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Artificial Intelligence in Support of People with Special Needs

SUMMARY

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Abstract

The thesis entitled **"Artificial Intelligence in Support of People with Special Needs"** is a study of great importance in the context of the evolution of technology, which highlights the positive impact of artificial intelligence (AI) in the lives of people with special needs.

In an increasingly digitized world, the access to appropriate technologies can make the difference between limitations and possibilities, between isolation and inclusion. This work aims to develop innovative solutions or improve existing ones, tailored to the specific requirements of this often neglected category in technological development process.

The use of AI in support of people with special needs is a promising direction but faces many obstacles ranging from high costs, the need for customization of solutions and education of those involved, in issues of infrastructure, accessibility, and data privacy. By interdisciplinary approaches, the lives of these people can be improved by developing assistive systems, making communication more efficient, supporting mobility and physical independence, improving healthcare, and extending social inclusion.

First of all, this paper examines the adaption of AI technologies to suit the specific requirements of people with special needs. This involves meticulous analysis of existing technologies used in AI, with a focus on their applicability in improving the quality of life of the aforementioned category. By exploring this, the aim is to develop tailored solutions for specific medical conditions and assistive systems for people with special needs.

Secondly, the thesis explores the application of AI technologies on low-power devices (edge computing). These technologies can create solutions for the efficient processing of time series that are prevalent in the medical field. A multi-functional assistive robot, which can be extended to other services is also being developed, using AI and edge computing solutions to support people with special needs in various aspects of their lives.

Lastly, the research focuses on the development and practical implementation of systems for people with special needs. These systems aim to improve human-machine interaction, detect medical conditions, and adapt to the individual needs of these people. For example, proposed solutions include the detection and classification of cardiac arrhythmias, as well as the classification of encephalographic signals associated with motor tasks and the proposal of new applications to improve the lives of these categories.

Chapter 1

Introduction

1.1 Motivation for Using AI to Support People with Special Needs

Applications of artificial intelligence (AI) can have a considerable impact on the lives of people with special needs [1, 2, 3]. Improving the quality of life of these people is an important development factor for many next-generation AI systems. Examples include speech recognition tools that add captions for the hearing impaired and language prediction algorithms that support communication for the disabled. However, large-scale AI systems can present problems in adapting to the specific needs of people with disabilities or can generate discrimination [4]. The World Health Organization estimates that there are over one billion people with special needs worldwide. Developing accessible technology products for all user groups has been a long process, but mainstream technologies have brought significant benefits for people with special needs [5, 6]. A notable example is the invention of the corded telephone by A. Graham Bell, who initially tried to help the hearing impaired, but created a device that revolutionised communication globally. Audio books and visual captions are other important innovations that have made information and culture more accessible to people with different needs.

AI is increasingly used to make decisions that directly impact people's lives [7] but there is a tendency to discriminate against marginalised groups, including people with disabilities [4]. Disability conditions are diverse and sensitive and information about them is not always shared because of the risk of discrimination [4, 6]. The use of advanced technologies can help expand social participation and employment opportunities for people with disabilities, given significant labour market inactivity rates such as 32% in Romania, according to a 2018 Eurostat study [8]. AI cannot provide sufficient solutions to every problem, but companies are already investing in [9] research projects that can overcome existing barriers.

1.2 The Challenges of AI in Support of People with Special Needs

The use of AI in support of people with special needs is a promising direction, but this application faces various obstacles. These impediments are both technical, requiring complex innovations, and ethical, with profound social implications that can be enumerated:

- **Personalisation**: each person with special needs has a unique set of characteristics, barriers and abilities so a blanket AI solution is impossible. Therefore, there is a need for solutions that can be adapted to meet the specific needs of as many individuals as possible;
- **Accessibility**: technologies using AI are not accessible/usable by this category;
- **Data privacy**: technologies that use artificial intelligence frequently require large amounts of personal information to function properly. Individuals with special needs are not always able to consent to the processing of certain data, which makes generalisation more difficult;
- **Cost**: existing solutions either consume a lot of energy or require expensive devices making them inaccessible to some people with special needs, especially those on low incomes;
- **Interdisciplinary approaches**: developing AI technologies for people with special needs requires knowledge not only of computer science but also of special education about certain pathologies, diseases or even psychology;
- **Education**: ordinary users need education to use AI), but this need is even more pronounced for people with disabilities. Thus education becomes essential for everyone, let alone the category mentioned above;
- **Training**: usually training of certain algorithms is done on certain databases annotated by clinicians, which may differ from the signals of ordinary individuals. This can lead to divergent results.

1.3 Doctoral Research Objectives

In this thesis, the objectives act as guiding principles, shaping the research direction, methodology and conclusions of the thesis. They are the foundation on which the whole study is built, defining precisely the aims and objectives of the research.

The general objective of the thesis is to improve the lives of people with special needs through the use and implementation of artificial intelligence techniques. The aim is to develop innovative solutions or improve current ones, which are adapted to the specific needs and requirements of this category of people often ignored.

OS1. The first specific objective is to investigate neural network architectures and technologies AI adapted to the special needs of certain categories. It focuses on a comprehensive exploration of neural network architectures, with a particular focus on their application in the medical field but also to align with the distinct needs of people with special needs. The aim is to obtain precise and relevant results to improve the quality of life of these individuals.

OS2. The second specific objective is to analyse the techniques of AI applied to low-power devices – edge computing, in two cases: one related to time-series processing and the other related to the realization of a multi-functional robotic system, with processing as close as possible to the data generating source. These are important because many of the systems used to meet the diverse requirements of certain categories of people with special needs require adaptive systems with local data processing, providing support in a spectrum of areas including communication, detection medical abnormalities and even mobility independence.

OS3. The third and final specific objective is to develop and implement systems for people with special needs, with reference to the technologies that have been mentioned in the previous objectives. These will be explored practically, through real-world examples, to address issues related to human-machine interaction, detection of certain abnormalities, medical conditions and interpret vital signals.

In conclusion, the objectives described converge to support the wider aspiration to use artificial intelligence as a catalyst for positive change in the lives of people with special needs and beyond. Achieving these objectives will achieve tangible and lasting improvements in the well-being, integration and autonomy of this under-emphasised segment of our society.

1.4 Structure and Content of the Thesis

The structure is organized into six chapters, each chapter having a distinct role in facilitating a comprehensive examination of the above objectives.

Chapter 1, entitled **"Introduction"**, provides an overview of the thesis topic, introduces the research problem and outlines the structure of this thesis. This chapter also presents the objectives of the doctoral research, the specific aims and the importance of the study. The objectives of the doctoral research present the direction of development of the research. This chapter clarifies the scope of the study, highlighting the main areas of investigation.

Chapter 2, entitled **"The state of the art of artificial intelligence and people with special needs"**, delves into the fundamental aspects of the research by exploring the current context of artificial intelligence. Different types of artificial intelligence are explained, including supervised and unsupervised learning. The chapter also covers the essential components of AI and obstacles in deep learning. In addition, this chapter presents an assessment of the current situation of people with special needs, including the definition of relevant terms and concepts, identification of different types of impairments, and exploration of appropriate technologies that can be applied to the problems of this group.

Chapter 3, entitled **"The impact of artificial intelligence on the lives of people with special needs"**, examines the practical implications of technology and artificial intelligence for people with special needs. The barriers faced by this group are presented, and then the potential of different technologies is examined. Brain-computer interfaces (BCI), heart condition detection devices and EKG monitoring designed to help people with special needs are explored, accompanied by real-world examples and challenges.

Chapter 4, called **"Contributions to the application of artificial intelligence on low-power devices"**, focuses on the practical implementation of edge computing and AI solutions. It also examines the impact of these solutions on improving the quality of life of people with special needs by providing support in a range of areas, including communication, detection of certain medical abnormalities and even mobility independence. In addition, a new practical application of artificial intelligence of a low-power device is presented through the design, development and implementation of a multi-functional autonomous assistive robot. This application uses AI in a dual and redundant person detection system and can describe the environment in which they are, to meet the requirements of certain vulnerable categories by providing them with a safer environment. This chapter also presents the impact of an autonomous multi-functional robot on improving the quality of life of people with special needs.

Chapter 5, entitled **"Contributions to the application of artificial intelligence in support of people with special needs"**, presents practical AI approaches to address the barriers faced by people with special needs. It describes the design, development and implementation of systems for people with special needs, making reference to the technologies that have also been mentioned in previous chapters. In the first part, applications and novel approaches for the detection and classification of cardiac arrhythmias are presented with outstanding results of over 98%. Data collection, preprocessing and model architecture, including convolutional neural networks and novel solutions applied are explained. The chapter also discusses applications of artificial intelligence for classifying encephalographic signals (EEG) associated with motor tasks that can result in solutions with a positive effect on the lives of people with special needs. Brain-computer interface impairments, data acquisition, filtering, feature extraction, calibration and data evaluation are addressed. This chapter details the process of performing an experiment to collect EEG data from various subjects, leading to remarkable results of temporal signal classification of motor tasks of over 90%. These results are obtained by means of a proprietary implemented system capable of using various proposed and existing convolutional neural architectures.

Chapter 6, called **"General conclusions"**, summarizes the main findings and contributions of the research. It highlights how the research results have been disseminated through publications, competitions and conferences. The chapter outlines the implications of the research and its contributions to the field. Potential avenues for future research based on the results are also explored.

Chapter 2

The State of the Art of Artificial Intelligence and People with Special Needs

2.1 The State of the Art of Artificial Intelligence

Artificial intelligence (AI) is the intelligence that machines exhibit, using methodologies from probability theory, statistics and computer science, mathematics, psychology and linguistics to develop algorithms capable of emulating human cognitive functions. AI is a rapidly growing field that develops intelligent machines capable of performing tasks that require human skills and working with large amounts of data being applied in diverse fields. This field encompasses various sub-fields and techniques including machine learning, deep learning, natural language processing illustrated in Figure 2.1.

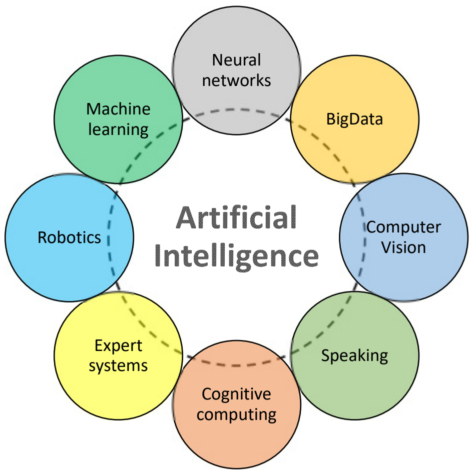

Figure 2.1: Artificial intelligence domains.

An iceberg floating above the ocean symbolises the vastness of AI, as shown in the Figure 2.2. Above the waterline, one often sees attention-grabbing headlines, groundbreaking achievements and applications that showcase the impressive capabilities of these systems.

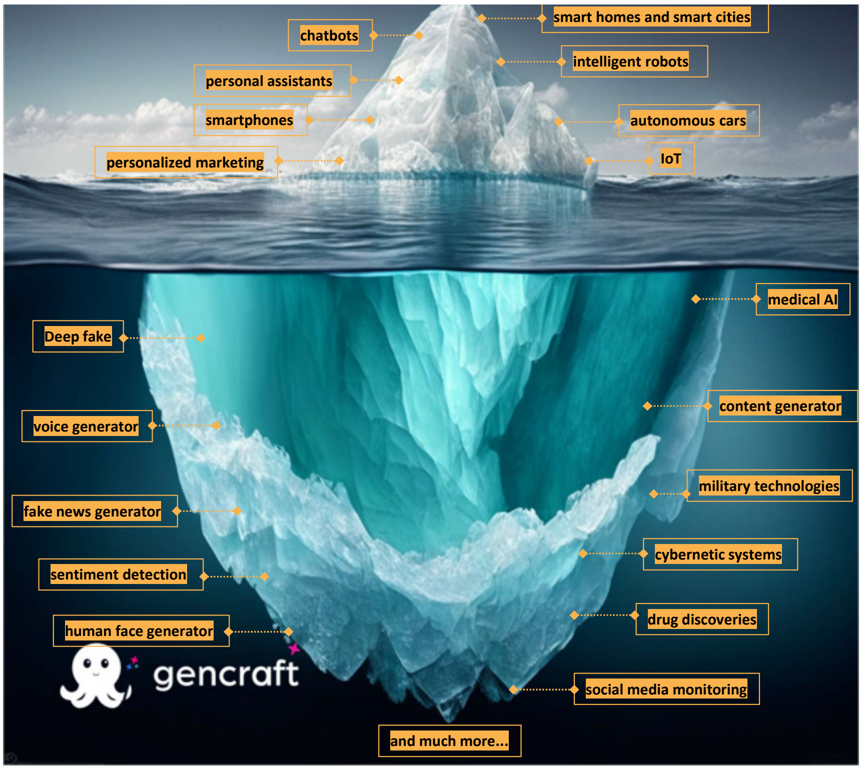

Figure 2.2: Iceberg analogy-artificial intelligence and the visible and less visible domains.[1]

Below the waterline one sees complex areas of research, algorithms involving complex mathematical models, extensive training procedures and substantial computing power.

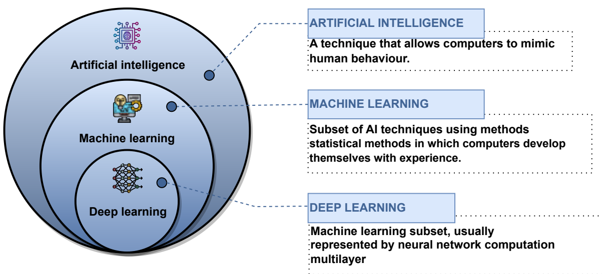

Figure 2.3: From deep learning to artificial intelligence, an adaptation after [10].

2.1.1 Supervised Learning

Uses a labeled data set to predict output, adjusting parameters based on feedback from errors. It is used in classification and regression problems such as medical diagnosis, fraud detection or predicting monthly average temperature. Other algorithms are logistic regression, k-Nearest Neighbors, decision trees, SVM, Naive Bayes [11, 12, 13, 14, 15].

[1] Artificial image generated using the text "iceberg in the ocean with what is seen and what is not seen" www.gencraft.com, with text added over.

2.1.2 Unsupervised Learning

Uses unlabeled data for the purpose of discovering unknown patterns and structures and is used for pattern detection and data dimensionality reduction.

2.1.3 Reinforcement Learning

Reinforcement learning [16] is a process by which the model "learns" to achieve goals in complex environments. It resembles a computer game, in which the model learns through trial and error, maximizing rewards so it uses trial-based approaches with high computational power.

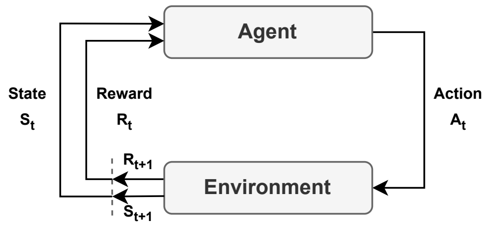

Figure 2.4: Reinforcement learning concept, adapted from [17].

2.1.4 The Key Concepts of Artificial Intelligence

Understanding the fundamentals of machine learning, including the perceptron, network architecture and performance indicators, is essential in this area.

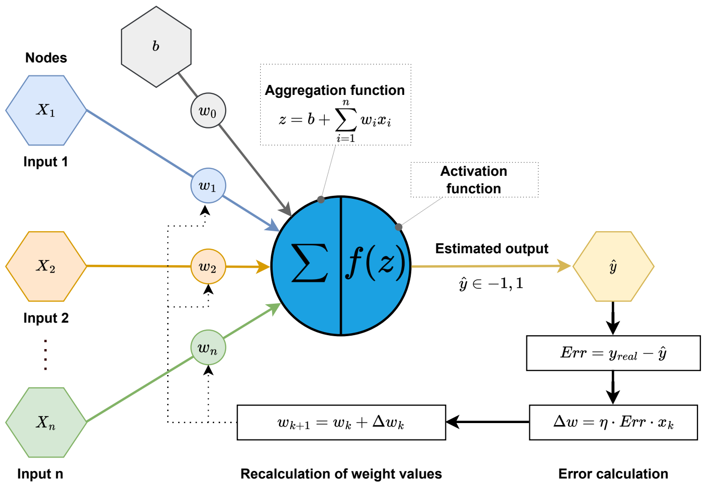

Figure 2.5: Perceptron and $f(z)$ activation function with a learning rate η, adaptation [18, 19, 20]

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2.1.4.1 Perceptron, Activation Functions and Architectural Layers

The perceptron (Figure 2.5) is the core of artificial neural networks, that through weights (w_i) and the activation function ($f(x)$), processes inputs (X_i) and bias to generate outputs (y_n). The activation function introduces nonlinearity, allowing complex relationships between inputs and outputs.

The activation function is a mathematical equation that determines the output of each neuron as a function of the input (Figure 2.5). It is computationally efficient and helps create a range between 0 and 1 and introduces nonlinearity, allowing the model to learn complex patterns from the data. Activation functions can be linear or nonlinear and are essential for the performance and flexibility of neural networks. The activation function in a neural network introduces non-linearity into the outputs of the neurons. There are three main types of activation functions: binary, linear and non-linear.

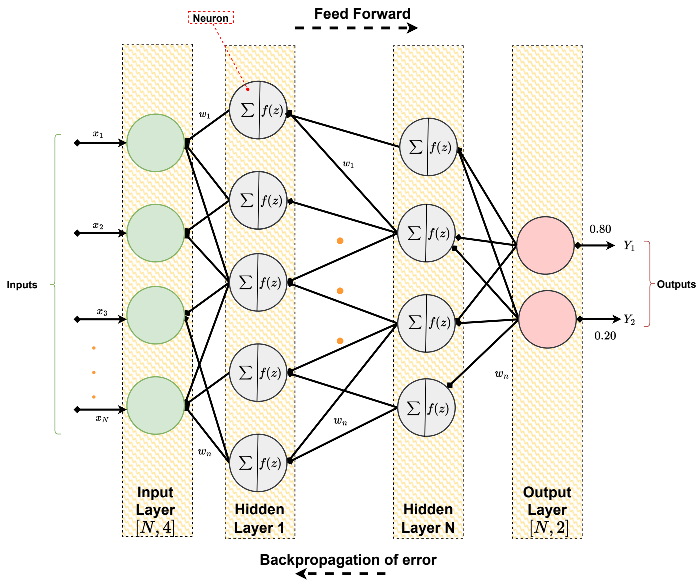


Figure 2.6: Architecture of a neural network: input, hidden layers and output, adaptation [19].

Binary step function is based on a threshold that sends an identical signal to the next layer when an input value exceeds or falls below a certain threshold. The **linear step function** performs better than the binary one with the disadvantage of using the Backpropagation method. **Nonlinear activation function** is the most widely used activation function to create complex mappings between inputs and outputs, essential for learning and data modeling. The most widely used such functions are the sigmoid/logistic activation function, the hyperbolic tangent function, ReLU (eng. Rectified Linear Unit), Leaky ReLU, (PReLU), ELU (which solves ReLU problems) and Softmax [21] etc.

Architectural Layers in Artificial Neural Networks

Layering neural networks into architectural layers is a key factor in determining network configuration and operation. The process involves the transmission of inputs in successive layers. The previous layer generates inputs for the next layer. Input layers, hidden layers and output layers each perform specific tasks. The initial layer is responsible for receiving raw data, while intermediate layers perform computations on the data to generate intermediate representations, and the final layer produces the prediction or classification result. The most commonly used layers include the convolution layer, the dropout [22], the maximum or average pooling [23, 24, 25, 26], the flattening and the fully connected layer.

