UNIVERSITY ROVIRA I VIRGILI

MASTER THESIS

Automatic Diagnosis and Rehabilitation Plan for Fine Motor Skills Based on Virtual Reality and Artificial Intelligence

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Declaration of Authorship

I, Erika LOZADA MARTÍNEZ, declare that this thesis titled, “Automatic Diagnosis and Rehabilitation Plan for Fine Motor Skills Based on Virtual Reality and Artificial Intelligence” and the work presented in it are my own. I confirm that:

- This thesis was prepared in whole or in large part as part of an application for a research degree at this university.
- Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated.
- Where I have consulted the published work of others, this is always clearly attributed.
- Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work.
- I have acknowledged all main sources of help.
- Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself.

Signed:

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“The real voyage of discovery is not to seek new landscapes, but to look with new eyes.”

Marcel Proust.

Abstract

This work addresses the development of a prototype system for the automatic diagnosis and rehabilitation of fine motor skills, utilizing emerging technologies such as Virtual Reality (VR) and Artificial Intelligence (AI). The upper limb, particularly the hand, plays a crucial role in performing complex movements and fine motor tasks essential for daily activities. Loss or impairment of these skills can significantly impact an individual's quality of life. Traditional methods for diagnosing and rehabilitating upper limb and hand injuries often involve subjective assessments by therapists, which can lead to suboptimal and inadequately personalized treatments.

The main objectives of this work include studying the state-of-the-art in rehabilitation using VR and AI, collecting and preprocessing data from patients with fine motor problems, evaluating Machine Learning (ML) algorithms and selecting the one with better results for being used in rehabilitation plan recommendations, and proposing a system prototype for automatic diagnosis and rehabilitation planning. This interdisciplinary approach aims to improve the effectiveness and efficiency of rehabilitation for fine motor disorders, ultimately enhancing patient outcomes.

Keywords: Upper limb, hand rehabilitation, fine motor skills, artificial intelligence, virtual reality, machine learning, personalized medicine, digital healthcare, rehabilitation technology.

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List of Abbreviations

ML	**M**achine **L**earning
AI	**A**rtificial **I**ntelligence
VR	**V**irtual **R**eality
PCA	**P**rincipal **C**omponent **A**nalysis
MLR	**M**ulti **L**inear **R**egression
SVM	**S**upporing **V**ector **M**achine
KNN	**K** **N**earest **N**eighbours
RF	**R**andom **F**orest
ANN	**A**rtificial **N**eural **N**etwork
ReLU	**R**ectified **L**inear **U**nit
MSE	**M**ean **S**quared **E**rror
LR	**L**earning **R**ate
TP	**T**rue **P**ositive
FP	**F**alse **P**ositive
TN	**T**rue **N**egative
FN	**F**alse **N**egative
D	**D**ropout
P	**P**ooling
F	**F**latten
BN	**B**atch **N**ormalization

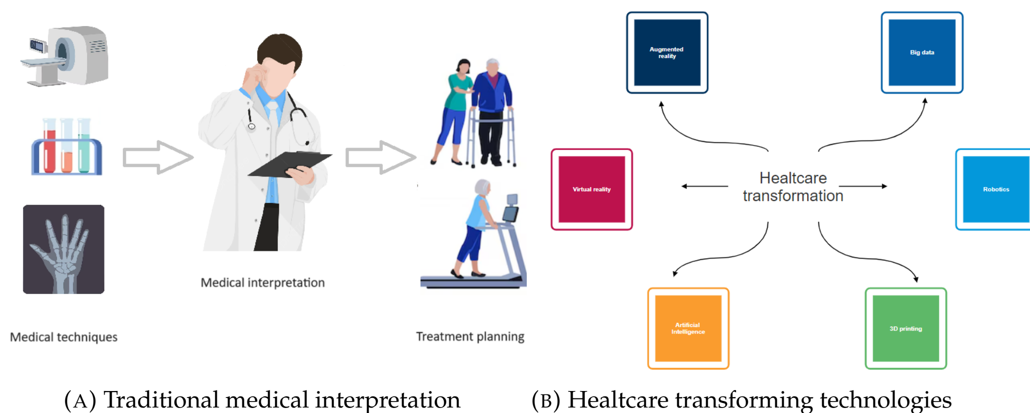
This work is dedicated to my family for their love, constant support and for being by my side at all times, which has been what has given me the strength to continue forward until achieving this goal.

Chapter 1

Introduction

Advancements in medical technology have revolutionized the diagnosis and treatment of various health conditions, including those affecting the upper limb, a crucial part of the human body comprising the shoulder, arm, forearm, and hand. These technologies have enabled the development of more precise and less invasive methods for detecting and treating medical problems, thereby improving outcomes for patients. Among these, the hand stands out for its ability to execute intricate movements and fine motor tasks essential for daily living, such as writing, typing, and manipulating objects. The complexity of the human hand due to its multiple muschles, bones, nerves and tendons makes it one of the most challenging body part to treat in medicine and specifically rehabilitation. So that, the loss or impairment of these fine motor skills can profoundly impact an individual's quality of life by limiting their independence and even more the ability to perform daily activities (Singh, 2014; Duman and Subaşı, 2020; Cartagena et al., 2019).

Traditionally, the diagnosis and rehabilitation of upper limb and hand injuries have relied on therapist and specialist evaluations based on acquired professional knowledge. However, these assessments often involve subjective interpretations, leading to variable treatment outcomes. Medical imaging techniques such as X-rays, Magnetic Resonance Imaging (MRI), Computed Tomography (CT), Ultrasound, and manual function tests play a pivotal role in determining the type and severity of injuries. Despite their utility, these methods are limited by their inability to access certain internal components of the hand directly, contributing to the subjectivity in diagnosis and subsequent treatment planning (Zhao et al., 2024). Traditional medical interpretation is presented in figure 1.1a.



(A) Traditional medical interpretation (B) Healtcare transforming technologies

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FIGURE 1.1: Medical interpretation and healthcare transformation

In recent years, emerging technologies such as Artificial Intelligence (AI), Virtual Reality (VR), Augmented Reality (AR), 3D printing, Big Data Analytics and Robotics have begun transforming the healthcare landscape, offering new tools to enhance medical diagnostics and therapies. These emerging technologies can be seen in figure 1.1b. AI, for instance, excels in pattern recognition and data analysis, providing healthcare professionals with valuable insights to improve diagnosis accuracy and personalize treatment strategies. VR, by creating immersive environments, allows for detailed simulations of patient interactions and behaviors, further enriching AI-driven decision-making processes (Garcia, Gonçalves, and Carbone, 2024; Naranjo et al., 2019).

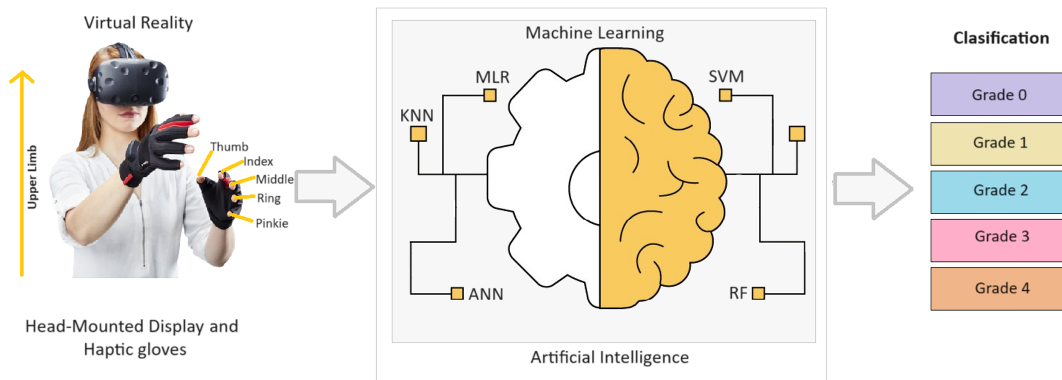


FIGURE 1.2: Virtual Reality and Artificial Intelligence integration

This work aims to explore the integration of AI and VR technologies in the development of a novel system for diagnosing and recommending rehabilitation plans for fine motor disorders. By leveraging these innovations, the proposed system will enable patients to engage with immersive virtual environments using devices like head-mounted displays (HMDs), sensors and haptic gloves. Through a series of interactive exercises, the system will assess fine motor functionality and, powered by machine learning algorithms (ML), automate injury severity diagnosis. Subsequently, the system will recommend personalized rehabilitation plans, aiming to optimize treatment outcomes and improve patient recovery rates. The proposed system diagram is presented in figure 1.2.

1.1 Objectives

The main goal of this thesis is to develop a prototype of a system for automatic diagnosis and rehabilitation plan for fine motor skills based on a Virtual Reality and Artificial Intelligence. For achieving this main goal, the following specific goals are stated:

- To study the state-of-the-art on rehabilitation with virtual reality and artificial intelligence.
- To collect and preprocess data from patients with fine motor problems.

- To evaluate and select a machine learning algorithm for the rehabilitation plan recommendation.
- To propose a system prototype for automatic diagnosis and rehabilitation plan for fine motor skills .

1.2 Thesis organization

This thesis is structured as follows:

In Chapter 2, the background knowledge is stated by reviewing related works and the technological background.

In Chapter 3, the metholodogy for the implementation of the system prototype is carried out by presenting the problem formulation, reviewing the rehabilitation background and descripting the proposed system.

In Chapter 4, the experiment is setup by stating the series of movements required for the data collection as well as descripting the proposed VR system scenes to finally present the results.

In Chapter 5, conclusions of the work are presented as well as possible future work.

Chapter 2

Background knowledge

2.1 Related works

In recent years, there has been significant progress in the use of Virtual Reality (VR), Artificial Intelligence (AI), and Machine Learning (ML) to enhance rehabilitation processes, especially for motor skill recovery. Dhanasree, Nisha, and Jayakrishnan, 2018 proposed a medical training system to help students to improve their skills in medical Intensive Care Unit (ICU). For this system, the authors used Head Mounted Display, a Leap Motion Controller with Unity 3D to develop the ICU immersive environment. The Leap Motion Controller was used to track the hand movement to replicate real moments into the virtual enviroment. Students are able to use the proposed system to explore the ICU and learn how to use equipment.

Oliveira et al., 2020 propose REHAB FUN that is a virtual reality enviroment developed for rehabilitation of patients from 3 to 8 years with an specific kind of motor disability caused by the lack of oxigen during or just after birth. As it was designed for kids, the tool consisted in a series of activities game oriented that let specialists to evaluate patients. REHAB FUN was used as a complement tool that let specialists follow patients evolution. This was the first approach so as future work the authors propose to prove the efectiveness of REHAB FUN as well as measuring some other variables.

Lai et al., 2021 proposed a Personalized Rehabilitation Recognition (PRR) system as a tool for tracking rehabilitation exercises for clinical diagnosis as an alternative for reducing pain and restoring physical functions of lower-limb in home-isolated rehabilitation. Six rehabilitation exercises for lower limb were selected. The MetaWearC sensor was used to detect the movement, aceleration and velocity in x, y and z axes. Collected data was preprocessed, rehab-exercise feature was extracted and used as input for the multiclass recognition model they propose based on Support Vector Machine (SVM) and Adaptive Neural Fuzzy Inference System (ANFIS) methods of Machine Learning (ML) for recognizing patterns. The proposed model was validated with k-fold cross-validation method with samples.

Modi et al., 2022 proposed a Augmented Reality (AR) telerehabilitation system for upper limb that allows the therapists and specialists to monitor sessions remotely. The system is based on a xARm-5 robotic arm with 5 degrees of freedom and the Industrial Internet of Things (IIoT) that enables the bidirectional communication for real time. The graphic engine Vuforia Studio was used for developing users' interfaces that let patients to see visual instructions to the system and to receive real time feedback by their movements being corrected throung the robotic arm. Results showed that the system had low latency and high accuracy so that the

system was probed to be a innovative and accurated tool for upper limb rehabilitation as it improved the access to quality and customized sessions for pattiens with reduced movement.

Yang et al., 2022 addresses research on the efficacy of an Augmented Reality Rehabilitation System named AR Rehab. For this, the authors designed an experiment in which chronic stroke survivors participed and were dividen into two groups. Each group was first trained by a human trainer and then used the AR Rehab that could be either the AR-Centre or the AR-Home version. As the name stands for, the the first one was performed in the rehabilitation center with AR tools support and the second one was performed at home. Results showed that hibrid rehabilitation programs had a significant functional improvement and an important reduction of the human effort by focusing on teaching how to use the system instead of guide the rehabilitation session.

Herrera et al., 2023 developed a cloud-based Virtual Reality (VR) platform for spinal cord injury rehabilitation oriented improve the quality of live of patients with limited movement or located in remote or distant areas. By the use of simulation environments patients can perform rehabilitation excercises in a controlled way. On the other hand, the use of haptic glove let patients to have feedback so that they can use their own hands to interact with the immersive virtual environment instead of external devices. The platform has hand-tracking functions let therapists and specialists to monitor exercises and analyze data to evaluate progress and adjust treatment plans in order to optimize the rehabilitation process.

Ponto et al., 2023 developed an Augmented Reality (AR) application for IOS and Android mobile devices using Unity 3D framework and ARKit and ARCore framework respectively for assessing home assessments, For this, the authors designed an experiment to compare the proposed set of tools angains tradicional assesment tools. The results of the experiment demostrated the Assesment tools enhanced with AR provide better support for home tools that tradicional ones, it means that activities are performed in a more accurate way and quicker. Furthermore, the authors conclude that AR approaches could be used in many other fields and applications that require assessment like construction, inspection and quality assurance.

Shilaskar et al., 2024 proposed a Virtual Reality (VR) and Mixed Reality (MR) hibrid system to improve learning in medical training and education as well as the practice of medical procedures. For this purpose the authors created a virtual environment using Unity 3D and Blender that interacts with the headsets and a build haptic gloves with Arduino board and 3D printed components, which purpose is to provide feedback to translate virtual interactions into physical sensations for enhancing the realism and immersion. That way patients can interact and manipulate virtual objects as they were real, thereby developing essential skills like muscle memory, hand-eye coordination, and spatial understanding.

These related works demonstrate that cutting-edge technologies, such as haptic gloves, sensors, headsets, and virtual reality (VR), have been increasingly utilized in research across various fields in recent years. Particularly in the medical and rehabilitation domains, these technologies have shown significant promise, underscoring their relevance to this study. Moreover, their integration offers substantial

potential to enhance diagnostic accuracy, treatment effectiveness, and rehabilitation outcomes.

