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Enhancing Virtual Physiotherapy Through Computer Vision and Pose Estimation

Francisco Manuel da Silva Luz

Master degree in Computer Science and Business Management

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Department of Information Science and Technology

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“I dedicate this work to all my family thanking them for their unconditional support and love throughout the development of this dissertation.”

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Resumo

Esta dissertação investiga como um sistema inteligente de fisioterapia pode melhorar a reabilitação física usando estimativa de pose e soluções baseadas em visão computacional. O objetivo é criar uma plataforma que ajude os pacientes a realizar reabilitação física em casa e forneça *feedback* em tempo real sobre os movimentos e o desempenho do exercício. Utilizando a estrutura *MediaPipe Pose* e algoritmos de *Machine Learning*, a plataforma é capaz de rastrear e avaliar automaticamente os movimentos das articulações, categorizando-os conforme o exercício em causa. Esta plataforma amplia a assistência corretiva para que o utilizador tenha a postura correta na execução dos exercícios para a sua reabilitação. O sistema responde às várias necessidades dos pacientes, facilitando a autonomia e a manutenção dos pacientes a longo prazo, com foco específico nos sobreviventes de acidentes vasculares cerebrais (AVC). Na verdade, este estudo aponta o caminho para uma forma otimizada de reabilitação motora que oferece atendimento personalizado e análise precisa da mobilidade, usando a Inteligência Artificial. Em última análise, o objetivo é melhorar a qualidade da recuperação através de outras funcionalidades, incluindo feedback em tempo real e a tecnologia de visão computacional, garantindo que esses exercícios sejam realizados com precisão durante a reabilitação física do paciente.

Palavras-chave: “Reabilitação Física”, “Acidente Vascular Cerebral”, “Visão Computacional”, “Aprendizagem Automática”, “Inteligência Artificial”, “Estimação de Pose”

Abstract

This dissertation investigates how a smart physiotherapy system is able to improve physical rehabilitation by using pose estimation and computer vision-based solutions. The objective is to create a platform that helps patients to do physical rehabilitation at home and provides them real-time feedback about the movements and the exercise performance. Utilizing the MediaPipe Pose framework and machine learning algorithms, the platform is able to automatically track and evaluate joint movements by categorizing them based on the exercise at hand. It extends corrective assistance so users can have the correct posture when performing the exercises for their rehabilitation. The system is responsive to variable patient requirements, facilitating patients' autonomy and maintenance over the long-term, with a specific focus on stroke survivors. In fact, this study points the way to a far superior form of remote rehabilitation that delivers personalized care and precise mobility analysis, using AI in unique and ground-breaking ways. Ultimately, the goal is to improve the quality of recovery through other great features including real-time feedback and computer vision technology ensuring that these exercises are conducted accurately during the patient physical rehabilitation.

Keywords: "Physical Rehabilitation", "Stroke", "Computer Vision", "Machine Learning", "Artificial Intelligence", "Pose Estimation"

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Glossary of Abbreviations and Acronyms

AVC – Acidente Vascular Cerebral

AI – Artificial Intelligence

ANN – Artificial Neural Networks

FPR – False Positive Rate

HAR – Human Activity Recognition

BMI – Body Mass Index

IoT – Internet of Things

IMUs – Inertial Measurement Units

MDS-UPDRS – Movement Disorder Society Unified Parkinson's Disease Rating Scale

ML – Machine Learning

PD – Parkinsons's Disease

RANSAC – Random Sample Consensus

RF – Random Forest

RGB-D – Red-Green-Blue and Depth

TPR – True Positive Rate

VR – Virtual Reality

1. Introduction

The new technologies are disrupting the way how physical rehabilitation is done. With the recent advancements in pose estimation and computer vision, virtual physiotherapy has a potential to transform traditional rehabilitation methods. The purpose of this work is to contribute in such an innovative landscape by following a different methodology that enhances the effectiveness of exercises monitoring during virtual physiotherapy and proposes a new way for exercise performance evaluation.

This study investigates the idea of a remote physical therapy. The versatility of the rehabilitation exercises is also taken into account, thus ensuring personalization and patient adherence. A smart physiotherapy framework and the process of personalized physical rehabilitation is our objective in this project. The exercises are performed at home, and because this approach is inherently flexible, exercises can be adapted on the moment to meet each patient where they are at in regard to their abilities and progress toward recovery allowing for more effective rehabilitation.

This dissertation highlights a particular focus on the distinct difficulties which arise when it comes to physical rehabilitation of stroke survivors. As well, many stroke survivors face specific motor control challenges that necessitate such precise and individualized treatment. The aim of the dissertation is to offer a specific platform through which, with integration of computer vision technologies can automatically analyze and respond in an appropriate manner according to each individual rehabilitation requirements. Its goal is to help inform the design of more effective, personalized approaches to rehabilitation for this high-risk group.

This research was motivated by a desire to help the patient perform the exercise autonomously and progress in the rehabilitation rapidly. By empowering people to keep improving in their physical rehabilitation without the need of going to the clinic, always respecting and following the decisions of the physiotherapists, it allows them not only autonomy over the process but encourages activity in that recovery. The proposed smart physiotherapy system has the potential to deliver instantaneous feedback on individual exercise performances with a view towards promoting self-efficacy and inculcating compliance practice of prescribed rehabilitation exercises. The goal of this research is to improve long-term outcomes by increasing patient engagement and incorporating autonomy in the rehabilitation process.

This opens up a unique opportunity to transform virtual physiotherapy using computer vision and pose estimation technologies. An extensible system is the end goal of this study to accurately analyze and interpret human movements in rehabilitation exercises using these technologies, and it has the potential to offer real-time feedback and assist patients perform the rehabilitation exercises in proper form during specific movements, which can potentially help improve therapeutic outcomes.

Furthermore, the proposed approach will help to advance this field by providing an extensive framework for evaluating exercise performance. This study aims to develop an objective, unbiased evaluation method for the effectiveness of rehabilitation exercises by utilizing state-of-the-art algorithms on movement analysis and pose estimation. This is a step forward of not only virtual physiotherapy but also to ushering in a new practice towards the objective assessment of exercise performance, what will allow an evidence-based reasoning by clinicians from all rehabilitation field.

Finally, this dissertation hopes that through the introduction of a new strategy involving pose estimation and computer vision, it can greatly promote smart physiotherapy based on VR serious games. The study sets a foundation for developing customized rehabilitation planning and efficient smart physiotherapy systems that will benefit patients in physical recovery. In particular it deals with prevailing constraints which exist in regard to rehabilitation practices and exercise performance tests.

1.1 Motivation

The motivation behind this dissertation is driven by the immediate challenges present towards modern physiotherapy initiatives today. In context to accessibility issues that are real-time responsive individual treatment plans and practical monitoring during rehabilitation. The results underline the dire need for new strategies that improve exercise adaptability in rehabilitation, target specific stroke population requirements as well as focus on enhancing autonomy to execute their prescribed exercises. One of the problems that traditional rehabilitation frequently encounters in providing more targeted and precise interventions are hindering an optimal recovery by some patients undergoing physical rehab. The world's movement towards digital health and the corresponding increase in demand for home-oriented solutions underscores another concern, which is that people cannot keep depending on traditional means to bridge these gaps.

Despite these challenges, the role that technology might play in changing physiotherapy processes for good cannot be overstated. The value of this technology as an aid to physiotherapists is underscored by the fact that clinics will benefit from it massively, and hence in a bid to create solutions compatible with modern-day medical establishments, we seek various options through this dissertation. Among the latest technologies associated with digital health care, artificial intelligence is one that is both new and significant. One of these is to potentially serve as an enabler for interventions that are customized more accurately than previously possible, and therefore contribute significantly toward the optimal recovery outcome in patients undergoing physical rehabilitation.

With the world becoming more and more centered on remote healthcare, there is a strong need for at-home solutions. Consequently, the aim of this dissertation is to explore alternative methods for technological integration (especially artificial intelligence) as a transformative innovator versus traditional physical techniques and adapt it into modern physiotherapy.

1.2 Research Questions

- What essential elements and features ought to be included in a virtual physiotherapy assistant framework to guarantee thorough assistance for patients and medical professionals?
- What aspects of the design of a virtual physiotherapy assistant contribute to long-term user engagement, and how can user autonomy be effectively preserved and enhanced?
- In light of legal requirements and new technological advancements, what are the most reliable and ethically compliant methods for guaranteeing patient data security and privacy in virtual physical therapy assistants?
- What opportunities and challenges exist for smoothly integrating a virtual physical therapy assistant with current healthcare information systems, and what approaches can be taken to get around any obstacles?
- How can inclusivity be promoted in its adoption across various demographic groups, and how can the virtual physiotherapy assistant be designed to ensure accessibility for a diverse user population, including those with disabilities or varying technological literacy?

1.3 Research Objectives

This dissertation has the following research objectives:

- Development of a Pose Estimation Framework for Virtual Rehabilitation

Incorporate pose estimation and computer vision to create a virtual physiotherapy system using MediaPipe and machine learning algorithms to track and classify physical rehabilitation exercises. The framework places emphasis on adaptability, offering a rehabilitation solution that is both targeted and user-friendly. Overall, it transforms physiotherapy using state-of-the-art technology for optimal results, especially attending to the special requirements of stroke survivors.

- Ensure User Autonomy and Engagement

Implement a monitoring system that can provide feedback during rehabilitation exercises in order to provide an interactive self-monitoring platform that keeps track of the movement being made. Additionally, gamification can be used to improve the virtual physiotherapy assistant's motivation and engagement. By sustaining positive results, this strategy guarantees the rehabilitation process's ongoing efficacy.

- Performance Evaluation of AI-driven Rehabilitation Systems

Investigate and compare the efficacy of machine learning algorithms, Random Forest and Artificial Neural Networks, in activity recognition for rehabilitation exercises, emphasizing precision, recall, and overall accuracy.

1.4 Research Contributions

This dissertation improves Human Activity Recognition (HAR) by making a model to process data via MediaPipe and provide a thorough classification using machine learning models such as Random Forest and Neural Networks to recognize physical activities. A scientific paper based on this research will be submitted to a conference in the area and it has potential to advance in the science framework. Furthermore, cooperation with Clínica Lambert facilitated data acquisition, which future implementation is aimed to track physical therapy, while ensuring the validity of the research.

2. Literature Review

This study focuses on the enhancement of smart physiotherapy using computer vision and pose estimation, giving a novel approach for physical rehabilitation and exercise performance evaluation. The protocol used in this review follows three major phases that consists in: planning the review, conducting the review, and reporting the review, and its understanding is essential for the fulfillment of its objectives. The Literature Review is divided by sections. In Section 2.1 is briefly explained the followed protocol and the criteria used to select the scientific studies and articles that will be used in this study. Section 2.2 is about the existing studies about rehabilitation exercises. To properly evaluate the impact that artificial intelligence can have in physiotherapy it is important to understand the current state that physical rehabilitation is in. Section 2.3 highlights virtual assistants and technologies (smartwatches, bands, cameras, etc.). These technological devices are being increasingly used in these days, so it is important to further analyze the impact that can be noticed by these technologies. The final Section 2.4 describes artificial intelligence and computer vision methodologies. This section is subdivided into subsections. Section 2.4.1 provides a comprehensive look at how Artificial Intelligence (AI) is reshaping physiotherapy by simulating human intelligence in machines. It highlights the potential of AI in revolutionizing rehabilitation practices through intelligent algorithms and machine learning techniques. Section 2.4.2 focus on interpreting visual information and where computer vision is increasingly used in physiotherapy for assessing patient movements, real-time monitoring, and innovative interventions. This section explores the applications of computer vision technologies in enhancing the analysis of visual data from cameras and sensors. Section 2.4.3 highlights key areas within machine learning, for example the artificial neural networks algorithm and the random forest algorithm to analyze sensor data and accurately identify human movements and activities. This section explores the role of deep learning algorithms in uncovering complex motion patterns, improving the accuracy of activity tracking, automatically identifying and assessing specific exercises performed by patients, and personalizing activity recognition systems for diverse applications such as healthcare, sports, and rehabilitation, and Section 2.4.4 shows how the serious games enhance physical rehabilitation by using deep learning algorithms to track patient progress and adapt exercises in real time. Additionally, it also explores how these games personalize rehabilitation, making therapy more engaging and effective, while providing valuable data to optimize treatment outcomes.

2.1 Literature Review Protocol

The Literature Review Protocol is structured in two subsections, selection criteria that describes the inclusion and exclusion criteria used to select the articles to use in this dissertation, and the search strategy, that describes the method used in the Literature Review.

2.1.1 Selection Criteria

The chosen scientific articles were selected due to their focus being on the effects that artificial intelligence can have on physical rehabilitation, exploring different related themes such as Rehabilitation exercises, Virtual assistants, and technologies (smartwatches, bands, camaras, etc.), AI overview, computer vision, deep learning, pose estimation, activity recognition and serious games. Although these were the preferable topics a stricter selection was made. There was a preference for computer vision and activity recognition. One of the criteria for accepting the study was its publication date, which was taken into account to guarantee the most up-to-date and reliable data. To ensure relevance, only studies published after 2014 were included. Studies' language also played a role in acceptance, in which English-language studies were preferred. These criteria were developed on the presumption that studies conducted in English frequently show greater significance and influence within the scientific community. When searching on the data bases the keywords and search string were always applied to the document title ensuring more accurate and precise information about the topic that was being searched. Studies that did not fit these requirements were not considered. Different perspectives for each previously mentioned topic were also a crucial factor in the acceptance criteria.

2.1.2 Search Strategy

The selected search string was administrated in every database, resulting in a wider variety of articles about the theme in question. The search string was applied in the following databases: IEEE Explorer, Scopus, ACM Digital Library.

The search string used was composed by a variety of keywords, combining them using the logical operator "AND" when written on the databases. By doing so, the search was more authentic. Due to the fact that this dissertation addresses several topics, several search strings and key words were used separately.

The keywords used to form the search string were:

- "Physical Rehabilitation" AND Stroke
- "Serious games"
- "Virtual assistants" AND "technologies"

- "AI" AND "computer vision"
    - "AI overview"
    - "Computer vision"
    - "Machine learning"
    - "Pose estimation" AND "activity recognition"

2.2 Rehabilitation Exercises

A stroke is a cardiovascular event that can cause paralysis or blindness, as well as memory loss and even the ability to speak or reason. Stroke survivors undergo extensive rehabilitation and long physiotherapy sessions to help them regain independence in their daily activities. This is why high motivation for treatment and therapy compliance is the key. This gamification of the exercises, via devices commonly used in tablet and smartphones could potentially make stroke recovery more cost effective as well as contribute to a much stimulating at-home rehabilitation. The rehabilitation games can be shown in these virtual reality scenarios on the screen of a smartphone or tablet. Additionally, other body parts can also serve as stable attachment points for wearable sensors, for monitoring adherence with these widely prescribed movements in a virtual environment. Finally, the other health metrics of patient's performance during rehabilitation exercises such as the heartbeat rate, can be immediate feedback to therapist by mobile phone [1].