2.1.4.2 Backpropagation, Loss Function, Hyperameters, Distortion Term and Model of an Artificial Neural Network

Backpropagation is an essential algorithm in training neural networks. It has two phases: forward pass (propagating data through the network) and backward pass (error calculation and weight adjustment). The goal is to minimize the error by updating the weights iteratively using the error gradient [27]) The loss function (or cost function) evaluates how well a model's predictions fit the training data. Different cost functions such as MSE Cross-entropy Loss [28, 29, 30] are used. Hyperparameters are parameters whose values control the learning procedure and decide the values of the model parameters that a learning algorithm eventually assimilates. The prefix "hyper" indicates that these parameters control the learning process and the resulting model parameters (adapted from [31]). The term distortion (bias [32, 33, 34]) represents the systematic error of algorithms in predicting true or predicted values, and a neural network model is a mathematical representation that learns and makes predictions based on input data.

2.1.4.3 Metrics for Evaluating Machine Learning Algorithm Performance, Epochs, Learning Rate, Overfitting and Underfitting

Metrics consist of various measurements used in the process of evaluating the performance and establishing the effectiveness of machine learning network architectures. Among the most used such metrics we can mention model accuracy, confusion matrix, precision and true positive rate, F1 score, AUC-ROC, MAE etc. The epoch represents an iteration over the training dataset, during which the model parameters are adjusted according to the calculated error between predicted and true values. The learning rate is a hyperparameter that determines how quickly parameters are changed during training, influencing convergence and avoiding overfitting or under-fitting [27, 35].

2.1.4.4 Optimizers and Methods to Manage Unbalanced Datasets

Optimizers are essential in training neural networks, adjusting model weights to obtain accurate predictions by varying them according to the loss function. Examples of optimizers include Adadelta, AdaGrad, Adam etc.[36, 27, 37, 38], each with different approaches to adjusting model parameters. Choosing the right optimizer influences the performance and convergence speed of the model.

To handle unbalanced datasets in machine learning, techniques such as random oversampling (duplicating samples from the minority class), random under-sampling (randomly removing samples from the majority class) or the SMOTE [39] technique (creating synthetic examples of the minority class by extrapolating features) can be used. These methods help to balance the dataset and improve model performance.

2.1.5 Significant Impediments to Deep Learning

Deep learning, while promising, faces many challenges, such as **high-quality data loss**, **the ever-changing environment** and the need for **considerable processing power**, with implications for energy consumption, **data privacy and security**. Also, the **specificity and complexity of neural networks** deepen the difficulties in developing these algorithms.

2.2 The State of the Art of People with Special Needs

As defined by OMS [40] disability is a complex problem that includes difficulties in performing tasks and restrictions in participating in society, reflecting the interaction between the characteristics of the individual and the society in which he or she lives.

2.2.1 Definition and Terms Used

In the context of people with special needs, the term "disability" refers to losses or limitations of physical or mental functions, impacting on the ability to perform daily tasks and participate actively in society, and the preferred language moves towards respectful expressions such as "people with disabilities" or "people with special needs", encompassing a variety of subdivisions from motor problems to sensory or intellectual disabilities. This diverse category of people with special needs includes the elderly with motor and cardiac problems, individuals with acquired paralysis from accidents or trauma, people with sensory disabilities, mental trauma, substance addictions, children from disadvantaged or marginalised backgrounds, and those with intellectual disabilities, chronic medical conditions or learning disabilities. In current work, the term "people with special needs" covers a diverse group of individuals with particular needs or requirements, which may include impairments or disabilities, but vary according to factors such as age, mental health, addictions, socio-economic status and educational background, and appropriate support is essential for the promotion of equal opportunities and human rights.

2.2.2 Types of Deficiencies

The most common deficiencies encountered among people with special needs can be grouped into three categories: physical and sensory impairments, cognitive disorders and impairments, and acquired physical disabilities, including paralysis and disabilities caused by brain injury.

2.2.2.1 Physical and Sensory Impairments

Motor and communication deficiencies can limit the independence and social participation of older people and may be caused by factors such as muscle weakness, cognitive decline or hearing and speech problems. Interventions, rehabilitation and technologies can help improve the quality of life of these people. Visual impairment refers to impaired vision that cannot be corrected with glasses or contact lenses. Hearing loss, on the other hand, is a partial or total impairment of the ability to hear, which can affect language in children and social interactions in adults, with the potential to isolate people from social groups. Both factors can affect a person's physical ability or sensory perceptions.

2.2.2.2 Cognitive Disorders and Conditions

These categories include a wide range of mental health conditions, intellectual disabilities and brain injuries, which affect cognitive function. Examples include autism spectrum disorders, Tourette syndrome and epilepsy. Mental health conditions, such as depression, anxiety and schizophrenia, can adversely affect daily life and can be managed through drug therapy and psychotherapy. Intellectual disability involves significant limitations in intellectual functioning and adaptation to everyday life, and the causes can be varied, including genetic and environmental factors. Brain damage can result from events after birth and can cause cognitive, emotional and physical impairments. Autism spectrum disorder affects social interactions and communication, while Tourette syndrome involves vocal and motor tics. Epilepsy causes recurrent seizures due to abnormal electrical activity in the brain and can have various causes, from brain damage to genetic factors.

2.2.2.3 Acquired Physical Disabilities

This category includes acquired physical disabilities such as brain injury, cerebral palsy, muscular dystrophy and spinal cord injury. Physical disability affects mobility and can be hereditary or acquired as a result of an accident or medical condition. Causes may include trauma, disease or congenital conditions. Cerebral palsy develops during birth and can cause muscle weakness and coordination problems. Muscular dystrophy is a genetic condition that leads to progressive muscle loss, and spinal cord injuries can cause loss of mobility.

2.2.3 Encephalography in the Study of Problems of People with Special Needs

Electroencephalography is a technique used to measure the electrical activity of the human brain by recording the electrical potentials generated. This test is easily accessible and provides concrete data about the state of brain function. Electroencephalography (EEG) is a commonly used tool among physicians and researchers to investigate brain processes and identify neurological pathologies. In addition, it has been found to be beneficial in addressing behavioural disorders such as autism, attention deficits, difficulties in acquiring knowledge and delays in language development [41]. Deep learning has recently demonstrated an impressive ability to interpret signals in time series [42, 43] and may have a strong impact on the interpretation of signals EEG present in some studies [44].

2.2.3.1 Types of Electroencephalography

Electroencephalography is used to diagnose certain neurological conditions. There is routine EEG for assessing brain status, outpatient EEG for monitoring brain activity outside hospital, sleep EEG for diagnosing sleep disorders and video EEG (video telemetry) which combines recording of brain activity with monitoring of patient behaviour for a more detailed assessment of brain function.

2.2.3.2 Data Format of Medical Signals

The European data format (EDF) is a free standard for storing biological and physical signals in electrophysiology and is essential in EEG and PSG recordings. EDF+ EDF Browser [45, 46] is an enhanced version that allows text annotations directly on signals, and the EDF Browser software [47] facilitates the visualization and analysis of these data, useful in research and clinical practice.

Chapter 3

The Impact of Artificial Intelligence on the Lives of People with Special Needs

In the modern world, technology and artificial intelligence have remarkably changed many aspects of life, especially for people with special needs [1, 2, 3]. Technology has revolutionised the abilities of people with special needs, including the development of communication, mobility, healthcare and is even being seen in decisions that have a major impact on people [7].

However, there are barriers such as customisation of solutions, data protection and high costs in the field AI. The brain-computer interface (BCI) is an important area, allowing control of devices with signals emitted by the brain, beneficial for people with disabilities, including in detecting health problems.

Another important aspect is the use of devices to detect medical conditions that are vital for people with special needs who are dealing with conditions such as heart disease.

3.1 Challenges Faced by Individuals with Special Needs on a Daily Basis

People with special needs face everyday challenges influenced by their type and severity and the availability of assistance as follows:

- **independent living**, namely that some people with disabilities may require assistance with everyday tasks such as personal hygiene or feeding;
- **Medical care and support services** which are often costly and require certain equipment;
- **Communication** with others to express basic needs, such as food and water, or even control of a wheelchair being closely linked to their integration into society in order not to be marginalised;
- **employment**;
- obtaining a quality education specific to their needs;
- **reduced inclusion** in society resulting in their marginalisation;

- **Mobility and accessibility** are major barriers for people with disabilities, affecting their ability to move and participate in society.

A comprehensive development strategy is essential to overcome these and future barriers, including improving accessibility, combating social prejudice and expanding health and mobility services for people with disabilities.

3.2 Potential Technologies for Supporting Individuals with Special Needs

While the contribution of AI to supporting vulnerable groups has been discussed above, we need to explore ways in which it can work with other technologies to overcome the barriers listed in section 3.1.

3.2.1 Brain-Computer Interfaces

The brain-computer interface (BCI) allows communication with the environment using brain signals without the need for muscular action. This system has a significant impact on the quality of life of people with severe motor disabilities by facilitating interaction with external devices such as computers, speech synthesizers and neural prostheses. Advances in neuroscience, signal processing and sensor technology have transformed BCI from concepts to reality, as recent studies indicate [48, 49, 50]. BCIs can make use of AI, specifically machine learning, and can recognize a particular set of patterns in the electrical signals produced by the brain. The process takes place in several consecutive steps: signal acquisition, signal preprocessing and enhancement, feature extraction, classification and training (using AI techniques) and control interface with real-time applications, steps described in the 5.2.2 section.

3.2.1.1 Electrical Activity of the Brain: Functions and Locations

Brain waves, also called **neuronal oscillations**, are periodic patterns of electrical activity generated by the brain, classified into distinct frequency ranges and related to cognitive processes, mental states and physiological functions. They are divided into several categories: delta (0.5-4 Hz) are observed in deep sleep, theta (4-8 Hz) associated with dreaming, deep relaxation and creativity, alpha (8-12 Hz) for relaxation and meditation with eyes closed, beta (12-30 Hz) associated with increased concentration, while gamma (30-100 Hz) indicates advanced cognitive processes such as attention and memory. Brainwave patterns vary from person to person, influenced by moods and mental activities. Neuroscience, psychology and cognitive science study these oscillations to understand neural function and human behaviour.

Brain functions and locations, (with frontal, occipital, parietal, temporal lobes), which designate specific functions, are essential aspects in the complexity of the human brain. Extensive research has led to significant advances in identifying crucial areas responsible for functions such as perception, motor control, language processing and memory consolidation [51]

Brodmann areas represent a system of anatomical divisions in the human cerebral cortex similar to those in the Figure 3.1. They have been defined by neurologist K. Brodmann who divided the cortex into 52 areas. There is some research that has shown that the organisation of the brain is much more complex [52, 53].

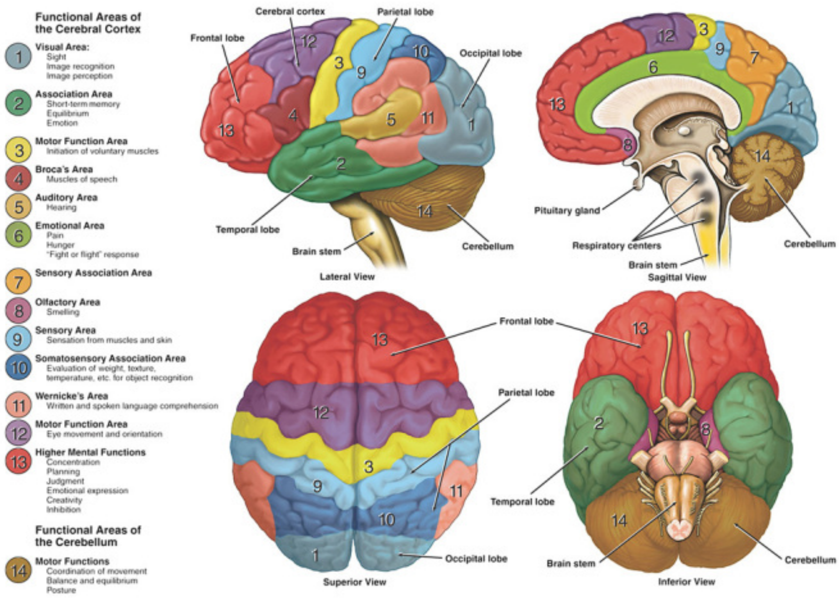


Figure 3.1: Brain locations and functions, source [54, 55].

3.2.1.2 The Efficacy of Encephalography in Diverse Pathologies

Electroencephalography helps to diagnose neurological and psychiatric disorders by analysing the electrical activity of the brain, contributing to accurate diagnosis and patient progress, especially in central or peripheral nervous systems [56, 57, 58, 59]. These include the use of EEG for locating areas responsible for epileptic seizures, assessing deterioration of brain function and post-acrshortavc complications, identifying functional areas during brain tumour surgery and detecting subtle brain wave changes in the early stages of Alzheimer's dementia. On the other hand, psychiatric disorders affect a person's mental, emotional and behavioural functioning and EEG can be used to adjust treatment and assess its effectiveness. The most common conditions include depressive disorder, schizophrenia, depression and anxiety, and post-traumatic stress disorder.

3.2.1.3 Electrodes, Their Placement in Montages and Possible Artifacts

Electrodes EEG fall into two categories: active and passive electrodes. Active electrodes have amplification circuits for signal enhancement and interference reduction, requiring specialised equipment and additional power supply. Passive electrodes measure electrical potentials directly, without internal amplification, and require a separate amplification system, and come in a variety of designs and materials, such as Ag/AgCl gel electrodes, single gold pin electrodes or multi-pin hybrid electrodes, each with specific advantages and disadvantages [60].

Electrode placement is accomplished through montages, which are logical and ordered arrangements of channels used to display EEG activity on the scalp. The number of channels in a montage varies (from 2 to over 100) depending on the number of electrodes available and the purpose of the recording. The 10-20 system, with 21 electrode locations and 16 channels, is just one of many possible configurations. The classification of mountages includes variants such as longitudinal, transverse or reference bipolar.

Number of channels, or the number of electrodes used on the scalp for recording, influences the spatial resolution and ability to detect conditions. More channels improve the accuracy of localizing brain activity and provide sufficient data for machine learning algorithms, avoiding the need to generate synthetic data (section 2.1.4.4).

Artefact types are undesirable signals that can interfere with the correct interpretation of brain activity. The most common artifacts are those produced by blinking (Figure 3.2), sweating artifacts, artifacts of lateral eye movement, EKG artifacts, artifacts generated by the pulsation of a vein, and breathing artifacts.

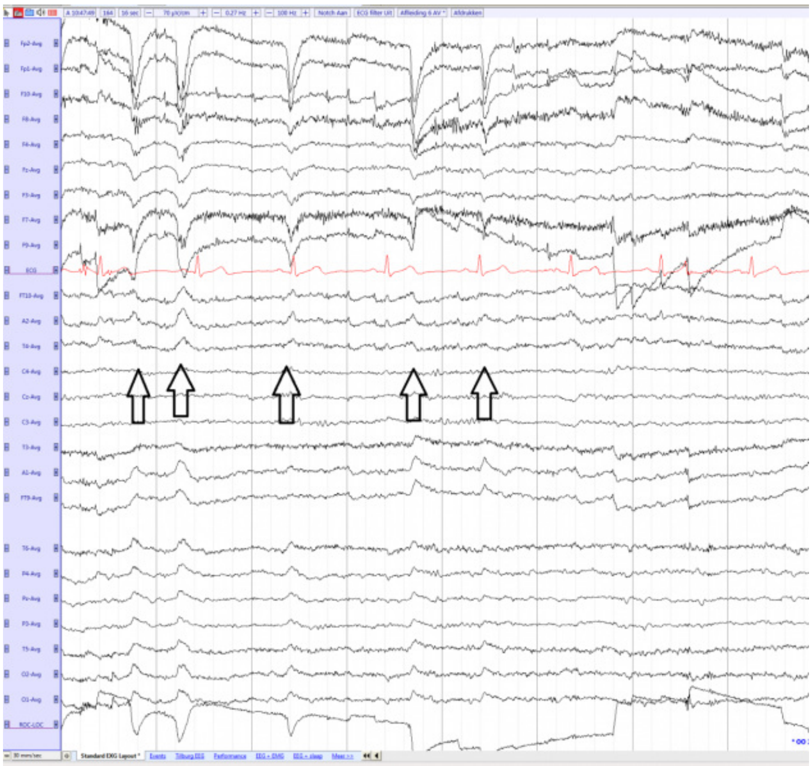


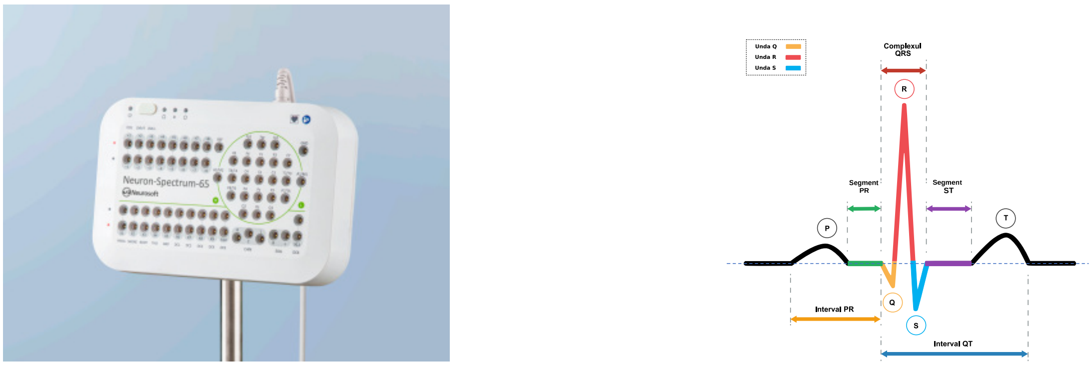
Figure 3.2: Artifact produced by blinking, source [61].

Independent component analysis (ICA) [62, 63] is a signal processing methodology used in EEG to efficiently separate signals into their fundamental components, eliminating artifacts such as eye blinking and electrical noise.

3.2.1.4 Devices for brain signal acquisition

Brain signal acquisition devices are non-invasive instruments that capture electrical activity in the brain from the scalp, with multiple applications in research, medical treatment and the development of brain-controlled technologies.

The Neuron Spectrum 65 System is a medical device developed by Neurosoft used in medical institutions around the world for brain signal acquisition. This advanced system offers 39 EEG channels, EKG channels for artifact removal, as well as EMG and EOG channels, incorporating a portable unit for connecting and disconnecting sensors, ensuring excellent signal quality and providing a flexible solution. Various EEG devices are available for research and clinical applications, such as Emotiv EPOC+



(a) (b)

Figure 3.3: Neuron Spectrum 65 device, source [64] (a), QRS complex, adapted from [65] (b).

with 14 channels and a sampling rate of 2048 Hz, Muse with seven electrodes and filtering functions, OpenBCI a programmable and low-cost EEG platform, MindWave Mobile 2 for monitoring attention and relaxation levels, and advanced EEG systems from g.tec, such as g.Nautilus.

Therefore, non-visual technologies such as EEG headsets and brain-computer interfaces can significantly improve the quality of life of people with special needs. These advanced technologies enable people to achieve autonomy, communication, mobility and overcome limitations such as paralysis or motor impairments. They also promote social integration and inclusion, contributing to a more inclusive and peaceful society.

3.2.2 Electrocardiography

The EKG is a non-invasive test that collects the electrical activity of the heart using electrodes on the chest and wrists. In some cases, to detect rare or irregular events in cardiac activity there are two monitoring options: **Holter monitoring** (24-48 hours) and **event monitoring** devices. Figure 3.3b shows the main components of a EKG signal: the P-wave (atrial depolarization), the QRS complex (ventricular depolarization), and the T-wave (ventricular repolarization). The components of the EKG signal are assessed in terms of their shape, amplitude and duration. Abnormalities in these characteristics may indicate various cardiac conditions.

3.2.2.1 Scope and applications of EKG in medical diagnosis

The main purpose of EKG is to diagnose various cardiac conditions, including arrhythmias, myocardial ischemia or infarction, and ventricular hypertrophy [66, 67]. This is done by identifying abnormalities in the rhythm and electrical activity of the heart, which allows doctors to detect and evaluate these conditions and establish appropriate treatment plans for patients.

