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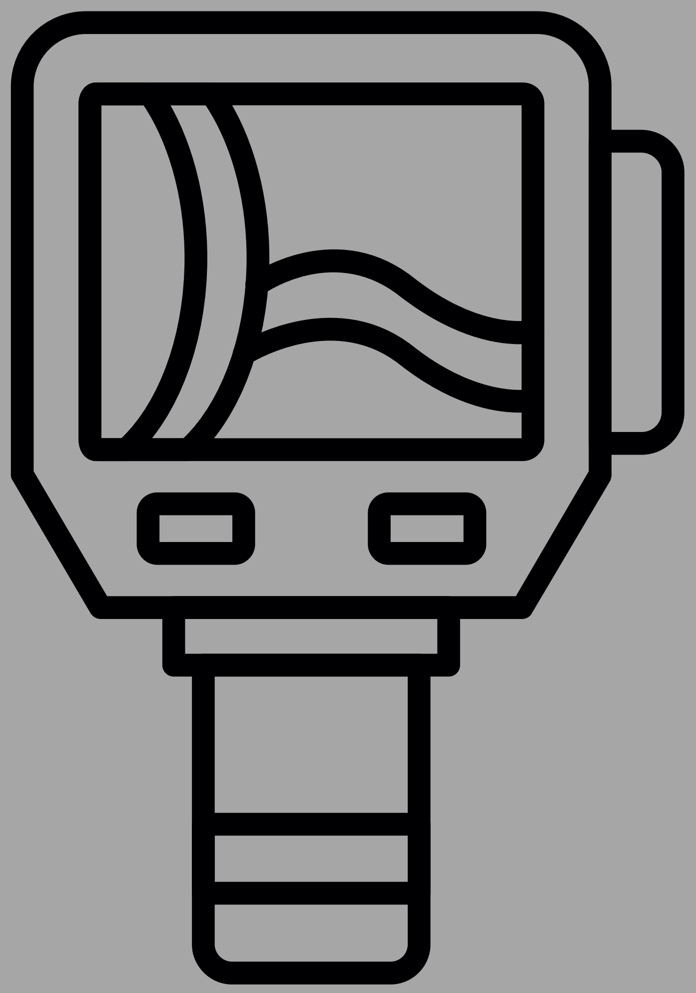
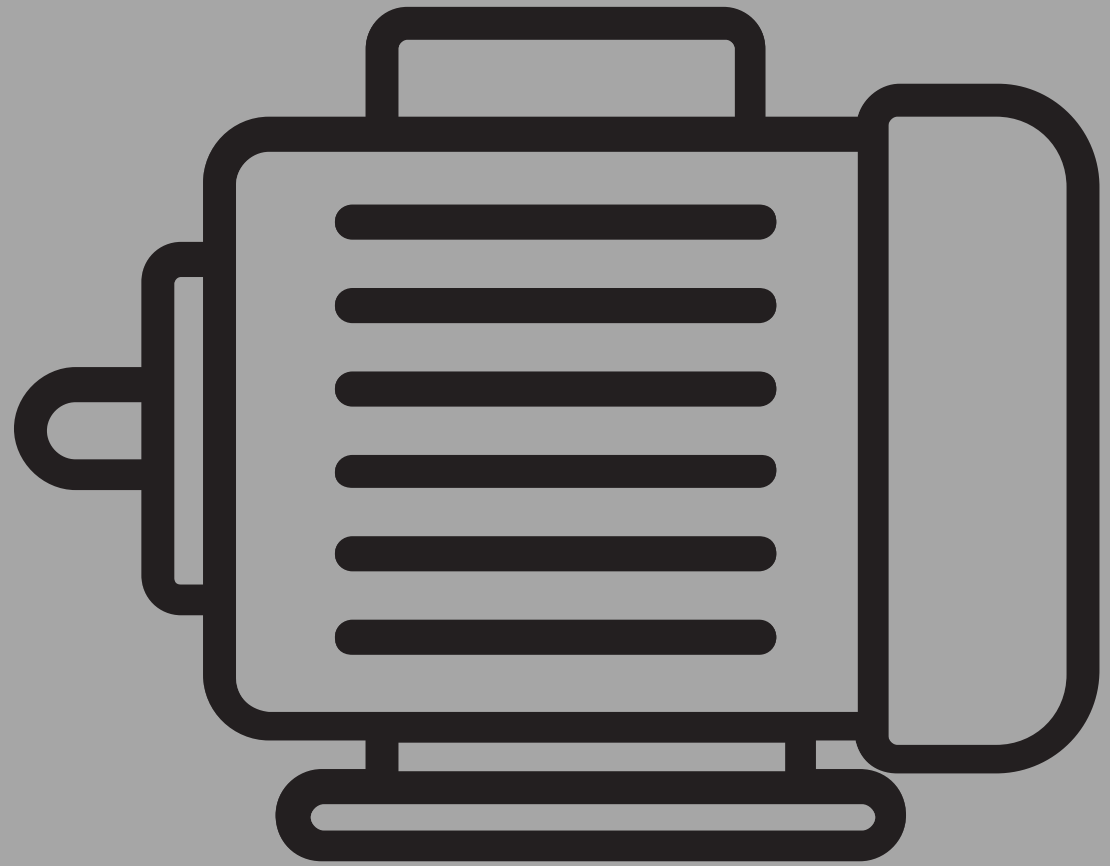
DETECTION OF MECHANICAL FAILURES IN AC MOTORS USING THERMOGRAPHIC IMAGING

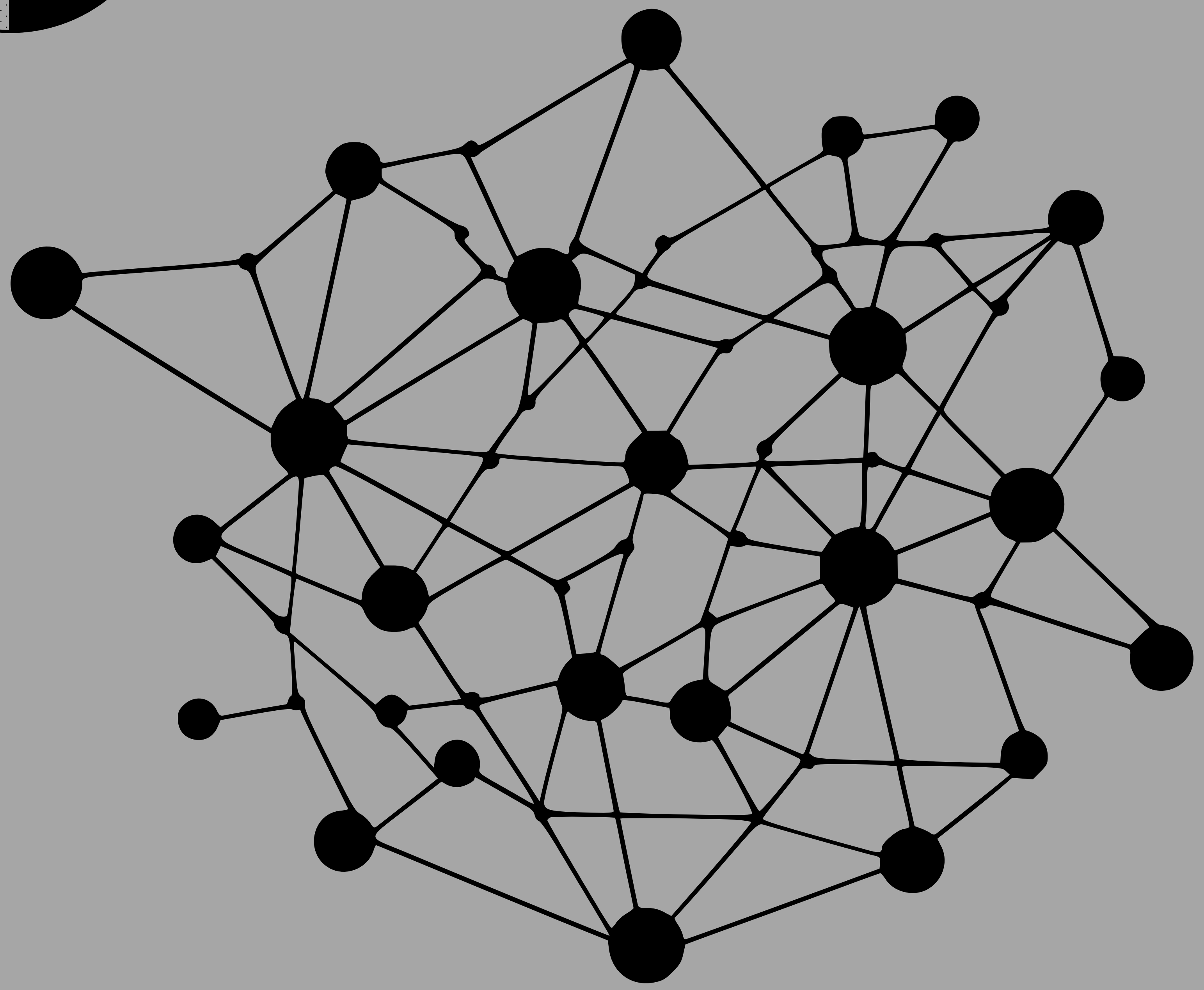




Group 10

Data and Model Based Control

November, 2024



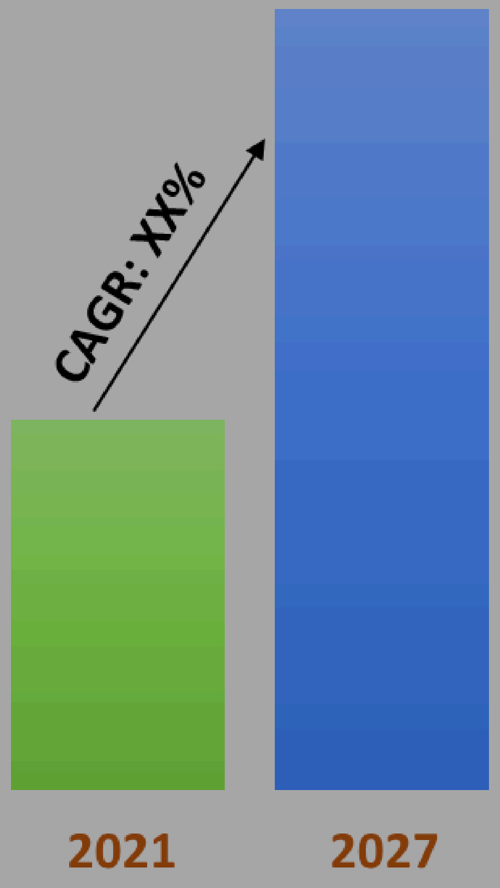
Content

Introduction

INDUSTRY AT A GLANCE

Global Electric Motor Market

Industry Size Forecast



Base Year

2020

Forecast Period

2021-2027

Largest Type

AC Motor

Largest Market

North America

Output Power

- IHP
- FHP

Application

- Industrial Machinery
- Motor Vehicle
- HVAC Equipment
- Aerospace & Transportation
- Household Appliance

Regions Covered

- **North America** (US, Canada, Rest of North America)
- **Europe** (UK, France, Germany, Spain, Rest of Europe)
- **Asia-Pacific** (China, Japan, Australia, India, South Korea, Rest of Asia-Pacific)
- **Rest of World**

Key Industry Players

ABB, ASMO, FAULHABER, EMERSON, ARC Systems Inc., BROOK CROMPTON, maxon, REGAL

AC electric motors account for 53% of electricity consumption in industrial and commercial environments.

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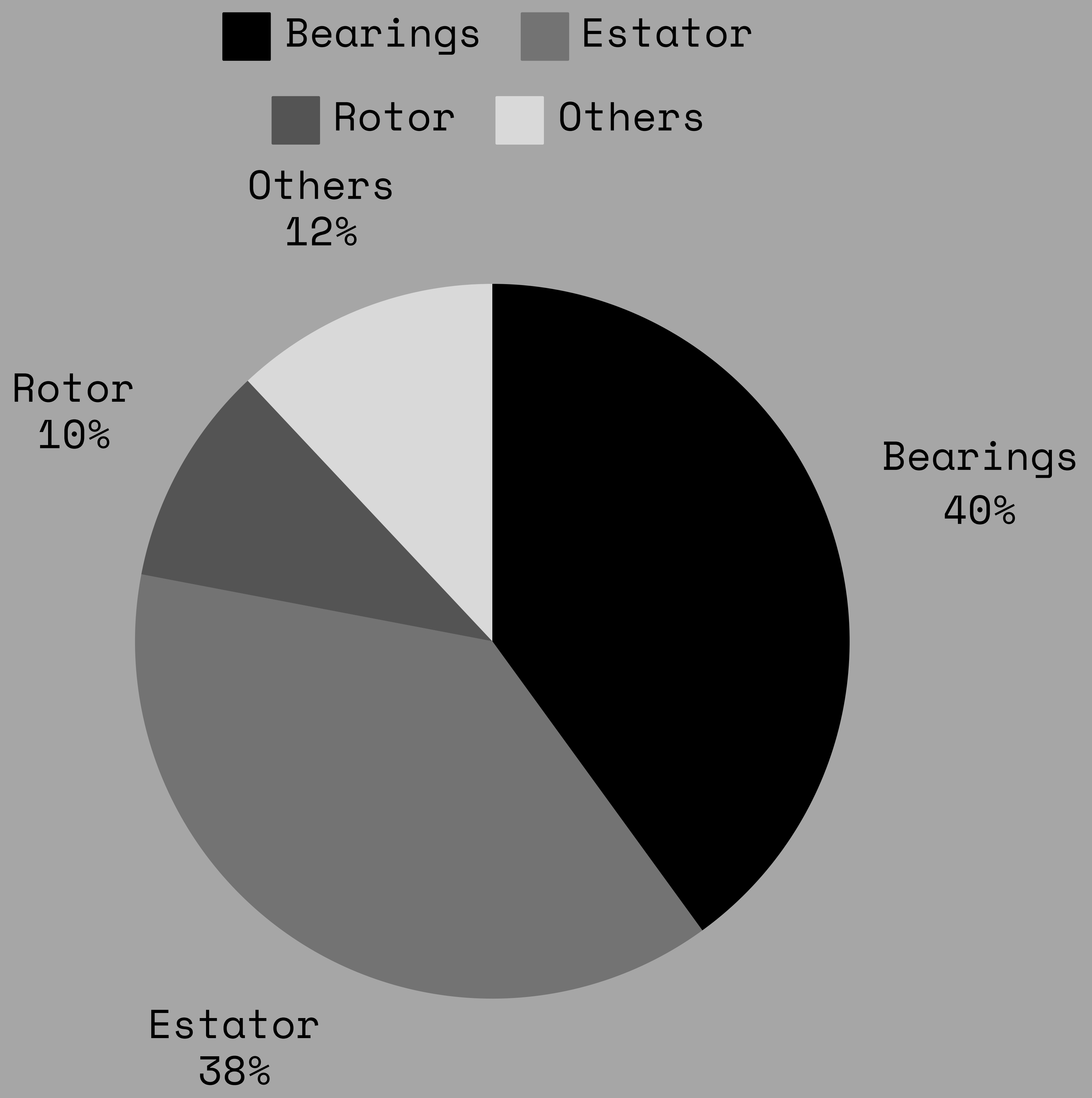
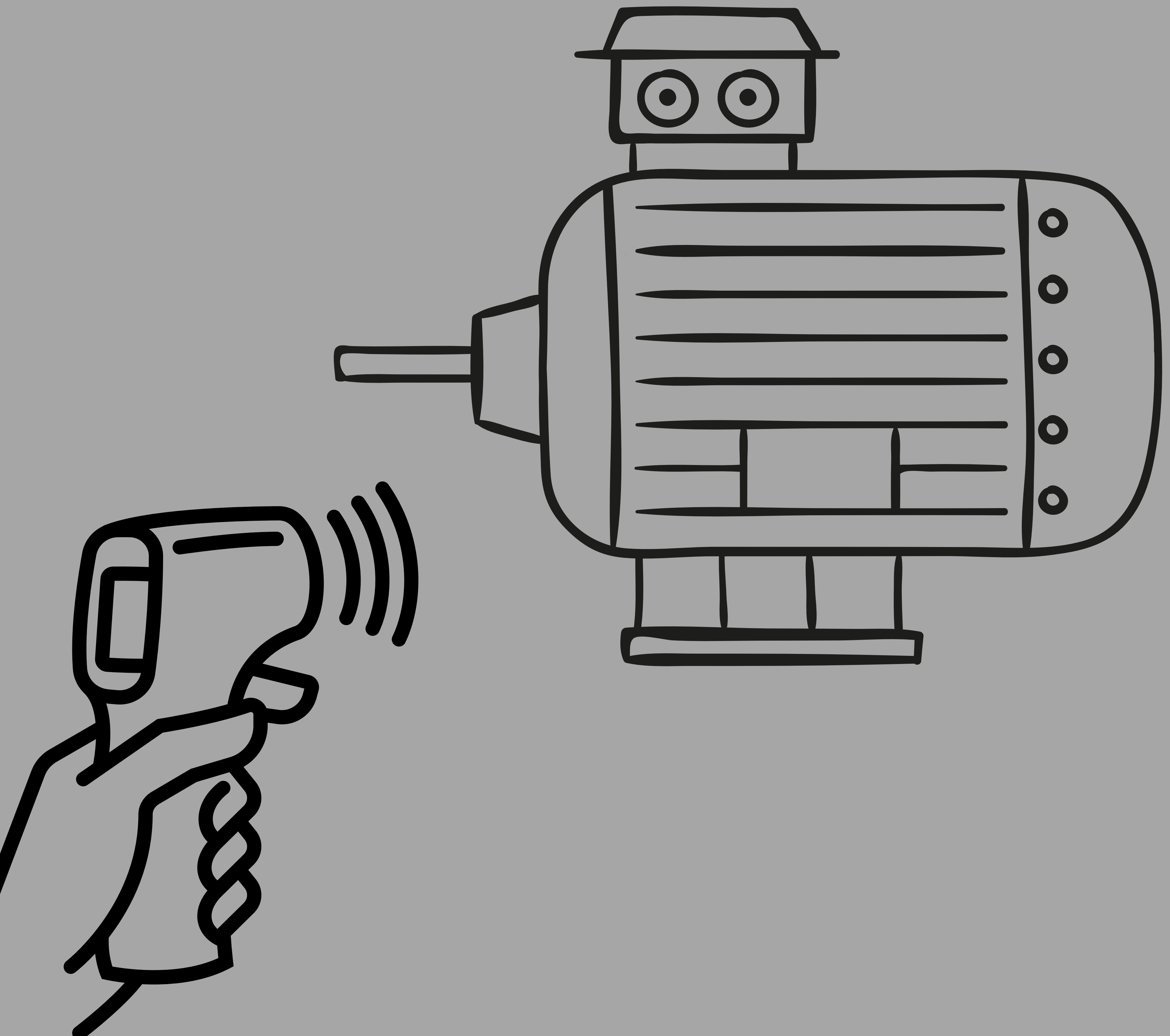
Failures in the AC motors

They manifest themselves in overheating, vibrations and abnormal noises and/or loss of power.
They can lead to serious and costly plant damage.



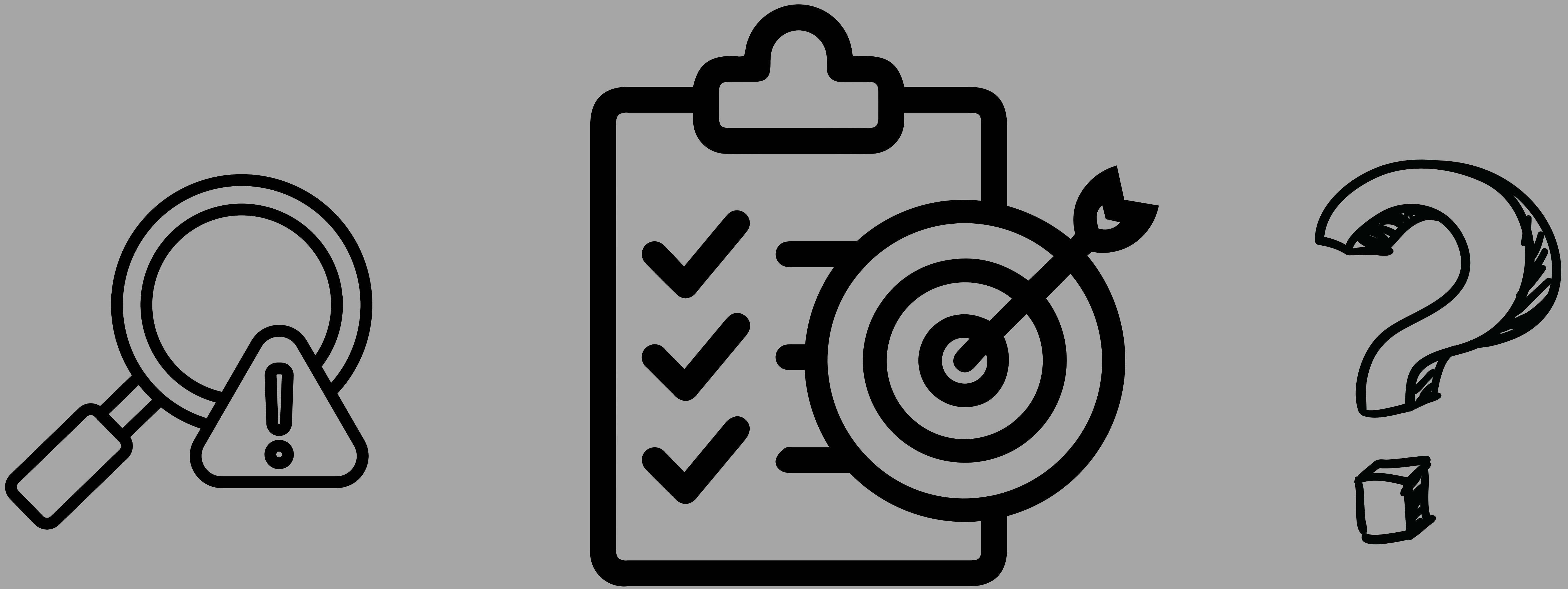


AC Motor Fault Detection Methods

The surface temperature distribution of the engine components is shown.

Abnormal heat patterns are detected indicating the presence of internal faults.

PROBLEM AND OBJECTIVES



Problematic

- High frequency of mechanical failures in MCLs
- Deficiency of early detection of these problems
- Need for the use of non-invasive methods
- Lack of precision in conventional methods

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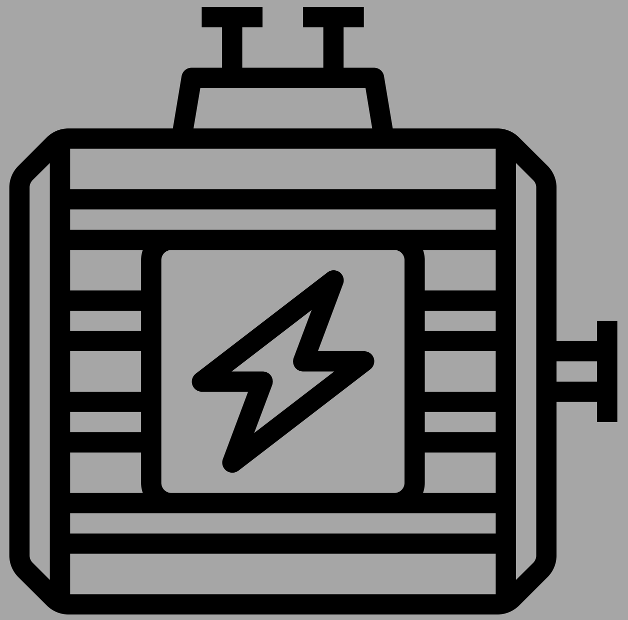
General Objective



To explore and evaluate the effectiveness of using the method under study (thermographic analysis + CNN) as a technique for the detection of mechanical failures in AC motors (ACM).

Specific objectives

Identify the types of MCA failures to be studied.

Search through previous studies.

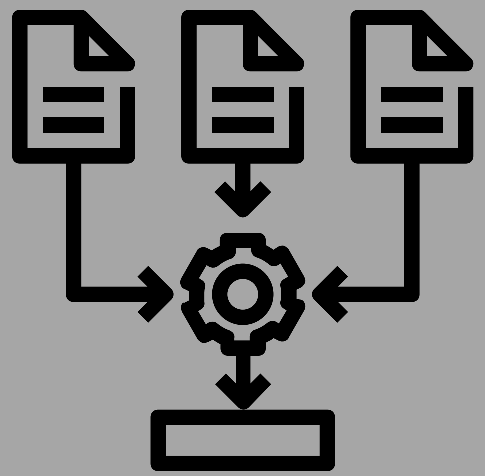
Data collection

Gather relevant thermographic image data sets that include previously selected mechanical failures.

Data preprocessing

Improve data quality, eliminate noise and enhance class differences.

Specific objectives

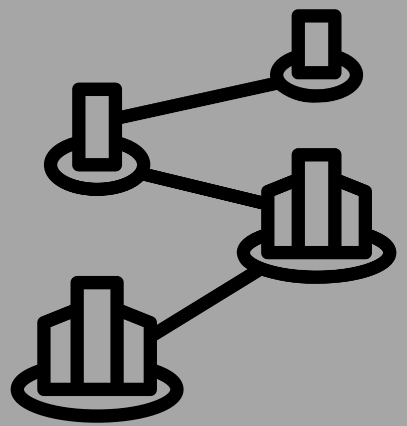


Classifier method training

Test different architectures and adjust necessary parameters to maximize performance and accuracy.

Evaluation of the chosen classifier method

Tests to corroborate the performance of the classifier method: Accuracy, F1-score, Recall.



