration in these critical components, ultimately improving their safety and reliability. While there are still challenges to overcome, the benefits of this development in the energy and aviation industries cannot be overstated.

For future studies, together with more data, a study can be conducted to predict what kind of damage will occur in which component at which stage. Thus, this process can be achieved by using vibration data. In addition, joint studies can be carried out with aviation authorities such as EASA, FAA, DGCA, and ICAO.



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BIOGRAPHY

Ahmet Devlet Özçelik, After finishing primary, secondary and high school in Denizli, he settled in Ankara to get his university education. Ahmet Devlet Özçelik, who completed his undergraduate education in the Department of Mechanical Engineering at TOBB University of Economics and Technology, moved to İzmir to pursued for his master's degree Department of Mechanical Engineering at Dokuz Eylül University. Having started to work as a research assistant at Istanbul Gelişim University Aircraft Maintenance and Repair Department in October 2019, Ahmet Devlet Özçelik settled in Istanbul. To complete his master's degree at a nearby university, he is selected for the Department of Mechanical Engineering at Gebze Technical University. Since 2020 Ahmet Devlet Özçelik published 3 articles about Kamikaze Drones and working on Thermodynamics, Artificial Intelligence and Computer Vision.



PUBLICATIONS AND PRESENTATIONS FROM THE THESIS

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