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# Computing Velocity, Force and Power in Strength Exercises Using a Wearable Device and a Sport Performance Monitoring Machine (MYO-QUALITY)

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# ABSTRACT

Human activity recognition plays a critical role in fields such as healthcare, sports and rehabilitation, particularly in monitoring physical activity and strength exercises. Inertial Measurement Unit sensors, with accelerometers and gyroscopes are being increasingly more used in wearable devices, such as smartwatches, to track and quantify human activity movements during physical tasks. Velocity, force and power are three fundamental parameters to take in consideration in sports performance and strength exercises. This Masters' dissertation introduces a novel approach that combines commercial wearable technology with a specialized performance machine for velocity estimation. The high-precision sports performance machine (M1 MYO-QUALITY), engineered for strength training, delivers real-time measurements of force and velocity (power is the multiplication of these two parameters). Concurrently, a commercial wearable device collects data from its embedded IMS sensors through a custom designed application. The data collected from these two devices is then aligned, prepared and segmented in order to be inputted in a deep learning model that combines the feature extraction capabilities of Convolutional Neural Networks with the temporal sequence learning of Long Short-Term Memory networks. In the first part, the four exercises performed were classified by the model due to the fact that it is necessary to identify which exercise is being performed in order to predict any of the parameters. Excellent results were achieved to support the incoming research. Subsequently, our deep learning model estimated the velocity with excellent results and accurately predicted the force. For the last parameter, power, excellent results were also achieved. The deep learning model accurately estimating the velocity in relation to the professional sports machine, facilitates the measurement of these parameters in scenarios where M1 MYO-QUALITY is not accessible to athletes. To build an improved and more robust model, a bigger database and hyperparameter tunning are crucial.

**Keywords:** Strength Exercises · M1 MYO-QUALITY Machine · IMU-based Wearable · Exercise Classification · Variable Prediction

# RESUMO

Reconhecimento de Atividade Humana é uma área de estudo onde o principal objetivo é identificar e entender ações e comportamentos humanos através da recolha de dados provenientes dos mais diversos tipos de sensores. A aquisição dos mesmos é um aspeto fundamental para depois serem processados e serem retiradas características que possibilitam a identificação da atividade ou ação. Posteriormente a utilização de algoritmos de aprendizagem automática e/ou profunda é feita para ajudar a classificar atividades (correr, andar, saltar) ou a prever variáveis contínuas (batimento cardíaco, calorias queimadas) e tem um papel fundamental em áreas como saúde, desporto e reabilitação, especialmente no monitoramento de atividade física e exercícios de força que desempenham um papel crucial na nossa sociedade atual e asseguram uma manutenção da saúde física e mental. A integração de reconhecimento de atividade humana com exercício físico e exercícios de força permite personalizar programas de treino, obter dados em tempo real e um maior detalhe da performance do atleta, trazendo vantagens como o aumento da motivação individual, criação de rotinas de treino, melhor entendimento das necessidades de cada atleta e previsão e deteção de lesões através da análise dos movimentos e postura durante um determinado movimento permitindo identificar padrões inadequados na técnica. Os sensores de Unidade de Medição Inercial, com acelerómetros e giroscópios, estão a ser cada vez mais utilizados em dispositivos vestíveis, como os smartwatches, para rastrear e quantificar os movimentos da atividade humana durante tarefas físicas. A máquina M1 MYO-QUALITY é um dispositivo avançado com a capacidade de avaliar e melhorar o desempenho muscular, representando um avanço significativo no campo da avaliação e otimização do desempenho muscular. Utiliza um tipo de tecnologia eletromecânica motorizada para oferecer resistência variável ou constante durante os exercícios, permitindo um treino mais eficaz e seguro, podendo avaliar o desempenho muscular, identificar desequilíbrios, padrões de ativação, níveis de fadiga e tempos de recuperação. Tudo isto é feito através do cálculo da velocidade e força do movimento do fio da máquina. A utilização de algoritmos de aprendizagem profunda tem revolucionado a área devido as características dos mesmos. As CNNs – Redes neurais convolucionais - são altamente eficazes no processamento de dados espaciais, ao detetarem padrões e estruturas através de camadas de convolução, enquanto as LSTMs – redes de memória de curto longo prazo - conseguem processar dados sequenciais, capturar dependências temporais e padrões ao longo do tempo, através dos seus mecanismos. Desta forma, o principal objetivo deste trabalho passa por ser possível prever a velocidade, força e potência de um movimento através de um smartwatch.

Para tal, o primeiro passo é recolher uma base de dados com os dados do acelerómetro e giroscópio provenientes do smartwatch durante a realização de quatro exercícios e simultaneamente recolher os dados da velocidade e força do movimento obtido da máquina M1 MYO-QUALITY. Foram recolhidos um total de 96 ficheiros para cada uma das máquina – quatro exercícios, três sujeitos, dois pesos e 4 sets – sendo que cada um destes ficheiros tem 15 repetições do exercício a ser realizado. A recolha dos dados do smartwatch foi feita através do desenvolvimento de uma aplicação utilizando o Android Studio e de um TicWatch Pro 2020 com o sistema operativo Wear OS e com uma recolha de amostragem de 100 Hz. Os dados do relógio serão utilizados como entrada X do modelo sendo criado um ficheiro .txt. O nome do ficheiro corresponde à data e hora atuais apresentadas no smartwatch, o que significa que cada ficheiro terá um nome único. Cada ficheiro é composto por dez colunas: um timestep que começa em 1 e aumenta de 1 em 1; data; hora no formato (hora: minuto: segundo: milissegundo); tempo desde o início da recolha; eixo X do ACC; eixo Y do ACC; eixo Z do ACC; eixo X do GYR; eixo Y do GYR; eixo Z do GYR. Para a entrada Y do modelo, a máquina M1 MYO-QUALITY cria um ficheiro .xlsx composto por seis colunas, onde cada linha está

associada a um TS específico: número de repetições no conjunto para o movimento selecionado ("Repetição"); tipo de movimento realizado ("Fase"); tempo desde o início ("Tempo(s)"); comprimento do cabo ("Posição (cm)"); força aplicada no cabo ("Força (kg)"); velocidade do cabo ("Velocidade (cm/s)"). De seguida foi necessário alinhar os dois sinais porque não foi possível sincronizar as duas máquinas utilizadas e os pares de ficheiros têm tempos diferentes porque não foi possível iniciar a recolha de dados simultaneamente. Foi extremamente importante alinhar os dados de forma a apresentar resultados viáveis, classificando (modelo de classificação) os quatro exercícios diferentes e prevendo (modelo de regressão) a velocidade e a força do movimento. A máquina M1 MYO-QUALITY está programada para começar a recolher dados apenas quando uma das variáveis (posição do cabo, força ou velocidade) muda, e para parar de recolher dados quando a décima quinta repetição é concluída (cabo retorna à posição original). O dispositivo vestível não pôde ser programado para fazer o mesmo devido à falta de condições e, por essa razão, o início e o fim da recolha de dados foi uma tarefa manual. Um desfasamento inicial teve de ser calculado e inserido no ficheiro do smartwatch, de modo a alinhá-lo com o sinal da entrada Y. Para esta tarefa, devido à natureza cíclica de ambos os sinais (entrada X e entrada Y), foi utilizada a função *.corr* da biblioteca *pandas*, que calcula a correlação entre sinais. O método utilizado na função foi o coeficiente de correlação de Pearson, que mede a correlação linear (razão entre a covariância de dois pontos e o produto dos seus desvios padrão) entre dois sinais. Após o alinhamento dos dados, foi realizada a segmentação para inserir os dados no modelo de classificação e no modelo de regressão. Para classificar os diferentes exercícios, todos os dados recolhidos foram inseridos, mas para prever a velocidade e a força, tiveram de ser criados quatro modelos diferentes com quatro entradas distintas. Como os exercícios são independentes, um único modelo por si só não seria capaz de prever a velocidade, porque a máquina M1 MYO-QUALITY não possui eixos (valor único) e, para diferentes exercícios, uma velocidade ou força semelhante é exibida, tornando impossível para um único modelo prever esses valores. Este é um ponto de interseção entre estes dois tipos de modelos, pois é extremamente importante primeiro classificar o exercício e só depois aplicar um modelo capaz de prever a força e a velocidade de cada movimento. Para cada ficheiro .txt, é definida uma lista de janelas, com um intervalo de -2,5 a 2,5 segundos e um tamanho de passo de 100 milissegundos (com um comprimento de 50 janelas temporais). Com isto, o modelo consegue entender quais são os próximos passos do movimento. Cada segmento entre valores consecutivos da lista de janelas forma uma janela onde é aplicado um filtro mediano a todos os eixos do acelerómetro e giroscópio. Em seguida, é aplicada uma janela deslizante com um intervalo de 2,5 segundos até ao tempo final de cada ficheiro, menos 2,5 segundos, e um tamanho de passo de 0,1 segundos, o que significa que para cada nova janela, o tempo de início avança 100 milissegundos.

Com este estudo, demonstrámos novamente que é possível classificar quatro exercícios diferentes de ombro usando modelos de DL e de classificação com uma única pulseira vestível com um sensor IMU embutido. Os resultados das métricas de classificação foram muito promissores, com precisão, recall e F1-score a aproximarem-se de 1, enquanto a matriz de confusão para cada variação do modelo revela erros mínimos ao classificar cada segmento, destacando a robustez do modelo. Ao mesmo tempo, conseguimos demonstrar que o uso de DL – aprendizagem profunda - em modelos de regressão é um excelente método para prever variáveis contínuas – velocidade e força. Com os dados do ACC e do GYR da pulseira vestível, o modelo conseguiu rastrear e prever continuamente ambos os valores variáveis recolhidos da máquina de desempenho desportivo (M1 MYO-QUALITY). Para prever a velocidade, esta metodologia obteve resultados muito encorajadores, com valores de MSE, MAE e RMSE próximos de zero, indicativos de erros de previsão mínimos, enquanto os valores muito elevados de R-quadrado sugerem que o modelo explica

uma grande parte da variância. Os resultados na previsão da força não foram tão satisfatórios quanto os da velocidade, mas todas as métricas apresentaram valores próximos de zero, o que significa que o modelo não cometeu grandes erros de previsão e, em média, as previsões estavam muito próximas dos valores reais. Algumas razões para isto estão relacionadas com o facto de que a aceleração (Segunda Lei de Newton) é suscetível a ruído e desvios, e na presença de velocidade constante, o modelo irá prever a força como sendo zero, o que está errado. A última variável – potência – não foi prevista, foi calculada através da multiplicação da velocidade pela força, tendo sido obtidos ótimos resultados, com todas as métricas próximas de zero.

**Palavras-chave:** Exercícios de força · Máquina M1 MYO-QUALITY · Sensores Unidades Inerciais · Classificação exercícios · Estimação de variávies

# SCIENTIFIC OUTPUT

A. Lopes, Nuno M. Garcia, Ignacio Chirosa, Javier Medina Quero, Aurora Polo-Rodríguez. 2024. “Computing Velocity and Force in strength Exercises Using a Wearable and Sport Performance Monitoring Machine”. Short paper for presentation at the 16th Internation Conference on Ubiquitous Computing & Ambient Intelligence (UCAmI 2024), Belfast.

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# ACRONYMS

**ACC** – Accelerometer
**AI** – Artificial Intelligence
**ANN** – Artificial Neural Network
**ARIMA** – Autoregressive Integrated Moving Average
**CNN** – Convolutional Neural Network
**CV** – Cross Validation
**DL** - Deep Learning
**DOF** – Degrees of Freedom
**FP** – False Positive
**FN** – False Negative
**FNN** – Fastforward Neural Network
**GPS** – Global Positioning System
**GYR** – Gyroscope
**HAR** – Human Activity Recognition
**IDE** – Integrated Development Environment
**IoT** – Internet of Things
**IMU** – Inertial Measurement Unit
**KNN** – K Nearest Neighbour
**LDA** – Linear Discriminant Analysis
**LSTM** – Long-short Term Memory
**MAE** – Mean Absolute Error
**MSE** – Mean Squared Error
**MEMS** – Micro-Electromechanical Systems
**ML** – Machine Learning
**NVBS** – Non-Vision Based Sensors
**OS** – Operating System
**PCA** – Principal Component Analysis
**RFID** – Radio Frequency Identification
**RL** – Reinforcement Learning
**RMSE** – Root Mean Squared Error
**RNN** – Recurrent Neural Network
**SARIMA** – Seasonal Autoregressive Integrated Moving Average
**SDK** – Software Development Kit
**SL** – Supervised learning
**SVM** – Support Vector Machine
**SW** – Sliding Window
**TN** – True Negative
**TP** – True Positive
**tW** – Time Window
**UL** – Unsupervised Learning
**WS** – Wearable Sensors

# Chapter 1

## 1. INTRODUCTION

Human Activity Recognition (HAR) is an area of study and technology with the main objective of identifying and understanding human actions, activities and behaviours through data collected from different types of sensors. The key aspects of HAR start with sensor data collection, which will later be processed to be used as raw sensor data or to extract meaningful features that can help in identifying different activities or actions. Then Machine Learning (ML) algorithms or Deep Learning (DL) algorithms are used to classify or predict specific variables in various domains from our daily live, including healthcare, sports and fitness, smart homes and security. HAR is primarily focused on classifying discrete activities, but it can also be extended to predict continuous variables. While for classification the main objective is related with identifying specific actions, activities and behaviours (e.g. if the user is running, walking or cycling) for prediction of continuous variables it is more focused on specific areas such as energy expenditure, physical effort, biometric monitoring and contextual factors (estimate the user's heart rate and calories burned continuously) [1].

Human activities vary from simple gestures to complex group interactions and to effectively train models for HAR and to achieve good results we need to make sure that systems can accurately recognize and differentiate between those actions. While gestures involve basic hand movements or motions, actions are straightforward activities performed by humans, interactions are activities performed by two agents (human-human or human-object) and group activities involve the participation of more than two individuals. The distinction between these four levels of human activities is essential for developing HAR systems [2]. Different approaches are used to collect and analyse data in HAR. Vision-Based use cameras and image processing techniques to analyse and classify human activities in areas like security monitoring, sports analysis, human-computer interaction – Advantages: use of a single camera, yield excellent results, reliable data; Disadvantages: privacy issues, proper light dependency, power consumption, processing time. Sensor-based use devices like ACC, GYR and pressure sensors to detect movements and activities in fitness tracking, health monitoring, daily activity recognition – Advantages: privacy, security, power consumption, device free approach; Disadvantages: noisy data, accuracy issue, faulty sensors. Multimodal Strategies combines data from multiple sources to enhance the accuracy and robustness of HAR in advanced health monitoring, augmented reality and comprehensive activity tracking [3].

Physical activity has a major role in our society and there is substantial data that supports an inverse relationship between the amount of habitual physical activity performed and a variety of negative health outcomes throughout the lifespan. In modern society physical activity is crucial to ensure physical (healthy body weight, reduce cardiovascular problems, higher flexibility and resistance) mental (reduce stress, anxiety and symptoms of depression) and social (promoting inclusion and improving teamwork) health between individuals and societies since sedentary lifestyles are becoming more common due to the widespread of technology [4]. Merging physical exercise with HAR has a significant impact on promoting a healthier and more active lifestyle making it possible and more accessible to everyone. Some applications of combining HAR and physical exercise are: real time performance monitoring that enables a more detailed performance analysis; training personalization that helps to create routines, to increase motivation and to understand each individual personal needs; prevention and detection of injuries through the analysis of movement performance and posture that help to identify negative pattern and inadequate technique; physical rehabilitation ensuring the correct execution of each exercise [5], [6]. Strength exercises are an essential component of physical exercise aimed at enhancing muscle mass, strength and overall physical performance while offering numerous benefits as increased metabolism, improved bone density, better joint function and reduced risk of injury. The integration of HAR in strength exercises (tracking, analysing movements and predicting variables as velocity and strength in real time) can personalize strength training programs, helping the user to benefit from a smarter and much more data-driven approach, helping in recovery and leading to better health, well-being and performance [7].

## 1.1 Objectives

The main objective of this master dissertation is to present a merge integration between a commercial wearable smartwatch and a high-precision sports performance machine engineered for strength training (M1 MYO-QUALITY). Nonetheless, other secondary goals must be achieved:

1. Research and review of current literature related to HAR, NVBS, and DL models that are able to classify activities and predict variables;
2. Collect a database for four different exercises, using simultaneously the wearable smartwatch and the sports performance machine;
3. Find a viable way to align the data from both devices – smartwatch and performance machine;
4. Development of a classification model to classify four different activities and of a regression model to predict two different variables – velocity and force;
5. Application of both models to a set of CV methods in order to train the model with a specific amount of data and test it on unseen data. For velocity the objective is to find which external variables can influence the results and for force to test the viability of the prediction model;
6. Through the multiplication of the force by the velocity, predict a third variable – power – in order to understand if the results of this two variables enable the calculus of the third variable.

## 1.2 Structure

There are five chapters in this dissertation. Chapter 1 introduces the dissertation theme by giving some definitions while describing the context and motivation, as well as the dissertation's objectives and structure. In Chapter 2, the background theory merged with the current state of the art is presented. Chapter 3 discusses the materials and methods used in this study, starting with the data collection, preparation and segmentation and describing the model development and the CV methods used. In Chapter 4 the results are presented and discussed, and due to the in large number, Appendices A and B serve as a complement. To close the dissertation, Chapter 5 has a quick summary of the main finding and conclusions, while discussing some recommendations for future research about this topic.

# Chapter 2

## 2. Background Theory

For a better understanding of this dissertation, Chapter 2 focuses on the theory behind the main topics used to achieve the results and their conclusions. A state-of-the-art part is also included in every sub chapter to help the reader understand the decisions made and to be able to follow the line of thought that allowed this project to be successful.

### 2.1 Non-Vision Based Sensors

Non-Vision Based Sensors (NVBS) or Sensor Based devices are designed to detect and measure various physical and environmental parameters without relying on capturing and processing optical/visual data and that operate based on different physical parameters. For a successful HAR task it is essential to understand what the attributes of the targeted task are, answering three different questions: “where?” - body position-related (indoor positioning, proximity sensor, social distancing), “what?” - body action-related (fall detection, individual identification, gesture recognition) and “how?” - body status-related (emotion sensing, stress sensing, individual identification). These three questions merged with understanding to which sensing technique is our main task linked with is a key factor for choosing the best type of sensor to use.

There are five different sensing techniques: Mechanical Kinematic Sensing where the mobility and deformation are perceived by the mechanical sensors and then transformed into electric signals; Wave Sensing which is a non-contact sensing technique based on the propagation properties of waves – radio frequency signals are wireless electromagnetic signals ranging from 3 kHz to 300 GHz, Acoustic Signals are mechanical waves and Optical Signals are electromagnetic signals with high frequency (THz order); Physiological Sensing refers to natural physiological and kinematic signals from the organism such as the properties of the processes of living beings and relationships between intrinsic and extrinsic variables; Field Sensing inferring a region in which each point will be affected by force – Electric Field, Magnetic Field, Gravitational Field; and Hybrid Sensing that merge two or more sensing techniques [8], [9]. Sensor-based is an area of exponential growth and many datasets are becoming available online for students and scientists to test and learn from [10].

There are four types of sensors depending on the type of parameter they measure: Proximity Sensors detect the presence or absence of objects within a certain range – inductive, capacitive, infrared sensors; Environmental Sensors measure ambient conditions such as temperature, humidity, pressure – thermocouples, thermistors, piezoelectric pressure sensors; Motion Sensors detect movement and orientation – Accelerometer (ACC), Gyroscope (GYR), GPS; Chemical Sensors detect and measure the concentration of chemical substances – gas sensors, pH sensors, biosensors. Body Wearable Sensors (WS) include all the types of sensors that can be worn on the body and can monitor physiological and physical parameters [11]. The signals produced by NVBS contain noise due to miscalibration, malfunction, noisy ambient environments, placement errors and pre-processing techniques like denoising (using low-pass filters, mean filter, median filters) are essential to reduce noise and achieve better results. Segmentation is also a pre-processing technique that is essential since a single sample extracted from a sensor at a specific time instance does not give enough information about a certain activity. Studying the effect of changing the window size in segmentation and the number of sensors to be used (specifically for body WS) is also an excellent method to accomplish favourable results [12], [13].

NVBS have a major impact on a wide variety of areas due to their ability to provide real-time data, to control and to optimize processes and activities. In the Industrial Automation area, NVBS ensures a better process control and helps monitor health and safety of machinery. In the healthcare industry NVBS enable remote monitoring and WS that can track vital signs. NVBS can also enhance comfort, security and efficiency in smart homes. In Automotive industry NVBS contributes to vehicle safety and performance. Merging NVBS with sports has revolutionized performance tracking (WS are used to monitor athletes' biomechanics), health monitoring (athletes' physiological responses), injury prevention (measure impact forces) and sports equipment (embedded sensors) contributing to a safer and more efficient way of practicing all types of sports [14], [15].

Since NVBS are being used in almost every industry, addressing the challenges and future works in the area is crucial for optimization and expanding their utility. Energy efficiency, low power consumption devices and energy harvesting are essential to prolong battery life and reduce the need for frequent charging. A compact design and the use of nanotechnology without compromising performance and accuracy metrics are also very important challenges to enable the efficient integration of artificial intelligence (AI) and ML with HAR. Embracing future developments as advanced materials, wireless connectivity, biocompatible sensors and environmental sustainability are fundamental steps to continue to revolutionize the NVBS industry. NVBS sensors are fundamental to the Internet of Things (IoT) as they allow real-time monitoring and data collection across various areas and enhance safety and efficiency [16], [17].

### 2.1.1. Accelerometer and Gyroscope

ACC are technological devices that measure the acceleration forces acting on something and can be static (force of gravity) or dynamic (motion and/or vibrations). The measurement of acceleration always relies on classical Newton's mechanics and D'Alembert's principle to derive the motion equation where all real forces, acting on the proof mass, are equal to the inertia force on the proof mass. Since acceleration is measured by detecting changes in velocity over time it can be done using different mechanisms: Piezoelectric ACC – acceleration causes stress on piezoelectric material and generates an electrical charge that is proportional to the force applied (Piezoelectric Effect); Capacitive ACC – measures changes in capacitance between microstructures as they move due to acceleration (Capacitive Sensing); Piezoresistive ACC – under mechanical stress some materials' electrical resistance change (Piezoresistive Effect); Micro-Electromechanical Systems (MEMS) ACC – micro-machined structures who sense acceleration and provide high sensitivity and precision (MEMS Technology) [18].

Gyr measure the rotation of a certain object around a particular axis based on the principle of angular momentum being essential in systems that control the orientation and angular velocity. The main types of Gyr are: Mechanical GYR – spinning rotors do detect orientation; Optical GYR – light interference for rotation detection; MEMS GYR – micro-machined structures that vibrate and measure angular velocity (Coriolis Effect) [19].

For both devices, sensitivity (detect changes), range (maximum value), resolution (smallest detectable changes), bandwidth (range of frequencies) and accuracy (real vs predicted value) are key parameters to ensure excellent data collection. Noise, Drift, Stability and Response Time are performance metrics to ensure that these devices are performing well. Selecting appropriate sensor locations is an especially important key aspect to guarantee results as well as the number of sensors to use. A recent study, focused on the impact of sensor placement in predicting twenty-one common activities, concluded that the role of body locations can be specific to the activity being predicted. Right wrist and both upper arms capture a wide range of movements in various activities while the trunk shows unique capabilities in capturing less dynamic activities [20].

Inertial Measurement Unit (IMU) sensors are critical devices in modern sensor technology since combining data from ACC, provides information about linear movements, and GYR, information about rotational movements, can describe the complete motion and orientation of an object in a 3D space. An optional component of IMUs is the magnetometer that measures the magnetic field strength and direction [21]. IMUs with two sensor (type 1) consist of ACC and GYR combined, each typically with 3 DOF defined for x,y and z axis – 6 Degrees of Freedom (DOF) total. IMUs with three sensors (type 2) combine ACC, GYR and magnetometer with a total of 9 DOF and is usually used for dynamic orientation calculation in the short and long run when less drift errors occur. These types of devices are used in diverse areas such as manufacturing quality control, medical rehabilitation, robotics, navigation systems, sports learning and augmented reality systems using type 1 and type 2 IMUs. The following review summarises some of the references that work with these sensors and in which area they are being used on [22].

### 2.1.2. Operating systems and Android Studio

Wearable devices are advanced technology devices designed to be worn on the body to enhance functionality and convenience in daily life. There are several forms each serving a unique purpose: Fitness Trackers – focused on health and fitness and monitor metrics such as steps taken, heart rate, sleep patterns; Smart Glasses – provide hands-free information, augmented reality and enhanced visual experiences; Medical Devices – designed to track vital health metrics, assist in medical diagnostics and health management such as glucose monitors and heart rate monitors. The most common and that have experienced significant growth in the past years are Smartwatches, multifunction devices combined with traditional watch features with capabilities like notification receiving, fitness tracking and app integration. Apple watch series, Samsung Galaxy watch series, Fitbit Versa Series and Garmin Forerunner are some of the types of smartwatches currently available on the market, all having IMUs incorporated [23].

Before developing any project it is fundamental to study and analyse what are the advantages and disadvantages about programming on each smartwatch operating system [24], [25]:

- Watch Operating System (OS) makes necessary the use of Xcode, Apple’s integrated development environment (IDE); Typically written in Swift or Objective-C programming languages; Uses

WatchKit, Apple’s framework for building user interfaces and interactions for the Apple Watch, Apple provides extensive documentation, sample code and resources for developers interested in creating apps for Apple Watch. Disadvantages: Limited device compatibility since WatchOS is exclusive to Apple Watch devices and Apple's strict app review process and guidelines may result in longer approval times and limitations on app functionality.