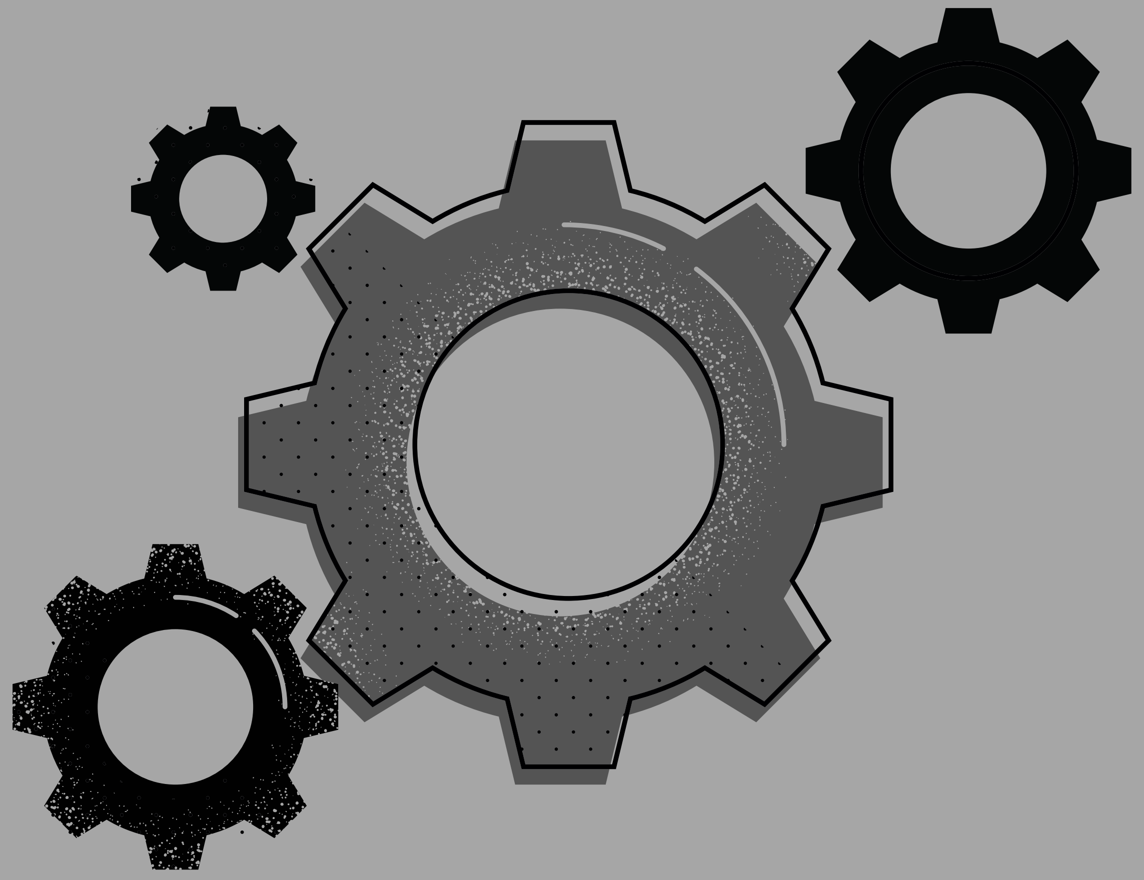
Scalability of the proposed model

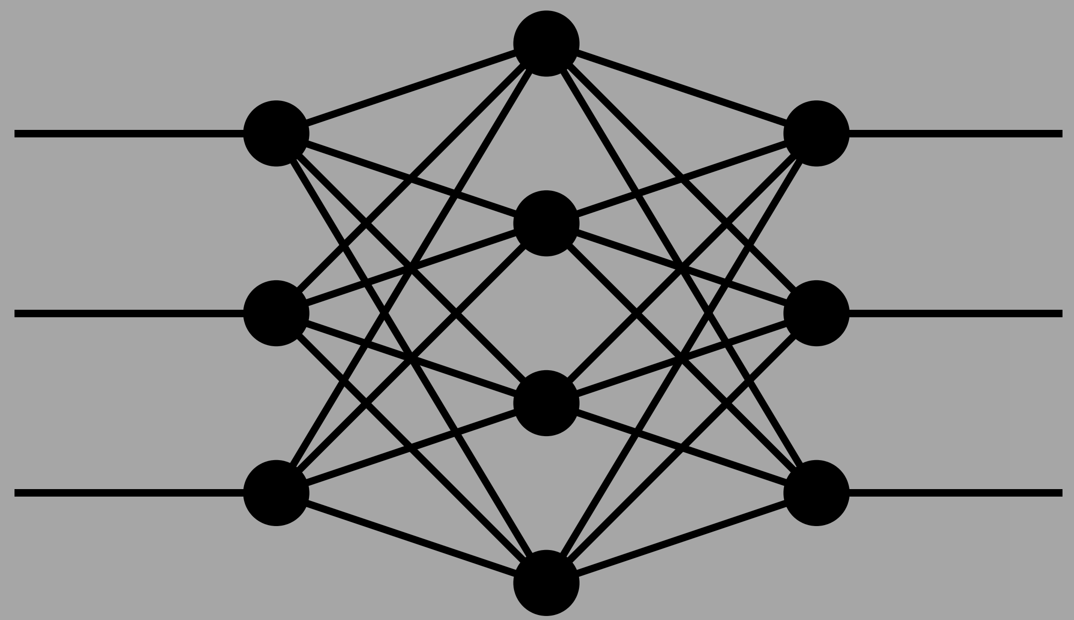
Adjustment of hyperparameters and use of assembled models.

Specific objectives

Contribution to the SDGs

Industry, Innovation and Infrastructure.
Responsible Production and Consumption.





KEY CONCEPTS

AC motors

Mechanical failures

Electrical faults

Thermography

Radiation

Infrared thermography

Mechanical failures

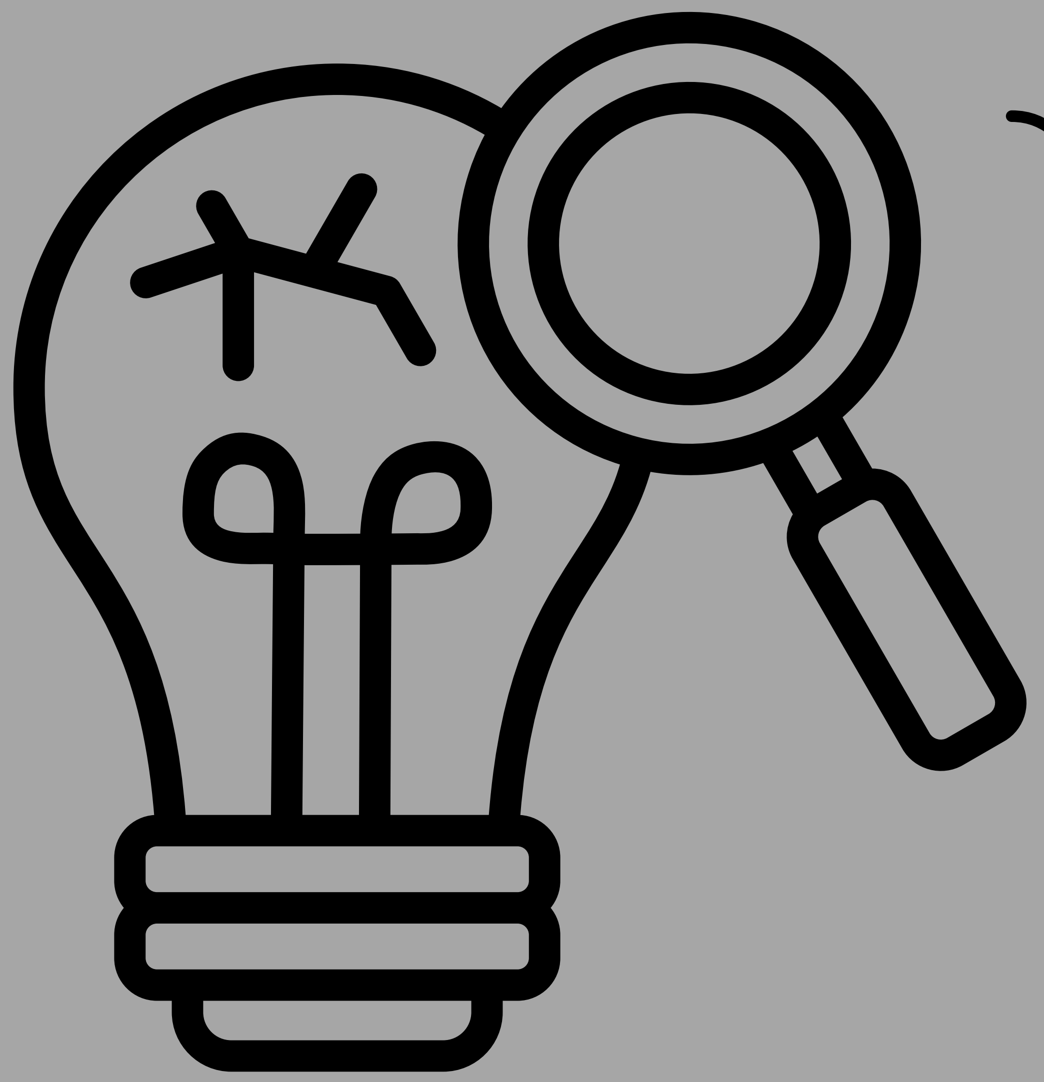
- **Bearing wear (BD):** Its main cause is friction and material fatigue producing excessive vibrations.

- **Misalignment (MSL):** Engine parts are not properly aligned causing vibration and accelerated component wear.

Electrical faults

- **Short circuit in the stator coils (ECF):** Due to excessive wear of the insulation between coils allowing unwanted current flows.

- **Rotor bar breakage (BRB):** Common in squirrel cage motors refers to the breakage of one or more conductor bars of the conductor. Caused by fatigue or vibration.



Radiation

Energy emitted by matter in the form of electromagnetic waves as a result of changes in the electronic configurations of atoms.

Infrared thermography

Science of study of optoelectronic devices to detect and measure radiation to obtain the temperature of the analyzed surface.

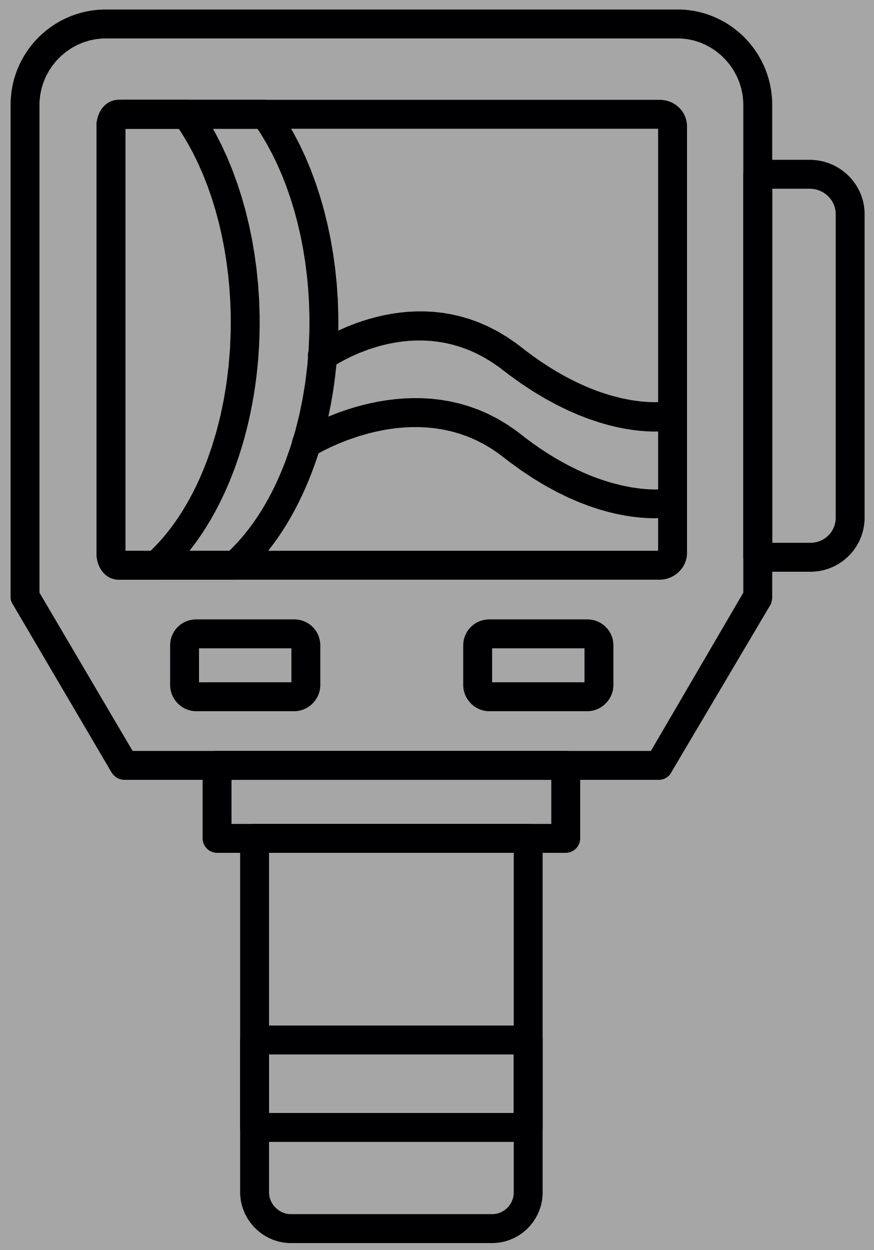


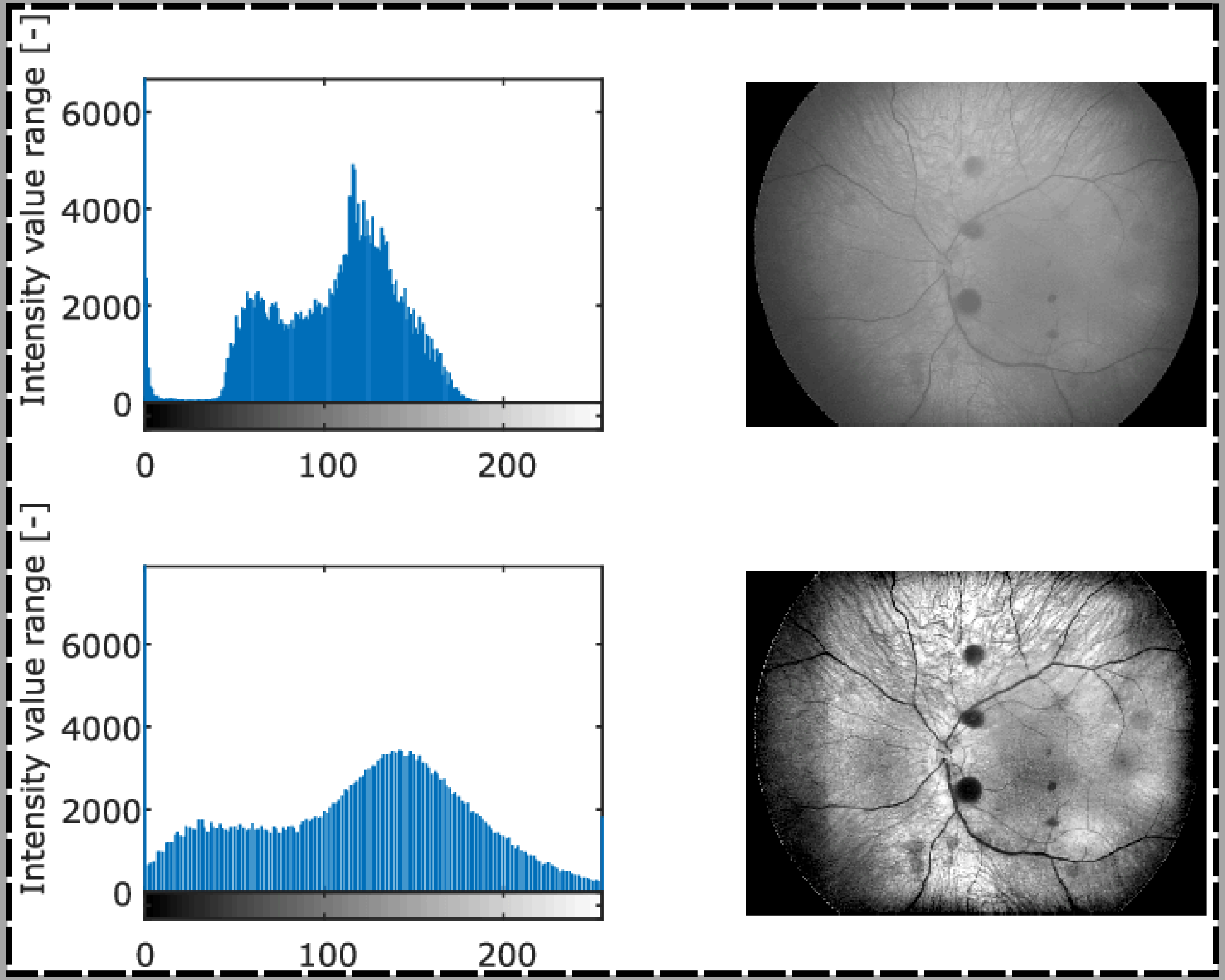
Image preprocessing

Contrast limited adaptative histogram equalization

Discrete Wavelet transform

Image segmentation

Hue Saturation Intensity (HSI)



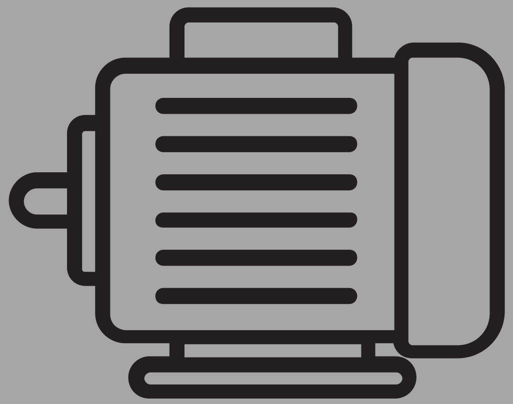
CLAHE

Method that constructs a histogram of pixel intensity and then increases the length of each value, thus increasing the contrast throughout the image.

Segmentation

Yolov5

Object detection model based on CNN known for its high speed and accuracy. Developed by Ultralytics, easy to use and train in pytorch.



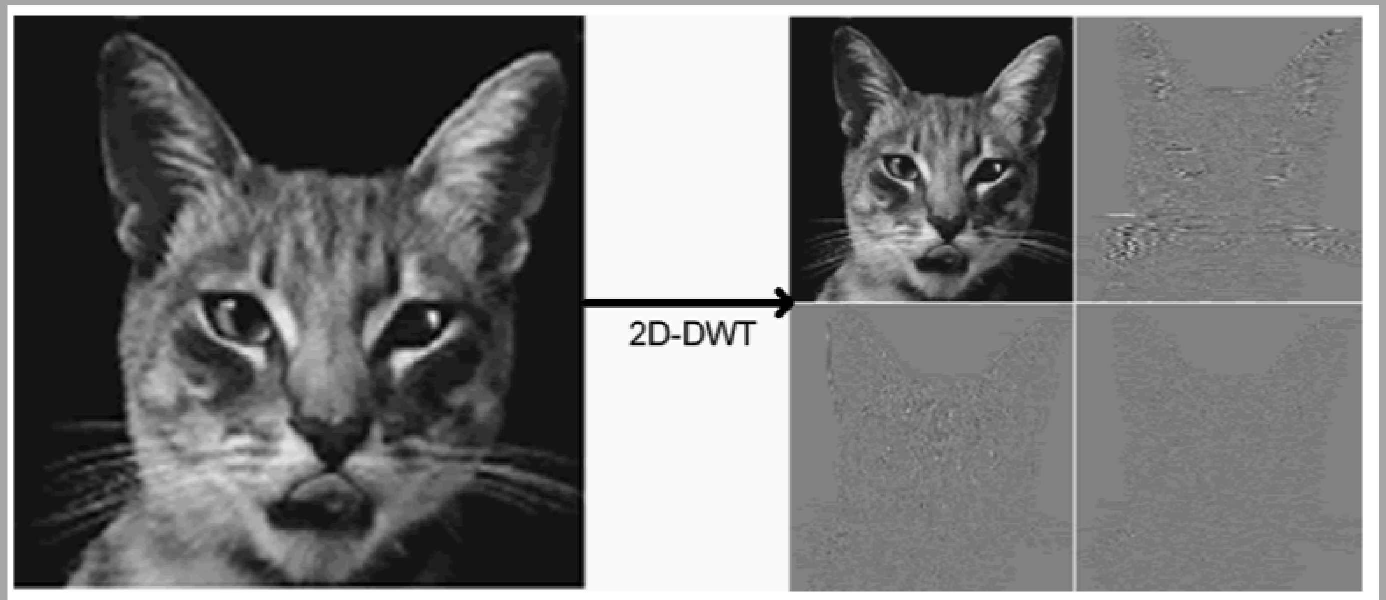
Otsu Threshold

It calculates an optimal threshold that separates background pixels automatically by analyzing intensity histograms.

K-means clustering

Divide the data into k groups according to their proximity to the centroids. Iterates by assigning points and recalculating centroids until the groups are stabilized.

Wavelet Discrete Transform



Decomposition of signals into frequencies. It is applicable to both images and audio.

cA

Low frequency subband:
Represents a simplified version of the original image while retaining its general characteristics and most of the energy information.

cH

High frequency subband in the horizontal direction:
Highlights transitions or rapid changes in image intensity along horizontal contours.

cV

High frequency subband in the vertical direction:
Represents sharp contrasts in vertical contours or edges.

cD

Subband of high frequencies in the diagonal direction:
Contains frequencies in both directions showing intensity changes in the diagonals highlighting edges and contours.

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Hue Saturation Intensity (HSI)

Hue

Represents the type of color defined as an angle in a color circle. It differentiates one color from another.

Saturation

Indicates how vivid or intense a color is.

Intensity

Color brightness measured on a scale from 0 (black) to 1 (white).

Image preprocessing

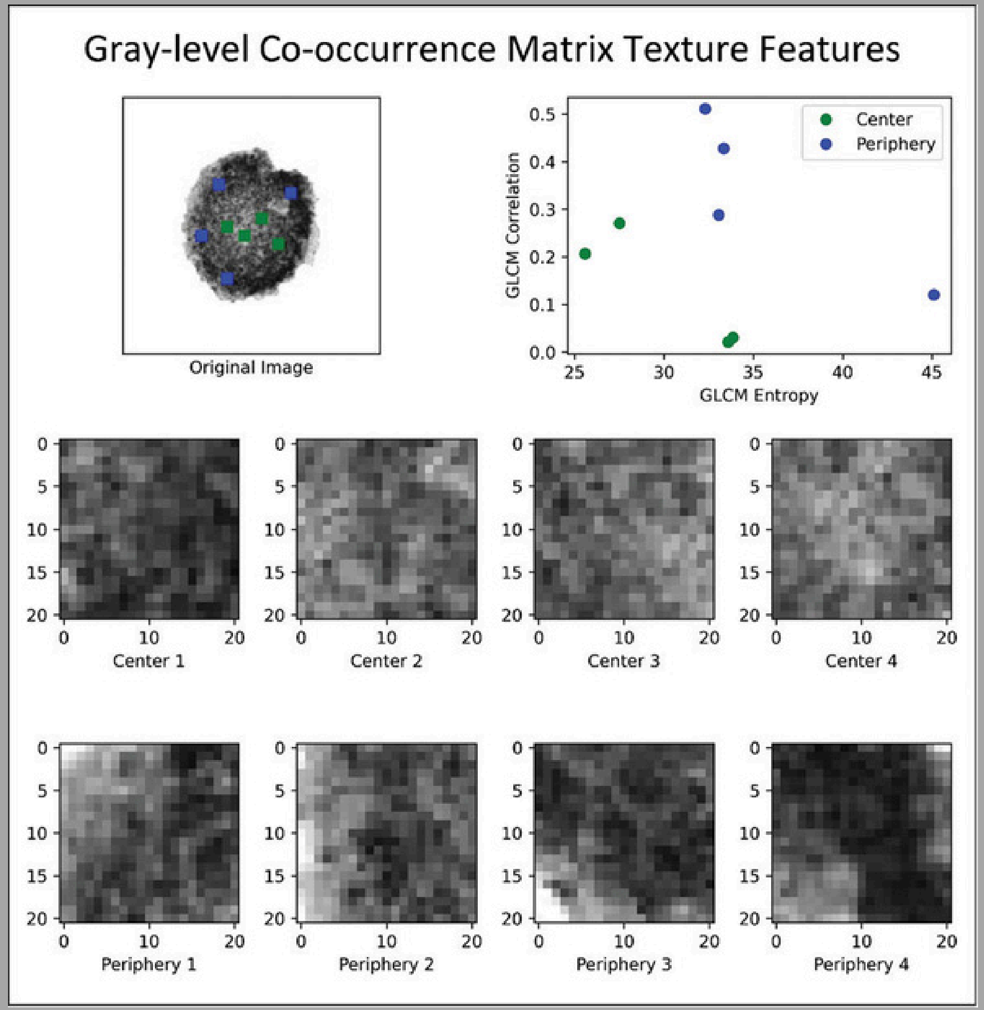
Gray Level Co-occurrence Matrix (GLCM)

Principal Component Analisis (PCA)

First Order Statistics (FOS)

Speeded-UP-Robust Features (SURF)

Gray Level Co-occurrence Matrix (GLCM)



Texture is analyzed by measuring the frequency of gray level combinations between neighboring pixels in an image.

01 **Contrast:**
Measures the difference between the gray levels of neighboring pixels.

02 **Correlation:**
Indicates how correlated the gray levels are between neighboring pixels.

03 **Energy:**
It represents the uniformity of the matrix (also known as "angular second moment").

04 **Homogeneity:**
Measures how similar the gray levels are between neighboring pixels.

First Order Statistics (FOS)

Unlike GLCMs, FOSs only look at individual pixel values and extract information about their distribution.

01 **Media:**
Average of the intensity values of the image.

02 **Standard deviation:**
It measures the variation or dispersion of intensity values.

03 **Variance:**
It is the square of the standard deviation, it also indicates the dispersion.

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First Order Statistics (FOS)

Statistical measures that describe the basic characteristics of the intensity distribution of pixels in an image without considering spatial relationships.

04 **Asymmetry:**
Describes the asymmetry of the intensity distribution.

05 **Kurtosis:**
It measures the sharpness of the intensity distribution.

06 **Entropy:**
Quantifies the randomness in the distribution of intensity values.

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Speeded-Up Robust Features

What is SURF?

- Algorithm for detection and description of local features in images.
- Designed to identify key points.
- Robust to changes in illumination, scale, rotation and some level of noise.

Main Features

- Detection of key points.
- Scale Invariant.
- Unique Descriptors.
- High speed.

Applications

- Object recognition and tracking
- Image stitching
- 3D Reconstruction
- Vision in Robotics

Principal Component Analysis (PCA)

01
Data normalization

They are normalized so that they have a mean of 0 and a standard deviation of 1.

02
Calculation of the covariance matrix

Show the relationship between the different variables in the data set.

03
Calculation of vectors and eigenvalues

The vectors represent the directions of the new axes and the values, the magnitude of variability in each direction.

04
Principal component selection and data transformation

The components with the highest eigenvalue are selected and a new smaller data set is generated.

Classification models

Support Vector Machine (SVM)

Convolutional Neural Networks (CNN)

K-Nearest Neighboors (K-NN)

Extreme Randomized Trees (ET)

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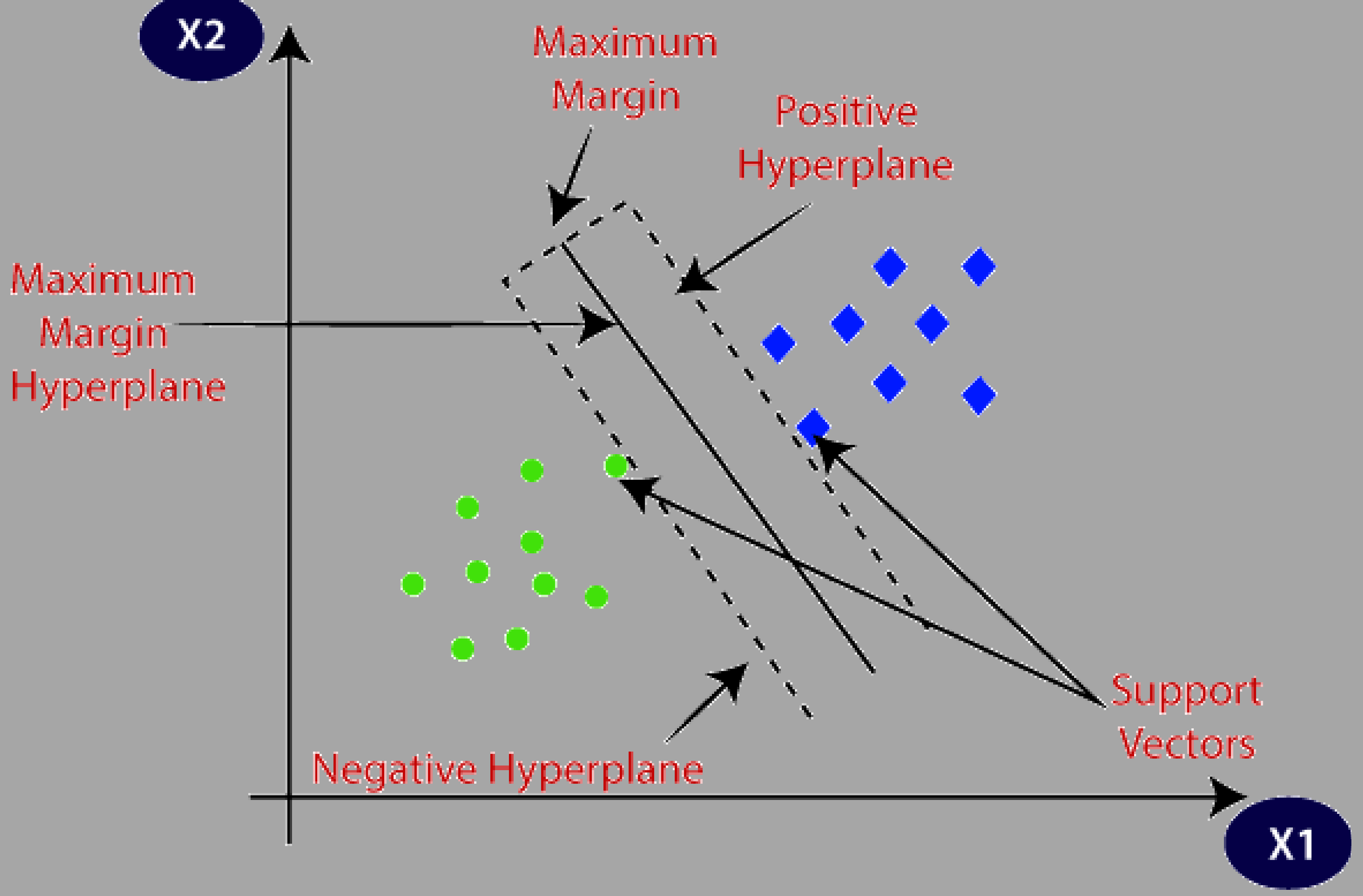


Support Vector Machine (SVM)

Supervised learning algorithm used in classification and regression problems.