Building upon these foundations, this thesis aims to integrate AI and VR in a more comprehensive manner, specifically targeting fine motor skills rehabilitation. Unlike previous work that has focused primarily on lower-limb rehabilitation or used VR as a supplementary tool, this research will explore the potential of AI-powered VR environments as the central platform for both diagnosis and rehabilitation. By incorporating advanced machine learning algorithms and immersive VR simulations, the proposed system seeks to offer a more precise, engaging, and personalized approach to fine motor rehabilitation, ultimately aiming to improve patient outcomes and recovery rates.

2.2 Technological background

2.2.1 Artificial Intelligence

Artificial intelligence is the field of computer science that creates systems capable of simulating human intelligence through learning, reasoning and self-correction processes for the execution of activities ranging from pattern recognition and decision making to language learning and understanding (Lima-Santos and Ceron, 2022). Artificial intelligence has several subfields which are detailed below:

Deep Learning (DL)

Deep learning focuses on artificial neural algorithms that replicate the structure and function of the human brain. These networks are composed of multiple layers of neurons that allow the model to learn data representations in a hierarchical fashion, capturing complex features from raw data. It has the ability to handle large volumes of data and extract relevant features automatically which requires great computational power.

Deep learning models can be trained to perform a wide variety of tasks, without having to manually design specific features, making it an indispensable tool in the era of big data and advanced artificial intelligence.

Natural Language Processing (NLP)

Natural Language Processing focuses on the interaction between computers and human language with the aim of enabling machines to understand, interpret and generate human language not only explicitly but also to understand the meaning and context of words and phrases in a text. To achieve this it combines techniques from linguistics, computer science and machine learning, enabling computers to process and analyze large amounts of natural language data.

NLP has many applications, including natural language generation, where machines produce text that simulates human-generated text. text analysis, where machines are trained to perform tasks such as information extraction, text classification, sentiment analysis and machine translation.

Computer Vision (CV)

Computer vision seeks to teach machines to interpret and understand visual content by using algorithms and mathematical models that allow computers to process, analyze and make decisions based on images and videos (Lima-Santos and Ceron, 2022).

The goal of computer vision is to replicate human visual perception capabilities in computer systems, allowing them to identify, classify and react to visual stimuli. Computer vision has significant applications in the healthcare field, especially in computer-aided medical diagnosis. Computer vision algorithms are used to analyze medical images.

Expert Systems (ES)

Expert systems are computer programs designed to simulate human reasoning in solving domain-specific problems. For this, they rely on human knowledge through an expert knowledge base, which consists of rules and facts gathered from human experts in the relevant field (Lima-Santos and Ceron, 2022).

Artificial intelligence is applied through the use of algorithms and inference techniques that enable the system to analyze information, make logical deductions and reach conclusions. Their ability to replicate human reasoning makes them a valuable tool for decision making and analysis in situations where specialized knowledge is crucial in a wide range of fields, such as medicine, engineering, business management and legal advice, among others.

Machine Learning (ML)

Machine Learning focuses on the development of algorithms and techniques that allow computers to learn, make predictions or decisions based on data. To do this, machine learning algorithms identify patterns and relationships in data on their own without the need of specific coding rules. This is achieved by training models with large datasets, allowing machines to improve their performance over time as they receive more information (Lai et al., 2021).

Machine learning can be divided into several categories, the main ones being supervised learning, unsupervised learning, which are detailed below.

Supervised Learning

Supervised learning algorithms train models in which the input data are labeled, i.e., for each input data the output is identified. Learning is done by mapping the outputs based on the inputs so that the model can make predictions about new unseen data based on the mappings made during training (Chen et al., 2024).

- **Linear regresion (LR)**

  Linear regression is a supervised parsing algorithm used to predict a value based on the linear relationship between dependent and independent variables. In this case it models the relationship between two variables by fitting a straight line to the data that can be used to make predictions on new data. The

objective of this algorithm is to find the coefficients that minimize the prediction error.

This model evolves to Multiple Linear Regression (MLR) when multiple independent variables are considered, so that the result to be predicted is influenced by several factors at the same time. It is used to model complex relationship between variables.

- **Support Vector Machine (SVM)**

  Support Vector Machine is a supervised machine learning algorithm used for classification and regression by searching for the optimal hyperplane that split data in different classes. In a two dimensions data is divided by a line, but when more dimensions are considered data is divided by a plane or hyperplane. For this SVM solves an optimization problem in which identify the best hyperplane by maximizing the distance between the hyperplane and the nearest data points from each class that are support vectors (Lai et al., 2021).

- **k-Nearest Neighbors - (KNN)**

  The k-Nearest Neighbors algorithm (k-NN) is a supervised learning method used for classification and regression.

  In the case of classification, the k-NN algorithm classifies a new data point based on most of the class labels of its nearest neighbors. To do this, the algorithm compares the distance between the new point and all data points in the training set. The k closest points where "k" is a user-defined number are selected and the most common class among those k neighbors is assigned to the new point.

  For regression, the k-NN algorithm predicts the value of a new data point based on the average or median of the values of the k nearest neighbors.

- **Decision trees**

  Decision trees can be used for classification problems to predict the class to which an element belongs or to predict a numerical value. The model is represented as a tree that is built by dividing the dataset into smaller and homogeneous subsets based on certain features. This is done by selecting the most relevant features and creating decision rules that separate the data into different classes or categories.

  One of the advantages of decision trees is that they are easy to understand and interpret, as they can be easily visualized. In addition, they can handle numerical and categorical data, and are robust to noisy or missing data.

- **Random Forest - (RF)**

  Random Forest is a supervised Machine Learning algorithm that can be used both in classification and regression problems so that it can handle both categorical and numerical features.

  This model builds multiple decision trees during training which conform a forest that makes it a strong model and improves the accuracy and stability of it. The forest is trained with a random sample of the dataset and a random selection of features which helps to create robust and accurate models that are less prone to overfitting compared to a single decision tree.

Each tree in a Random Forest provides a prediction, and the final decision is made by a majority vote in the case of classification, or an average of the predictions in the case of regression.

- **Artificial Neural Networks - (ANN)**

  Artificial Neural Networks are models inspired human brain. They are composed of artificial neurons that are interconnected in layers. An artificial neural network consists of three types of layers: th input layer receives input data and transmits the information to hidden layers, the hidden layer processes the information from the input layer by means of mathematical operations and activation functions and finally the output layer generates the final output of the neural network.

  To train a neural network, it must be trained with a set of data and the weights of the connections between neurons must be adjusted to minimize a loss or error function. Neural networks are known for their ability to learn and adapt to complex patterns in data. They are widely used in a variety of applications, including image recognition, natural language processing, weather forecasting, medical diagnosis, among others.

Unsupervised Learning

Unsupervised learning algorithms allow learning patterns from the data without having been labeled, so that the expected results are not known. For this purpose, the algorithms identify relationships, patterns or groups of data. This type of algorithms are used in scenarios in which additional information about trends or segmentations in the data is desired (Bertolini et al., 2021).

- **k-means clustering**

  K-means is an unsupervised learning clustering algorithm in machine learning which goal is to partition a dataset into k groups of data named clusters that doesn't overlap. The k in this algorithm represents the number of clusters that will be formed. For this, each data of the dataset is assigned to the cluster with the closest center and then centers are adjusted iteratively until data assigment is stabilized. This algorithm is used for segmentation, pattern identificacion and data grouping.

- **Agglomerative Hierarchical Clustering (AHC)**

  The Agglomerative Hierarchical Clustering (AHC) is a clustering technique that organizes data by building a tree-like hierarchy where each node represents a cluster to have a better undestanding of the hierarchical relation in data. It starts with individual points as separate clusters and merges them iteratively until a single cluster is reached and it is commonly used in biological taxonomy and text analysis.

- **Self-Organizing Map (SOM)**

  The Self-Organizing Map (SOM) is an unsupervised machine learning algorithm used for clustering and visualization of data with several dimensions. SOM is trained through a single-layer feed-forward neural network and learning models. SOM map input data into a grid of lower dimensions, preserving the relationships of the input data

- **Principal Component Analysis (PCA)**

  Principal Component Analysis (PCA) reduces the dimensionality of a dataset to simplify complex datasets facilitating their visualization and analysis. For this purpose, the algorithm transforms original variables into a new set of uncorrelated variables, called principal components. This process retains most of the variability present in the original data in a reduced number of components.

2.2.2 Virtual Reality

In technology, there are several types of realities such as virtual reality (VR), augmented reality (AR) and mixed reality (MR). The first one is the virtual representation of the real world, the second one overlays digital content onto the real world environment and the third one combines elements of both VR and AR.

VR is the virtual recreation of the real world in which users can interact and get immersed through a computer-generated simulation. This technology was first created for being used in video games but over the years it evolved and gained more relevance and usage in other fields such as education, training, healthcare, industry, among others, by means of the use of specialized devices such as VR headsets and hand controllers. This way users can can navigate and manipulate virtual objects letting them to experience a sense of presence within the virtual environment (Zafar, Langås, and Sanfilippo, 2024).

Virtual reality types

According to the immerssion level, that is the level in which someone can get into an environment, virtual reality is divided into the following types (He et al., 2024):

- **Non immersive virtual reality**

  In this type of virtual reality there is a computer-generated environment but the user is always in control of the real environment. It is presented on a normal screen, that is to say that it is used in daily activities such as a cell phone or a computer, so it can be used without the need for additional devices.

- **Semi immersive virtual reality**

  In this type of virtual reality there is a computer-generated environment that provides users with a partially realistic but not completely immersive experience. It is characterized by the use of screens with 3D graphics and sometimes virtual reality glasses. Users can still perceive stimuli from the real world which allows the user to differentiate between the real and virtual environment.

- **Immersive virtual reality**

  In this type of virtual reality there is a computer-generated environment that provides a completely realistic and immersive experience. For this level of realism to exist, the user is isolated in a certain way from reality through experiences that include image and audio. This requires additional devices such as goggles or virtual reality cases.

Main elements of virtual reality

Virtual reality elements are those devices that allow the creation of an immersive, interactive and immersive experience.:

- **Head-Mounted Display (HMD)**

  Head-mounted display (HMD) provide visual and audio interface that immerses users in virtual environments. They have key features that determine the clarity of the image, the width of the visible area, the fluidity of motion and how quickly the device responds to changes in head position.

  The most recognized brands in the HMD market include Oculus, HTC, Valve and Pimax. Oculus has the Oculus Rift and Oculus Quest 2, which are easy to use and accessible. HTC offers the Vive and Vive Pro, which stand out for their large room tracking capabilities. Valve Index offers a high quality VR experience with advanced controllers. Pimax provides ultra-high resolutions and wide fields of view. (Sudiarno et al., 2024).

- **VR Sensors**

  In order to accurately detect a user's motions in virtual space, sensors such as magnetometers, gyroscopes, accelerometers among others are essential components of virtual reality (YiFei and Othman, 2024). VR sensors have latency, range, and accuracy in tracking. For this, high precision sensors are required for providing submillimeter motion tracking that is essential for applications that demand great accuracy.

  There are several brands that provides this type of sensors such as Valve, Oculus and Microsoft. Valve produces devices that use Lighthouse base stations to track the position and orientation of the HMD and controllers. Oculus uses sensors for its Rift and integrated cameras for inside-out tracking. Microsoft uses cameras integrated into the tracking device for its Windows Mixed Reality.

- **VR gloves**

  VR gloves have evolved significantly to provide more immersive and natural interaction in virtual environments. VR gloves replicate touch and object manipulation with great accuracy using a combination of motion sensors and haptic actuators. Accurate tracking, minimal latency, and force and tactile feedback are important aspects. There are several brands such as HaptX Gloves, Manus VR and SensoryX VR.

  With the use of these gadgets, users are able to operate virtual things just like they would in the real world by capturing hand and finger movements (Wong and Lee, 2024).

- **Graphic engine**

  A graphics engine is a software that offers a set of tools to create video games and interactive applications in an easy and friendly way without the need for programming knowledge. These tools allows the creation of graphics for 2D and 3D environments, simulate movements, manage audio and implement real-time interactions (Kamran-Pishhesari, Moniri-Morad, and Sattarvand, 2024; Sariman et al., 2024).

The most commonly used graphics engines for virtual reality (VR) stand out for their ability to offer immersive experiences and high visual fidelity. The most widely used are Unity, Unreal Engine and CryEngine.

Chapter 3

Methodology

3.1 Problem Formulation

The absence of virtual reality systems that integrate machine learning algorithms for diagnosing fine motor injuries and recommending personalized rehabilitation protocols represents a significant gap in the field of health and rehabilitation. As virtual reality technology has advanced and become more accessible, its potential to revolutionize the assessment and treatment of injuries has increased substantially. However, the application of this technology to the specific domain of fine motor skills remains notably limited Bogar et al., 2024; Spiegel et al., 2024; Pillai et al., 2020.

This gap in technology presents several critical challenges. First, the continued reliance on traditional, subjective assessment methods can lead to inaccurate or incomplete diagnoses, which in turn may result in inappropriate rehabilitation protocols Naqvi et al., 2024; Ekambaram and Ponnusamy, 2023; Jurado, Rodriguez Vargas, and Penaloza, 2020. Second, it restricts healthcare providers' ability to deliver individualized care and optimize rehabilitation outcomes. Generic rehabilitation protocols, which do not account for the specific needs of each patient, often lead to suboptimal recovery and functionality. Third, the lack of automated tools hinders the prompt detection and timely intervention of fine motor impairments, potentially delaying treatment and adversely affecting patient prognosis and recovery. Lastly, the absence of standardized, automated systems contributes to variability in diagnoses and treatment plans across different practitioners, thereby impacting the consistency and quality of medical care Naranjo et al., 2019.

In summary, the lack of virtual reality systems equipped with automated learning algorithms for fine motor assessment and rehabilitation poses a significant barrier to enhancing the accuracy, efficiency, cost-effectiveness, and personalization of medical care in this area.

3.2 Rehabilitation Context

Physical rehabilitation is a therapeutic process aimed at restoring function, mobility, and quality of life for individuals who have experienced injuries, illnesses, or disabilities impacting their musculoskeletal system. The primary goal of rehabilitation is to help patients achieve the highest possible level of functionality, which may involve improving muscle strength, flexibility, coordination, balance, and endurance, depending on the specific condition. To accomplish this, therapists develop rehabilitation plans that may include a combination of active and passive exercises, along with various therapeutic techniques.

3.2.1 Active movement

Active movement is a therapeutic technique of physical rehabilitation in which the patient performs movements on the affected part of his or her body, in the upper extremities as far as this work is concerned, voluntarily, independently and controlled within his or her own body limits. For this purpose, therapists design specific rehabilitation treatments in which the patient can work unaided to prevent or alleviate various conditions such as muscle atrophy and joint stiffness. (Saunders et al., 2015)

This type of exercise is essential for improving muscle strength, flexibility, coordination and overall body function. Exercises can range from simple movements to more complex routines that mimic daily activities or sports. The progression in intensity and difficulty of the exercises is adjusted according to the patient's ability and progress. For these reasons, active movemente can be a very useful tool to maintain and improve the range of motion of the joints or by contracting and relaxing the muscles, thereby stimulating blood circulation to the affected areas and improving the recovery process.