- Wear OS uses Android Studio, typically written in Java or Kotlin programming languages. To create apps that run on WearOS devices we can use Android Software Development Kit (SDK) along with the Wearable support library. Google provides documentation, samples and guidelines for designing and developing Wear OS apps. On the other hand, fragmentation across different hardware manufacturers can lead to inconsistent user experiences, performance issues and battery life concerns on some Wear OS devices and Limited market share compared to Apple Watch.
- TizenOs develops apps using Tizen Studio IDE provided by Samsung. Apps can be developed using languages such as C, C++ or HTML5/CSS/JavaScript. Samsung offers the Samsung Galaxy Watch SDK for developers, which includes tools, documentation, and samples for building Tizen apps. Some negative aspects are limited device compatibility since Tizen OS is exclusive to Samsung Galaxy Watch devices; Smaller developer community compared to platforms like Watch OS and Wear OS; Limited third-party app ecosystem compared to Apple Watch and Wear OS.
- FitbitOs provides a development platform called Fitbit SDK for building apps and clock faces for Fitbit OS devices. Fitbit apps can be developed using web technologies like JavaScript, CSS, and SVG. Fitbit Studio is a web-based development environment provided by Fitbit for creating and testing apps and clock faces. Disadvantages: limited hardware capabilities compared to other smartwatches; Smaller user base and market share compared to Apple Watch and Wear OS; Less flexibility in terms of app development compared to platforms like Watch OS and Wear OS.
- GarminOs offers the Connect IQ SDK for developing apps, data fields, and watch faces for Garmin devices. Connect IQ apps can be written in languages like Monkey C or JavaScript. Garmin provides documentation, tutorials, and a development forum for Connect IQ developers. Disadvantages: Limited mainstream appeal compared to Apple Watch and Wear OS devices; Development platform may have a steeper learning curve for developers new to Garmin's ecosystem; Smaller developer community compared to other smartwatch platforms.

After analysing all the positive and negative aspects of the most common operative systems, for this study, was decided that using Wear OS was the correct choice due to the fact that it was the best one to fulfil our main objectives of creating an app to collect data from the IMUs and in future work incorporate it with DL models to analyse new collected data. Android Studio is the official IDE for android application development and when building an android studio project there are 4 basic key components for a successful application: Manifest (‘*AndroidManifest.xml*’) contains essential information about the application such as permissions and hardware requirements; Java/Kotlin Files are the source files where the application logic is written; Resource Files, located in the ‘res’ directory define the visual and textual content of the application (layouts, strings, images); Gradle Scripts is the build system that manages dependencies, build configurations and other settings. Android Studio also includes a virtual emulator where the application being developed can be tested in real-time. Mastering this environment ensures that the application is well designed and will work without any trouble [26].

Applications using android studio are being developed in all different areas with a wide variety of purposes. ‘FICO’ is an application developed using android studio with the main objective of facilitating the finding of a new sports coach, benefiting all people involved in and the society itself since the lack of physical exercise is a very serious problem [27]. ‘Cyclist Diary’ is a cyclist training accounting application that was also developed using android studio and has functions of searching for other users, comparing records, exporting, or importing data in checked periods and customizing the user’s preferences. Once again, it is an application developed with the main objective of encouraging users to practice more physical exercise [28]. ‘Analisis Biomekanika Jurus Tunggal Pencak Silat ’ it is an application that analyses the user’s body movement and helps them to learn how to properly practice Pencak Silat (martial art) [29].

### 2.1.3. M1 MYO-QUALITY

The M1 MYO-QUALITY machine is an advanced device for evaluating and improving muscle performance and represents a significant advancement in the field of muscle performance evaluation and enhancement. It uses motorised electromechanical technology to offer variable or constant resistance during exercise, enabling more effective and safe training as it can assess muscle performance, identify imbalances, activation patterns, fatigue levels and recovery times. Real-time feedback, customizable training programs and cloud-based data storage and analysis are also some of the features that this advanced device offers to the users besides featuring an intuitive touch-screen interface with user-friendly software.

The MYO-QUALITY M1 machine has 65 x 65 x 20 cm and weighs 45 kg (see Figure 2.1) which makes it a large machine, hard to carry around easily. It features a cord length of 4 metres, with programmable velocities up to 1.5 m/s and a maximum achievable velocity of 3 m/s. The machine resistance can be programmed up to 120 kg, with a maximum of 240 kg and a minimum of 1 kg, boasting a sensitivity of 100 g. Myoquality Solutions, SL, based in Granada, Spain, manufactured the device.

Figure 2.1: M1 MYO – QUALITY machine and touch screen to select the training plan (images and schemes provided by the manufacturer and reproduced with permission)

A lot of applications areas are being merged with the use of this advanced machine such as health and rehabilitation – diagnosing and treating muscles, rehabilitation programs and monitoring patient progress; Fitness and Athletic training – muscle performance, optimize training programs and enhance athletic performance; Research and Development – study of biomechanical movements and discover ways of improving training interventions. This is only possible due to the fact that it offers seven different modes of operation – tonic, kinetic, elastic, conic, inertial, isometric and vibratory - which are adaptable to various exercises and needs, as presented in Figure 2.2:

Figure 2.2: M1 MYO – QUALITY machine different modes - tonic, kinetic, elastic, conic, inertial, isometric and vibratory (images and schemes provided by the manufacturer and reproduced with permission)

This dissertation focuses on classifying four different exercises and predicting the velocity and force in time when performing each one of the four exercises. Another objective is to stop needing the machine every time we want to collect data and to perform strength exercises while analysing data since sometimes due to lack of time, availability or injuries, athletes and normal users cannot afford to use the machine. Velocity is a particularly important variable when performing strength exercises because it can show what type of adaptations a specific training needs, the exercise efficiency and helps understanding how the technique is being performed. Force is another important variable since it is essential for muscle hypertrophy, functional strength and performance enhancement. Predicting both these variables when performing an exercise optimizes athletic performance, functional capacity, overall health and injury recovery. Through this equation:

$$Power = Force \times Velocity \tag{2.1}$$

We can calculate another especially important variable that is Power. With it we can study the explosive strength of a specific movement, functional capacity in daily activities and neuromuscular efficiency enhancing coordination and the ability to generate force quickly.

A lot of other studies have already been conducted using this advanced device: advances in AI for isometric training [30]; an explanatory model for elite canoeists' performance [31]; exploring lower limb muscle activity and performance variation [32]; sex-related and performance differences in contractile properties [33]; reliability of dynamic shoulder strength test [34]. All the excellent results achieved show the importance of using this advanced machine and the advantage of using it in all types of areas. Replacing it by a smartwatch would be a huge step in the investigation and performance area.

## 2.2 Time Series

Time Series are observations collected sequentially over time, so for a time series *Z* of size m we can formulated it as an ordered sequence of observations, Z = (z1, z2 , … , zm). Time Series are deterministic if their values are synthesized by a mathematical function y = f (time) and stochastic or nondeterministic if a random term ϵ is added to the mathematical function, y = f (time,ϵ). This type of Series has a unique characteristic that is the fact that each observation can be influenced by the previous observations, making the data points correlated over time and is a fundamental aspect for analysing time series. There are three key characteristics of time series and all of them are present in Figure 2.3 [35]:

- Trend is a long-term increase (demographic development or demand for technologies) or decrease (mortality rates or number of epidemics) in the data which can assume a great variety of patterns (linear, exponential, polynomial).
- Seasonality is the occurrence of cyclic patterns of variation that repeat, at relatively constant time intervals, along with the trend component.
- Residues are the short-term fluctuations that are neither systematic nor predictable.

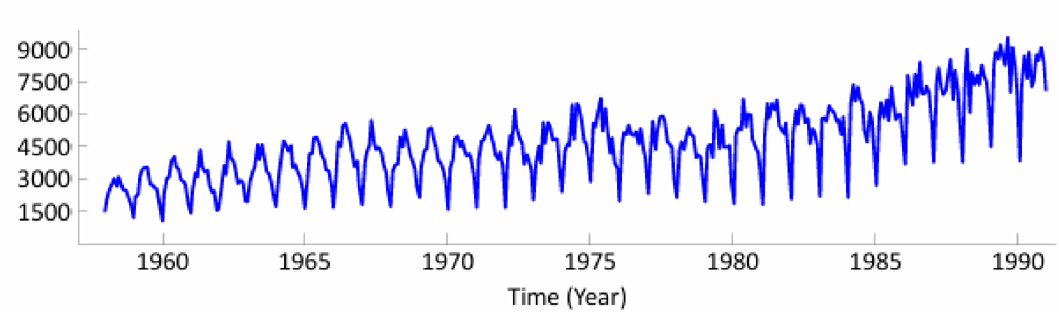


Figure 2.3: Example of a time series without a specific Y axis variable with the main objective of showing to the reader the three main characteristics.

Predicting or forecasting time series values is the process of using known values to predict future values in a sequence of time-ordered observations and can be applied to a wide variety of areas such as finance, economics, weather forecasting, healthcare and sports. To this purpose we can use parametric methods that require a priori knowledge about the data distribution – Moving Averages, Simple Exponential Smoothing, Holt's Exponential Smoothing or SARIMA/ARIMA [36] – or we can use non-parametric methods that are able to predict values without prior knowledge of their distribution – ML Models (Support Vector Machines - SVM, K nearest neighbours - KNN) and DL Model using Artificial Neural Networks (ANN) . This second type of models outperform the traditional models, only SARIMA can perform and obtain results like the non-parametric models. Studying and analysing time series data with the objective of producing good results brings the importance of following a structured workflow that usually start with data collection, data processing (cleaning and transformation of data), data visualization and statistical summary, feature engineering (feature extraction and dimensionality reduction), modelling (appropriate model for prediction or classification), evaluation (using metrics to compare the obtained values with the real values) [37], [38].

Time Series are very important in sports since they provide deep insights about athletic performance, health, game dynamics and can be applied to several areas: Skill Assessment - classifying a certain activity, types of movement or technique used by athletes (exercise done or swing move done by a tennis player); Injury Detection and Prevention – abnormal patterns or wrong moves are identified to indicate; Strategy Analysis – game tactics and strategies depend on temporal patterns in player movements and actions. Traditionally, analysis of sport data is based on expert knowledge and statistical analysis but with a good understanding on the data of the sport domain, merging the old methods with time series prediction is an excellent way to increase the sports and physical activity domain [39], [40].

### 2.2.1. Data Cleaning and Noise Reduction

Time Series data often contains imperfections that can hide meaningful patterns and trends that may come from measurements errors, missing values or random fluctuations. To ensure the accuracy and reliability of the analysis it is fundamental to perform time series data cleaning and noise reduction in order to have the best results possible in all the fields that are merged with time series data, such as finance, healthcare, meteorology and sports or physical activity analysis. Time Series data cleaning focuses on identifying and correcting errors, anomalies and inconsistencies in the data including handling missing values, removing outliers and aligning data points correctly. Noise reduction is related with eliminating or mitigating the impact of random variation that do not carry significant information about the Time Series data that can arise from sensor inaccuracies, environmental factors and other external factors that we cannot control [41], [42]. This part is of major importance for the success of any study and are foundational for any data-driven decision-making process since without this initial process, misleading results, poor forecasting, incorrect insights or costly mistakes can be produced and be devastating for the entire study. In healthcare and injury diagnostic, unclean data can lead to incorrect diagnoses and wrong treatments which could be catastrophic. In today's literature there are several types of time series data cleaning techniques each one with a different purpose [43], [44]:

- Smoothing based – often used to eliminate data noise, especially numerical data noise. Moving Average calculates the average of the most recently observed $N$ time series values which is used to predict the value at a time $t$. Autoregression model is a process that uses itself as a regression variable and uses the linear combination of the previous $k$ random variables to describe the linear regression model of the random variable at time $t$. Kalman Filter can deal with time-varying systems, non-stationary signals and multi-dimension signals. Autoregressive Moving Average Model, Interpolation and State-space Models are other examples of smoothing based models to clean the data.
- Constraint based – Order Dependencies are simple and effective methods suitable for solving some time series data cleaning problems, used as an integrity constraint for error detection and data repairing in databases. Sequential dependencies algorithms focus on the difference of values between two consecutive data points in a time series. Speed Constraint algorithms consider the restrictions of speed on value changes in a certain interval.

- Statistics based – algorithms that learn from data to clean data. Maximum Likelihood algorithm can be converted to find a cleaned time series, which is based on the probability of speed change that has the greatest likelihood. Markov Model is a stochastic process and in order to find patterns that change over time, this model attempts to build a process model that can generate patterns. Binomial Sampling is an adaptive method that exploits techniques based on sampling and smoothing theory to improve the quality of Radio Frequency Identification (RFID) data. Spatial-Temporal probabilistic models learn from detailed data patterns.
- Anomaly Detection – there may be two types of outliers, namely single-point anomalies and subsequence anomalies. Abnormal Point Detection is based on the idea that the predicted values of the established model and the observed values for each data point are compared and in case that the difference between the two values exceeds a certain threshold, the observed value is considered an abnormal value. Abnormal Sequence Detection aim to maintain a normal database and then compare the test sequence with the sequence in the normal database. Density-based Spatial Clustering divides the time series into parts with sufficient density and finds clusters of arbitrary shape in the spatial database.

In terms of emerging trends and new challenges in data cleaning research: Scalability – to large and growing datasets of Big Data, it is important to have techniques that include blocking for duplicate detection, sampling for data cleaning and distributed data cleaning; User Engagement – involving humans in other data cleaning tasks, besides data deduplication, such as taking user feedback in discovering data quality rules; Semi-structured and unstructured data – data quality problems for semi-structured and unstructured data remain largely unexplored; New applications for streaming data – how qualitative data cleaning approaches will work on distributed streams of data; Growing Privacy and Security Concerns – reconcile the need for data provenance, access to unaggregated data and privacy [45].

### 2.2.2. Segmentation

Time Series segmentation is used in data analysis to split up a continuous sequence of temporal data points into distinct segments or regions. Each of them is characterized by homogenous properties or patterns that distinguish them from the other segments in the time series. This technique is used in a wide range of areas such as: Finances with the objective of identifying different market phases and economic cycles; Healthcare by monitoring patient data for detecting diseases and physiological states; Manufacturing in a way of detecting operational states and/or maintenance needs by analysing machine performance data; Sports to assess performance and risk of injury [46], [47].

Segmentation is of great importance to data analysis and the main purpose is to simplify and understand the complex time series data into meaningful segments for pattern recognition, anomaly detection, behavioural analysis and may also be used for feature extraction. The main challenge of time series segmentation is that the technique and their parameters may have a significant impact on the results making it a process that needs to be adaptive and requires continuous monitoring and updating to reflect new data accurately. The main types of segmentation used are [48], [49]:

- Sliding Window (SW) – technique that involves moving a fixed-size window across the time series data to identify local patterns and short-term trend within each window.
- Top-Down – begins with the entire time series as a single segment and iteratively splits the series into smaller segments based on a specific criterion and continues until it reaches a pre-defined threshold.
- Bottom-Up – starts with the time series divided into the smallest possible segments and then merges them based on similarity, forming larger segments until it reaches a pre-defined threshold.
- SWAB – uses the SW technique to create initial segments and then applies the Bottom-up method to improve these segments.
- Dynamic Time Warping – used for measuring the similarity between two time series and is very useful to deal with non-linear time distortions.
- Model-Based Methods – related with fitting a statistical model to the time series data and the model parameters or states often represent different segments of the time series.

The effects of the window size when performing segmentation is the most important factor so Banos et al. in a study with WS and inertial sensors tested several window sizes on a dataset that comprises motion data recorded for 17 volunteers while performing 33 fitness activities and concluded that reduced ones (2 seconds or less) lead to a better recognition of the activities and provide the most accurate detection performance [50].

### 2.2.3. Using Features or Raw Data

Depending on the study we are working on and on the main objective, choosing between using raw data values or performing feature extraction, selection and transformation from the data and inputting it on a model depend on several factors.

Performing feature extraction is used in very complex and high-dimensional data with a large number of variables from which it can be beneficial to extract the most relevant features to avoid overfitting, reduce computational power and to help the model to focus on relevant information. Domain knowledge and expertise in a specific area makes it easier to extract meaningful features for the model. Feature extraction for some models such as linear models can benefit from feature extraction that captures non-linear relationships between variables and can transform the data into a more suitable representation of the problem, improving accuracy and generalization. Since Time Series are data with temporal dependencies extracting features like trends, seasonality and cyclic features can be more informative than raw time series data. For non-stationary data, feature extraction may help transforming it into a stationary format, making it more suitable for model analysis [51].

Raw values are usually imputed in types of models that are very powerful and can inherently handle complex relationships, such as DL models (CNNs and RNNs), because these models can learn about the data without the need for manual feature extraction. Tree-based models (Random Forests, Gradient

Boosting) are also very effective using only raw values as they can capture non-linear relationships and do not require scaling. In addition, using raw values can save time, effort and computational power since it avoids the additional step of feature engineering, and it may be challenging to determine what feature to extract if there is a lack of knowledge about the data that is being analysed. Starting without feature extraction is also a good starting point because it helps establish a baseline that is then compared with feature engineering. In some cases, a hybrid approach can be beneficial starting with raw values to understand the baseline performance and then iteratively and gradually add feature extraction techniques to improve model performance and interpretability.

The main types of feature extraction are [52], [53], [54], [55]:

- Time-Domain Features – include basic waveform characteristics and signal statistics and they are directly derived from a data segment. Mean, Median, Variance and Root Mean Square are common features extracted from data with time relevance.
- Frequency-Domain Features – focus on the periodic structure of the signal, such as coefficients derived from Fourier transforms. Spectral Energy is used to capture data periodicity in the frequency domain and Spectral Entropy using discrete Fast Fourier Transform component magnitudes of the signal calculate the frequency-domain entropy.
- Time-Frequency Domain Features – used to investigate both time and frequency characteristics of complex signals and they generally employ wavelet techniques. Wavelet Coefficients enable the signal to be analysed with a resolution matched to the scale of coefficients.
- Heuristic Features – features which have been derived from a fundamental understanding of how a specific movement would produce a distinguishable sensor signal. Signal Magnitude Area, Signal Vector Magnitude and Inter-axis Correlation are heuristic way of extracting features.
- Domain Specific Features – for real life scenarios there is a need for more features that are tailored to specific applications and that are possible with Time-Domain Gait Detection.

Dimensionality Reduction is also a very important technique used in data analysis and the main objective is to reduce the number of features in a dataset while preserving important information, simplifying high-dimensional data and allowing better understanding and insights. Reducing dimensions can also enhance the performance and efficiency of many ML models that struggle with high-dimensional data, help to eliminate noise by discarding irrelevant features and with fewer features, the storage requirements are reduced. There are two types of dimensionality reduction: Feature Selection – select the most important features that contribute the most to the performance of the classifier (SVM-Based Feature Selection, K-Means Clustering, Forward-Backward Sequential Search); Feature Transformation – map the high-dimensional feature space into a much lower dimension (Principal Component Analysis - PCA, Independent Component Analysis, Linear Discriminant Analysis - LDA) [56], [57].

## 2.3 Machine Learning in Sports Performance

ML is a field of study of AI that enables models to learn from data and are able to improve their performance over time without being explicitly programmed to, are able to recognize patterns, make predictions or decisions based on historical data. ML is divided into: Supervised Learning (SL) – algorithm is trained on labelled data and learns the relationship between features (input) and the output; Unsupervised Learning (UL) – unlabelled data is provided to the algorithm and it must discover hidden patterns and structures within the data (clustering and dimensionality reduction); Reinforcement Learning (RL) – training an agent to make a series of decisions by rewarding it for good actions and penalizing it for poor ones (game playing and robotic control); DL – ANN's with multiple layers to model complex patterns in data [58], [59].

ML merged with sports science and physical activity has substantial implications for the field due to the improvement of the devices used to acquire data, the information extracted from the data, the processing of the data and the utility of it to enhance our understanding of sports performance and injury risk prediction and rehabilitation [60].

Using traditional supervised ML models applied to sports science and physical exercise has been widely used in the past few years and there are many studies proving it is worth. Crema et al. exploited a combination of PCA and LDA for analysing data coming from wearable IMU's and classifying and counting specific exercises (9 upper and lower body exercises) has reached an average accuracy in the exercise detection of 85% [61]. O'Reilly et al. used multiple IMU's positioned on the lumbar spine, thighs and shanks on 82 healthy participants extracted descriptive features from the signals of the different 5 common multijoint exercises performed. Using Random Forest models to perform classification, 99% accuracy was achieved when using signals from all 5 IMU's, 99% accuracy when using signals from the thigh and lumbar IMU's and 98% with just a single IMU on the shank [62]. IMU's and ML can also be applied to smart sports and in this study by Wang et al. [63] stroke motion recognition in table tennis was achieved. Data was collected using an IMU, features were extracted and reduced using PCA and with a SVM model a 96% recognition rate of five typical strokes was achieved. Seeger et al. [64] used embedded IMU's in combination with a smartphone as an aggregator to classify daily activities and specific gym exercises and their counts are recognized and logged. For monitoring a user's daily activity, a simple distinction was made between sitting or standing (100% accuracy), walking or cycling (one outlier) and intense physical activity as running (fourteen outliers) that was then correlated with the user's heart rate. For the classification of the 16 gym exercises two IMU's sensors were used, one attached around the torso and the other on the right weightlifting glove, and the same gaussian model-based classifier as for the daily activity detection was used, ranging from 71% to almost 100% accuracy depending on the exercise being studied. Burn et al. [65] developed and evaluated the potential of performing home shoulder physiotherapy monitoring using a commercial smartwatch. Through the use of an IMU of the smartwatch data was collected from the active extremity from twenty healthy adult subjects with no prior shoulder disorders who performed seven exercises. KNN, Random Forest and SVM were the ML algorithms used to classify the exercises and all of them got the accuracy metric above 94%. Convolutional Recurrent Neural Network, a DL algorithm was also used, and it yielded the best performance – 99,4%. Here we have an example study of how DL can, in some cases, be better than traditional ML models. RecoFit is a system by Morris et al. for automatically tracking exercises in weight training and calisthenics using an IMU with the main objective of giving post-workout feedback, no user-specific training and no intervention during the workout. To achieve this, in the study segmenting exercises from intermittent non-exercise periods was performed in order to enable the model to recognize which exercise was being performed using a SVM model and at the same time count the repetitions for each exercise [66]. Ishii et al. introduced a real-time segmentation and classification algorithm that recognizes physical exercises and that works well both in indoor and outdoor environments achieving 95% of accuracy with a Dynamic Time Warping model [67]. The last study by Chang et al. used probabilistic classifiers – Naïve Bayes and Hidden Markov models – to recognize the exercises being done and count the number of repetitions for each exercise achieving an accuracy of 90% over nine different exercises [68].

From the few example studies given we can see the promising results in the sports and physical activity area that can be achieved using IMU's and ML and how important it is to keep expanding it and to make it general and accessible to everyone. The type of native ML model (all the presented in this subchapter) depends on the main objective of the study, the type and quality of the data, model interpretability, deployment environment and even training time and complexity of the model.

### 2.3.1. Basics of Deep Learning for Sports Performance

DL is a subset of ML that focuses on the use of ANN's, which are mathematical models inspired by the functioning of the human brain and it is neurons. In the last years DL has been being used in the most wide variety of areas, earning a big importance in specific ones such as image recognition, language processing and understanding and even AI games. An artificial neuron, also known as perceptron, is the basic unit of an ANN and operates by combining a set of weights with the input vector followed by an activation function. Mathematically, it can be represented as [69]:

$$y = f\left(\sum_{i=1}^{n} w_i x_i + b\right) \tag{2.2}$$

Where $x_i$ are the inputs, $w_i$ the weight given to each input, $b$ (bias) an element that adjusts the boundary away from origin without any dependence on the input value, and $f$ is the activation function that determines the output based on the weight sum of the inputs and the bias term while introduction non-linearity to the model, allowing the model to learn more complex patterns.

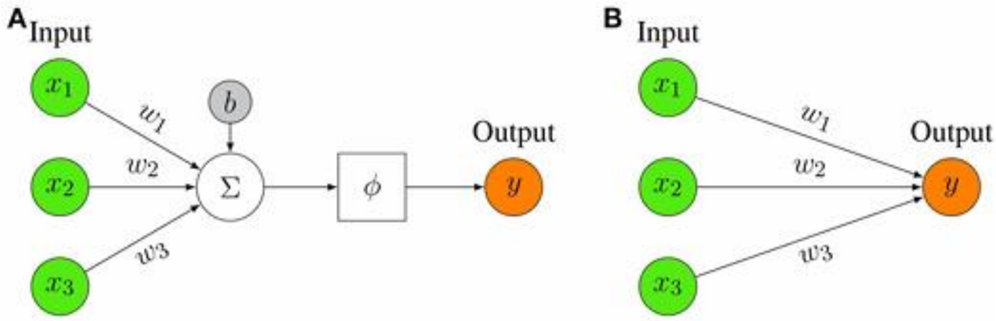


Figure 2.4: (A) visual representation of an artificial neuron model with the sum of the input being filtered by an activation function. (B) Representation of an artificial neuron model with only the key elements – inputs and output.