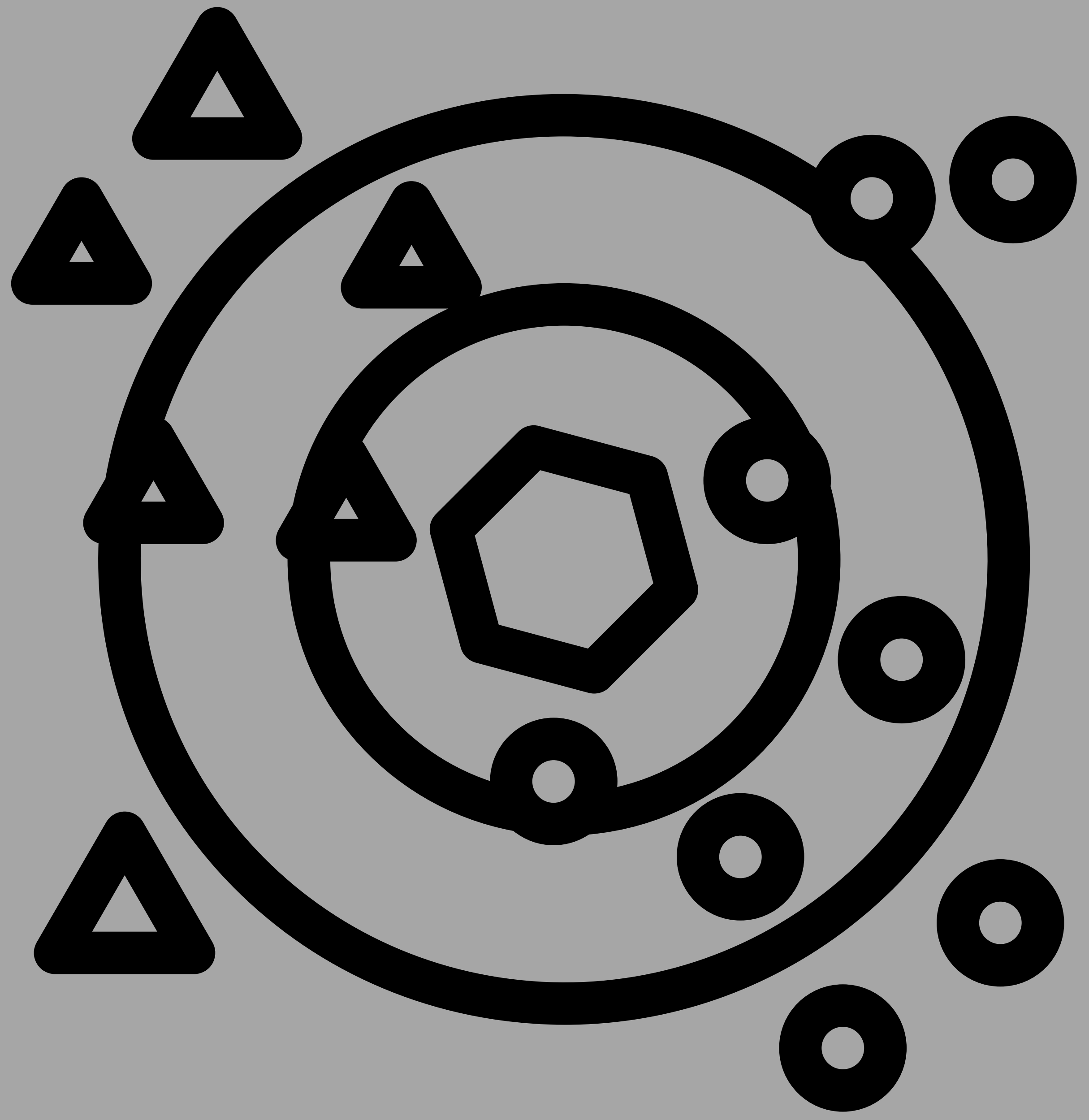
It finds the hyperplane that separates classes with the largest possible margin.

It uses parameters such as:

- Kernel: linear, polynomial, BF and sigmoid.
- C (Penalty parameter)

K-Nearest Neighboors (K-NN)

Non-parametric supervised learning classifier that performs classifications on the clustering of a data set, based on proximity. This algorithm works by choosing the “K” nearest neighbors, calculates the distance between the new point and the training data and makes a prediction by assigning the majority class among the “K” neighbors.



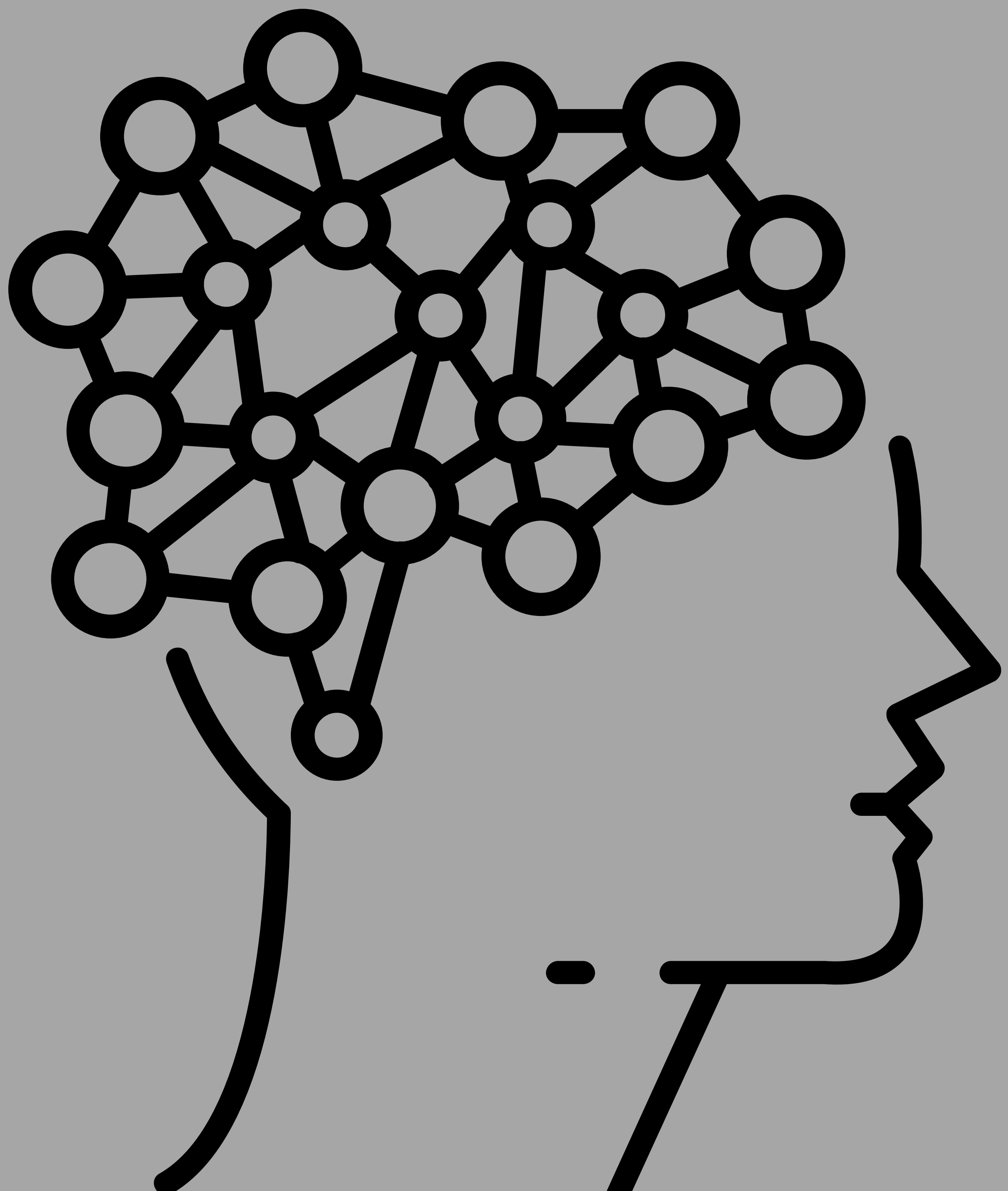
Convolutional Neural Networks (CNNs)

Deep neural networks specialized in image processing and analysis. They are applied in computer vision tasks, image recognition, object classification, among others.

Structure:

- Convolution layers.
- Pooling layers.
- Activation layers.
- Fully Connected Layers (Dense layers).

- They provide the facility of automatic feature extraction.
- They have special invariance thanks to the use of shared filters as they recognize patterns regardless of position.



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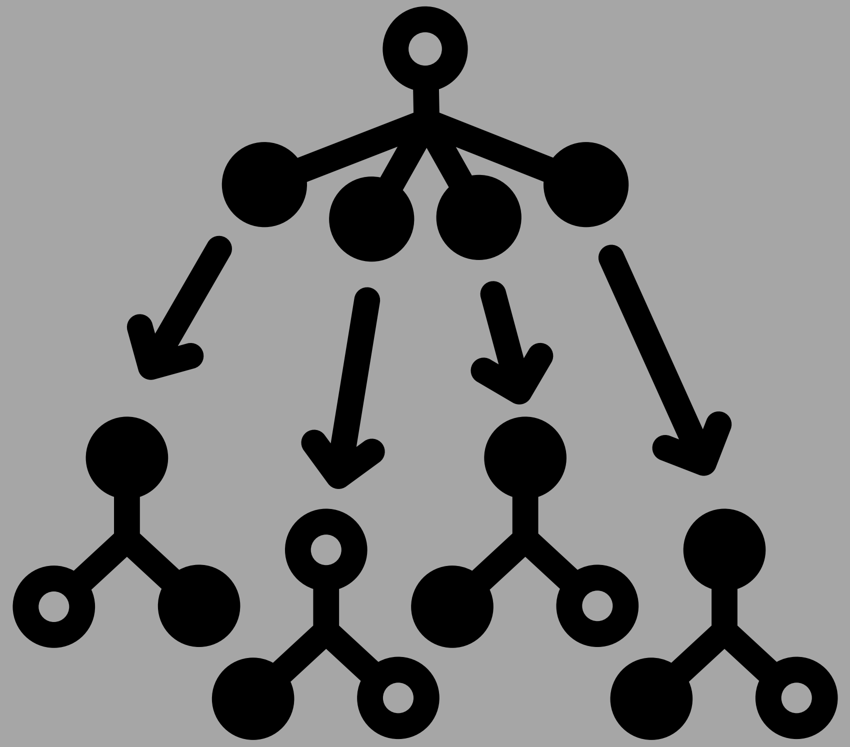
Extreme Randomized Trees (ET)

Fast supervised learning algorithm based on decision trees.



Advantages

01

Creation of multiple decision trees

To make final predictions based on the average results of all trees.

02

Extreme random splits

They select random splits of the data and features at each node.

03

Reduction of overadjustment

Thanks to the extreme randomness it is less prone to overfitting compared to a single decision tree.

- Fast and efficient on large data sets
- Reduces overfitting due to randomness
- Scalable and effective in regression and classification problems.

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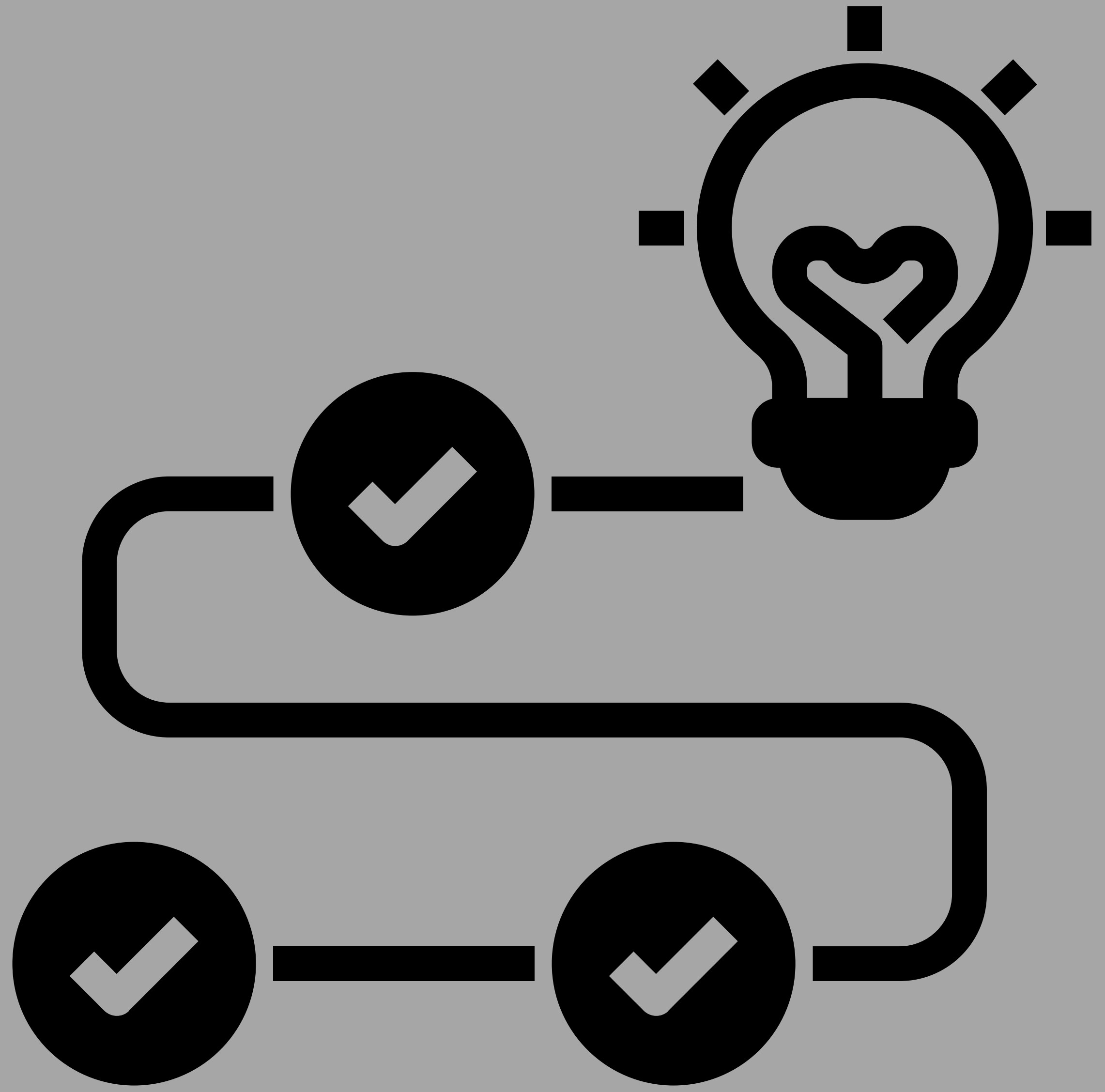
METHODOLOGY



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Research method used

Research

Search for papers or research papers using IEEE Xplore, Scopus, SciELO.
Compilation of datasets from Kaggle Github, Google, etc.

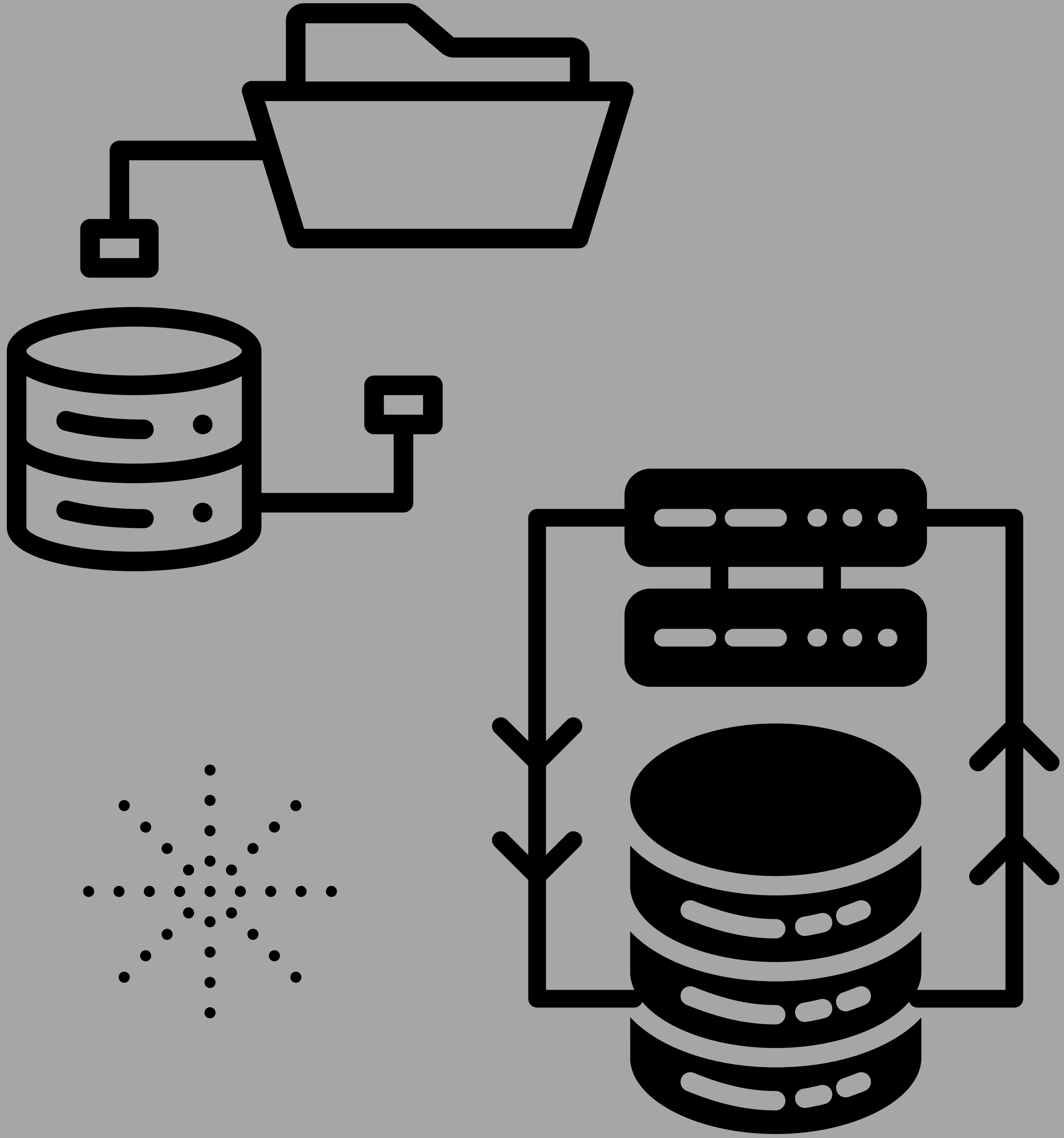
Experimentation

Evaluate the results obtained with the collected preprocessing techniques and classification methods investigated.

Validation

Metrics obtained such as standard deviation, maximum and minimum value, correlation, confusion matrices, etc. are compared.

THE DATASET



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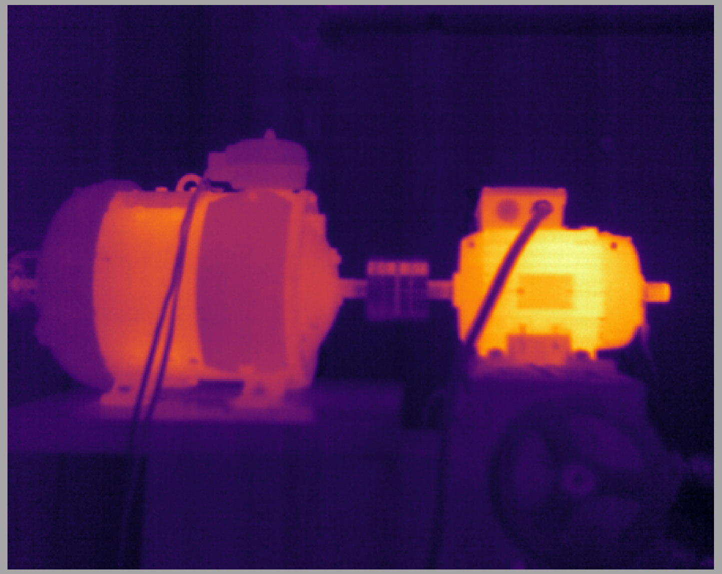
General composition of the dataset

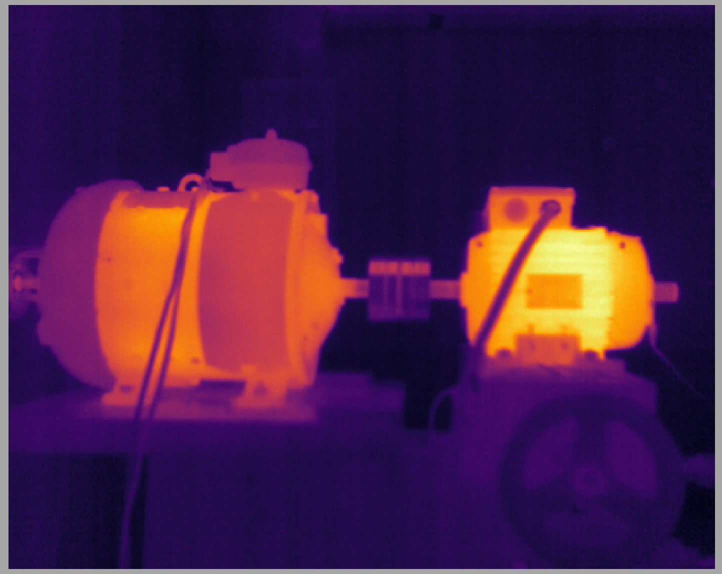
Dataset	Source	N° Images	N° Classes
Data 1	Eksploatacja i Niezawodność Journal	10007	105
Data 2	Babol Noshirvani Univeristy of Technology	369	11
Data 2	Universidad Autónoma de Querétaro	80	4
Data 4	Universidad de Piura	479	1

Dataset 1

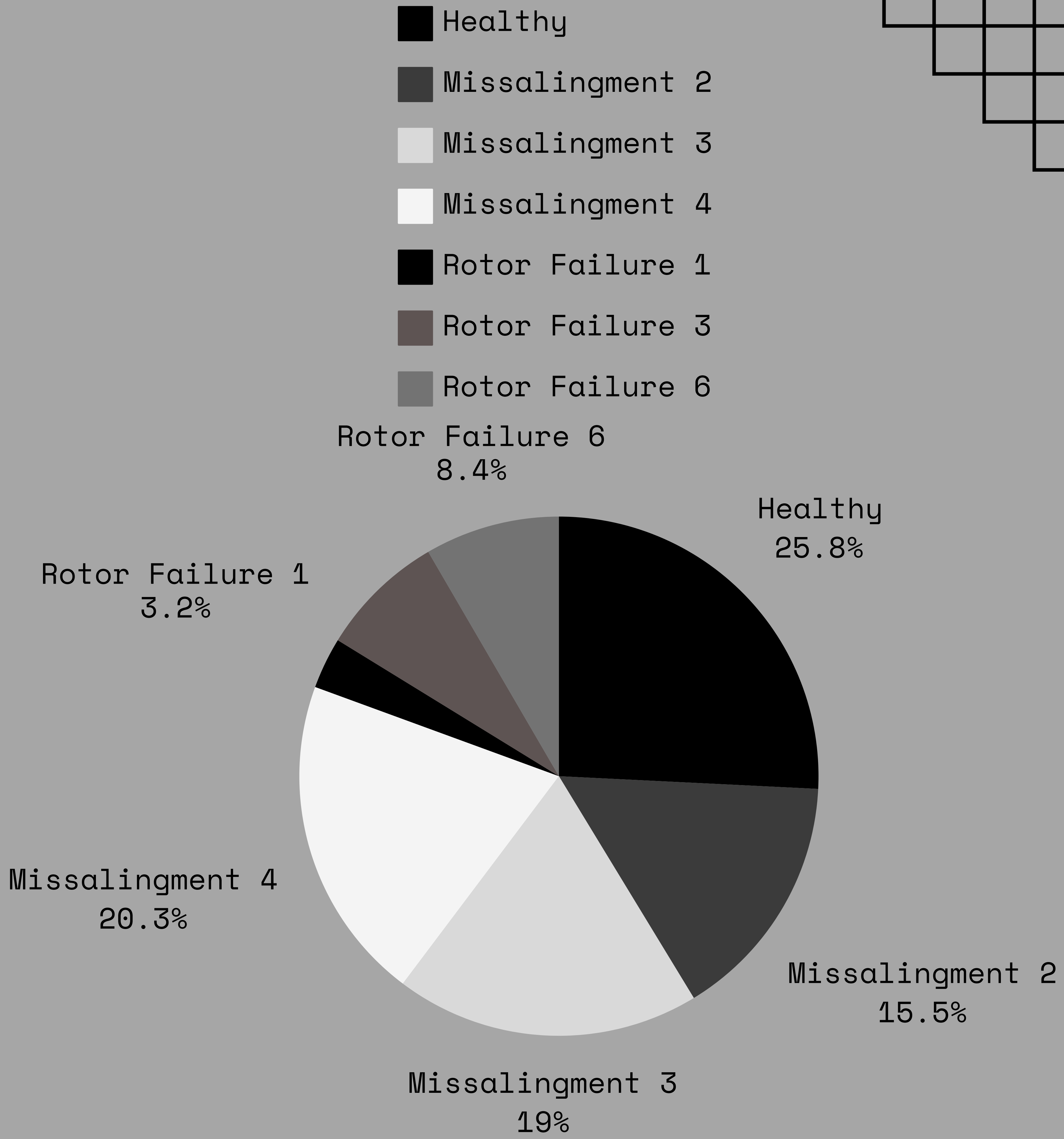


Healthy

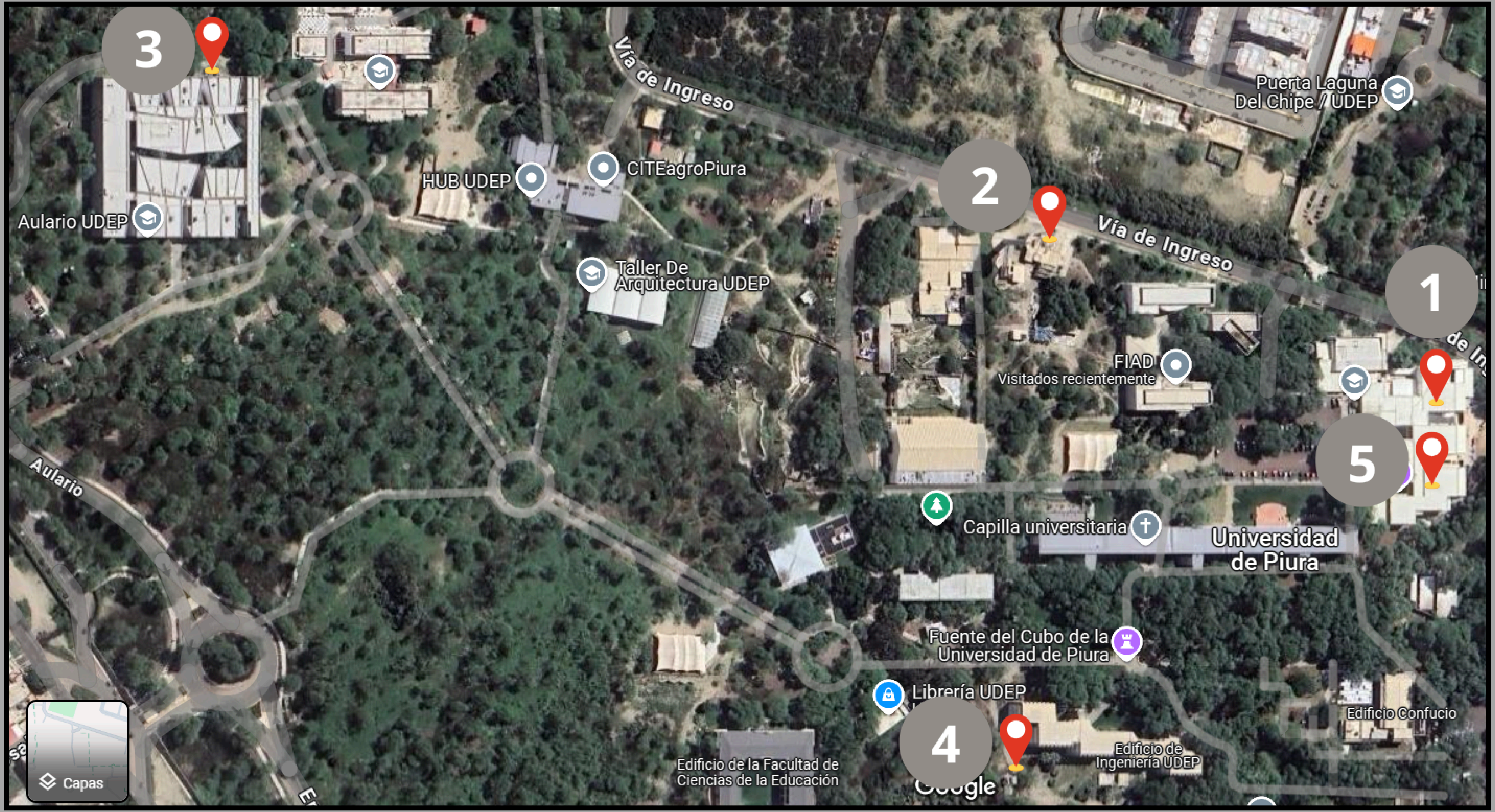
Missalingment



Rotor Failure



Location of image collection points at the University of Piura



01 Automatic Control Systems Laboratory

02 Water pumping station for the School of Communication

03 Water pumping station for the E Building

04 Building 80 waste pumping station

05 Electrical Engineering Laboratory

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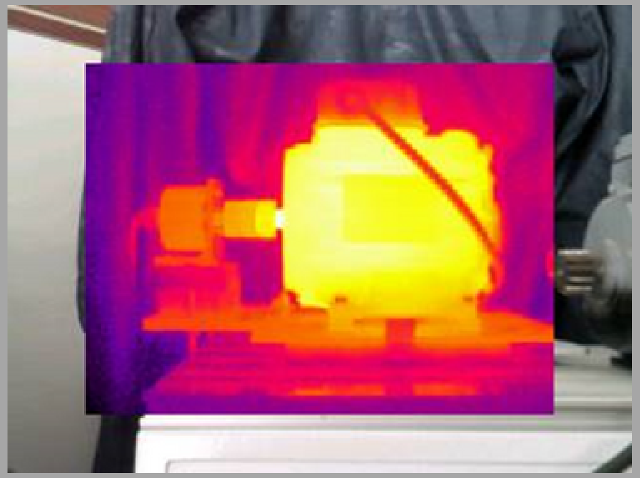
Dataset 4