A stroke is a major cause of long-term disability in the developed world; 77% of first-time stroke survivors in the UK suffer upper limb weakness, and although significant advances have been made in stroke prevention over recent decades, with improvements in treatment and rehabilitation across many centers worldwide, there is still much progress to be made as stroke remains one of the leading causes of disability globally. This renewed interest has arisen in the wake of reports on the limited efficacy of traditional rehabilitation approaches and new directions have been taken with attempts to develop novel modalities for training including VR platforms. VR can increase the repetitive nature of upper limb training and provides immediate feedback through maximized attention on sensory stimulation that favors neuroplastic changes which are underlying poor motor function. VR is also praised for boosting patient engagement and motivation in stroke rehabilitation [2].

Intensive practice improves motor recovery following a stroke, with the optimal benefit linked to requirement for rehabilitation until close to maximal recoveries have been achieved. But this kind of intensive training, while effective in the short term to restore damaged movements after a stroke, is too expensive over time, hospitalization alone costs thousands per day and therapist salaries combined with leasing sites for rehabilitation can be very high. Hence, given the undue burden on existing healthcare resources as well as prior practices in physical interventions and self-management utilization for self-directed training at home. Self-directed refers to patients and their caregiver's attempting rehabilitation on their own as opposed during one or a series of visits in-person with direct medical professional supervision. The advantages of this form of home training are numerous; sheltered, living room learning uses naturalistic environments to foster generalizability and reduced expense for supervised therapy. Wearable technology provides a cost-effective and potentially advantageous strategy for home-based self-directed rehabilitation. Wearable technology has its own host of benefits over traditional methods. Printed biosensors are inexpensive, light and more flexible than their traditional counterparts. Wearable technologies are electronic hand-free devices that fit with the human body externally to record activity without impeding freedom of motion. In rehabilitation applications, wearable tech such as smart textiles are utilized to capture body kinematics during rehabilitation sessions and facilitate immediate feedback or assist with active/passive correct movement patterns [3].

Self-administered exercise is often encouraged by therapists when they are unable to supervise and guide repeated rehabilitation therapy. How much a patient adheres to the rehabilitative exercises post- physical rehabilitation therapy determines the course and pace of their improvement. On the other hand, patients have difficulty adhering to multiple repetitions of rehabilitation therapy for a long period without a therapist. Non-adherence to the self-directed exercises prescribed is a common problem encountered in most physiotherapy-related healthcare disciplines by patients. One solution that has received considerable attention in this respect is the use of artificial intelligence (AI) and robotic coaches. AI methods take care of patients' workouts through these devices autonomously. In addition to that, also by enabling social interaction those systems can help the patients take part in rehabilitation or well-being related activities. Previous research on AI and robotic exercise coaches, each with a limited number of design factors addressing the impact physical embodiment or matching the interaction style to user personality suggests that there are benefits in improving patient motivation, engagement. Even though previous research has demonstrated functioning AI and robotic exercise coach capabilities, there are ongoing challenges to deploy them at scale. The difficulties may include the need of time and research in multiple aspects such as usability, cost-effectiveness, clinical efficacy and safety [4].

Figure 2.1 – Diagram demonstrating how an AI and robotic coach communicates with a depicts the robotic coach and AI flow diagram that communicates with a patient and a therapist to assist in rehabilitation techniques

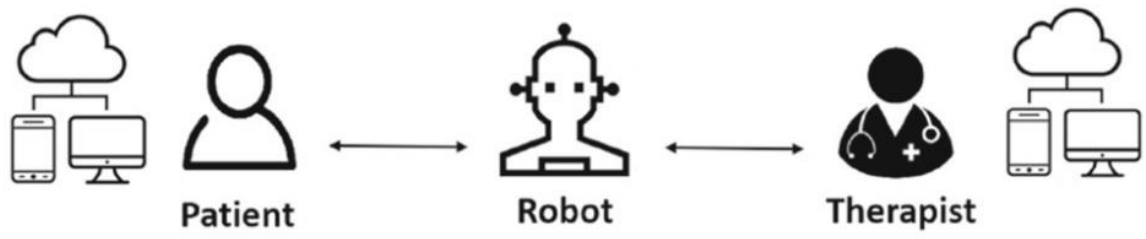

Figure 2.1 – Diagram demonstrating how an AI and robotic coach communicates with a patient [4].

Patients are referred to a lot of self-directed exercises and so need high compliance with the approach. A major problem that plagues many physiotherapy-related healthcare specialties is low treatment adherence. One solution for this problem is to propose social robot coaching systems that would act as the physiotherapist, the first offer would be a wearable fitness tracking gadget that monitors the user, then encourages clinically proven social activities to reinforce their health or rehabilitation [5]. Figure 2.2 depicts the flow chart for an interactive method using a social robot to provide individualized physical treatment.

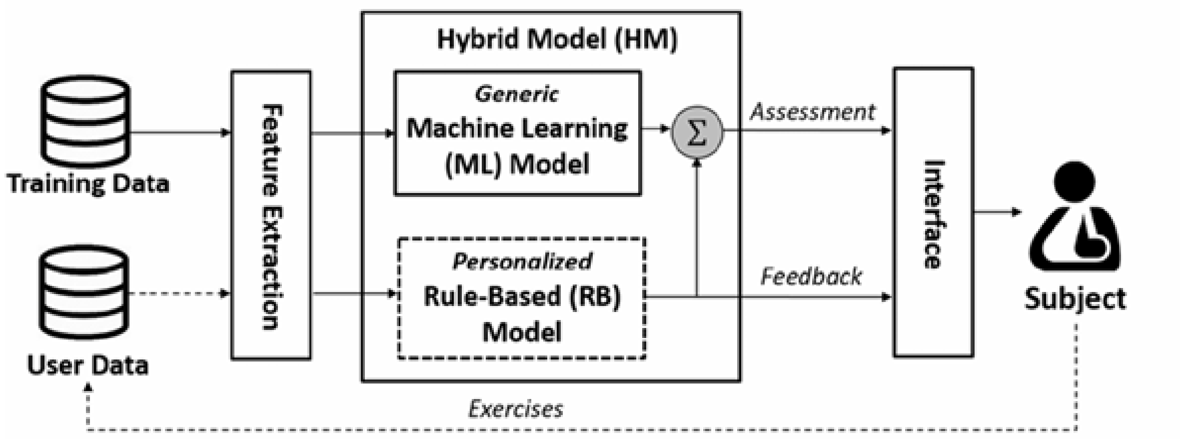

Figure 2.2 – Diagram demonstrating an interactive method for personalized physical rehabilitation using a social robot [5].

Firstly, the data is processed and the important features are extracted, then it goes through the models integrated in this specific system and finally goes to the interface providing information to the subject. Such rehabilitation is crucial in minimizing the effects of a stroke, and many people have professional systematic rehabilitation shortly after the acute phase with complete recovery. This could be inferred from a previous review. However, it was indicated that based on the type of exercise and stage (passive isometric. Isokinetic, isotonic) different habits in rehabilitation exercises were used. Indeed, evidence suggests that commencing rehabilitation exercise in the aftermath of a stroke is effective, but exercises are almost never taught in the early stages of rehabilitation because physical or occupational therapy is preponderantly aimed at this phase. There is another important point that the appropriate rehabilitation exercise would be effective when conducted in a timely manner and fitted to each individual's functional direction [6].

2.3 Virtual Assistants / Rehabilitation

Traditional tools are giving way to virtual rehabilitation, a technology in which therapy literally takes place using immersive settings and simulations generated by what we have come to know as Virtual Reality (VR). Its versatile maneuvers target a sweeping array of dysfunctions and lesions making for an active, innovative therapeutic model. VR therapy provides a more interactive and engaging experience which contributes to better outcomes, proving its effectiveness in improving results. This technology-based strategy underscores the possibility of better individual participation and rehabilitation achievements, denoting a therapy change [7].

These virtual rehabilitation modes are given the term of telerehabilitation, and they include treatments which will be provided at home to patients and is a game-changer for how patients are treated. The vCare system is a very good example, the product is introduced as a movement-centered digital assistant for senior citizens to receive physical rehabilitation and an active lifestyle. Virtual rehabilitation improves cardiovascular parameters, exercise capacity and quality of life just by the advantages it can provide such as enabling more consistent daily workouts, as patients can exercise at home at their convenience, and reducing the stress associated with traveling to and from the clinic, particularly in more complex or severe cases. The primary aims of the system are to reduce cardiovascular risk factors and promote individual therapy adherence. A special mention of the User experiences reviews, they are an important factor in optimizing a system, so that multiple devices could be brought across for various data type [8].

This particular virtual rehabilitation system, which includes a haptic device, Kinect sensor and screen as well as audio box and personal computer enabling rich user experience, game elements can be controlled by users using the haptic device, which gives a tactile experience. The Kinect sensor helps increase capacities by accurately measuring trunk motion and providing immediate feedback for effective rehabilitation, this hardware system is a merged technology of numerous components that helps in offering an immersive and all-inclusive rehabilitation environment [9].

Virtual Reality technology is being used in virtual rehabilitation, where games are played with the help of a VR device and some examinations will be done using that. This approach can be adopted by various forms of treatment, making it something mainly enjoyable to look forward to and reducing the rate at which people fail (adherence). Clinicians are aided by computerized evaluations, used not only to keep track of how their patient is doing but also in setting personalized goals. Through virtual rehabilitation, patient must involve in treatment rather than passive observer and can be delivered remotely through telerehabilitation programs which provide broader access to a non-typical healthcare setting that promotes better results for patients [10].

Figure 2.3 depicts how modern technology is changing the way that clinical treatment is provided, including robots, telerehabilitation, virtual reality, and advanced machine learning algorithms.

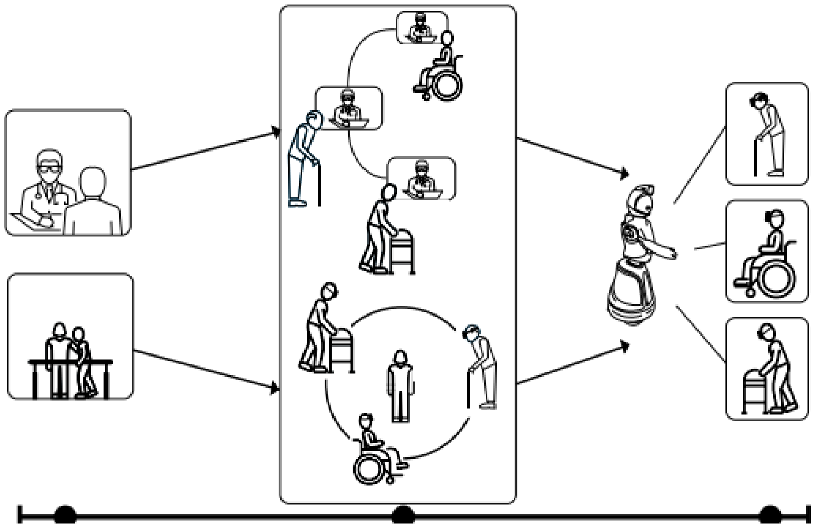

Figure 2.3 – The evolving roles of technology and physicians in the field of rehabilitation [10].

By using virtual reality to deliver customized high-intensity exercise regimens, stroke sufferers may receive specialized rehabilitation treatments at home, reducing their recuperation time. The EDNA-22 system showcases this idea, which is a transportable virtual rehabilitation system that offers a practical alternative for at-home rehabilitation through a series of customized mobility exercises and performance tracking using cloud computing data storage, where the efficacy of rehabilitation practices can be individualized and tailored through using virtual reality [11].

By using VR technology in rehabilitation, virtual reality treatment focuses on improving motor skills and motivating patients. However, robust findings require larger numbers and consistent methods across studies. To improve the therapeutic potential of treatments, there are several obstacles that need to be overcome, this includes establishing protocols and more robust outcome measures. Results of body mass index (BMI) follow-up was generally poor, but increasing the motivation and adherence of patients in general should probably start by keeping system usability up, this consideration will further promote the use of virtual rehabilitation for patient care [12].

2.4 Artificial Intelligence and Computer Vision for Healthcare

2.4.1 Artificial Intelligence Overview

Machine learning engines trained on extensive datasets, can be matched or even bettered by Artificial Intelligence (AI) in a slew of tasks. However, this also means that the biases in these datasets will cripple AI use (especially for older people and other minority groups) before it starts. Efforts and policies are needed to guarantee diversity of data sets, as well as the role efficacy plays in collaborative development transparency between AI systems. Healthcare professionals will need to be trained in AI technique, and supporting the AI literacy of older adult populations is also critical. AI could exacerbate access-based health outcome gaps, due to lack of transparency and external validation in AI models that can impinge upon privacy and autonomy. To harness the potential benefits of AI and avoid harm, it is essential to educate clinicians and patients on how to use this technology appropriately with a "people-first" driven approach for effective governance around treatment plans using AI powers. Expensive investments in technology infrastructure are needed to make sure everyone has access to AI and that such a platform does not cause health disparities [13].

Figure 2.4 depicts a synopsis of newly developed AI applications in healthcare, including instances of its application in the treatment of the elderly

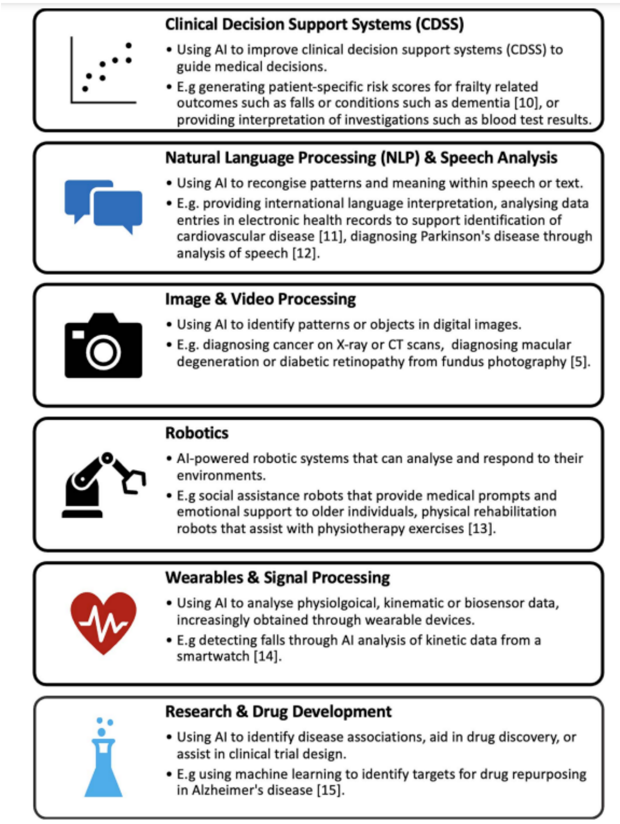

Figure 2.4 – Recent Artificial intelligence applications in healthcare [13].