3.2.2.2 Signal acquisition and processing EKG

This is done with the help of an instrument, which consists of several main components: **electrodes**, **connection cables**, **amplifier** and **display unit** or recorder. The electrodes are placed on the patient's skin to capture the electrical signals generated by cardiac activity. A 12-lead EKG uses 10 electrodes in strategic locations on the legs, shoulders and chest to create a complete picture of the heart's electrical activity from 12 distinct angles. The EKG signal must be processed to remove noise and interference, including filtering for high and low frequencies, and can then be analysed to identify abnormalities, heart rate or other information.

3.2.2.3 Technological advances in EKG – wearable devices and remote monitoring systems

Technological advances in this area have revolutionized data collection and processing EKG. These smart devices (watches), offer convenience, accessibility and non-visual, real-time monitoring. However, these systems are still in the early stages of development and are not yet medically valid. Therefore, better cardiovascular health management for people with special needs can be discussed, including continuous monitoring, early detection and personalised therapy, potentially improving their overall health.

3.2.2.4 Open access resources for physiological signals

PhysioNet [68][1] provides physiological signals and time-series data to health researchers. It also provides software tools and techniques for data processing and analysis.

3.2.3 Final Considerations

In conclusion, technology and AI have made significant changes in the lives of people with special needs, providing opportunities to optimize communication, mobility, autonomy and health care. Brain-computer interfaces are an emerging field with promising potential to help overcome the above-mentioned barriers. It offers the opportunity to non-invasively control devices and detect medical conditions. Through the appropriate use of these technologies, new horizons can be opened to improve the lives of people with special needs and to facilitate their active participation in society.

[1] PhysioNet is a freely available medical database managed by the MIT Laboratory for Computational Physiology, available at `https://physionet.org/`.

Chapter 4

Contributions to the application of artificial intelligence on low-power devices

Significant advances in various industries due to machine learning solutions often face high costs related to processing devices such as graphics cards or ASIC [69]. An alternative is to run these solutions on servers in the Cloud, but this generates latency and increased dependency on network infrastructure, especially in areas with limited or no connectivity.

These impediments can be effectively overcome and processed closer to the source, i.e. at the edge (hence the name edge computing, EC) [70, 71, 72, 73] which is important for robot assistants and anomaly detection algorithms in vital signals.

4.1 Development of an efficient time series processing system using artificial intelligence and edge computing techniques

In the field of artificial intelligence, especially in the medical field, time series is a predominant format. These series consist of a multitude of observations resulting from measurements taken over successive periods of time and are applicable not only in EKG and EEG, but also in monitoring vital signs (blood pressure, glucose level, respiratory rate, etc). They are also essential for improving the lives of people with special needs, monitoring movements and vital signs, facilitating medical assessment and problem detection.

However, running these algorithms efficiently and economically is a challenge, as they require expensive devices such as graphics cards, remote servers or dedicated controllers (ASIC), involving additional costs and increased energy consumption. Thus, there is a trend to migrate [74, 75, 76] from these power-hungry devices to some low-power devices as close to the source as possible (edge computing).

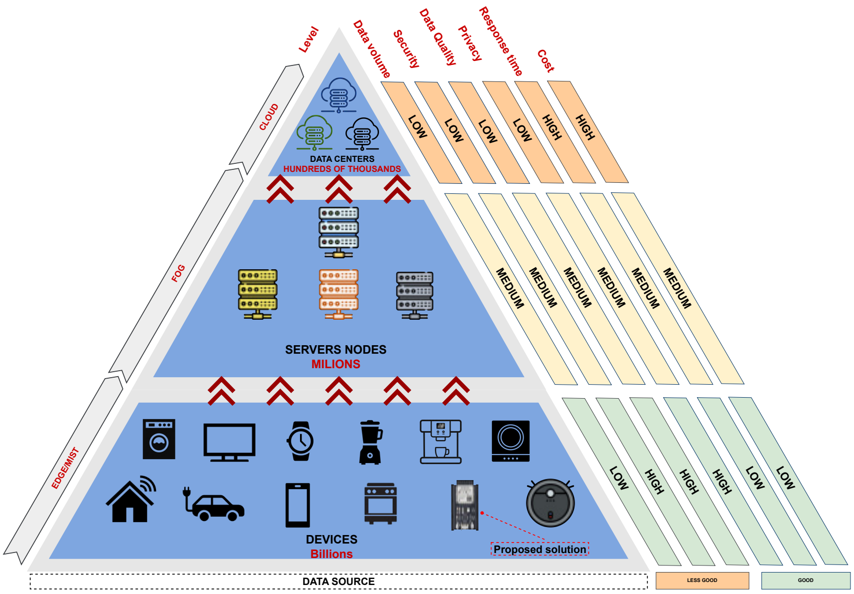


Figure 4.1: The hierarchical architecture of smart device data processing (IoT) in Cloud, fog and edge computing difficulties and limitations, adapting after source [77].

4.1.1 Devices for Brain Signal Acquisition

This is known as edge computing, offering increased efficiency and faster speeds, counteracting the dependence on centralized Cloud infrastructure. This concept, developed to reduce costs and enable real-time analytics, eliminates the need for constant internet connection for bulky machine learning models. Architectures such as "fog" and "mist computing" (Figure 4.1) have been developed to overcome the limitations of Cloud, but the key differences between them make them suitable for specific contexts, depending on needs and available resources.

Eurostat[1] [78] shows that in 2021, 41% of EU businesses will have adopted Cloud Computing (5% increase from 2020). In industry, predictive maintenance is vital for maintaining the optimal condition of equipment, early detection of failures can be costly and time-consuming.

4.1.2 Improving the Quality of Life of People with Special Needs through Efficient Time Series Processing on Edge Computing Devices

Integrating AI and EC on low-power devices improves the quality of life of people with special needs by enabling efficient time series processing, a common data representation format.

This approach offers significant benefits, including **creating customized solutions** for people with special needs, providing low-cost **permanent care**, **extending accessibility**, interpreting data close to the source, and **system autonomy**. These aspects contribute to improving quality of life and ensuring data security and privacy.

[1]Eurostat is the statistical office of the European Union, responsible for the publication of high-quality statistics and indicators at European level.

4.1.3 Implementation of an Intelligent Time Series Anomaly Detection System on Low Power Devices

Time series is a commonly used format in the AI domain in the healthcare sector and only with a significant challenge to migrate solutions from large infrastructures to low-power devices. Therefore, although this thesis focuses on improving the lives of people with special needs, EC solutions based on AI and efficient time series processing can be applied universally. The same techniques that enable anomaly detection in motor bearing vibration time series can be adapted for other use cases for medical applications and sensors by leveraging AI abilities. As such, it is important to address this impediment methodically and practically, step by step, with a clear goal: **demonstrate the ability of artificial intelligence to process time series on low-power devices**, such as microcontrollers, in edge computing as close as possible to the data generating source.

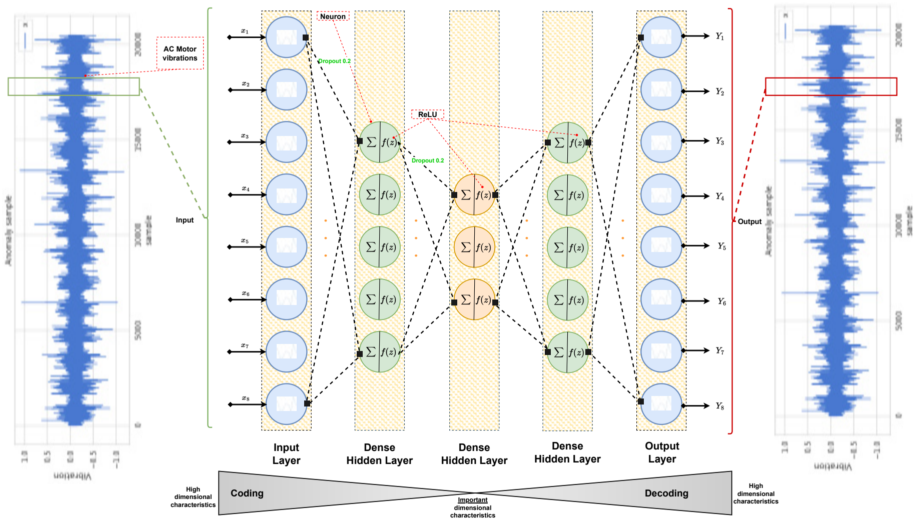


Figure 4.2: Architecture of the proposed artificial neural network model.

4.1.3.1 Overview of Neural Network Architecture Approach and Design

The traditional approach of running machine learning algorithms on servers poses issues of latency, privacy, bandwidth and network connectivity (Figure 4.1). To address these limitations, the processing side should be moved as much as possible to the edge of the infrastructure, directly on the devices acquiring the data. An efficient solution is proposed for anomaly detection in time series, focusing on motor-generated vibrations, with an emphasis on local data processing. This solution can be deployed on microcontrollers without requiring Cloud infrastructure and is compared to other faster data approaches that jeopardize data privacy and security. Detecting anomalies in time series requires defining a pattern of normal behavior and can identify deviations from these patterns in monitored data [79, 80].

The proposed solution uses an Autoencoder, to detect anomalies in industrial motor bearing vibration patterns using the absolute median values (MAD) of accelerometer measurements. For energy efficiency the algorithm constantly calculates, on an ESP32, MAD and generates alerts for predictive maintenance and can be adapted to other time-series applications such as biosensors, being of significant importance in equipment failure assessment and prevention. To obtain an accurate model, simple low-pass filtering (FTJ) was applied to clean the data. The model consists of a 5-layer lattice, including 3 hidden layers, with regularization layers dropout to avoid overfitting. Placed after the first hidden layer, the regularization layer has a dropout rate of 0.2. An input size of 8 data points is used, corresponding to 4 bearings measured on 2 channels. The number of neurons decreases in the hidden layers to extract essential information and for noise removal. The encoding and decoding process is illustrated in Figure 4.2, and the activation function ReLU is used in all hidden layers [80].

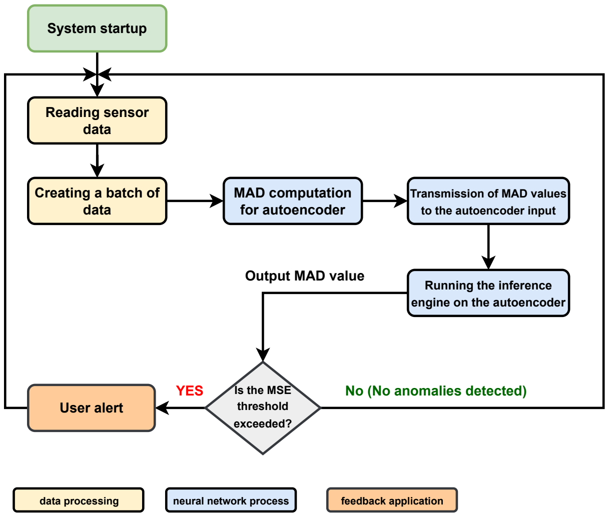


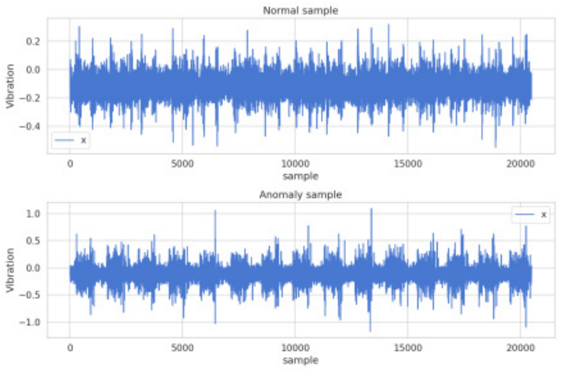
Figure 4.3: Workflow diagram of the proposed system.

4.1.3.2 Pre-processing of Data

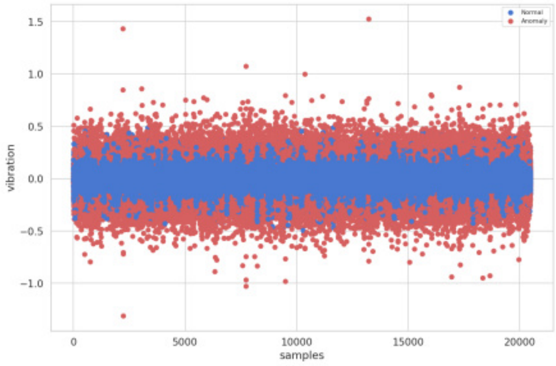
In the first stage of system development, a suitable model for vibration analysis was designed, requiring a corresponding data set, namely the "Bearing Data Set NASA" [81] containing records from industrial bearings that failed during operation. This approach was chosen because of the significant duration required for such industrial equipment to suffer failures [81]. According to the same source, four bearings were subjected to a radial load of approximately 2721 kg at a constant speed of 2000 RPM. The data set consists of individual files, each representing one second of vibration signal recorded at specified intervals. Each file contains 20480 points and a sampling rate of 20 kHz. Developing an efficient model requires a significant amount of data, including both normal behaviour and obvious anomalies (see Figure 4.4a).

The next step was to extract features and identify outliers. Although the raw data may be sufficient to develop a model, it is necessary to determine the specific features that the network will analyze. To achieve this goal, the DC component of the signal was removed by subtracting the average amplitude. This method allows visualization of the vibration component of the signal and identification of outliers, as can be seen in Figure 4.4b.

The significant difference between the anomaly sample (red) and the normal sample (blue) is evident. The red area is much larger, while the blue area is more compact. Further analysis of the data



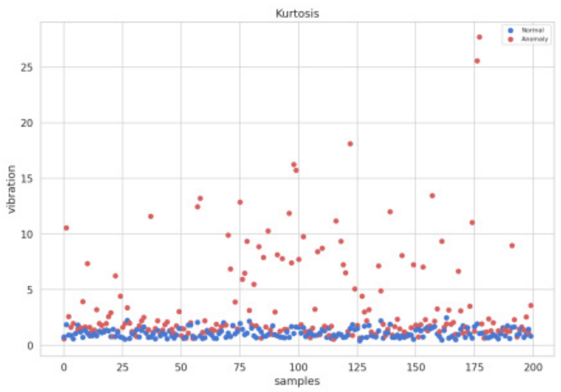
(a) Normal and abnormal samples.



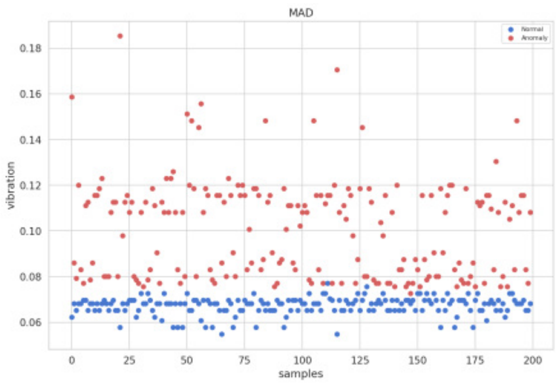
(b) Signal after removal of the DC component.

Figure 4.4: Bearing vibrations observed in various situations as time series.

reveals significant differences between the two groups, revealed by analysis of variance, skewness (Skew[1]), Kurtosis[2], and the median absolute deviation (MAD). The variance is illustrated in the Figure 4.5b and measures how far individual values in the dataset are from their mean, making it easier to separate the data. High kurtosis in a data set indicates the presence of outliers and is used to describe extreme values compared to a Gaussian distribution, as illustrated in Figure 4.5a.



(a) Comparison of kurtosis of normal and abnormal vibration samples.



(b) Comparison between the MAD component of a sample of normal and abnormal vibrations.

Figure 4.5: Methods for understanding time series data from engine vibrations.

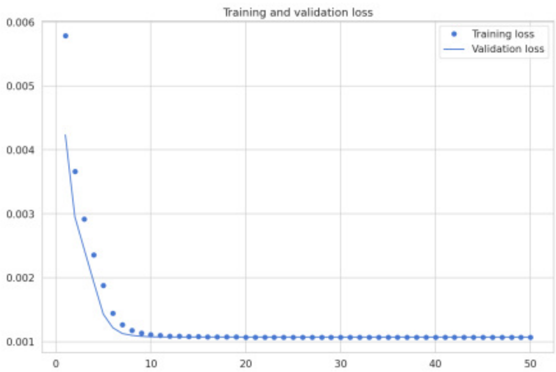
Kurtosis, assesses the degree of concentration and more precisely the height of the "hump" compared to a normal distribution. In the context of analyzing data with outliers or non-normal values, MAD is a more robust [83] measure, as can be seen in Figure 4.5b. It facilitates a clearer separation of normal data from anomaly data, and this aspect contributed to its choice in the proposed solution, as illustrated in the system workflow diagram in Figure 4.3.

[1] Skewness in statistics is the degree of skewness observed in a probability distribution.
[2] Kurtosis refers to the height of the curve compared to the normal [82].

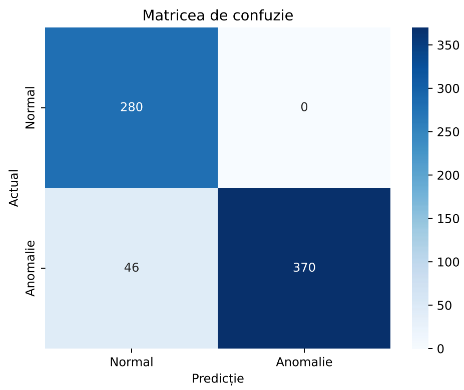
4.1.3.3 Model Training

For training the model, the data were divided into training data ($\sim 55\%$ - 701 samples), cross-validation ($\sim 10\%$ - 420 samples) and test sets ($\sim 35\%$ - 280 samples). The training set is characterized by the fact that it contains only data that do not contain outliers. This is because the Autoencoder is supposed to train itself to recognize the normal operation of an engine very well, so that anything that does not resemble normal behaviour is classified as an abnormality. In this experiment, data prior to bearing failure in the motor is used as the training data set. The validation set contains both normal and abnormality data, and the network is trained to recognize them accurately. The test set contains data similar to real-time data. The training lasts for 50 epochs (the batch is 55) using the optimizer Adam, and the loss function being MSE. Weights are randomly generated at the beginning of the training.

The graph of the training loss for both the test and validation sets shows that the model converges in the first 15 epochs, keeping the losses to small values around 0.001 (Figure 4.6a) and the histogram of the training sets, with normal data compared to those with anomalies, illustrates a clear separation of the MSE of the loss function. This confirms the effectiveness of the method in detecting anomalies.



(a) Loss and validation.



(b) Confusion matrix.

Figure 4.6: Comparisons of results obtained from training the neural network model.

Table 4.1: Comparison between testing with and without inference.

Testing	Samples/file	Time (μs)	Anomalies	Error (%)
MAD	20000	2102	NO	6.57
MAD	20000	2153	**YES**	6.57
MSE + Inf.	20000	150	NO	6.57
MSE + Inf.	20000	45	**YES**	6.57

At this stage, a two-class classifier is constructed to decide whether the analysed data are normal or abnormal. The classification threshold is set to the last root mean square error value in the validation set, which in this case is 1.1001×10^{-3}. The confusion matrix (Figure 4.6b) gives indices of model performance with high performance, 280 cases correctly classified as normal and 370 as abnormal. Also 46 cases were incorrectly classified as anomaly and 0 as normal. Model accuracy is calculated by dividing the total number of correctly classified cases by the total number of cases. In this case, the accuracy of the model reaches a classification rate of 85%.

In the test phase, the model implemented on the ESP32 microcontroller achieved an outstanding performance of 93.42% in detecting abnormal data, as shown in Table 4.2. For a normal test sample used in the calibration, the algorithm required 6795 mus to compute MAD, and the inference result for previously unseen data was completed in 161 mus.

Table 4.2: Test results of the model implemented on the ESP32 microcontroller.