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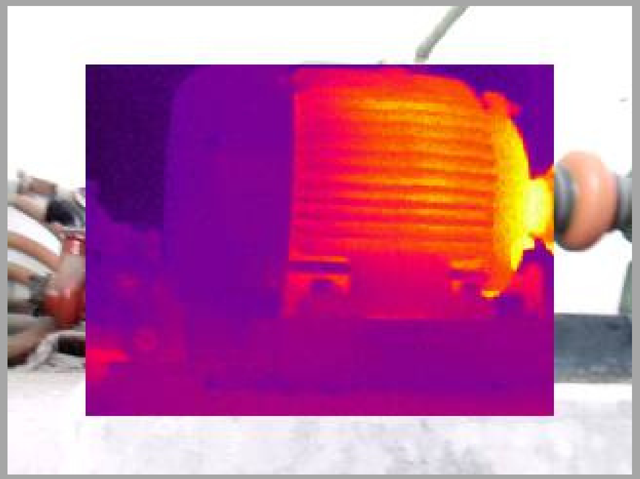

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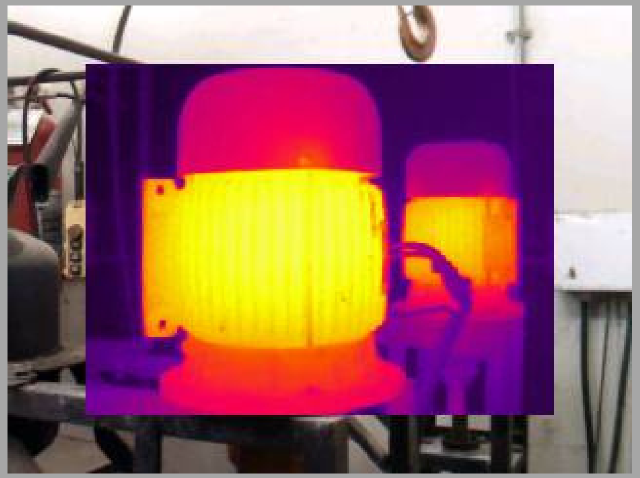

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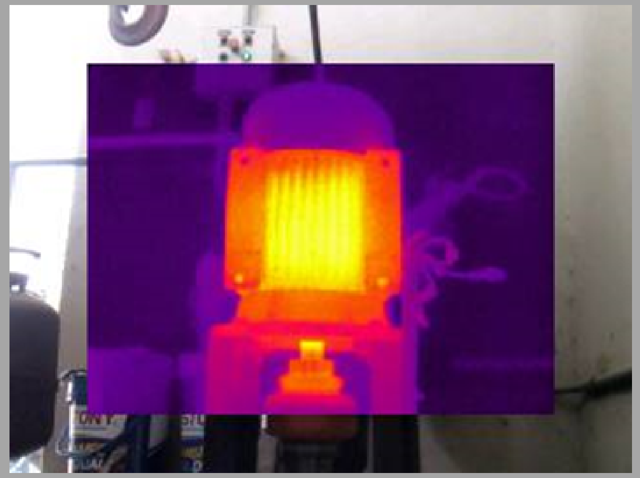

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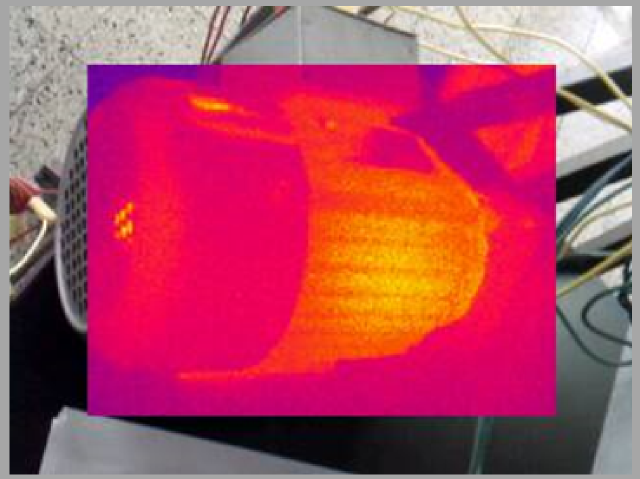

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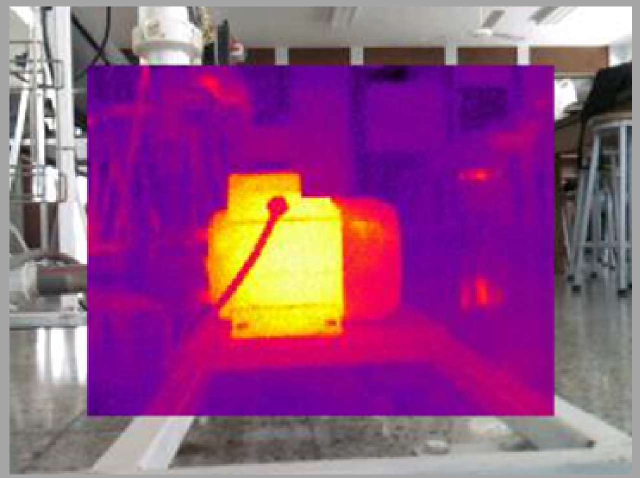

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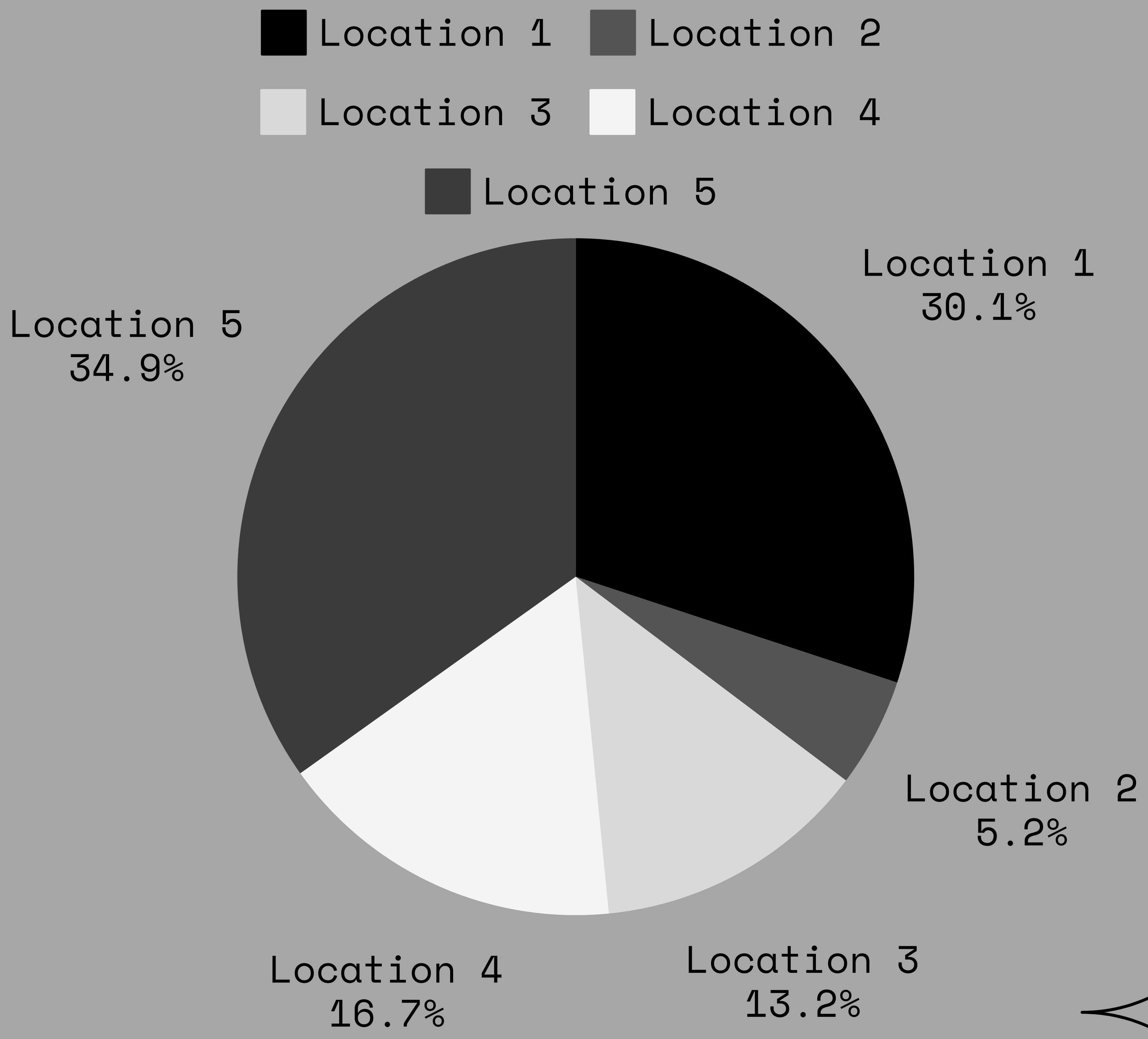

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Division of the datasets tested for training purposes

Dataset train	Sources	N° Data	Classes
Train1	Data1 Coupling2	939 img (80%) + metadata (4GLCM x 939 img) 1480 img (80%) + metadata (4GLCM x 1480 img)	Healthy Missalingment1
Train2	Data1 Coupling2	939 img (80%) + 1878 img (Data augmentation) + metadata (4GLCM x 2817 img) 1480 img (80%) + 1480 img (Data augmentation) + metadata (4GLCM x 2960 img)	Healthy Missalingment1
Train3	Data1 Coupling2	1009 img (80%) + 4 sub-bands per image (DWT) 1439 img (80%) + 4 sub-bands per image (DWT)	Healthy Missalingment1
Train4	Data1 Coupling1 y 2	1511 img (80%) 3538 img (80%)	Healthy Missalingment1

Division of the datasets tested for training purposes

Dataset train	Sources	N° Data	Classes
Train5	Data1 Coupling2 gris	1196 img (80%) 720 img (80%) 888 img (80%) 942 img (80%) 148 img (80%) 363 img (80%) 390 img (80%)	Healthy Missalingment2 Missalingment3 Missalingment4 RotorBar1 RotorBar3 RotorBar6
Train6	Data1+Data4	1782 img (80%) + 4 sub-bands per image (DWT) + metadata (2GLCM x 1782 img) 3530 img (80%) + 4 sub-bands per image (DWT) + metadata (2GLCM x 3530 img) 901 img (80%) + 4 sub-bands per image (DWT) + metadata (2GLCM x 901 img)	Healthy Missalingment Rotor Bar

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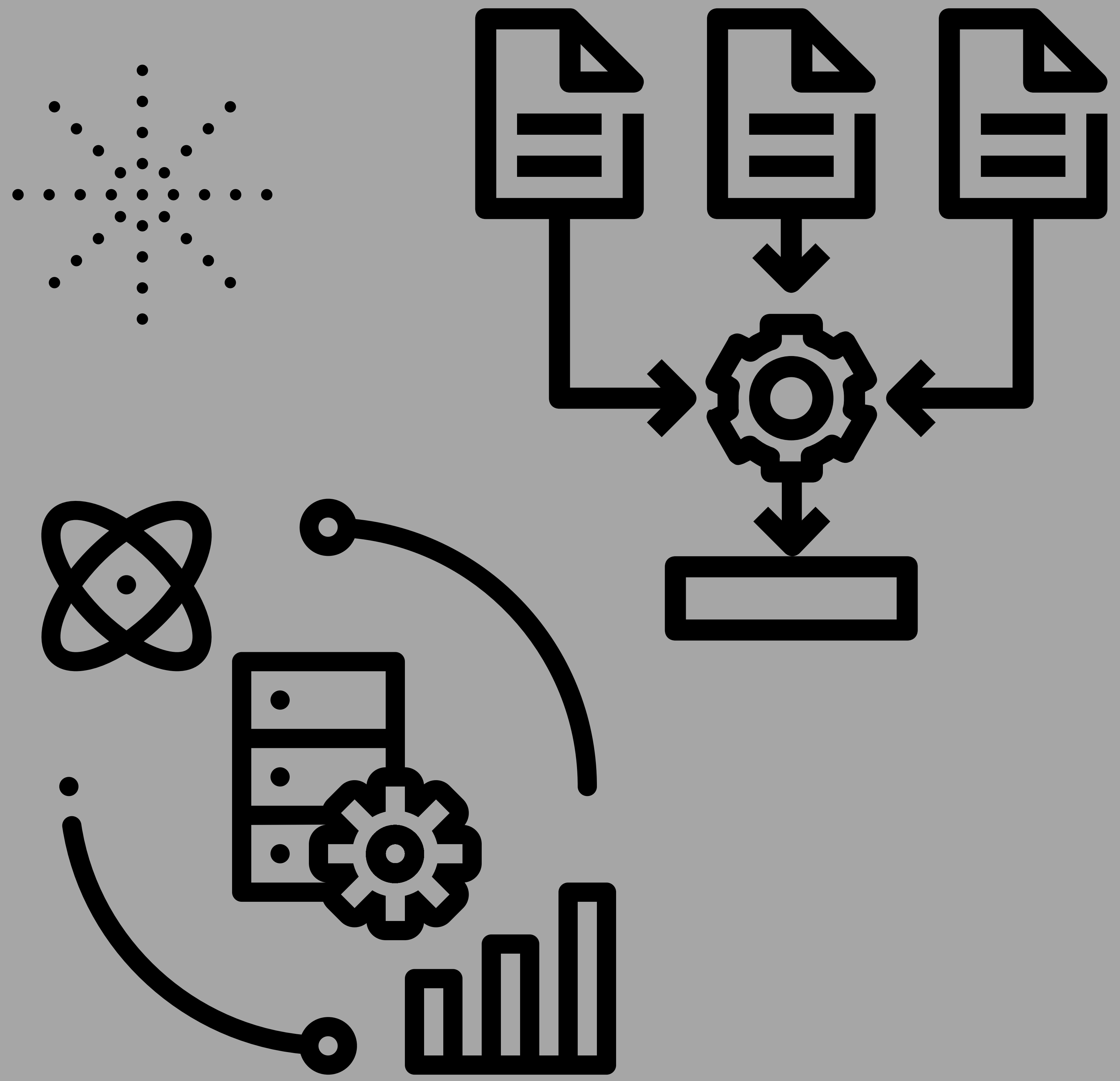
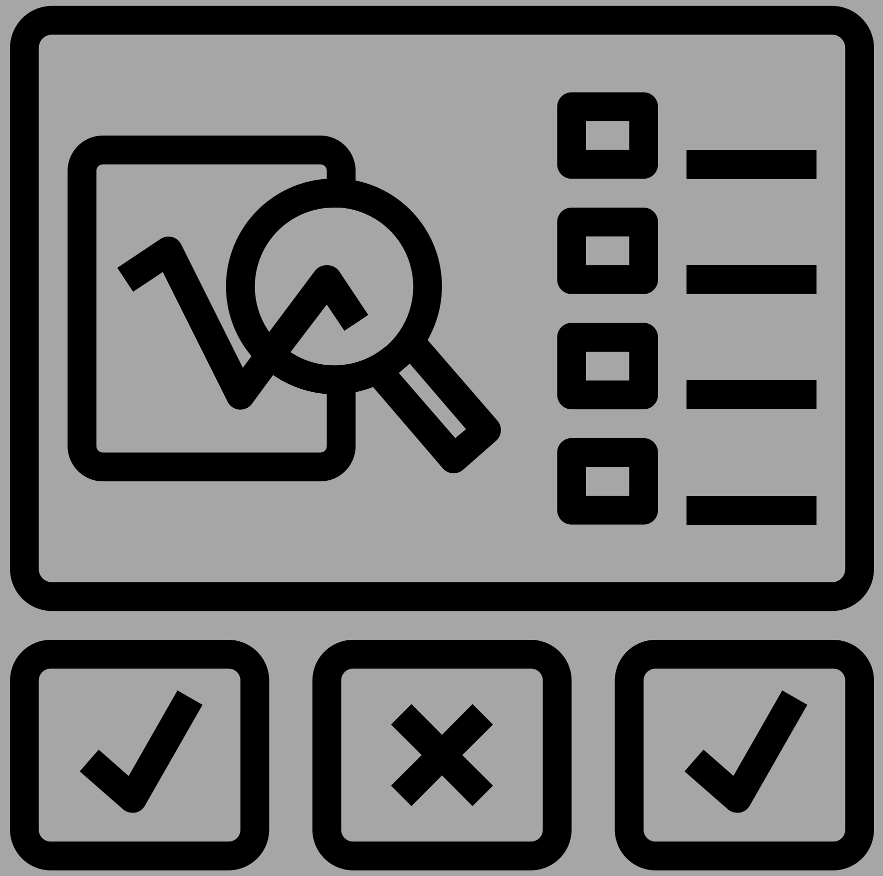
PREVIOUSLY TRAINED AND EVALUATED MODELS PREVIOUSLY



Model	Preprocessing	Classifier	Data
Model 1	YOLOV5+Otsu+FFT+CLAHE+GLCM	VGG16-1	Train-test1
Model 2	YOLOV5+Otsu+FFT+CLAHE+GLCM+Data Augmentation	ResNet50	Train-test2
Model 3	YOLOV5+Otsu+FFT+CLAHE	SVM-1	Train-test3
Model 4	YOLOV5+Otsu+FFT+CLAHE	EfficentNetB2	Train-test4
Model 5	YOLOV5+Otsu+FFT+CLAHE	EfficientNetB5	Train-test4
Model 6	YOLOV5+Otsu+FFT+CLAHE	EfficientNetB7	Train-test4
Model 7	YOLOV5+Otsu+FFT+CLAHE	VGG16-2	Train-test4

Model	Preprocessing	Classifier	Data
Model 8	YOLOV5+Otsu+FFT+CLAHE	InceptionV3-1	Train-test4
Model 9	YOLOV5+Otsu+FFT+CLAHE	SVM-2	Train-test4
Model 10	YOLOV5+Otsu+FFT+CLAHE	KNN	Train-test4
Model 11	YOLOV5+Otsu+FFT+CLAHE	InceptionV3-2	Train-test4
Model 12	YOLOV5+SIFT-BoVW	ERT	Train-test5

RESULTS OF THE TRAINED AND PREVIOUSLY EVALUATED MODELS PREVIOUSLY



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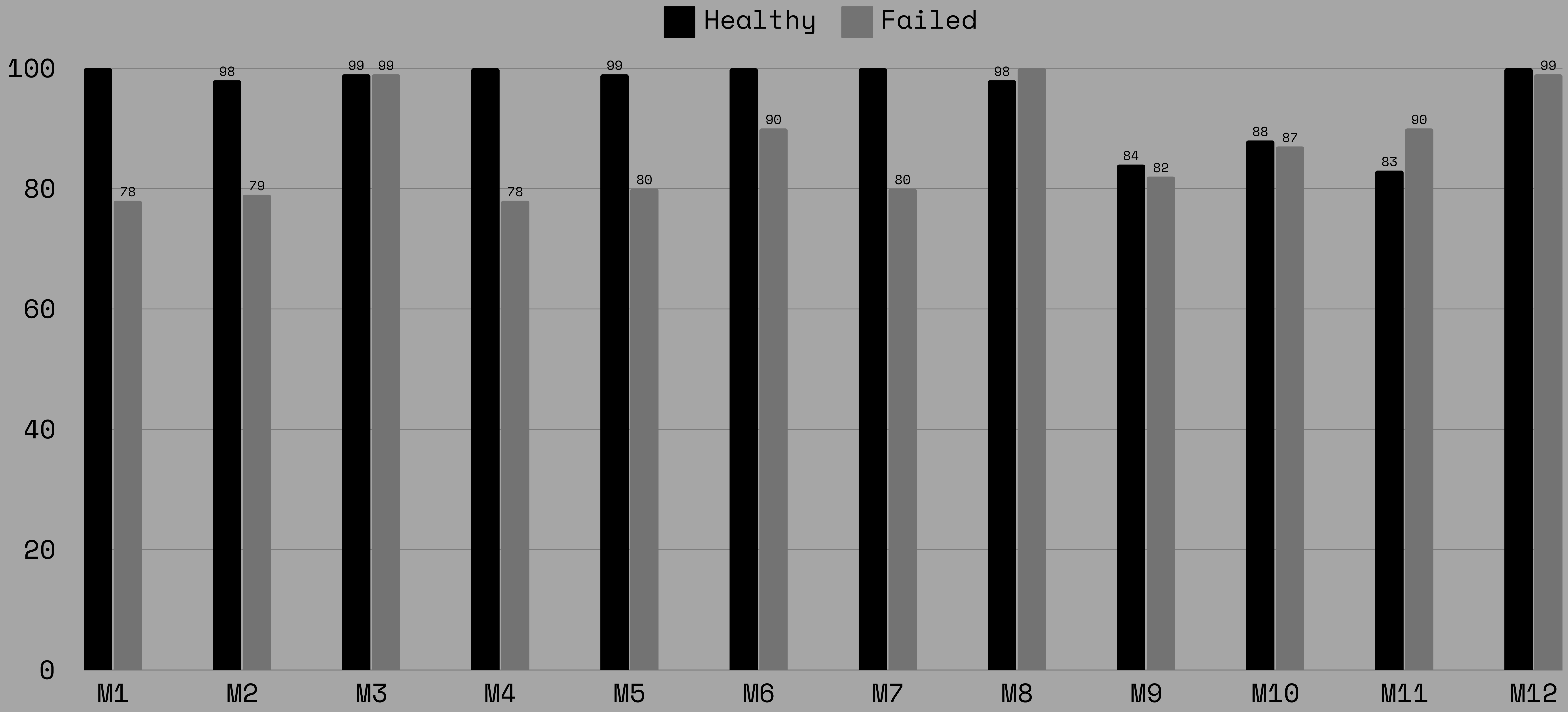
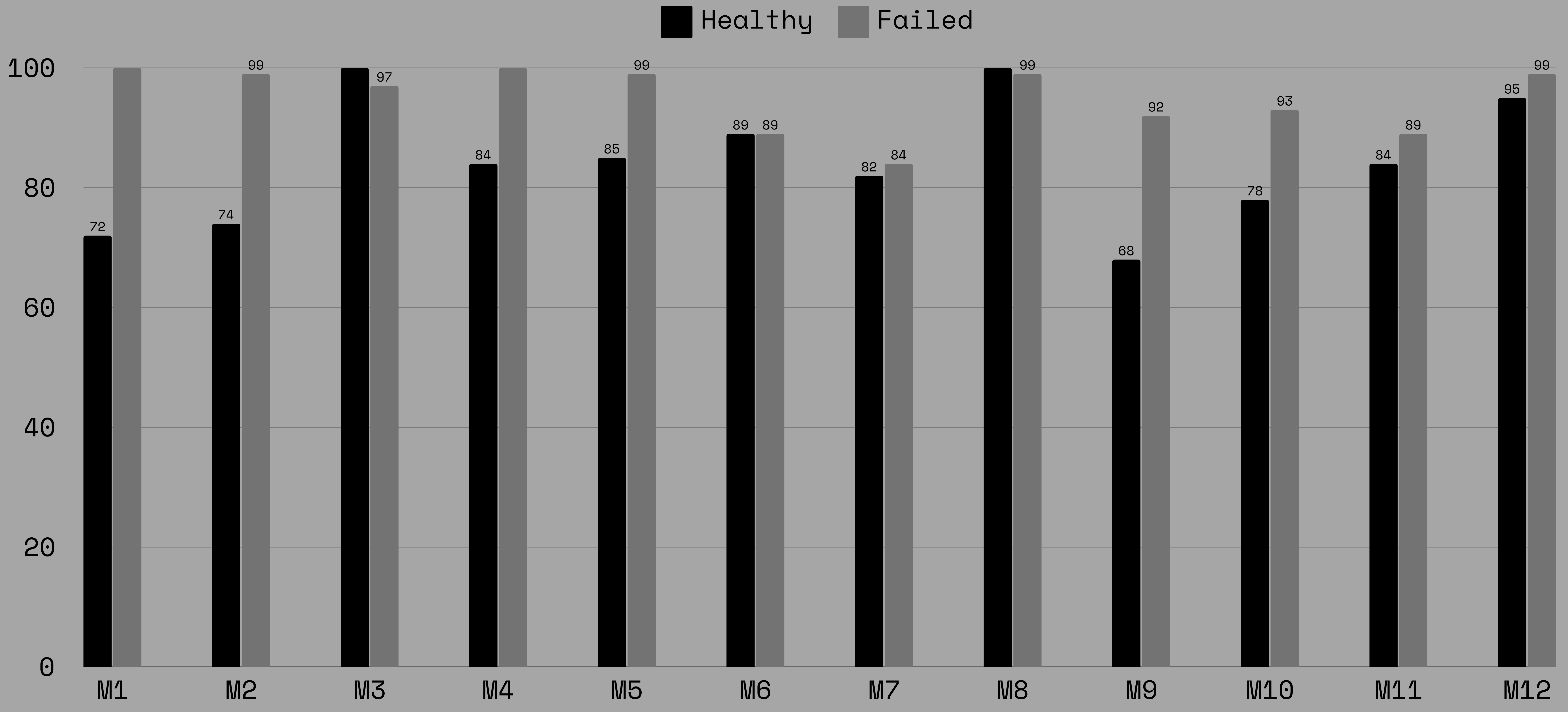
Accuracy (%)