Common activation functions used include ReLU – $f(x) = \max(0, x)$ – a simple and efficient activation function, Sigmoid function that bounds the output values between 0 and 1, Hyperbolic Tangent function that bounds the output values between -1 and 1. Even though the perceptron is a fundamental construction block it is a very limited model only being able to solve binary classification problems that present some linearity. To overcome these limitations it is fundamental to work with ANN's with multiple layers [70].

An upgrade and more complex model than the perceptron is FNN a type of ANN that is characterized by the unidirectional flow of information between its layers and where there are not any cycles or loops inside the network. The input layer receives the input data and each neuron of this layer is associated with a characteristic. Hidden layers are between the input and the output layer and vary in number depending of the main objective, enabling the network to learn more abstract representations and complex patterns. Each neuron of the hidden layer is connected to all the other neurons of the previous layer. The output layer generates the final result of the model and the number of neurons in it depends on the type of task (binomial classification means 2 output neurons). To train FNNs a process known as backpropagation is used and it can be divided in two phases: Forward Propagation where the input data moves from layer to layer until it reaches the output layer and the predicted value is compared with the real value; Backward Propagation where the error value returns to the input layer to adjust the weights and biases and restart the process. Gradient descent relies on backpropagation to find the minimum value of the cost function [71].

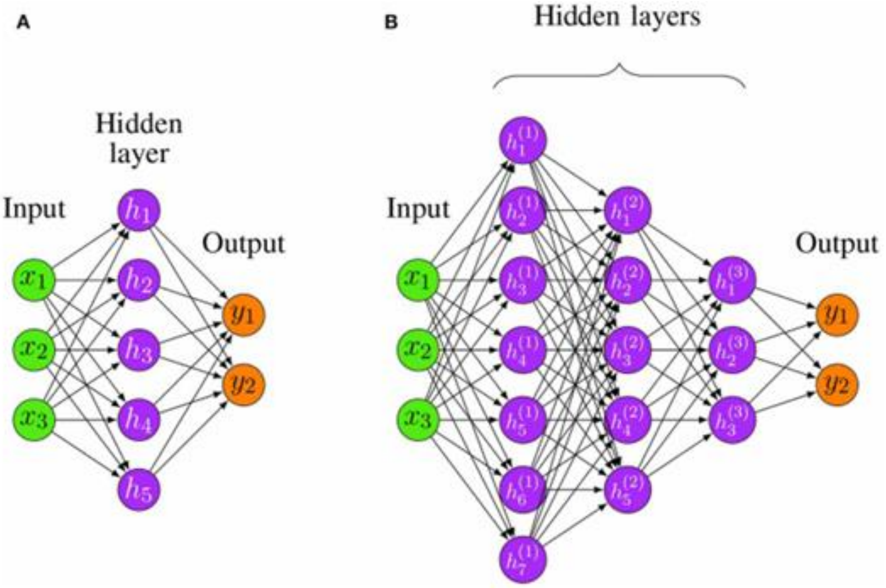


Figure 2.5: (A) simple FNN with three inputs, a single hidden layer with five neurons and two output. (B) deep feedforward neural network with the same input and the same output but with 3 hidden layers.

Research on sports training recognition based on DL has become a very popular topic in the field of the application system and academic research. It can be used to study signals related with sports activity and physical activity or to analyse and recognise actions in sports videos during the process of sports training. The main key to the success of human motion recognition is to capture the spatiotemporal motion patterns [72]. Experimental work has been carried out in order to show the advantages of using DL models compared with native ML models and how the results can improve when using these far more complex models. The ability to learn features from raw sensors data and discover the most efficient patterns to improve recognition accuracy, the readiness of capturing spatial and temporal dependencies and the fact that data pre-processing is not mandatory in order to obtain improved results are all advantages of using DL models [73]. Some of the most common DL models are: Deep Neural Networks, CNNs, RNNs and hybrid models that serve different purposes and choosing between all these models mainly depend upon the main objective of the study. A survey comparing all these DL models for sensor-based activity recognition used nineteen public HAR datasets with different sensors and for different purposes (ACC, GYR, object sensor, ambient sensor and electrocardiograph) concluded that there is no model which outperforms all the others in all situations and that it is recommended to choose models based on the scenarios and objectives. In datasets where the ACC and GYR are the only sensors being used CNN models and Long – Short Term models (LSTM) achieve better results than any other DL model. For this reason and based on the main objective of this dissertation a merged model using CNN+LSTM was chosen due to the characteristics of each of the models and to the fact that only IMU's units were used [74].

## 2.3.2. Convolutional Neural Networks

CNN's are a type of ANN that have proven highly effective in tasks related with image and video recognition, classification, prediction and analysis due to the fact that this type of model is designed to automatically and adaptively learn spatial hierarchies of features from input data making them ideal for tasks where spatial patterns are fundamental. CNN's architecture is typically built with several layers: convolutional layers that apply filters to the input data and detect patterns such as edges, textures and to create a feature map that highlights important parts of the data; pooling layers that reduce the dimensionality of the feature map (down-sampling) while retaining important information, lowering the computational complexity of the problem and preventing overfitting; fully connected layers that conclude about the features that were extracted by the convolutional and pooling layers and lead to a final output (classification or prediction). The main idea when using CNN's is that they are particularly useful in handling visual data due to their ability to capture local dependencies and spatial hierarchies [75].

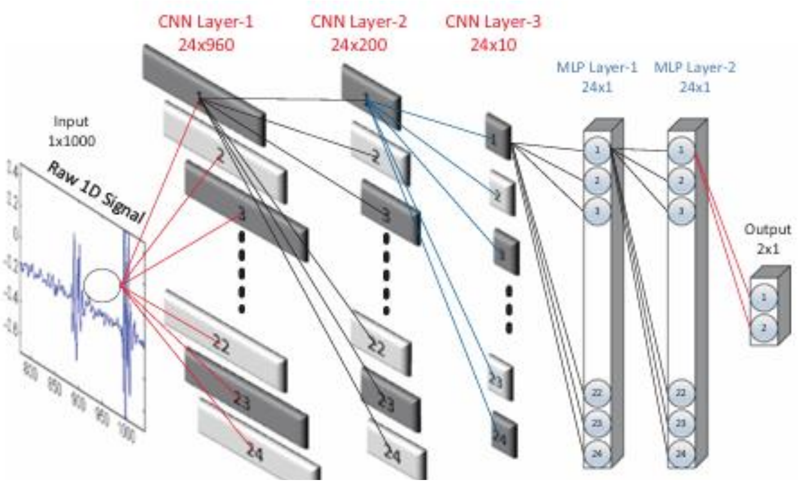


Figure 2.6: Sample 1D CNN configuration with 3 CNN and 2 MLP layers.

CNN's are being widely used and growing rapidly in the field of physical exercise and sports because of their rooted relationship based in the fact that the area involves visual and movement-based data that can effectively be analysed and interpreted by CNN's. Some examples of where this type of model can be used include: pose estimation and movement analysis using the network to analyse athlete's body in real time, helping coaches and athletes to assess form, technique and performance; injury prevention by analysing video and/or 1D signals from the athletes during training and competition that could help in the early identification of improper technique or strain and leading to an implementation of corrective measures before series injuries occur; performance enhancement comparing the athlete's movements to ideal or professional standards, providing detailed feedback about their performance and enabling them to adjust their training routines to achieve better results; sports analysis and extract strategic insights can be achieved using CNN's with video or signal data with the objective of tracking movements, identifying patterns and providing recommendations for optimizing team performance; integrate this model in wearable devices that monitor physical activity and analyse the data from their sensors (e.g. IMU's) to classify different types of physical activity, provide feedback on performance and allow for more personalized training programs; rehabilitation and recovery by tracking the progress of patients recovering from injuries by analysing and comparing them with standard recovery trajectories and monitoring recovery progress in real-time [76].

When working with CNN's in the field of sports and physical exercise there are still challenges to be addressed such as the need for large and labelled datasets to effectively train the network, hyperparameters optimization is computationally expensive, privacy concerns with video-based analysis and the need for real-time processing capabilities in dynamic sports environments.

State-of-the-art addressing CNN's in the sports field is widely studied specifically in terms of classification of activities. Zhuang et al. focused on the detection and recognition of two types of activities, non-periodic activity with complex motion states (badminton with serving and swinging as target motion states) and the weakly periodic activity with complex motion states (swimming with freestyle, breaststroke, backstroke and butterfly stroke as the target motion). The authors collected two relatively small datasets with few participants achieving an average accuracy of 87.3% on the proposed interval-based activity recognition method [77]. Um et al. acquired large-scale exercise motion data obtained from a forearm-worn WS (with a 200 Hz sampling rate) used by over fifty professional sports teams and their athletes (49,194 sets and 449,260 repetitions of exercises, 1441 males and 307 females athletes). With this dataset and using a 3-layer CNN an approach for classifying 50 different exercises was proposed achieving an accuracy of 92.14% [78]. Zaher et al. investigated the performance of different DL models for classifying exercises using the benchmark KIMORE (78 participants and 5 exercises) and UI-PRMD (ten healthy participants, 20 exercises and 2000 repetitions) datasets. CNN model outperformed all the other models for both datasets with accuracy rates of 93.08% on the KIMORE dataset and 99.7% on the UI-PRMD dataset. The model could also consistently detect the differences between correct and incorrect exercise techniques with an accuracy of 89.87% [79]. Kautz et al. presented an unobtrusive automatic monitoring system for characterizing risk of injury factors for beach volleyball based on WS. Three-axial acceleration data (39 Hz of sample rate) was recorded from 30 subjects while being video recorded and ten different exercises were labelled based on the videos. Two different approaches were investigated: the first one included generic features (e.g. median, mean, kurtosis) in combination with classification algorithms and the second one, raw values from the IMU were inputted in a CNN model. An accuracy of 83.2% was achieved with the CNN outperforming the other algorithms by 16% [80]. Soro et al. presented an end-to-end DL approach, able to provide probability distributions over 10 complex full-body exercises typical in CrossFit. To collect the data, a wearable smartwatch with IMU sensors (100 Hz sampling rate) was used and a total of 61 people participated. A 99.96% recognition accuracy on the constrained exercise data was obtained and an error of ±1 error for 91% of the sets when counting the number of repetitions for each exercise [81]. Muller et al. evaluated the applicability of CNN's to the fitness activity recognition task using IMU data. A total of 20 participants performed 5 different exercises using four sensor boards during all recordings, one at each ankle and each wrist. When using the data of only one of the sensors the CNN model exceeds all the other models [82]. Bevilacqua et al. proposed the use of CNN's to classify human activities using raw data obtained from a set of inertial sensors. A dataset was collected from a group of participants using 5 sensors while performing 16 lower-limb activities. It was concluded that CNN models can be used to address activity recognition problems [83]. Zeng et al. studied an approach to automatically extract discriminative features for activity recognition using a CNN due to the model characteristics. Three different datasets were used, Skoda (assembly-line actions), Opp (home environment activities), and Actitracker (daily activities) and the conclusions were that using a CNN-based approach to extract the local dependency and scale invariant characteristics of time series outperforms the state-of-the-art when classifying human activities [84]. Xu et al. aimed to construct a CNN to identify human activities using data from the three-axis ACC commonly found on a smartphone. Inputting raw ACC data for CNN training, the proposed method showed 91.97% accuracy, outperforming a Support Vector Machine model – 82.27% trained and tested with six features extracted from the same data [85]. Ha et al. presented a CNN model using partial weight sharing and full weight sharing for multi-model data. The dataset used was the Mhealth with 12 daily activities, from 10 subjects and recorded with 4 different sensors (50Hz sampling rate). An accuracy of 99.66% was achieved and a demonstration about the efficiency of this type of CNN model was presented compared with other CNN models [86]. Um et al. classified 50 gym exercises with a CNN and that were collected with a forearm-worn WS. The time-series were formatted as images (Euler angle, 2D square and rectangle) to allow the CNN to automatically extract discriminative features and an accuracy of 92.1% was achieved [87].

### 2.3.3. Long Short-Term Memory

LSTM's are a specific type of RNN with an architecture designed to learn and remember over long sequences of data due to the fact that traditional RNN's do not cope with long-term dependencies because of issues like vanishing and exploding gradients, which make this type of model very difficult to retain information over extended periods. With LSTM's these limitations are addressed through a unique architecture that allows them to maintain and make use of information from past data in a very effective way. The primary innovation of these networks lies in their memory cell structure: forget gate decides what information to discard from the previous cell state; input gate decides which new information to store in the cell state; output controls what information to output from the current cell state. This mechanism allows the model to remember or forget information selectively and to be highly effective working in tasks involving sequential data such as time series [88]. Merging LSTM's with physical exercise and sports focus on their ability to analyse and predict patterns over time and the fact that it is a field that often involves time-dependent sequences. Movement and gait analysis for capturing the dynamic movement patterns of athletes; performance prediction and monitoring based on historical data and sensor's time-series; injury prevention by identifying abnormal patterns in the athlete's movement over time; sports strategy and tactics by analysing time-series related with in game features; load management analysing training data over time, such as intensity, duration and optimal training loads; rehabilitation and recovery similar to injury prevention by modelling the progression of an athlete's recovery over time. The integration of LSTM's with real-time data streams for wearable devices and sensors leads to a more adaptive and responsive sports analytics system and can further enhance athletes and ordinary users performance in sports and physical exercise by changing the way of training, competing and recovering [89].

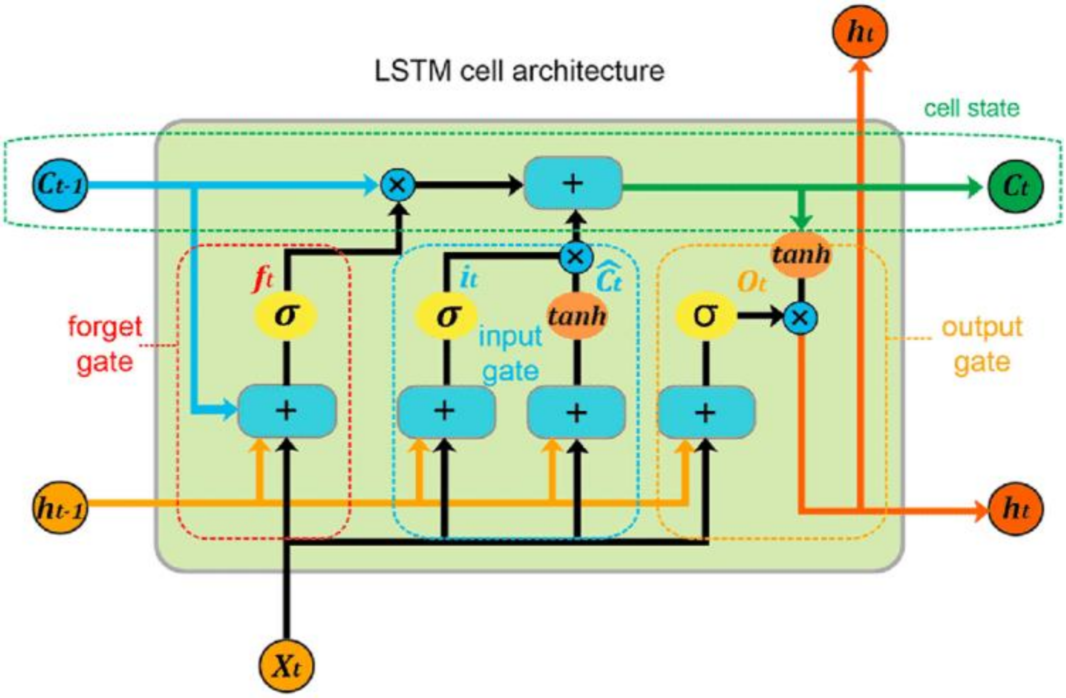


Figure 2.7: Illustration of the architecture of a LSTM cell with three gates – forget, input and output gate.

LSTM's have been widely used and gaining popularity due to the characteristics of the model that by itself increases the performance of other models such as RNN's and CNN's. A state-of-the-art with some studies showing the power of LSTM's models will be presented. Chen et al. [90] explored an LSTM-based model approach using a publicly available dataset related to six different human activities recorded using triaxial ACC (1 098 207 records). The data was segmented using a SW with a size of fifty continuous samples and the acceleration values were normalized to have zero mean and unit standard variance. When classifying the six different activities an accuracy of 95,1% was achieved. Hussain et al. [91] presented an LSTM network that could classify different exercises. A dataset focused on forty-two gym exercises arranged into six muscle groups was collected using a single chest-mounted triaxial ACC (100 Hz sampling rate). Overlapping windows for muscle group classification yielded higher average accuracy than non-overlapping windows and the general accuracy when classifying all the different exercises was satisfactory. Mekruksavanich et al. [92] proposed a generic HAR framework for smartphone sensor data based on a LSTM network for time-series domains. A dataset was collected with the help of thirty participants , each one conducting six different tasks, and a mobile phone with ACC and GYR (50 Hz sampling rate). The LSTM network resulted in an accuracy of 92,62% proving that this model takes full advantage of the temporal dependency of the data to significantly improve the feature extraction of HAR.

### 2.3.4. Convolutional Neural Networks + Long Short-Term Memory

Merging these two types of model is incredibly powerful since both of them are ANN that exceed all expectations in different domains. CNN's are highly effective at handling spatial data by detecting patterns and structures through convolutional layers and LSTM's are able to process sequential data, capture temporal dependencies and patterns over time though their unique gating mechanisms. This hybrid model (spatial and temporal) follows a specific architecture: CNN layers that process the input data and extract spatial features through convolutional filters (detect edges and textures) and pooling layers (reduce dimensionality); flattening layers that make the spatial features extracted by the CNN a sequence suitable for the LSTM layer; LSTM layers capture temporal dependencies between features and allow for time-dependent patterns; output layer that generates classifications and predictions based on the processed data. Such as CNNs and LSTMs individually, merging both models have numerous applications in physical exercise and sports such as: action recognition and movement classification, real-time performance monitoring, injury prediction and prevention, sports strategy and tactic analysis, activity recognition in wearable technology, rehabilitation and recovery tracking [94].

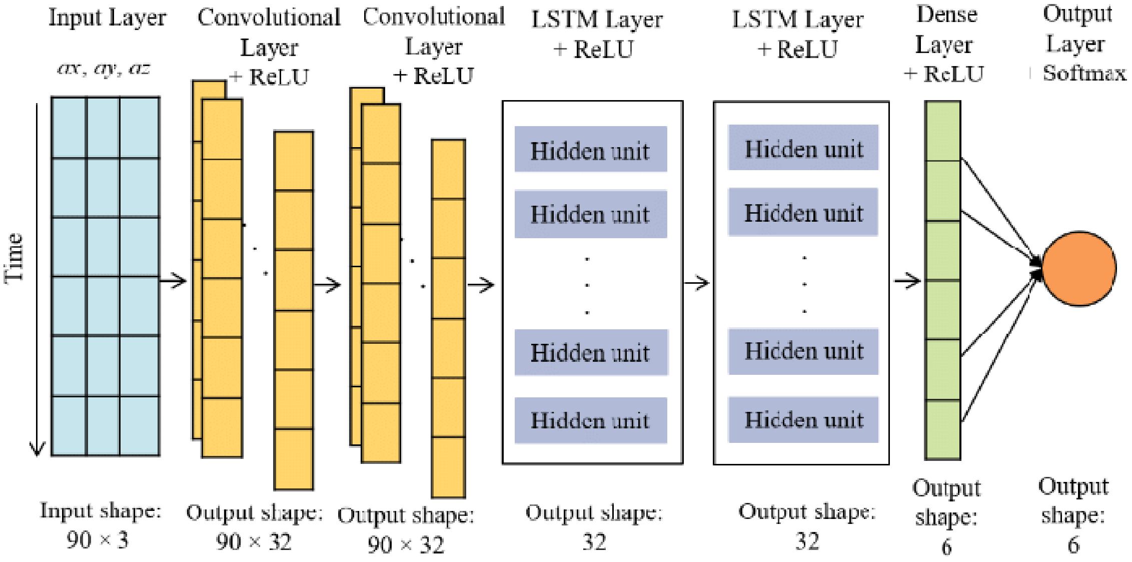


Figure 2.8: Example of a CNN + LSTM model with two convolutional layers and two LSTM layers.

A. Polo-Rodriguez et al. [94] proposed a CNN + LSTM model to classify and estimate the progression of repetition for four strength exercises using an IMU sensor embedded in a wearable device. An accuracy of 98% was achieved after classifying four different exercises and a mean absolute error under 0.2 for the estimation of the progression level. Clouthier et al. [95] aimed to use a CNN + LSTM model to automatically identify movements typically found in movement screens and assess the feasibility of performing the classification based on WS data. For optical and full body simulated IMU data an accuracy of 90.1% and 90.2% was achieved, respectively. Ordóñez et al. [96] proposed a generic deep framework for

HAR based on CNN's and LSTM's tested on two public datasets, Opportunity and Skoda. The number of optimal convolutional layers was searched to remove the dependency of engineered features.

### 2.3.5. Evaluation Metrics

When evaluating the performance of a classification model, the primary focus is on four specific measures derived from the confusion matrix: True Positives (TP), False Positives (FP), True Negatives (TN) and False Negatives (FN). The metrics used provide different perspectives about the performance of the model and should be selected based on the specific needs of the study [97].

- **Accuracy** is the proportion of correctly predicted instances out of all instances and while it might be very useful, may lead to misleading results when dealing with imbalanced datasets. For this reason, even though it is usually a primary metric, it will not be used in this study.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{2.3}$$

- **Precision** is used to evaluate the proportion of TP predictions among all positive predictions. It indicates the model's ability to correctly identify relevant instances.

$$Precision = \frac{TP}{TP+FP} \tag{2.4}$$

- **Recall**, also known as sensitivity or TP rate, is a metric used to evaluate the ability of a classification model to identify all relevant instances within a dataset. It measures the proportion of TP predictions among all actual positive instances.

$$Recall = \frac{TP}{TP+FN} \tag{2.5}$$

- **F1 Score** is the harmonic mean of precision and recall and is useful to balance both metrics being especially useful for imbalanced datasets.

$$F1\,Score = 2 \times \frac{Precision \times Recall}{Precision+Recall} \tag{2.6}$$

When evaluating the performance of a regression model, the primary focus is to use metrics that measure how well the model fits the data. These metrics help to assess model accuracy, precision and robustness in predicting continuous outcomes. As in classification problems the choice of metric depends on the problem context and the importance of penalizing large errors or accounting for outliers [98].

- **Mean Absolute Error (MAE)** is the average of the absolute differences between predicted and actual values and gives a straightforward interpretation of the model's error in the same units as the target variable. The smaller the MAE, the better accuracy the model possesses.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad (2.7)$$

- **Mean Squared Error (MSE)** calculates the average squared difference between the real and the predicted values giving more weight to larger errors and making this metric sensitive to outliers. Smaller values are associated with better models.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \quad (2.8)$$

- **Root Mean Squared Error (RMSE)** is the measure of the difference between predicted values and real values, offering a similar interpretation as MAE but penalizing more larger errors. To achieve a good model, lower values of this metric are desired.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (2.9)$$

- **R-Squared (R²)** is the proportion of the variance between predicted values and real values that can be explained by the model. This metric ranges from zero to one, where values closer to 1 indicate a better model.

$$\mathrm{R}^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2} \quad (2.10)$$

With the theoretical introduction and current state-of-the-art given, there is enough information for the user to understand all the steps and decisions of the next chapter. The reason to collect the data and program the wearable app with an Android Operating system device was presented comparing it with all the other modern devices in the market. For data cleaning and noise reduction, a moving median filter was tested due to prior studies that show the benefits of using it. For segmentation, overlapping SW method was used on raw data in order to be inputted in a CNN + LSTM model, that was concluded from the state-of-the-art that is a very promising model and is able to handle lot of data. To compare the classification model there are similar studies but to compare the regression model this is a unique study due to the fact that M1 MYO-QUALITY is a revolutionary machine that brings together functions never seen before and the prediction of the velocity and force of strength exercises with a wearable device and it is IMU´s has never been tried for this specific machine.