AI, including machine learning algorithms and smart computers, have been effective in cancer diagnosis, diagnostic imaging as well as pharmaceutical development applications. With AI integration, patient care has enhanced in the health domain. Educational background impacts patient acceptability, with higher education being related to greater acceptance. AI familiarity underpins positive sentiment, comfort in healthcare. People may be plenty comfortable with chatbots online, but the comfort levels start to drop when thinking of actual physical robots taking care in their hospitals. Whether AI will succeed in the future remains contingent on how well patients are reassured, which is why further research needs to be carried out so that all potential ethical and implementation-related consequences can finally occur [14].

Nowadays AI is used throughout healthcare, as part of complex clinical systems and has a major influence regarding drug discovery especially in transcriptomics and bio simulation. While they are complicated to many, healthcare AI regulations serve an important purpose of protecting patients and providing a high standard of care. An awareness of AI's potential dual use implies a requirement for ethical instruction and mechanisms to report misuse. One can always say that AI applications should be tested with other demographics as well in order to catch and avoid those biases. Key considerations will need to relate how AI products in scope are defined clear criteria for software updates and monitoring, limits on how these can be separated out as follows the proper embedding in healthcare processes will involve a trade-off between amount of data required by AI algorithms vs. the interests underpinning data protection regulations [15].

AI is disrupting the healthcare industry with cheaper methods than its traditional equivalent. AI is expected to eliminate wastage and enhance affordability of healthcare. Thus, AI therapy has larger monetary benefits over AI diagnostics, these include improvements in measuring and diagnostic accuracy of established mechanisms but not only images for disease detection. Its integration with ML and Internet of Things (IoT) further strengthens AI being used in healthcare. Cost-effectiveness studies are an important element in the evaluation of corporate management and emphasize that artificial intelligence-based solutions for automated diagnosis or disease evolutionary stages categorization. One of the many benefits to AI is that it can advance predictive algorithms in cardiovascular disease risk estimation with incorporation of image-based phenotypes [16].

Figure 2.5 depicts a Machine Learning-based system’s architecture

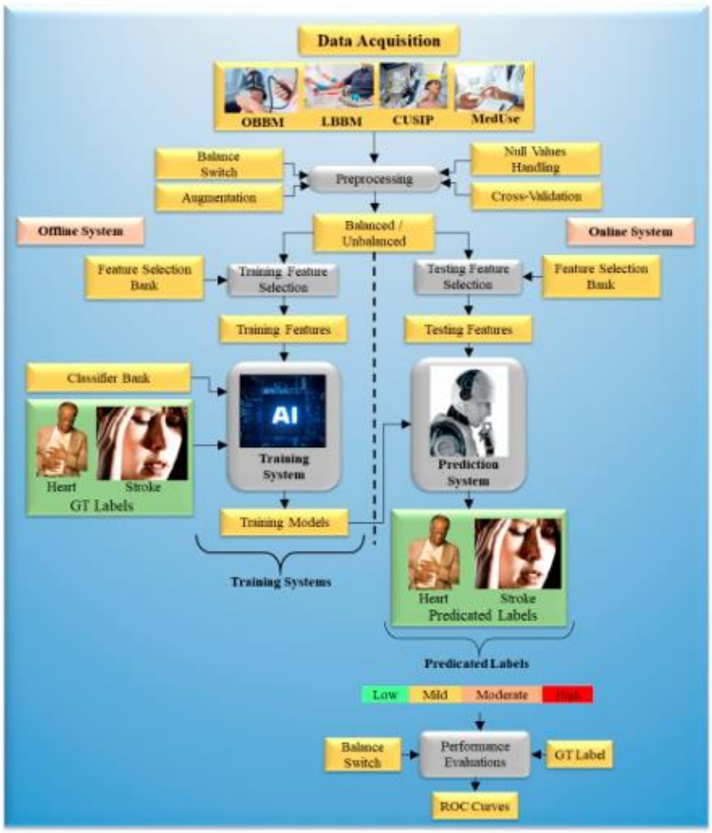

Figure 2.5 – A Machine Learning based system's generic architecture
[16].

Regarding research topic distribution in AI healthcare literature, a relative shortage exists regarding “ethics” and far fewer studies focus on human emotion or trust compared with those focusing solely on ethical impact. We need systematic ways to understand how trust is built as AI applications are developed. Confident results rely on an in-depth insight into user characteristics and attitudes, as well as a more detailed understanding of the processes of trust formation that includes both qualitative and quantitative methods. Language prejudice and undervalued research specific to other languages highlight the importance of an inclusive approach for promoting moral, reliable AI applications in healthcare [17].

The fundamental challenge to the wide practical implantation of AI in healthcare is, that doctors and healthcare workers are not familiar with it. It is difficult to compare how different professions within the healthcare industry see AI since practitioners have different levels of experience, knowledge, and acceptance. Closing this gap in knowledge and encouraging cross-disciplinary collaboration is crucial if we want to leverage the power of AI to improve outcomes for patients [18].

Due to a global increase in public and commercial investments on artificial intelligence, Japan has emerged as another major player particularly in the healthcare sector, the intention behind Japan's ambitious AI investments is providing a supportive regulatory framework. However ethical concerns such as bias, privacy, and the need for human oversight persist. Problems include insufficient attention towards ethics, little focus on making AI sustainable and responsive to the public good or even less transparency about the depth of a committee that coaches ethics. The combination of an aging population and tech are causing serious issues with the healthcare system in Japan thus complicating the interaction between AI, ethics & their applications in healthcare [19].

Medical systems must carefully undergo through a thorough review to ensure that the AI solutions deployment is both safe and ethical, these must be effective techniques that increase positive effects and decrease negative ones. Since these AI advances are complex, any practical implementation science approaches will need to consider context-dependent differences in model performance. The most important step will be to proactively eliminate bias and limit iterative customization based on the problem [20].

2.4.2 Computer Vision

Computer vision is a vibrant field which has a lot of potential and falls under the category of artificial intelligence. In computer vision applications, for instance, the form of the human body may be mapped on video recordings by computer algorithms in the case of human posture estimation and movement analysis, using for example skeletal models. This technical ability allows real time tracking and more directly double-checking human motion. Thus, one can gain a full understanding of biomechanics. Computer vision analysis can extract specific objective and statistical information from videos, which is very helpful for the clinical evaluation and motor function assessment. Furthermore, computer vision analytics plus video capture together not only find vulnerable digital endpoints but also open new opportunities to evaluate emerging therapies in the future. This could fundamentally transform the area of human movement analysis and provide the basis for a new objective, quantitative approach in clinical assessments and therapeutic interventions [21].

Machine vision and computer vision are both types of visual intelligence, but they each perform different roles. The distinction is that computer vision aims to reproduce visualizations of perception on the level similar to human vision, while machine vision attempts for processing and extraction of information in numerical form necessary for machines. There is a plethora of use cases where the field of computer vision is harnessed to provide visual surveillance. Those scenarios range from transportation, security and medical services to robots. What is even more impressive, however, is its superior performance to human vision in dangerous or tricky non-visual situations.

Convolutional neural networks are crucial to Computer Vision with superior results in image and pattern recognition. In the 1960s and 1970s, research within it grew to include three-dimensional scenes when MIT's Artificial Intelligence Laboratory made use of its findings working with three-dimensional photographic data. This historical path positions computer vision as one of the most renowned research areas in AI and visual perception, signifying continued success [22].

Computer vision is indispensable in the realm of upper limb rehabilitation using robotic devices as it assists with increasing efficiency and precision. A new sensor system based on accurate wrist location estimation utilizing the OpenPose library (open-source software) to track local motions more easily and sophisticated algorithms has been implemented in discovering the wrist area during the rehabilitation process. Extensive experimental assessments have been carried out to determine the efficacy of this technology, closely examining the computer vision algorithm's performance. The algorithm's expertise at filtering coordinate values from the video camera is one outstanding feature that demonstrates how it may improve and enhance the data for an upper limb rehabilitation experience that is more responsive and dependable. These systems, that combine advanced algorithms with computer vision constitute a significant development in the field of upper limb rehabilitation robots and could serve as an underpinning layer for future developments [23].

A recent paper presented a new method for remote surveillance of body joints using computer vision, in order to attempt to change the paradigm physical therapy practice with rehabilitation, the suggested method uses a modular neural network design that has two main sub-modules, one for checking the accuracy and another to detect the physical workouts, the purpose is about recording the motions of patients via a regular camera, and then the use of OpenPose once again derives joints exactly on each frame, also kinematic data including joint angles are saved for training and testing. Furthermore, the technique shows flexibility, by including more movement varieties to broaden of daily actions and allowing the measure module in such a use case (so that acts be performed wrongly). This novel synthesis of kinematic data, computer vision and modular neural networks could have broad implications for further development in automated monitoring tools used by remote physiotherapy. It is a comprehensive, automatic way to make rehabilitation treatments even more accurate and effective [24].

Figure 2.6 depicts how the hip extension exercise should be performed.

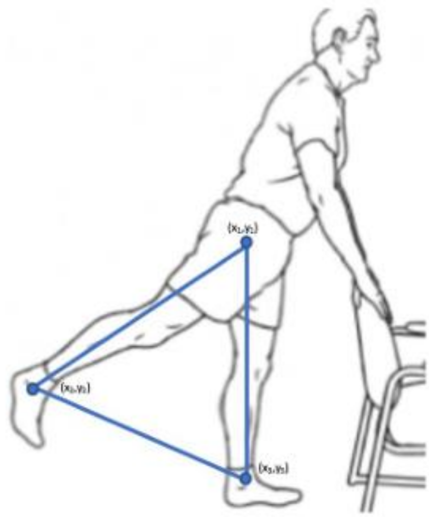

Figure 2.6 – Calculation of joint angle in the hip extension exercise [24].

The angles are calculated using trigonometrical functions combining three joints to the get the pretended joint angle.

Within the field of virtual rehabilitation services, computer vision is a key technology that is coordinating a paradigm-shifting method designed to assist the patient. This amazing machine is the answer to a much more correct and flexible rehab, allowing any movement of the patient or training posture verified immediately. One significant benefit is that it obviates the need for external markers, commonly employed to capture motion which is essential in effective patient recovery and comfort.

For remote patient care in the context of physical rehabilitation, especially if there is no actual presence or physical simulation possible, computer vision is a major improvement and far easier to operate. Additionally, computer vision enables seamless integration with augmented reality to provide personalized and interactive digital therapy that enhances recovery. A further complementary system, this time extremely similar to and co-existent with maximalism movement analysis in flexibility of human led intervention could well provide an insight for how computer vision drives futuristic interactive technology health solutions [25].

A new human activity detection system emphasizes computer vision integration, demonstrating how this field can be a game changer when it comes to understand, recognize and deduce the actions done by humans. The newness of this technology delves beneath the surface by examining, in exquisite detail, key-joint angles (knee flexion and extension), gaps (in part to demonstrate muscle contractions or laxity) as well as slopes between significant joint movements. This is interesting because it solves many drawbacks of traditional sensor networks and offers a more flexible, efficient alternative. Although its use is acute, computer vision integration in these systems could revolutionize senior

assisted living, they even help in monitoring behaviors creating responsive and adaptable environments consequently allowing these solutions with computer vision capabilities to offer a better level of well-being and quality of life for senior citizens [26].
An innovative computer vision technique has been used to estimate the Movement Disorder Society Unified Parkinson's Disease Rating Scale (MDS-UPDRS) scores for "arising from chair," an assessment of mobility in patients with Parkinsons's disease (PD). This novel approach uses location estimation data acquired from monocular videos recorded inside medical locations. A data-driven ordinal classification system that leverages random forest classifiers is developed via a rigorous training procedure, enabling the measurement of Parkinson's patients' ability to fulfill this task with high accuracy. Interestingly, this automated technique provides an increased objective and consistent evaluation tool by perhaps discouraging the human mistakes included in typical physician assessments. Beyond therapy, the method is well suited for use in clinical trials and remote home monitoring conferring great versatility enabling assessment improvements that are essential to advance precision of Parkinson's disease assessments [27].
Recent research presents a computer vision-based algorithm for estimating human position from Microsoft Azure Kinect cameras inside cars to monitor tiredness. It utilizes both convolutional neural networks as well traditional machine learning techniques to predict levels of tiredness. Remarkably, the proposed method might be able to predict fatigue-related internal and external load variables with reasonable accuracy for several output measures. This helps in enhancing human posture assessment accuracy through Microsoft Azure Kinect cameras and builds prediction models on them more effectively. In addition to its technical prowess, the method also is highly practical for real-world use and provides a way with which coaches or players could receive constructive feedback, in sports and physical activities the use of this technology can make possible smart monitoring systems to track performance levels for better general results, or even optimize training based on tiredness measured through computer vision algorithms [28].
Computer vision technology is the basis of this e-rehabilitation system, which marks as a significant breakthrough in therapeutic treatments. The sophisticated tool imbues a dynamic and interactive component to the healing proceedings thanks to its ability of enabling real-time monitoring and analysis of therapeutic actions with computer vision functionalities. Surprisingly, the system relies on a commercial RGB-D (Red-Green-Blue and Depth) device for computer vision processing using color as well as depth information about patient motions, this dual-mode analysis helps to undertake more specific evaluation of therapeutic workouts, and it enhances the accuracy of movement measurement. The virtual rehabilitation system will allow healthcare professionals to seamlessly integrate computer vision insights into how patients are performing. This encourages flexible and personalized treatment, which could lead to improved results for patients [29].