Description	**Value**
ESP32 model accuracy in anomaly detection (validation)	93.42%
Time required for MAD calculation on a normal sample	$6795\mu s$
Inference time for previously unseen data	$161\mu s$
Inference runtime and MAD calculation on an anomaly sample	$106\mu s$
Difference between predicted values in design and run phase	< 0.1

The inference run time and the time to calculate the MAD for an anomaly sample was 106mus. Comparing the results obtained in the test environment during the model design phase with those obtained after running the algorithm on the validation data, the error between the predicted values was found to be less than 0.1. This indicates that the algorithm is safe and reliable for implementation in various scenarios.

4.1.4 Final Considerations

The project has therefore reached a safe operating phase for anomaly detection, achieving high performance ($\sim$93.42%) in the test phase. The fully developed system uses a Autoencoder to compute the MAD values and compares them to a threshold to alert the user about abnormal samples. The system is versatile and adaptable to various domains in edge computing.

In the AI domain, especially in the special needs domain, time series is a common format in many applications. The same techniques that allow us to detect anomalies in motor bearing vibration time series can be easily adapted to other use cases for medical applications and sensors by leveraging AI skills. One of the biggest impediments is processing these time series with keeping efficiency high and cost low. These intelligent algorithms are based on a multitude of data from specific processes or sensors and are designed to make complex decisions, like human intelligence. Energy efficiency has become a point of interest and alternatives need to be explored. These solutions will be run close to the source (edge computing) on low-power devices with applications in robotics, wearable medical devices, improving current medical procedures and creating personalised assistants that can certainly improve the lives of certain categories of people.

4.2 The Development of an Autonomous Robot with Multiple Functions to Improve the Quality of Life of People with Special Needs

Lately, in the field of robotics and AI, innovative solutions have been generated for people with specific requirements [84, 85, 86]. It can be seen that interest is growing in multi-functional autonomous robots developed to improve the quality of life of these people. Because of an increasingly ageing population, there is a growing demand for home health services, suggesting the need for the development of reprogrammable autonomous robots capable of providing various services tailored to current needs. These robotic systems have the potential to significantly improve the lives of those with physical, cognitive or emotional difficulties, offering them autonomy, assistance and increased comfort.

4.2.1 Assistive Robots

These are a distinct category of robots that have been specifically designed to provide aid and reinforcement to those with disabilities or unique needs.

In the field of assistive robotic systems, four main directions are observed, which include understanding the environment through sensory perception, mobility of the systems and the assisted persons, monitoring the condition and health of the assisted persons, and communicating with them and understanding their needs. These systems are equipped with advanced sensors, including cameras, LiDAR, ultrasonic distance sensors and temperature sensors, which enable the robots to gain a detailed understanding of the environment. This facilitates efficient navigation and interaction. Assistive robots use various technologies, including exoskeletons, wheelchairs and robotic arms, to provide assistance to those with movement limitations, controlled through various interfaces. In terms of the health status of assisted persons, solutions can be implemented that provide cleaning, sterilisation in the case of infectious diseases, and at the same time monitor the patient's condition remotely and communicate with them. By applying natural language processing and speech recognition technologies, communication is facilitated and opportunities are created for social bonding and companionship between individuals and robotic entities and beyond.

4.2.2 Improving the Quality of Life of People with Special Needs through the Use of an Autonomous Robot with Multiple Functions

The solutions proposed further serve as examples to highlight the multifunctionality of autonomous robotic assistance systems. Through the use of AI and low-power devices, these robots have the ability to be adapted to respond to a wide range of requirements providing significant support through various applications to people with special needs as follows:

- **Personal assistants** for providing people with special needs with personalised daily assistance thereby reducing the need for medical staff and the costs associated with their care;

- **Monitoring** of the space of interest allowing the robot to monitor and measure environmental factors such as temperature, humidity and air quality, identifying potential risks such as gas leaks or fires or even in case of contagious diseases (without direct contact);
- **Delivery and logistics** for the safe and efficient transport of medical supplies, medicines or food in healthcare facilities;
- **Social inclusion** can be facilitated through the use of robots for the elderly, people with disabilities, or those living in care homes;
- **Education** which can benefit students with learning difficulties or those requiring additional assistance by facilitating their participation in interactive learning sessions;
- **Virtual locomotion** would enable people with movement problems, such as paralysis or other impairments, to stay connected to the outside world.

4.2.3 Implementation of an Autonomous Robot on Low-Power Devices to Address the Needs of Certain Vulnerable Groups

The importance of autonomous assistive systems in the medical field is highlighted by the increasing incidence of infectious diseases, including SARS-CoV-2 virus, and the limitations of conventional sterilization methods. The elderly in particular require tailored sterilisation solutions [87]. Studies show that 20-30% of patients in intensive care units develop nosocomial infections (Healthcare-Associated Infections) [87, 88, 89], highlighting the need to address this issue.

In this section, the main focus is on the implementation of a service of a asitive robot "RoboCoV Cleaner" and more precisely on achieving a safe environment by reducing certain pathogens, e.g. viruses (SARS-CoV-2) and other micro-organisms on surfaces that can be life-threatening for some people thus contributing to a healthy and normal life. This autonomous mobile robot (AMR) is mainly equipped with five 18W UV-C lamps in combination with a control system. The robot is autonomous and can operate without human intervention, but can also be remotely controlled via a web application developed in Python using the Flask[1] development framework. This system has the potential to neutralize bacteria and viruses in closed spaces, improving safety and protecting staff in universities, nursing homes and hospitals. The robot is versatile and can be easily adapted to support different needs, for example, assisting people with different requirements, as described in 4.2.2.

4.2.3.1 Assistive Robots in the Sterilization Process

The previous pandemic situation with the rapid spread of SARS-CoV-2 virus has highlighted the importance of effective sterilization to prevent disease transmission, as wearing masks is not sufficient to protect against surface contamination [90, 91]. Sterilisation aims to remove micro-organisms from

[1] Flask is a lightweight and minimalist Python web tool used for creating web applications.

surfaces to prevent the spread of pathogens and infections through direct or airborne contact. Ultraviolet light type C (UV-C) with a wavelength between 200-280 nm has been shown to be effective in destroying microorganisms, including the SARS-CoV-2 virus, and can help prevent infections in hard-to-reach places such as hospitals [92].

In this context, the proposal to use an autonomous robot to sterilise rooms using UV-C lamps has multiple advantages: it eliminates human intervention, avoids toxic chemicals, and has the potential to serve other purposes, such as healthcare or simple reprogramming.

Features of Existing Sterilization Robots and Potential Directions for Development

Recent advances in technology have enabled the development of advanced robotic sterilisation systems that use light UV-C to eliminate pathogens, necessitating an assessment of their potential in various areas (advantages, disadvantages and possible development directions).

Commercial devices have substantial costs (average $50 000) and a wide range of movement options, ranging from mobile bases [93, 94, 95] (move in any direction on the floor), focusing light wherever needed, to stationary platforms (vertically or horizontally oriented light source) such as [96, 97, 98] systems. In the field of these robots, the detection of human presence has been approached differently, with some systems having detection mechanisms and others remaining limited or even absent. These systems do not detect objects in real time and limit the components to a certain generation which may hinder future improvements. Of these robots, not all have an energy-saving mode and process their data on Cloud systems, losing the benefits of local processing. A review of the scientific literature shows a trend of innovation with the integration of robot arms with different degrees of freedom [99], but also other categories of mobile bases [100, 101]. Neither have a robust method of detecting human presence, which creates a vulnerability in case of miscommunication between subsystems. This omission of redundancy, a fundamental security principle, requires a thorough assessment of system resilience and associated risks.

Therefore, issues that were once limited to the commercial domain have now become fundamental principles in academic research. The concepts of real-time video transmissions and the increased autonomy that have gained prominence in the commercial environment continue to be topics of interest in academia. However, almost non-existent is the field of object recognition in video streams, scene understanding and report generation as in commercial systems. Furthermore the approach of separating the logic between sensor and actuator modules and the basic robot logic, energy saving, local processing near the generating source are other improvements that can be made to these systems.

According to [102, 92, 103, 104], UV-C light destroys the ADN of bacteria and viruses. The UV zone is divided into three sections: UV (320-400 nm), UV-B (280-320 nm) and UV-C (200-280 nm) and is divided into two categories: non-ionizing (380-121.6 nm) and ionizing (below 121.6 nm). There are currently three types of UV lamps used for germicidal purposes: low-pressure mercury lamps (LPM), pulsed xenon flash lamps (PXF) and Far-UV-C lamps. **The dose required to inactivate an organism** can be thought of as the level of light UV an organism receives. This is measured in milliJoules per square

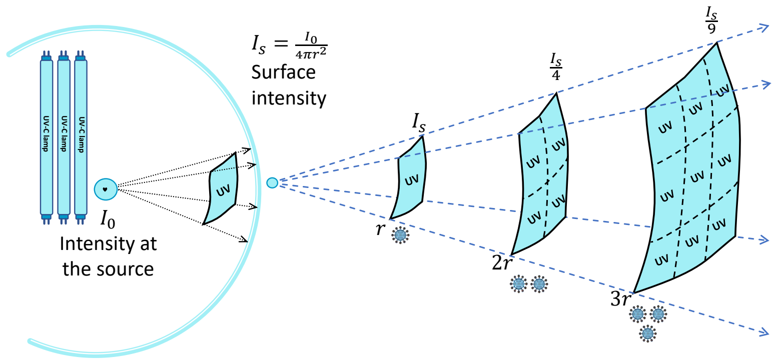


Figure 4.7: Inverse square law from a source point. I_s is the intensity at the surface and I_0 is the source intensity in watts, and r is the radius of the sphere, fitted by the source [105].

centimetre (mJ/cm^2). It can be determined by multiplying the irradiance by the exposure time (dosage formula 4.1). According to [106], corona viruses will be inactivated by UV light without changing the technology of this type of sterilization light. The realistic value is probably only 3.7mJ/cm^2 (average) according to [106, 107, 108, 109, 110].

$$Dosage(mJ/cm^2) = Irradiance(mW/cm^2) * Duration(sec) \tag{4.1}$$

Irradiance is measured in watts per square metre (W/m^2 or milliwatts per square centimetre (mW/cm^2) and varies according to lamp power, robot configuration and distance to the surface to be disinfected, following the inverse square law, as illustrated in the Figure 4.7.

4.2.3.2 Software Implementation of the Robotic System

This robot is a complex and complete system. Its implementation required knowledge of mechanics, electronics, automation and software development (used for image processing, the use of real-time operating systems and their combination with different programming languages) which is essentially a mechatronic system. The use of this type of light sterilisation robot UV-C offers significant advantages, as it is capable of rapidly sterilising various rooms, including classrooms, laboratories, bathrooms and hallways, is effective over a wide range of distances, and requires no consumables, operating for an extended period of time (8000 hours - the operating time of the UV lamps). It can also be controlled remotely using a web application, the only requirements being an internet connection and a browser. The app allows you to start, stop and control the robot's movement both inside and outside the room, and the attached camera monitors activity even in the dark, thanks to a IR filter. The robot's display also provides useful information such as battery status and emergency messages.

Conceptually, this robot is made up of two separate modules, both in terms of hardware components and associated software. Due to the complexity of the hardware, which involves a multitude of sensors and components (Figure 4.9), the software design is also elaborate, requiring two different systems with distinct architectures and technologies.

Figure 4.8: Robot in the corridor of the V Building, Transylvania University of Brasov.

The control module is called the Central Control Unit (UCC) and runs on Linux (Raspberry Pi 4 8GB) and can be seen as the brains of this system. It controls the secondary unit, also called the Secondary Sensor and Actuator Unit (USSA) running FreeRTOS.

USSA is a software and hardware module that has been specifically designed to abstract the hardware layer. It is also intended to manage the processing of sensor data, to control any actuators in the system and to facilitate communication with UCC. The system was built using an Atmel Atmega2560 microcontroller [1] with an operating frequency of 16Mhz, which was selected based on its specifications and the extended pin availability it offers (100 pins). The USSA update rate can be configured individually for each driver and experiments have shown that the most efficient rate, both computationally and for sampled values, is 10 milliseconds per sampling cycle. In order to use the resources in the most efficient way and to optimize the responsiveness of the system, the use of a real-time operating system, FreeRTOS that provides multitasking capabilities, was chosen. For software development as a development environment, Atmel Studio 7 was used together with a specially designed debugging board that facilitates efficient identification and resolution of problems encountered during the development process, thus increasing the efficiency of debugging activities during software development using the Atmel Ice debugger.

[1] Atmel Atmega2560 is an 8-bit RISC architecture microcontroller developed by Microchip Technology (formerly Atmel Corporation)

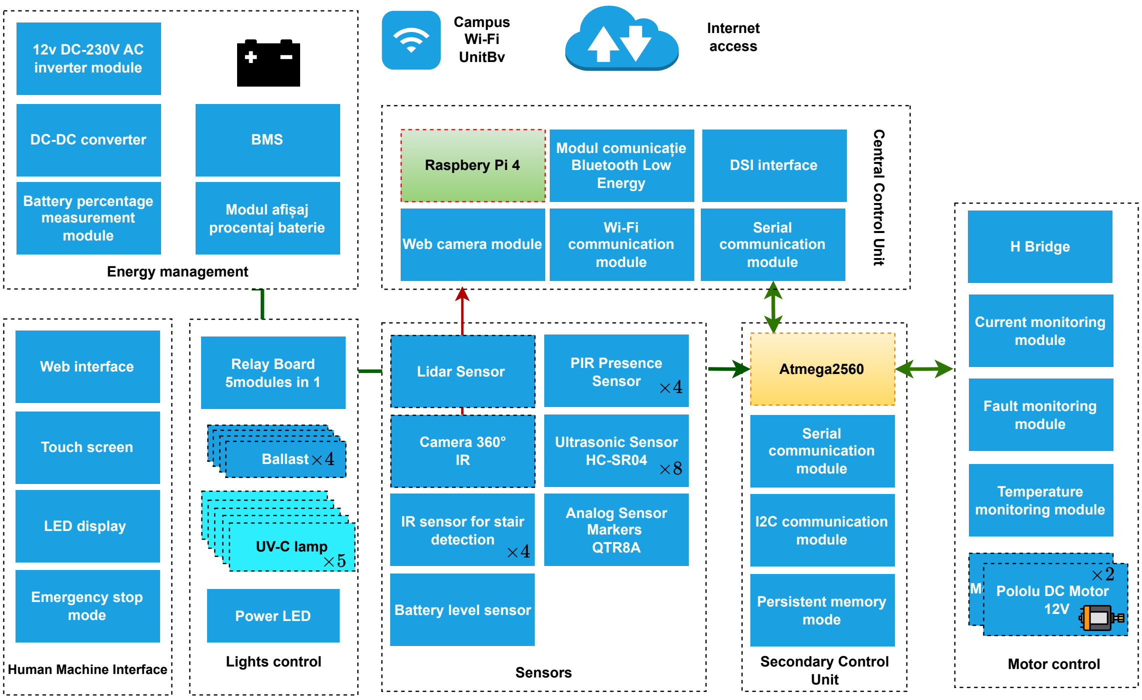


Figure 4.9: System block diagram.

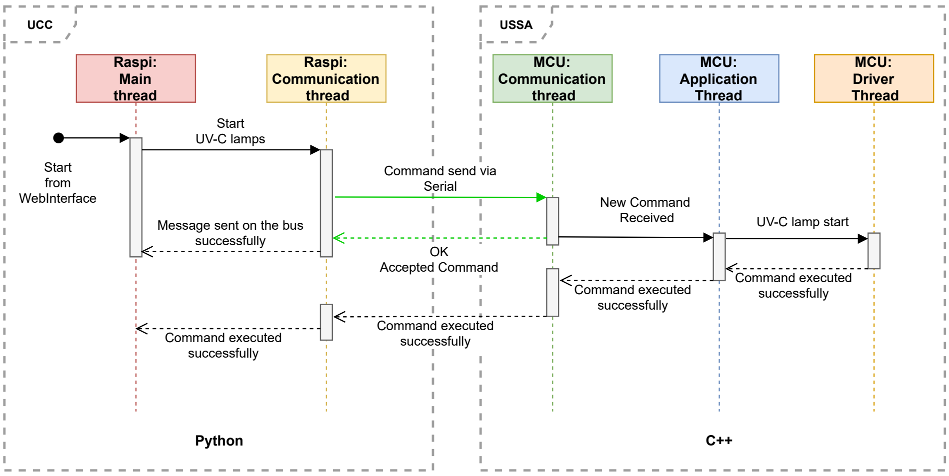


Figure 4.10: Sequence diagram between the two logical units UCC and USSA.

In order to facilitate the implementation of new services for this robot, it was decided to use a programming language as close as possible to human programming, namely Python, which generically controls actuators and acquires data from sensors without the need for the technical specifications of each individual physical driver. UCC will control the USSA board via the serial interface. This method is similar to the Leader-Follower model[1] where the Leader is the UCC. Moreover, UCC is able to support the image processing system, hence human detection is performed on this unit. Other tasks such as the web server or processing data from the LiDAR sensor, checking the internet connection and running

[1]The Leader-Follower model is a new adaptation of the established Master-Slave concept.

the system logic are also part of its duties.

The software architecture running on USSA incorporates several separate threads of execution for better segregation of tasks. The execution threads for both UCC and USSA are also shown in Figure 4.10. On USSA **communication execution thread** maintains data synchronization between USSA and UCC and **application execution thread** contains system logic and decision making only in emergency situations, ensuring rapid system shutdown in the absence of a response from the central unit. **Driver execution thread** acquires data and controls sensors and actuators, ensuring fast data update (10 ms) and prompt execution of actions. Unitatea Centrală de Comandă runs on Raspbian OS and has various threads of execution like UCC the difference is that on it there are more resources and other programs can run in parallel such as the web application program, the GUI program displayed on the display and the main program (communication between UCC and USSA). The system transmits instructions to the device, such as the movement of motors, without the need to know the individual specifications of each component.

4.2.3.3 Implementation of Advanced System for Human Detection

The use of UV lamps in the presence of humans is not safe, so it is important to detect humans or animals. The first system, based on PIR sensors, works independently on USSA and switches off the UV-C lamps if human presence is detected. The second system, present UCC, uses a 360°camera for human detection and code reading QR to manage the sterilization process.

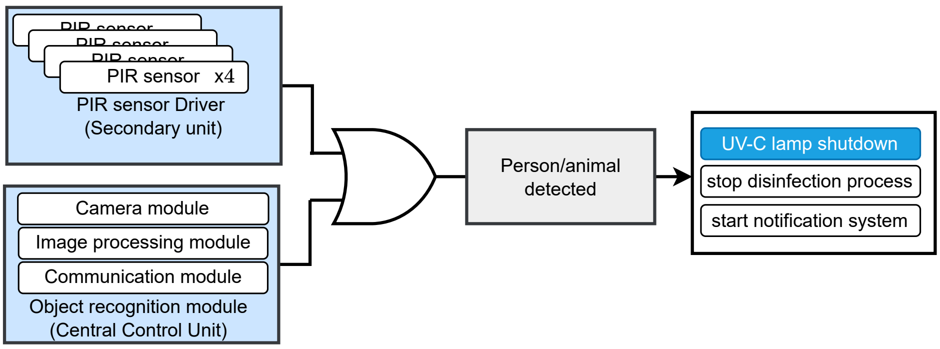


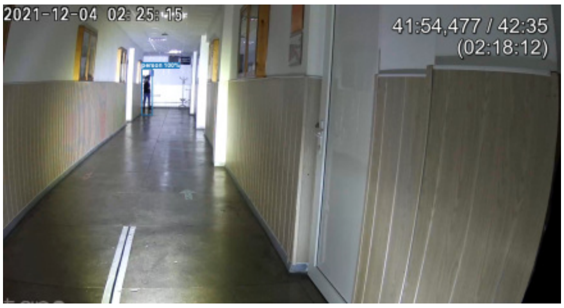
Figure 4.11: Simplified block diagram of the human and animal detection module.