# Chapter 3

## 3. MATERIALS AND METHODS

Chapter 3 focuses on giving the reader a better understanding of the decisions and processes that took place in order to achieve the initial objectives proposed and final results that are going to be shown in the next chapter. For it, a workflow will now be schemed:

- Data Acquisition – to acquire data for this project it was necessary to build a smartwatch app, using Android Studio due to the fact that the smartwatch available was a TicWatch Pro 2020 with WearOS as operating system. While acquiring data with the smartwatch, data from the M1 MYO-QUALITY was also being collected. An example of each type of data is presented as well as the number of samples and time for each file acquired;
- Data Preparation – since input X data (smartwatch) and input Y data (M1 MYO-QUALITY) were not aligned due to the fact that the signals were coming from two different devices that could not be synchronized, the first step was to find a method that could align these two signals. To achieve it and because of the cyclic behaviour of both signals, correlation between the signals was studied to achieve alignment. A segmentation method and the type of SW is also presented;
- Classification Model – four different exercises were performed and the main objective is to understand how well an algorithm could differentiate between them. This part was also developed to enable future work where it is essential to know first which exercise is being performed and only then more complex models are applied to calculate continuous variables;
- Regression Model – using the IMU's data from the smartwatch as input X and the M1 MYO-QUALITY as input Y, an algorithm was developed with the main objective of calculating the velocity and force variables presented by the M1 MYO-QUALITY machine;
- GitHub – an online repository to access the dataset and models developed during this thesis will be available for readers with interest in the topic and as state-of-the-art starting point (contact author);

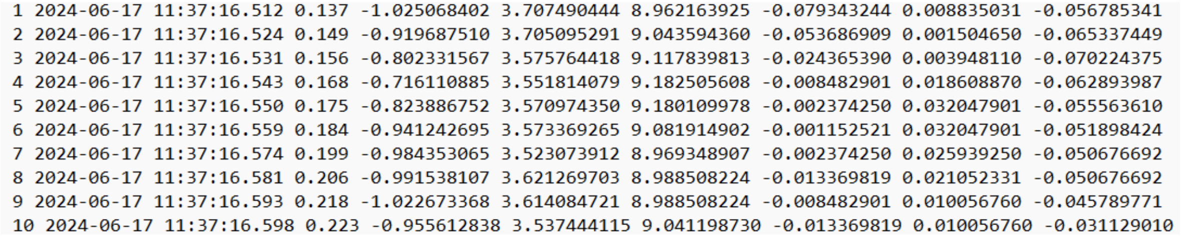
### 3.1 Data Acquisition

In order to collect the input X  and Y data for the model an Android application was designed to collect and record sensor data from the device's ACC and GYR. The application is structured within a '*ComponentActivity*' and implements the '*SensorEventListener*' interface to enable real-time sensor events and acquisition. An explanation of the main Android Studio file will be done to ensure a better understanding of the rationale and a possible replication of the entire project in case the reader has any interest in doing so. Besides the main file and Android Studio application there is the '*AndroidManifest.xml*' which is used to define essential information about a specific application and all the permissions, services and activities that it will be working with. A quick explanation about the main lines of code of this file necessary to ensure a well-functioning of the application will also be presented.

- Main File – When we start the application, the interface is designed to ensure that the screen will stay on while the data is being acquired, preventing that the device goes to a sleep mode and interrupts the data collection. The sensor managing is done through the ‘SensorManager’ with the ‘getSystemService(SENSOR_SERVICE)’ command, making sure both the ACC and GYR will ensure precise and consistent readings. To enable the application to record the data in a file, it asks for the necessary permissions for reading and recording in the external memory. This step is fundamental to ensure that the application is able to do it in a safe way the respecting the privacy policies of the Android operating system. The data collection begins when the user presses the start button and the application immediately creates a file in the external memory of the device. The name of the file is a timestamp generated with ‘SimpleDateFormat’ ensuring each file has a single name. The frequency of the data collection was set to 100 Hz meaning that, per second, 100 samples are recorded in the file and the sensor values are updated in real time and shown in the interface of the device, giving instant feedback to the user and enabling a better monitoring of the data collection. When the user presses the stop button, the application immediately cancels the acquisition of the ACC and GYR data and stores the file that is easily accessed through the external memory.
- Android Manifest – xml file that defines essential information for the well-functioning of the device as well as necessary permissions and configurations. The command ‘android.hardware.type.watch’ ensures the compatibility of the application only with wearable smartwatches. ‘WAKE_LOCK’ keeps the screen on and ‘BODY_SENSORS’ allows the application to access the ACC and GYR. Permission to read and record the data gathered by both sensors in the external memory is also needed. Without this file, the application would not work in any device with an Android operating system due to the in policies.

Figure 3.1: TicWatch Pro 2020 with the Android Wear application developed

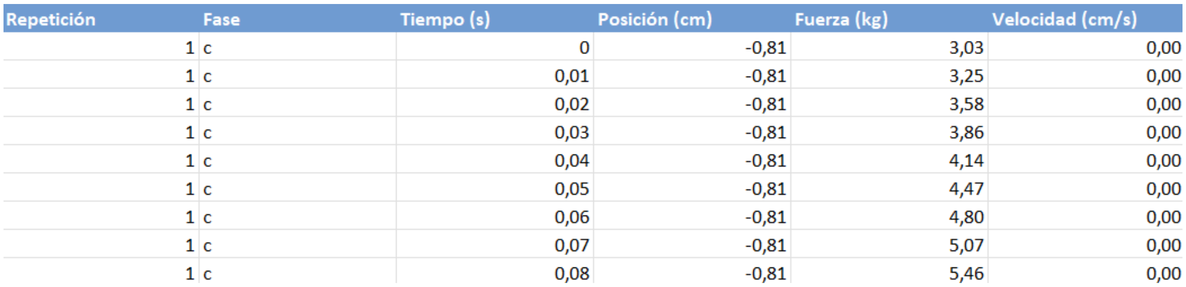
A .txt file is created with the smartwatch, which will then be used as the input X to our model. The name of the file is the current data and hour presented in the smartwatch meaning that each file will have a unique name – ‘*SensorData_20240902_161031.901.txt*’. Each file is composed by ten columns: a timestep starting at 1 and increasing by 1; date; time with format (hour: minute: second: millisecond); time since beginning; X axis of ACC; Y axis of ACC; Z axis of ACC; X axis of GYR, Y axis of GYR; Z axis of GYR. It is possible to see an example in Figure 3.2:



```
1 2024-06-17 11:37:16.512 0.137 -1.025068402 3.707490444 8.962163925 -0.079343244 0.008835031 -0.056785341
2 2024-06-17 11:37:16.524 0.149 -0.919687510 3.705095291 9.043594360 -0.053686909 0.001504650 -0.065337449
3 2024-06-17 11:37:16.531 0.156 -0.802331567 3.575764418 9.117839813 -0.024365390 0.003948110 -0.070224375
4 2024-06-17 11:37:16.543 0.168 -0.716110885 3.551814079 9.182505608 -0.008482901 0.018608870 -0.062893987
5 2024-06-17 11:37:16.550 0.175 -0.823886752 3.570974350 9.180109978 -0.002374250 0.032047901 -0.055563610
6 2024-06-17 11:37:16.559 0.184 -0.941242695 3.573369265 9.081914902 -0.001152521 0.032047901 -0.051898424
7 2024-06-17 11:37:16.574 0.199 -0.984353065 3.523073912 8.969348907 -0.002374250 0.025939250 -0.050676692
8 2024-06-17 11:37:16.581 0.206 -0.991538107 3.621269703 8.988508224 -0.013369819 0.021052331 -0.050676692
9 2024-06-17 11:37:16.593 0.218 -1.022673368 3.614084721 8.988508224 -0.008482901 0.010056760 -0.045789771
10 2024-06-17 11:37:16.598 0.223 -0.955612838 3.537444115 9.041198730 -0.013369819 0.010056760 -0.031129010
```

Figure 3.2: Example of the file format in which the input X data was recorded

For the input Y of the model, M1 MYO-QUALITY machine creates a *.xlsx* file composed of six columns where each line is associated with a specific TS: repetition number in the set for the movement selected (“Repetición”); type of movement being performed (“Fase”); time since beginning (“Tiempo(s)”); length of cable (“Posición (cm)”); force done on the cable  (“Fuerza (kg)”); velocity of the cable (“Velocidad (cm/s)”). It is possible to see an example in Figure 3.3:



| Repetición | Fase | Tiempo (s) | Posición (cm) | Fuerza (kg) | Velocidad (cm/s) |
|---|---|---|---|---|---|
| 1 | c | 0 | -0,81 | 3,03 | 0,00 |
| 1 | c | 0,01 | -0,81 | 3,25 | 0,00 |
| 1 | c | 0,02 | -0,81 | 3,58 | 0,00 |
| 1 | c | 0,03 | -0,81 | 3,86 | 0,00 |
| 1 | c | 0,04 | -0,81 | 4,14 | 0,00 |
| 1 | c | 0,05 | -0,81 | 4,47 | 0,00 |
| 1 | c | 0,06 | -0,81 | 4,80 | 0,00 |
| 1 | c | 0,07 | -0,81 | 5,07 | 0,00 |
| 1 | c | 0,08 | -0,81 | 5,46 | 0,00 |

Figure 3.3: Example of the file format in which the input Y data was recorded

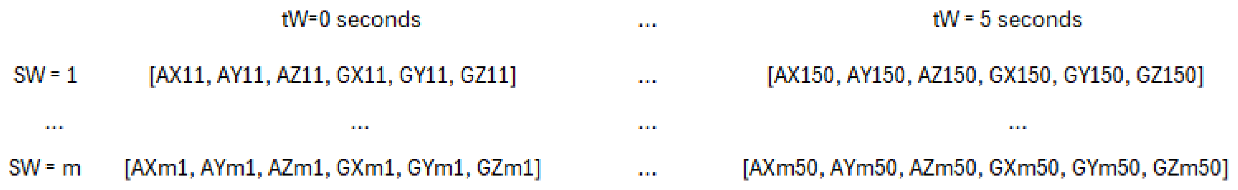
To evaluate the performance of our models, three subjects with similar physical conditions were involved in this study: Subject A (age = 23, weight = 74kg, height = 187 cm), Subject B (age = 27, weight = 77,5kg, height = 178 cm) and Subject C (age = 32, weight = 81kg, height = 178cm). Each subject wore a wearable sensor on their left wrist, with a sampling frequency of 100 Hz. The three subjects performed four different exercises (shoulder flexion, shoulder extension, horizontal abduction, horizontal adduction) in multiple sessions (four sets for each exercise), using two different weights (3kg and 5kg). A total of 300 983 sensor samples were collected from the IMU of the wearable device and as the ground truth for our model, we collected 254 646 samples from the professional sports performance machine (M1 MYO-QUALITY), recording both the force and the velocity data. For each exercise there are 24 .txt files and 24 *.xlsx* files – 3 subjects × 4 sets × 2 weights – and in each file (set ) there are 15 repetitions of the exercise being performed. An indication of the number of samples and time for each of the four exercises (1, 2, 3, 4), weights, subjects and set repetition for both input X and input Y are specified in Appendix B.1, Appendix B.2, Appendix B.3,

Appendix B.4, respectively. For exercise 1, shoulder flexion, a total of 75 113 samples were collected with the smartwatch and 64 809 samples with M1 MYO-QUALITY machine in a session with around 12 minutes (719 seconds). For exercise 2, shoulder extension, a total number of 72905 samples were collected with the wearable device and 62 971 samples with the external machine in a 11.5 minutes (698 seconds) session. For exercise 3, horizontal abduction, a total of 80 227 samples were collected with the smartwatch and 67 505 samples with M1 MYO-QUALITY in a session with around 12.7 minutes (767 seconds). For exercise 4, horizontal adduction, a total number of 69 738 samples were collected with the wearable smartwatch and 59 361 samples with the external machine in a 11.1 minutes (667 seconds) session. The number of samples collected is directly proportional to the time that each subject took to perform each set for each different exercise. In the four first tables presented in Appendix B it is possible to see that Subject 3 needed less time to perform each exercise while Subject 1 needed more time in every exercise, highlighting that weight is a subjective variable and mainly depends on the subject strength or way of performing each exercise. For this reason, the force variable (Input Y file) was divided by the weight (3kg or 5kg) in order to normalize it and to be possible to predict it.

## 3.2 Data Preparation

In the previous section it is possible to see that for the same file pair (*.txt* and *.xlsx*), the input X signal and the input Y signal have different time sizes due to the fact that it was not possible to synchronize the smartwatch and the M1 MYO-QUALITY, making the collection of the data from both devices impossible to be precisely started at the same moment. It was extremely important to align the data in order to present feasible results, classifying (classification model) the four different exercises and predicting (regression model) the velocity and the force of the movement. M1 MYO-QUALITY machine is programmed to start collecting data only when one of the variables (position of the cable, force or velocity) change and to stop collecting data when the fifteenth repetition is over (cable returns to the original position). The wearable device could not be programmed to do the same due the lack of conditions and for this reason, starting and stopping the collection of data was a manual task. An initial offset had to be calculated and inputted in the smartwatch file in order to align it with the input Y signal. For this task, due to the cyclic nature of both signals (input X and input Y), the function *.corr* that computes pairwise correlation between signals from pandas library was used. The method used within the function was the Pearson correlation coefficient that measures linear correlation (ratio between the covariance of two points and the product of their standard deviations) between two signals. To ensure better results, a median filter was applied every 100 milliseconds interval of the signal to reduce the noise and to clean the data from both signals. A moving sliding window with a TS of 50 milliseconds was applied to the input X signal in order to change its initial point and find the alignment between input X and input Y signals with the higher absolute correlation value (initial offset of the input X file). A total of 96 offsets had to be calculated since it is the number of file pairs that there are – 4 exercises × 3 subjects × 4 sets × 2 weights. All the exercises are independent and different ways of calculating the higher absolute correlation value for each pair of files had to be studied. For each pair of files of exercise 1, the lowest Pearson correlation coefficient value between the input Y and the fifth column of the input X (Y axis of the GYR) was calculated. A graphical example is given in Appendix A.1, the correlation coefficient value between pairs is given in Appendix B.5 and the initial value for each input X is in Appendix B.6. For each pair of files of exercise 2, the highest Pearson correlation coefficient value between the input Y and the fifth column of the input X (Y axis of the GYR) was calculated. A graphical example is given in Appendix A.2, the correlation coefficient value between pairs is in Appendix B.5 and the initial value for each input X is in Appendix B.6. For each pair of files of exercise 3, the highest correlation coefficient value between the input Y and the fourth column of the input X (X axis of the GYR) was calculated. A graphical example is given in Appendix A.3, the correlation coefficient value between pairs in Appendix B.5 and the initial value for each input X is in Appendix B.6. For each pair of files of exercise 4, the lowest correlation coefficient value between the input Y and the fourth column of the input X (X axis of the GYR) was calculated. A graphical example is given in Appendix A.4, the correlation coefficient value between pairs in Appendix B.5 and the initial value for each input X is in Appendix B.6. The same approach (Pearson correlation coefficient) was taken for all file pairs of the same exercise – 1, 2, 3, 4 – and it is very important to analyse the raw signals in order to study the best way to align the signals and type of correlation to use when working with new exercises, to achieve the best results possible.

After aligning the data, segmentation was done in order to input the data on the classification model and on the regression model. To classify the different exercises, all the collected data was inputted but to predict the velocity and the force, four different models with four different inputs had to be created. Since the exercises are independent, a single model by itself would not be able to predict the velocity because M1 MYO-QUALITY machine does not have an axis (single value) and for different exercises, a similar velocity or force is displayed making it impossible for a single model to predict it. This is a merging point between these two type of models since it is extremely important to first classify the exercise and only then apply a model that is able to predict the force and velocity of each movement. For each *.txt* file a list of tW, with an interval from -2.5 to 2.5 seconds and a step size of 100 milliseconds is defined (length of 50 time windows). With this, the model is able to predict what the next steps of the movement are. Each segment between consecutive values of tW forms a window where a median filter is applied to all axis of the ACC and GYR. A SW is then applied with and interval from 2.5 to the final time of each file minus 2.5 seconds and a step size of 0.1 seconds meaning that for each new window, the start time shifts forward by 100 milliseconds.



| | tW=0 seconds | ... | tW = 5 seconds |
|---|---|---|---|
| SW = 1 | [AX11, AY11, AZ11, GX11, GY11, GZ11] | ... | [AX150, AY150, AZ150, GX150, GY150, GZ150] |
| ... | ... | ... | ... |
| SW = m | [AXm1, AYm1, AZm1, GXm1, GYm1, GZm1] | ... | [AXm50, AYm50, AZm50, GXm50, GYm50, GZm50] |

Figure 3.4: Illustration of the proposed segmentation process

In Figure 3.4, it is possible to see the format of the input X matrix, where m represents the final TS. This value for the classification input X is the sum of the SW of all *.txt* files of all the exercises, being the final matrix represented by (20610, 50, 6). For the prediction input X, since there are four models, one for each exercise, it is the sum of the SW of all *.txt* files of each exercise result in the final matrices with dimensions (5269, 50, 6), (5084,50,6), (5535, 50, 6) and (4722, 50, 6), respectively. The input Y matrix of the classification model is very simple, having only four classes that are associated with each one of the exercises. For each SW there is a number corresponding to the exercise (1, 2, 3, 4) being performed and the final input Y can be represented by (20610, 1). To predict the velocity and the force, for each SW there is a continuous value associated that is the median filter of the velocity interval corresponding to the first tW of each SW. The input Y matrices of the prediction models with dimensions (5269, 1), (5084,1), (5535, 1) and (4722,1), respectively. This method where each SW is associated with a class or a continuous value (velocity and force) and merged with the tW technique, is very popular in time series analysis and in most cases is able to capture temporal  and spatial patterns. Median filters were used due to their efficiency in removing outliers or spikes in the data without blurring the signal and edge preservation to maintain the boundary information. Five second windows were chosen for the model due to the characteristics of the movement since we are dealing with fast exercises and this window length is able to capture multiple repetitions. With overlapping windows, we are assuring that the model does not miss important transitions or edges of movements.

## 3.3 Classification  and Regression Model

For both tasks, an ANN model combining CNNs and LSTMs was used – one model for classification and eight models for regression (for each exercise and variable: velocity and force). The combination of the two DL models ensures that local patterns and temporal data are captured in sequential data. The following bullet points explain the common methods applied to build the model used to classify each exercise and to predict each variable:

- Input Layer – Specifies the input shape of the data, receiving two variables: X.shape[1] that is the number of SW and X.shape[2] that is the number of tW, each one having six features corresponding to the axis of the ACC and GYR (median filter applied to each axis of the tW);
- Conv1D – Convolutional layer that applies 16 filters with a kernel size of 2 and uses a ReLu activation function;
- Batch Normalization – Technique used to normalize the output of layers in an ANN, ensuring that the input to each layer has a stable distribution across batches during training.
- Conv1D – convolutional layer that applies 32 filters with a kernel size of 3 and uses a ReLu activation function;
- Dropout – Randomly drops 25% of the neurons during training to prevent overfitting;
- Conv1D – Convolutional layer that applies 64 filters with a kernel size of 3 and uses a ReLu activation function;
- Conv1D – Convolutional layer that applies 128 filters with a kernel size of 3 and uses a ReLu activation function;
- LSTM – Layer with 256 units that returns the full sequence of outputs for each timestep;
- Dropout – Randomly drops 25% of the neurons during training to prevent overfitting;
- LSTM – Layer with 256 units that returns the full sequence of outputs for each timestep;
- Flatten Layer – Flattens the 3D output from the LSTM layers into a 1D vector to connect with the fully connected (Dense) layers;
- Dense – Fully connected layer with 2048 units and a ReLu activation function;

Before running both models, the input X data was normalized using min-max normalization in order to reduce the model complexity and eliminate redundant data and inconsistencies. For the regression models, input Y was also normalized with the same method. For the regression model an output layer with one unit and a sigmoid activation function was added because the model predicts a single continuous value between zero and one, which is then scaled back to the original shape. MAE was used as loss function of the model and MSE, MAE, RMSE and R-squared were all used as metrics to evaluate it. For the classification model an output layer with four units (4 exercises) and a SoftMax activation function was added, categorical cross-entropy was used as loss function and precision, recall, F1-score and confusion matrix were used as metrics to evaluate the classification model.

To study the effect of external variables when classifying and predicting each variable for each exercise, four different k-fold cross validation (CV) approaches were used. The first one was a 2-fold CV, where the external variable studied was the weight (three kg and five kg), meaning that we trained the model with only a weight (50% training data) and tested on the other (50% testing data) as data never seen by the model. The main objective was to assure that the weight is a subjective variable and it is not a relevant factor if the exercise is being performed correctly. The second approach was a 3-fold CV, where the external variable studied was the subject (A, B and C) meaning that we trained the model with two subjects was tested on the other. This was done to study how the model would respond to a variation in performing the same exercise, because even though the movement is similar, different people tend to have slight variations and velocities executing it. The third one was a 4-fold CV, where the external variable studied was the number of the set (1, 2, 3, 4), with three of them being used to train the model and the other one being used to test the model. The main objective was to test if continuous set repetition of the same exercise could limit the model due to factors such as fatigue and exhaustion. The last approach was used to simulate a real life environment. For each exercise, a total of 24 sets was done, 3 subjects × 2 weights × 4 sets and with it a 24-fold CV approach was tested. The model was trained with 23 sets and tested on the one remaining as data never seen by the model. The main objective was to understand how the model would react with the amount of data collected and if it is suitable for real life application and completely new and independent data. With the velocity and with the force variable was still possible to calculate power, to analyse the behaviour of this variable.

Following this methodology it is expected that the final results produced by the classification model follow the same and even better results than the current state-of-the-art. For the regression model, since it is a new study due to the innovative machine we were working with, it is expected that good results will be achieved but there are always ways of improving them that will be considered in the conclusion.

## 3.4 GitHub Repository

To facilitate future studies or independent research to validate this Masters' dissertation work all the collected data, processing of the data and the source code of the DL models (classification and regression) are available in GitHub. Detailed information about each file and code can be found in the README file. Additionally, inside each code there are notes to help the user.

# Chapter 4

## 4. RESULTS AND DICUSSION

This chapter presents the dissertation's results and discusses its findings. Firstly, the classification results are displayed and discussed with the current state-of-the-art. Then, the regression results are exhibited where each exercise is presented individually for each variable being predicted due to the fact that they are all independent. Afterwards, the power was calculated with the velocity and the force.

### 4.1 Classification of each Exercise

The first cross validation (weights) confusion matrix is presented in Figure 4.1 and the metrics of the model in Table 4.1. Equivalent and even better results, when comparing with the current state-of-the-art, were achieved, suggesting once again that deep learning models, specifically merging CNN's with LSTMs, are an excellent method to classify physical activity movement and strength exercises.

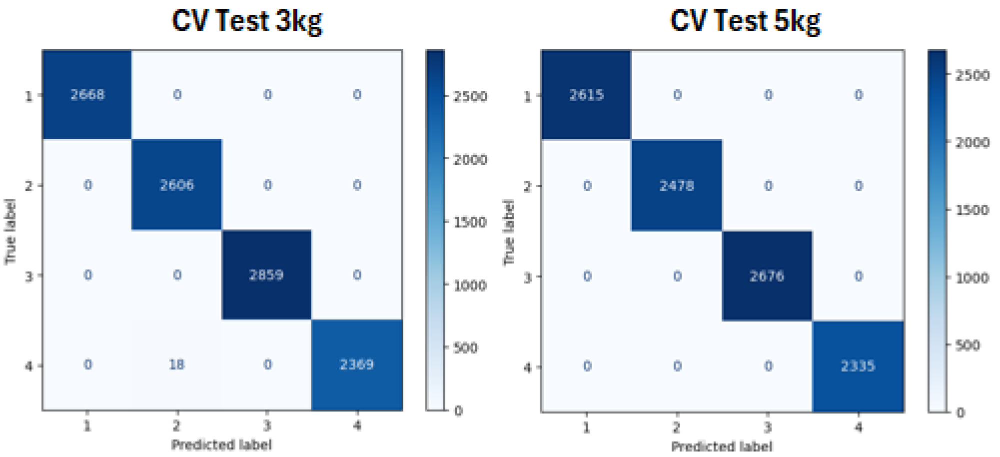


Figure 4.1: Weight CV confusion matrices – two iterations.

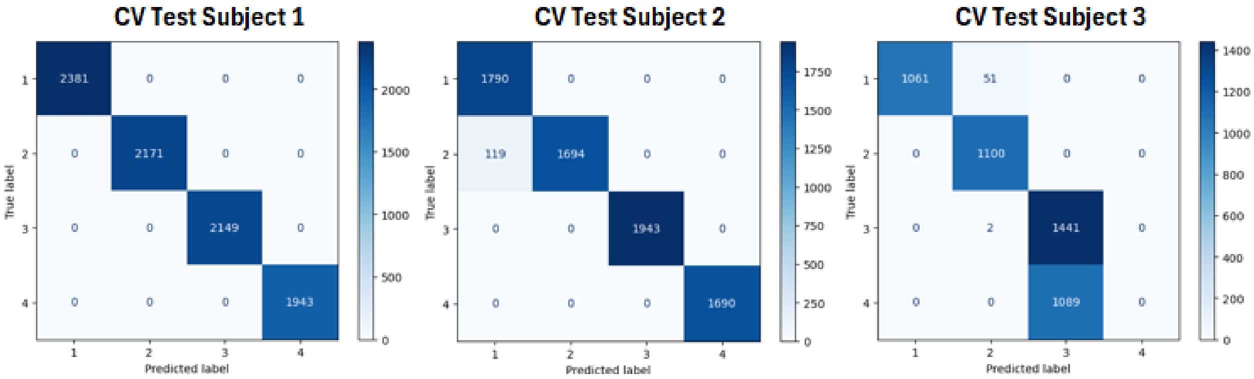
The model only committed a few mistakes classifying exercise 4 as exercise 2 in 18 segments achieving an excellent final accuracy, demonstrating that the weight is not a relevant external variable.

Table 4.1: Summary of metrics performance for Weight CV

| | **Exercise** | **Precision** | **Recall** | **F1-Score** |
|---|---|---|---|---|
| **3kg** | **1** | 1.00 | 1.00 | 1.00 |
| | **2** | 0.99 | 1.00 | 1.00 |
| | **3** | 1.00 | 1.00 | 1.00 |
| | **4** | 1.00 | 0.99 | 1.00 |

| | **Exercise** | **Precision** | **Recall** | **F1-Score** |
|---|---|---|---|---|
| **5kg** | **1** | 1.00 | 1.00 | 1.00 |
| | **2** | 1.00 | 1.00 | 1.00 |
| | **3** | 1.00 | 1.00 | 1.00 |
| | **4** | 1.00 | 1.00 | 1.00 |

The second cross validation (subjects) confusion matrix is presented in Figure 4.2 and the metrics of the model in Table 4.2. Training the model with data from subjects B and C and testing it on subject A data originated perfect results and the model did not commit any false prediction. The same happened when testing only on subject B data, having only 119 false predictions. When analysing the data collection presented in Appendix B.1, Appendix B.2, Appendix B.3, Appendix B.4, it is possible to see that subject A and B took more time than subject C to perform every single exercise. Taking more time to perform the exercise means less velocity during the whole movement. For this reason, when testing the model on subject C data the model could not predict exercise 4, mistaking it with exercise 3 every single time. The lack of information that the model had about different ways of performing the exercise than the way subject A and B did it and the way subject C performed exercise 4 was probably the cause for the failure classifying it.