Figure 2.7 depicts a system made up of an RGB-D camera linked to a laptop, a database that is only accessible by clinical personnel, and an algorithm capable of analyzing the captured frames

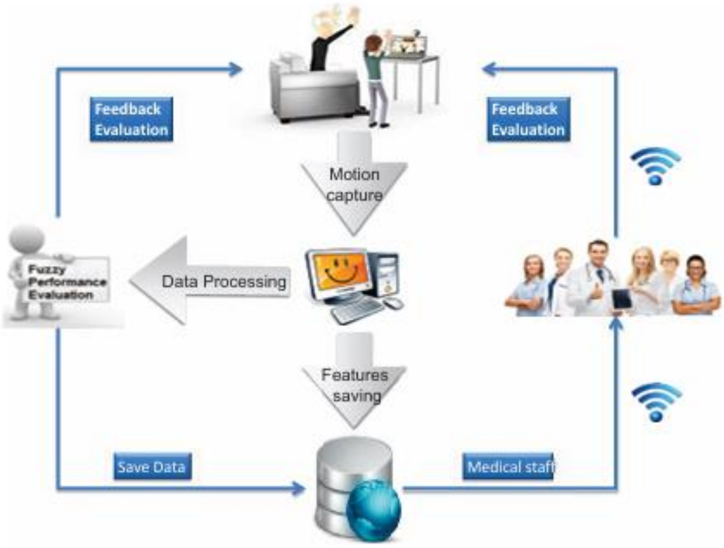

Figure 2.7 – Example of a system workflow [29].

As evidenced by devices like Azure Kinect from Microsoft the RGB-D sensor has fostered a lot of innovative computer vision research. These sensors that combine depth data with classic RGB information gained a lot of interest in the field of biomechanical movement research. This shows the inevitability of depth sensors with respect to marker less 3D motion capture algorithms, which is a huge shift from traditional ones demanding external markers. In order to drive home its commitment of making real world applications for the technology, Microsoft has dropped a real-time algorithm that can be used in conjunction with the Kinect sensor setup right into practical applications. Random Sample Consensus (RANSAC) is a popular method to estimate model parameters, and it works well with data from sensors like RGB-D cameras. By merging these methods and technologies, the ability of computer vision to support complex analysis in fields such as biomechanics and human posture estimation can be improved [30].

2.4.3 Pose Estimation and Activity Recognition

There are two main types of approaches for pose-estimation, detection based, and regression based. While detection-based methods provide heat map-based solution and regression-based solutions maps input pixels with joint coordinates, well-known for their separability. Deep architectures improve accuracy by using high-resolution 3D representations. Skeletal representation is enforced by lower resolution, and continuous regression function. Pose refinement maximizes pose estimation for practical use. Activity recognition using videos faces challenges that are usually handled the classical way such as manipulating visual features or body joints. Other features that are unique to the model is 3D convolution, which uses more memory than other techniques, and a two-stream network, where RGB images are merged with optical flow maps, such drawbacks are avoided by combining pose estimation and activity recognition concurrently. Skeleton data, provided by Microsoft Kinect, is one of the key features in 3D activity recognition. Thanks to a combined multi-mode strategy, combining skeleton data with visual cues has significantly contributed to improving recognition. An appearance-based method extracts local features from visual features and probabilistic maps to construct a complete system for video analysis [31].

The system undertakes real-time 2D pose estimations by analyzing video recordings of targeted activities, yielding valuable skeleton data crucial for determining the optimal sensor location. In addition to the very simple task of estimating poses, it further assists in data anonymization that serves for privacy policies and ensures security during analytics. Furthermore, it is also context aware and provides multi-modal classification which shows how flexible the solution could be proven useful across various use-cases. This integrated framework reduces these obstacles and can therefore serve as a general solution for the joint inference of real-time pose estimations without privacy issues into multimodal classification pipelines. Sensor-based Human Activity Recognition (HAR) employs Inertial Measurement Units (IMUs) to discern and classify movements. The application of HAR extends across various domains, including healthcare, sports, and smart environments, in order to enhance recognition accuracy. Multimodal HAR integrates data from multiple sensory sources. HAR effectiveness is closely tied to the optimal placement of sensors, a critical factor influencing classification performance. Real-time 2D pose estimations derived from video recordings can be used to guide sensor placement so that they are best positioned for their target use like a joint or a body part, collecting more accurate and relevant data. This collaboration between inertial sensors, multimodal data integration and informed sensor placement displays the rich context-awareness functionality of Sensor-based Human Activity Recognition which accounts for its potential to be a powerful overseer in large scale usage [32].

The underlying architecture focuses on multi-dimensional feature analysis aimed at marker less human pose estimation. It builds a comprehensive framework that also recognizes human activities in addition to two-dimensional skeletal pose data by using three-dimensional skeleton data. In the context of HAR, the architecture is designed uniquely by combining with activity recognition, visual attention and pose estimation. This considers a three-dimensional HAR and human pose estimation approach that leverages deep learning by arising with an integrated multi-task architecture. Additionally, a new method to estimate the pose of robotic construction equipment is presented in video data which demonstrates that this overall framework can be easily adapted to various tasks such as human pose estimation and action recognition, or object pose estimation in industrial settings.

The recently developed KPE-DCNN structure differs from other activity recognition models in how the key point extraction is carried out integrating deep convolutional neural networks, his innovative model leverages the RMSProp optimizer to fine-tune hyperparameters, thereby enhancing overall performance. Using key point extraction and DCNN together in the activity recognition process is a move that strategically combines meaningful feature generation with motion related information.

Through meticulous hyperparameter tuning with RMSProp, the model attains commendable results, showcasing its effectiveness in comparison to established benchmark algorithms. This model shows a promising path in the field of activity recognition providing higher accuracy along with robust feature extraction capabilities by KPE-DCNN implementation [33].

Human activity identification and posture estimation are attracting corresponding applications of video-based recognition and human-computer interactions. However, we have yet to establish and test its speed and accuracy. What normally happens is that the pose estimation and the subsequent activity identification are done independently. Though naturally conducive to it, little work is being done on utilizing postures in order to assist activity recognition with a comparison of concurrent problem solving. Recently, deep neural networks have been exploited to improve activity recognition using human postures, yet the pose estimation and activity classification are performed in parallel. Given their close relationship, the posture estimation approach and the activity detection method can be processed simultaneously to obtain improved accuracy if this difficulty is resolved [31].

Most works that address pose estimation and activity recognition are used separately. While posture and activity identification are strongly correlated, it is yet to be found any prior research to simultaneously solve both the problems of activities recognition, and even though video data is growing, automated detection and understanding human action still largely don't work. This is mostly due to several issues that are exclusive to detection tasks, such as the challenging nature of what is seen in terms of camera motion, a greater degree of variability in the way humans apply ideas, changes in perspective, background noise, and so on [33].

2.4.4 Serious games in physical rehabilitation

Combined with their ability to monitor joint trajectory, intuitive interaction (no sensor required) and accurate detection of diverse activities greatly enhance the experience for both physical therapists as well patients at home, Kinect data is used to develop custom training regimens, serious games with motion-based gameplay enhance interest and efficacy by decreasing recovery times. Perhaps the most promising advancement in physical therapy comes from combining Kinect technology and virtual reality tools to develop personalized, interactive experiences that improve range of motion and accurate motion detection [34].

Figure 2.8 depicts a system composed by a Kinect device, a server, composed by an API and a database and lastly a mobile application on the client device.

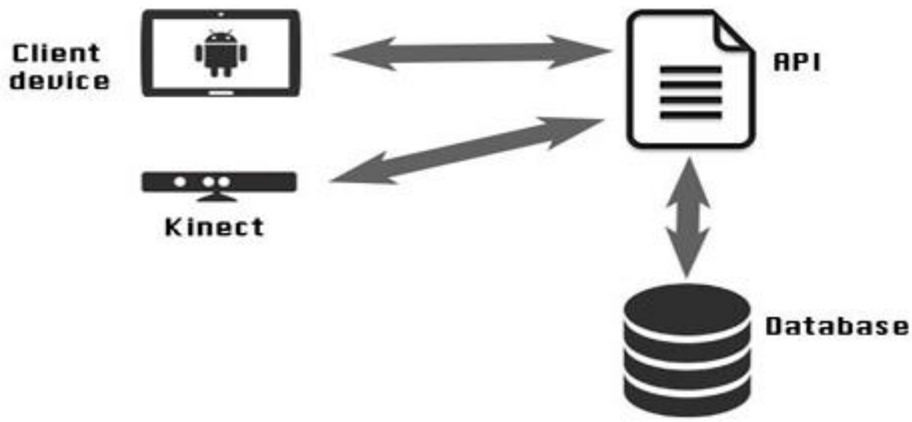

Figure 2.8 – Example of the architecture of a system using a Kinect device [34].

The Microsoft Kinect system has a built-in accurate measure of full body joint angles, providing real-time whole-body recognition excellent for training and the unbiased evaluation of physical treatment outcomes. Remote sensing capabilities allow the continuous monitoring of mobility of the users in a remote way. This system is created to develop upper limb rehabilitation workouts using the virtual reality (VR) and serious games. Its aim is to improve the progress of motor therapy by augmenting patient engagement. Therapists can also keep their patient records using an app which increases the tractability of information and reduces a bridge between communication [35].

Figure 2.9 demonstrates the interaction flow and the procedure between the patient and the physical therapist

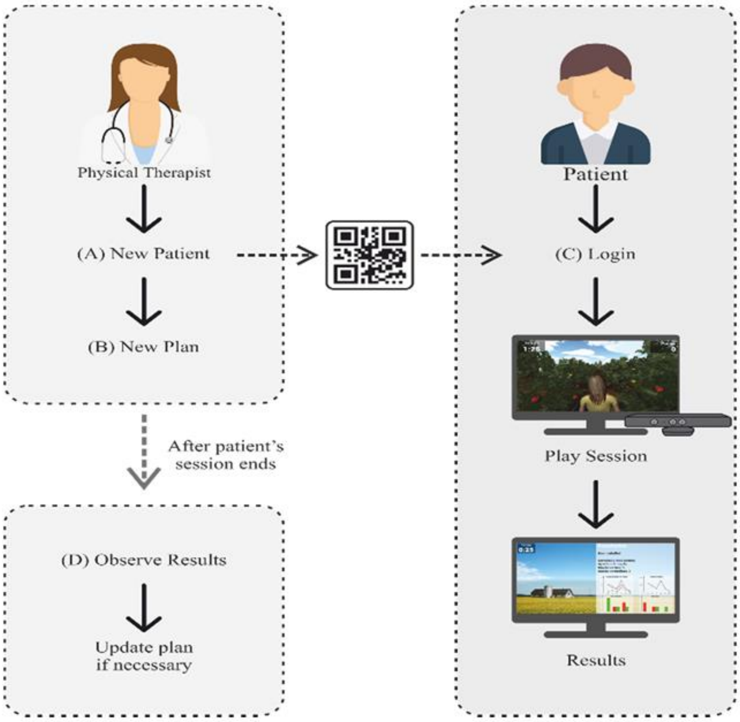

Figure 2.9 – Interaction flow between the Kinect Serious Game (patient) and the mobile application (physical therapist) [35].

The system uses wearable technology and flexion sensors to capture rotation values, linear accelerations, and angular flexion and extension data to accurately estimate position for physical therapy applications, and when combined with VR video games, it enhances patient engagement and activity recognition. By bringing together IoT and VR technology, it is possible to record progress of patients staying at home. This approach not only makes sure that the workout is personalized, it helps increase a patient's own evaluation as well as their participation and motivation to become better which further aids in rehabilitation outcomes [36].

3. Methodology

In this study it is explored the human posture estimation approach, with particular attention to the combination of pose estimation methods, machine learning algorithms, and MediaPipe, it provides a flexible and configurable framework for constructing perceptual pipelines. Machine learning typically further increases the accuracy of pose inference by recognizing patterns. The purpose is to allow comprehensive understanding of human pose analysis techniques by describing the methodologies behind these technologies.

3.1 Data acquisition

The Kinect sensor is an important device for posture estimation in rehabilitation activities because it captures precise joint position data with excellent quality. It can also produce detailed 3D reconstruction of human body joints, which make the action detect smoothly in combination with wearable devices. It integrates in serious games with Kinect sensors enhancing patient motivation through entertaining rehabilitation scenarios. Kinect data is used by physiotherapists to help evaluate patients, along with providing them with personalized rehabilitation plans resulting in maximum results, especially for stroke survivors who stand to benefit the most from self-training at home. The integration of sensors for motor and balance evaluation will further improve the effectiveness of rehabilitation. A 3D motion detection is achievable with the help of a Kinect sensor needed as alternative motor evaluation, this increases precision and patient activity towards rehabilitation [37].

Figure 3.1 shows human movements being captured in an unobtrusive way during the physical rehabilitation exercises

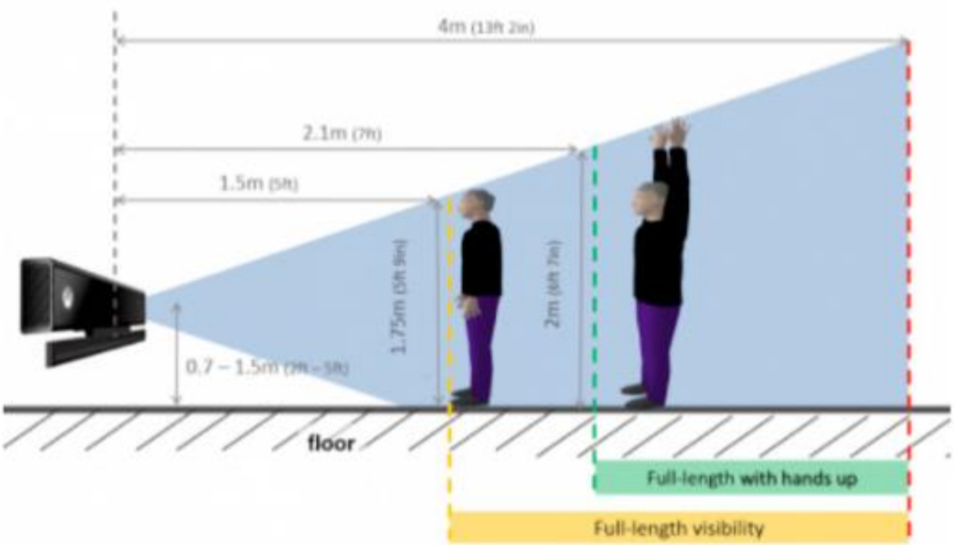

Figure 3.1 – Kinect sensor recording human movements [37].

For this study, data was collected in a physical rehabilitation clinic with the assistance of three physiotherapists, the data was collected in the form of video to capture the movements of the chosen rehabilitation exercises. The data was recorded using an Azure Kinect DK camera, set at a resolution of 1080p and a frame rate of 30 frames per second, no depth sensors were used, only the RGB visual sensor. This setup helped ensuring high-quality video data for further analysis of physical rehabilitation exercises, providing precise and trustworthy exercise execution from the physiotherapists in order to obtain reliable data for the purpose of the study

3.2 Pose Estimation with MediaPipe

Human Pose estimation is one of the most fundamentally challenging tasks in computer vision. The goal of human posture estimation is to build a universal human posture representation using continuous media files such as images and video files while locating the various body parts of humans. Posture estimation of human body has been one of the basic devices in related areas such as human-machine interaction and extended (virtual) reality.