Healthy
Failed
100
80
60
40
20
0
78
98
79
99
99
78
99
80
90
80
98
84
82
88
87
83
90
99
M1
M2
M3
M4
M5
M6
M7
M8
M9
M10
M11
M12

Recall (%)


Healthy
Failed
100
80
60
40
20
0
72
74
99
97
84
85
99
89
89
82
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99
68
92
78
93
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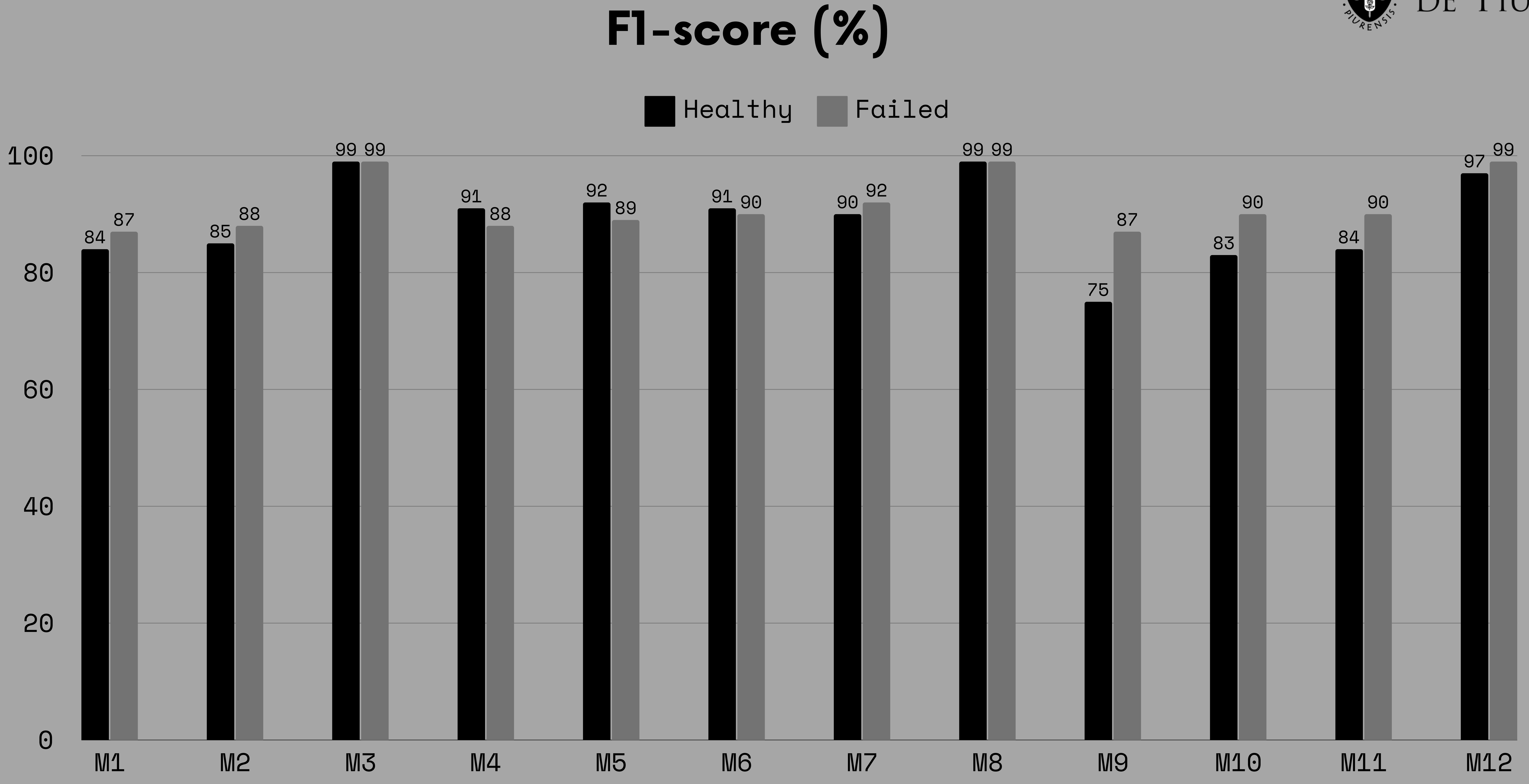
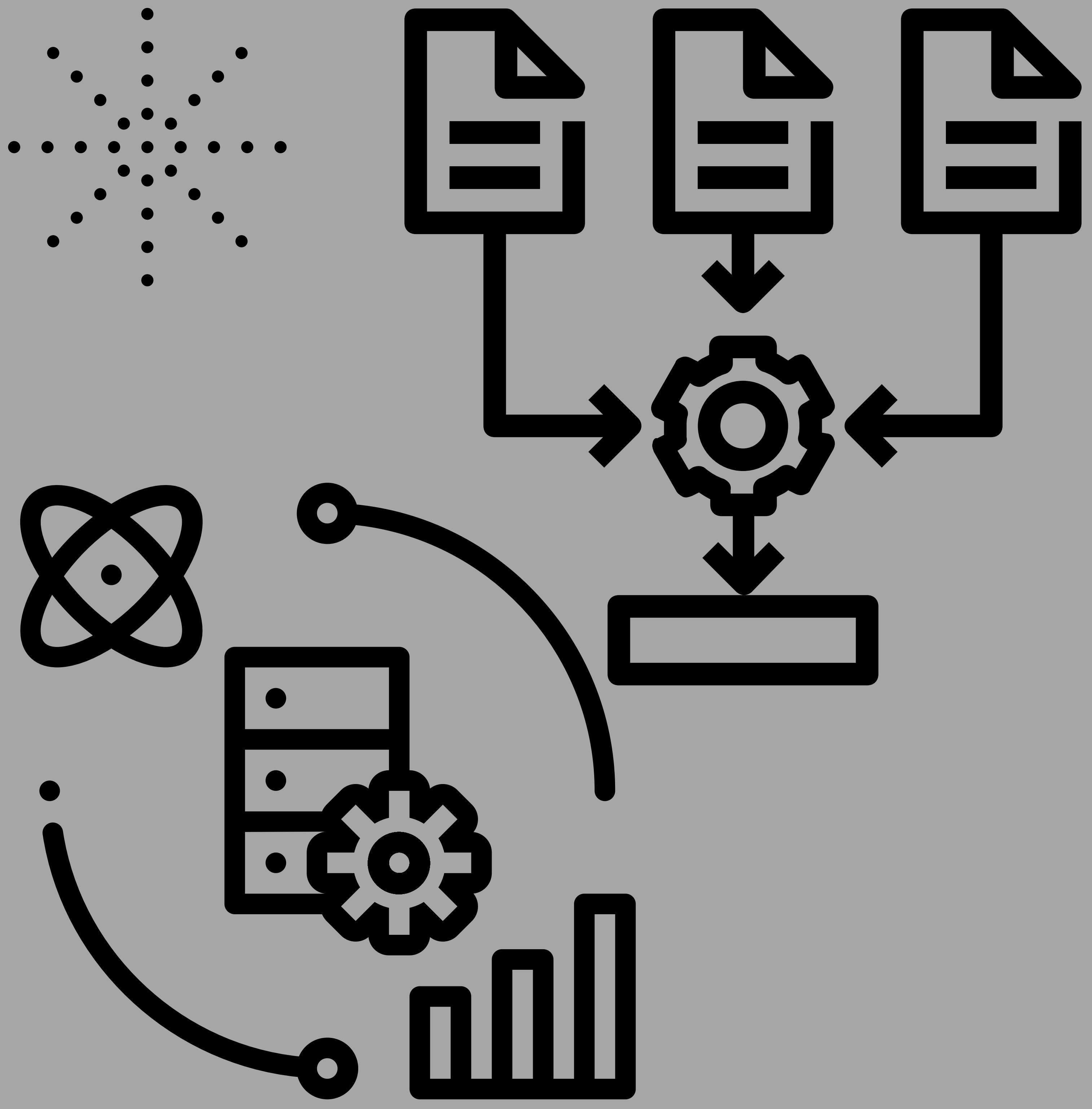
M1
M2
M3
M4
M5
M6
M7
M8
M9
M10
M11
M12


F1-score (%)
Healthy
Failed
100
80
60
40
20
0
84
87
85
88
99
99
91
88
92
89
91
90
90
92
99
99
75
87
83
90
84
90
97
99
M1
M2
M3
M4
M5
M6
M7
M8
M9
M10
M11
M12

SELECTED TRAINED AND EVALUATED MODELS



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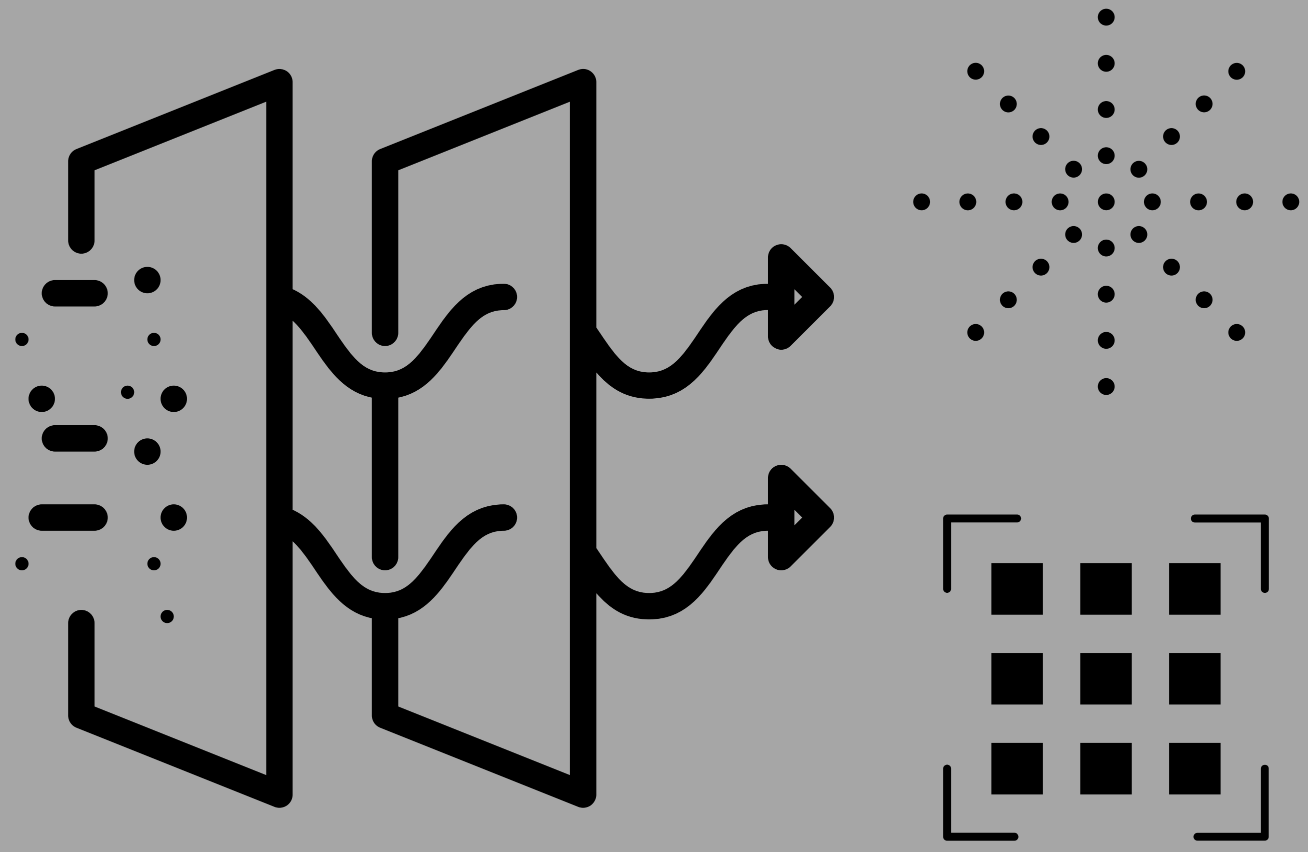
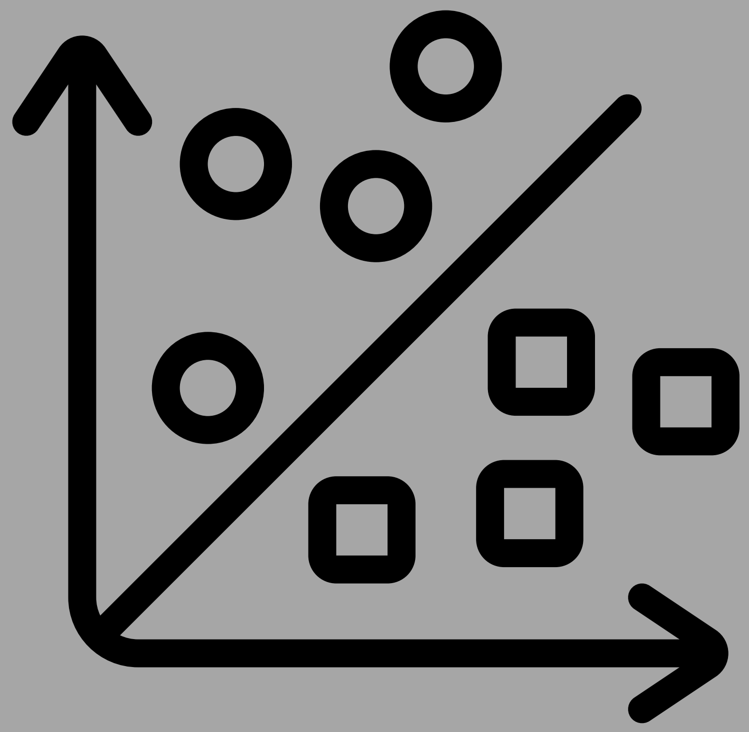
FIRST MODEL: PREPROCESSING AND SVM





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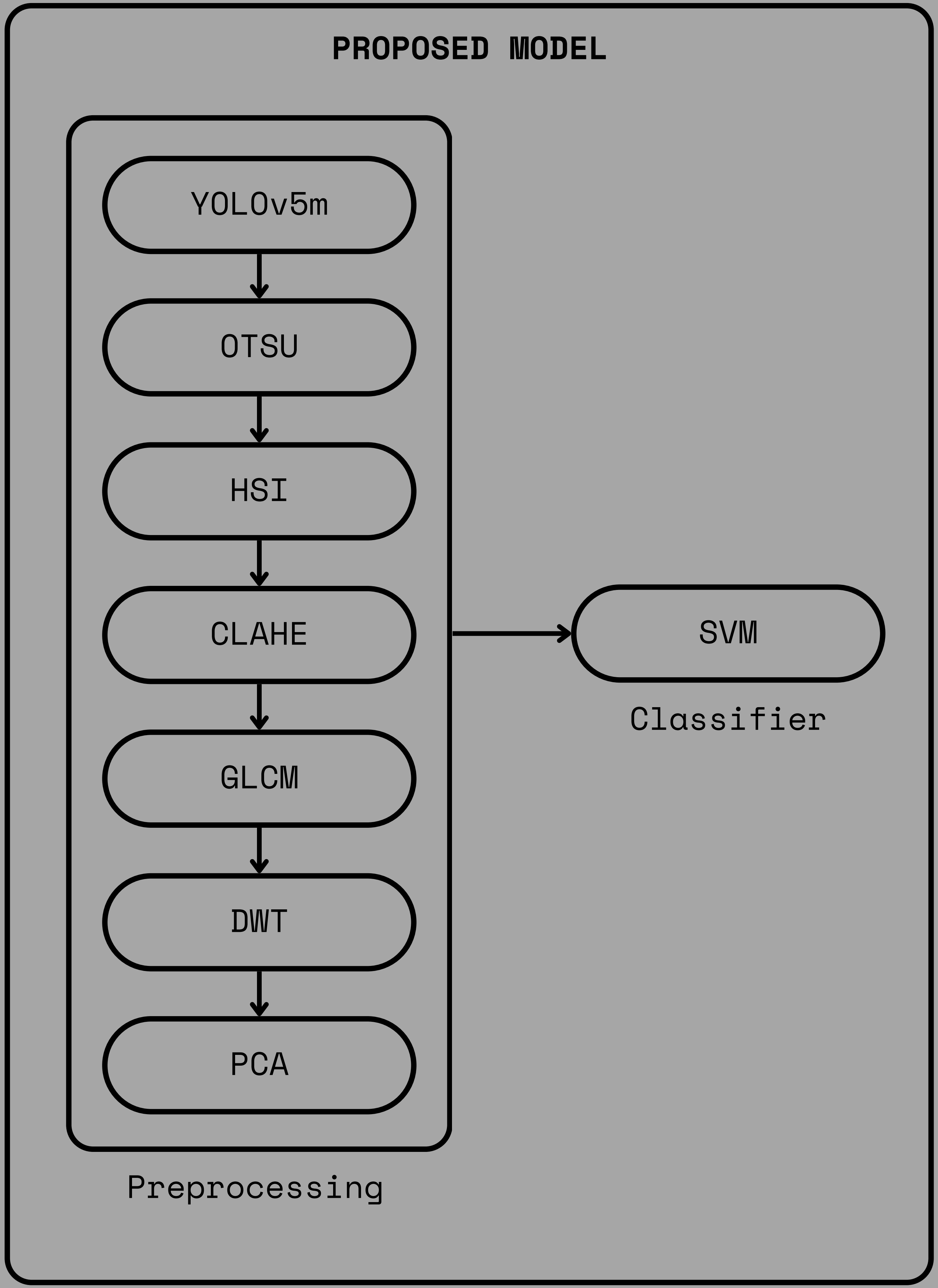
PROPOSED MODEL



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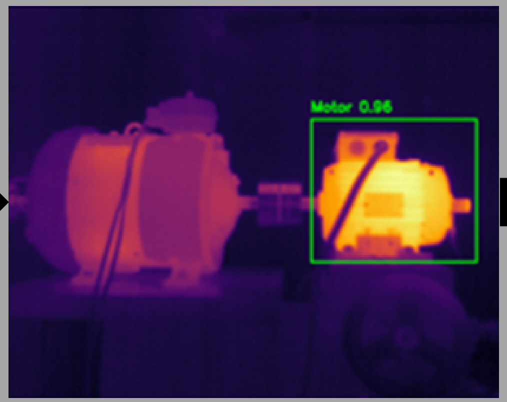
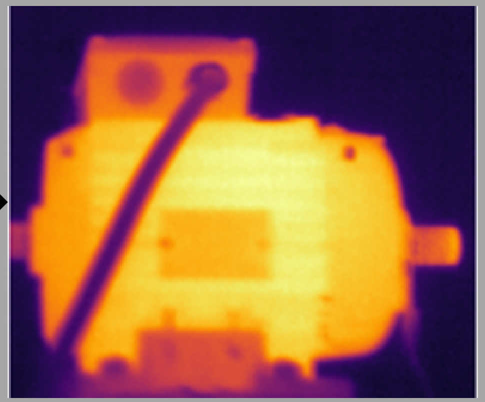
Preprocessing

YOLOv5m

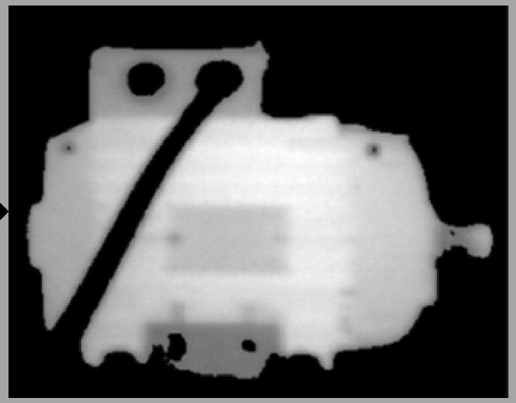
01 Detects areas of interest (motors only).
The coordinates of the motor image are obtained, extracted and cropped..





OTSU

02 The algorithm changes the image to grayscale and finds a threshold where the covariance between the intensity of image pixels below and above the threshold is the minimum possible.

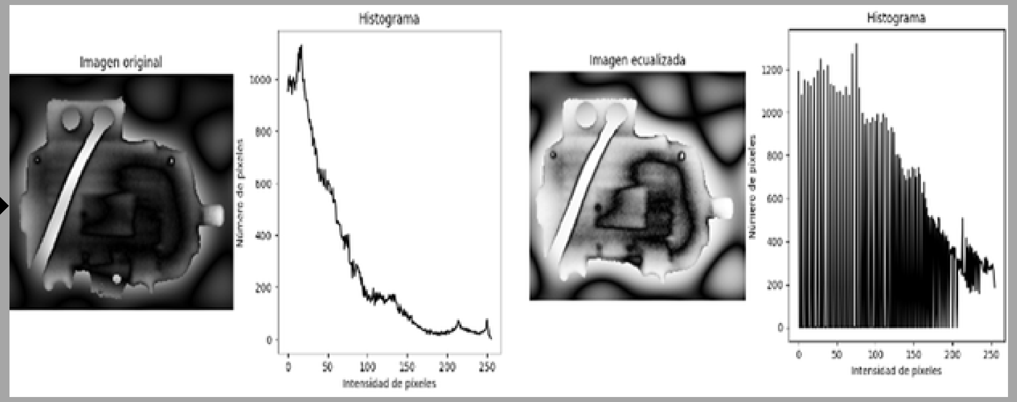


HSI

03 LThe images are converted to RGB and normalized from 0 to 1.
The pixel intensity is extracted as the average of the 3 channels.

CLAHE

04 Image resolution is changed to 224x224.
Local histogram equalization is applied by redistributing the intensities to make the histogram more uniform.



Preprocessing

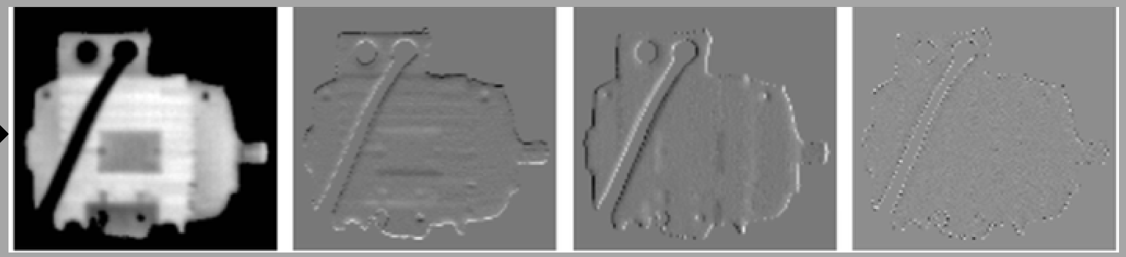
GLCM

05 The normalized symmetric gray level co-occurrence matrix with a distance of 1 pixel between neighbors is used to return the contrast and homogeneity characteristics.

```
GLCM Properties current-load-4A
Contrast: [[     309.87      550.58      275.69      340.75]
 [     699.56      550.58      639.08      340.75]
 [     1071.7      1190.6      1045.4      765.06]]
Correlation: [[    0.97174     0.94967     0.97477     0.96885]
 [    0.93627     0.94967     0.94138     0.96885]
 [    0.90249     0.89105     0.90388     0.92999]]
Energy: [[   0.034106    0.027298    0.030457    0.027841]
 [   0.025862    0.027298    0.022853    0.027841]
 [   0.022017    0.020457    0.019395    0.021023]]
Homogeneity: [[    0.27917     0.17759     0.21708     0.18844]
 [    0.16852     0.17759     0.12844     0.18844]
 [    0.12646      0.1016    0.093506     0.11422]]
```

DWT

06 The 4 approximate subbands are extracted: cA, cH, cV and cD.
The subbands contribute a large number of features to be considered by the classifier.



PCA

07 The subbands are converted into a one-dimensional vector, the features are stored in an “x” matrix that is reduced to 52 to increase their training efficiency and a “y” matrix with the class names.

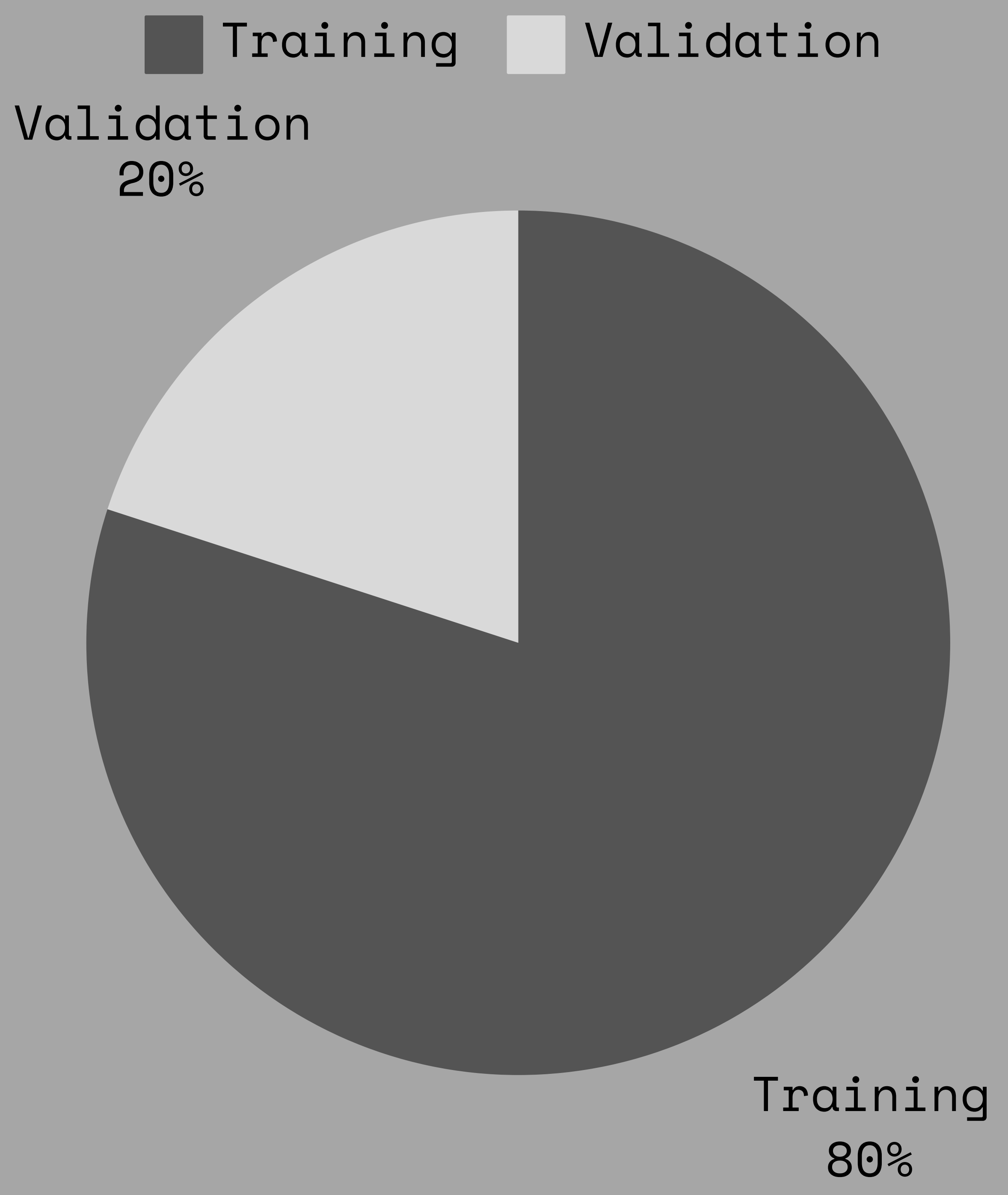
```
Matrices X y y cargadas con éxito.
Forma de la matriz X: (9071, 50178)
Forma de la matriz y: (9071,)
```

```
(9280, 52)
```

Classifier: SVM

Parameters chosen by GridSearch

1	0.01	Linear
C	Gamma	Kernel



The training is executed and the following results are obtained....