CV Test Subject 1

CV Test Subject 2

CV Test Subject 3

Figure 4.2: Subject CV confusion matrices – three iterations.

With the results it is possible to conclude that it is necessary to collect more data from more subjects because without it the model cannot predict correctly which exercise is being performed in case that a new subject performs them with a slight variation (time or angle performing the movement). It is a possibility that is a crucial external factor to the model classifying the exercise and to build a better model it is essential to collect data from many more subjects, with different physical attributes (height, weight, strength, speed, endurance). It is also essential to ensure that the exercises are being well performed when collecting a bigger data base for the model to be able to identify wrong or dangerous movements (prove to injury).

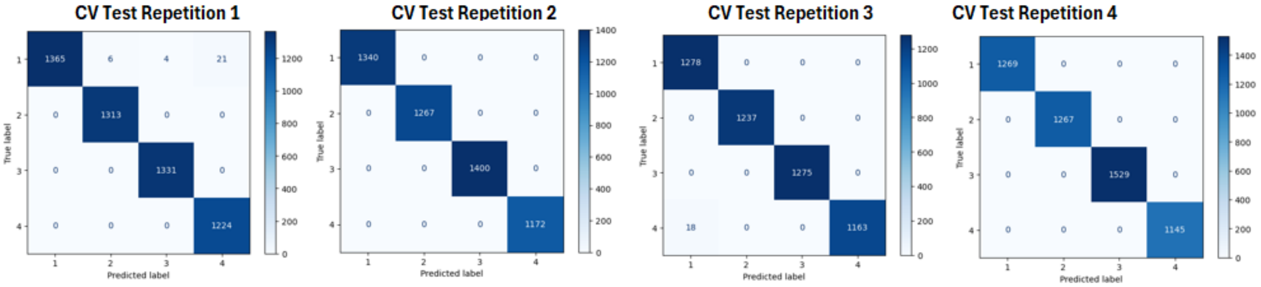
Table 4.2: Summary of metrics performance for Subject CV.

| **Subject 1** | **Exercise** | **Precision** | **Recall** | **F1-Score** |
|---|---|---|---|---|
| | **1** | 1.00 | 1.00 | 1.00 |
| | **2** | 1.00 | 1.00 | 1.00 |
| | **3** | 1.00 | 1.00 | 1.00 |
| | **4** | 1.00 | 0.99 | 1.00 |

| **Subject 2** | **Exercise** | **Precision** | **Recall** | **F1-Score** |
|---|---|---|---|---|
| | **1** | 0.94 | 1.00 | 0.97 |
| | **2** | 1.00 | 0.93 | 0.97 |
| | **3** | 1.00 | 1.00 | 1.00 |
| | **4** | 1.00 | 0.99 | 1.00 |

| **Subject 3** | **Exercise** | **Precision** | **Recall** | **F1-Score** |
|---|---|---|---|---|
| | **1** | 1.00 | 0.95 | 0.98 |
| | **2** | 0.95 | 1.00 | 0.98 |
| | **3** | 0.57 | 1.00 | 0.73 |
| | **4** | 0.00 | 0.00 | 0.00 |

The third cross validation (set number) confusion matrix is presented in Figure 4.3 and the metrics of the model in Table 4.3. When testing on the data related with set number two and set number four it is possible to see that the model did not commit any mistake and achieved excellent results. In set number one and set number three the model performed almost perfectly committing a few minor mistakes in some of the segments and misinterpreting some exercises. All the metrics used to evaluate the model (precision, recall, f1-score and accuracy) achieved very good results and with it was possible to conclude that the set number when performing the exercise was not a relevant external factor. This was also done to prove that it is possible to perform at least four times each exercise without affecting the model performance due to limitations as fatigue and exhaustion. With a larger dataset and a more refined model it is possible to identify when there are exercises being poorly performed due to these factors.


CV Test Repetition 1

CV Test Repetition 2

CV Test Repetition 3

CV Test Repetition 4

Figure 4.3: Set Repetition CV confusion matrices – four iterations.

Table 4.3: Summary of metrics performance for Set Repetition CV

| | **Exercise** | **Precision** | **Recall** | **F1-Score** |
|---|---|---|---|---|
| **Set Repetition** 1 | **1** | 1.00 | 0.98 | 0.99 |
| | **2** | 1.00 | 1.00 | 1.00 |
| | **3** | 1.00 | 1.00 | 1.00 |
| | **4** | 0.98 | 1.00 | 0.99 |

| | **Exercise** | **Precision** | **Recall** | **F1-Score** |
|---|---|---|---|---|
| **Set Repetition 2** | **1** | 1.00 | 1.00 | 1.00 |
| | **2** | 1.00 | 1.00 | 1.00 |
| | **3** | 1.00 | 1.00 | 1.00 |
| | **4** | 1.00 | 1.00 | 1.00 |

| | **Exercise** | **Precision** | **Recall** | **F1-Score** |
|---|---|---|---|---|
| **Set Repetition 3** | **1** | 0.99 | 1.00 | 0.99 |
| | **2** | 1.00 | 1.00 | 1.00 |
| | **3** | 1.00 | 1.00 | 1.00 |
| | **4** | 1.00 | 0.98 | 0.99 |

| | **Exercise** | **Precision** | **Recall** | **F1-Score** |
|---|---|---|---|---|
| **Set Repetition 4** | **1** | 1.00 | 1.00 | 1.00 |
| | **2** | 1.00 | 1.00 | 1.00 |
| | **3** | 1.00 | 1.00 | 1.00 |
| | **4** | 1.00 | 1.00 | 1.00 |

The last cross validation had a total of 96 scenes, 24 for each exercise and the main objective was to understand if the model could classify each segment correctly. All the confusion matrices and metrics of exercise 1, 2, 3 and 4 are in the Appendix A.5, Appendix B.7, Appendix A.6, Appendix B.8, Appendix A.7, Appendix B.9, Appendix A.8, Appendix B.10, respectively. Another objective was to test a real-life situation with a wearable application working, where a person with a simple wearable smartwatch starts training and the model is able to identify which exercise is being performed. Of course this is a simple dataset with only four exercises and many more exercises are needed to build a training routine application. Even though the results were excellent showing that the model is able to continuously classify an exercise for different subjects, weights and sets.

## 4.2 Prediction of the Velocity

As referred before, to predict the velocity of the movement for each exercise it is necessary to separate them in four different models due to the fact that there is only one axis in the M1 MYO-QUALITY machine and to the fact that each exercise is independent from the other. For each exercise model, four different CV were done to study the effect of external factors (weight, subjects, repetition) on the results. Due to the large number of graphics and tables and due to the similarity of conclusions between exercises, for exercise 1 there is visual support while for the remaining ones there is only discussion of the results.

### 4.2.1. Exercise 1

The CV confusion matrix and the metrics results, to study the effect of the weight in exercise 1, are presented in Figure 4.4 and Table 4.4, respectively.

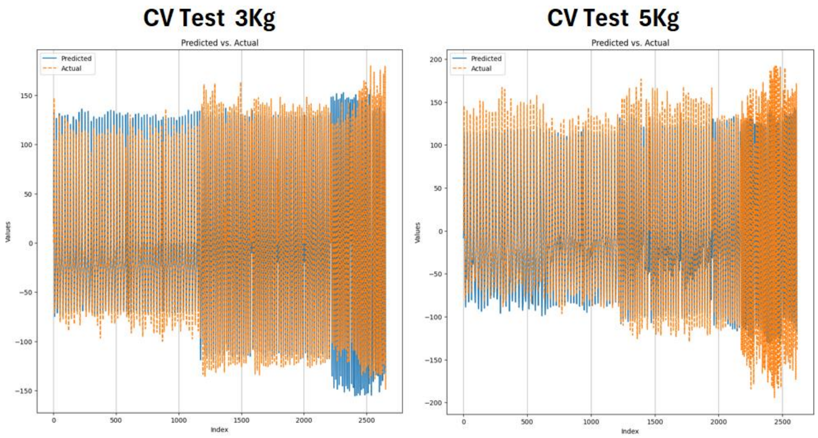


Figure 4.4: Weight CV with 3KG to predict the Velocity (cm/s) for Exercise 1 (left) | Weight CV with 5KG to predict the Velocity (cm/s) for Exercise 1 (right)

We can observe in the graphics that the model, when training with a single weight and testing on the other, is able to predict very well the velocity values. Highly encouraging results have been achieved with MSE (0.0056), MAE (0.0571) and RMSE (0.0732) values close to zero, indicative of minimal predicting errors and high R-squared (0.9015) values suggest that the model explains a large portion of the variance. With this it is possible to conclude that the weight is not an external variable that affects the model.

Table 4.4: Metric values of the Weight CV for Exercise 1 - Velocity

| CV Method Weight | MSE | MAE | RMSE | R-squared |
|---|---|---|---|---|
| **3 Kg** | 0.0034 | 0.0452 | 0.0582 | 0.9226 |
| **5 Kg** | 0.0078 | 0.0689 | 0.0882 | 0.8803 |
| **Mean** | **0.0056** | **0.0571** | **0.0732** | **0.9015** |

The CV confusion matrix and the metrics results, to study the effect of the weight in exercise 1, are presented in Figure 4.5 and Table 4.5, respectively.

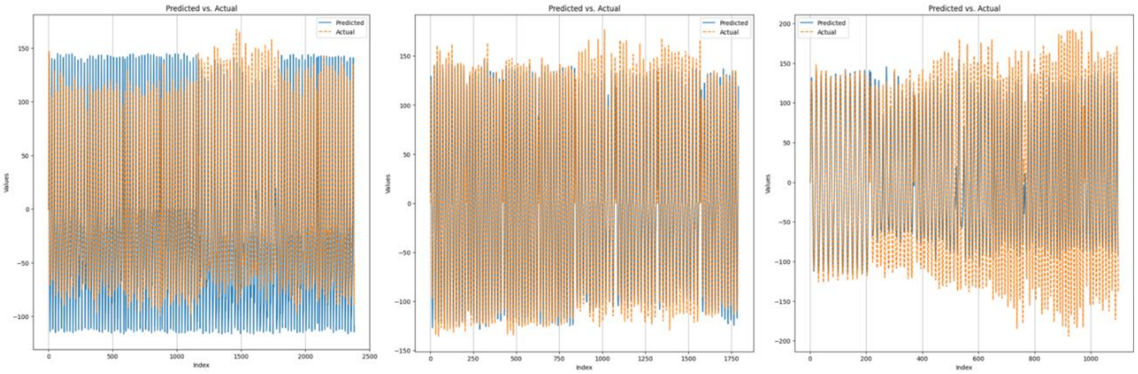


Figure 4.5: Subject 1 CV to predict the Velocity (cm/s) for Exercise 1 (left) | Subject 2 CV to predict the Velocity (cm/s) for Exercise 1 (left) | Subject 3 CV to predict the Velocity (cm/s) for Exercise 1 (left)

It is possible to see in the graphics and in the metric table that when we remove one of the subjects from the training group and we use it exclusively to test the model, the results are worse compared to the results from the weight CV. Even though MSE (0.0119), MAE (0.0871) and RMSE (0.1051) mean values are close to zero we can see from subject B results that it is possible to achieve much better results for the other two subjects as well. When analysing the data collection, it is possible to see that subject A took more time to perform every exercise and subject C needed less time. Even though the exercise is being well performed, the subjects do it with slight variations and the model is not able to recognize precisely the velocity. Since subject B time is in between the time of the other two subjects, the model is able to understand that the velocity should also be in between and it achieves better results. Because the other two subjects are extremes (more and less time) the model is not able to predict with the same precision the velocity and it is visible in the graphics the model predicting excessive velocity for subject A and limited velocity for subject C. Three different subjects are not enough when building a model and it is essential to collect more data from different subjects to create a more robust and better model. We suggest that the subject variable is an external factor to the model which is very important to achieve good results.

Table 4.5: Metric values of the Subject CV for Exercise 1 - Velocity

| **CV Method Subject** | **MSE** | **MAE** | **RMSE** | **R-squared** |
|---|---|---|---|---|
| **Subject A** | 0.0140 | 0.1063 | 0.1183 | 0.5109 |
| **Subject B** | 0.0043 | 0.0525 | 0.0656 | 0.9183 |
| **Subject C** | 0.0173 | 0.1024 | 0.1314 | 0.8373 |
| **Mean** | **0.0119** | **0.0871** | **0.1051** | **0.7555** |

The CV confusion matrix and the metrics results, to study the effect of the set number in exercise one, are presented in Figure 4.6 and Table 4.6, respectively. When training with three sets and testing on the remaining one excellent results were achieved with MSE (0.0021), MAE (0.0336) and RMSE (0.0457) mean values very close to zero, indicative of minimal predicting errors and high R-squared values suggest that the model explains a large portion of the variance. Since we are testing 25% of the dataset (four sets) it is easier to see on the graphics, the difference between the actual values and the predicted values, being perceptible the excellent results of the model corroborated by the metric table. With these results it was possible to rely on the idea that the number of the set is not a relevant external factor that could interfere with the model performance.

Figure 4.6: Set 1 Repetition CV to predict the Velocity (cm/s) for Exercise 1 (first) | Set 2 Repetition CV to predict the Velocity (cm/s) for Exercise 1 (second) | Set 3 Repetition CV to predict the Velocity (cm/s) for Exercise 1 (third) | Set 4 Repetition CV to predict the Velocity (cm/s) for Exercise 1 (fourth)

Studying the effect of the number of the set is very important because situations where the subject is suffering from fatigue or exhaustion and are interfering with the velocity of the movement can be identified. With a larger dataset and a more refined model it is possible to identify when there are exercises being poorly performed due to these factors.

Table 4.6: Metric values of the Set Repetition CV for Exercise 1 - Velocity

| CV Method Set Repetition | MSE | MAE | RMSE | R-squared |
|---|---|---|---|---|
| **Set Repetition 1** | 0.0017 | 0.0311 | 0.0409 | 0.9623 |
| **Set Repetition 2** | 0.0018 | 0.0318 | 0.0423 | 0.9584 |
| **Set Repetition 3** | 0.0028 | 0.0376 | 0.0528 | 0.9460 |
| **Set Repetition 4** | 0.0022 | 0.0340 | 0.0467 | 0.9522 |
| **Mean** | **0.0021** | **0.0336** | **0.0457** | **0.9547** |

The final CV method trained every scene leaving one unseen by the model out in order to simulate a real life approach where a wearable application is developed. Due to the number of graphics and the size of the metric table, these are presented in Appendix A.9 and Appendix B.11. The results achieved with this method were excellent and all the metrics mean values, MSE (0.0021), MAE (0.0336) and RMSE (0.0457), are very close to zero, indicative of minimal predicting errors and high R-squared values (0.9547) suggesting that the model is able to explain a large portion of the variance. Since the training set is larger than the testing set, it is very easy to confirm the metric table results with the graphics. On average, the predictions align closely with the actual values, and when discrepancies arise, they remain consistently small. We can assume that for exercise 1, it was possible to predict the velocity of the movement while studying the external factors that could impact negatively the model and that should be taken into consideration when collecting a larger dataset.

### 4.2.2. Exercise 2, Exercise 3 and Exercise 4

Even though the exercises are independent and it was necessary to build a different model to predict the velocity of the movement for each one, there are some generals conclusions that can be drawn. For each exercise four different CV methods were used in order to understand which external variables would be relevant to the model results. Some specific conclusions for each exercise were also achieved. Since there are a lot of graphics, metric tables and conclusions for very similar results between exercises, a paragraph for each CV method will take place and the visual results are available in the Appendix.

Starting with the first CV method of each exercise (weight), in Table 4.7, it is possible to see that very similar results were achieved, with all the mean metrics values, MSE, MAE and RMSE, close to zero, indicative of minimal predicting errors and high R-squared values suggesting that the model is able to explain a large portion of the variance. The graphics and metric tables from exercise 2, 3 and 4 can be found in Appendix A.10, Appendix B.12, Appendix A.14, Appendix B.16, Appendix A.18 and Appendix B.20, respectively. We can conclude that for this group of four exercises, the weight is not an external variable that can influence the model results. If new exercises are added, the weight variable is expected to behave the same way. In case wrong velocity values are constantly being predicted it may be an indication of an excessive training load or poor technique and both could lead to an injury.

Table 4.7: Mean of the metric values of the Weight CV for Exercise 2, 3 and 4 - Velocity

| CV Method Weight | MSE | MAE | RMSE | R-squared |
|---|---|---|---|---|
| **Exercise 2** | 0.0037 | 0.0439 | 0.605 | 0.9013 |
| **Exercise 3** | 0.0030 | 0.0395 | 0.0528 | 0.9517 |
| **Exercise 4** | 0.0046 | 0.0482 | 0.0672 | 0.9138 |

In the second CV method of each exercise (subject), a different phenomenon happened comparing with exercise one. The graphics and metric table results from exercise 2, 3 and 4 can be found in Appendix A.11, Appendix B.13, Appendix A.15, Appendix B.17, Appendix A.19 and Appendix B.21, respectively. Since the subject C performed each exercise faster, he also took less time to do it. This changes completely the ACC and GYR signals and the model cannot exactly predict the velocity when testing on this subject because it is a completely new scenario. Unlike exercise 1, for these three exercises subject A and B did it with approximately the same speed and consequently took the same time, having very similar signals. Due to this, the metrics of subject A and B were much better and closer to zero as we can see in Table 4.8, than the metrics of subject C. It is possible to assume that for all these exercises, subject is a very important external variable and to build a robust model it is essential to have a database with lots of different subjects allowing the model to learn multiple correct variations of the same movement.

Table 4.8: Mean of the metric values of the Subject CV for Exercise 2, 3 and 4 - Velocity

| CV Method Subject | MSE | MAE | RMSE | R-squared |
|---|---|---|---|---|
| **Exercise 2** | 0.0100 | 0.0680 | 0.0916 | 0.8594 |
| **Exercise 3** | 0.0059 | 0.0457 | 0.0636 | 0.9302 |
| **Exercise 4** | 0.0104 | 0.0723 | 0.0896 | 0.5841 |

For the third CV method of each exercise (set number), excellent results were achieved with all the metrics mean values, as we can see in Table 4.9, MSE, MAE and RMSE, very close to zero, indicative of minimal predicting errors and high R-squared values suggesting that the model is able to explain a large portion of the variance. The graphics and metric table results from exercise 2, 3 and 4 can be found in Appendix A.12, Appendix B.14, Appendix A.16, Appendix B.18, Appendix A.20 and Appendix B.22, respectively. It is possible to conclude that sets are not an external variable that can lead to wrong velocity predictions and as discussed for exercise 1, wrong velocity predictions in a set can be related to fatigue and exhaustion or poor technique performing the exercise.

Table 4.9: Mean of the metric values of the Set Repetition CV for Exercises 2, 3 and 4 - Velocity

| CV Method Set Repetition | MSE | MAE | RMSE | R-squared |
|---|---|---|---|---|
| **Exercise 2** | 0.0016 | 0.0295 | 0.0396 | 0.9541 |
| **Exercise 3** | 0.0010 | 0.0245 | 0.0310 | 0.9811 |
| **Exercise 4** | 0.0024 | 0.0365 | 0.0484 | 0.9510 |

For the last CV method (scenes) it was shown that for all exercises the use of this model is a promising way of predicting the velocity of each movement. The graphics and metric table results from exercise 2, 3 and 4 can be found in Appendix A.13, Appendix B.15, Appendix A.17, Appendix B.19, Appendix A.21 and Appendix B.23, respectively. The best results were achieved with this method with all the metric values, Table 4.10, MSE, MAE and RMSE, very close to zero, indicative of minimal predicting errors and high R-squared values suggesting that the model is able to explain a large portion of the variance. When observing the graphics it is clear how well it is predicting the real velocity values. With this method it is possible to think in a real life application to predict the velocity of each movement when performing physical activity and strength exercises.

Table 4.10: Mean of the metric values of the Scene CV for Exercise 2, 3 and 4 - Velocity

| CV Method Weight | MSE | MAE | RMSE | R-squared |
|---|---|---|---|---|
| **Exercise 2** | 0.0016 | 0.0286 | 0.0373 | 0.9604 |
| **Exercise 3** | 0.0018 | 0.0300 | 0.0381 | 0.9646 |
| **Exercise 4** | 0.0030 | 0.0417 | 0.0529 | 0.9407 |

## 4.3 Prediction of the Force

As was done for the velocity, to predict the force of the movement for each exercise it is necessary to separate them in four different models due to the fact that there is only one axis in the M1 MYO-QUALITY machine and to the fact that each exercise is independent from the other. For each exercise model, four different CV were used to study the effect of external factors (weight, subjects, repetition) on the results and the graphs and metric used to evaluate the models are all presented and explained. Due to the large number of graphics and tables and due to the similarity of conclusions between exercises, all the exercises are explained in a single subchapter and the graphics and metric tables are in the Appendices.

### 4.3.1. Exercise 1, Exercise 2, Exercise 3 and Exercise 4

The main objective of calculating the force of the movement for each exercise was to understand if it was viable and how far from the real results would the model be with this amount of data. All the CV methods done (for velocity) were repeated for predicting the force. For all exercises and for all CV, decent metric results were achieved with all metrics used to evaluate the regression model close to zero but when compared to the velocity model it is possible to conclude that worse results were produced. The mean value of the metrics for each exercise and CV are presented in Table 4.11, Table 4.12, Table 4.13 and Table 4.14.

Table 4.11: Mean of the metric values of the Weight CV for Exercise 1, 2, 3 and 4 - Force

| CV Method Weight | MSE | MAE | RMSE | R-squared |
|---|---|---|---|---|
| **Exercise 1** | **0.0214** | **0.1034** | **0.1458** | **0.4219** |
| **Exercise 2** | 0.0169 | 0.0866 | 0.1299 | 0.2865 |
| **Exercise 3** | 0.0177 | 0.0840 | 0.1269 | 0.5474 |
| **Exercise 4** | 0.0243 | 0.1045 | 0.1520 | 0.3189 |

Table 4.12: Mean of the metric values of the Subject CV for Exercise 1, 2, 3 and 4 - Force

| CV Method Subject | MSE | MAE | RMSE | R-squared |
|---|---|---|---|---|
| **Exercise 1** | 0.0262 | 0.1098 | 0.1417 | 0.6934 |
| **Exercise 2** | 0.0302 | 0.1194 | 0.1484 | 0.3599 |
| **Exercise 3** | 0.0088 | 0.0657 | 0.0914 | 0.6675 |
| **Exercise 4** | 0.0311 | 0.1309 | 0.1580 | 0.3979 |

Table 4.13: Mean of the metric values of the Set Repetition CV for Exercise 1, 2, 3 and 4 - Force

| CV Method Set Repetition | MSE | MAE | RMSE | R-squared |
|---|---|---|---|---|
| **Exercise 1** | 0.0073 | 0.0509 | 0.0785 | 0.6673 |
| **Exercise 2** | 0.0078 | 0.0555 | 0.0869 | 0.5455 |
| **Exercise 3** | 0.0033 | 0.0390 | 0.0567 | 0.8557 |
| **Exercise 4** | 0.0072 | 0.0535 | 0.0843 | 0.3331 |

Table 4.14: Mean of the metric values of the Scene CV for Exercise 1, 2, 3 and 4 - Force

| CV Method Repetition | MSE | MAE | RMSE | R-squared |
|---|---|---|---|---|
| **Exercise 1** | 0.0109 | 0.0602 | 0.0805 | 0.7138 |
| **Exercise 2** | 0.0139 | 0.0698 | 0.0887 | 0.6651 |
| **Exercise 3** | 0.0061 | 0.0409 | 0.0569 | 0.8538 |
| **Exercise 4** | 0.0088 | 0.0590 | 0.0803 | 0.4539 |

For exercise 1, the graphics for each CV are presented in Appendix A.22, Appendix A.23, Appendix A.24 and Appendix A.25 and the metric tables are in Appendix B.24, Appendix B.25, Appendix B.26 and Appendix B.27. For exercise 2, the graphics for each CV are presented in Appendix A.26, Appendix A.27, Appendix A.28 and Appendix A.29 and the metric tables are in Appendix B.28, Appendix B.29, Appendix B.30 and Appendix B.31. For exercise 3, the graphics for each CV are presented in Appendix A.30, Appendix A.31, Appendix A.32 and Appendix A.33 and the metric tables are in Appendix B.32, Appendix B.33, Appendix B.34 and Appendix B.35. For exercise 4, the graphics for each CV are presented in Appendix A.34, Appendix A.35, Appendix A.36 and Appendix A.37 and the metric tables are in Appendix B.36, Appendix B.37, Appendix B.38 and Appendix B.39.