By combining the YOLO [111, 112] algorithm with the HAAR[113, 114, 115] algorithm, the detection of persons or objects of interest is achieved, with the lamps turning off in case of person detection. After a predefined interval, the presence of persons is re-examined and the sterilisation process is resumed in their absence. The HAAR algorithm is an object detection technique in machine learning, suitable for tasks such as face detection. These algorithms can be easily changed, provided the processing power is adequate for object detection.

(a) Human detection (ultraviolet light).

(b) Human detection in poor lighting conditions.

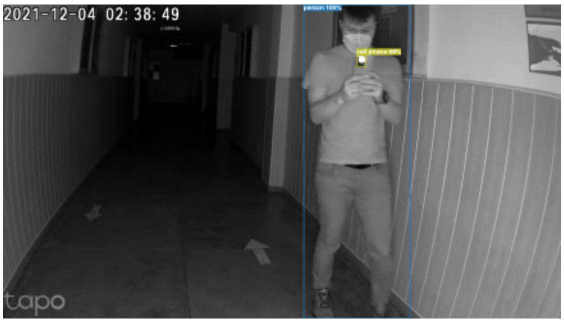
(c) Human detection adjacent dark room.



(d) Human detection 50m (high power LED).

Figure 4.12: Detection system under different lighting conditions in the visible light spectrum.

(a) Light UV, moving subject with mask.



(b) Light IR, moving subject with mask.

(c) Light IR, moving subject with mask.

(d) Poor illumination at a distance of 50 m.

Figure 4.13: Special condition detection system.

4.2.3.4 Using Markers to Define Specific Rules

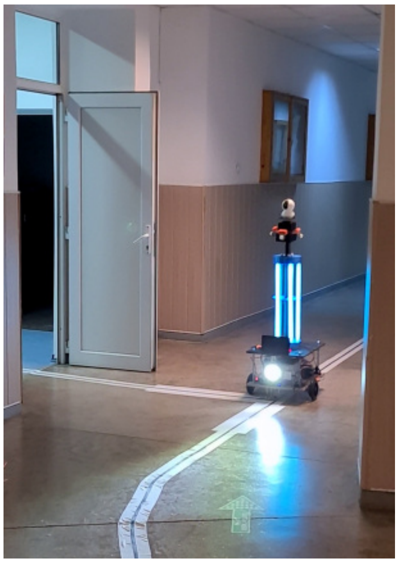
The efficiency of the system is improved by scanning the QR codes placed along the hallways on the doors (Figure 4.14) from which meaningful information about the current process can be collected.

These convey important data, including room infection probability and sterilization protocols, and n Python programming allows for easy rule changes and improved navigation. These tags also increase the flexibility, accuracy and multi-functionality of the system, ensuring a reliable and efficient system.

(a) Markers placed on the floor and QR code placed on the door. The QR codes contain the rules of the respective room regarding the sterilisation process.

(b) RoboCoV Cleaner using markers to sterilize the hallway of Transilvania University of Brasov, 2021.

(c) Markers placed on the floor can have different paths, and the object detection algorithm can be used to understand the path.



(d) RoboCoV Cleaner using markers placed on the floor and code QR placed on the door to make the decision at an intersection of the markers.

Figure 4.14: RoboCoV Cleaner and autonomous sterilization mode using markers.

4.2.3.5 Object and Location Recognition Information

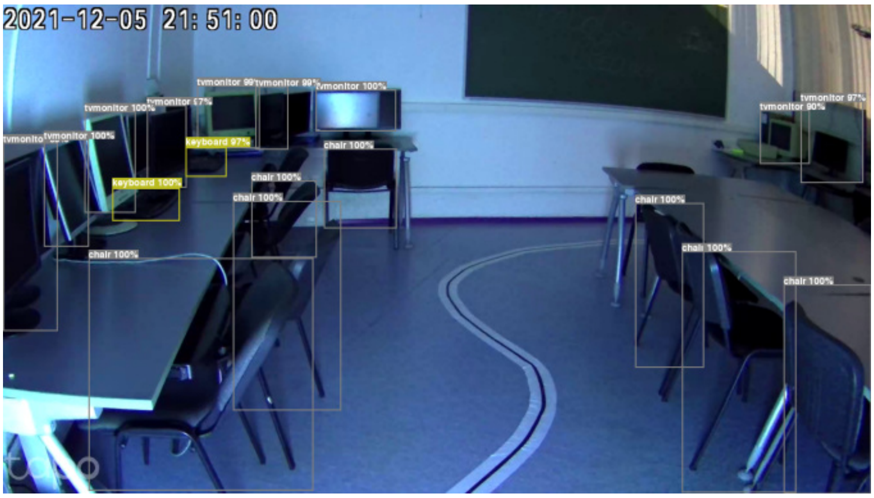


Figure 4.15: Detection of objects in a room during light sterilization UV.

The system also has functionality that extends beyond human detection, as illustrated in Figure 4.15. The system has the ability to provide statistical data, thereby enhancing its performance with an additional level of analytical insight into surrounding objects. This can be used to better understand how many objects exist in its field of view and what kind they are, and whether light UV will affect them in the long term.

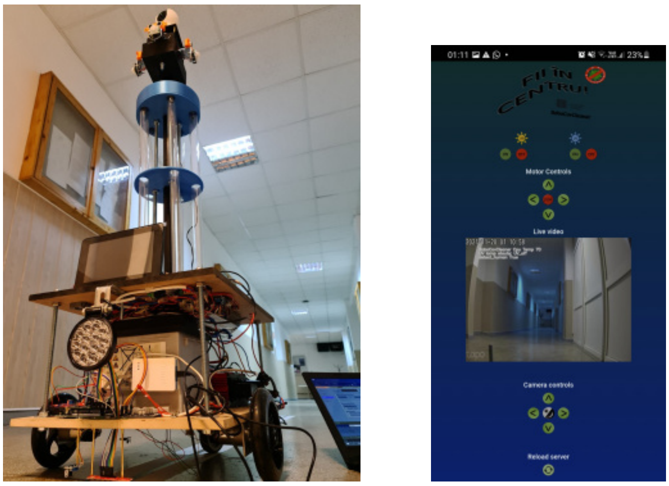
In the experimental analysis, the optimal sterilization distance and duration for a robot was determined to be between 2 and 2.5 meters, while the optimal duration should be 10 seconds to effectively cover a given area while maintaining an extended battery life for the robot.

4.2.3.6 Electrical and Mechanical Design

The electrical design focused on simplifying the system to reduce costs, with priority given to user safety at voltages of 220V or UV-C radiation. The robot includes 5 Philips UV-C 18W lamps (Figure 4.9), a 220V inverter, a 12V battery for up to 4 hours of operation, as well as sensors such as PIR for person detection and RPLidar A1 for environment mapping used to plan and optimise the disinfection process according to the room surface.

Infrared sensors are used for detecting stairs and gaps for emergency shutdown purposes. For obstacle detection and protection of UV-C lamps, the robot uses 8 ultrasonic sensors, especially for objects such as desks or chairs. This robot is equipped with two powerful 12V motors and an H-bridge from Pololu[1], controlled by an Atmega2560 microcontroller. The relays control the UV-C lamps, and the 5W LED improves visibility at long distances but decreases battery life, with a positive effect on human detection.

[1] Pololu is an electronics manufacturer Pololu founded in 2000 by three students at the Massachusetts Institute of Technology



(a) (b)

Figure 4.16: The assembled RoboCoV Cleaner robot (a) and its web interface (b).

The robot base was constructed of plywood, reinforced with two "L" brackets for the DC motors. M10 screws (30 cm) were used for a solid foundation, and the UV-C lamps were fixed to the 3D printed supports with an aluminium pipe attached to the robot base to keep the centre of gravity low.

The system has two modes of operation: autonomous (with pre-defined rules) and manual (via a web interface, Figure 4.16b). Through the app, the user can monitor the environment in real time, control the camera and the movement of the robot, as well as the UV and LED lamps. The manual mode can be activated in emergencies or for access to unusual areas, providing complete control and safety.

4.2.4 Final Considerations

In this section, autonomous robotic assistive systems for people with special needs were presented, as well as current obstacles and future directions for improving the quality of life of these people. By addressing the issues "Monitoring the condition and health of assisted persons", "Mobility of these systems and assisted persons" and "Understanding the environment with sensory perception" presented at the beginning of this section, a service in the form of a multi-functional autonomous assistive robot has been implemented with the aim of providing a safer environment for vulnerable groups prone to various threats.

The robotic system, based on AI, detects people, animals and objects and can be customised for various services such as medical assistance or virtual locomotion. It has the potential to improve the quality of life for vulnerable groups and support carers and medical personnel, reducing their work overload.

Chapter 5

Contributions to the Application of AI in Support of People with Special Needs

Artificial intelligence has emerged as a rapidly developing technology that is revolutionising many aspects of human life.

Supporting people with special needs is an area where AI is having an increasingly significant impact. For example, it can apply to the elderly but also to those affected by conditions such as paralysis or neurological motor problems such as amyotrophic lateral sclerosis[1] which can cause loss of muscle control.

Systems based on AI can improve the quality of life and accessibility for healthy people and those with special needs, but face various obstacles. This chapter explores applications of AI in supporting people with special needs.

5.1 Applications of AI for Cardiac Arrhythmia Detection and Classification

Ischemic heart failure and stroke are among the most common causes of death globally. Monitoring of cardiac activity, especially with the help of EKG, plays a crucial role in the prevention and treatment of these conditions. The electrocardiogram records the electrical activity of the heart and, helps to detect abnormalities and to diagnose and manage heart disease.

Today, machine-interpreted EKGs, which are widely used in medical devices, have limitations in predicting diagnoses and often require human interpretation. The use of machine learning algorithms for accurate and fully automated EKG assessments could significantly improve diagnostic accuracy and efficiency, especially in the context of wearable [116] devices. The annotations by certified cardiologists and the availability of databases on PhysioNet provide the system with robustness in detecting arrhythmia-specific disorders in EKGs. With the increasing volume of EKG data collected daily, machine learning-based methods are becoming increasingly essential for monitoring and interpretation.

In recent years deep learning has generated a fundamental shift in both industry and academia, with

[1]Amyotrophic lateral sclerosis being a disease suffered by physicist Stephen Hawking.

healthcare being one of the most influenced areas. An advanced deep learning strategy is proposed in this approach for identifying arrhythmias in EKG using different methods: one-dimensional EKG image raw signals and Wavelet Transform.

5.1.1 Obstacles Encountered in the Electrocardiography Process

The increasing use of electrocardiography in medical practice brings with it various obstacles affecting education, financial issues, data security and technical expertise, putting pressure on medical specialists. The main obstacles in the education and interpretation of EKG according to [117] are:

- absence of formal education available for EKG;
- difficulty in developing a comprehensive curriculum;
- EKG difficulty in tailoring resident training programs for interpreting EKG;
- EKG over-reliance on computer interpretation;
- EKG inaccuracies and limitations associated with computer interpretation software.

In addition to these, more can be added:

- **noise and artifacts** affecting signal quality;
- **waveform variability EKG** which can be influenced by factors such as the patient's age, gender and heart conditions;
- **limited specificity** in the diagnosis of certain heart conditions;
- **complexity of arrhythmias** significantly increases the interpretation of the electrocardiogram;
- EKG remote **monitoring and interpretation** of data due to security and privacy issues related to patient information.

5.1.2 Data Collection and Pre-processing

The data, used were annotated by board-certified cardiologists and come from the PhysioNet database and include EKG records acquired between 1975 and 1979 from the Beth Israel Hospital Arrhythmia Laboratory. This database contains 48 EKG (approximately 30 minutes) two-channel recordings from 47 subjects aged 23 to 89 years, including men and women.

Databases used from PhysioNet include the supraventricular arrhythmia database MIT-BIH, the St. Petersburg Institute of Cardiological Technology database, and the sudden cardiac death database.

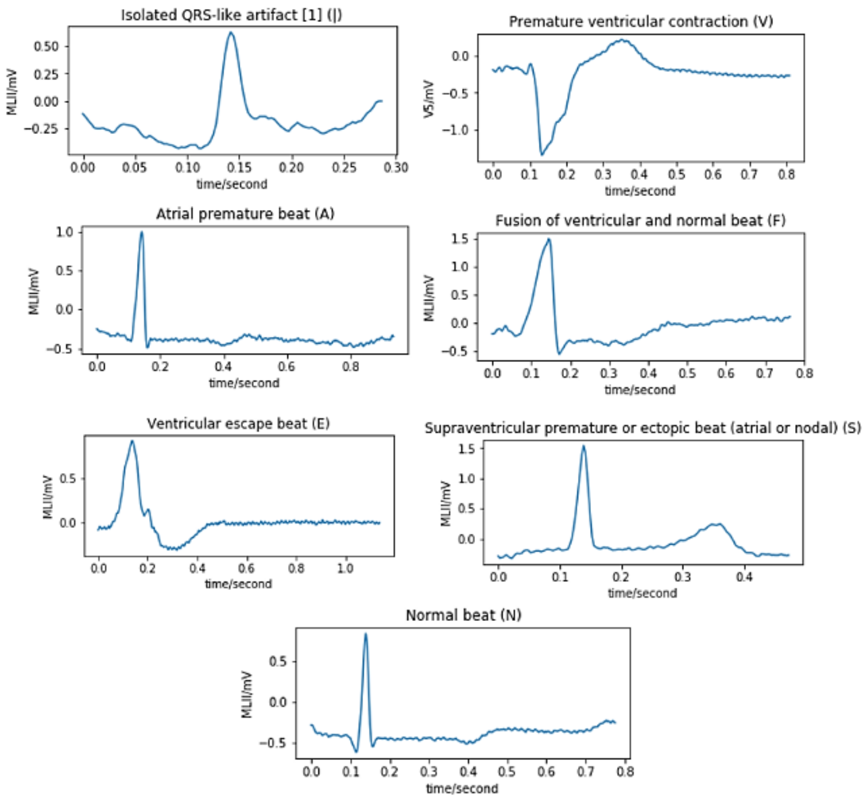


Figure 5.1: Raw EKG signals, 7 classes.

For the initial research, a deep neural network was trained to detect seven types of arrhythmias from EKG signals. These arrhythmia types are: normal beats ("N"), atrial premature ("A"), ventricular and normal beat fusion ("F"), isolated artifact-like QRS ("|"), ventricular premature contraction ("V"), ventricular escape beats ("E"), and premature or ectopic (atrial or nodal) beats ("S"). In the process of training the network, a Python script was used to save the samples as .PNG images.

The window frame, approximately one second long (variable depending on the R-peak annotation), was used to detect the relevant section of signals based on the R-peak. This implies that each signal window contains a single R-peak, and the cardiac cycle was identified by extracting the signal from 150 milliseconds before the current R-peak to 150 milliseconds before the next R-peak.

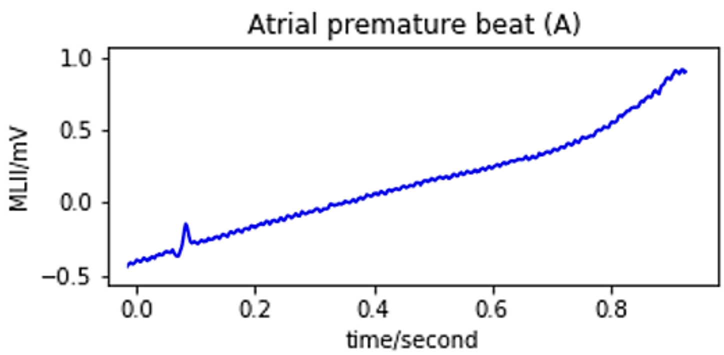


Figure 5.2: Noisy atrial premature beat.

5.1.3 Proposed Neural Network Architecture

The following subsection describes the network architecture that was used in all experiments. The model architecture (12 layers in Figure 5.3) is a sequential one, as it allows the user to create models layer by layer, so that each layer is connected to the next [116] . The optimizer used was Adam with a learning rate of 0.0008 which is computationally efficient and suitable for handling a large volume of data and parameters, requiring few adjustments to the hyperparameters [118].