In addition to the physical benefits that can be obtained from the application of this type of movement, which have been detailed in previous paragraphs, active movement has been shown to have a positive psychological effect on the patient. Therefore, the fact that the patient is actively involved in the performance of the exercises increases their motivation and therefore leads to better results.

3.2.2 Range of motion - ROM

Range of motion is the measure of a joint's ability to move through its arc including the extension and flexion of the joint that starts from rest position to where the motion stops without being harmfull. An adequate range of movement is essential to perform daily activities without restrictions and without pain or with as little pain as possible.

This measure is required for assessing the functionality and mobility of patients who have suffered limb affections as well as the patient's progress during rehabilitation. To obtain this measurement, therapists use tools that allow them to measure joint angles such as goniometers, inclinometers, electrogoniometers, mobile applications and software, etc... Based on these measurements, therapists can design rehabilitation programmes that include specific exercises that help improve flexibility and mobility to address specific restrictions (Skirven et al., 2011).

There are active and passive ranges of motion, the former is the measurement of joint angles in movements that can be performed by the patient without any assistance and the latter is the measurement of those angles in movements performed with external force such as that of a therapist or machine without patient intervention.

3.2.3 Arthritis

Arthritis is inflammation of the joints, commonly affecting the hands, knees, hips and spine. This inflammation is characterized by symptoms such as pain, swelling, stiffness, redness and can lead to a decreased range of motion in the affected joints.

In severe cases, arthritis can cause joint deformities and significantly affect functionality and movement. This can affect the patient's quality of life by affecting their ability to perform daily activities and work and can even affect patients psychologically by causing depression and anxiety (Acton, 2012).

The treatment of arthritis depends on the type and severity of the disease. The treatments that can be applied are medications, physical therapies and in some cases surgery. In the physiotherapy part of the work, regular exercise is essential to maintain joint mobility and strength.

There are several types of arthritis, the most common are the rheumatoid arthritis and the osteoarthritis. Rheumatoid arthritis is a disease in which the body's immune system mistakenly attacks the lining of the joints causing inflammation and pain. On the other hand, Osteoarthritis is a degenerative disease that occurs when the cartilage that cushions the ends of bones wears away over time.

In arthritis it is more difficult to set up focus groups for research because of the diversity of its types and the variability of symptoms due to the immune-dependent nature of the patient's. This variability introduces greater complexity in the selection and grouping of participants, follow-up and data analysis. In contrast, osteoarthritis allows clearer selection of focus groups, facilitating research design and execution due to its more predictable progression and more specific symptoms related to ageing. This makes osteoarthritis more suitable for focal studies in measurement and analysis activities. This is the reason why in this work patients with osteoarthritis are considered for this work.

Figure 3.1 shows a comparition of the two common types of arthritis. The Osteoarthritis example is on the left and the Rheumatoid Arthritis on the right.

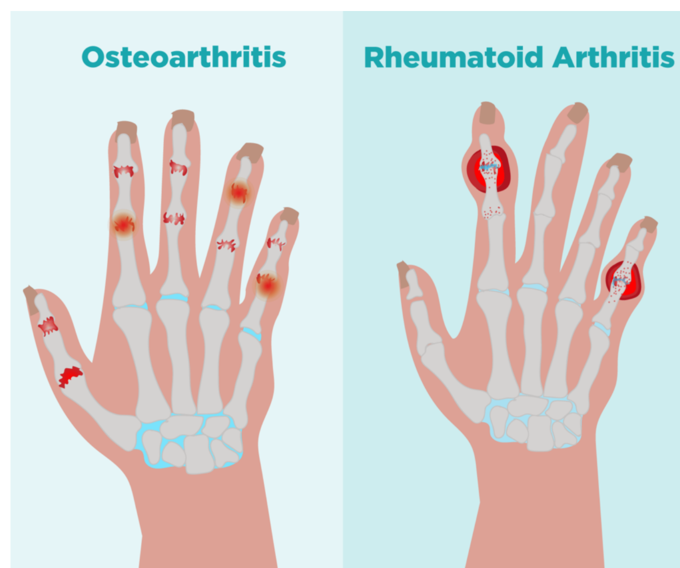


FIGURE 3.1: Osteoarthritis and Rheumatoid Arthritis comparation
Rheumatoid Arthritis Vs Osteoarthritis - Prof Dr. Robert Hierner 2024

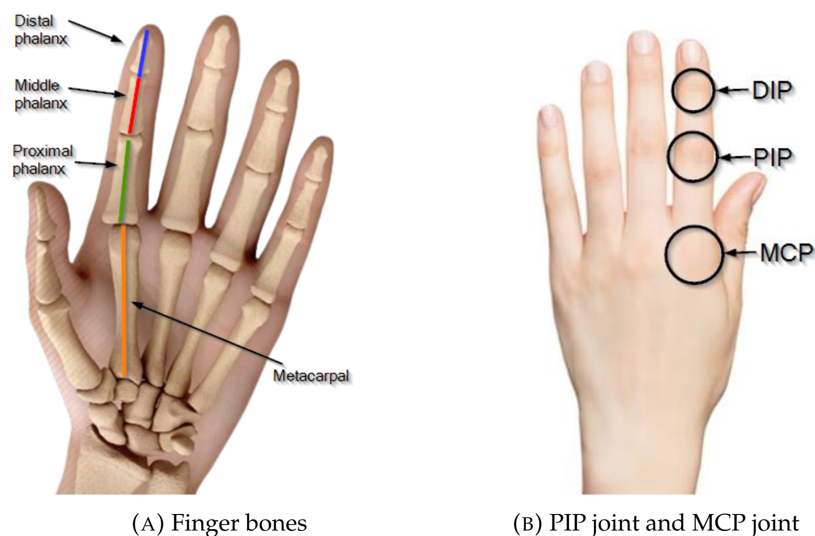
To determine the range of motion of the finger joints it is important to review the relevant finger and hand bones, the main joints, which are the Proximal Interphalangeal Joint (PIP) and the Metacarpophalangeal Joint (MCP), as well as the main

movements, which are Flexion and Extension (Skirven et al., 2011).

The Proximal Interphalangeal Joint (PIP): Is the intermediate joint between the proximal and middle phalanges of the fingers. It is located in the middle of the fingers except for the thumb, which does not have a PIP joint. This joint allows flexion and extension of the finger.

The Metacarpophalangeal Joint (MCP): Is located at the base of the fingers, where the metacarpal bones of the hand connect with the proximal phalanges of the fingers. These joints allow a wide range of movements, including flexion, extension, abduction and adduction. The MCP joints are crucial to the functionality of the hand and the ability to perform complex and coordinated movements.

Figure 3.2b shows PIP and MCP hand joints.



(A) Finger bones

(B) PIP joint and MCP joint

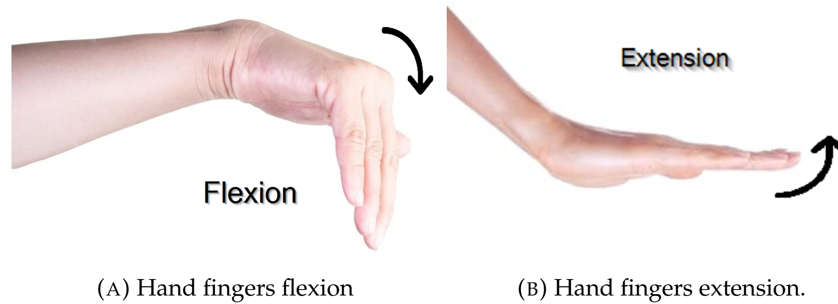
FIGURE 3.2: Proximal Interphalangeal Joint and Metacarpophalangeal Joint

Flexion: Is the movement that decreases the angle between two fingers by bending the finger towards the palm of the hand. This movement is used to grasp and hold objects.

Extension: Is the movement that increases the angle between two fingers by straightening the finger away from the palm. This movement is used to release objects and restore the normal position of the hand.

Figure 3.3 shows hand flexion and extension movements.

Osteoarthritis can be classified according to the severity of the condition and the functional limitation of the joints into 5 grades. This can be done by measuring the angles of the joints during finger movements and stablishing ranges of motion for each grade (Skirven et al., 2011). The five grades are described below:



(A) Hand fingers flexion (B) Hand fingers extension.

FIGURE 3.3: Hand fingers flexion and extension

- **Grade 0 - Normal Range of Motion**: Joint angles during movement are within the normal range expected for healthy individuals.
- **Grade 1 - Mild Limitation of Motion**: There is a slight reduction in angles of movement compared to normal values.
- **Grade 2 - Moderate Limitation of Motion**: Moderate reduction in angles of motion. The fingers may not reach full extension or full flexion.
- **Grade 3 - Severe Limitation of Motion**: Significant reduction in angles of movement. Extension and flexion movements are severely restricted.
- **Grade 4 - Inability to Move the Joint**: Almost total absence of movement in one or more finger joints. Angles of movement are extremely limited or non-existent

A classification scheme according to ROM is presented in table 3.1:

Class	PIP Extension degrees	PIP Flexion degrees	MCP Extension degrees	MCP Flexion degrees
Grade 0	0-5	90-110	0-20	85-100
Grade 1	5-15	75-90	20-30	70-85
Grade 2	15-30	50-75	30-45	50-70
Grade 3	30-45	30-50	45-60	30-50
Grade 4	>45	<30	>60	<30

TABLE 3.1: Classification of Osteoarthritis based on finger joint ROM

3.2.4 Osteoarthritis rehabilitation plan

According to the classification of osteoarthritis based on fingers joint ROM, hand osteoarthritis can be classified into 5 different grades, from grade 0, where mobility is normal, to grade 4, characterised by the inability to move the finger joints. Each grade of osteoarthritis requires a specific focus on physical rehabilitation exercises to maintain and improve mobility, reduce pain and stiffness, and improve the patient's quality of life (Saunders et al., 2015). Table, build with an rehabilitation expert, provides detailed guidance on the objectives, types of exercises, number of repetitions or duration and recommended frequency for each degree of hand osteoarthritis, thus ensuring appropriate and personalised rehabilitation.

Osteoarthritis grade 0

Table 3.2 shows the rehabilitation plan for patients diagnosed with osteoarthritis grade 0.

Osteoarthritis grade	Grade 0	
Objective	Prevention and maintenance of joint health	
Mobility and flexibility exercises	- Fist opening and closing - Hamstring slide - Thumb stretch	- 10-15 times - 10-15 times per finger - 10-15 times
Strengthening exercises	- Squeezing a foam ball - Gripper exercise - Finger push-ups	- 10-15 times - 10-15 times per finger - 10-15 times per finger
Stretchig exercises	- Finger Stretch - Wrist Stretch - Thumb Stretch	- 15-30 sec, 3 times per finger - 15-30 sec, 3 times - 15-30 sec, 3 times
Coordination and precision exercises	- Thumb opposition exercise - Join and separate fingers - Marble exercise	- 10-15 times per finger - 10-15 times - 10-15 marbles

TABLE 3.2: Osteoarthritis grade 0 rehabilitation plan

Osteoarthritis grade 1

Table 3.3 shows the rehabilitation plan for patients diagnosed with osteoarthritis grade 1.

Osteoarthritis grade	Grade 1	
Objective	Maintain flexibility, strength and function	
Mobility and flexibility exercises	- Fist opening and closing - Wrist flexion and extension - Thumb stretching	- 10-15 times - 10-15 times per finger - 10-15 times
Strengthening exercises	- Squeezing a foam ball - Gripper exercise - Finger push-ups	- 10-15 times - 10-15 times per finger - 10-15 times per finger
Stretchig exercises	- Finger Stretch - Wrist Stretch - Thumb Stretch	- 15-30 sec, 3 times per finger - 15-30 sec, 3 times - 15-30 sec, 3 times
Coordination and precision exercises	- Thumb opposition exercise - Join and separate fingers - Marble exercise	- 10-15 times per finger - 10-15 times - 10-15 marbles
Pain management	- Thermotherapy - Cryotherapy	- 10-15 minutes - 10-15 minutes

TABLE 3.3: Osteoarthritis grade 1 rehabilitation plan

Osteoarthritis grade 2

Table 3.4 shows the rehabilitation plan for patients diagnosed with osteoarthritis grade 2.

Osteoarthritis grade	Grade 2	
Objective	Improving flexibility, strength and function	
Mobility and flexibility exercises	- Fist opening and closing - Tendon slippage - Thumb slippage	- 10-15 times - 10-15 times per finger - 10-15 times
Strengthening exercises	- Squeezing a foam ball - Gripper exercise - Finger push-ups	- 10-15 times - 10-15 times per finger - 10-15 times per finger
Stretchig exercises	- Finger Stretch - Wrist Stretch - Thumb Stretch	- 15-30 sec, 3 times per finger - 15-30 sec, 3 times - 15-30 sec, 3 times
Coordination and precision exercises	- Thumb opposition exercise - Join and separate fingers - Marble exercise	- 10-15 times per finger - 10-15 times - 10-15 marbles
Pain management	- Thermotherapy - Cryotherapy	- 10-15 minutes - 10-15 minutes

TABLE 3.4: Osteoarthritis grade 2 rehabilitation plan

Osteoarthritis grade 3

Table 3.5 shows the rehabilitation plan for patients diagnosed with osteoarthritis grade 3.

Osteoarthritis grade	Grade 3	
Objective	Reduce pain and stiffness	
Mobility and flexibility exercises	- Passive finger mobilisations - Passive wrist rotations	- 5-10 times per finger - 10 rotations each direction
Strengthening exercises	- Squeezing a foam ball - Towel clip - Isometric handstand push-ups	- 10-15 times - 5-10 times per finger - 5-10 seg 5 times
Stretchig exercises	- Whole hand stretching - Thumb Stretch	- 15-30 sec, 3 times - 15-30 sec, 3 times
Pain management	- Thermotherapy - Cryotherapy - Deep breathing exercises	- 10-15 minutes - 10-15 minutes - 5-10 minutes

TABLE 3.5: Osteoarthritis grade 3 rehabilitation plan

Osteoarthritis grade 4

Table 3.6 shows the rehabilitation plan for patients diagnosed with osteoarthritis grade 4.