Force, derived from the ACC, provides a direct link to the physical interaction between objects and through Newton's second law, $F = m \times a$, it is a simple way of calculating it knowing the mass (3Kg and 5Kg). The results when predicting the force of the movement were not as good as the results when predicting the velocity of the movement. This can be explained by the fact that acceleration data is prone to noise and drift, especially over time or during small, subtle movements and force calculations can suffer from these inaccuracies. Another major explanation is the fact that if the object is at rest or moving at a constant velocity, the accelerometer will not collect significant data (acceleration will be zero), meaning that the force will also be calculated as zero. When performing the exercises, during the movement, if the subject is performing them at a constant velocity, it will interfere with the results. This is an excellent way of understanding if specific types of strength exercises (involving explosive strength) are being well performed. Usually force is ideal for detecting sudden forces, impacts or dynamic changes and less useful for continuous tracking that is the main objective of our study.

## 4.4 Power as a Result

Power is another major variable when performing physical exercise and strength exercises. As introduced in Chapter 2, it is the multiplication of the velocity by the force. A single CV method testing each scene was done to understand how the propagation error of each variable was affecting the prediction of the power compared to the real value. The graphics (power) are presented in Appendix A.38, Appendix A.39, Appendix A.40, Appendix A.41 and the metric tables in Appendix B.40, Appendix B.41, Appendix B.42, Appendix B.43. Table 4.15 presents the mean values of the metrics for each exercise and the results are in between the results of the velocity and the results of the force. Since the force prediction results were not as good as the velocity prediction results, when predicting the power it is clear that they are affected by the force model. We can conclude that the error of the force model produced is propagated to the power variable and in order to improve the model values it is necessary to improve the force prediction model.

Table 4.15: Mean of the metric values of the Scene CV for Exercise 1, 2, 3 and 4 - Power

| CV Method Repetition | MSE | MAE | RMSE | R-squared |
|---|---|---|---|---|
| **Exercise 1** | 0.0033 | 0.0351 | 0.0475 | 0.8609 |
| **Exercise 2** | 0.0025 | 0.0311 | 0.0411 | 0.8202 |
| **Exercise 3** | 0.0012 | 0.0240 | 0.0327 | 0.9460 |
| **Exercise 4** | 0.0022 | 0.0290 | 0.0416 | 0.7768 |

# Chapter 5

## 5. DISCUSSION AND FUTURE WORK

With this study, we have demonstrated again that it is possible to classify four different shoulder exercises using DL and classification models with a single wearable wristband with a IMU sensor embedded. The classification metric results were very promising with precision, recall and F1-score approaching 1 while the confusion matrix for each model variation reveals minimal error classifying each segment, highlighting the robustness of the model. Additionally, we were able to suggest that the use of DL in regression models is an excellent method to predict continuous variables – velocity and force. With the data from the ACC and GYR of the wearable wristband, the model was able to continuously track and predict both variable values collected from the sports performance machine (M1 MYO-QUALITY). To predict velocity, this methodology has yielded highly encouraging results with MSE, MAE, and RMSE values close to zero, indicative of minimal prediction errors, while presenting very high R-squared values suggesting that the model explains a large portion of the variance. The results when predicting the force were not as satisfactory as the results for velocity but all metrics still presented values close to zero, meaning that the model was not committing major prediction errors and, on average, the predictions were aligning closely with the actual values. Some reasons for this are related with the fact the acceleration (Newton's seconds law) is prone to noise and drift and in the presence of constant speed, the model will predict the force as being zero, which is wrong. The last variable – power was not predicted, it was calculated through the multiplication of the velocity by the power and achieved very good results with all metrics close to zero. This suggests that CNNs + LSTMs networks ensure that our model efficiently extracts relevant features and simultaneously captures temporal dependencies.

Strength training exercises are a very important part of physical activity and are fundamental to a multitude of health benefits. Thus, investigations of this nature are indispensable to facilitate the accessibility of such exercises and ensure their correct execution. It was discovered with this study that external factors such as weight and set number do not affect the precision of the model when computing variables, such as velocity and force. Yet, if wrong predictions are happening when cross validating weight, the subject might be performing the exercise incorrectly or with excessive weight and when cross validating set repetition it might be due to fatigue and exhaustion. A very important external factor is the subject performing the exercise because due to the distinct manner in which each subject performs the exercises, the variability in stature, mass, and physical fitness, the model might not be able to correctly recognize the exercise and predict variables.

Future research efforts aim to collect a bigger database, including more exercises, weights, subjects with more heterogeneous characteristics and with more set repetitions in order to achieve a more comprehensive dataset and to enhance the precision, efficacy and robustness of the model. Another very important aspect is to acquire computational power to grid search other hyperparameters of the model such as the number of hidden layers, batch size, number of epochs, activation functions and model optimizers with the main goal of achieving the best possible results . Ultimately, this could lead to more effective and personalised strength exercises, which benefit participants and advance the field.

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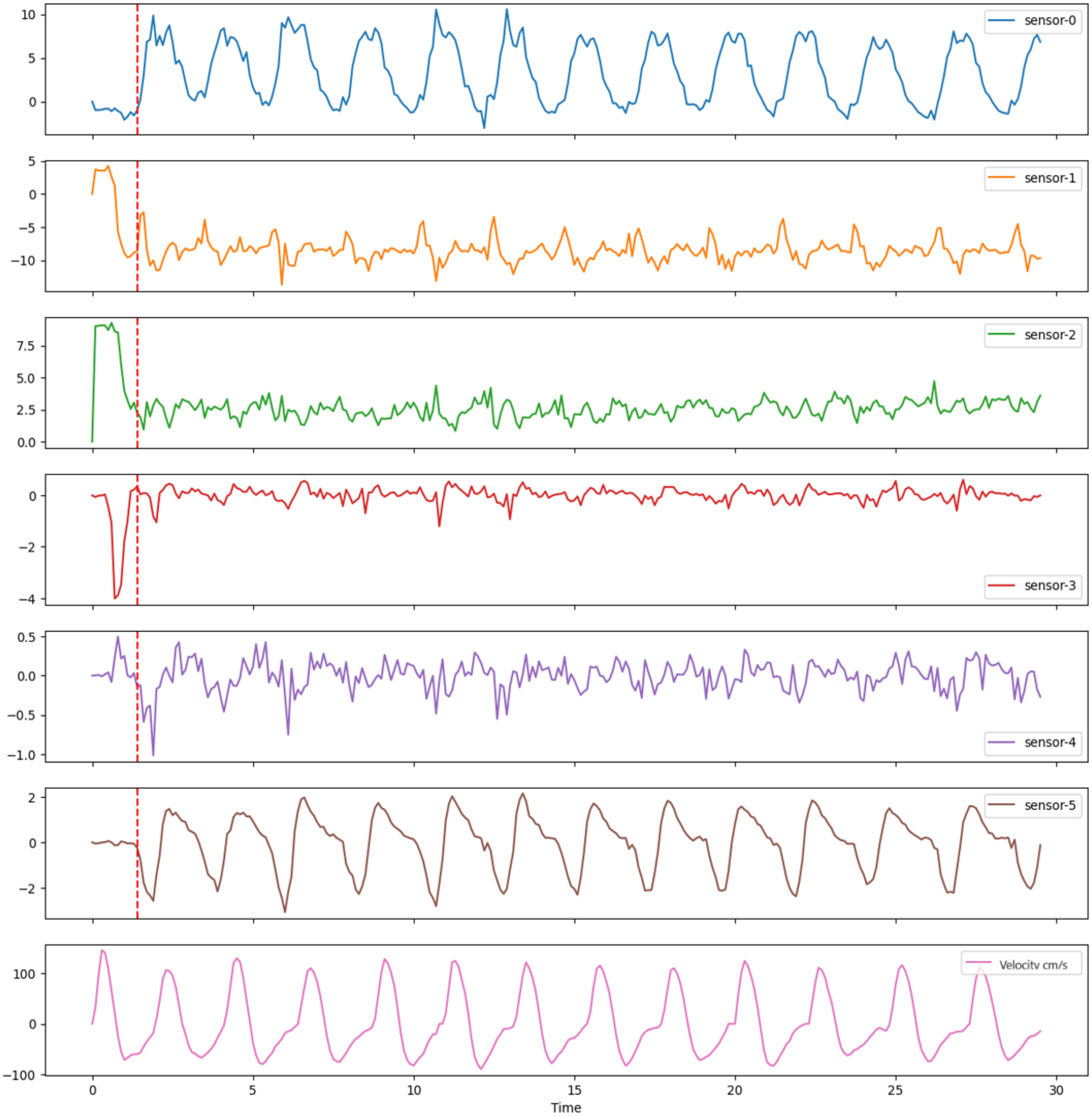
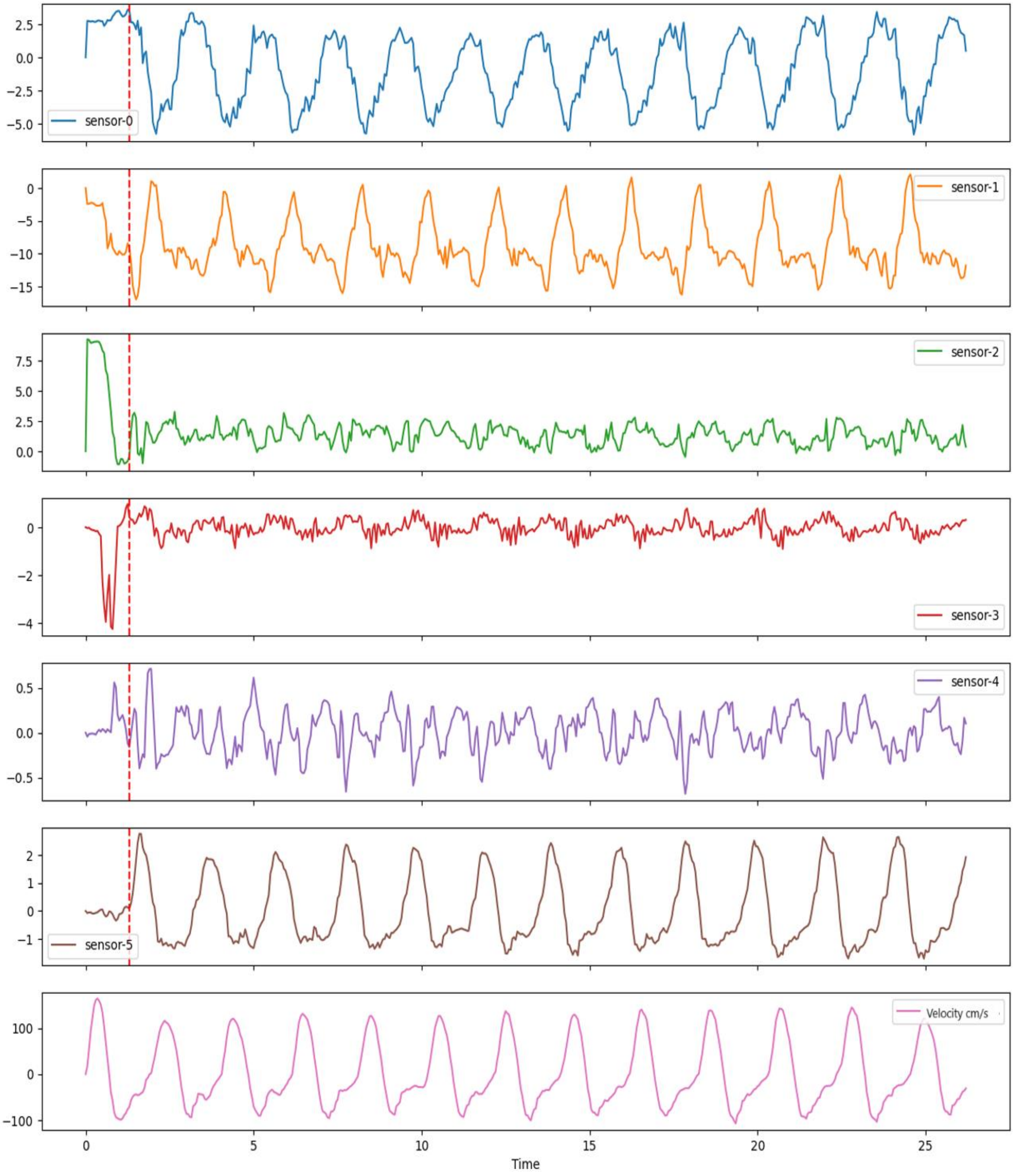
# APPENDIX

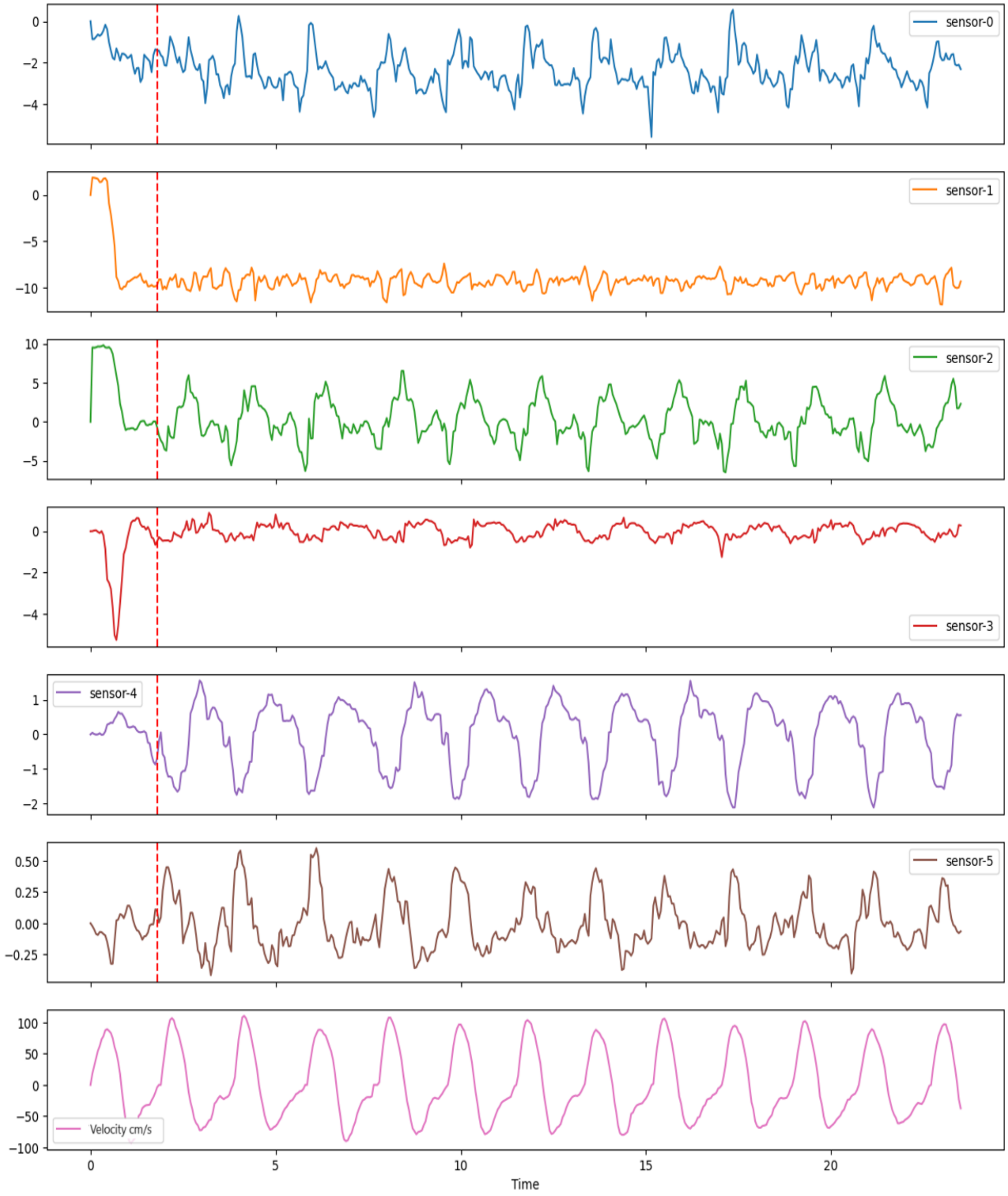
## A.1 – Complementary Figures



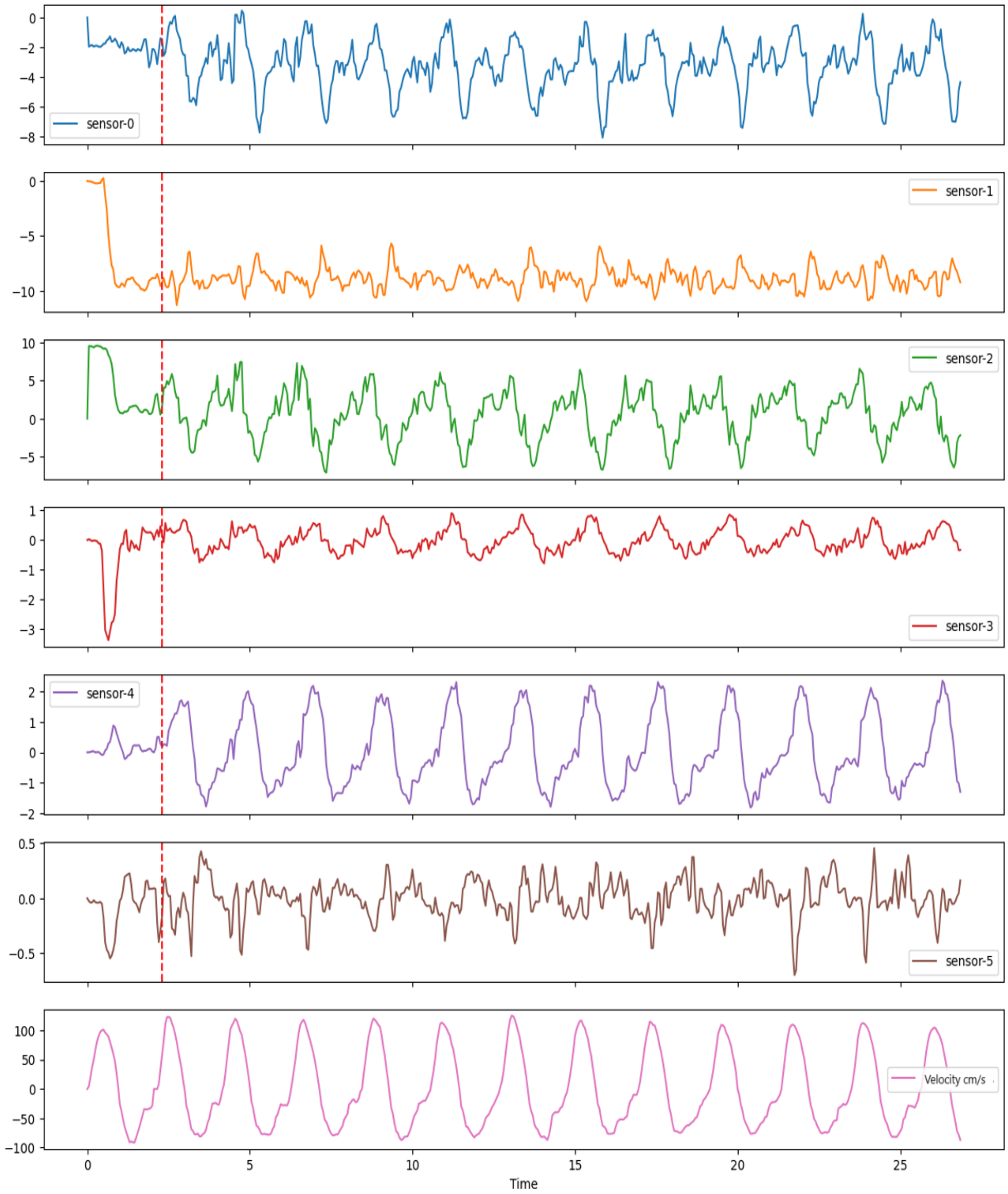
Appendix A.1: Exercise 1 - Example of lowest Pearson correlation between sensor five and velocity



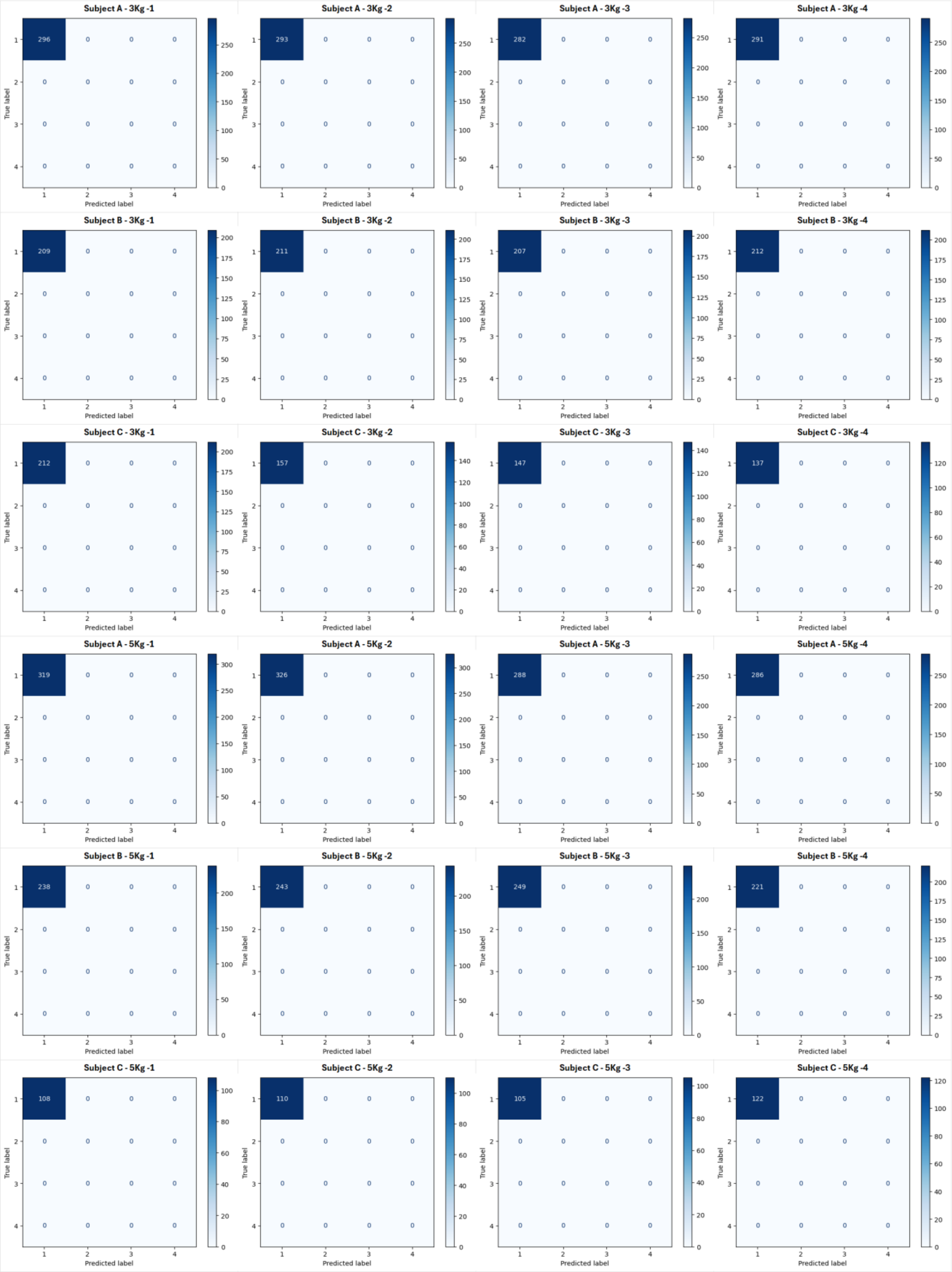
Appendix A.2: Exercise 2 - Example of highest Pearson correlation between sensor five and velocity



Appendix A.3: Exercise 3 - Example of highest Pearson correlation between sensor four and velocity



Appendix A.4: Exercise 4 - Example of lowest Pearson correlation between sensor four and velocity