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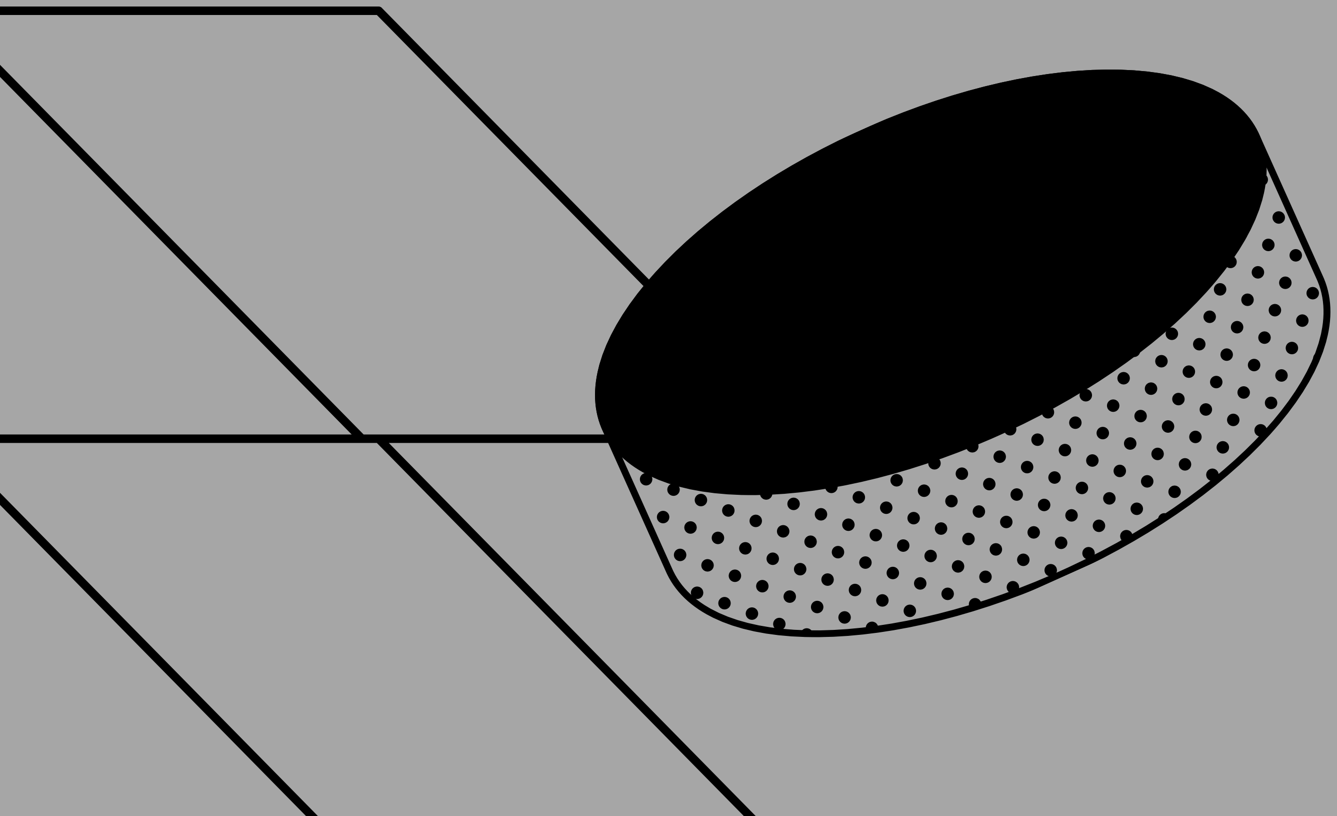
Model evaluation: Metrics



100%

Precision
Motor running at rated conditions

100%

Precision
Misaligned motor

100%

Precision
Motor with broken rotor bars

100%

Recall
Motor running at rated conditions

100%

Recall
Misaligned motor

100%

Recall
Motor with broken rotor bars

100%

F1-score
Motor running at rated conditions

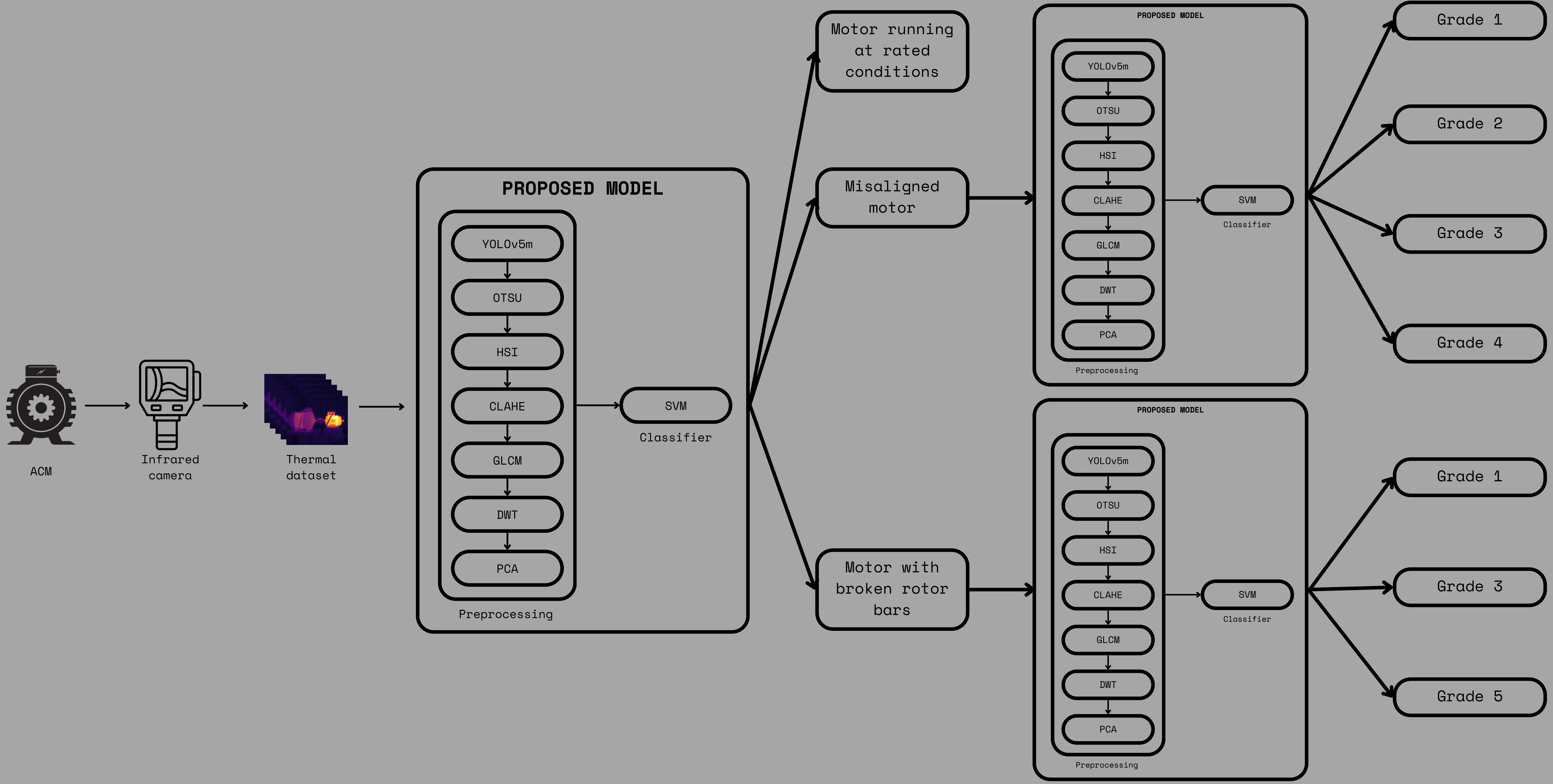
100%

F1-score
Misaligned motor

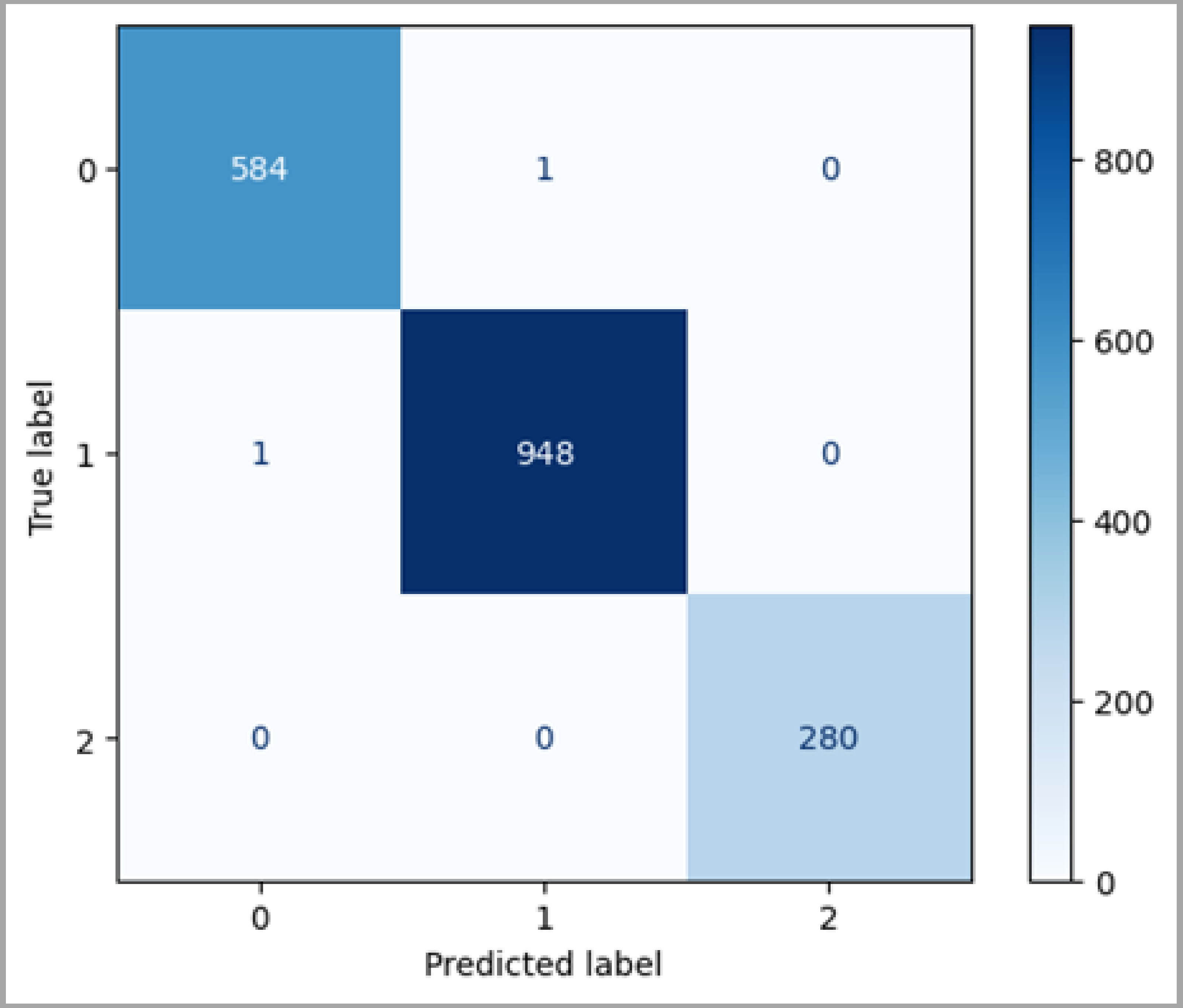
100%

F1-score
Motor with broken rotor bars

Hierarchical classification system architecture



Confusion matrices obtained from the hierarchical classification: General Classification

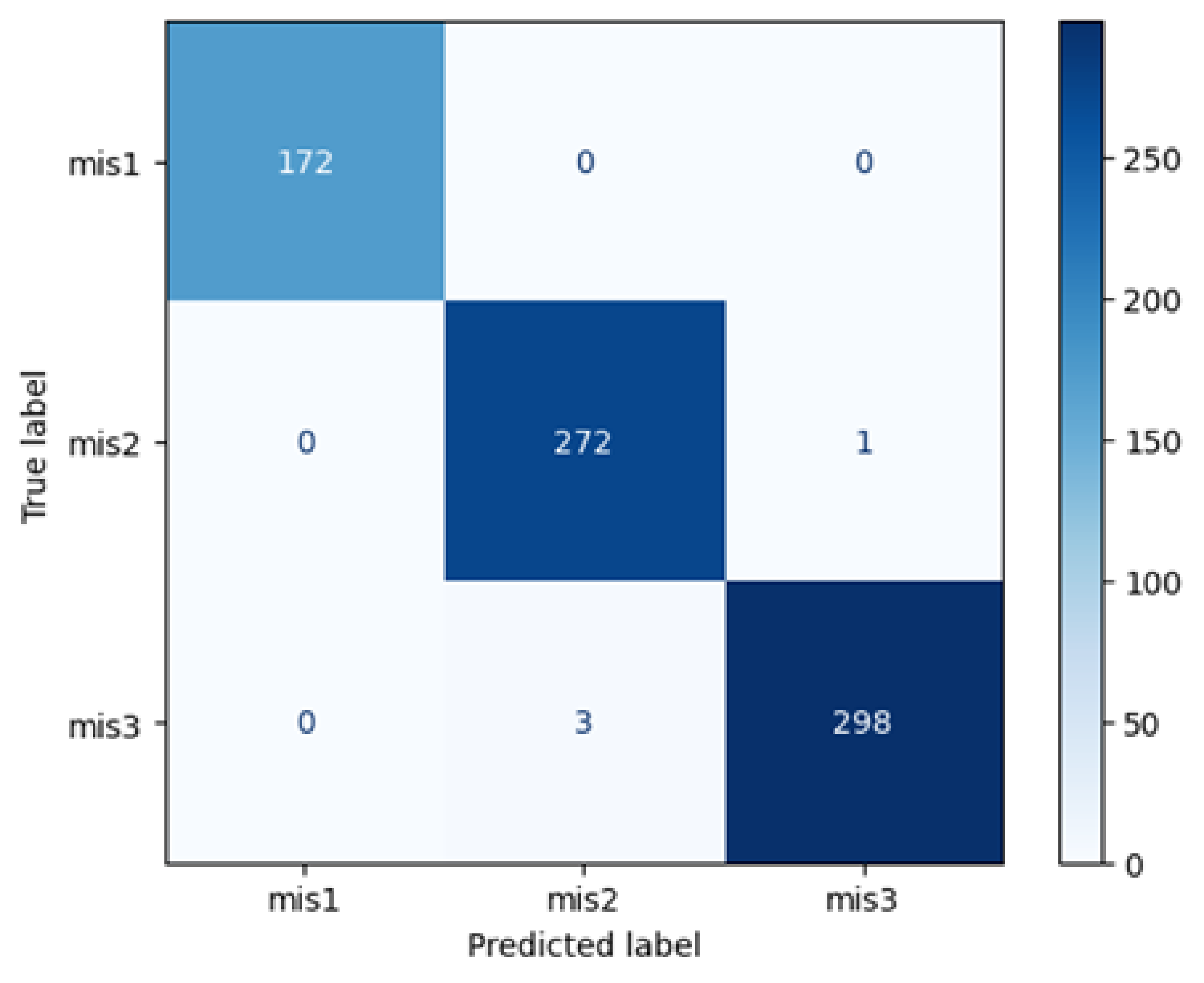


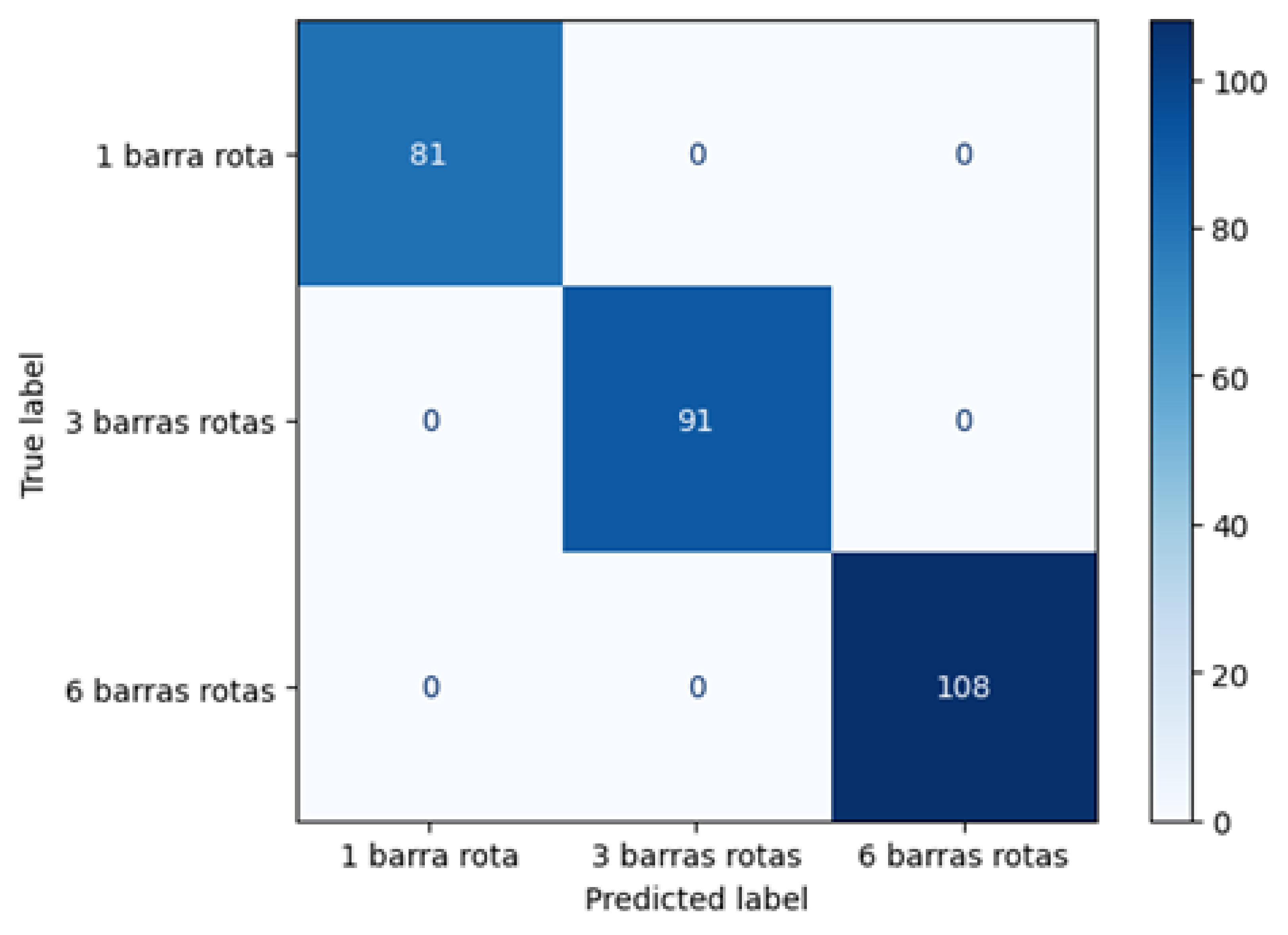
0 Motor operating at rated conditions

1 Misaligned motor

2 Motor with broken rotor bars

Confusion matrices obtained from the hierarchical classification: Gravity classification for misaligned engine and broken rods.





SECOND MODEL: AN INTERESTING APPROACH OF VISUAL TRANSFORMERS

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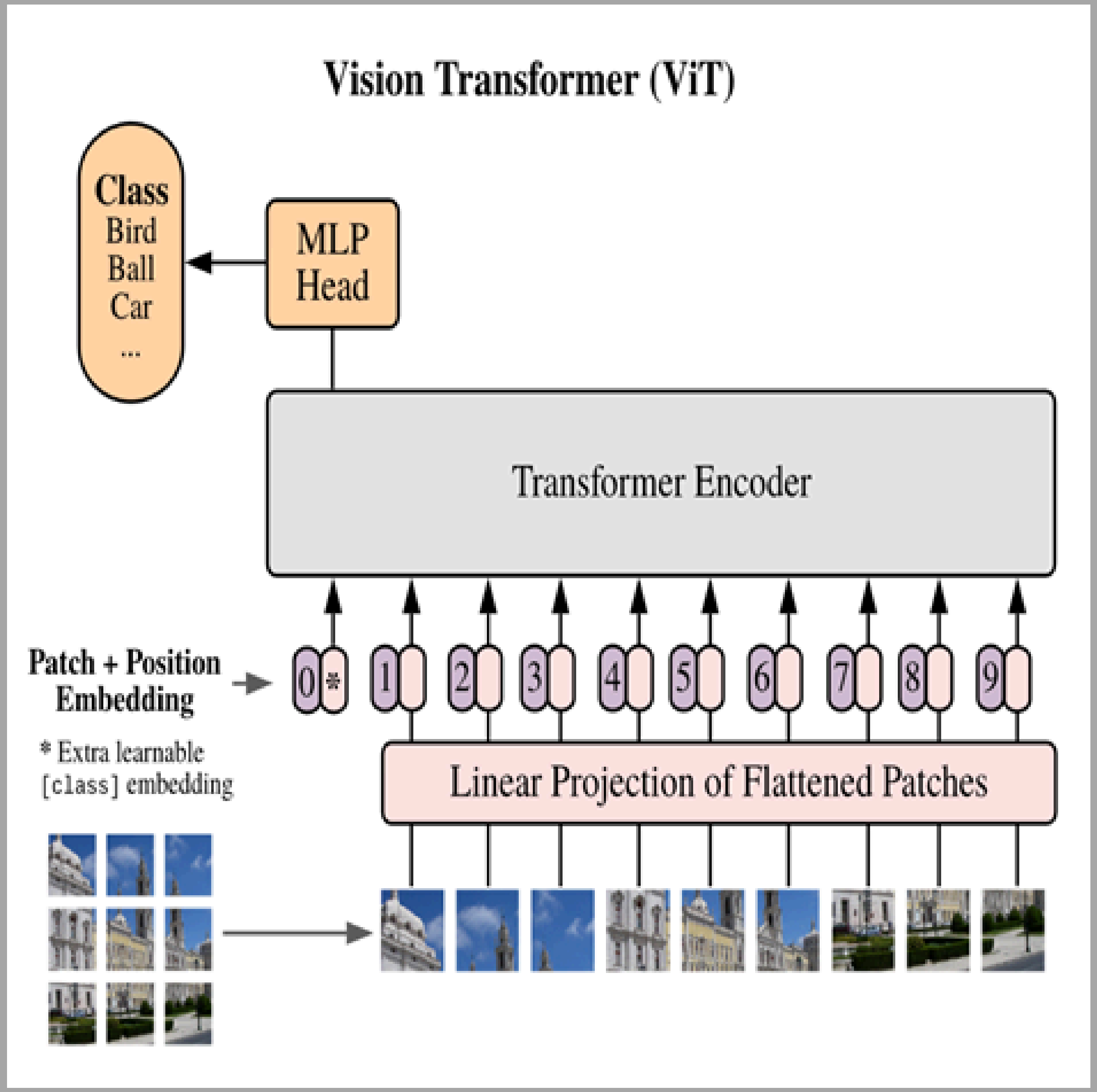
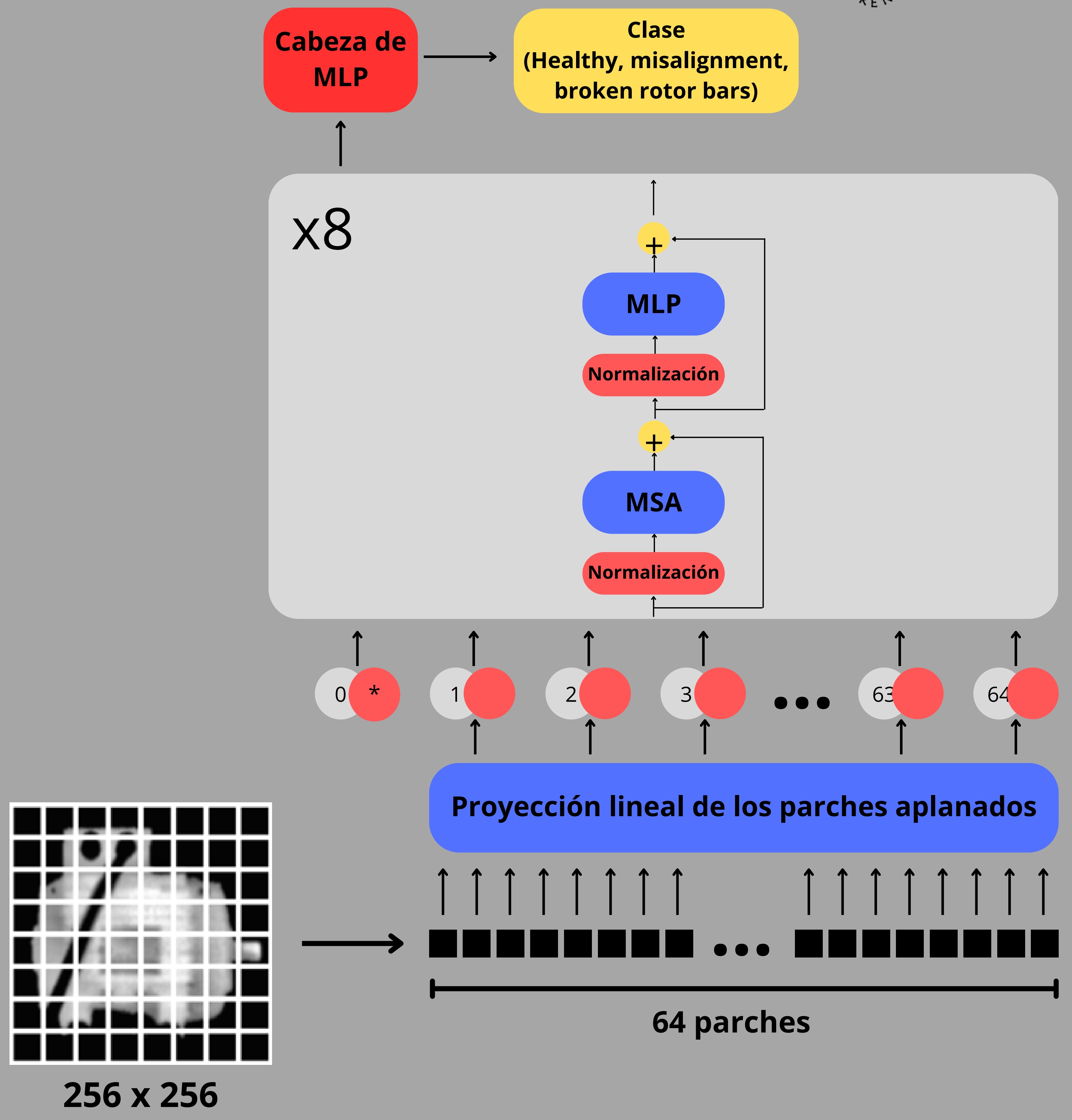
What are ViTs?