3.3 Proposed system description

3.3.1 System technologies

The technologies used in the proposed system are detailed below:

Osteoarthritis grade	Grade 4	
Objective	Reducing pain and improving quality of life	
Mobility and flexibility exercises	- Passive finger mobilisations - Passive wrist rotations	- 5-10 times per finger - 10 rotations each direction
Strengthening exercises	- Squeezing a foam ball - Towel clip - Isometric handstand push-ups	- 10-15 times - 5-10 times per finger - 5-10 seg 5 times
Stretchig exercises	- Whole hand stretching - Thumb Stretch	- 15-30 sec, 3 times - 15-30 sec, 3 times
Pain management	- Thermotherapy - Cryotherapy - Deep breathing exercises	- 10-15 minutes - 10-15 minutes - 5-10 minutes
Adaptation and Compensation	- Assistive devices - Compensation techniques	- Daily activities - Daily activities

TABLE 3.6: Osteoarthritis grade 4 rehabilitation plan

Unity 3D

Unity 3D is a software development platform that came out to create video games but evolved to create real-time immersive and interactive applications, virtual reality (VR) and augmented reality (AR) experiences. Unity 3D allows to render 2D and 3D graphics, to create physics for simulating realistic behaviour of objects and characters, it supports audio resources and has a wide range of resources and assets available. It is used in several applications that include games, industry and research for a variety of platforms, including PCs, game consoles, mobile devices, and virtual and augmented reality devices (Unity, 2024a).

For this, Unity has a wide compatibility with VR devices that includes devices such as headsets, hand controllers, haptic gloves, tracking devices among others. Furthermore it provides an integrated development environment (IDE) that includes versatile and robust tools for design, programming, animation, physics, audio and more. Developers can create games and applications using the C# or JavaScript programming language, as well as an intuitive graphical user interface for creating scenes and setting properties.

HTC vive

The HTC Vive is a virtual reality headset that delivers an immersive experience to users. It is equipped with two high resolution OLED displays that lets it to deliver detailed images and a 110-degree field of view that provides a wide and peripheral view that contributes to the feeling of total immersion in a virtual world. Figure 3.4 shows HTC Vive headset, controllers and base stations.

The HTC Vive includes features like the advanced motion tracking system, the intuitive motion controllers, a variety of sensors, the integrated audio and the comfortable and ergonomic design that lets it to deliver an outstanding virtual reality experience. The advanced motion tracking system consists in two base stations located in the corners of a room that can accurately track the user's position and movement in a space of up to 4.5 by 4.5 metres. The intuitive motion controllers and the variety of sensors provides a wide range of interaction options. These features combined

FIGURE 3.4: HTC Vive

with the integrated audio and the comfortable and the ergonomic design make it possible to allows users to move freely within the virtual world, creating a fully immersive and unrestricted virtual reality experience (Vive, 2024).

Due to the features previously described, the HTC Vive headset has become one of the most popular VR headsets in the industry. Furthermore, it provides robust and easy to use tools for the integration with Unity 3D that allows developers to create immersive VR experiences. With Unity, developers can easily create interactive experiences in several fields and allows users to immerse themselves in immersive virtual worlds and engage in interactive experiences.

Leap motion

Leap motion is a motion tracking device that detects the position of the arms, wrist, hand and fingers. This device emits infrared light and uses cameras and sensors to capture the reflection of this light on the arms, hands, wrist and fingers (Ultraleap, 2024). Figure 3.5 shows Leap Motion Controller device.

FIGURE 3.5: Leap Motion

The Leap Motion hardware connects to a computer via a USB port and through the drivers the captured information can be processed in real time using advanced algorithms that translate physical movements into accurate digital data. The device also has an API and SDK that allow access to the captured information, the skeleton model and the positions of the individual bones. It also offers functionalities to execute complex queries and operations with the information, such as obtaining rotations, angles and force, among others (Bachmann, Weichert, and Rinkenauer, 2018).

This real-time tracking capability makes Leap Motion ideal for virtual reality (VR) applications. By integrating the device with VR headsets, users can see and use their own hands within virtual environments, eliminating the need for physical controllers. This enhances user immersion and opens up new possibilities for interaction and manipulation of virtual objects.

Haptic glove

A haptic glove is a human-computer interface device that has sensors and actuators to simulate tactile sensation and provide haptic feedback in virtual or digital environments. This allow users to feel textures, resistances and forces just as if they were interacting with real physical objects (Perret and Vander Poorten, 2018).

The most simple haptic glove or the traditional one is the one who at least receives one signal from the vr interface and provides feedback in any way.

In this case, the haptic glove has five actuators (one vibration motor per each finger) which are activated once the patients hand position is set in order to get fingers data.

3.3.2 Proposed VR system

Once technologies to be used in the system have been selected, the proposed system, denominated **AI HandRehab**, was defined as shown in figure 3.6.

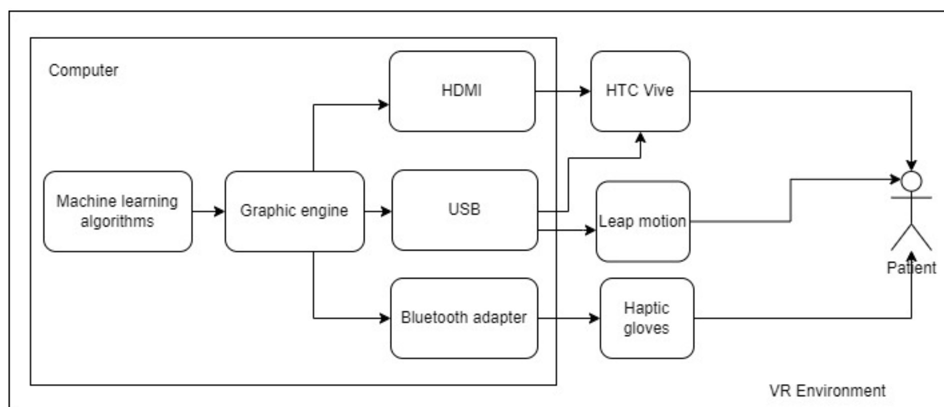


FIGURE 3.6: AI HandRehab system diagram

AI HandRehab combines hardware and software to create an automatic tool for diagnosis and rehabilitation plan for fine motor skills based on Virtual Reality (VR) through an immersive virtual environment and Artificial Intelligence through the use of Machine Learning (ML) algorithms.

For this, Leap Motion Controller is connected to the computer to capture data from the user's fingers. These device sensors record the position and movement of the fingers, allowing the system to accurately track the movements of the user's hands and fingers. Data captured by Leap Motion Controller is transmitted to the computer to the Unity programm. To complete the hand interaction with the system, the hapic gloves were connected to the computer to provide feedback from the system to the users to provide a more immersive experience.

HTC Vive headsets are used to provide the virtual reality experience to the user. These headsets are equipped with motion tracking sensors and provide an immersive user experience by allowing the user to explore and interact with 3D virtual environments. The virtual environment created with unity is transferred to the HTC

Vive headset to be displayed to the user.

Unity runs on a Windows-based computer and is used to design and develop the virtual rehabilitation environment. There data is processed by a Unity 3D script written in the C# programming language. This script acts as a bridge between the haptic gloves and the virtual environment created in Unity.

The integration of the Leap Motion Controller, haptic gloves, HTC Vive headsets and Unity enables the creation of a highly interactive and personalised virtual rehabilitation environment. Data captured by the haptic gloves is used to replicate the user's hand and finger movements within the virtual environment, enabling specific diagnosis and rehabilitation activities tailored to the patient's needs.

In summary, the design of this system leverages the combination of haptic hardware, sensors, virtual reality technology, machine learning algorithms and software development to create an immersive and effective rehabilitation environment for fine motor diagnosis an rehabilitation plan recomendation.

3.3.3 Joint angles calculation

To calculate PIP and MCP join angles the dot product formula is used between two vectors, that in this case are representing the directions of individual finger segments (Pujol, 2018). The dot product formula is presented in formula 3.1

$$\mathbf{u} \cdot \mathbf{v} = |\mathbf{u}||\mathbf{v}| \cos(\theta) \tag{3.1}$$

The angle θ between the two vectors can be calculated using formula 3.2:

$$\theta = \cos^{-1}\left(\frac{\mathbf{u} \cdot \mathbf{v}}{|\mathbf{u}||\mathbf{v}|}\right) \tag{3.2}$$

Where $\mathbf{u} \cdot \mathbf{v}$ is the product of vectors $\mathbf{u}$ and $\mathbf{v}$ and it is calculated with formula 3.3:

$$\mathbf{u} \cdot \mathbf{v} = u_x v_x + u_y v_y + u_z v_z \tag{3.3}$$

and $|\mathbf{u}||\mathbf{v}|$ is the product of the vectors magnitudes' that are calculated with formulae 3.4 and 3.5:

$$|\mathbf{u}| = \sqrt{u_x^2 + u_y^2 + u_z^2} \tag{3.4}$$

$$|\mathbf{v}| = \sqrt{v_x^2 + v_y^2 + v_z^2} \tag{3.5}$$

For calculating the PIP angle the directions of the proximal bone and the middle bone were used. So that, in this case $\mathbf{u}$ is the proximal bone and $\mathbf{v}$ is the middle bone.

$$\mathbf{u} = u_x, u_y, u_z$$

$$\mathbf{v} = v_x, v_y, v_z$$

For calculating the MCP angle the directions of the metacarpal bone and the proximal bone were used. So that, in this case $\mathbf{u}$ is the metacarpal bone and $\mathbf{v}$ is the

proximal bone.

Unity engine has functions to work with 3D vectors and points such as **Vector3.Angle**. This function calculates the angle in degrees between two provided vectors, being the first one the from vector and the second one the to vector (Unity, 2024b). The function uses the calculations presented above.

Chapter 4

Experiment and Results

This section describes the procedures executed to gather data and to evaluate Machine Learning models to select the one with better performance metrics to be used in the experiment.

4.1 Hand series of hand movements

The flexion and extension movements of the fingers of the hand allow, by analysing the positions of the joints, the calculation of the proximal interphalangeal (PIP) and metacarpophalangeal (MCP) angles.

In order to capture this data, a series of specific hand movements were designed with the support of experts to obtain the PIP and MCP joint angles. These movements include both flexion and extension of the fingers, as well as considering the orientation of the palm of the hand to differentiate the movements so that data capture performed by sensors is more automated and accurate. The series of movements is as follows:

- 1. Hand palm up and fingers extended.
- 1. Hand palm down and fingers flexed.

4.1a and 4.1b shows the movements that were included in the designed series of movements.

(A) Hand with extended fingers   (B) Hand with flexed fingers

FIGURE 4.1: Series of hand movements

4.2 System Description

The virtual reality system developed includes four interfaces or scenarios, all designed in an environment equipped for physical exercise. An information panel has been incorporated into this environment for user interaction and feedback.

4.2.1 Initial scene

The first interface corresponds to the initial scene of the system. The central panel displays an image of hands and the name of the system. It also presents two buttons: the "Empezar" button to enter the system and the "Salir" button to close the application. Figure 4.2 shows the initial scene.

FIGURE 4.2: Initial scene

4.2.2 Menu scene

The menu scene is the second interface. This screen contains all available options of the system. The central panel shows the name of the system and three buttons:

- **"Captura de datos"**: leads to the data capture scene to form the dataset.
- **"Diagnóstico"**: leads to the data capture scene for new patients and outputs the corresponding diagnosis.
- **"Regresar"**: returns to the initial scene.

Figure 4.3 shows the menu scene.

4.2.3 Data capture scene

The data capture scene presents in its central panel a description of the series of movements required for data capture, including numbered steps and a descriptive image. Figure 4.4 shows the data capture scene.

This interface is connected to the Leap Motion sensors, allowing 3D visualisation of the patient's hands and capture of joint positions.

FIGURE 4.3: Menu scene

FIGURE 4.4: Data capture scene

Once the patient completes the series of movements correctly, he or she receives feedback via the haptic gloves and an on-screen message, and the data is stored in the dataset file. There is also a "Back" button that returns to the menu scene.

4.2.4 Diagnosis scene

The diagnostic scene, similar to the data capture scene, includes a detailed description of the movements to be performed, with numbered steps and a descriptive image in the central panel. This screen is also connected to the Leap Motion sensors for 3D visualisation and capture of the hand joint positions.

Once the movements are correctly completed, the patient receives feedback via the haptic gloves and the selected Machine Learning model is applied to the captured data. The grade of osteoarthritis determined by the ML model is presented to the patient on the dashboard along with the percentage accuracy of the diagnosis.

This scene also includes a "Back" button to return to the menu. Figure 4.5 shows the diagnosis scene.

FIGURE 4.5: Diagnosis scene

The virtual reality system developed includes four interfaces or scenarios, all designed in an environment equipped for physical exercise. An information panel has been incorporated into this environment for user interaction and feedback.

Rehab assistants or authorized people has access to all scenes in the system but pacients can only access to the initial and the diagnosis scenes. The reason for these limitations in the system is due to the sensitivity of the information in the data capture, which must be carried out in a controlled manner by an expert.

4.3 Data collection

Data collection interface guides the patient in the execution of specific movements, ensuring consistency and accuracy in the performance of each task. The series of movements was carefully designed by rehabilitation experts, who considered the capabilities and limitations of the motion sensors and capture devices used in the system. These movements were selected to maximise the collection of relevant data and minimise the risk of error.

The study involved the voluntary participation of 402 people, including patients and those attending the activities of the municipal public centre for older adults in the city of Ambato in Ecuador. Each potential participant was given a detailed explanation of the purpose of the study and the procedure to be followed. They were informed that they would be asked to perform a series of controlled movements of flexion and extension of the fingers, which would be guided through a virtual reality system. It was ensured that all participants understood that their participation was voluntary and it was explained to them that the data collected would be used to develop artificial intelligence models aimed at identifying the grade of osteoarthritis in patients, thus contributing to the advancement of diagnosis and treatment of this

condition.

The collection was carried out with the participation of volunteers, who underwent the designed series of movements. Each participant positioned their hand with fingers extended and palm up, and then changed the position to one with fingers flexed and palm down. Throughout the process, clear and precise instructions were provided through informative messages on the VR system's screens. It was emphasised to the participants that they should perform the flexion and extension movements to the limit of their ability, i.e. flex or extend their fingers as far as possible.

Once the patient completes the series of movements, a rehabilitation expert assesses the performance and determines the grade of osteoarthritis present. This assessment is based on established clinical criteria and direct observation of the patient's movement. Subsequently, a detailed record is stored in the dataset file, which contains data on the movements performed and the grade of osteoarthritis diagnosed. This process ensures the integrity and usefulness of the collected dataset.

4.3.1 Dataset

The head of the dataset is presented in figure 4.6:

	HandType	ThumbPIPFlexion	ThumbMCPFlexion	IndexPIPFlexion	...	RingMCPExtension	PinkiePIPExtension	PinkieMCPExtension	ExpertDiagnosis
0	Right	19,04546	29,47664	79,08056	...	13,48658	25,72078	18,96495	2
1	Right	22,82422	52,21658	74,03168	...	9,550675	29,50572	21,56422	2
2	Right	17,88132	33,73827	88,09374	...	12,73729	23,62979	29,06553	1
3	Right	21,71603	48,54413	66,07719	...	3,024074	16,09164	20,59326	3
4	Right	18,64435	36,64872	80,15741	...	3,820852	22,19725	11,15367	1

FIGURE 4.6: General overview of the dataset.