The computer vision project may also be useful in sports analysis where the demo can be used to automatically track and evaluate the human motions in real time. Later advancements in deep learning have made it possible to detect and recognize human poses with high efficiency and accuracy. Despite a great progress being made in this field, the suggested strategies still face some serious challenges and the key factors for such practices as the human appearance, noisy backgrounds, poses, occlusions etc.

Human posture estimation has progressed significantly in recent years, only very recently, a paper of Kim (2023) presented an optimization method on MediaPipe and Humanoid Model to extract the human posture. The methodology suggested contains two main segments that are MediaPipe and Humanoid Model. MediaPipe uses deep learning models to predict the distinct poses from a dataset of images. Detection and recognition of human joints plays a critical role in understanding human posture the exact identification of these key points is supported by the MediaPipe system [38].

Selecting MediaPipe in this study for pose estimation is mostly due to its proven high-performance in accuracy real-time physical landmark detection, the formidable real-time posture identification capabilities of MediaPipe are backed by many research papers that use MediaPipe for analyze and monitoring human motions. To perform the physical rehabilitation exercises and experiences of this study, it was necessary to keep an accurate identification of physical landmarks, which were automatically evaluated by means of its sophisticated machine learning models. This choice to use MediaPipe is based on its performance history in related problems like pose estimation.

Occlusions of body joints, multiple degrees of freedom and realistic human movement variability get good results in position estimate/tracking over video frames. Fortunately, in recent times pose estimation results have significantly been enhanced directly due to modern advancements in computer vision applications specifically in the discipline of artificial intelligence.

One of the top solutions in this area is MediaPipe, a machine learning system designed to make sense of subjective sensory input. In real-time, up to 33 skeleton points (body joint landmarks) can be identified and tracked from RGB inputs using the MediaPipe due to each frame being processed as an individual RGB image. Some other face landmark prediction using BlazeFace and hand landmark prediction with MediaPipe Hands has also demonstrated good results on this method based upon an application of detectors and trackers.

The actual MediaPipe framework is impressive, being able to pick up points of posture on an image and even skip landmarks detected in the last frame to adapt its tracking to a new set of images. Its characteristic of long spaced consistency helps in this manner and successfully localizes landmarks in the present and following frames, which makes it extremely reliable for accurate posture estimation in real time application [39].

Human pose estimation technology is under active research in domains such as across sports, entertainment, home based workouts for seniors at home, gesture control, surveillance and even metaverse avatars globally.

MediaPipe Pose (MPP) is a class of pipelines being built to connect Machine Learning experiences and process cognitive data, such as video [40]. Figure 3.2 shows how BlazePose is used in MediaPipe Pose to extract 33 forward-facing 2D landmarks for the human body.

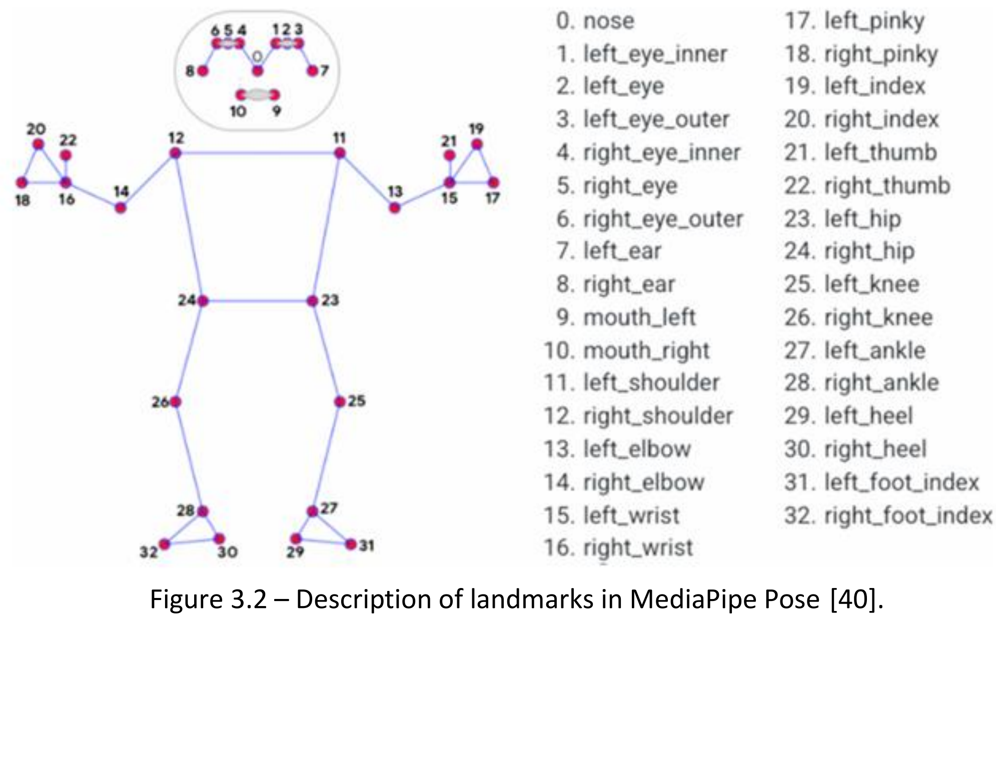

Figure 3.2 – Description of landmarks in MediaPipe Pose [40].

New techniques for evaluating human posture are continuously being created and perfected on a daily basis. Human-pose estimation has achieved new levels using only a basic web camera and computer vision techniques, so, naturally with computer vision, human posture estimation is now an interesting area for research. In human pose estimation the key is to model the human body as best as possible. In other words, taking a picture and detecting or working out which are the skeleton joints and how good is the stance. In most tasks, the procedures refer to kinematic models representing a shape and structure of the body through the joints and limbs [41].

3.3 Machine Learning Algorithms

A powerful subset of AI, Machine Learning (ML) has been adopted across the globe, especially in areas of science and technology for instance health care, medicine, robotics, smart transportation and digital twin technology [42].

Random Forests and Artificial Neural Networks have become admired machine learning algorithms to perform predictive modelling task and extract information from datasets having large number of features in data analysis. This combined with the fact that both algorithms offer their own unique advantages in terms of performance, interpret sensitivity and flexibility makes them extremely useful in various tasks like classification, regression or even just plain pattern recognition.

3.3.1 Random Forests

Random Forests (RFs) are used for their robustness to overfitting and makes important features easy to interpretate. Random Forests are best for key features analysis and even though they normally work well with high-dimensional data, they can be slower due to the increased computational cost.

They are a ML algorithm that is widely practiced for classification tasks and works very well with human activity recognition. It integrates several decision trees to be able to manage complex, non-linear relationships as well as to reinforce prediction accuracy. Random Forest is a go-to method for many competitions because it so robust to missing or noisy data, can handle completely non-linear data, and tends to be extremely good against overfitting, and is also easy to implement [42].

Random Forests turn into effective classifiers and regressors if you increase the right amount of randomness. The framework also identifies how the correlations and power of individual predictors contribute to the prediction ability of random forest [43].

3.3.2 Artificial Neural Networks

Artificial Neural Networks (ANN) are preferable when the problem is from more complex patterns or requires higher flexibility in learning non-linear relationships. They are well suited to model very large variable spaces and complex, hidden target generated patterns that simpler models might not be able to pick up on.

ANN, a subset of deep learning, which is itself a subset of machine learning are now being implemented for their innate scalability and ability to learn and adapt from raw data such as in context human activity recognition. An ANN is composed of a large number of processing elements with their connections. What ANN do well is that it can process sequential sensor data, which makes them a good option for feature extraction from this type of time-series data. More flexible than traditional ML methods as they can adapt to new data [42].

3.4 System Architecture

This section presents a diagram illustrating the system architecture used in this study.This diagram depicts a process for activity recognition using 3 phases, including data acquisition, data processing, and predictive modeling.

Figure 3.3 depicts this study system architecture.

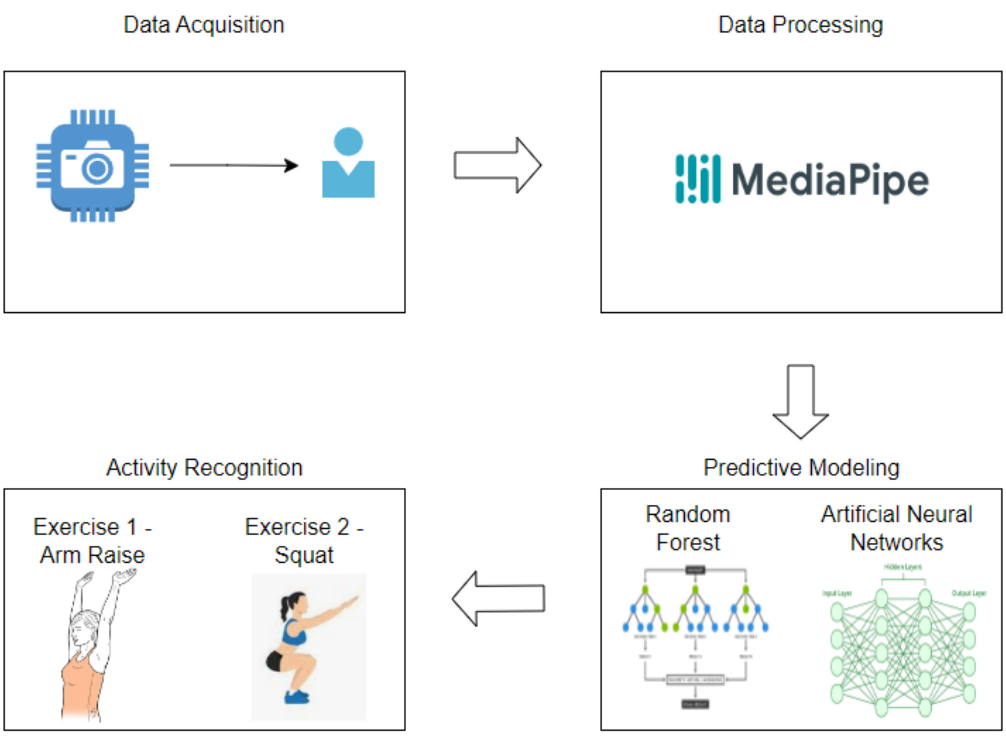

Figure 3.3 – System Architecture

- **Data Acquisition**: An Azure Kinect DK camera collects visual data in the form of a video of a person performing exercises.
- **Data Processing**: The visual data is processed using MediaPipe, for the extraction of the key features from the video.
- **Predictive Modeling**: The extracted features from the video are considered as inputs for machine learning algorithms such as Random Forest and Artificial Neural Networks to predict the performed physical activity.
- **Activity Recognition**: The system recognizes and classifies the exercises, such as Exercise 1 - Arm Raise and Exercise 2 - Squat, based on the predictive models' output, this classification is crucial for providing accurate feedback about the user’s movement.

4. Experimental Tests and Results

Rehabilitation is key to reducing cerebral stoke complications, and continued patient care means quicker improvement. These exercises may passive or active, as well as resistance training and balance or gait exercises. This matching of behavioral rehabilitation to stroke stage and type of exercise is supported by experimental studies, as well as in one study shows how early intervention often appears more effective at behavioral recovery [6].

Timing for stroke rehabilitation is hyper-early (24 h), early (1–7 days), subacute (7d—3 month). While the importance of early rehabilitation is generally agreed, there has been recent discussion about the timing and methods. While a few studies indicate that early intervention may worsen neurologic deficits, others suggest it can shorten recovery and complications [44].

The problems in exercise intervention delivery include economic barriers, therapist-to-patient ratios and a shortage of experts. Telerehabilitation designed by electronic media might overcome these barriers in stroke rehabilitation, which provide services evaluation, intervention and education. Telerehabilitation (including virtual reality exercises) may improve cognitive status and possibly pain, although overall effectiveness is not well supported by the evidence [45].

4.1 Tests

This section covers the testing that was done to examine how well the system tracked and analyzed rehabilitation exercises using computer vision. To determine the movement that was performed, two key experiments were made, one for classification of exercise movements using joint angles and the other for detecting the movement accuracy using joint coordinates. Both experiments used MediaPipe Pose, a machine learning framework by Google that extracts key landmarks from video footage and analyze body movements in real time.

4.1.1 Exercise 1 – Raise your arms (shoulder flexion)

The movement of the shoulder wrists and arms joints occurs in the sagittal plane, against the pull of gravity, the shoulder flexors contract concentrically from 0 to 180 degrees.
The glenohumeral joint is the primary site of movement, but the acromioclavicular, sternoclavicular, and scapulothoracic joints all play a role in the action. Therefore, concentric contraction of the shoulder flexors is primarily responsible for the elevation of the upper limb. The serratus anterior muscle, which oversees the scapula's inferior glide, is more activated at the last degrees of its accessible range of motion by concentric contraction as well. It is crucial to consider compensatory

movements of the spine and rib cage, which might be misinterpreted for a wider range of shoulder flexion.

Movement

- Starting Position: Arms along the body (Shoulder 0º / Elbow 0º) - Support base aligned with the shoulders.
- Final position: shoulder 130º flexion/ elbow 0º - Support base aligned with the shoulders.

Considerations

- Arm must always follow a line parallel to the torso.
- Hand/Wrist (depends on the functional task to which you want to associate the movement).
- Avoid lifting the shoulder during the movement.

Figure 4.1 and Figure 4.2 demonstrate the initial and final position from exercise 1 respectively

Figure 4.1 – Initial position exercise 1.

Figure 4.2 – Final position exercise 1.

4.1.2 Exercise 2 – Sit/Stand (Squat)

The movements of the hip, knee, and ankle joints occur in the sagittal plane. The movement begins with a slight flexion of the trunk and hip (eccentrically) to transfer the center of gravity forward. Subsequently, the hip flexors and trunk extensors perform an anterior tilt of the pelvis, and simultaneously, the knee flexors slightly flex the knees to initiate the descending movement.

The descending movement is executed through the flexion of the hip, knee, and dorsiflexion of the ankle joint (all with reversed origin and insertion points). Hip flexion is performed eccentrically by the hip extensors and is accompanied by slight forward flexion of the trunk, also executed eccentrically by the trunk extensors. Knee flexion is performed eccentrically by the knee extensors, and ankle dorsiflexion is performed eccentrically by the plantar flexors (and toe flexors). During this phase of the movement, there is isometric contraction of the hip adductors and abductors, as well as the ankle invertors and evertors, to maintain lateral stability in the various joints. After reaching 90 degrees of knee flexion, a posterior tilt of the pelvis occurs, initially eccentrically by the hip flexors and trunk extensors, followed by concentric contraction by the trunk flexors and hip extensors.