This model adapts the transformres architecture for image processing. Learning the relationships between them in an efficient way



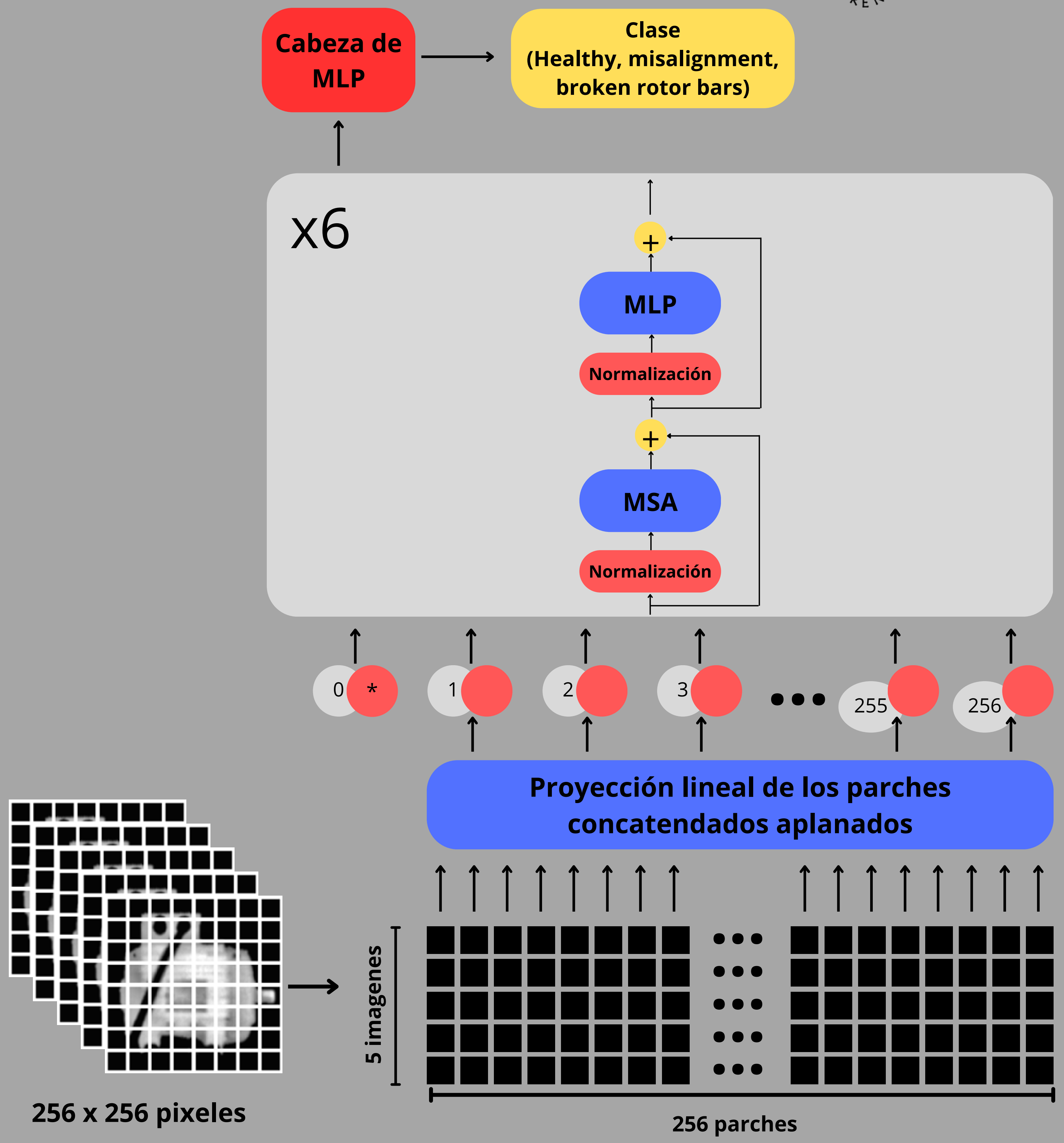
ViT or Simple ViT

- Image: 256x256 pixels, divided into 64 patches of 32x32 pixels.
- Classes: 3 (Healthy, Misalignment and Broken rotor bars).
- Embedding: Each patch projected in a vector of 512 dimensions.
- Transformer: Depth of 8 blocks with 8 attention heads.
- MLP: Hidden dimension of 1024.
- Dropout: 0.2 in attention and feed-forward blocks, and in embeddings, to avoid overfitting.



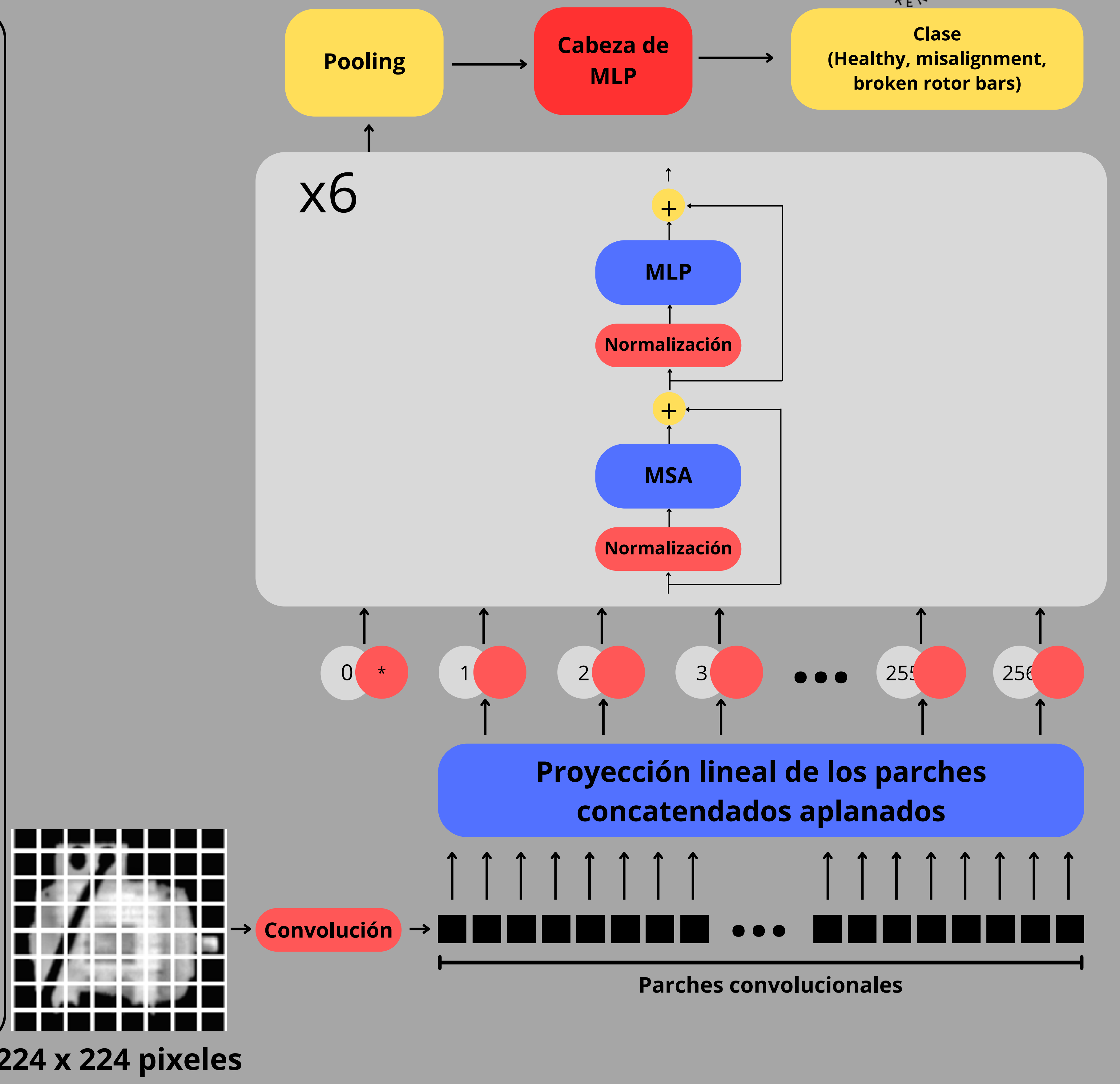
ViT For Smaller Data (ViTFSD)

- Image: 256x256 pixels, divided into 256 patches of 16x16 pixels.
- Classes: 3.
- Embedding: Each patch projected in a vector of 1024 dimensions.
- Transformer: 6 layers with 16 attention heads per layer.
- MLP: 1024 hidden dimension.
- Dropout: 0.12 on attention layers and input embeddings.



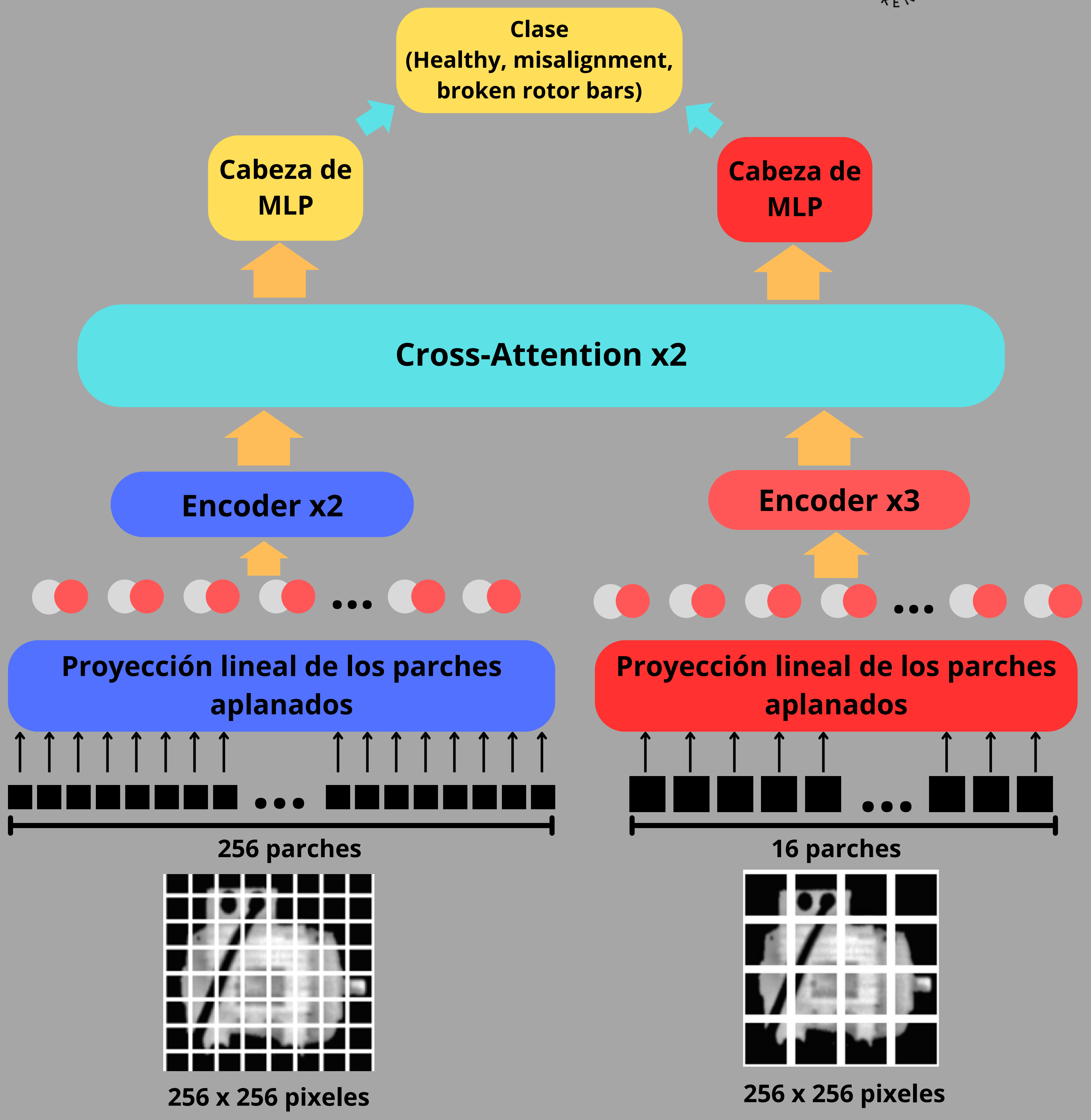
Compact Convolutional Transformers (CCT)

- Image: 224x224 pixels.
- Embedding: 384 dimensions per token.
- Convolutions: 4 layers with filters of size 7 and stride of 2 to reduce dimensions.
- Transformer: 12 layers with 6 attention heads per layer.
- Dropout: 0.3.
- Classes: 3.



CrossViT

- Image: 256x256 pixels.
- Classes: 3.
- Multi-scale coding: 4 blocks.
- High resolution patches: 16x16 pixels, with a 2-layer encoder and 8 attention heads.
- Low-resolution patches: 64x64 pixels, with a 3-layer encoder and 8 attention heads.
- Crossed attention: 2 rounds with 8 attention heads.
- Dropout: 10% in blocks and embeddings.



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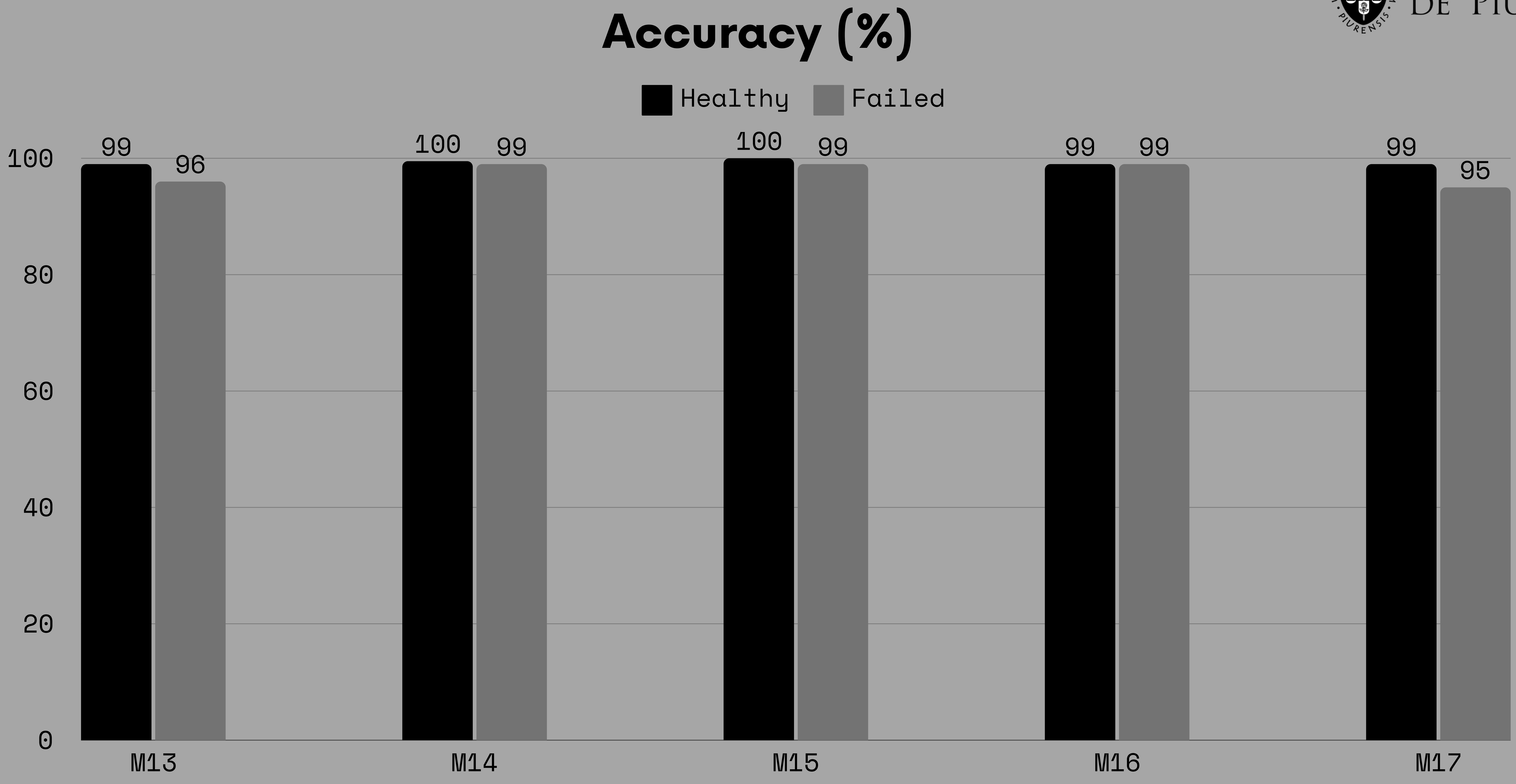
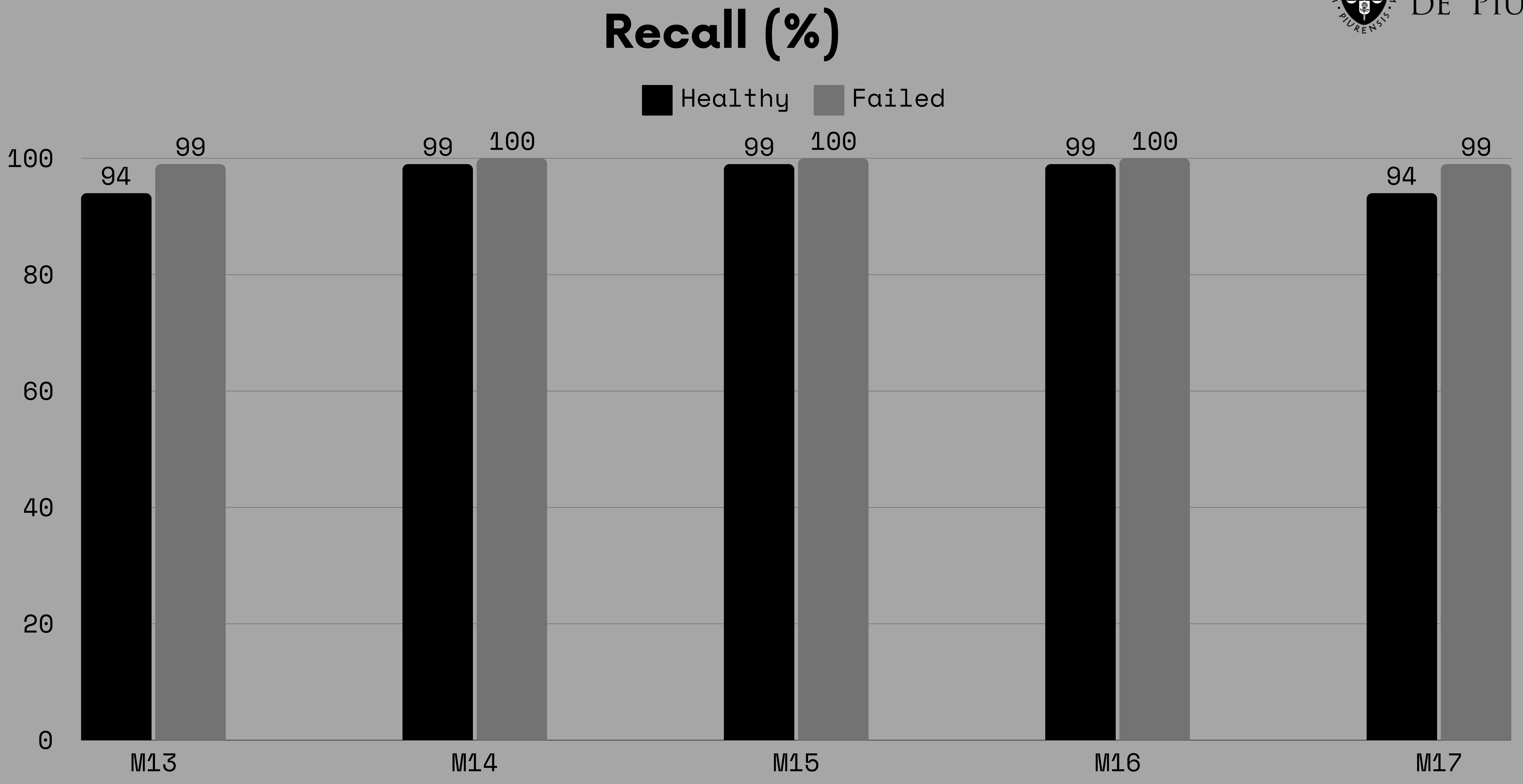
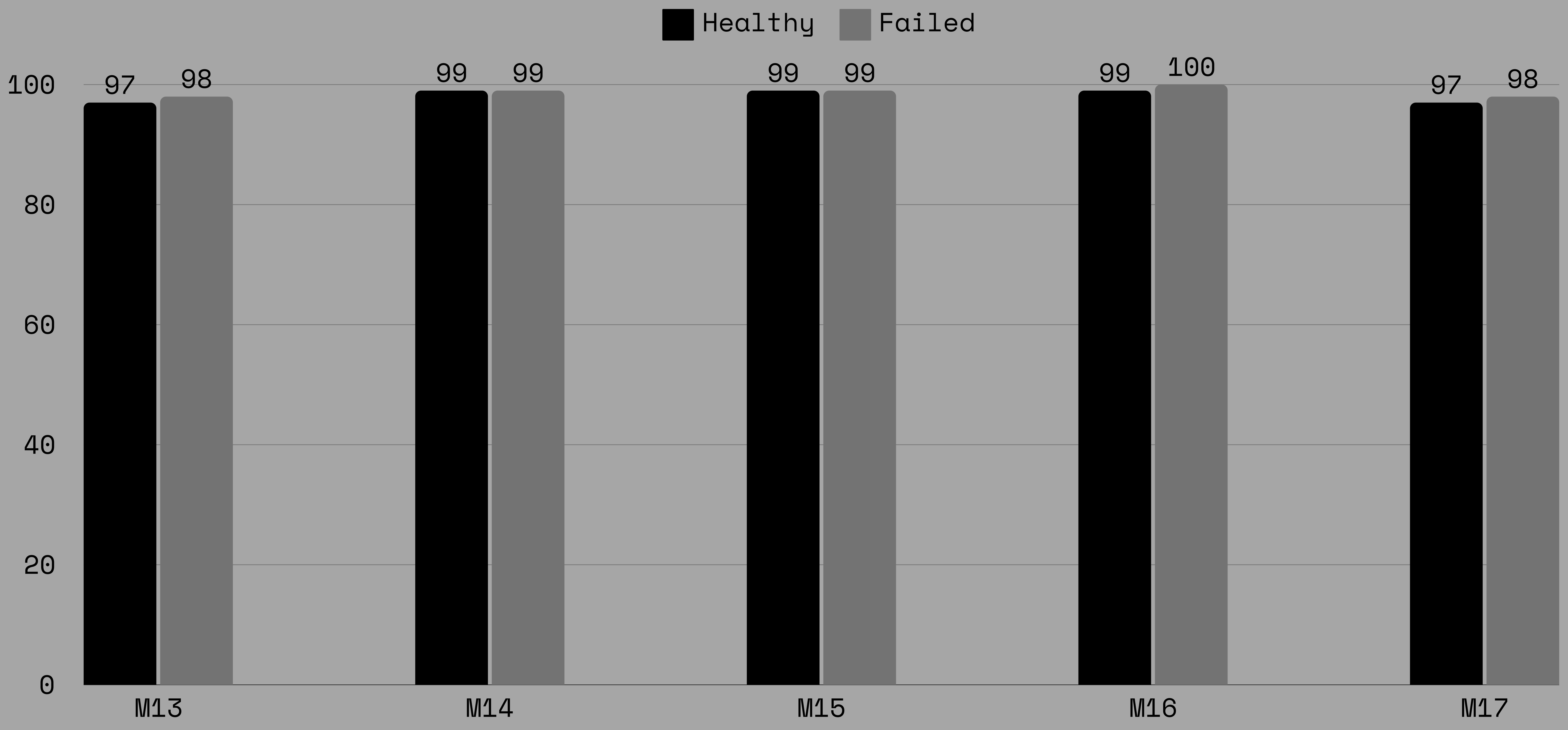
Modelos de ViT entrenados y evaluados

Model	Preprocessing	Classifier	Data
Model 13	YOLOV5m+Otsu+HSI+CLAHE+ GLCM+DWT+PCA	ViT	Train-test6
Model 14	YOLOV5m+Otsu+HSI+CLAHE+ GLCM+DWT+PCA	ViTFSD	Train-test6
Model 15	YOLOV5m+Otsu+HSI+CLAHE+ GLCM+DWT+PCA	CCT	Train-test6
Model 16	YOLOV5m+Otsu+HSI+CLAHE+ GLCM+DWT+PCA	CrossViT	Train-test6
Model 17	YoloV5m	ViT	Train-test6


Accuracy (%)
Healthy
Failed
100
80
60
40
20
0
99
96
100
99
100
99
99
99
99
95
M13
M14
M15
M16
M17


Recall (%)
Healthy
Failed
100
80
60
40
20
0
94
99
99
100
99
100
99
100
94
99
M13
M14
M15
M16
M17

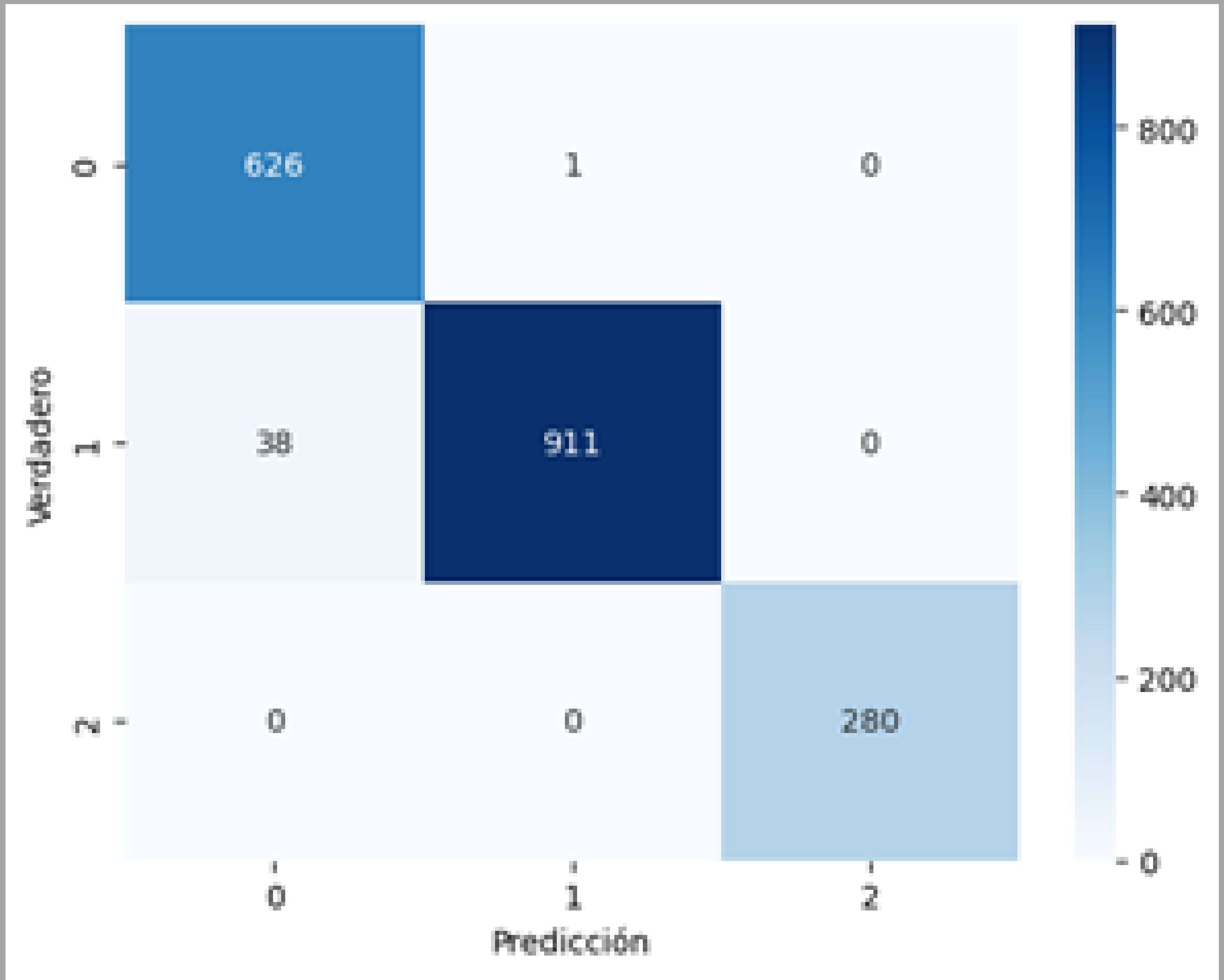
F1-score (%)