Dataset has 22 columns, 20 of them are numerical and the other 2 are text. All of the numerical values are continuous. Table 4.1, shows a detailed description of the dataset.

There are 2 text columns so the dataset has to be preprocessed. The values of the text columns were transformed into categorical values and there were not missing or additional values that had to be converted. Once data was transformed general descriptive statistics of the dataset was obtained to identify if normalization is required.

Data was normalized with Z-Score normalization since values range is not wide. It means, it was standarized so data was scaled to have a mean of 0 and a standard deviation of 1. This scales data without distorting differences in the ranges of values, which is adequate for some classification such as Supporting Vector Machine (SVM) for distances operations.

Dataset head after the preprocessing and normalization is presented in figure 4.7
:

	HandType	ThumbPIPFlexion	ThumbMCPFlexion	...	PinkiePIPExtension	PinkieMCPExtension	ExpertDiagnosis
0	0	0.483854	-0.857350	...	0.155525	0.154078	2
1	0	1.560510	2.058450	...	0.698041	0.556931	2
2	0	0.152163	-0.310908	...	-0.144187	1.719538	1
3	0	1.244761	1.587555	...	-1.224670	0.406445	3
4	0	0.369568	0.062281	...	-0.349521	-1.056571	1

FIGURE 4.7: Dataset after preprocessing.

#	Column	Data type	Description
1	HandType	Text	Hand type.
2	ThumbPIPFlexion	Continuous	Thumb PIP joint flexion angle.
3	ThumbMCPFlexion	Continuous	Thumb MCP joint flexion angle.
4	IndexPIPFlexion	Continuous	Index PIP joint flexion angle.
5	IndexMCPFlexion	Continuous	Index MCP joint flexion angle.
6	MiddlePIPFlexion	Continuous	Middle PIP joint flexion angle.
7	MiddleMCPFlexion	Continuous	Middle MCP joint flexion angle.
8	RingPIPFlexion	Continuous	Ring PIP joint flexion angle.
9	RingMCPFlexion	Continuous	Ring MCP joint flexion angle.
10	PinkyPIPFlex	Continuous	Pinky PIP joint flexion angle.
11	PinkyMCPFlexion	Continuous	Pinky MCP joint flexion angle.
12	ThumbPIPExtension	Continuous	Thumb PIP joint extension angle.
13	ThumbMCPExtension	Continuous	Thumb MCP joint extension angle.
14	IndexPIPExtension	Continuous	Index PIP joint extension angle.
15	IndexMCPExtension	Continuous	Index MCP joint extension angle.
16	MiddlePIPExtension	Continuous	Middle PIP joint extension angle.
17	MiddleMCPExtension	Continuous	Middle MCP joint extension angle.
18	RingPIPExtension	Continuous	Ring PIP joint extension angle.
19	RingMCPExtension	Continuous	Ring MCP joint extension angle.
20	PinkyPIPExtension	Continuous	Pinky PIP joint extension angle.
21	PinkyMCPExtension	Continuous	Pinky MCP joint extension angle.
22	ExpertDiagnosis	Text	Osteoarthritis grade determined by an expert.

TABLE 4.1: Osteoarthritis dataset

For visualization purposes Principal Component Analisys (PCA) was applied to the dataset to reduce the dataset dimensions while ranking them by importance. Figure 4.8 shows on the left side the two principal components of PCA highlighting each class, in this work each class represents each one of the 5 grades of Osteoarthritis. The right side shows the cumulative explained variance which indicates the amount of information each principal component captures cumulatively from the dataset. In this case, the accumulated variance shows that the three first components there cover more that the 60% of the information and that there is not a big difference between the rest of components.

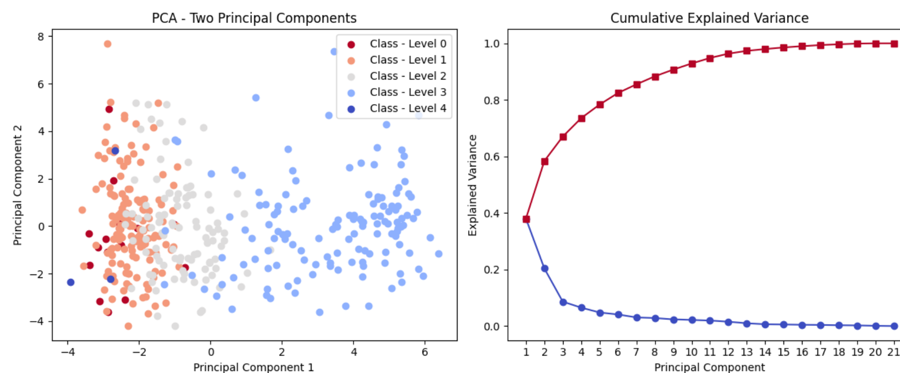


FIGURE 4.8: Visualization and variances of the dataset PCA.

The contribution of each feature detailed in table 4.1 to the principal components in PCA is obtained through the PCA loadings that are coefficients that leds to understand relationships between features and the components in a positive or negative way. Figure 4.9 shows the PCA loadings which indicates that PC1 is dominated by negative contributions from almost all features but significant positive contributed by ThumbMCPFlexion while for PC2 has negative contributions from ThumbPIPExtension, IndexPIPExtension, MiddlePIPExtension, RingPIPExtension, and PinkiePIPExtension and notable positive contributions come from ThumbMCPExtension, MiddleMCPExtension, and RingMCPExtension.

So that PC1 is mainly influenced by finger flexion characteristics with only one notable positive contribution from ThumbMCPFlexion and PC2 is influenced by both finger extension characteristics with negative contributions and some extension characteristics with positive contributions.

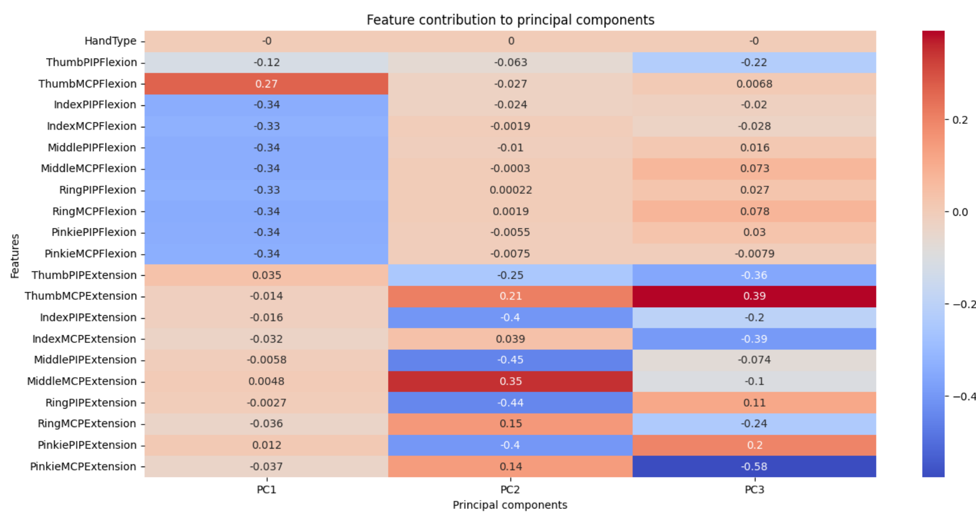


FIGURE 4.9: Dataset after preprocessing.

The original dataset consists of 402 symbols from which the classification into 5 classes is derived based on the data of the finger joint angles which are disaggregated into 21 columns. However, for the process of constructing and evaluating the models it is important to work with several generalised or fixed data sets. For this purpose, a proper separation of the original dataset into training, validation and test datasets has to be performed.

Initially, a stratified division of the dataset into two parts was made: a training set consisting of 80% of the data, and a test set consisting of the remaining 20%. This division was done in a stratified way in order to make the distribution of classes in both sets representative of the distribution of the original dataset and to avoid biases. Subsequently, the training set was subdivided into a dataset intended exclusively for model validation consisting of 20% of the training data. This separation was also done in a stratified manner.

These datasets were stored and subsequently used in the evaluation of each of the models considered in this work.

Table 4.2 presents a breakdown by class of the records found in each of the 3 subsets.

Class	Training	Validation	Test
0	11	3	3
1	92	23	29
2	65	16	21
3	87	22	27
4	1	1	1
Total	**256**	**65**	**81**

TABLE 4.2: Training, validation and testing datasets detail

4.4 Machine learning algorithms evaluation

Now that dataset was preprocessed it is ready to be used in Machine Learning algorithms. As it can be seen in table 4.1, the last column of the dataset is the Osteoarthritis grade determined by an expert, so that supervised algorithms will be applied to the dataset.

In order select the optimal model for this scenario, based on performance metrics, Multiple Linear Regresion (MLR), Supported Vector Machine (SVM), Random Forest (RF), K-Nearest Neighbors (KNN) and Artificial Neural Networks (ANN) Machine Learning algorithms were implemented in python and then trained and evaluated.

Multiple Linear Regresion (MLR)

The model was executed with the training dataset. An additional step was applied for discretising to integers because the model predict continuos values instead of discrete values for classification. The performance metrics presented in table 4.3 were obtained with the test dataset:

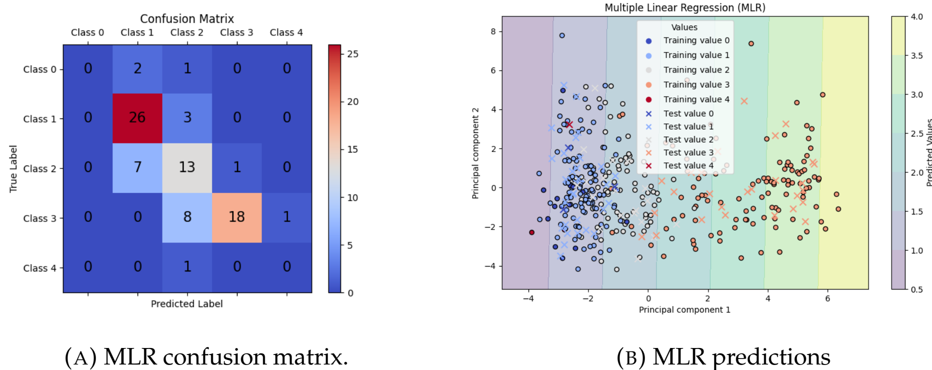
Metric	Value
Accuracy	70.37%
Mean Cross-Validation Score	71.60%
Mean Squared Separable Error	0.37

TABLE 4.3: Multiple Linear Regresion metrics

The accuracy of the validation dataset was obtained to corroborate the accuracy of the test dataset in order to assess the model's ability to generalise to data not seen during training. When comparing the validation accuracy of 73.85% with the test accuracy of 70.37%, a difference of 3.48% was observed with is relatively small indicating that the model can generalise adequately to new data.

The confusion matrix in figure 4.10a shows in the diagonal squares the amount of True Positives while the values in the rest of squares shows the Fake Negatives (FN) and Fake Positives (FP). As can be seen there are 24 FN an FP and 57 TP which shows that most values where correctly predicted by Multiple Linear Regresion Model.

The plot of predictions in figure 4.10b shows a comparition between Real and predicted values. and the MLR decision boundary of the main principal component.



(A) MLR confusion matrix.

(B) MLR predictions

FIGURE 4.10: Multiple Linear Regression

Support Vector Machine (SVM)

The model was excuted for the parameters detailed in table 4.4.

Parameter	Values
Kernel	linear, poly, rbf, sigmoid, precomputed
Constant	1-15
Degree	1-5

TABLE 4.4: SVM parameters

From them, the parameters with the best performace were linear kernel and 2 for the constant. The performance metrics detailed in table 4.5 were obtained with the test dataset.

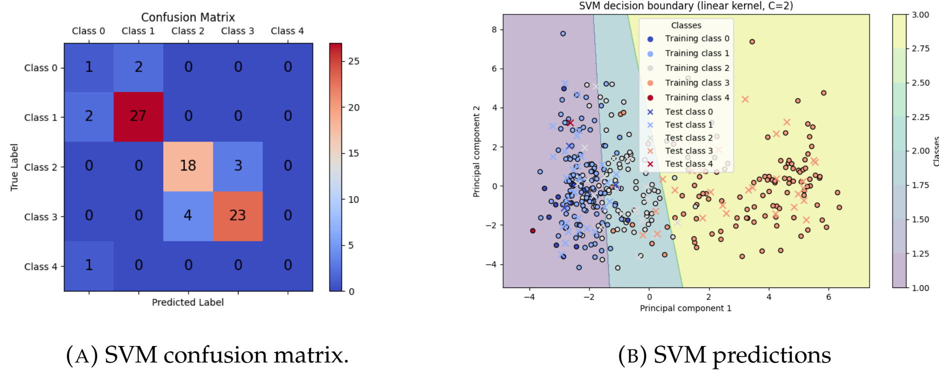
Metric	Value
Accuracy	85.19%
Mean Cross-Validation Score	88.30%
Mean Squared Separable Error	0.33

TABLE 4.5: Supporting Vector Machine

The accuracy of the validation dataset was obtained to corroborate the accuracy of the test dataset in order to assess the model's ability to generalise to data not seen during training. When comparing the validation accuracy of 87.69% with the test accuracy of 85.19%, a difference of 2.5% was observed with is relatively small indicating that the model can generalise adequately to new data.

The confusion matrix in figure 4.11a shows in the diagonal squares the amount of True Positives while the values in the rest of squares shows the Fake Negatives (FN) and Fake Positives (FP). As can be seen there are 12 FN an FP and 69 TP which shows that most values where correctly predicted by Supporting Vector Machine.

The plot of predictions in figure 4.11b shows a comparition between Real and predicted values.



(A) SVM confusion matrix.

(B) SVM predictions

FIGURE 4.11: Supporting Vector Machine

K-Nearest Neighbors (KNN)

The model was excuted for 1 to 20 as the number of neighbors. From them, the best performace results were obtained with 5 neighbors with the test dataset as detailed in table 4.6.

Metric	Value
Accuracy	79.01%
Mean Cross-Validation Score	72.69%
Mean Squared Separable Error	0.31

TABLE 4.6: K-Nearest Neighbors

The accuracy of the validation dataset was obtained to corroborate the accuracy of the test dataset in order to assess the model's ability to generalise to data not seen during training. When comparing the validation accuracy of 80.00% with the test accuracy of 79.01%, a difference of 0.99% was observed with is relatively small indicating that the model can generalise adequately to new data.