Movement

- Initial Position: Standing (hip extension at 0 degrees, knee extension at 0 degrees, ankle in a neutral position) – Base of support aligned with the shoulders.
- Final Position: Seated (hip flexion at 90 degrees, knee flexion between 100-110 degrees, ankle dorsiflexion with the foot supported on the ground) – Base of support aligned with the shoulders.

Figure 4.3 and Figure 4.4 depicts the initial and final position from exercise 2 respectively.

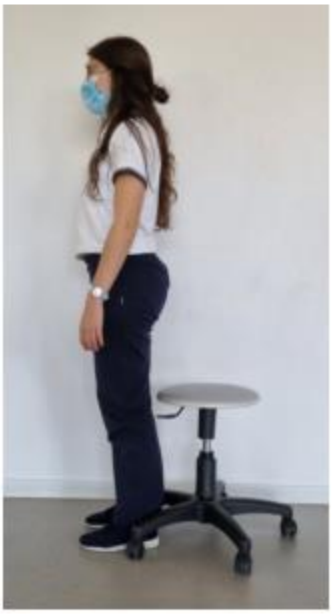

Figure 4.3 – Initial position exercise 2.

Figure 4.4 – Final position exercise 2.

4.1.3 Experiments

In this dissertation, two distinct experiments were conducted, each aimed at analyzing human body movements using computer vision techniques, with a particular focus on classifying arm positions as either "arms up" or "arms down" and squat positions as either “up” or “down”.

Experiment A: Upper and Lower Body Joint Angles Analysis

The Experiment A consists in the analysis of upper and lower body joint angles during exercise routines, the angles between the different joints (elbow, shoulder, wrist, ankle and hip) were calculated using trigonometric functions to evaluate body movements.

However, only shoulder, elbow and wrist joint angles will be considered for exercise 1, and hip knee and ankle will be considered for exercise 2, due to the nature of exercise classification.

In this study, a video recording of an individual performing exercises was captured to serve as the input data. The recorded video was then processed using the MediaPipe Pose framework to detect key landmarks within each frame. These landmarks were extracted as pixel coordinates, facilitating the analysis of the subject's movements.

Next, for the exercise 1, joint angles were calculated by determining the arctangent of the slopes between specific joints, allowing for a precise measure of the body's posture throughout the video. These angles were then used to classify a person's arm position, the system classified arm movements as arms up or arms down based on the angles of the two shoulder joints. Arms were described as "armsdown" when both angles were equal or less than 90 degrees and "armsup" when the angles were higher than 90 degrees.

For exercise 2 the system then used the calculated knee angles to classify the subject's posture as either "Up" or "Down", for both sides. When both knee angles were less than 90, the position was classified as "down" (relative to a crouched or bent-knee stance). Otherwise, it would categorize the position as "up" (indicating an upright stance). This categorization was useful for identifying the postural changes during the exercise.

The results were stored in a CSV file containing the calculated angles and classification outcomes. Also, the frames of the video were labeled based on these distinctions, and a video was stored in an output file for visualization and review.

This experiment showed that MediaPipe Pose is usable for live processing of upper and lower body model data, which could be useful in fitness and rehabilitation for mapping Increased accuracy movement.

Experiment B: Joint Coordinate Analysis and Classification

The second experiment focused on evaluating the positions based on joint coordinates rather than angles. Here, the system analyzed the relative coordinates of the arms, forearms, legs and the hip during exercise movements.

The input for this system consisted of a recorded video of an individual performing physical exercises, with each frame processed to extract pose data. Using MediaPipe Pose, important key landmarks such as the shoulders, elbows and wrists were identified along with pixel coordinates of each joint which was necessary for processing further. The system calculated the joint positions with respect to its adjacent joints and worked out their relative coordinates of the arms & forearms. This step facilitated the accurate tracking of arm movements across consecutive video frames.

For the exercise 1, based on these coordinates, the system classified the arm positions. Specifically, the arms were classified as "arms up" when the y-coordinates of both the arms and forearms were negative, indicating that they were positioned above shoulder level. In all other instances, they were considered to have their "arms down."

For exercise 2 the system categorized the posture of a subject as ‘up’ or ‘down’ by those whose hips have y-coordinates greater than others. We labeled it “down” if both left and right hip were above a particular threshold (y >= 710 pixels) Otherwise, the pose was categorized as “up”. After this, the joint coordinates and labels for intended movements were stored in a CSV file by the system for post-analysis. Visually, the model output was also overlaid on video frames: both with bounding boxes delineating key point heats and actual movements drawn directly over these categories in real time to improve interpretability.

This experiment demonstrated the advantage of movement analysis by joint coordinates to represent motion behavior for real-time visualization and labeling body movements. This study demonstrated its potential of MediaPipe in experiment's aspects, and sports science related applications such as performance monitoring, training e-health and movement correction.

For exercise 1, 5 volunteers participated in both experiments. For exercise 2, 4 volunteers participated in both experiments, the volunteers were qualified physiotherapists (acting as patients).

4.1.4 Model Configuration

For the random forest application, initially, the features with strong correlations to the target variable are dropped, and the dataset is split into 80% training and 20% test sets using *train_test_split ().* A Random Forest classifier is then built using 100 trees, and the *n_jobs=-1* argument was used ensuring parallel processing for faster computation.

For the artificial neural network, the architecture consists of an input layer with 8 features. The model has two hidden layers: the first hidden layer contains 12 neurons with a ReLU activation function, while the second hidden layer has 6 neurons, also using ReLU activation. The output layer consists of a single neuron with a sigmoid activation function, making the model suitable for binary classification.

The network uses the Adam optimizer with a learning rate of 0.01 and binary cross-entropy as the loss function, given that this is a binary classification problem. The ANN is trained for 200 epochs, with a batch size of 24. During training, 20% of the data is reserved for validation. After training, predictions on the test set are made, using a threshold of 0.5 to classify the results.

4.2 Results

This section presents the performance of the system on tracking and classifying rehabilitation exercises conducted in the tests. The results address the detection accuracy of the system in terms of joint angles and coordinates (both true positive and true negative), through machine learning algorithms like RFs and ANN.

Figure 4.5 and Figure 4.6 depicts the angles from the initial and final position in exercise 1, respectively.

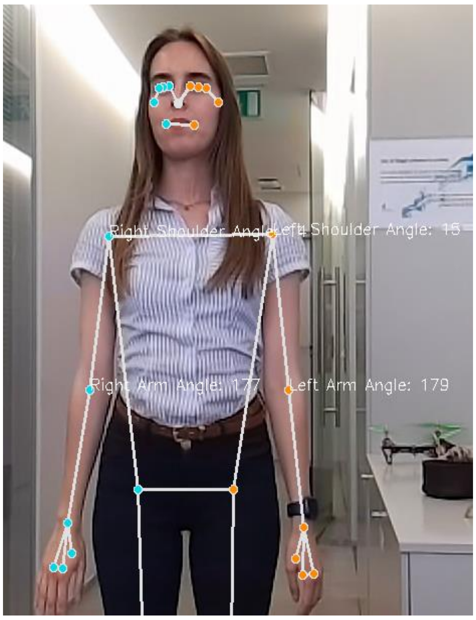

Figure 4.5 – Angles from initial position exercise 1.

Figure 4.6 – Angles from final position exercise 1.

As it is shown in Table 4.1 if the left and right shoulder angle is less than 90 the classification is considered “armsdown”, if the left and right shoulder angle is more than 90 the classification is considered “armsup”.

Table 4.1 – Exercise 1 classification

Left Shoulder Angle	Right Shoulder Angle	Class
<90º	<90º	armsdown
>90º	>90º	armsup

Figure 4.7 and Figure 4.8 demonstrate the angles from the initial and final position in exercise 2, respectively.

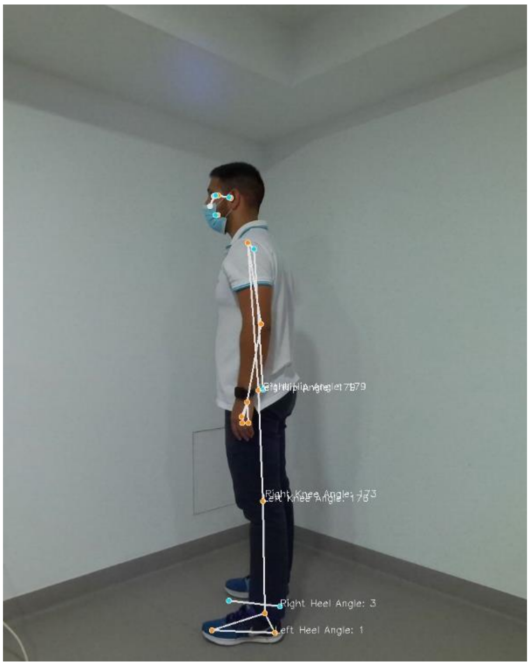

Figure 4.7 – Angles from the initial position exercise 2.

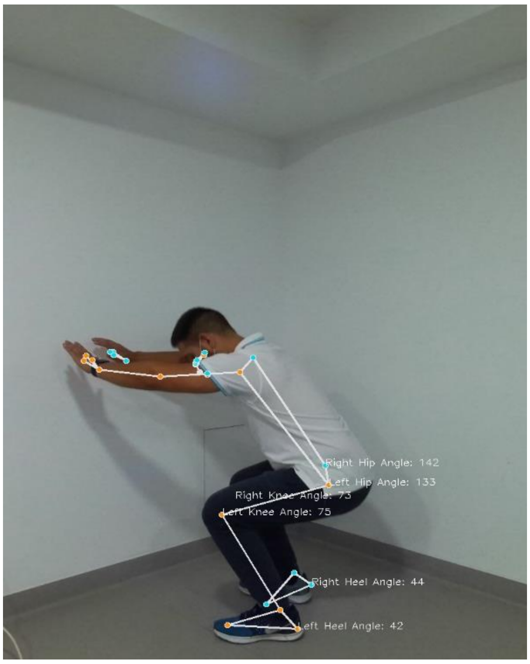

Figure 4.8 – Angles from the final position exercise 2.

As it is shown in Table 4.2 if the left knee angle and the right knee angle is less than 90 the classification is considered “down”, if the left knee angle and the right knee angle is more than 90 the classification is considered “up”.

Table 4.2 – Exercise 2 classification

Left Knee Angle	**Right Knee Angle**	**Classification**
> 90 º	> 90 º	up
< 90º	< 90º	down

Accuracy is a general measure of model performance, defined as the ratio of correctly predicted observations to the total number of observations. Precision, on the other hand, focuses on how many of the predicted positive observations were positive. The F1-score is the harmonic mean of precision and recall, providing a balanced measure of both metrics, particularly useful for imbalanced datasets.

The following subsections show the results achieved in these performance metrics averaged to every exercise for every dataset collected from the videos.

4.2.1 Model training exercise 1 (Experience A)

Random Forests

Table 4.3 depicts the results achieved by the Random Forest algorithm for the Exercise 1 – Experiment A.

Table 4.3 – Random Forests algorithm evaluation metrics value experience A exercise 1

	Precision	**F1-score**
Armsdown	0.82	0.87
Armsup	0.85	0.75
Accuracy		0.83

In terms of Precision, both classes achieved similar results (0.82 and 0.85 for “armsdown” and “armsup” labels, respectively). In terms of F1-score, the “armsdown” class clearly achieved a higher value than the “armsup” class (0.87 and 0.75 for “armsdown” and “armsup” labels, respectively). The overall accuracy was 0.83, which is a reasonable value when applying these kinds of algorithms on activity recognition tasks.

Artificial Neural Networks

Table 4.4 depicts the results achieved by the Artificial Neural Networks algorithm for the Exercise 1 – Experiment A.

Table 4.4 – Artificial Neural Networks algorithm evaluation metrics value experience A exercise 1

	Precision	**F1-score**
Armsdown	0.94	0.90
Armsup	0.82	0.85
Accuracy		0.88

In terms of Precision, the “armsdown” class achieved an higher result than the “armsup” class (0.94 and 0.82 for “armsdown” and “armsup” labels, respectively). In terms of F1-score, both classes achieved similar results (0.90 and 0.85 for “armsdown” and “armsup” labels, respectively). The overall accuracy was 0.88, which is a reasonable value when applying these kinds of algorithms on activity recognition tasks.

Table 4.5 depicts the results of the train and validation set for experience A exercise 1

Table 4.5 – Train and Validation set values experience A exercise 1

Train Accuracy	0.86
Train Loss	0.32
Validation Accuracy	0.86
Validation Loss	0.31

The train accuracy (0.86) and train loss (0.32) suggests the model is neither overfitting nor underfitting. Similarly, the validation accuracy (0.86) and validation loss (0.31) are consistent with training results, confirming the model's stability and effective learning.

Figure 4.9 depicts the loss / accuracy values and their convergence during the training process.

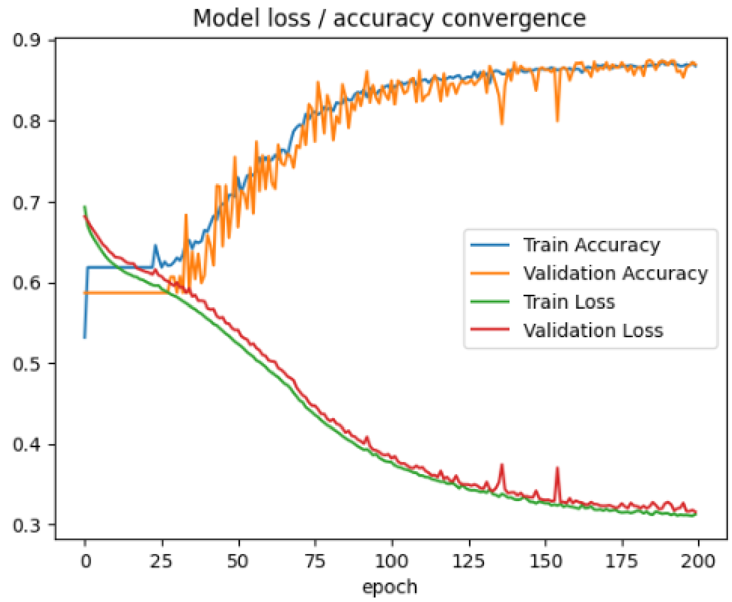

Figure 4.9 – Loss/accuracy graph exercise 1 experience A

It is possible to conclude that training process occurred smoothly, with no signs of over or underfit, achieving a good level of convergence in all metrics (train accuracy, validation accuracy, train loss and validation loss). At the end of the training process, the accuracy values were very satisfactory, achieving accuracy values of 0.88. It is possible to conclude that the training process occurred smoothly due to the low jitter.