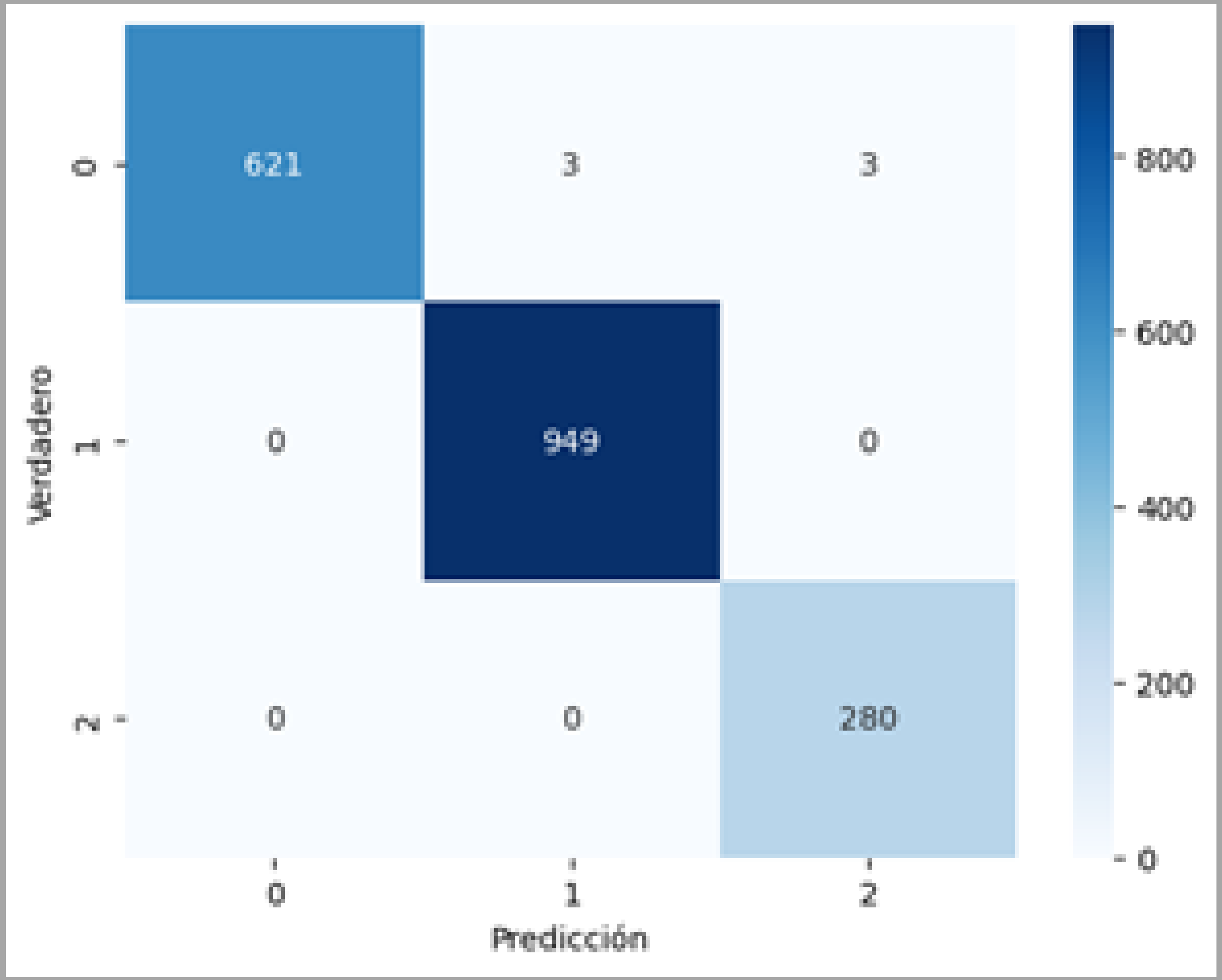
Healthy
Failed
100
80
60
40
20
0
97
98
99
99
99
99
99
100
97
98
M13
M14
M15
M16
M17

Confusion matrices obtained in ViTs

Simple ViT

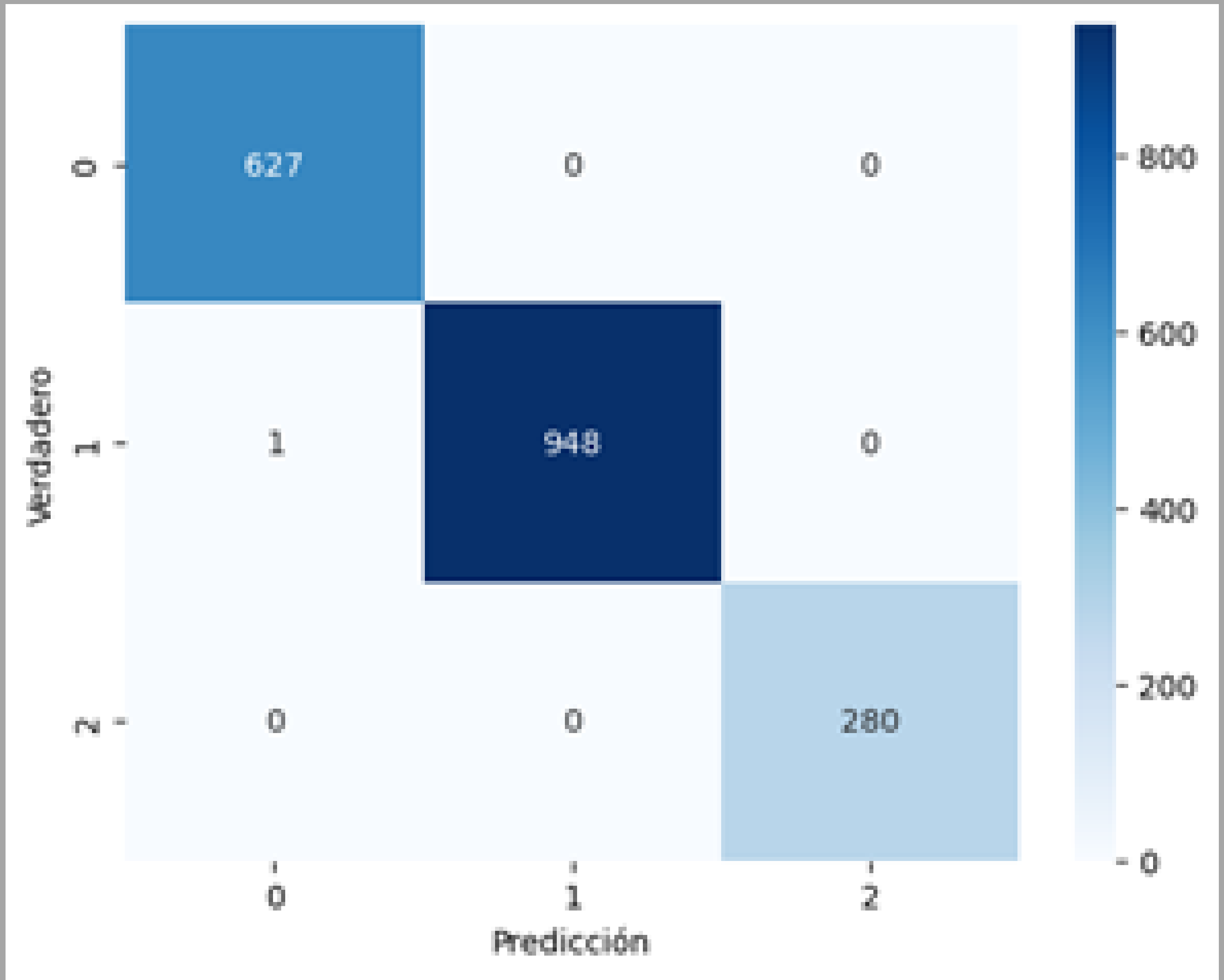


ViTFSD

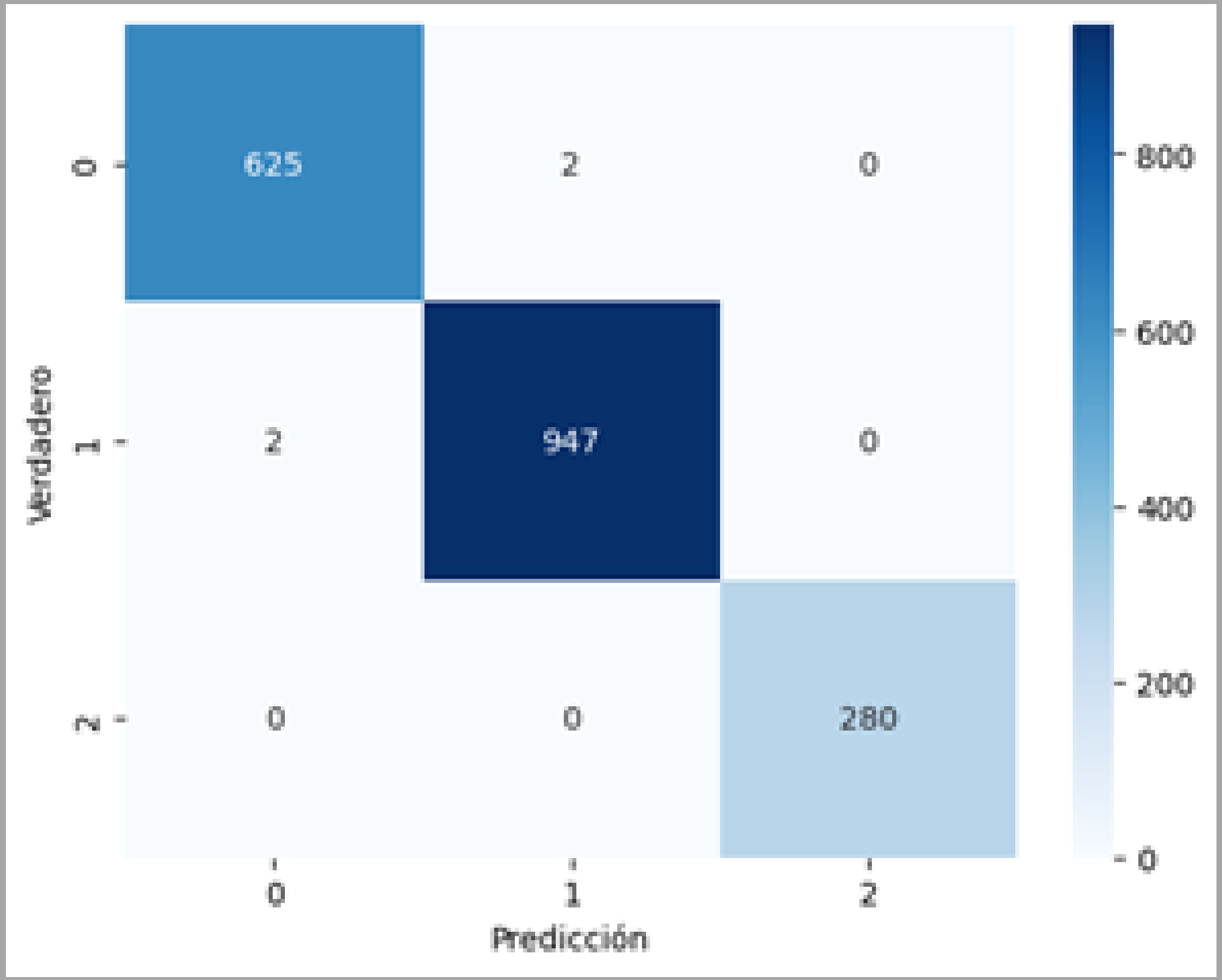


Confusion matrices obtained in ViTs

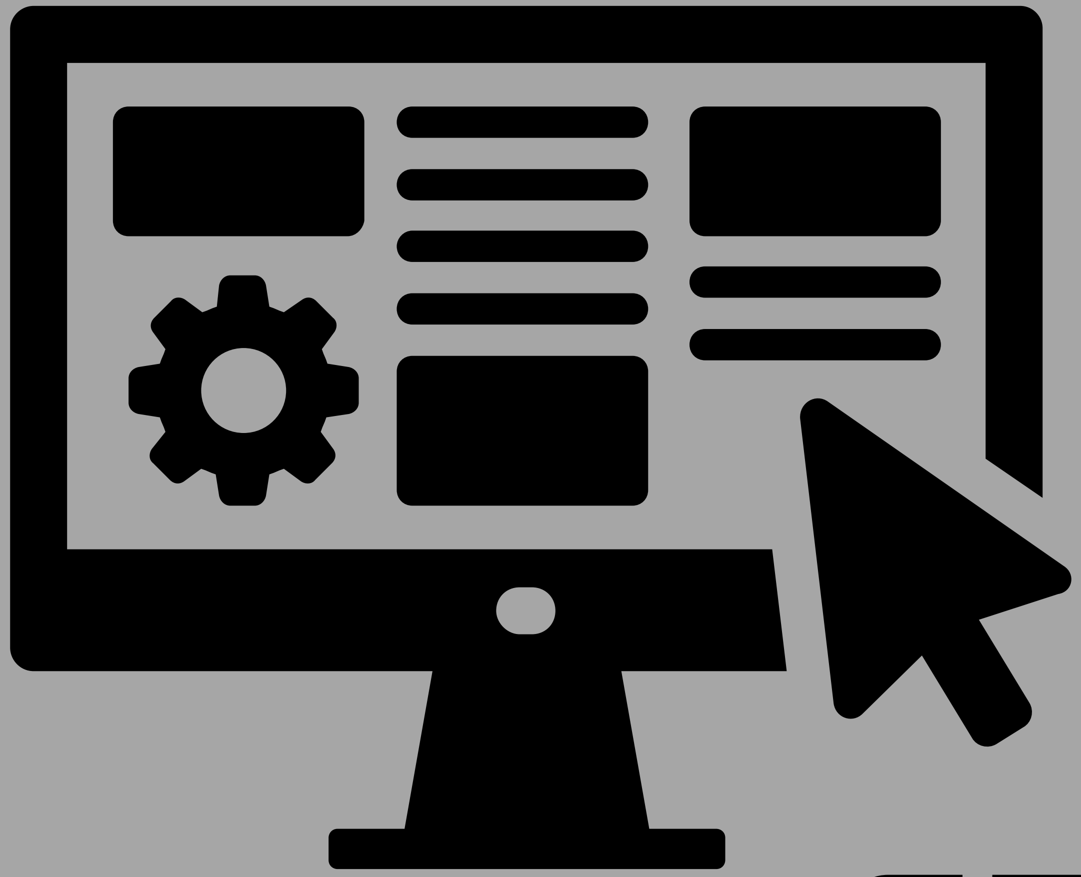
CCT

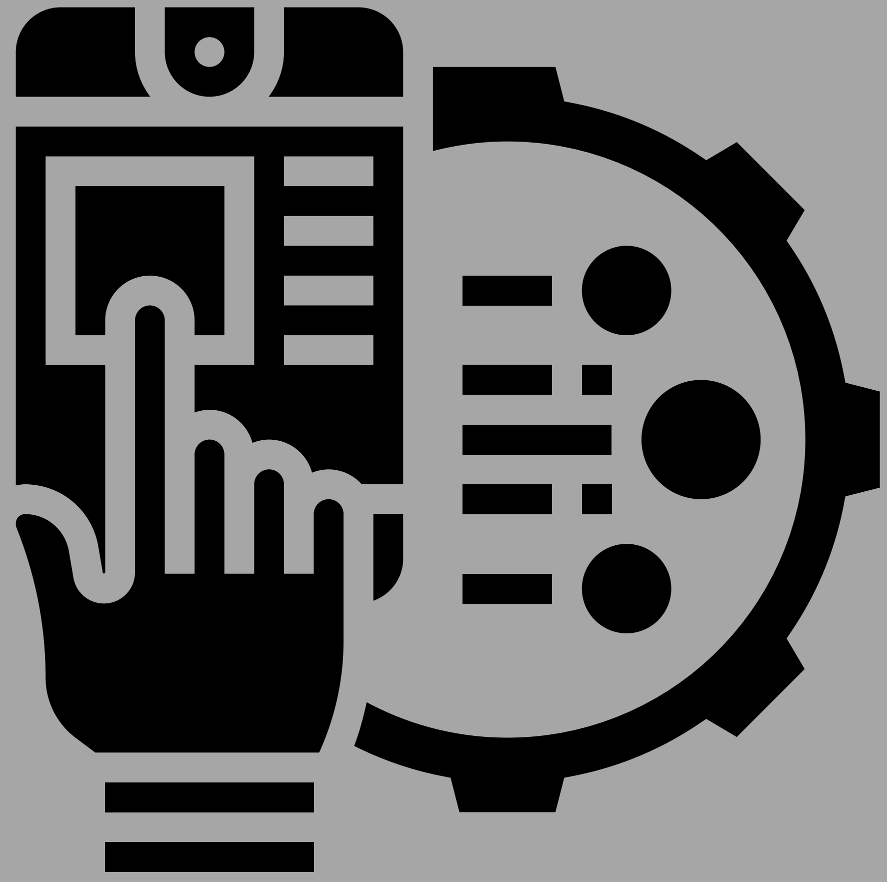


CrossViT



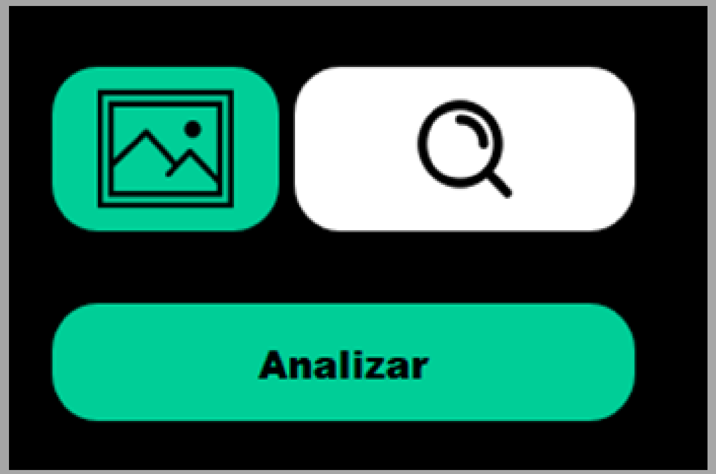
INTERFACE

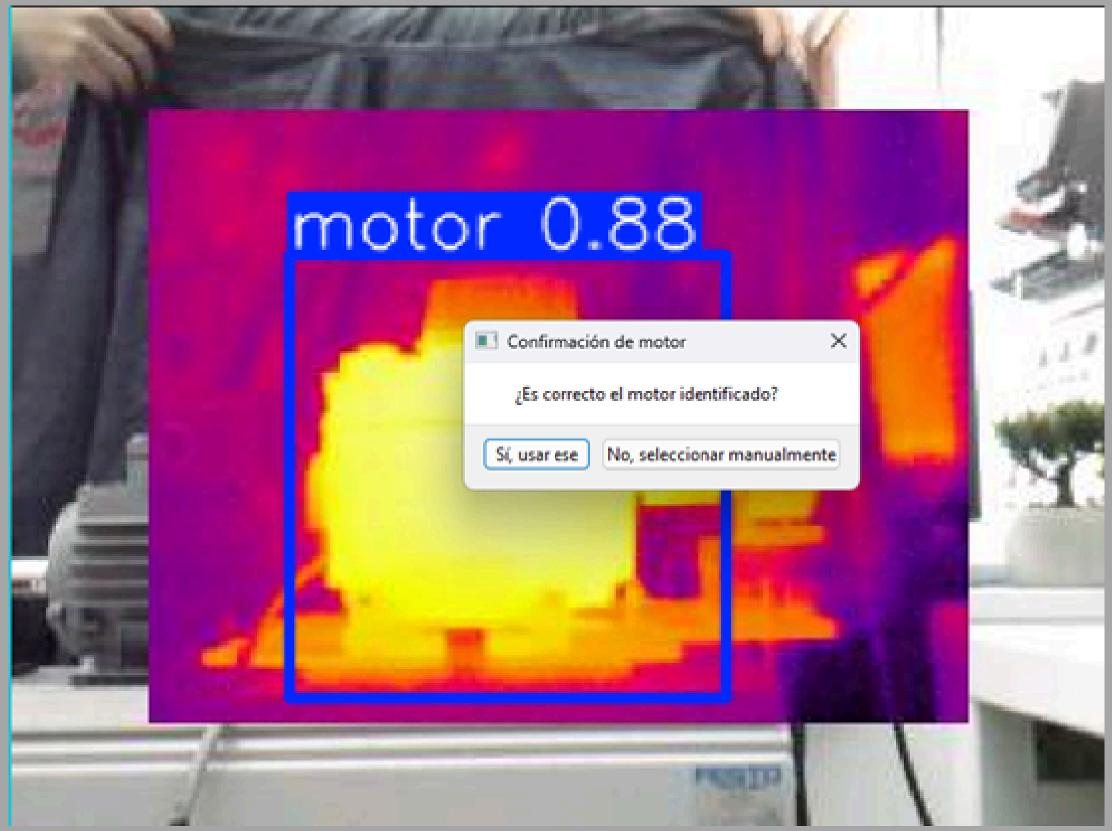




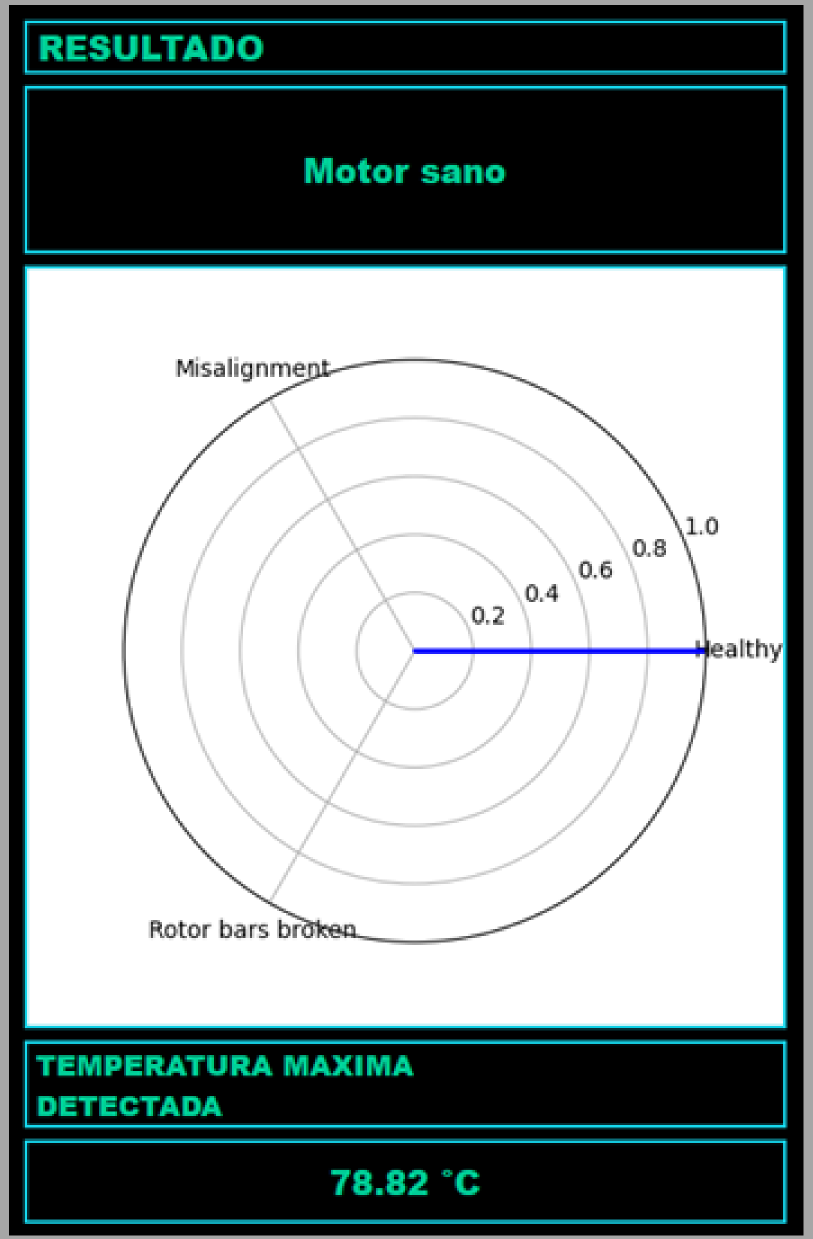

IDENTIFICACIÓN DE FALLAS EN MOTORES AC
Analizar
RESULTADO
TEMPERATURA MAXIMA DETECTADA

Identification of the motor to be analyzed in the image

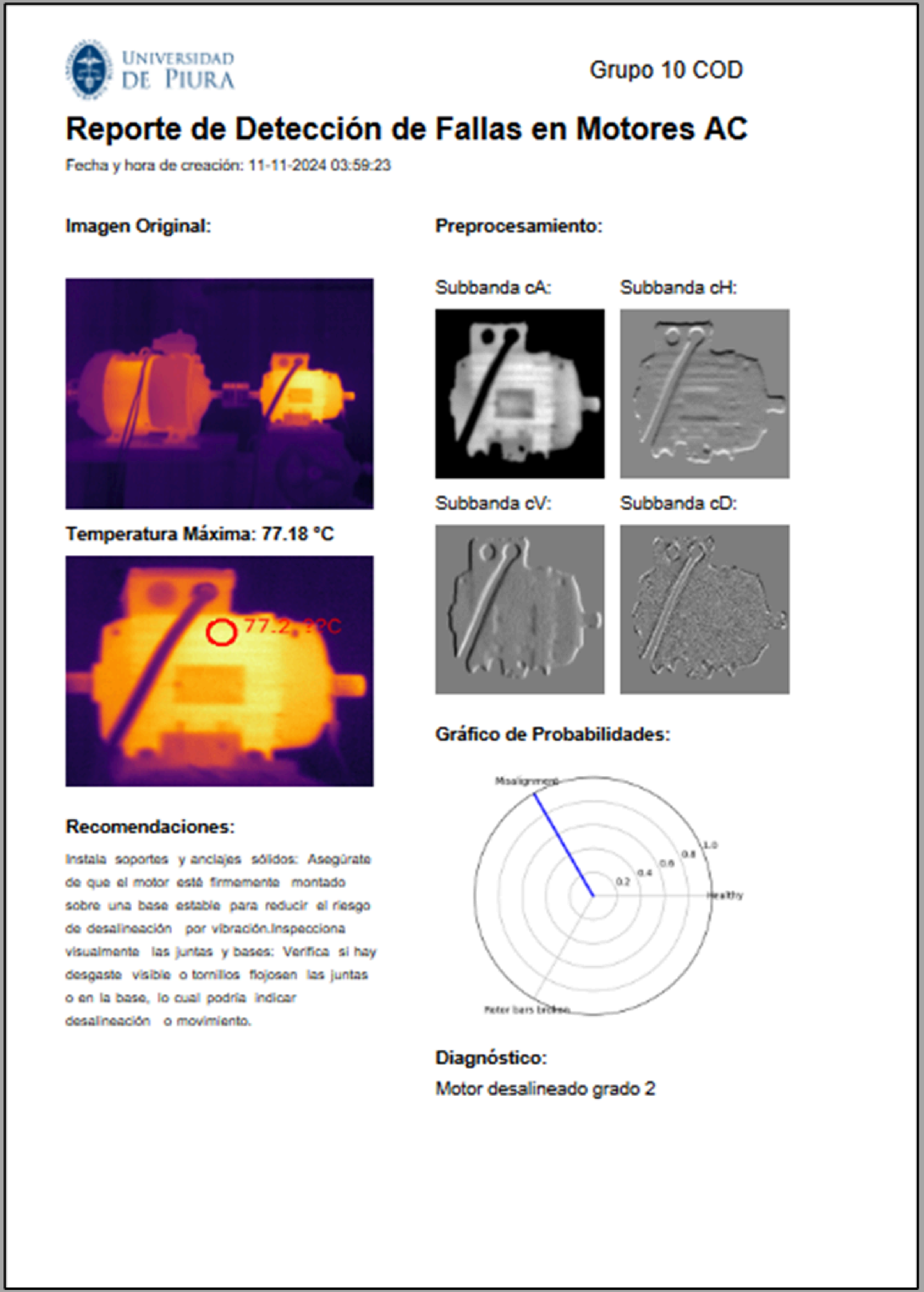




Results



Results report



Grupo 10 COD

Reporte de Detección de Fallas en Motores AC

Fecha y hora de creación: 11-11-2024 03:59:23

Imagen Original:

Temperatura Máxima: 77.18 °C

Recomendaciones:

Instala soportes y anclajes sólidos: Asegúrate de que el motor esté firmemente montado sobre una base estable para reducir el riesgo de desalineación por vibración.Inspecciona visualmente las juntas y bases: Verifica si hay desgaste visible o tornillos flojosen las juntas o en la base, lo cual podría indicar desalineación o movimiento.

Preprocesamiento:

Subbanda cA: Subbanda cH:

Subbanda cV: Subbanda cD:

Gráfico de Probabilidades:

Diagnóstico:

Motor desalineado grado 2

CONCLUSIONS

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THANKS

Group 10

Data and Model Based Control