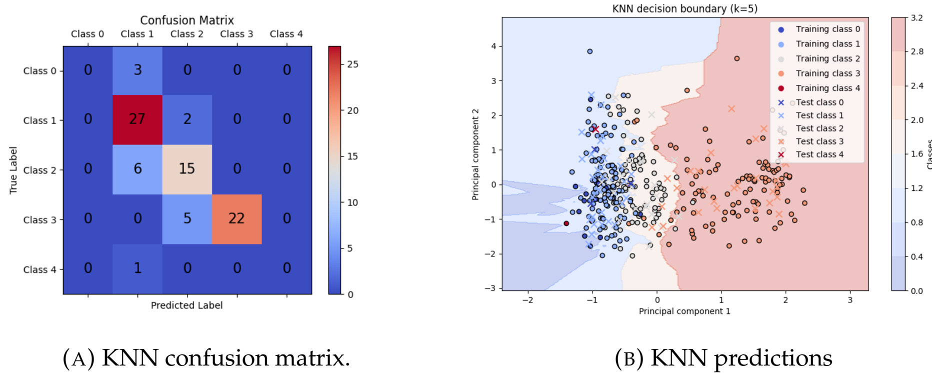
The confusion matrix in figure 4.12a shows in the diagonal squares the amount of True Positives while the values in the rest of squares shows the Fake Negatives (FN) and Fake Positives (FP). As can be seen there are 17 FN an FP and 64 TP which shows that most values where correctly predicted by Random Forest Model.

Figure 4.12b shows the KNN decision boundary for k=5 of the two principal components with a comparison betwen real and predicted values.

Random Forest (RF)

The model was excuted for 1 to 50 as the number of trees in the forest. From them, the best performace results were obtained with 34 trees with the test dataset as detailed in table 4.7.

The accuracy of the validation dataset was obtained to corroborate the accuracy of the test dataset in order to assess the model's ability to generalise to data not seen during training. When comparing the validation accuracy of 96.92% with the test accuracy of 92.59%, a difference of 4.33% was observed which is moderated indicating that the model can generalise adequately to new data and not significant enough to



(A) KNN confusion matrix. (B) KNN predictions

FIGURE 4.12: K-Nearest Neighbors

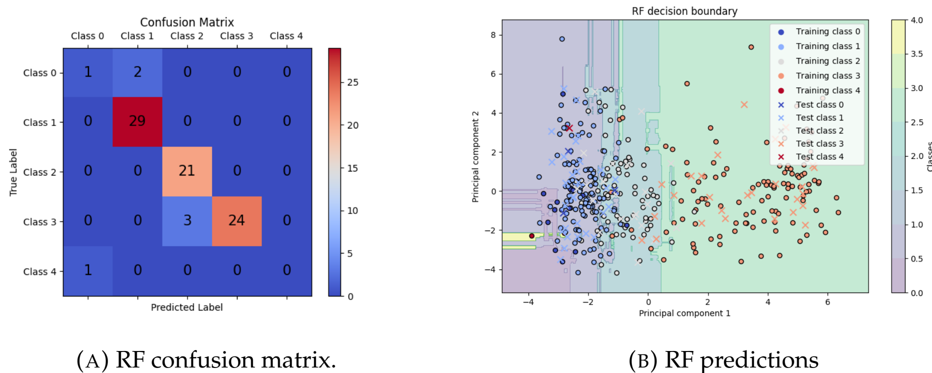
Metric	Value
Accuracy	92.59%
Mean Cross-Validation Score	95.31%
Mean Squared Separable Error	0.26

TABLE 4.7: Random forest

indicate an overadjustment.

The confusion matrix in figure 4.13a shows in the diagonal squares the amount of True Positives while the values in the rest of squares shows the Fake Negatives (FN) and Fake Positives (FP). As can be seen there are 6 FN an FP and 75 TP which shows that most values where correctly predicted by Random Forest Model.

The plot of predictions in figure 4.13b shows a comparition between Real and predicted values.



(A) RF confusion matrix. (B) RF predictions

FIGURE 4.13: Random forest

Figure 4.14 shows the Random Forest for the the dataset.

Artificial Neural Networks (ANN)

5 different ANN with different complexity were defined whose layer diagrams are presented in 4.15, 4.16, 4.17, 4.18 and 4.19.

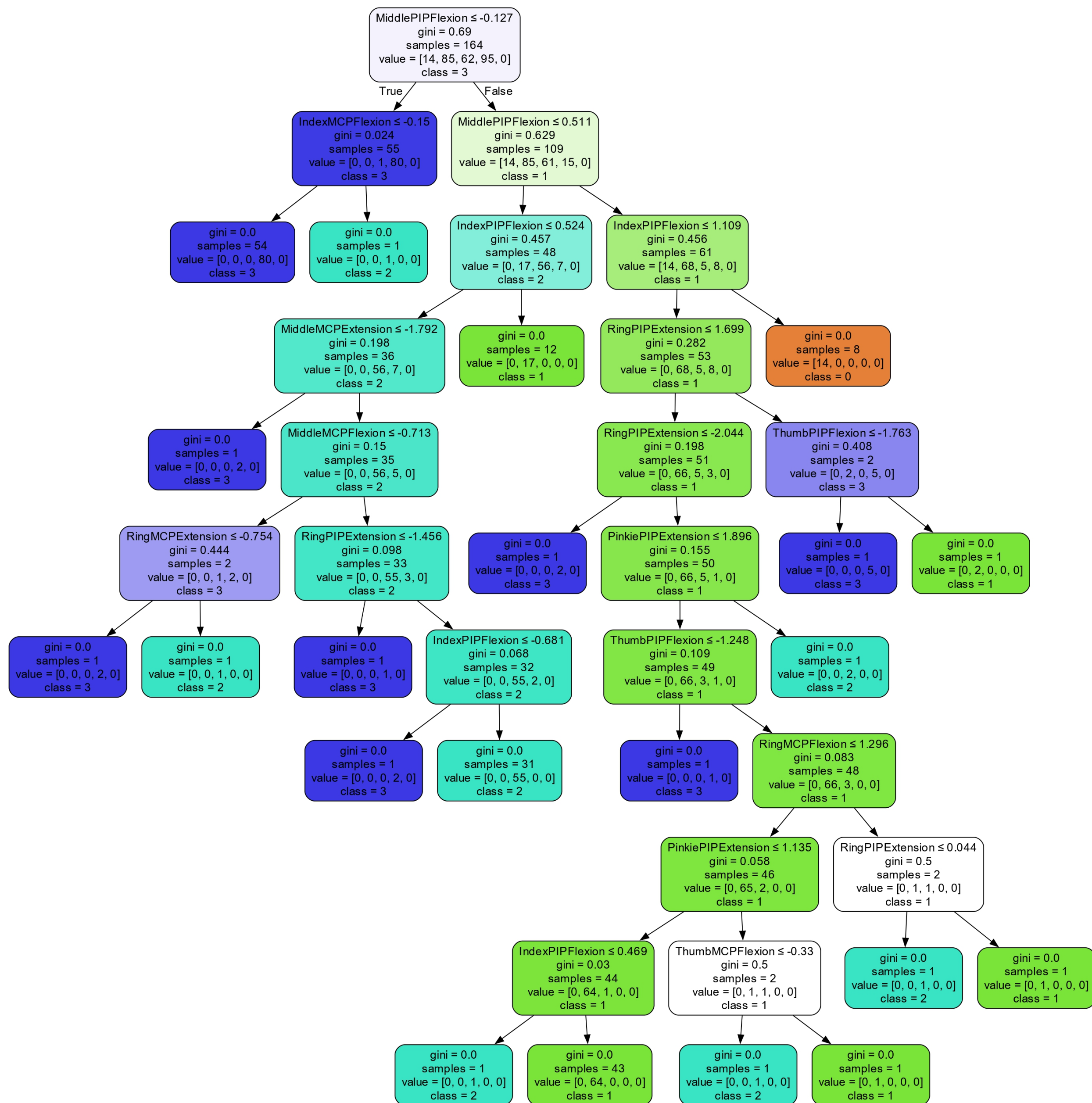


FIGURE 4.14: Random forest tree.

For the creation of these ANN models, several numbers of hidden layers with different numbers of neurons were considered, as well as the use of different techniques between the layers, such as Dropout to avoid overfitting, dimensionality reduction maintaining features and avoiding redundancy by Pooling, Flattening after dimensionality reduction to prepare the data as input for the following layers and Batch Normalisation for stabilisation and acceleration of the training. In the same way, Dense layers where all neurons are connected were used to capture global relationships and Conv1D layers were used to extract linear features and identify patterns.

Each model was excuted with automatic learning rate (LR) and momentum (m) for the parameters detailed in table 4.8 in each ANN.

Parameter	Values
Epochs	1-200
Optimizer	Adam
Learning rate	Automatic
Momentum	Automatic
Metric	Accuracy
Loss function	sparse_categorical_crossentropy
Activation function	ReLU
Output activation function	Softmax

TABLE 4.8: ANN parameters

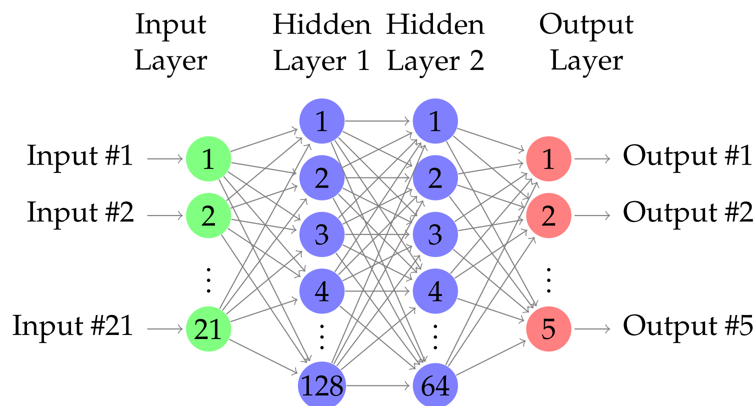


FIGURE 4.15: ANN Model 1

Adaptive Moment Estimation (Adam) optimizer was used as compiler due to its effectiveness and computational efficiency and because it adjusts learning rates and momentum for each parameter which results in fast adjustment and convergence. The accuracy is a metric that indicates how well the model is performing. The loss funtion sparse_categorical_crossentropy is used because the dataset has a multiclass objective feature with integer labels. There were used ReLu and Softmax activation function, the first one for hidden layers and the last one for the output layer due to the type of data. ReLU is used in hidden layers with continuous values and Softmax for the multiclass output layer.

In table 4.9 labels used in hidden layers of the ANN layer diagramas are explained.

Parameter	Values
D	Dropout
P	Pooling
F	Flatten
BN	Batch Normalization

TABLE 4.9: ANN layer diagram label description

The best performace results were obtained with Model 3 with 110 epochs and are detailed in table 4.10 with the test dataset.