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_9 (Conv2D)            (None, 275, 105, 32)      320
_________________________________________________________________
max_pooling2d_9 (MaxPooling2 (None, 137, 52, 32)       0
_________________________________________________________________
conv2d_10 (Conv2D)           (None, 135, 50, 64)       18496
_________________________________________________________________
max_pooling2d_10 (MaxPooling (None, 67, 25, 64)        0
_________________________________________________________________
conv2d_11 (Conv2D)           (None, 65, 23, 128)       73856
_________________________________________________________________
max_pooling2d_11 (MaxPooling (None, 32, 11, 128)       0
_________________________________________________________________
conv2d_12 (Conv2D)           (None, 30, 9, 128)        147584
_________________________________________________________________
max_pooling2d_12 (MaxPooling (None, 15, 4, 128)        0
_________________________________________________________________
flatten_3 (Flatten)          (None, 7680)              0
_________________________________________________________________
dropout_3 (Dropout)          (None, 7680)              0
_________________________________________________________________
dense_5 (Dense)              (None, 512)               3932672
_________________________________________________________________
dense_6 (Dense)              (None, 7)                 3591
=================================================================
Total params: 4,176,519
Trainable params: 4,176,519
Non-trainable params: 0
```

Figure 5.3: Convolutional neural network-Network architecture.

The optimizer parameters were left in the initial state as recommended ($beta_1 = 0.9$, $beta_2 = 0.999$, $epsilon = 1 \times 10^{-8}$, $textdecomposition = 0.0$) [118].

The loss function was the mean squared error, since it is sensitive to outliers. To have proper output results, the model requires knowledge of the input shape and what it should look like. The first layer in the Sequential model must be given information about the shape of its input (277, 107, 3), this representing the size of the image in pixels and channels (3 is for color mode RGB). The next layer is a Conv2D layer, which is a convolution layer. Whereas the whole network is a convolutional neural network (CNN) specialized for working in this case with data in two-dimensional image format. The convolutional layer in this network applies a linear operation. and the activation function used was the nonlinear function ReLU.

The following layers contain the Maximum Pooling and results in its dimensionality decreasing and allows assumptions to be made about the features included in the sub-regions (clustered). In order to avoid data overload and high computational costs the Dropout layer was also used which removes 50% of the nodes during training. In the last layer, which is a dense layer where all inputs are connected to the output with a weight, the activation function was chosen Sigmoid (values between 0 and 1). Consequently, it is applied in particular for models where the probability has to be provided as an output.

5.1.4 Wavelet Transform Application

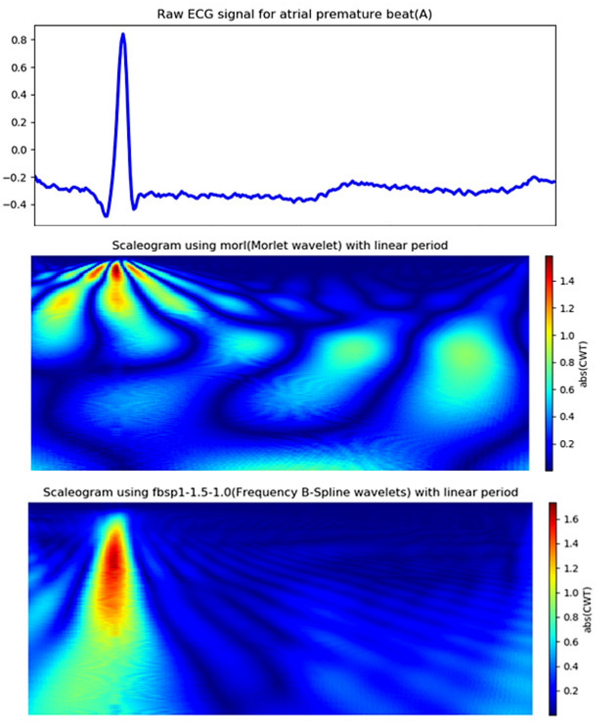


Figure 5.4: Graphical representation of a premature atrial beat and its transformation into wavelet scalograms (morl and fbsp).

Wavelet transform [119] is a mathematical method for performing signal analysis when its frequency is spread over a period of time. Wavelet analysis provides more precise information about signal data than other signal analysis techniques such as the Fourier Transform (FT). This type of transform can be used in speech processing, image processing, audio signal processing, even in the biomedical field [120, 121, 122].

Wavelet transform (WT) is widely applied [123, 122, 121, 124] to represent morphology features

EKG and differences between arrhythmia signals will be more easily detected by neural network.

The proposed system uses Morlet Wavelet transform and B-Spline frequency wavelet transform to better identify arrhythmias in the EKG signal. The image of the scalogram shows in Figure 5.4.

5.1.5 Evaluation of Performance Obtained

In this section, the results of the experiments are presented. As previously mentioned, several notable experiments were conducted in this study.

Table 5.1: Training results - grayscale images of raw signals with seven classes, filtered (1000 balanced samples).

Epoch	Loss	Precision	Loss	Precision	Time (s)
1	0.1228	0.2200	0.0401	0.8247	9
2	0.0435	0.8122	0.0166	0.9253	8
3	0.0303	0.8663	0.0194	0.9155	8
4	0.0241	0.8888	0.0122	0.9513	8
10	0.0094	0.9594	0.0080	0.9696	8
11	0.0097	0.9566	0.0135	0.9416	8
30	0.0034	0.9869	0.0068	0.9805	8

The input data consisted of images (size 277x107 pixels) with different representations and a distinct number of samples.

5.1.5.1 Time Series Classification, Seven Classes (1000 Samples)

For the first experiment 1000 samples were used of which 20% were used for testing and the remaining 80% were used for training. The signals were divided into seven classes, with a detection rate of 98.05% after 30 epochs, but training stopped after epoch 30 due to lack of improvement of the "val_acc" metric.

5.1.5.2 Morlet Wavelet Transform Classification, Seven Classes (1000 Samples)

In the second experiment, the input data were the same except that the signal was transformed into a scaleogram using the Morlet Wavelet Transform (Figure 5.4). From the first epoch, the "acc" and "val_acc" metrics had higher values, highlighting the benefits of CWT. Also, in the sixth epoch, the model reached the best value for the metric "val_acc" and, as a result, the training was terminated as it was no longer yielding improvements.

Although a longer time per epoch is observed, the second experiment obtained more than twice as good results as the first. This phenomenon is explained by adjusting the network for the RGB mode instead of the grayscale color mode, to use a convolution kernel that handles the various colors required for the Wavelet Transform.

Table 5.2: Training results - Wavelet (morl) images of the seven filtered classes (1000 balanced samples).

Epoch	Loss	Precision	Loss	Precision	Time (s)
1	0.0720	0.8549	0.0221	0.9594	16
2	0.0326	0.9399	0.0403	0.9115	15
3	0.0234	0.9579	0.0263	0.9469	15
4	0.0211	0.9612	0.0323	0.9311	15
6	0.0166	0.9702	0.0105	0.9869	15

5.1.5.3 Time Series Classification, Three Classes (3000 Samples)

For the third and fourth experiments (Table 5.3), the samples used were only from the MIT-BIH Arrhythmia database and were trained for only three classes: normal beats ("N"), atrial premature ("A") and fusion between ventricular and normal beats ("F").

Table 5.3: Training results - colour images of raw, unfiltered signals (3000 balanced samples) with three classes.

Epoch	Loss	Precision	Loss	Precision	Time (s)
1	0.1054	0.7789	0.0436	0.9313	23
2	0.0437	0.9194	0.0292	0.9406	19
3	0.0301	0.9493	0.0271	0.9556	21
4	0.0249	0.9568	0.0145	0.9688	20
5	0.0216	0.9619	0.0144	0.9778	21
7	0.0185	0.9686	0.0119	0.9810	20
10	0.0149	0.9760	0.0091	0.9844	20

In this configuration with 3000 samples, keeping the proportion 20% test and 80% training, noisy samples without manual filtration were also used. Already in the first epoch, the "val_acc" reached 93.13%, showing that accuracy increases with more samples and that noisy data have a reduced impact. In this experiment, the images contain only the one-dimensional EKG signal. The model stopped at the tenth epoch, obtaining higher accuracy than in the first experiment, but not significantly higher than in the second Wavelet Transform experiment, however with a higher time per epoch.

Table 5.4: Training results - unfiltered (fbsp1-1.5-1.0) colour wavelet images (3000 samples) with three classes.

Epoch	Loss	Precision	Loss	Precision	Tim (s)
1	0.1290	0.7269	0.0981	0.7844	25
2	0.0772	0.8559	0.0637	0.8594	23
3	0.0485	0.9063	0.0481	0.9139	24
4	0.0339	0.9406	0.0335	0.9406	23
5	0.0314	0.9413	0.0297	0.9470	24
7	0.0261	0.9550	0.0197	0.9719	24
43	0.0055	0.9916	0.0033	0.9938	23

This improvement is due to increasing the number of samples and configuring the network for RGB color mode, similar to the second experiment. Also, in the fourth epoch, the third experiment achieved the best value for the "val_acc" metric, exceeding 96%, compared to the other two experiments.

5.1.5.4 B-Spline Wavelet Transform Classification, Three Classes (3000 Samples)

In the fourth experiment, the Frequency Wavelet B-Spline Transform (fbsp1-1.5-1) with 3000 samples was used, similar to the third experiment. The data were not filtered, which resulted in slower training, but with excellent accuracy of 99.38% in epoch 43. The complexity of the images increased, justifying the increased time per epoch.

5.1.6 Final Considerations

In conclusion, training a convolutional neural network for the detection of cardiac arrhythmias from electrocardiograms led to outstanding performance of up to 99.38%. The network consisting of 12 layers proved effective when the data is represented two-dimensionally by Wavelet Transforms such as Morlet Transform or B-Spline Frequency Transform. However, there are still difficulties in detecting sparse or unusual arrhythmias, as well as handling noisy data. Automated arrhythmia detection can speed up diagnosis, especially for EKG arrhythmias collected over longer periods. Smart devices, wearable EKG and affordable holters for a wide range of people, including the vulnerable, allow patients to monitor and detect arrhythmias themselves, as well as receive early medical care.

5.2 Applications of Artificial Intelligence in the Classification of Motor Tasks

In recent years, there has been a significant increase in interest in the application of machine learning techniques for the development of assistive technologies for people in various areas even those with special needs [125, 126, 127, 128]. Signals EEG provide valuable information about the electrical activity of the brain, offering a direct and non-invasive method for detecting certain abnormalities or even diseases. Machine learning methods, especially those for extracting features from EEG signals, allow classification of patient activities, providing personalised and adaptive care for people with special needs. Accurate recognition and classification of actions, such as motor activities, facilitates real-time feedback and independent interaction of people with special needs with their environment. For the classification of motor activities based on EEG signals, issues such as data acquisition, electrode placement, electrode number, privacy and comfort of participants, especially for people with special needs, need to be considered. Convolutional neural networks (CNN) have shown promise in the field of brain-computer interfaces (BCI) [129, 130, 48] as they can process raw signals without the need for manual feature extraction. This reduces process complexity, improves system efficiency and increases accuracy.

5.2.1 Obstacles Encountered in Brain-Computer Interfaces

Classification of EEG signals is of key importance in brain-computer interfaces (BCI), neuroscience, cognitive neuroscience and other fields, but it involves some significant hurdles:

- **confidentiality and ethics** that can create ethical dilemmas and challenges when it comes to the use and storage of this data;
- **artifacts** (blinking eyes) that can introduce significant distortions and interference;
- **signal differences** that can occur from one individual to another and in the long term the signal from the same subject may be different;
- **lost annotated data** or even incorrect annotation of signals EEG;
- **interpretation of data** may be difficult, due to the complexity of the signals EEG.

The use of learning algorithms for classifying raw EEG signals has many advantages, such as increased classification accuracy, automatic feature extraction, and real-time operation. These algorithms have the potential to improve a wide range of applications, including brain-computer interfaces, post-acrshortavc rehabilitation, video games, virtual reality, etc.

5.2.2 System Architecture in Brain-Computer Interface Applications

Brain-computer interface systems (BCI) use EEG signals to convert brain activity into commands. Motor image classification is a topic of growing interest in neuroscience, with notable advances in signal processing algorithms and neuroimaging technologies. These developments aim to improve the efficiency and accessibility of BCI interfaces, with significant potential to help people with disabilities or conditions such as spinal cord injury or amyotrophic lateral sclerosis (ALS).

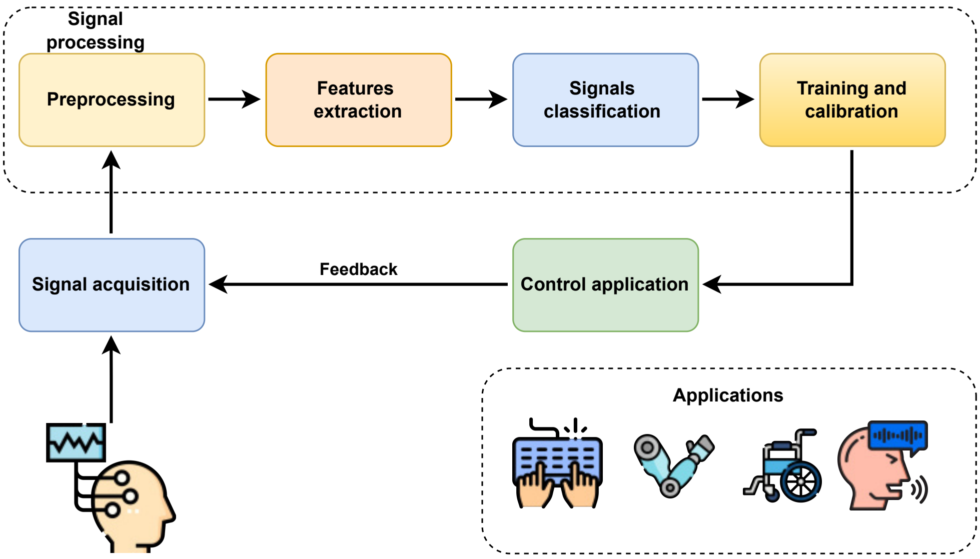


Figure 5.5: Block diagram of an BCI system based on encephalographic signals.

A typical BCI architecture based on machine learning consists of components that facilitate communication between the brain and an external device. The general block diagram (Figure 5.5) illustrates the following steps:

1. **Brain signal acquisition** by electrodes EEG detects electrical activity in the brain;
2. **Data preprocessing** in which acquired brain signals containing abnormalities and noise must be filtered out;
3. **Feature extraction** where relevant features are extracted after being pre-processed;
4. **Data classification** the extracted or selected features are fed into a machine learning model;
5. **Training and calibration** where the classification model is trained with labeled data correlated with certain actions;
6. **Real-time applications** once the model has been trained and calibrated, it can be used for real-time prediction in certain existing systems (wheelchair, robotic arm).

5.2.2.1 Improvements to Architectures Used for Brain-Computer Interfaces

The data analysis and classification process EEG is complex and involves acquisition, preprocessing, feature extraction, model building and validation, and signal classification. Each step is essential for the correct classification of signals. The generic diagram of this process can be seen in Figure 5.12.

The data preparation and filtering stage follows raw data acquisition and feature extraction, improving signal quality by removing noise and unwanted signals. In this phase, relevant channels are selected, noisy signals are removed, and the processed features are used as inputs to classification models, often based on convolutional neural networks.

In this phase of model development and training, the training strategy is selected and convolutional neural networks (CNN), recurrent neural networks (RNN), or other architectures are used to classify the data. In this study, 1D convolutional networks were preferred for their superior performance and shorter execution time compared to other methods, such as wavelet transforms. Also, the choice of model architecture depends on the characteristics of the data, providing flexibility for tuning and performance optimization.

After training the model, an initial validation is performed to evaluate performance using a separate dataset from the training dataset, with a focus on parameters such as accuracy, sensitivity and specificity. The model is saved only if the performance is satisfactory, for computational resource saving reasons. If the initial model has unsatisfactory performance, it can be improved by adjusting the hyperparameters, modifying the architecture or using transfer learning, which can speed up training and improve model performance.

In the final stage, the chosen model is subjected to rigorous verification to assess its robustness. This model is used to classify signals EEG, identifying the type of brain activity corresponding to each signal. The final model has a wide range of applications, including in brain-computer interfaces and the diagnosis of neurological diseases. The iterative approach to this process requires multiple rounds of validation and improvement and can vary from individual to individual, but using pre-trained models can speed up and improve results in specific applications.

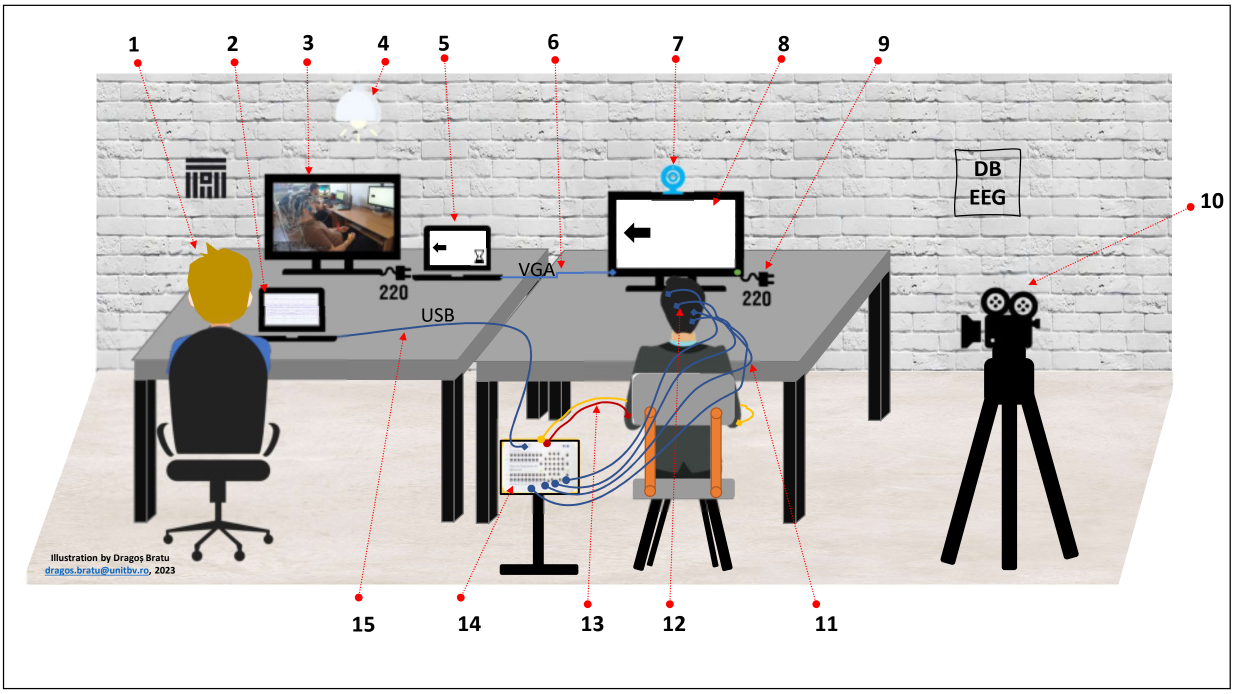


Figure 5.6: Illustrated data acquisition procedure for local experiments.

5.2.3 Methods for Collecting and Preprocessing Experimental Data Sets

In the field of data classification EEG, researchers are faced with the choice between using their own or established datasets. The use of a custom dataset allows for customization of data acquisition and a deeper understanding of the process, but may have generalizability limitations. On the other hand, established datasets provide standardised protocols, detailed documentation and have been used in numerous studies, facilitating comparison and replication of results. A hybrid approach that leverages the benefits of both methods may be beneficial in EEG research.

5.2.3.1 Method of Acquiring Local EEG Datasets. Investigation of Motor Tasks

According to the Table 5.6, various experiments were carried out using equipment from Neurosoft which was borrowed from SC LIAMED SRL, a local company specialized in medical equipment.

There were three subjects (Table 5.5). The author of the thesis manages and conducts the study, while being actively involved in the whole process (Figure 5.6).

A laptop**(2)** was used for acquisition, isolated from the electric grid to avoid interference, and another multimedia laptop**(5)** was used for recording and playback of the experiment, connected to an LCD monitor for the participant**(8)**. A second monitor**(3)** was also used for real-time monitoring of the

Table 5.5: Encephalograph experiment participants.

Subject	Age	Sex	Occupation
Subject 0 (s0)	30	M	Author
Subject 1 (s1)	20	M	Student
Subject 2 (s2)	20	M	Student

experiment and other relevant data. Two recording devices**(7)** are used to capture the experiment from different perspectives. A webcam for a frontal view **(7)** and a smart phone **(10)** for a side view. The participant**(2)** is essential for the experiment. Electrodes on the scalp are connected to the Neuron Spectrum 65**(14)** acquisition equipment. and record both EEG and EKG activity. It is powered exclusively from a USB cable, ensuring accurate readings without network interference. The first subject (denoted s0 in this thesis and s0d in the EDF records) is the 30-year-old author of the thesis. He participated in a training session at SC LIAMED SRL Brasov, which included the use of medical equipment and software. Subsequently, the author performed several experiments on 1, 21, 22, 25 and 28 March 2022, recording various types of signals, including artefacts, to familiarise himself with the system and data acquisition.

Subject 2 (s1 in this thesis and s0 in the recordings) is a 20 year old working as a student being known as a calm person, able to concentrate easily on tasks. To diversify the results, experiments with this subject were conducted at different times and in different contexts, including in the evening after college classes, in the morning after sleep, and after physical activities such as gym workouts. Also, varied samples were recorded, covering different activities and artefacts, such as eye blinks or heartbeats.

The last subject (s2 in the recordings) is a 20-year-old (student) who mainly participated in the first experiments and in collecting data on different artefacts. To ensure the best possible data acquisition, care was taken to keep the impedance as low as possible and within parameters.

Experiment Description

Most of the experiments took place in a building of the Transilvania University of Brasov. Each participant had an LCD monitor in front of him/her at a distance of about 45 cm, on which the instructions for the experiment were running.

Experiment "0 - The Initiation"

This experiment was the first experience of the author and the two subjects with a medical equipment EEG. In the experiment, a training session was held at the premises of the company SC LIAMED SRL in Brasov, followed by an experiment in which the subjects (s1 and s2) were exposed to a presentation on an LCD screen. They were instructed to remain calm and avoid excessive movements, with pulse monitoring below 90 beats per minute, opening their eyes only when they heard beeping sounds.

Subjects were subjected to various tasks such as blinking, swallowing, smiling, and moving their eyes in different directions. They were then presented with geometric figures of different shapes and

(a) Bottom right side view.

(b) Top right side view.

(c) Rear right side view.

(d) Front view, webcam.

Figure 5.7: Captures "The Initiation" experiment with subject s1, location SC LIAMED SRL headquarters.