Figure 4.10 represents a Roc curve with a score of 0.927

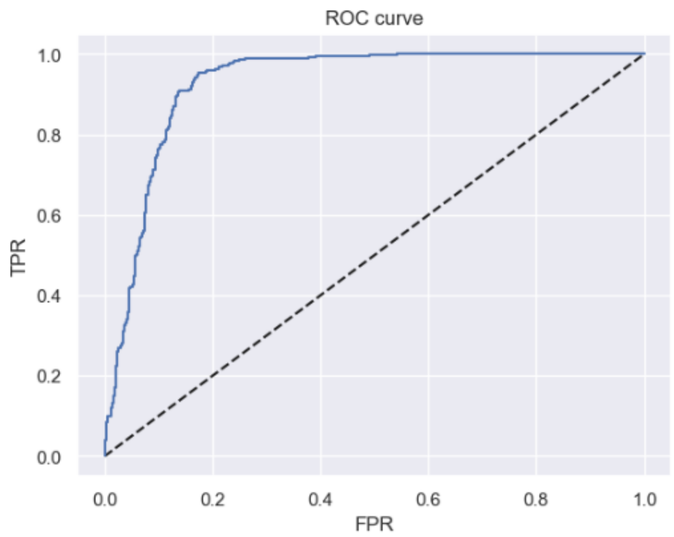

Figure 4.10 – ROC curve graph exercise 1 experience A

This ROC curve represents the trade-off between the True Positive Rate (TPR) and the False Positive Rate (FPR) for a classification model. The blue line reflects the model’s performance, while the diagonal dashed line signifies the performance of a random classifier. With a ROC score of 0.927 which means that it is able to correctly predict positive and negative cases at high rate, but better scores mean closer to perfect. The curve is very close to the top-left corner, indicating good classification performance with a low false positive rate and great sensitivity but could be improved a bit further by improving its accuracy.

A comparison of Random Forests and Artificial Neural Networks (ANN) performance measures provides some crucial information. The Random Forests model receives a precision score of 0.82 for the "Armsdown" class, whereas the ANN model achieves a higher score of 0.94. This indicates that the ANN model can detect more true positives for "Armsdown", so it is more likely to predict this class when it appears.

The Random Forests model is slightly better for the "Armsup" class as well, with a precision of 0.85 compared to ANN model's 0.82. This implies that Random Forests can manage “Armsup” class in a bit better way compared to “Armsdown”, but not heavily.

In general, ANN model outperforms Random Forests with accuracy of 0.88 vs 0.83 on average respectively. That tells us that the ANN model has a better generalization over different postures, because its more accurate when it comes to classifying "Armsup" or "Armsdown" images on all datasets.

Model Comparison:

- **Random Forests**: This model seems to have slight better precision for the "Armsup" class but way lower recall, resulting in a lower F1-score on this class. More importantly, visual inspection shows that in general it is less accurate when compared with our ANN model which suggests that it would have more misclassification.
- **ANN:** The ANN model outperforms in terms of metrics with a higher precision and F1-score for the class "Armsdown" as well as a better balanced distribution among predictions of the "Armsup" class resulting in a higher accuracy. This indicates that the ANN model better fits data patterns, most likely due to its greater capability to capture complicated relationships than Random Forests.

4.2.2 Model training exercise 1 (Experience B)

Random Forests

Table 4.6 depicts the results achieved by the Random Forest algorithm for the Exercise 1 – Experiment B.

Table 4.6 – Random Forests algorithm evaluation metrics value experience B exercise 1

	Precision	**F1-score**
Armsdown	0.99	0.99
Armsup	0.98	0.98
Accuracy		0.99

In terms of Precision, both classes achieved similar results (0.99 and 0.98 for "armsdown" and "armsup" labels, respectively). In terms of F1-score, both classes achieved similar results (0.99 and 0.98 for "armsdown" and "armsup" labels, respectively). The overall accuracy was 0.99, which is an excellent value when applying these kinds of algorithms on activity recognition tasks.

Artificial Neural Networks

Table 4.7 depicts the results achieved by the Random Forest algorithm for the Exercise 1 – Experiment B.

Table 4.7 – Artificial Neural Networks algorithm evaluation metrics value experience B exercise 1

	Precision	**F1-score**
Armsdown	0.96	0.92
Armsup	0.82	0.88
Accuracy		0.90

In terms of Precision, “armsdown” class achieved a higher result than the “armsup” class (0.96 and 0.82 for “armsdown” and “armsup” labels, respectively). In terms of F1-score, both classes achieved similar results, with the “armsdown” class value being a little higher (0.92 and 0.88 for “armsdown” and “armsup” labels, respectively). The overall accuracy was 0.90, which is a reasonable value when applying these kinds of algorithms on activity recognition tasks.

Table *4.8* depicts the results of the train and validation set for experience B exercise 1

Table 4.8 – Train and Validation set values experience B exercise 1.

Train Accuracy	0.90
Train Loss	0.23
Validation Accuracy	0.88
Validation Loss	0.28

The train accuracy (0.90) and train loss (0.23) are slightly lower than the test metrics but still close, indicating that the model is well-trained without overfitting. The validation accuracy (0.88) and validation loss (0.28) closely align with train results, confirming the model’s stability.

Figure 4.11 depicts the loss / accuracy values and their convergence during the training process.

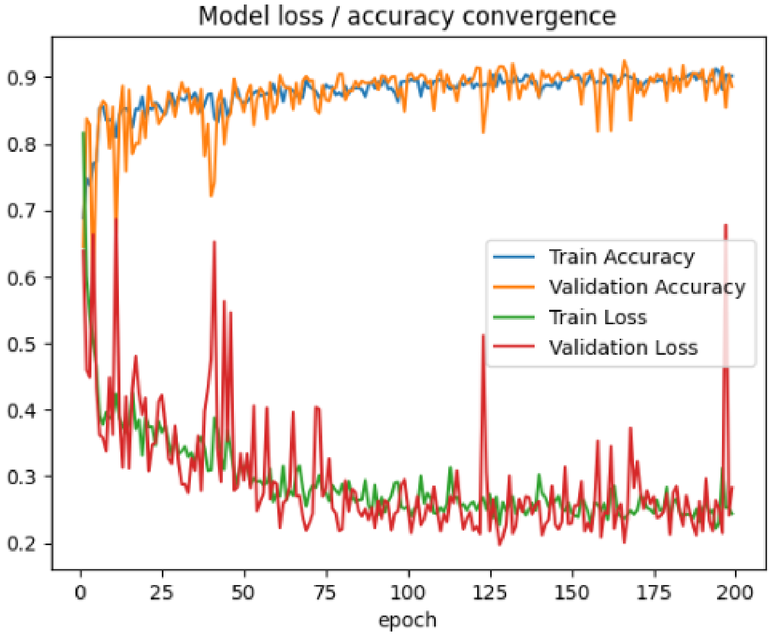

Figure 4.11 – Loss/accuracy graph exercise 1 experience B.

It is possible to conclude that training process occurred smoothly, with no signs of over or underfit, achieving a good level of convergence in all metrics (train accuracy, validation accuracy, train loss and validation loss). At the end of the training process, the accuracy values were very satisfactory, achieving accuracy values of 0.89. In comparison with the previous experiment, it is possible to conclude that this test had more jitter during training process, but it didn't affect overall accuracy.

Figure 4.12 represents a ROC curve with a score of 0.966.

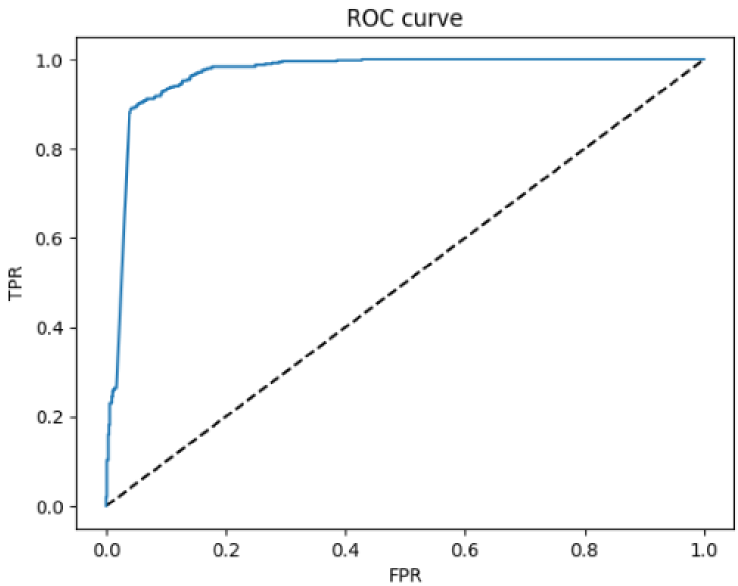

Figure 4.12 – ROC curve graph exercise 1 experience B.

With an ROC score of 0.966, the model demonstrates a strong ability to distinguish between positive and negative classes. The curve's shape, approaching the top left corner, indicates a high sensitivity and a low false positive rate, though it is visible that there is room for minor improvements in classification accuracy.

The Random Forest model outperforms the ANN model for 'Armsdown' class, achieving an accuracy score of 0.99 opposed to 0.96. This is to say that, the Random Forest model is more accurate at detecting true positives for the class "Armsdown", making it likely to correctly predict whenever there are actual cases where arms on idle.

The Random Forest model easily outclasses the ANN model with an accuracy score of 0.98 in the class 'Armsup' This shows that in predicting the "Armsup" class, Random Forest can get a 16% precision advantage, which is fairly precise.

Here, Random Forest performs better than ANN when it comes to overall accuracy per class with 99% (whereas for the former only a mere 90%). According to the model, Random Forest is a far more reliable classifier in this case, as it performs much better categorizing both "Armsup" and "Armsdown" throughout the dataset.

Model Comparison:

- **Random Forest:** In all the metrics, this model substantially outperforms other models but specifically precision and F1-score for both "Armsdown" and "Armsup". This model has 99% accuracy, meaning it is much less mistake-prone when predicting classes and indeed a very dependable one for the purposes of this experiment.
- **ANN:** The ANN model has an overall good performance with the 92% F1-score for the "Armsdown" class, but it is bad at trying to predict the "Armsup" class where the F1- score and the precision are significantly. The ANN model had an overall accuracy of 90%, and so perhaps does not generalize across the different postures as well as the Random Forest Model.

4.2.3 Model training exercise 2 (Experience A)

Random Forests

Table 4.9 depicts the results achieved by the Random Forest algorithm for the Exercise 2 – Experiment A.

Table 4.9 – Random Forests algorithm evaluation metrics value experience A exercise 2

	Precision	**F1-score**
Down	0.95	0.96
Up	0.99	0.99
Accuracy		0.98

In terms of Precision, “down” class couldn’t achieve such a high result as the “up” class, but they are considerably close (0.95 and 0.99 for “down” and “up” labels, respectively). In terms of F1-score, both classes achieved similar results, with the “up” class value being a little higher (0.96 and 0.99 for “down” and “up” labels, respectively). The overall accuracy was 0.98, which is an excellent value when applying these kinds of algorithms on activity recognition tasks.

Artificial Neural Networks

Table 4.10 depicts the results achieved by the Artificial Neural Networks algorithm for the Exercise 2 – Experiment B.

Table 4.10 – Artificial Neural Networks algorithm evaluation metrics value experience A exercise 2

	Precision	**F1-score**
Down	0.93	0.88
Up	0.96	0.97
Accuracy		0.95

In terms of Precision, both classes achieved similar results (0.93 and 0.96 for “down” and “up” labels, respectively). In terms of F1-score, the “up” class achieved a considerably higher result than the “down” class (0.88 and 0.97 for “down” and “up” labels, respectively). The overall accuracy was 0.95, which is a really good value when applying these kinds of algorithms on activity recognition tasks.

Table 4.11 depicts the results of train and validation set for experience A exercise 1

Table 4.11 – Train and Validation set for experience A exercise 2

Train Accuracy	0.96
Train Loss	0.08
Validation Accuracy	0,94
Validation Loss	0.11

The train accuracy is slightly higher at 0.96, and the train loss is lower at 0.08, showing that the model fits the training data well without signs of overfitting. The validation accuracy (0.94) and validation loss (0.11) closely match the train metrics, confirming that the model is stable and consistent.
Compared to previous models, this one demonstrates significantly improved accuracy and reduced loss across all datasets, indicating a better fit and stronger generalization ability.
Figure 4.13 depicts the loss / accuracy values and their convergence during the training process.

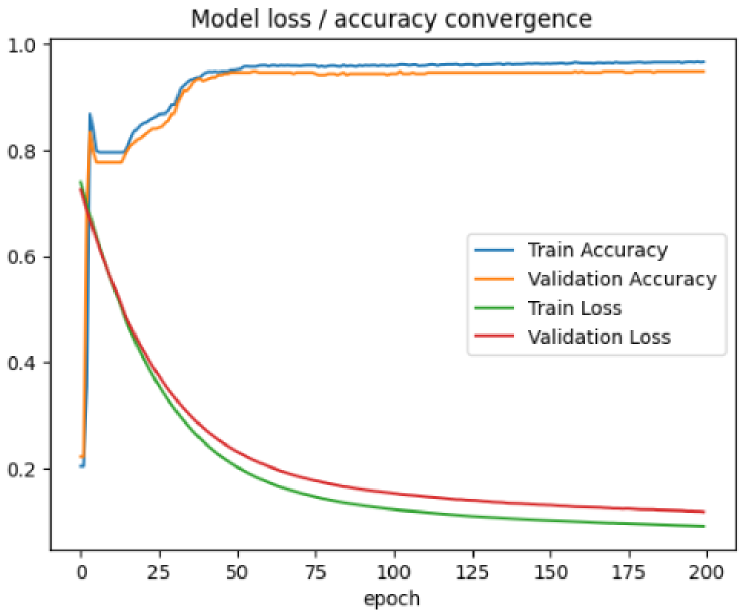

Figure 4.13 – Loss/accuracy graph exercise 2 experience A.

It is possible to conclude that training process occurred smoothly, with no signs of over or underfit, achieving a good level of convergence in all metrics (train accuracy, validation accuracy, train loss and validation loss). At the end of the training process, the accuracy values were very high, achieving accuracy values of 0.95. It shows a model that performs better, converges faster, and displays minimal fluctuations, while the model in the previous graph achieves good results but with some instability and lower overall accuracy.
Figure 4.14 represents a Roc curve with a score of 0.990.