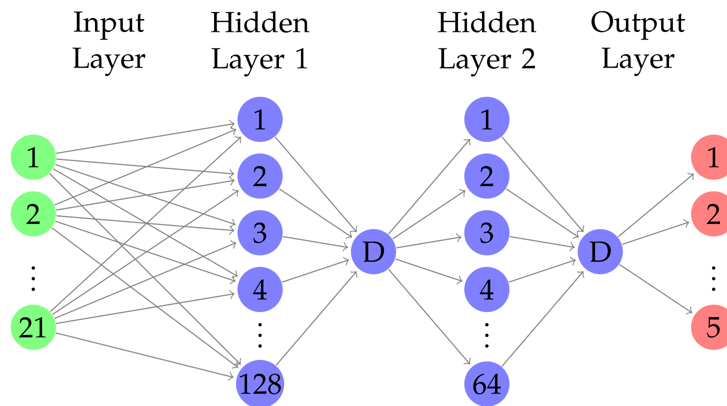


FIGURE 4.16: ANN Model 2

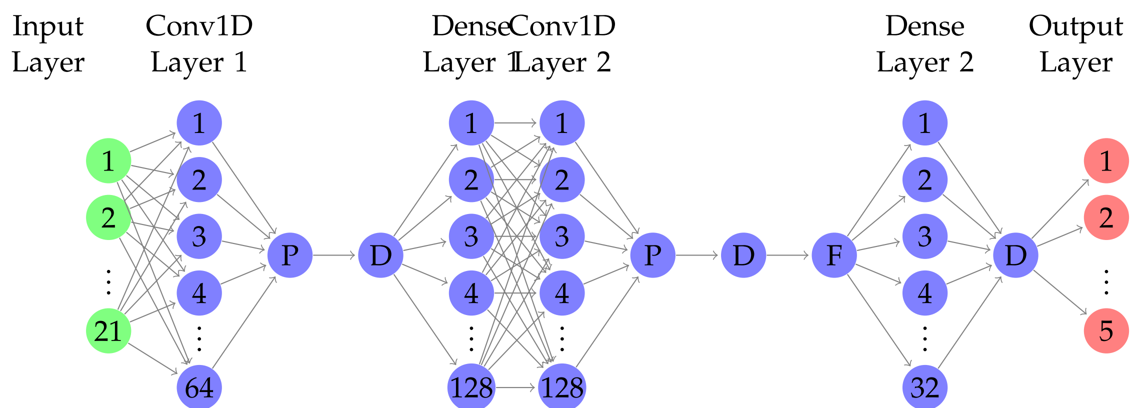


FIGURE 4.17: ANN Model 3

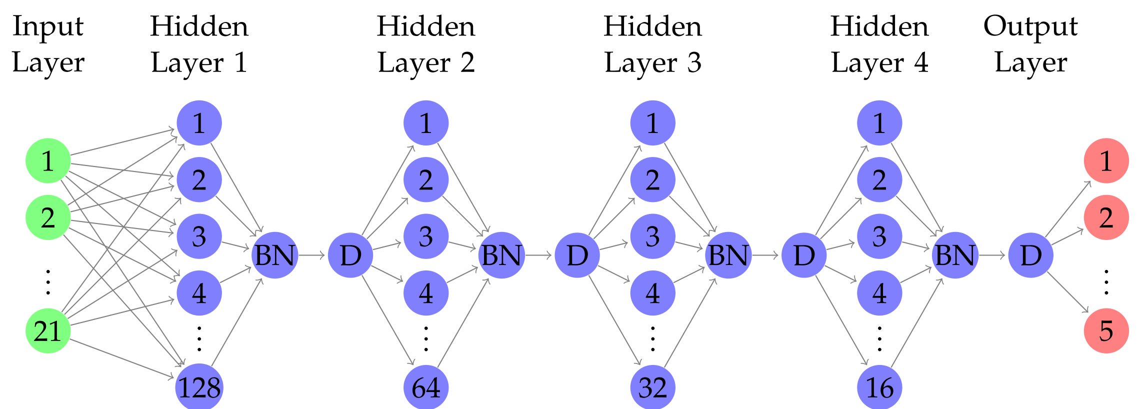


FIGURE 4.18: ANN Model 4

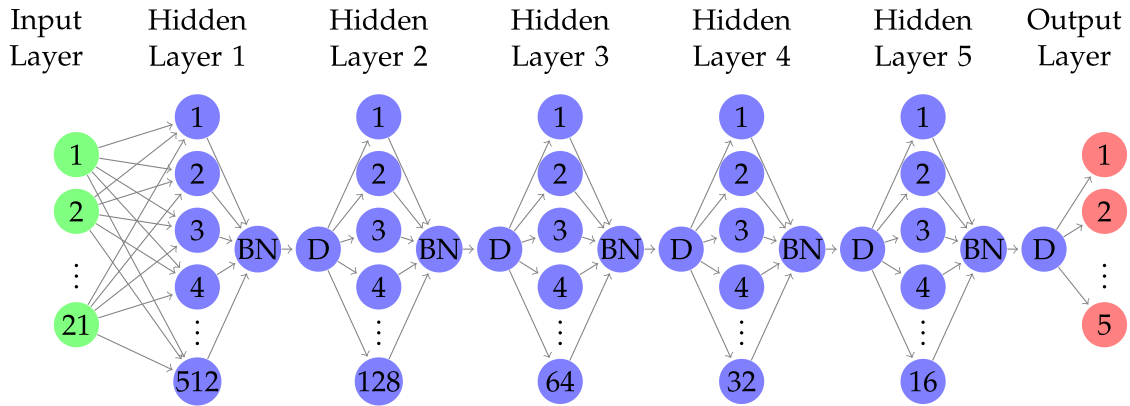


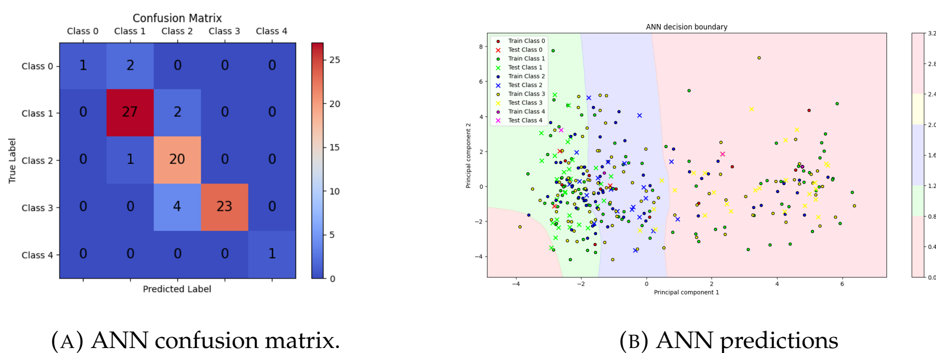
FIGURE 4.19: ANN Model 5

Metric	Value
Accuracy	88.89%
Mean Cross-Validation Score	96.90%
Mean Squared Separable Error	0.28
Leanrning rate	0.001
Momentum	0.9

TABLE 4.10: ANN Metrics

The accuracy of the validation dataset was obtained to corroborate the accuracy of the test dataset in order to assess the model's ability to generalise to data not seen during training. When comparing the validation accuracy of 87.35% with the test accuracy of 88.89%, a difference of 1.54% was observed which is relatively small indicating that the model can generalise adequately to new data.

The confusion matrix in figure 4.20a shows in the diagonal squares the amount of True Positives while the values in the rest of squares shows the Fake Negatives (FN) and Fake Positives (FP). As can be seen there are 9 FN an FP and 72 TP which shows that most values where correctly predicted by Random Forest Model. The plot of predictions in figure 4.20b shows a comparition between real and predicted values.



(A) ANN confusion matrix.

(B) ANN predictions

FIGURE 4.20: Artificial Neural Network

Figure 4.21 displays the accuracy and loss of the model with the best performance for this algorithm.

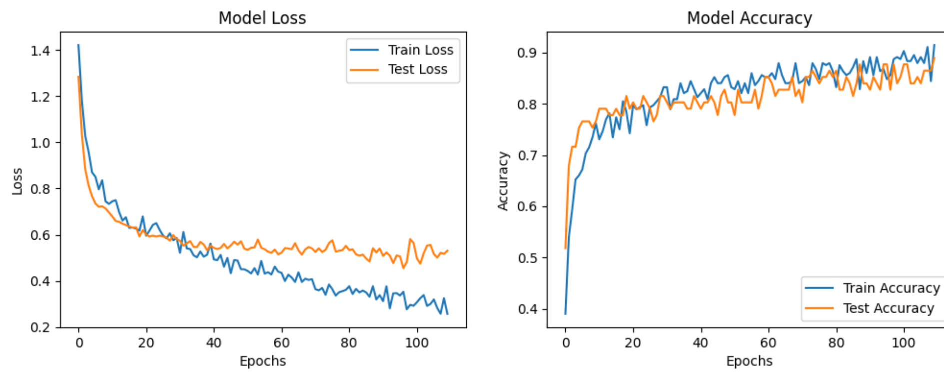


FIGURE 4.21: ANN accuracy and loss.

4.5 Results and Discussion

4.5.1 Machine learning algorithm selection

To compare the models three metrics were selected for evaluating different aspects of the performance of machine learning models. These three metrics are accuracy, mean cross-validation score and mean squared error.

The accuracy measures the amount of correct predictions over the total of predictions. The mean cross-validation score is used to assess the robustness of a model by dividing the dataset into 5 subsets for this work, where 4 of them are used for training and the other one for validation. Lastly, the mean squared error measures the mean squared errors between the values predicted and the real values. So that, lower values indicates that predictions are closer to real values.

Multiple Linear Regression (MLR) obtained an accuracy of 70.37%, which is lower compared to the rest of values of the table, indicating that this model has a good performance but does not fit the dataset well. It's mean cross-validation score of 71.60% indicates that although being robust in linear relationships is limited. It's MSE of 0.37 shows that there is a significant amount of errors in classification.

Supporting Vector Machine (SVM) obtained an accuracy of 85.16%, which is the third highest value of the table, indicating that this model classification for the dataset is excellent. It's mean cross-validation score of 88.30%, indicates that it is strong an that has a consistent performance. It's MSE of 0.33 shows an excellent classification performance that minimises errors in predictions.

K-Nearest Neighbors (KNN) obtained an accuracy of 79.01%, which is the lowest of the table, indicating that this model has a good performance but does not fit the dataset well. It's mean cross-validation score of 72.69%, indicates that there is variability between the data partitions so that this model is less stable. It's MSE of 0.31 shows that the model classification is acceptable but indicates its sensitivity.

Random Forest (RF) obtained an accuracy of 92.59%, which is the highest of the table, indicating that this model has a really good performance with the dataset due to its ability to handle feature variability and avoid overfitting. It's mean cross-validation score of 95.31%, indicates that it is robust and can maintain high performance across multiple partitions of the dataset. It's MSE of 0.26, that is the lowest

value of the table, shows that the model classification is good and indicates high class prediction accuracy and robustness to noise.

Artificial Neural Network (ANN) obtained an accuracy of 88.89%, which is one of the highest values of the table, indicating that this model has a quite good performance with the dataset. It's mean cross-validation score of 96.90%, indicates that it is robust and can maintain high performance across multiple partitions of the dataset. It's MSE of 0.28, that is the one of the lowest values of the table, shows that the model classification is good and that has high class prediction accuracy.

Random Forest obtained the best results in accuracy and cross-validation score ant the least MSE, suggesting that it is the most suitable model for the dataset. SVM and ANN also showed high performance, while MLR was the least effective.

Therefore, based on this analysis Random Forest model was selected for the proposed AIHandRehab VR system.

Table 4.11 shows a comparision between the metrics obtained for the dataset with each model. Random Forest had the best accuracy and least mean square error so this model makes more accurate predictions, and is therefore selected for the proposed VR system.

Model	**Accuracy**	**Mean Cross-Validation Score**	**Mean squared separable error**
Multiple Linear Regresion	70.37%	71.60%	0.37
Supporting Vector Machine	85.16%	88.30%	0.33
K-Nearest Neighbors	79.01%	72.69%	0.31
Random Forest	**92.59%**	**95.31%**	**0.26**
Artificial Neural Network	88.89%	96.90%	0.28

TABLE 4.11: Model performance metrics comparison

4.5.2 VR system automatic diagnosis

Once the model with the best metrics was selected, that is Random Forest, it was integrated to the AI HandRehab VR system in the Diagnosis scene.

Now the VR system was used for the automatic diagnosis and rehabilitation plan for fine motor s kills with new patients. For this, 20 patients different from those who participated in the data collection were asked to voluntarily participate. In this new stage of the study only 20 patients participated, as they had to be different from those who had participated in the data collection, so it was need to wait for new patients or attendees at the care centre.

For the automated diagnosis, a person from the care centre was trained in the use of the VR system, which includes entering the diagnostic scene, instructing the patient on the series of movements to be performed and visualising the results for the performance of the exercises. Each of the 20 participants used the system with

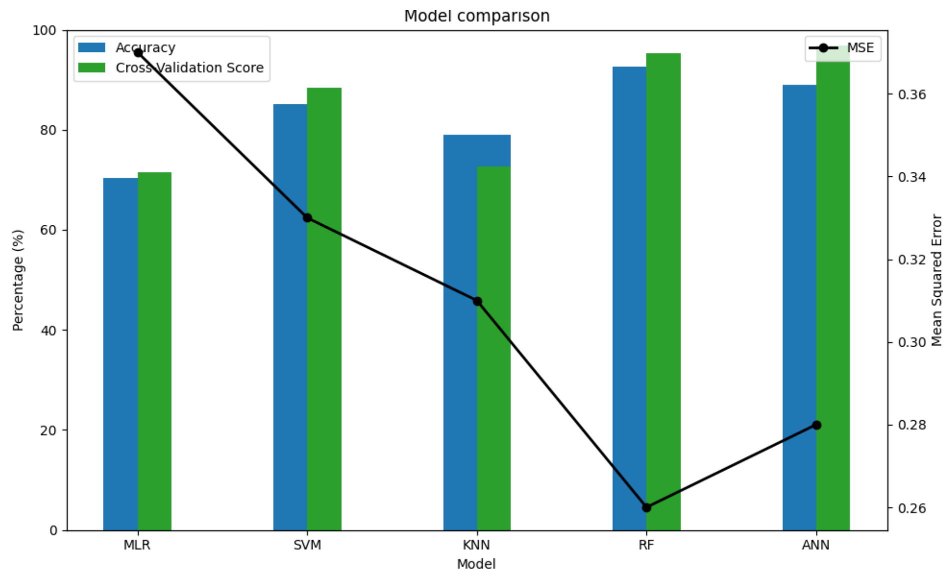


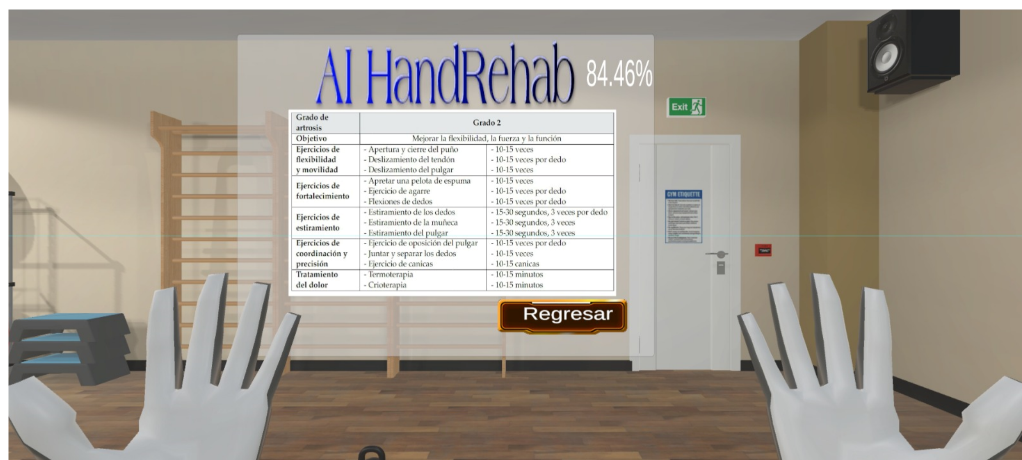
FIGURE 4.22: Models comparison.

the guidance of the trained person and obtained the result of the prediction of the degree of osteoarthritis and the corresponding series of rehabilitation exercises.

From the 20 patients evaluated with the VR system automatic diagnosis 2 of them where diagnosed with Grade 0, 2 of them were diagnosed with Grade 1, 6 were diagnosed with Grade 2 and 10 were diagnosed with Grade 3. The prediction results for the 20 patients shows high prediction accuracy with prediction probabilities above 70% but for patient 3. This indicates that the Random Forest model is reliable and with different patient profiles. For patient 3, the low diagnosis percentage indicates that should be checked with an specialist.

Table 4.12 shows a summary of the automatic diagnosis with the 20 new patients.

Figure 4.23 and 4.24 shows the Diagnosis scene with the automatic diagnosis and rehabilitation plan for patient 1 and patient 2 respectively.

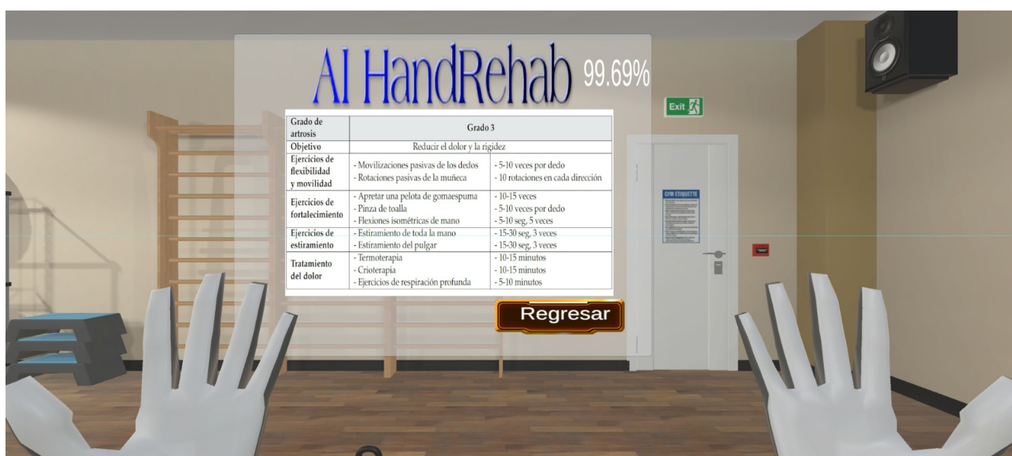


Grado de artrosis	Grado 2	
Objetivo	Mejorar la flexibilidad, la fuerza y la función	
Ejercicios de flexibilidad y movilidad	- Apertura y cierre del puño - Deslizamiento del tendón - Deslizamiento del pulgar	- 10-15 veces - 10-15 veces por dedo - 10-15 veces
Ejercicios de fortalecimiento	- Apretar una pelota de espuma - Ejercicio de agarre - Flexiones de dedos	- 10-15 veces - 10-15 veces por dedo - 10-15 veces por dedo
Ejercicios de estiramiento	- Estiramiento de los dedos - Estiramiento de la muñeca - Estiramiento del pulgar	- 15-30 segundos, 3 veces por dedo - 15-30 segundos, 3 veces - 15-30 segundos, 3 veces
Ejercicios de coordinación y precisión	- Ejercicio de oposición del pulgar - Juntar y separar los dedos - Ejercicio de canicas	- 10-15 veces por dedo - 10-15 veces - 10-15 canicas
Tratamiento del dolor	- Termoterapia - Crioterapia	- 10-15 minutos - 10-15 minutos

FIGURE 4.23: Automatic diagnosis and rehabilitation plan for patient 1.