colours, such as squares, triangles, circles or stars in black, red or green. The experiment ended with the presentation of pictures of food, facial expressions and lines from famous poems, in order to arouse different feelings and emotions in the subjects.

After completing the first experiment, participants were interviewed, citing difficulty concentrating during the experience. This feedback led to adjustments in subsequent experiments. Throughout this initial experiment, the author gained experience using the equipment and learned to minimize artifacts, with a focus on the subjects' natural reactions.

The "Spring" Experiment

The second experiment, titled "Spring" due to March 1, 2022 where the author made adjustments based on feedback received from the original experiment, shortening the duration and keeping only black figures with white slides interspersed. Subjects had to close their eyes during the white slides and wait for the beep to open them. Feedback from subjects indicated improved concentration, but discomfort from headphones remained a problem.

(a) Side view left, ”star” class.

(b) Left side view, ”triangle” class.

(c) Left side view, ”circle” class.

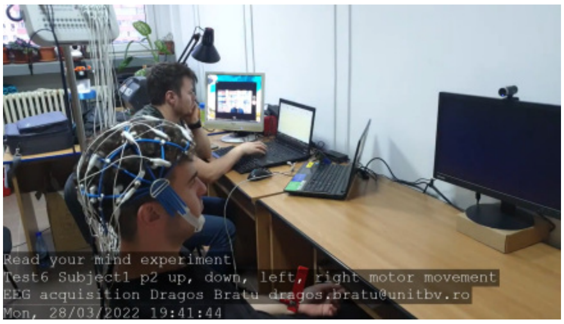
(d) Left side view, white screen.

Figure 5.8: Captures from the ”Spring” experiment with subject s1.

Subjects testified that after viewing a black shape on a white background, after closing their eyes they still saw the geometric figure, and at times they still involuntarily thought about it and the sound produced when the slides changed was perceived as unfriendly, and the predictability of the slides was another aspect noted. The author identified significant fluctuations in the signal recorded by EEG during sounds produced from different directions, possibly due to subjects' reactions or activation of parts of the brain responsible for auditory perception. In addition, noises from outside the room, such as an ambulance siren, induced distortions in the signal, but were not removed from the experiment to preserve its authenticity.

The ”Black-White” Experiment

It was conducted a few weeks after the previous experiments, included processing the previous data, creating automatic annotation algorithms and developing an annotation algorithm for the video sequences. In order to obtain more relevant data, the classes and rest screen exposure time between classes were reduced.



(a) Black transition displayed on monitor.

(b) Front view subject s2 (see Table 5.5).

(c) Preparation of subject s2 (see Table 5.5).

(d) Front view of subject s1.

Figure 5.9: Captions from the "Force" and "Finals" experiment with subject s1 and s2.

The "Black-White" experiment involved eliminating the sound, replacing white sequences with black sequences and requiring participants to blink 2-3 times during the black screen. The author continued to familiarize himself with the medical equipment and artifacts recorded for calibration and training. The artifacts were valuable information for distinguishing them from real signals.

Experiment "Resting"

The experiment took place after a period of good sleep and involved data acquisition from subject s1. Signals EEG were not significantly different from those in other experiments, but the subject's heart rate was lower. The subject was more comfortable and focused in this experiment, which took place on March 22, 2022, with a duration of 3600 seconds.

Experiment "Force"

The fifth experiment in the series involved examining subject s1 after a session in the weight room. The participant's pulse rate was increased following intense physical activity.

In this experiment it was decided to focus predominantly on people with special needs, to understand how such a system should be used by people who have or are prone to problems such as motor impairments requiring assistance. So instead of the participant thinking about their own sense of left, right, up or down, they had to imagine moving one hand at a time according to the direction of the arrows, sometimes performing the action, and when the arrow was pointing down they had to imagine or move the soles of their feet and squeeze the soles of their feet. When the up arrow was shown they had to imagine that they would move their gaze upwards. This is especially important for people who lose mobility over time and who may have such systems that they can train and then use in physical activities to improve their daily lives. This way of imagining is called "motor imagery".

Figure 5.10: Capture from the "Finals" experiment, left arrow.

Experiment "Finals"

The final investigations took place on 25 and 28 March 2022 and were similar to the "Force" experiment, but only subjects s0 and s1 were involved and the experiments were repeated in order to have as much data as possible for training.

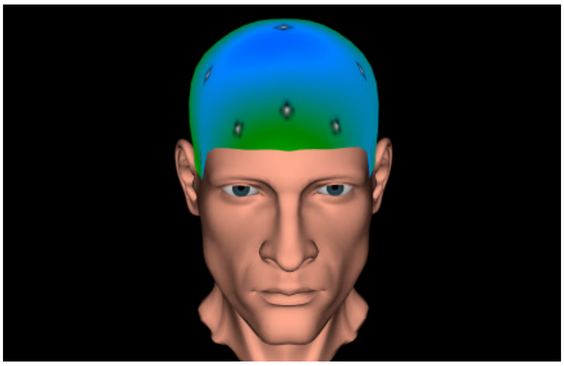
5.2.3.2 Data Acquisition

Ag/AgCl bridge electrodes are the suitable choice for EEG recordings due to signal stability, reusability, low electrical compensation potential and low cost. These electrodes offer longevity and compatibility with patients' scalps without causing irritation, making them ideal for long-term EEG recordings.

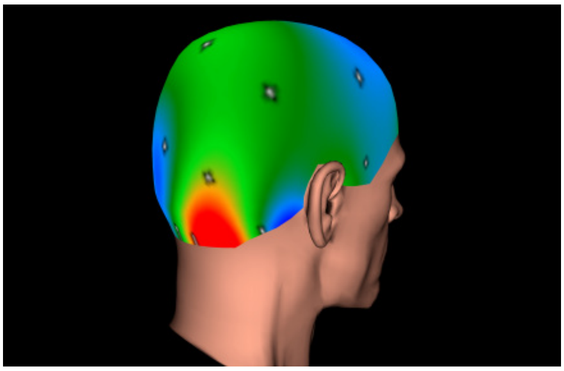
Information is collected using Neurosoft-Spectrum-65 [64], which captures brain signals using 22 channels (with EKG signal included) at a sampling rate of 500 Hz.

The Neuron-Spectrum-65 is a 39-channel sixth-generation EEG device designed for medical use in public and private institutions. It includes extensive video-EEG monitoring, polysomnography, patient portability, continuous impedance monitoring, advanced mathematical analysis, and allows data export for further statistical analysis.

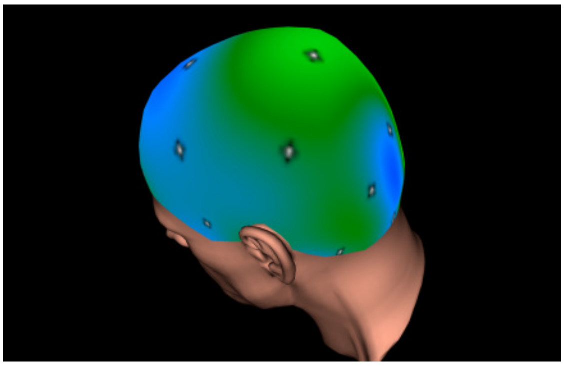
Montages are certain logical, ordered arrangements of leads or encephalographic channels that are created to display brain activity. Most commonly, monopolar, bipolar and referential montages are used for EEG montages.



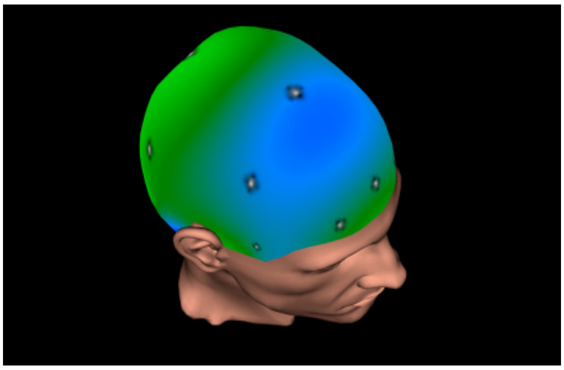
(a) Front view.



(c) Side view.



(b) Top left side view.



(d) Top right side view.

Figure 5.11: Spectral map of theta and alpha waves and location of electrodes on the scalp. Captured from Neurosoft-Spectrum.NET.

Final Considerations of the Local Experiment

It can be seen from the Table 5.6 that multiple participants were involved over approximately 7 experiments with an average duration of 16 minutes each, influenced by the availability and comfort of the subjects. Subjects experienced discomfort from the electrodes and sometimes experienced headaches or migraines. Mounting the electrodes and securing the connection with the acquisition device required 10 to 15 minutes per patient.

Repetitive experiments helped the researcher understand the equipment and the data acquisition process, identifying reasons for triggering artefacts and observing the varied reactions of the participants. Choosing the right location was crucial to minimise acoustic and electrical noise.

Table 5.6: Experiments, subjects involved, date of experiments and total duration of experiments.

Exp.No.	**Date**	**Subjects**	**Duration exp. (s)**
1	24.02.2022	s0, s1, s2	9705
2	01.03.2022	s0, s1, s2	5155
3	21.03.2022	s1, s2	3106
4	22.03.2022	s1	3676
5	24.03.2022	s0, s1, s2	6357
6	25.03.2022	s0, s1	3036
7	28.03.2022	s1	5778

These experiments were a real success, bringing the author closer to the medical field and giving him a detailed insight into the field. The researcher understood crucial aspects that could not be obtained from existing databases, such as the purchase of medical equipment, the careful sourcing and training of participants. Interaction with professionals and enthusiasts in the field allowed valuable connections to be made for future research studies, and the promptness of participants in responding and assisting brought a human and practical dimension to the research.

5.2.3.3 The Method of Using a Dedicated Dataset

The EEG Motor Movement/Imagery Dataset V1.0.0[1] [131] on PhysioBank consists of signal recordings EEG from 103 participants, comprising 14 experimental trials and 4 motor imagery tasks. The recordings were made with a BCI2000 system and EEG configuration with 64 channels at a frequency of 160 Hz. The dataset offers potential for motor imagery research and the development of brain-computer interfaces. Each annotation is labeled as **T0**, **T1**, or **T2**, and each session consists of 4-second sequences of each type, totaling 15 **T0** signals, 8 **T1** signals, and 7 **T2** signals. Some records were excluded from the experiment due to annotation errors (S105, S104, S101, S100, S092, S089, S088, S038, and S001).

In the research, four distinct classes were established to represent different mental states and motor imagery tasks. These classes include baseline state, motor imagery of left fist movement, motor imagery of both fists movement, and motor imagery of both feet movement, each labeled appropriately in the data analysis with "B", "S", "P", and "D".

The data set showed an initial class imbalance, and to correct for this, balancing techniques were applied during both the training and testing periods. A balanced distribution of the validation dataset was also ensured by selecting 1000 samples per class. In the training phase, initially, the class distribution was adjusted to address imbalance, including the use of the synthetic minority oversampling technique (SMOTE [39] [132]).

In addition, to improve accuracy, specific channels were selected that were considered most relevant to motor activities. These selected channels included FC1, FC2, FC3, FC4, FC5, FC6, C5, C6, C3, C4, C1, C2, CP1, CP2, CP3, CP4, CP5 and CP6. The aim was to highlight these channels to capture the most informative signals associated with motor movements. Thus, after applying the SMOTE technique, the classes used for training had the form [30000 30000 30000 30000] now the classes are balanced.

Table 5.7: Annotations code meanings from the EEG Motor Movement/Imagery Dataset [131].

Tag	Movement Description	Experiment Number
T0	Basic state (rest)	-
T1	Left fist movement (real or imaginary)	3, 4, 7, 8, 11, 12
	Movement of both fists (real or imaginary)	5, 6, 9, 10, 13, 14
T2	Right fist movement (real or imaginary)	3, 4, 7, 8, 11, 12
	Movement of both feet (real or imaginary)	5, 6, 9, 10, 13, 14

[1] available at https://physionet.org/content/eegmmidb/1.0.0/

5.2.3.4 Final Considerations. Own Experiments or Recognised Databases

After conducting EEG data acquisition experiments with real participants, several advantages are observed, including detailed knowledge of the experimental setup, complete control over the experimental design, data confidentiality, standardization of data acquisition, and selection of participants by criteria of interest. Also, direct feedback from patients and the possibility to choose the equipment are real benefits. However, there are also some drawbacks to self-acquisition of signals, such as the need to acquire technical skills, the data annotation process, the identification of suitable participants and the high cost of equipment.

The choice between using a public dataset and generating your own data in EEG research can benefit from a hybrid approach that combines the advantages of both methods. Researchers can use their own data for specific investigations, testing hypotheses and exploring new research directions, while existing datasets can serve as references for validation and applicability of results. With careful planning and adequate resources, researchers can overcome the challenges of acquiring and managing data EEG, making significant contributions to the research field despite these obstacles.

5.2.4 Extraction of Relevant Characteristics

5.2.4.1 Data Filtering

Filters in signal processing EEG are essential for removing unwanted frequencies and noise, but must strike a balance between cleaning the signal and preserving relevant neural activity, especially brainwaves related to motor imagery. High-pass, low-pass and band-stop filters are the most commonly used in this context, allowing focus on specific frequency bands, such as beta waves (11-30 Hz), associated with sensory and motor activity. In this case, a frequency of 0.5 Hz was chosen for this LFF (Low Frequency Filter), for HFF 35 Hz and the Notch filter disabled. The Low Frequency Filter (LFF) has a cut-off frequency of 0.5 Hz. The stop-band filter is used for frequencies of 50 Hz – the frequency of the local power grid.

5.2.4.2 Automatic Annotation of Local Experiment Data

Signal annotation EEG is often a laborious and time-consuming task in which human experts manually examine and identify relevant events or segments in recorded signals. In the present scenario, a program was developed to automate the generation of signal annotations by taking advantage of the fact that the start and end points of the experiment were known, but more importantly, the duration of each activity was known. Once the automated annotations were created, they were imported into EDFBrowser and significantly sped up the annotation process.

5.2.4.3 Selecting Channels of Interest

Selecting EEG channels is important especially since artifacts produced by eye movements and blinking can affect the signals. Even though participants were instructed not to move their eyes too often there were some actions that affected channels close to the eyes. The AI algorithm initially achieved poor results, but after removing the affected channels, accuracy increased significantly, exceeding 90%.

5.2.4.4 Selection of Relevant Data from the Local Experiment

The data selection process for the experiment involved initial trimming of the EDF files to include only relevant experiment data, followed by automatic annotation based on knowledge of experiment duration, allowing identification of activity-specific events. Subjects were instructed to perform various actions, including eye movements, to provide identifiers for artefact location, thus contributing to the selection of data with few artefacts (in experiments).

Four EDF files were chosen due to the substantial amount of data they provided, covering a larger time range for subject 0 (s0) and ensuring reduced noise in the data. These data were intended for subsequent analysis and classification tasks in the EEG signal processing experiment.

Table 5.8: Files information EDF subject s0 and their duration for motor activities.

EDF file	Start time	End time	Duration (MM:SS)
s0p0.edf	19:17:04 28.03.2022	19:30:45 28.03.2022	13:41
s0p1.edf	19:40:26 28.03.2022	19:56:52 28.03.2022	16:26
s0p2.edf	21:15:30 28.03.2022	21:31:50 28.03.2022	16:20
s0p3.edf	21:41:30 28.03.2022	21:57:21 28.03.2022	16:16

5.2.5 Data Training, Calibration and Classification

Current research has used neural networks as flexible signal processing and feature extraction tools to investigate complex patterns within EEG brain wave data. This section explores the use of both conventional and other neural network architectures for data decoding purposes.

5.2.5.1 Artificial Neural Network Architectures Used to Classify Signals from Actions or Motor Imagery

To provide a solid foundation for the experimental procedures, a variety of pre-existing or enhanced artificial neural network topologies were used, specifically designed to exploit the distinctive attributes inherent in electroencephalogram data. The architectures EEGNet [133], EEGNetSSVEP [134, 135], DeepConv, ImprovedNet, ImprovedNet2 and ImprovedNet3 built specifically for EEG analysis, were used due to its ability to efficiently capture temporal relationships.

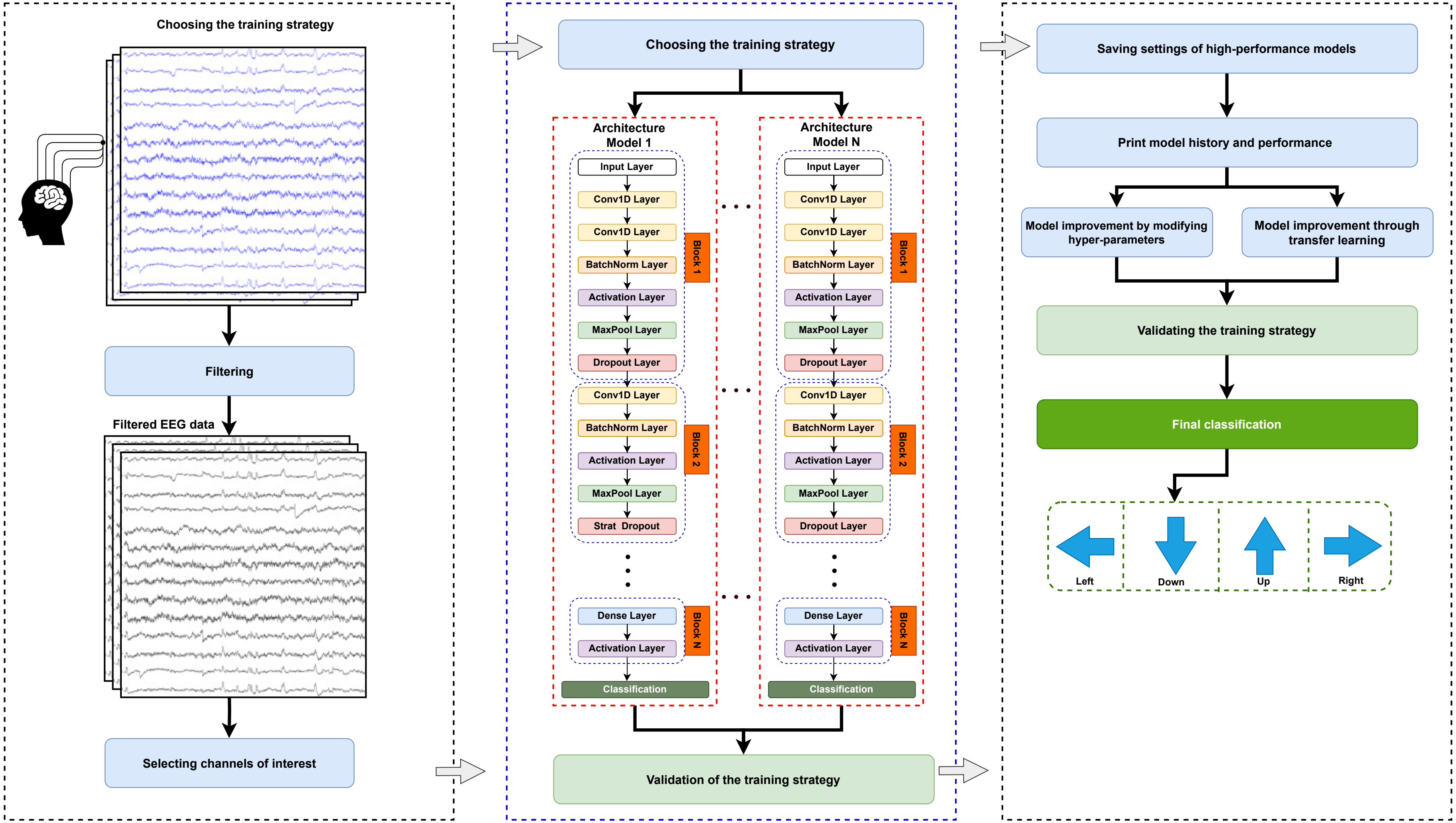


Figure 5.12: Description of the training, calibration and validation process using different neural architectures, especially convolutional neural networks, and some techniques by which the accuracy and robustness of a system can be improved (e.g. by combining several networks using transfer learning techniques) – implementation proposal.

The above architectures have been carefully designed with the aim of increasing convolutional depth and implementing unique arrangements to enhance classification performance. The selected architectural decision serves as the basis for the ability to easily modify settings and, more importantly, support the implementation of transfer learning approaches. This provides the ability to customize neural network architectures to the unique characteristics of different datasets EEG without requiring extensive redesign. This process is depicted in Figure 5.12. The architectural specifications of the artificial neural networks used are also provided in the appendices of the thesis.

5.2.6 Evaluation of Performance Achieved

This section summarizes the results of the performance evaluation of neural networks, highlighting accuracy, losses and confusion matrices in two distinct approaches, one using a specific dataset and the other a local dataset. The evaluation of neural network architectures started, as a first approach, using the dataset **EEGMMIDB**[1].

Table 5.9: Sample distribution for the two approaches using different datasets.

Approach	Class	Instruction	Validation	Testing
EEGMMIDB	Class 1 (B)	30000	1000	1000
	Class 2 (S)	30000	1000	1000
	Class 2 (P)	30000	1000	1000
	Class 4 (D)	30000	1000	1000
Local	Class 1 (B)	921	116	115
	Class 2 (S)	921	115	116
	Class 2 (P)	922	115	115
	Class 4 (D)	922	115	115

The training procedure included the implementation of measures to ensure fair representation of the four chosen classes. Both the validation and test sets were chosen so that there were balanced class distributions and the oversampling technique was used for classes with less data, resulting in a more balanced allocation of 30,000 samples per class for training, as shown in the Table 5.9.

The following shows the highest performance obtained with the ImprovedNet2 network with high performance using the EEGMMIDB dataset and the local dataset. Both result in high accuracy of over 90%. After obtaining promising results in the first approach, the validation process focused on an author-acquired local dataset with a balanced class distribution and a total number of 3688 samples for training and 461 for validation.

[1] Available at https://physionet.org/content/eegmmidb/1.0.0/

Table 5.10: Results of the ImprovedNet2 architecture using the EEGMMIDB dataset.

Class	**Precision**	**Recall**	**F1 Score**	**Support**
Class 1 (B)	0.95	0.97	0.96	1000
Class 2 (S)	1.00	0.98	0.99	1000
Class 2 (P)	0.96	0.97	0.97	1000
Class 4 (D)	0.99	0.98	0.98	1000
Accuracy			0.97	4000
Avg.	0.97	0.97	0.97	4000
Weighted Avg.	0.97	0.97	0.97	4000

Table 5.11: The results of the ImprovedNet2 architecture using the local dataset.

Class	**Precision**	**Recall**	**F1 Score**	**Support**[1]
Class 1 (B)	0.92	0.90	0.91	115
Class 2 (S)	0.96	0.94	0.95	116
Class 2 (P)	0.94	0.89	0.91	115
Class 4 (D)	0.87	0.96	0.91	115
Accuracy			0.9197	461
Avg.	0.92	0.92	0.92	461
Weighted Avg.	0.92	0.92	0.92	461

[1] This column indicates the number of instances in each class that were used to calculate these metrics.

The network results ImprovedNet2 presented in the Table 5.11 show the performance indicators of the different classes. Of these, class "S" achieved the highest precision of 0.96 and the highest Recall value of 0.94, resulting in an impressive F1 score of 0.95. On the other hand, class "D" demonstrated an outstanding Recall value of 0.96, while class "B" showed balanced precision and Recall values, contributing to an overall precision of 0.9197 for all classes.

Table 5.12: Comparison of accuracy and F1 score of different architectures.

Architecture	**Precision**	**F1 score**
ImprovedNet2	0.91	0.92
ImprovedNet3	0.88	0.88
EEGNetSSVEP	0.83	0.82
EEGNet	0.90	0.90
ImprovedNet	0.85	0.85
DeepConvNet	0.78	0.78

In conclusion, a brief comparison of accuracy and F1 score values for different neural network architectures in the context of the local experiment is presented in Table 5.12. In particular, the ImprovedNet2 architecture shows a high accuracy of 0.9197, accompanied by an F1 score of 0.92. The ImprovedNet network is a reliable classifier for EEG signals, exhibiting superior accuracy, F1 score and precision, making it a strong choice for this specific classification task.

5.2.7 Final Considerations

In recent years, interest in the use of machine learning in assistive technologies, including for people with special needs, has grown significantly. Signals EEG provide valuable information, allowing classification of tasks performed or imagined by patients and facilitating the development of various applications. By decoding the signals produced by the brain, applications can be created that can improve the interaction of people with special needs with their environment, enhance their mobility and ultimately increase their independence. Examples of real-world applications include non-invasive control of a wheelchair or communication with outsiders in the event of a mobility loss accident.