Appendix A.5: Scene CV confusion matrices for Exercise 1 – 24 iterations

Subject A - 3Kg -1

Subject A - 3Kg -2

Subject A - 3Kg -3

Subject A - 3Kg -4

Subject B - 3Kg -1

Subject B - 3Kg -2

Subject B - 3Kg -3

Subject B - 3Kg -4

Subject C - 3Kg -1

Subject C - 3Kg -2

Subject C - 3Kg -3

Subject C - 3Kg -4

Subject A - 5Kg -1

Subject A - 5Kg -2

Subject A - 5Kg -3

Subject A - 5Kg -4

Subject B - 5Kg -1

Subject B - 5Kg -2

Subject B - 5Kg -3

Subject B - 5Kg -4

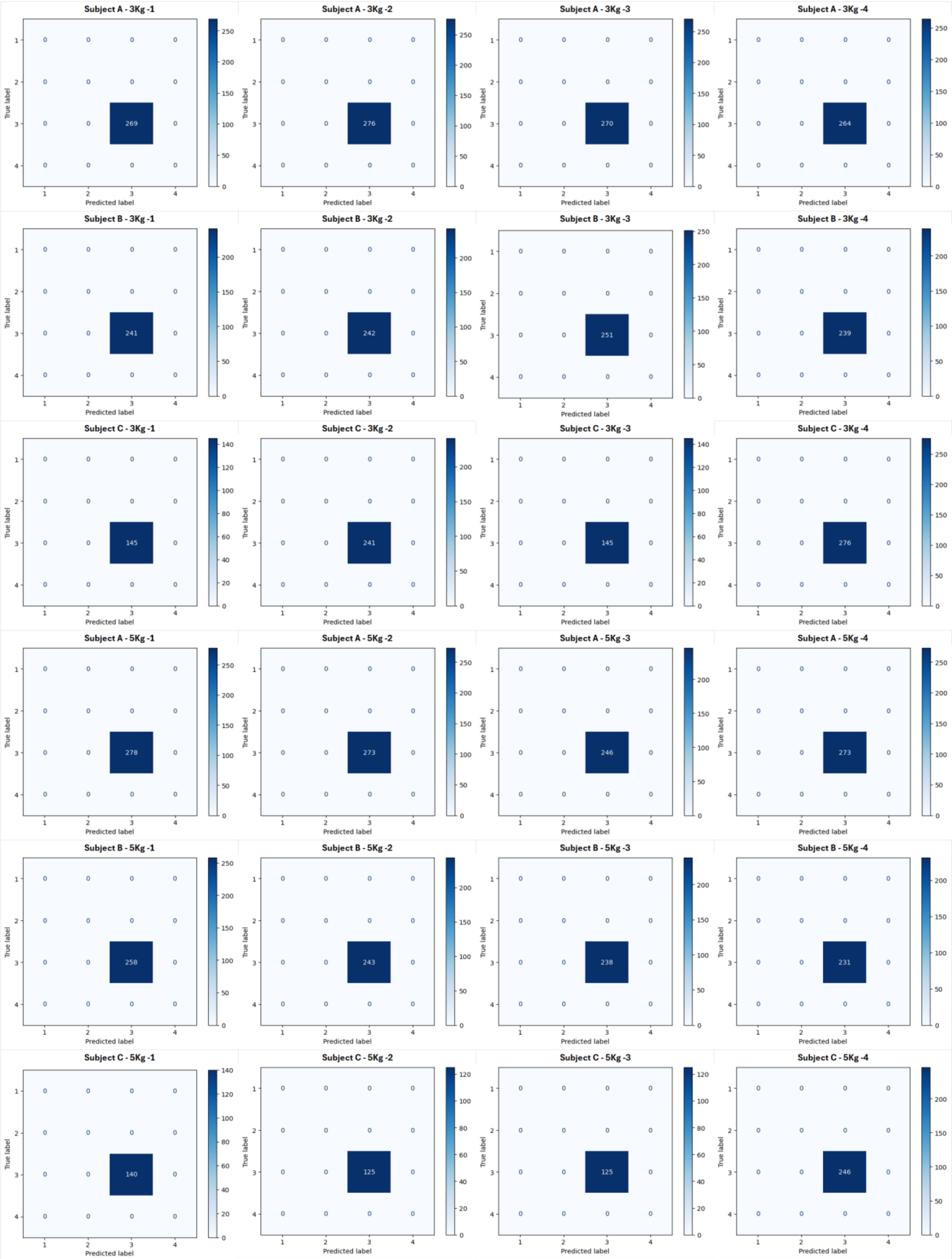
Subject C - 5Kg -1

Subject C - 5Kg -2

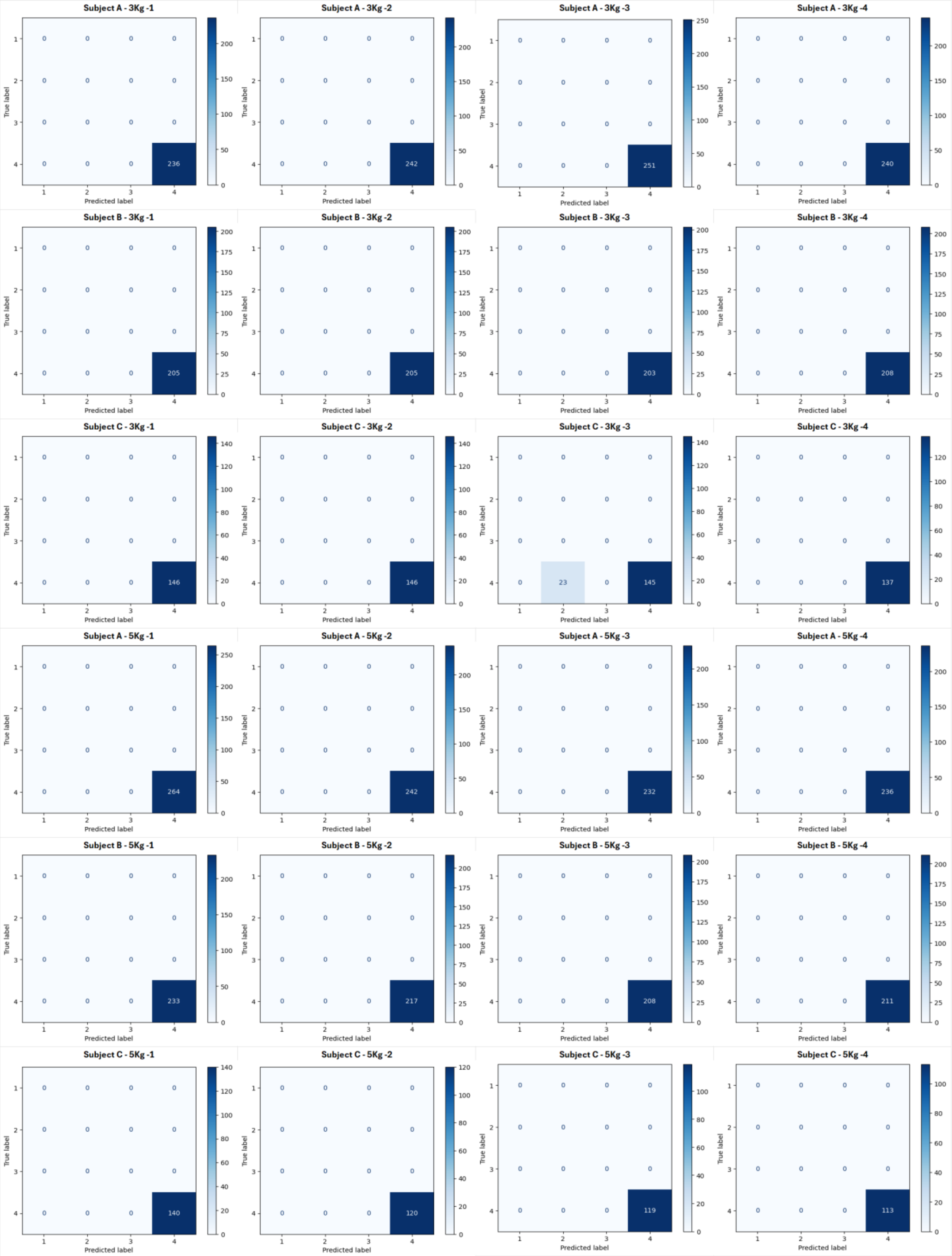
Subject C - 5Kg -3

Subject C - 5Kg -4

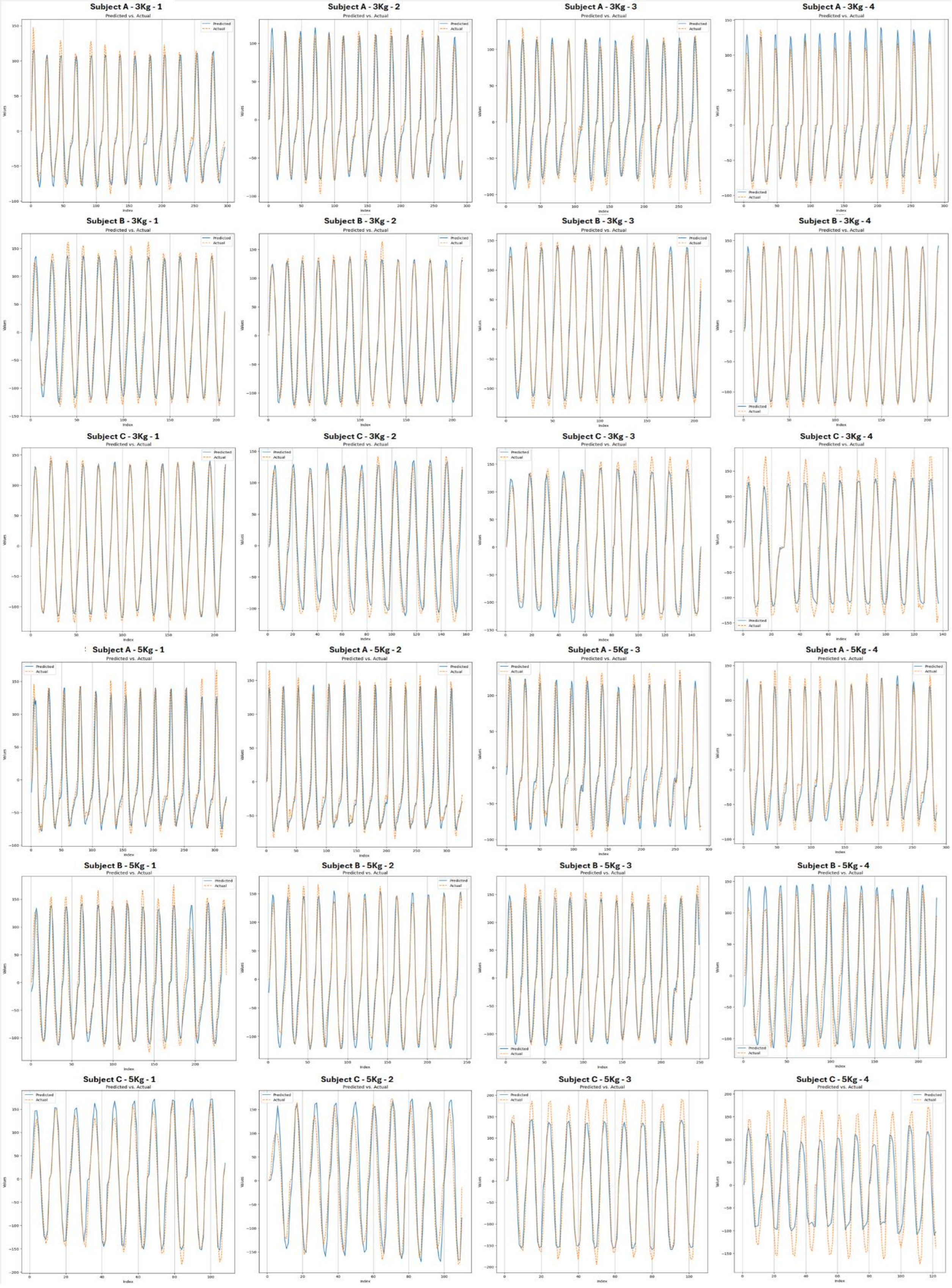
Appendix A.6: Scene CV confusion matrices for Exercise 2 – 24 iterations



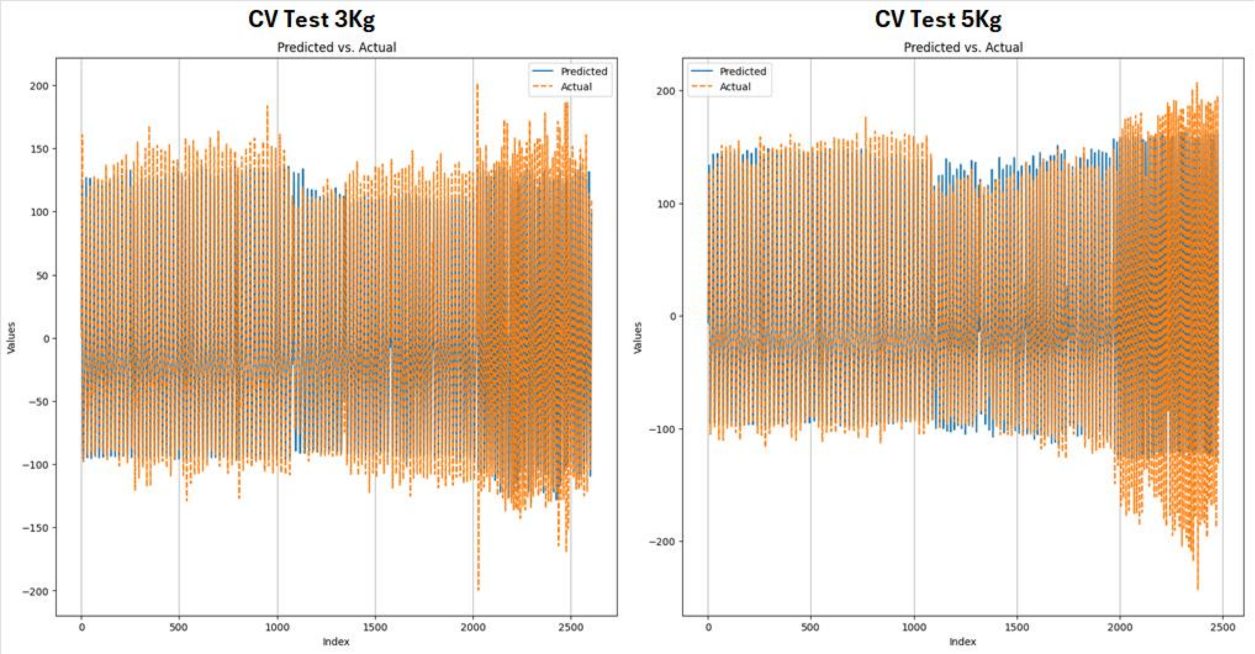
Appendix A.7: Scene CV confusion matrices for Exercise 3 – 24 iterations


Subject A - 3Kg -1
Subject A - 3Kg -2
Subject A - 3Kg -3
Subject A - 3Kg -4
Subject B - 3Kg -1
Subject B - 3Kg -2
Subject B - 3Kg -3
Subject B - 3Kg -4
Subject C - 3Kg -1
Subject C - 3Kg -2
Subject C - 3Kg -3
Subject C - 3Kg -4
Subject A - 5Kg -1
Subject A - 5Kg -2
Subject A - 5Kg -3
Subject A - 5Kg -4
Subject B - 5Kg -1
Subject B - 5Kg -2
Subject B - 5Kg -3
Subject B - 5Kg -4
Subject C - 5Kg -1
Subject C - 5Kg -2
Subject C - 5Kg -3
Subject C - 5Kg -4

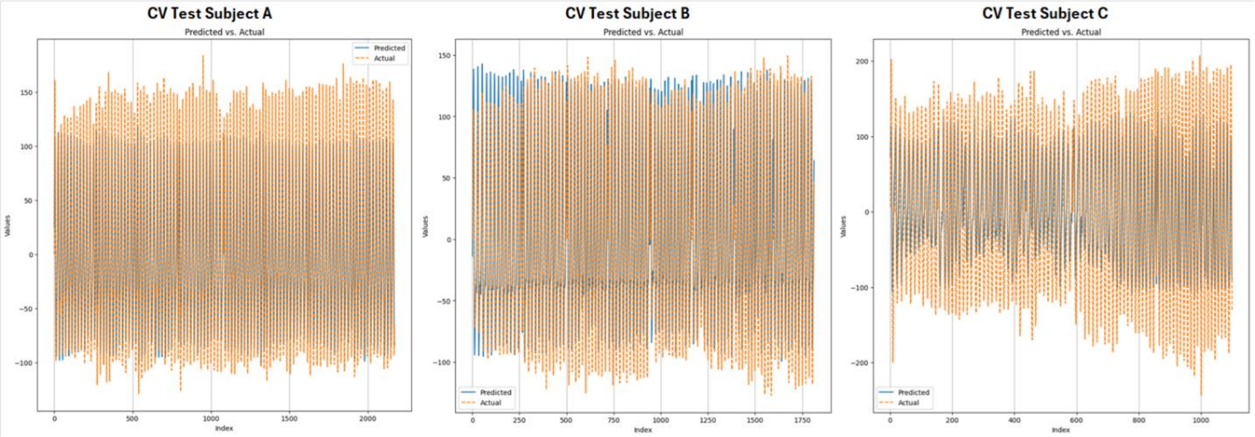
Appendix A.8: Scene CV confusion matrices for Exercise 4 – 24 iterations



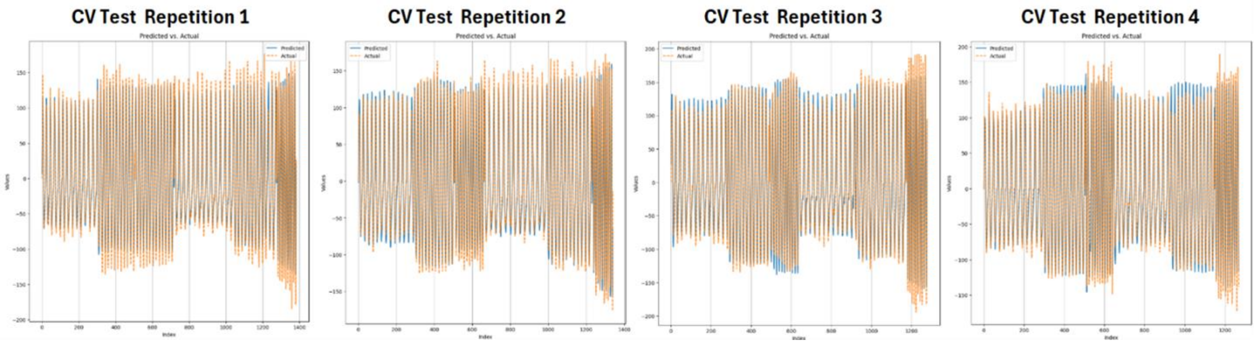
Appendix A.9: Graphics of the Scene CV to predict the Velocity (cm/s) for Exercise 1



Appendix A.10: Graphics of the Weight CV to predict the Velocity (cm/s) for Exercise 2

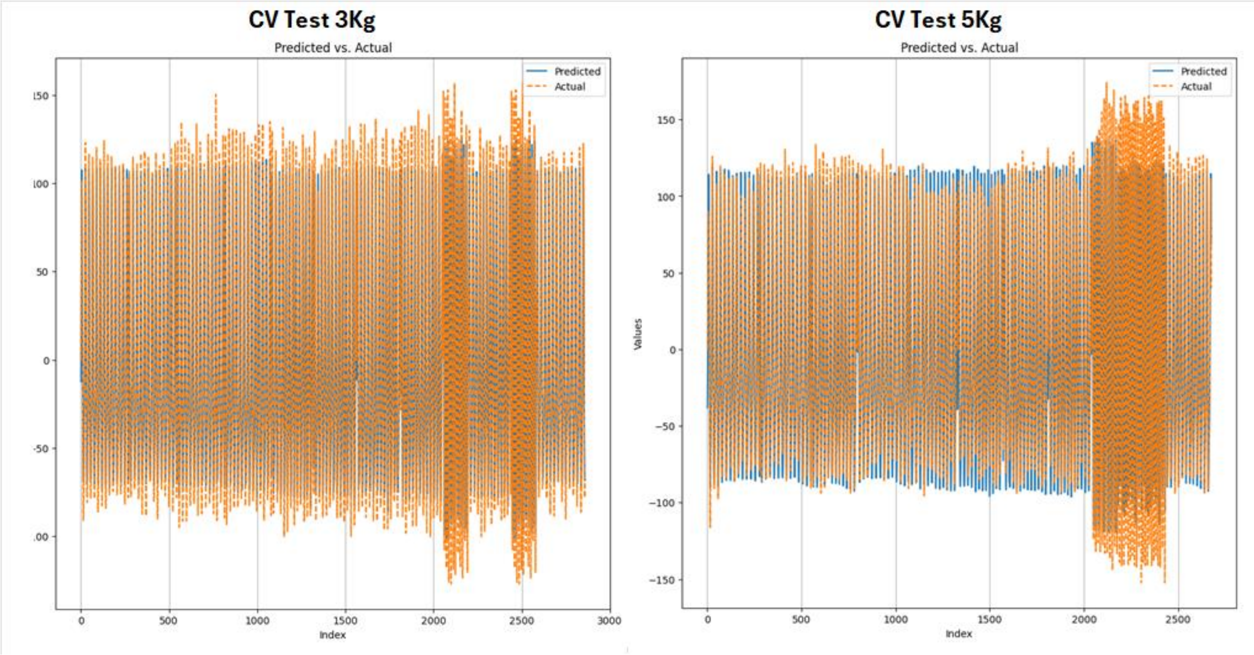


Appendix A.11: Graphics of the Subject CV to predict the Velocity (cm/s) for Exercise 2

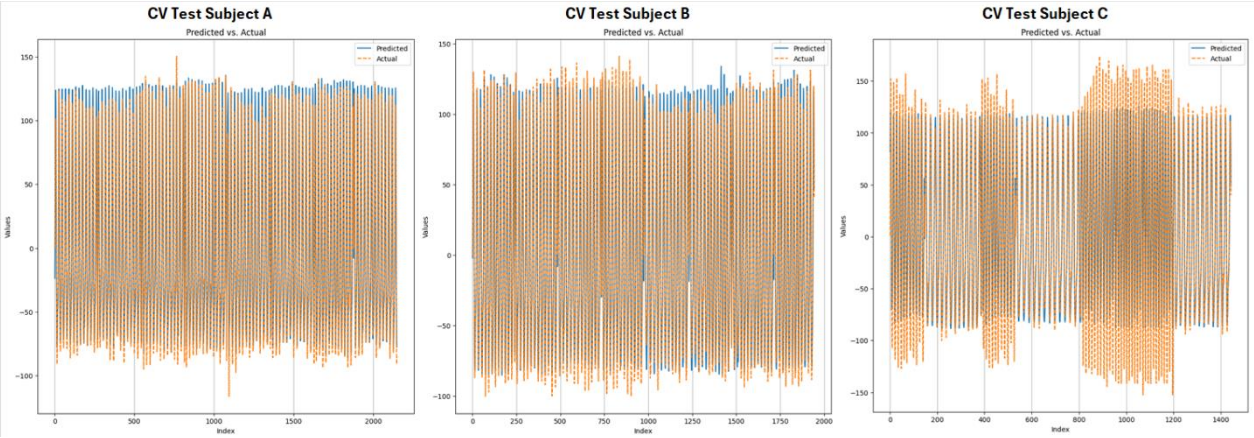


Appendix A.12: Graphics of the Set Repetition CV to predict the Velocity (cm/s) for Exercise 2

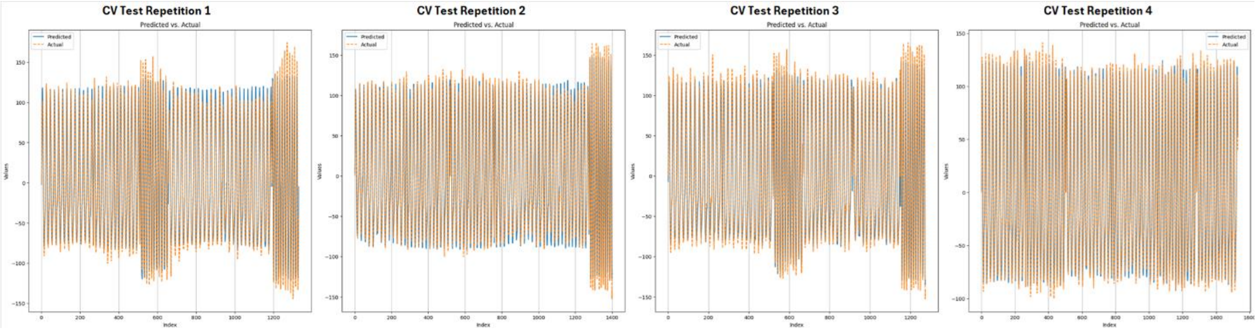
Appendix A.13: Graphics of the Scene CV to predict the Velocity (cm/s) for Exercise 2



Appendix A.14: Graphics of the Weight CV to predict the Velocity (cm/s) for Exercise 3



Appendix A.15: Graphics of the Subject CV to predict the Velocity (cm/s) for Exercise 3



Appendix A.16: Graphics of the Set Repetition CV to predict the Velocity (cm/s) for Exercise 3