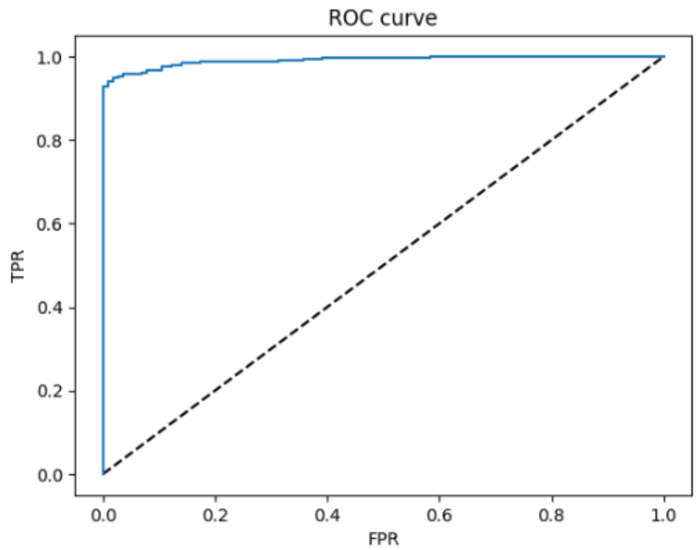

Figure 4.14 – ROC curve graph exercise 2 experience A.

A ROC score of 0.990 means the model has a near-ideal balance for sensitivity and a very low rate of false positives, that it distinguishes extremely well between the two classes. A point near the top left of the curve indicates good prediction from these class labels by our model.

Through the comparison of Random Forest and ANN model performance measures, several significant conclusions are drawn. The Random Forest model performs slightly higher for the Down class, with an accuracy of 0.95 vs 0.93 for the ANN model. Random forest predicts this posture with a slightly better accuracy due to the fact that random forest models have a little edge in predicting true positives for "Down" class.

Conversely, in the “Up” class, the Random Forest model has a better result of 0.99 precision and for the ANN model only 0.96. This means that the Random Forest enhances precision by 3% over the ANN model for predicting the 'Up' class.

Random Forest model performs an overall better than the ANN model with 98% opposed to 95% accuracy. That means the conclusion is the Random Forest model overall makes less errors and usually does a better job at classifying both "Up" and "Down" postures.

Model Comparison:

- **Random Forest:** This model shows better performance, in particular for the F1-scores of both "Down" and "Up". It is great to see that 98% of the predictions (precision) agree with both postures, along with strong F1-scores in the model showing it balances precision and recall.
- **ANN:** The ANN model performs fairly well, but it is sort of disappointing in the "Down" class because its F1-score is 0.88 which means this model has an imbalanced precision and recall. The accuracy is to be seen as good performance, but here it is clearly inferior to the Random Forest model.

4.2.4 Model training exercise 2 (Experience B)

Random Forests

Table 4.12 depicts the results achieved by the Random Forests algorithm for the Exercise 2 – Experiment B.

Table 4.12 – Random Forests algorithm evaluation metrics value experience B exercise 2

	Precision	**F1-score**
Down	0.90	0.94
Up	1.00	0.98
Accuracy		0.97

In terms of Precision, “down” class achieved lower results than the “up” class (0.90 and 1.00 for “down” and “up” labels, respectively). In terms of F1-score, both classes achieved similar results, with the “up” class value being a little higher (0.94 and 0.98 for “down” and “up” labels, respectively). The overall accuracy was 0.97, which is an excellent value when applying these kinds of algorithms on activity recognition tasks.

Artificial Neural Networks

Table 4.13 depicts the results achieved by the Artificial Neural Networks algorithm for the Exercise 2 – Experiment B.

Table 4.13 – Artificial Neural Networks algorithm evaluation metrics value experience B exercise 2

	Precision	**F1-score**
Down	0.83	0.90
Up	1.00	0.97
Accuracy		0.96

In terms of Precision, “down” class achieved way lower results than the “up” class (0.83 and 1.00 for “down” and “up” labels, respectively). In terms of F1-score, the “up” class achieved a considerably higher result than the “down” class (0.90 and 0.97 for “down” and “up” labels, respectively). The overall accuracy was 0.96, which is an excellent value when applying these kinds of algorithms on activity recognition tasks.

Table 4.14 – Train and Validation set for experience B exercise 2.

Train Accuracy	0.95
Train Loss	0.11
Validation Accuracy	0.95
Validation Loss	0.09

The train accuracy is slightly higher at 0.95, and the train loss is 0.11, suggesting the model fits the training data well with no signs of overfitting. The validation accuracy also stands at 0.95, and the validation loss at 0.09, showing consistent performance across the validation dataset.

Figure 4.15 depicts the loss / accuracy values and their convergence during the training process.

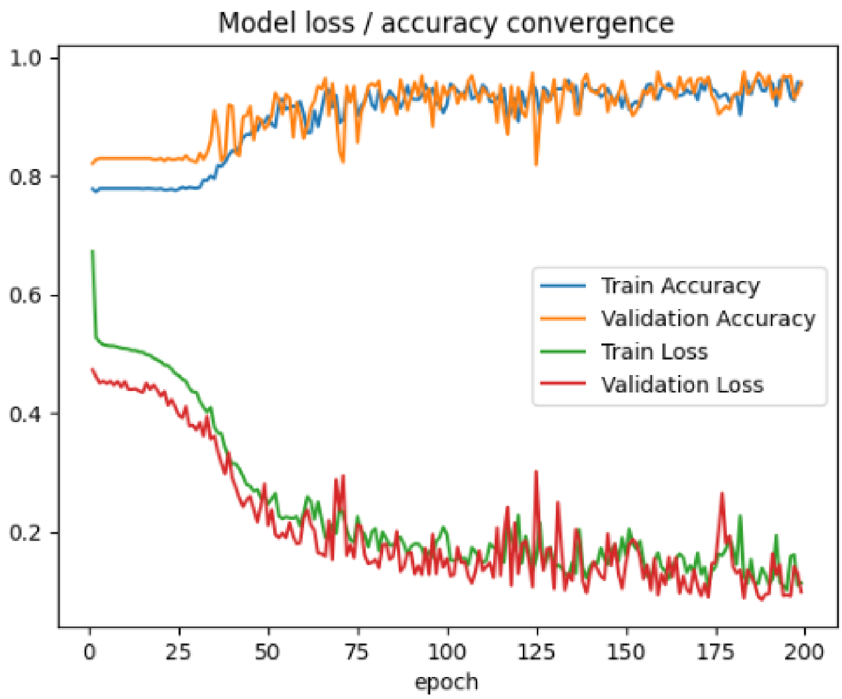

Figure 4.15 – Loss/accuracy graph exercise 2 experience B.

It is possible to conclude that training process occurred smoothly, with no signs of over or underfit, achieving a good level of convergence in all metrics (train accuracy, validation accuracy, train loss and validation loss). Overall, the graph indicates good convergence in terms of accuracy, it has a test accuracy value of 0.94. In comparison with the previous graph, it is possible to conclude that this test had more jitter during training process, but it didn't affect overall accuracy.

Figure 4.16 represents a Roc curve with a score of 0.994.

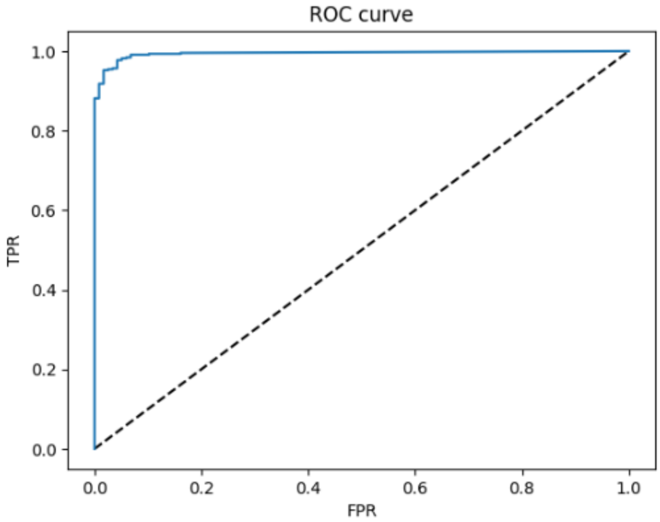

Figure 4.16 – ROC curve graph exercise 2 experience B.

The model's ROC score of 0.994 reflects an outstanding ability to distinguish between positive and negative classes, approaching near-perfect classification. The sharp rise and the curve's proximity to the top left corner highlight the model's excellent predictive accuracy, with minimal false positives and high sensitivity.

Some significant insights are obtained from comparing the Random Forest and Artificial Neural Networks (ANN) models' performance measures. The Random Forest model outperforms the ANN model in terms of precision for the "Down" class, achieving 0.90 as opposed to 0.83. It means the Random Forest model will have a higher probability of making correct predictions in this class because it can recognize the true positives more correctly for “Down” movements.

Each model shows perfect 1.00 accuracy when it comes to the "Up" class. This tells us that both the Random Forest and ANN models are the same in how many correct "Up" movements they can be expected to predict, but not expect too much false positives.

In the end, there is not a big difference between both, with Random Forest model performing slightly better than ANN model having accuracy around 0.97 in comparison to 0.96 for that of an ANN. The Random Forest model slightly outperforms the other model in both classes but does so more consistently which should lead to fewer overall mistakes.

Model Comparison:

- **Random Forest:** For both classes, it is perhaps the top-performance model It has a higher precision and F1-scores on “Down”, and it gains the same perfect precision in “Up” as ANN model with a slightly better F1-score. The Random Forest has the best average accuracy as well, much more reliable for classification tasks with both postures.

- **ANN:** The F1-score (0.90) and the precision rate (0.83) of this model even though they are high, they are still behind in “Down” class. It still keeps perfect F1-score for “Up” as well with a strong 0.97, but overall, its performance is slightly worse than the Random Forest model especially in balancing precision and recall on class “Down”.

4.2.5 Results Summary

These results are a summary of the comparison of the performance of Random Forest (RF) and Artificial Neural Networks (ANN) across two exercises and two experiments using accuracy and precision as metrics.

Table 4.15 depicts a summary of all the results collected throughout the machine learning algorithms.

Table 4.15 – Results summary of the model trainings

	Exercise 1				**Exercise 2**			
	Experiment A		**Experiment B**		**Experiment A**		**Experiment B**	
	Accuracy	**Precision**	**Accuracy**	**Precision**	**Accuracy**	**Precision**	**Accuracy**	**Precision**
RF	0.83	0.83	0.99	0.99	0.97	0.98	0.97	0.95
ANN	0.88	0.88	0.90	0.89	0.95	0.95	0.96	0.92

For Exercise 1, Experiment A demonstrates that RF has an accuracy and precision of 0.83, while ANN performs a little bit better with 0.88 for both metrics, outperforming RF in this scenario. On the other hand, in Experiment B, RF stand out with both accuracy and precision at 0.99, which are significantly higher than ANN's 0.90 accuracy and 0.89 precision, demonstrating a more reliable performance from the RF algorithm in this case.

For Exercise 2, Experiment A demonstrates that RF achieves 0.97 accuracy and 0.98 precision, while ANN scores 0.95 for both metrics, meaning that RF does better in this case. Likewise, in Experiment B, RF maintains strong results with 0.97 accuracy and 0.95 precision, while ANN is behind at 0.96 accuracy and 0.92 precision, showing that once again a better performance from RF.

Overall, RF outperforms ANN in most scenarios, especially in Experiment B from both exercises with high precision. Nevertheless, ANN performs competitively against the RF model especially in Exercise 1, suggesting that ANN can outperform RF under some circumstances. The decision to use one over the other may rely on the nature of the data and and the specific requirements of the task.

5. Conclusions and Future Work

5.1 Conclusions

In conclusions, by investigating the use of computer vision and artificial intelligence in rehabilitation activities, this dissertation makes an important contribution in the field of smart physiotherapy. Consequently, the study could help to provide a real-time-based tracking of human motions during rehabilitation exercises, further enhancing precision and effectiveness in exercise performance feedback. This was accomplished with the use of technologies such as posture estimation via MediaPipe.

It was showed how machine learning techniques (Random Forest, and Artificial Neural Networks) can provide the possibility to achieve accurate classification of body motions, especially for those stroke patients that require individualized care, the fast response of the system enhances an increased patient autonomy, compliance and engagement in their rehabilitation process.

The selected algorithms have some useful charecteristics. Random Forests are easy to interpret, they work well with structured data and they do not tend to overfit depending on the data quality and the hyperparameter finetuning. Artificial Neural Networks generally are better for high-order data, specifically unstructured, but also require a lot more of it and compute to learn. They are both flexible and solution-oriented for various job types.

Furthermore, an AI-empowered rehabilitation offers specific, scalable and flexible solutions, while traditional rehabilitation is constrained by its limitations. This shift opens up the door to virtual rehabilitation, which is more available, individualized and cost effective all of which could help deliver better outcomes to a larger portion of patients.

This study lays the foundation for future developments in telerehabilitation as AI can significantly increase patient outcomes, speed up healthcare delivery and improve rehabilitation overall.

Based on everything researched and done, an intelligent physiotherapy system that uses MediaPipe and machine learning algorithms such as, RF and ANN, was well implemented to estimate the pose and classify the movements of rehabilitation exercises such as shoulder flexion (“Raise Your Arms”) and squats (“Sit/Stand”). The system achieved levels of accuracy always higher than 0.80, getting to a maximum of 0.99 with RF and 0.96 with ANN demonstrating its ability to provide accurate information about the execution of the movements being made. The achieved results shows the potential of this system to support stroke survivors in the performance of the rehabilitation exercises.

5.2 Future Work

A major area of future work would be the creation of a mobile app that could assist patients with rehabilitation exercises. The app would use such developments to help users perform their prescribed exercises and then track, assess, and deliver personalized feedback on how they are moving.

This mobile app would be able to count the repetitions of each exercise automatically without human intervention, the app could use real-time pose estimation technology to accurately determine when a user has completed an entire movement cycle. That way it would get rid of the manual input and leave training patients to concentrate on their exercise in case, say a stroke or an injury recovery patient for whom the cognitive load had to be as minimal as possible.

Beyond counting repetitions, the app would grade the quality of those movements. The app, would determine whether or not the user performed an exercise "correctly," based on machine learning models constructed from correct and incorrect forms of each motion the patient aimed to train. If we wanted to identify if a user had moved in a way that wasn't proper for improving overall health and wellness, the app model could categorize movement as “bad” for example.

One of the most important features of the app would be to provide real-time feedback, cues and hints on how to correct faulty movement. For instance, if the application knows that the user is doing a squat exercise with an incorrect hip position (inappropriate knee bending), it could suggest real-time modifications such as correcting the movement angle.

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