Patient	Prediction	Probability
1	Grade 2	84.46%
2	Grade 3	99.69%
3	Grade 3	84.21%
4	Grade 1	84.46%
5	Grade 1	42.02%
6	Grade 3	89.47%
7	Grade 3	99.69%
8	Grade 3	78.24%
9	Grade 2	88.01%
10	Grade 2	78.76%
11	Grade 0	70.72%
12	Grade 2	94.29%
13	Grade 2	73.47%
14	Grade 0	82.31%
15	Grade 3	100.00%
16	Grade 3	94.74%
17	Grade 2	90.27%
18	Grade 3	99.69%
19	Grade 3	99.54%
20	Grade 3	99.54%

TABLE 4.12: AI HandRehab automatic diganosis



Grado de artrosis	Grado 3	
Objetivo	Reducir el dolor y la rigidez	
Ejercicios de flexibilidad y movilidad	- Movilizaciones pasivas de los dedos - Rotaciones pasivas de la muñeca	- 5-10 veces por dedo - 10 rotaciones en cada dirección
Ejercicios de fortalecimiento	- Apretar una pelota de gomaespuma - Pinza de toalla - Flexiones isométricas de mano	- 10-15 veces - 5-10 veces por dedo - 5-10 seg, 5 veces
Ejercicios de estiramiento	- Estiramiento de toda la mano - Estiramiento del pulgar	- 15-30 seg, 3 veces - 15-30 seg, 3 veces
Tratamiento del dolor	- Termoterapia - Crioterapia - Ejercicios de respiración profunda	- 10-15 minutos - 10-15 minutos - 5-10 minutos

FIGURE 4.24: Automatic diagnosis and rehabilitation plan for patient 2.

In addition to the prediction of the degree of osteoarthritis, the VR system provides rehabilitation exercise recommendations for the specific needs of each patient. These recommendations are designed to address the specific degree of osteoarthritis predicted, ensuring that each patient receives optimised treatment to improve their quality of life and joint function. Analysis of the results also highlights the system's ability to correctly identify cases with severe and very severe degrees of osteoarthritis, enabling early and appropriate interventions. This level of accuracy is crucial for osteoarthritis management, where timely treatment can make the difference in disease progression.

Chapter 5

Conclusion and Future Work

5.1 Conclusions

The analysis of the state-of-the-art revealed that the integration of artificial intelligence (AI) with virtual reality (VR) has significantly advanced the field of upper limb rehabilitation. These technologies have enhanced the accuracy and effectiveness of assessments conducted in controlled environments, leading to improved patient engagement and better rehabilitation outcomes.

Osteoarthritis, a common degenerative disease that severely impacts fine motor skills in the upper limbs, was selected as the focus of this work due to its widespread prevalence and substantial effect on patients' quality of life.

Data was collected on the flexion and extension movements of the hand fingers from 402 volunteer participants at a senior care center in the city. An expert was involved in the data collection phase to classify osteoarthritis by its severity grade. The dataset underwent a rigorous cleaning and normalization process to ensure high data quality and proper formatting for subsequent use.

This osteoarthritis dataset was then used to train and evaluate various machine learning algorithms, including Multiple Linear Regression (MLR), Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Random Forest (RF), and Artificial Neural Networks (ANN). Among these, the Random Forest algorithm demonstrated superior performance, achieving an accuracy of 92.59%.

A prototype system, named AI HandRehab, was developed for the automated diagnosis and rehabilitation planning of osteoarthritis. This system, powered by the Random Forest algorithm, is capable of diagnosing the condition and suggesting expert-designed rehabilitation plans for new patients, eliminating the necessity for the expert's physical presence.

5.2 Future Work

Future work will explore the application of unsupervised machine learning methods, enabling the development of datasets without the need for continuous expert input, while still allowing expert criteria to guide the process. Additionally, there is potential to expand the scope of the system by integrating various sensors and advanced technologies to capture and evaluate a broader range of variables. This could lead to more comprehensive assessments and enhanced rehabilitation protocols, further improving patient outcomes.

Bibliography

Acton, Q.A. (2012). *Joint Diseases: Advances in Research and Treatment: 2011 Edition*. ScholarlyEditions. ISBN: 9781464924859.

Bachmann, Daniel, Frank Weichert, and Gerhard Rinkenauer (2018). "Review of Three-Dimensional Human-Computer Interaction with Focus on the Leap Motion Controller". In: *Sensors* 18.7. ISSN: 1424-8220. DOI: 10.3390/s18072194.

Bertolini, Massimo et al. (2021). "Machine Learning for industrial applications: A comprehensive literature review". In: *Expert Systems with Applications* 175, p. 114820. ISSN: 0957-4174. DOI: 10.1016/j.eswa.2021.114820.

Bogar, Peter Zoltan et al. (2024). "Validation of a novel, low-fidelity virtual reality simulator and an artificial intelligence assessment approach for peg transfer laparoscopic training". In: *Scientific Reports* 14.1. DOI: 10.1038/s41598-024-67435-6.

Cartagena, Patricio D. et al. (2019). "Multifunctional Exoskeletal Orthosis for Hand Rehabilitation Based on Virtual Reality". In: *Information and Communication Technologies of Ecuador (TIC.EC)*. Ed. by Miguel Botto-Tobar et al. Cham: Springer International Publishing, pp. 209–221.

Chen, Zhaoming et al. (2024). "Assessment and machine learning prediction of heavy metals fate in mining farmland assisted by Positive Matrix Factorization". In: *Journal of Environmental Management* 350, p. 119587. ISSN: 0301-4797. DOI: 10.1016/j.jenvman.2023.119587.

Dhanasree, K.S., K.K. Nisha, and R. Jayakrishnan (2018). "Hospital Emergency Room Training Using Virtual Reality and Leap Motion Sensor". In: *2018 Second International Conference on Intelligent Computing and Control Systems (ICICCS)*, pp. 924–928. DOI: 10.1109/ICCONS.2018.8662900.

Duman, Çiçek and Feryal Subaşı (Apr. 2020). "Effects of Pinch, Grip and Upper Extremity Muscle Strength on Fine Motor Skills". In: pp. 11–22. ISBN: 978-3-631-79216-2.

Ekambaram, Dilliraj and Vijayakumar Ponnusamy (2023). "AI-assisted Physical Therapy for Post-injury Rehabilitation: Current State of the Art". In: *IEIE Transactions on Smart Processing and Computing* 12.3, 234 – 242. DOI: 10.5573/IEIESPC.2023.12.3.234.

Garcia, Gabriella Faina, Rogério Sales Gonçalves, and Giuseppe Carbone (2024). "A Review of Wrist Rehabilitation Robots and Highlights Needed for New Devices". In: *Machines* 12.5. ISSN: 2075-1702. DOI: 10.3390/machines12050315.

He, Qiqi et al. (2024). "From Digital Human Modeling to Human Digital Twin: Framework and Perspectives in Human Factors". In: *Chinese Journal of Mechanical Engineering (English Edition)* 37.1. DOI: 10.1186/s10033-024-00998-7.

Herrera, Vanesa et al. (2023). "Rehab-Immersive: A framework to support the development of virtual reality applications in upper limb rehabilitation". In: *SoftwareX* 23. DOI: 10.1016/j.softx.2023.101412.

Jurado, Israel Campero, Ulises Rodriguez Vargas, and Christian Penaloza (2020). "AI-VR Platform for Hand Rehabilitation". In: vol. 2020-October. Cited by: 1, 726 – 730. DOI: 10.1109/SMC42975.2020.9283413.

Kamran-Pishhesari, Alireza, Amin Moniri-Morad, and Javad Sattarvand (2024). "Applications of 3D Reconstruction in Virtual Reality-Based Teleoperation: A Review in the Mining Industry". In: *Technologies* 12.3. DOI: 10.3390/technologies12030040.

Lai, Yi-Chun et al. (2021). "Aiot-enabled rehabilitation recognition system— exemplified by hybrid lower-limb exercises". In: *Sensors* 21.14. DOI: 10.3390/s21144761.

Lima-Santos, Mathias-Felipe de and Wilson Ceron (2022). "Artificial Intelligence in News Media: Current Perceptions and Future Outlook". In: *Journalism and Media* 3.1, pp. 13–26. ISSN: 2673-5172. DOI: 10.3390/journalmedia3010002.

Modi, Preet Parag et al. (2022). "Interactive IIoT-Based 5DOF Robotic Arm for Upper Limb Telerehabilitation". In: *IEEE Access* 10, 114919 – 114928. DOI: 10.1109/ACCESS.2022.3218053.

Naqvi, Waqar Mohsin et al. (2024). "The future of telerehabilitation: embracing virtual reality and augmented reality innovations". In: *Pan African Medical Journal* 47. DOI: 10.11604/pamj.2024.47.157.42956.

Naranjo, Jose E. et al. (2019). "User Experience Evaluation of an Interactive Virtual Reality-Based System for Upper Limb Rehabilitation". In: *2019 Sixth International Conference on eDemocracy eGovernment (ICEDEG)*, pp. 328–333. DOI: 10.1109/ICEDEG.2019.8734389.

Oliveira, Juliana M. de et al. (2020). "REHAB FUN: an assistive technology in neurological motor disorders rehabilitation of children with cerebral palsy". In: *Neural Computing and Applications* 32.15, 10957 – 10970. DOI: 10.1007/s00521-019-04059-2.

Perret, J. and E. Vander Poorten (2018). "Touching Virtual Reality: A Review of Haptic Gloves". In: *ACTUATOR 2018; 16th International Conference on New Actuators*, pp. 1–5.

Pillai, Mayaank et al. (2020). "Artificial intelligence-based interactive virtual reality-assisted gaming system for hand rehabilitation". In: vol. 11318. Cited by: 6. DOI: 10.1117/12.2549372.

Ponto, Kevin et al. (2023). "The Benefits of Utilizing Augmented Reality as a Tool for Assessments". In: 393 – 398. DOI: 10.1109/ISMAR-Adjunct60411.2023.00085.

Pujol, Jose (2018). "The linear combination of vectors implies the existence of the cross and dot products". In: *International Journal of Mathematical Education in Science and Technology* 49.5, pp. 778–792. DOI: 10.1080/0020739X.2017.1408149.

Rheumatoid Arthritis Vs Osteoarthritis - Prof Dr. Robert Hierner (2024). URL: https://dubaihandsurgeon.com/rheumatoid-arthritis-vs-osteoarthritis-what-you-need-to-know/.

Sariman, Muhammad Shazmin et al. (2024). "A Review: Current Trend of Immersive Technologies for Indoor Navigation and the Algorithms". In: *Pertanika Journal of Science and Technology* 32.2, 955 – 977. DOI: 10.47836/pjst.32.2.25.

Saunders, R. et al. (2015). *Hand and Upper Extremity Rehabilitation: A Practical Guide*. Elsevier Health Sciences. ISBN: 9781455756490.

Shilaskar, Swati et al. (2024). "VR Based Medical Procedure Simulator with Haptic Feedback Gloves". In: 533 – 537. DOI: 10.1109/ESIC60604.2024.10481573.

Singh, V. (2014). *Textbook of Anatomy*. Elsevier India. ISBN: 9788131237298.

Skirven, T.M. et al. (2011). *Rehabilitation of the Hand and Upper Extremity, 2-Volume Set E-Book: Expert Consult*. Elsevier Health Sciences. ISBN: 9780323081269.

Spiegel, Brennan M. R. et al. (2024). "Author Correction: Feasibility of combining spatial computing and AI for mental health support in anxiety and depression". In: *npj Digital Medicine* 7.1, p. 60. ISSN: 2398-6352. DOI: 10.1038/s41746-024-01060-5.

Sudiarno, Adithya et al. (2024). “Investigating the future study area on VR technology implementation in safety training: A systematic literature review”. In: *Journal of Safety Science and Resilience* 5.2, 235 – 248. DOI: 10.1016/j.jnlssr.2024.03.005.

Ultraleap (2024). *Leap Motion Controller 2 - Ultraleap*. URL: https://leap2.ultraleap.com/products/leap-motion-controller-2/.

Unity (2024a). *Plataforma y Editor de desarrollo 3D en tiempo real | Unity*. URL: https://unity.com/es/products/unity-engine.

— (2024b). *Unity - Scripting API: Vector3.Angle*. URL: https://docs.unity3d.com/ScriptReference/Vector3.Angle.html.

Vive (2024). *VIVE Focus 3 - Standalone VR Headset*. URL: https://www.vive.com/us/product/vive-focus3/overview/.

Wong, Eugene Yin Cheung and Philip Tin Yun Lee (2024). “Virtual reality in transportation and logistics: A clustering analysis of studies from 2010 to 2023 and future directions”. In: *Computers in Human Behavior* 153. DOI: 10.1016/j.chb.2023.108082.

Yang, Zhen-Qun et al. (2022). “Augmented reality for stroke rehabilitation during COVID-19”. In: *Journal of NeuroEngineering and Rehabilitation* 19.1. DOI: 10.1186/s12984-022-01100-9.

YiFei, Li and Mohd Kamal Othman (2024). “Investigating the behavioural intentions of museum visitors towards VR: A systematic literature review”. In: *Computers in Human Behavior* 155. DOI: 10.1016/j.chb.2024.108167.

Zafar, Muhammad Hamza, Even Falkenberg Langås, and Filippo Sanfilippo (2024). “Exploring the synergies between collaborative robotics, digital twins, augmentation, and industry 5.0 for smart manufacturing: A state-of-the-art review”. In: *Robotics and Computer-Integrated Manufacturing* 89. DOI: 10.1016/j.rcim.2024.102769.

Zhao, Jinwei et al. (2024). “Wearable sensors for monitoring vital signals in sports and health: progress and perspective”. In: *Sensor Review* 44.3, 301 – 330. DOI: 10.1108/SR-02-2024-0080.