In this section the applications of artificial intelligence in classifying motor tasks have been discussed, with a significant impact in improving the lives of people with special needs. A flexible system for transitioning between different convolutional neural network architectures was developed. Experiments were performed on established databases and some local experiments were created. These tests led to the exploration of new approaches and the proposal and development of new artificial neural network architectures, achieving significant accuracy percentages. The contributions made have a significant impact in the field of EEG research and artificial intelligence especially in relation to people with locomotion problems.

Chapter 6

General Conclusions

In the everyday technological landscape, artificial intelligence (AI) has emerged as a transformative force, reshaping society and improving the quality of life. In the context of this technological revolution, it is essential to pay attention to people with special needs, such as the elderly, those with reduced mobility or with various disabilities and medical conditions. The use of AI techniques has the potential to benefit the majority as well as improve the lives of those with special needs. Exploring edge computing technologies on low-power devices has the potential to improve areas such as robotics, medical devices and personalised care, but unresolved issues remain.

Throughout the thesis, a number of approaches to some of the existing obstacles have been outlined. These approaches refer to the development and implementation of intelligent solutions in the form of an autonomous multi-functional assistive robot or solutions using non-invasive technologies such as EKG or EEG. In addition, by classifying EEG signals we can perform "mind reading" and restore communication or locomotion capabilities to those with motor problems. All these solutions can be implemented on energy-efficient devices.

6.1 Achievement of Objectives and Original Contributions

This section highlights the successful achievement of the objectives described by means of an effort supported by the use of AI to meet the requirements of people with special needs and which also constitutes the general objective as presented in section 1.3. The goals of investigating neural network architectures, creating tailored solutions, and developing adaptive technologies have been rigorously pursued, making possible tangible advances that have a positive impact on the lives of this category of people. Therefore, the objective OS1 has been achieved through the following original achievements and contributions:

- Conducting a comprehensive state-of-the-art analysis of artificial neural network architectures and technologies AI tailored to the special needs of certain categories;
- Identify the advantages and highlight the current impediments both in people with special needs

and the application of AI techniques on this specific category. This is intended to advance medical applications through AI, while addressing the specific needs of certain groups with certain conditions.

The OS2 objective has been fulfilled through the following original achievements and contributions:

- Develop an efficient time series processing system using AI techniques and edge computing on low power devices. This system has the potential to significantly improve the quality of life of people with special needs in applications where time series are prevalent:

  - Proposal and implementation of an artificial neural network architecture for the purpose of anomaly detection in time series using a Autoencoder network enhanced with classical classification methods for running on low-power devices. After training and validation, this neural model achieved high performance of over 80% and is a demonstrator in running artificial intelligence algorithms and time series anomaly detection on edge computing devices;
  - Proposal and implementation of an embedded system for migrating AI applications from an energy-intensive server infrastructure to low-power devices as close as possible to the data generating source. The implementation of this system for intelligent and decentralized time series processing, has benefits such as increased privacy and reduced data latency, decreased bandwidth and reduced overhead. The system can also have medical applications, providing specialists with accurate, real-time data on brain or muscle signals and heart or breathing rates.

- Proposal of six new benefits that can be brought to improve the quality of life of people with special needs. Efficient time-series processing using artificial intelligence techniques and edge computing on low-power devices opens up important perspectives in the areas of accessible personalised solutions, lifelong care, data monitoring and interpretation, autonomy, security and privacy;

- Design and development of a multifunctional assistive robotic system running on edge computing and artificial intelligence technologies to support specific vulnerable groups. This robot can also provide other support services in areas such as personalised assistance, environmental monitoring, virtual means of locomotion and education:

  - Proposal and implementation of a modularised system that decouples the control part (the logical part) from the physical part of the robot by combining different technologies, running on low-power devices. This solution provides an efficient and easy-to-use platform eliminating the need for detailed knowledge of specific hardware in the control logic. This system has resulted in a multi-functional robotic assistive system in support of certain vulnerable categories designed with the aim of extending new services for the benefit of the aforementioned category;

- Proposal and implementation of a dual and redundant detection and safety system, using artificial intelligence techniques combined with data from specific sensors for the detection of animals and people. At the same time this system provides statistics on surrounding objects and describes their environment. It ensures a higher level of safety in robot operation in different environments and can support certain categories of people to improve their quality of life.

- Propose six new applications for autonomous robotic assistive systems to provide support to people with special needs, opening important perspectives in the areas of assistance, monitoring, education, virtual means of locomotion and social inclusion;

The objective of OS3 has been achieved through the following original achievements and contributions:

- Develop a deep learning system for arrhythmia detection and classification for people with heart disease. This system can also support healthcare professionals in the identification of cardiac arrhythmias, with a positive impact on clinical practice:
  - Design and implementation of an architecture for a convolutional neural network (CNN) using samples from established medical databases annotated by cardiologists. Following training and validation, this neural model achieved high performance of up to 98.05%;
  - Proposing a novel method using deep learning 2D artificial neural networks for the detection and classification of cardiac arrhythmias from electrocardiogram data (EKG) using Wavelet, Morlet and B-Spline transforms. This solution enhances the effectiveness of the previous method, and after training and validation, the performance obtained increased to 99.38%.

- Development of a deep learning system for classifying motor tasks from encephalographic signals:
  - Development of several experiments in the field of people with special needs, where the main goal was the interpretation of signals from the encephalograph. Subsequently, using artificial intelligence techniques, applications can be created to improve the quality of life of people with certain disabilities;
  - Proposal and development of four new convolutional neural network architectures that can be used in signal classification EEG. Following training and validation, these networks have achieved high performance of up to 91%;
  - Testing and validation of the previously proposed architectures in various scenarios from established databases (EEG Motor Movement/Imagery Dataset) as well as on locally acquired samples, thus demonstrating the effectiveness of these networks.

- Development of a software script for automatic annotation of EEG signals and related videos, contributing to the analysis and improvement of the data pre-processing stage;

- Design, development and elaboration of a flexible, innovative system to ensure the transition between different convolutional artificial neural network architectures facilitating training, testing, validation and selection of high performance models.

In conclusion, this thesis has successfully achieved its general objective of using artificial intelligence technologies to support and improve the lives of people with special needs.

By exploring specific research topics such as cardiac arrhythmia detection and classification using innovative methods and efficient time series processing using artificial intelligence technology on edge computing devices, significant contributions have been made to the field. Also, the creation of a versatile autonomous robotic assistive system, with perspectives of extending to new services, and the classification of EEG signals have added value to this research.

All these development directions can be seen as a symbiosis, in which individual elements contribute to a complex system designed to provide significant support and benefits to categories of people with special needs.

6.2 Future Research Directions

The thesis presented opens up possibilities for future research directions in the use of technology and artificial intelligence to support people with special needs. As such, the following areas present opportunities for continued exploration and improvement:

- **Advanced medical diagnostics by integrating smart devices** – addresses the development of algorithms that can run wearable devices for diagnosing and other medical conditions. One possible direction may involve adapting the algorithm to run on smart phones or smart watches, allowing people with such conditions to detect potential problems at an early stage, thereby avoiding a worsening of their condition. Another direction is integrating the system into medical devices, such as EKG holters, which can help medical staff quickly identify problems when data needs to be analysed over a longer period of time. Extending the algorithm's capabilities to detect and improve the lives of patients with various medical conditions is another promising direction. Future research could involve training the algorithm on a wider range of arrhythmias and using techniques such as SMOTE (described in 2.1.4.4) to generate samples for less common conditions;

- **Improved systems for efficient time series processing** on low-power devices as close as possible to the data generating source. The use of various artificial intelligence algorithms, such as LSTM, can be explored to evaluate their performance in various contexts. Progress can also be made in developing compact models to efficiently test new scenarios, and in integrating specialised AI chips into the edge computing infrastructure to enable real-time anomaly detection in critical applications. This approach represents a promising direction for research;

Development of multifunctional robotic assistive systems by extending existing services, covering a wide range of areas including the provision of personalised care, fostering social engagement, education and environmental monitoring for specific patients, which have also been described in the 4.2.2 section. Another direction is the embedding of new sensors and actuators or upgrading the central processing unit for more computing power that can improve the robot's capabilities by processing more complex artificial intelligence algorithms;

Improvements in signal classification EEG, providing a complex and multidimensional research area with many potential applications. Future research may explore expanding the scope, for example, by enabling people to type on virtual keyboards or communicate with others without physical movement. Another example may be adding more classes corresponding to more actions and using high-performance equipment with more electrodes and better amplification or filtering stages that will make for a more robust system. Another important direction is the acquisition and validation of results, reflected in real applications. For example, in cases of locomotor impairments in elderly people, a wheelchair controlled by interpreting the EEG signals can be implemented. In addition, real-time processing of EEG data on low-power devices such as EEG headsets is intended, leading to more efficient and affordable solutions for people with special needs.

6.3 Dissemination of Research Results

This section provides an analysis of dissemination initiatives implemented during the doctoral research work. Research results have been valorised, validated and disseminated through active involvement in various international conferences, as well as publications in national and international journals, as lead or contributing author. The quality of coordinator in several research projects underlines the author's leadership position and illustrates his commitment to share his expertise. At the same time, the author's knowledge has been strengthened by participation in numerous workshops or conferences in the field.

6.3.1 List of Publications

- **D.-V. Bratu**, R.Ș.T. Ilinoiu, A. Cristea, M.-A. Zolya, S.-A. Moraru, **"Anomaly Detection Using Edge Computing AI on Low Powered Devices"**, IFIP Advances în Information and Communication Technology (Book series), Vol. 646 IFIP, 18th IFIP WG 12.5 **Int. Conf. on Artificial Intelligence Applications and Innovations, AIAI 2022**, **Hersonissos, Grecia, 2022**, pag. 96 – 107. (Scopus, DOI: 10.1007/978-3-031-08333-4_8);
- **D.-V. Bratu**, M.-A. Zolya, S.-A. Moraru, **"A Different View on Artificial Intelligence Applications for Cardiac Arrhythmia Detection and Classification"**, Book Series: Lecture Notes in Networks

and Systems, Vol. 298, Proceedings of the 18th I**nternational Conference on Remote Engineering and Virtual Instrumentation REV2022**, **Hongkong**, **2022**, pag. 415 – 427. (ISI Web of Science, Scopus, DOI: 10.1007/978-3-030-82529-4_41);

- **D.-V. Bratu**, S.-A. Moraru, L.G. Guşeilă, **"A Performance Comparison between Deep Learning Network and Haar Cascade on an IoT Device"**, **Lisabona, Portugalia, 2019 International Conference on Sensing and Instrumentation in IoT Era (ISSI)** doi:10.1109/issi47111.2019.9043714;
- A.F. Popov, D.M. Kristaly, **D.-V. Bratu**, M.-A. Zolya, S.-A. Moraru, **"A Method for Using GSM Technology and SCADA Systems to Monitor and Control Decommissioned and Partially Decommissioned Railway Stations"**, **2023, Applied Sciences**, 13 (8), 4874, doi: 10.3390/app13084874;
- L.G. Guşeilă, **D.-V. Bratu**, S.-A. Moraru, **"Continuous Testing in the Development of IoT Applications"**, **2019 International Conference on Sensing and Instrumentation in IoT Era (ISSI), Lisabona, Portugalia, 2019**, pp. 1-6, doi: 10.1109/ISSI47111.2019.9043692;
- A.F. Popov, **D.-V. Bratu**, S.-A. Moraru, **"Remote Control of Railway Switch Heating Using GSM Modems"**, The Annals of "Dunarea de Jos" University of Galati. Fascicle IX, **Metallurgy and Materials Science 42 1**, **2019**, 42–47. Remote Control of Railway Switch Heating Using GSM Modems;
- L.G. Guşeilă, **D.-V. Bratu**, S.-A. Moraru, **"DevOps Transformation for Multi-Cloud IoT Applications"**, **2019 International Conference on Sensing and Instrumentation in IoT Era (ISSI), Lisabona, Portugalia, 2019**, doi: 10.1109/ISSI47111.2019.9043730.

6.3.2 Coordinator, Competitions and Participation in Scientific Sessions

- **Scientific coordinator**, SCSS, year **2019**, title **"Wall-e, intervention tank"**, section **ROBO**, location **ICDT Brașov**, students **Mădălin-Andrei Sava** (AIA) and **Petruț Condrea** (ROBO);
- **Scientific coordinator**, SCSS, year **2019**, project title **"Mailo"**, section **TI**, location **ICDT Brașov**, student **Nicolae Iosif**, (AIA);
- **Scientific coordinator**, SCSS, year **2021**, project title **"RoboCovCleaner"**, section **SAATI**, location **ICDT Brașov**, students **Maria-Alexandra Zolya**, (SAATI) and **Ana-Maria Andrei** (SAATI);
- **Scientific coordinator**, SCSS, year **2022**, project title **"Sistem pentru automatizarea procesului de sterilizare în spațiile interioare - RoboCovCleaner"**, section **SAATI**, location **ICDT Brașov**, students **Maria-Alexandra Zolya** (SAATI) and **Ana-Maria Andrei** (SAATI);
- **Scientific coordinator**, Dissertation project , year **2022**, title **"Sistem pentru automatizarea procesului de sterilizare în spațiile interioare - RoboCovCleaner"**, students **Maria-Alexandra Zolya** (SAATI) and **Ana-Maria Andrei** (SAATI);

- **Scientific coordinator**, Dissertation project and project within the event **Absolvenții în Fața Companiilor - AFCO** , year **2021**, title **"Tehnici de Machine Learning Aplicate in Smart Home si IoT"**, Facultatea de Inginerie electrică și știința calculatoarelor, student **Alexandru Cristea** (SECI);

- **Scientific coordinator**, Bachelor Degree and project within the event **Absolvenții în Fața Companiilor - AFCO** , year **2021**, title **"Tehnici de Machine Learning Aplicate in Smart Home si IoT"**, **ATI** Department, student **Rareș Ștefan Tiberius Ilinoiu** (TI).

6.3.3 Participation in Field Conferences

- **Technical presenter** of the topic **"Artificial intelligence and new technologies in our everyday lives"** at the conference **"Future Summit Brașov"**. Data **30.03.2023**, location **Brașov, România**;

- **Coordinator and participant of the task force** for **"RoboCovCleaner"**, on **"Fii în centru!"** competition, year **2020-2021**, location **Brașov, România**;

- **Participant** in the innovation specialist summit **"Bucharest tech week - Inovation Summit"**. Topics covered: AI, CleanTech, Wearables, Sustainability, IoT, Web3, and robotics, year **2023**, location **București, România**;

- **Technical coordinator** practical workshop **"MMWM - Miele - Mini Washing Machine"**, **12.02.2020**, location **ETI, UPB, București, România**;

- **Coordonator tehnic** workshop for students at **BuzzCamp**, date **20.11.2018**, location **Hotel Ambient Brașov, România**;

- **Technical coordinator** at the workshop for students at the event **BuzzCamp**, topic **"Connect to Miele Smart World – Create your own smart washing machine"**, date **19.11.2019**, location **Hotel Ambient Brașov, România**;

- **Participant** at the **workshop** organised in the framework of the **"Future co-creation exercise"** conference. Objective: discussions on sustainability, new technologies and the future of Brasov. Date **30.03.2023**, location **Brașov, România**;

- **Participant** in the **conference** of software development and artificial intelligence technologies **"DevTalks 2022"**. Date **08.06.2022-10.06.2022**, location **hibdrid, online-physical (Bucharest, Romania)**;

- **Participant** in the **conference** of the specialized **"Romanian AI Days 2023"**. Date **20.09.2023-21.09.2023**, location **Brașov, Romania)**;

  Participant in the **conference** of the software development and artificial intelligence technologies **"DevTalks Reimagined 2021"**. Date **09.06.2021-11.06.2021**, location **online**;

Participant in the **conference** of the development topic **"Artificial Intelligence: The Future of Software"**, date **06.06.2019**, location **Bucuresti, Romania**;

Participant in the **conference** of the **"Embedded world 2022"** low-consumption devices **"Embedded world 2022"**. Date **21.06.2022-23.06.2022**, location **Nuremberg, Germany**;

Presenter session **"Strategic Partnership between University and Electronics Industry"** at **IEEE 25th International Symposium for Design and Technology in Electronic Packaging SIITME** conference and exhibition, date **23-26.11.2019**, location **Cluj, Romania**;

Conference Participant expert in the field of Artificial Intelligence and Cloud technologies, within the **"Google Cloud Day"** conference, date **12.11.2019**, location **Bucuresti, Romania**.

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