Subject A - 3Kg - 1

Subject A - 3Kg - 2

Subject A - 3Kg - 3

Subject A - 3Kg - 4

Subject B - 3Kg - 1

Subject B - 3Kg - 2

Subject B - 3Kg - 3

Subject B - 3Kg - 4

Subject C - 3Kg - 1

Subject C - 3Kg - 2

Subject C - 3Kg - 3

Subject C - 3Kg - 4

Subject A - 5Kg - 1

Subject A - 5Kg - 2

Subject A - 5Kg - 3

Subject A - 5Kg - 4

Subject B - 5Kg - 1

Subject B - 5Kg - 2

Subject B - 5Kg - 3

Subject B - 5Kg - 4

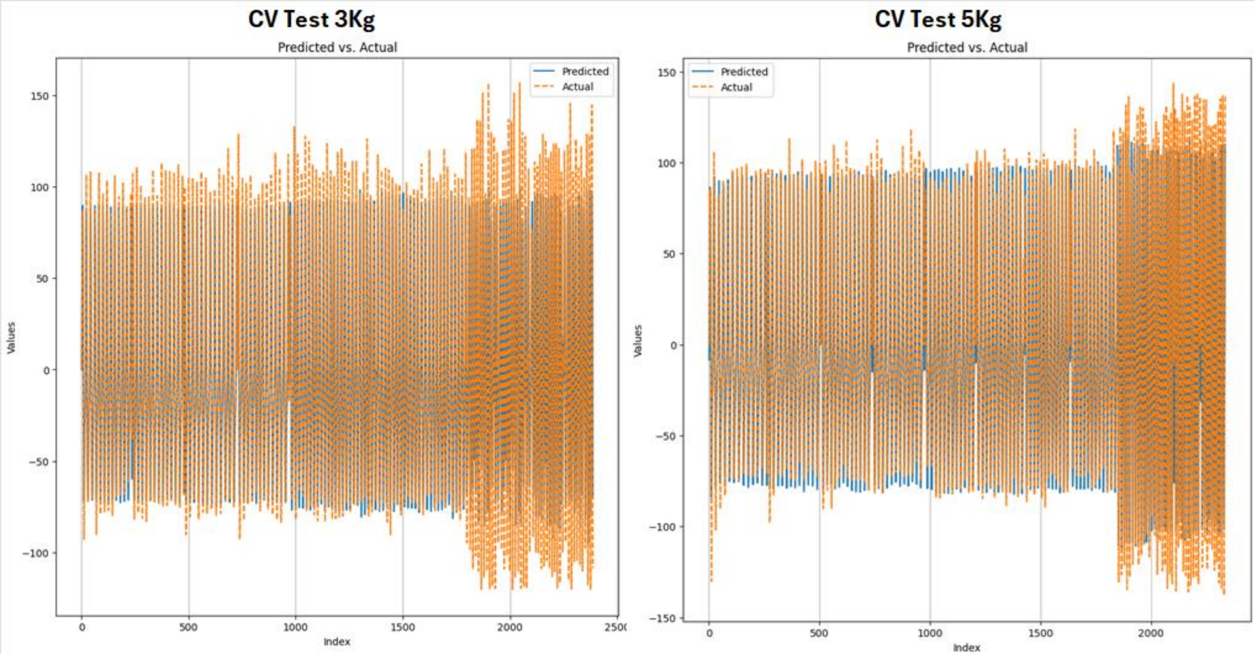
Subject C - 5Kg - 1

Subject C - 5Kg - 2

Subject C - 5Kg - 3

Subject C - 5Kg - 4

Appendix A.17: Graphics of the Scene CV to predict the Velocity (cm/s) for Exercise 3



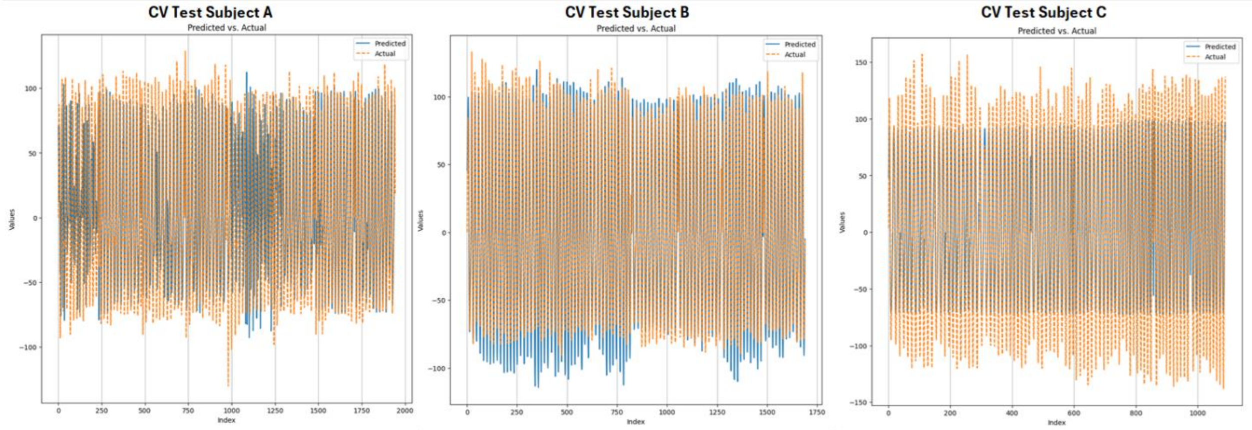
CV Test 3Kg

Predicted vs. Actual

CV Test 5Kg

Predicted vs. Actual

Appendix A.18: Graphics of the Weight CV to predict the Velocity (cm/s) for Exercise 4



CV Test Subject A

Predicted vs. Actual

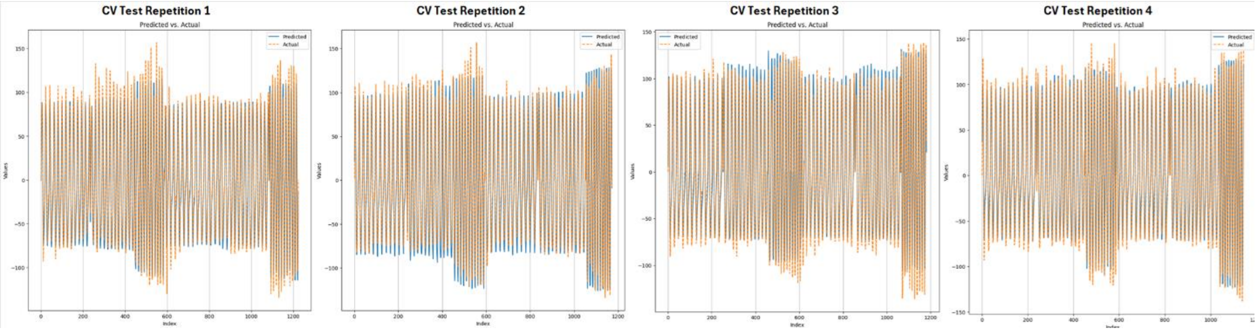
CV Test Subject B

Predicted vs. Actual

CV Test Subject C

Predicted vs. Actual

Appendix A.19: Graphics of the Subject CV to predict the Velocity (cm/s) for Exercise 4



CV Test Repetition 1

Predicted vs. Actual

CV Test Repetition 2

Predicted vs. Actual

CV Test Repetition 3

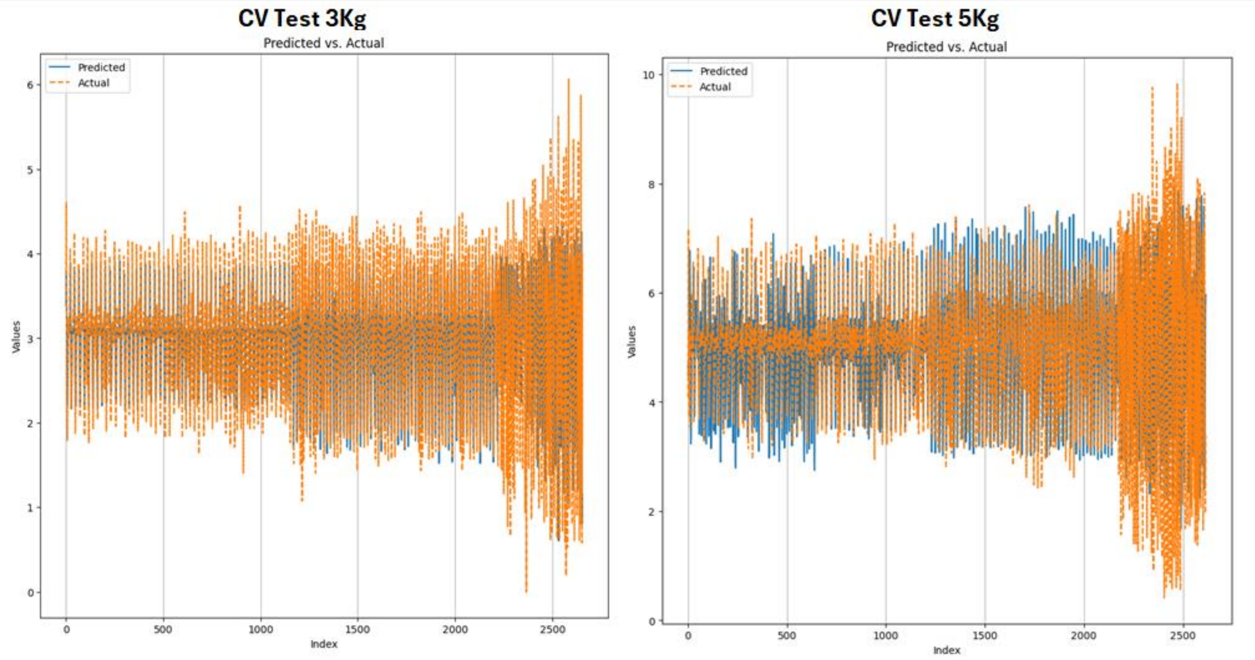
Predicted vs. Actual

CV Test Repetition 4

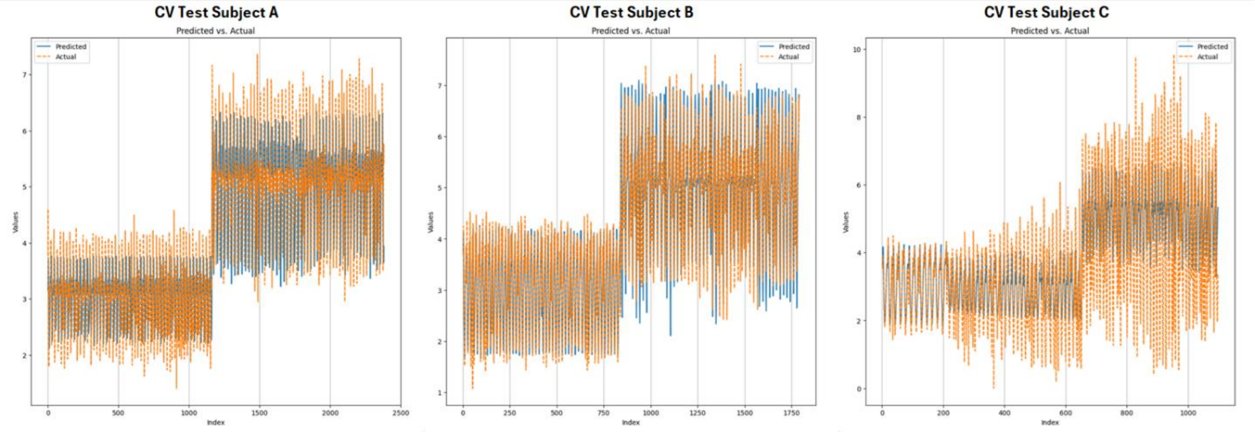
Predicted vs. Actual

Appendix A.20: Graphics of the Set Repetition CV to predict the Velocity (cm/s) for Exercise 4

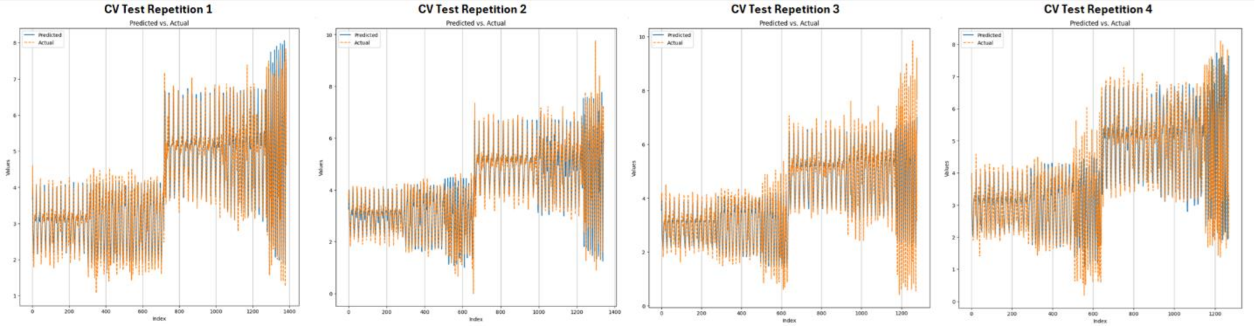
Appendix A.21: Graphics of the Scene CV to predict the Velocity (cm/s) for Exercise 4



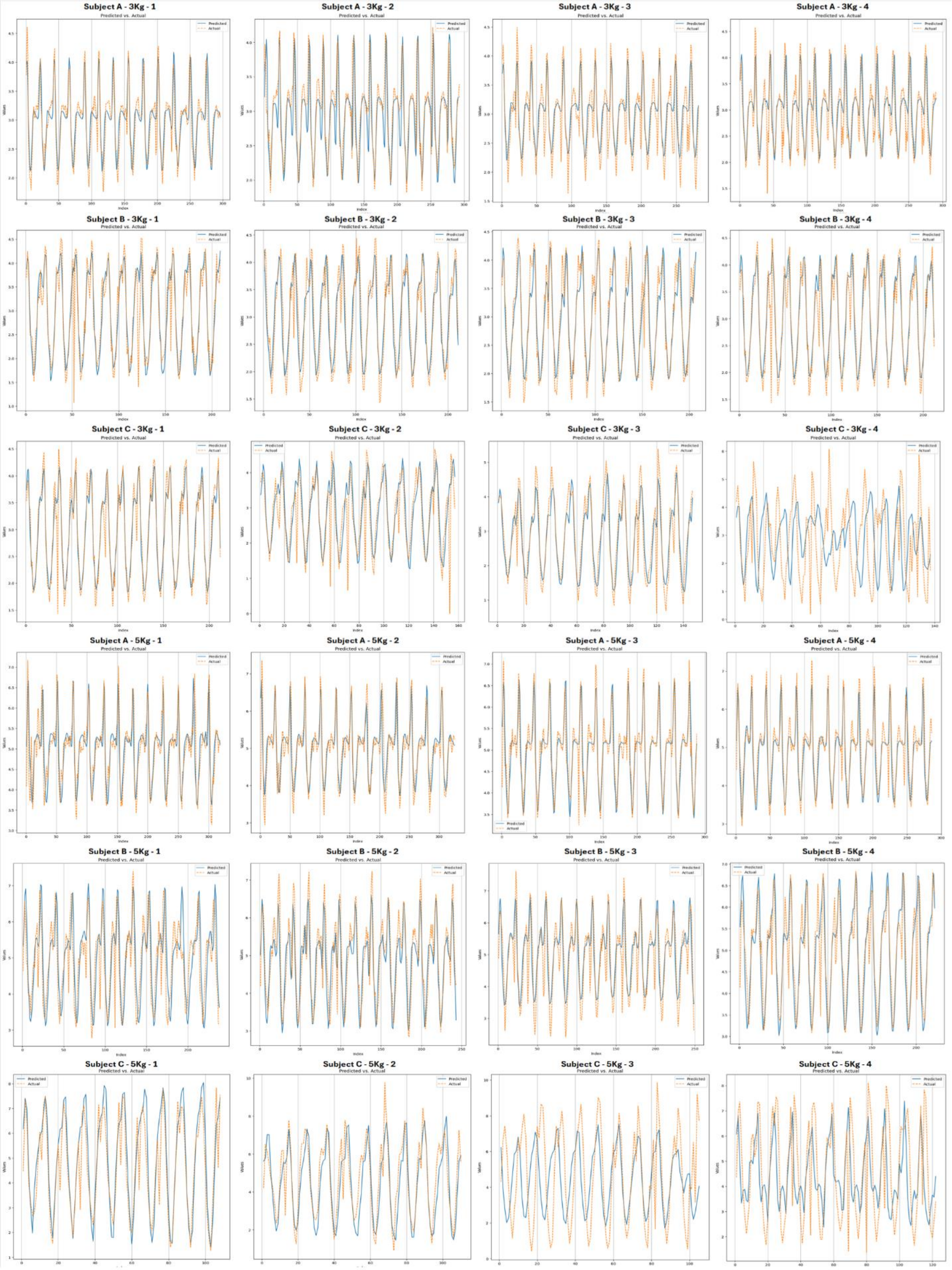
Appendix A.22: Graphics of the Weight CV to predict the Force (Kg) for Exercise 1



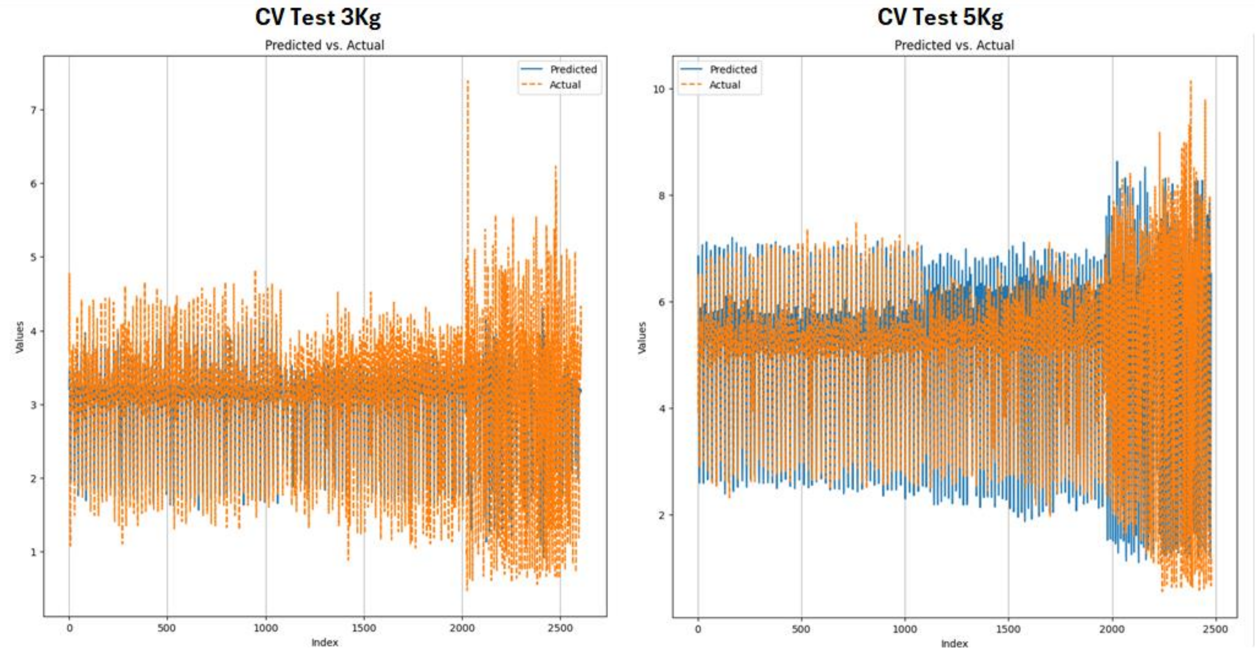
Appendix A.23: Graphics of the Subject CV to predict the Force (Kg) for Exercise 1



Appendix A.24: Graphics of the Set Repetition CV to predict the Force (Kg) for Exercise 1

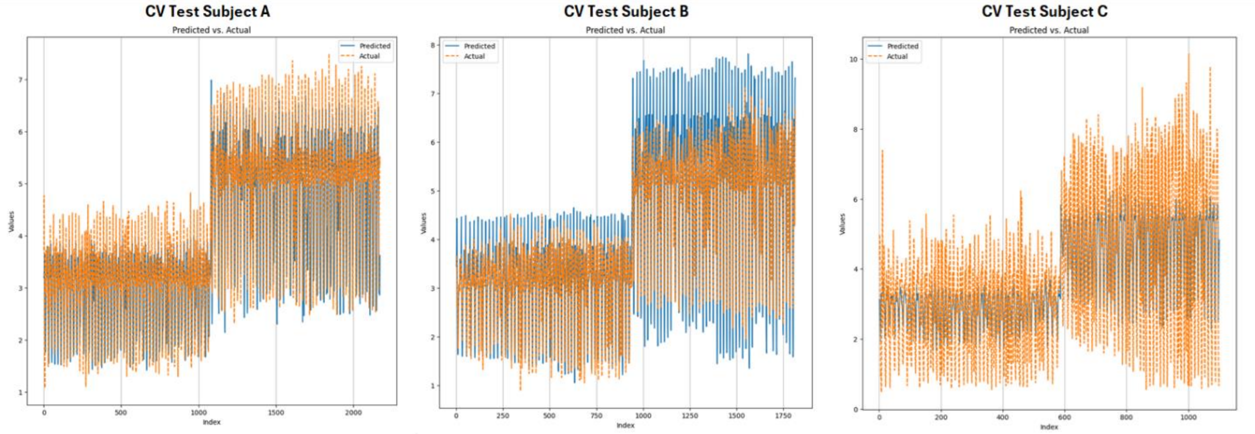


Appendix A.25: Graphics of the Scene CV to predict the Force (Kg) for Exercise 1


CV Test 3Kg

CV Test 5Kg

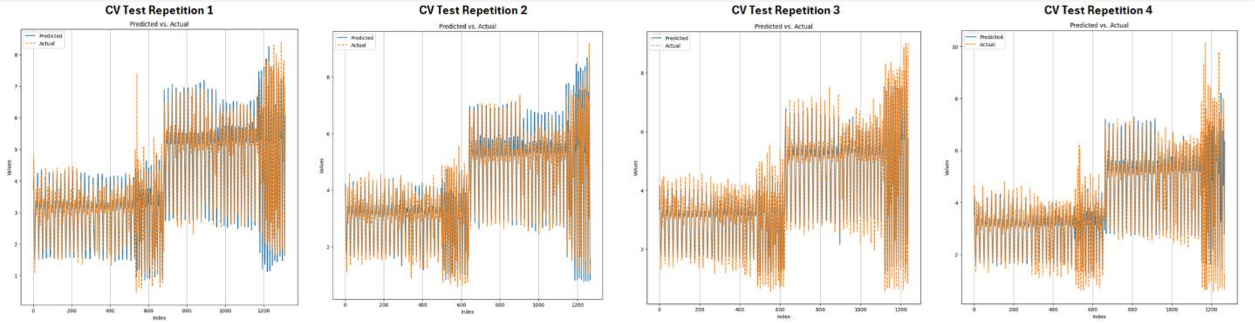
Appendix A.26: Graphics of the Weight CV to predict the Force (Kg) for Exercise 2


CV Test Subject A

CV Test Subject B

CV Test Subject C

Appendix A.27: Graphics of the Subject CV to predict the Force (Kg) for Exercise 2

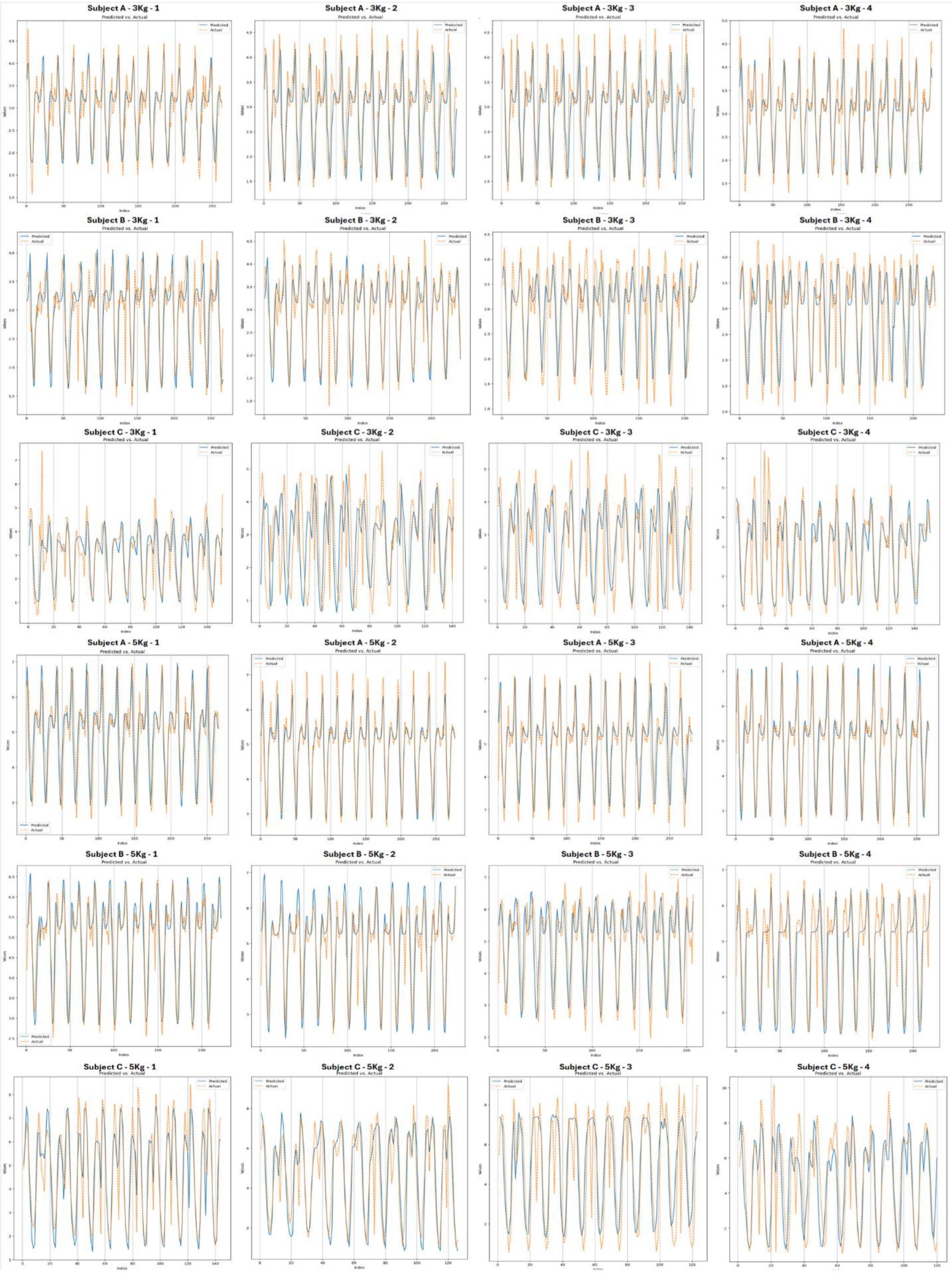

CV Test Repetition 1

CV Test Repetition 2

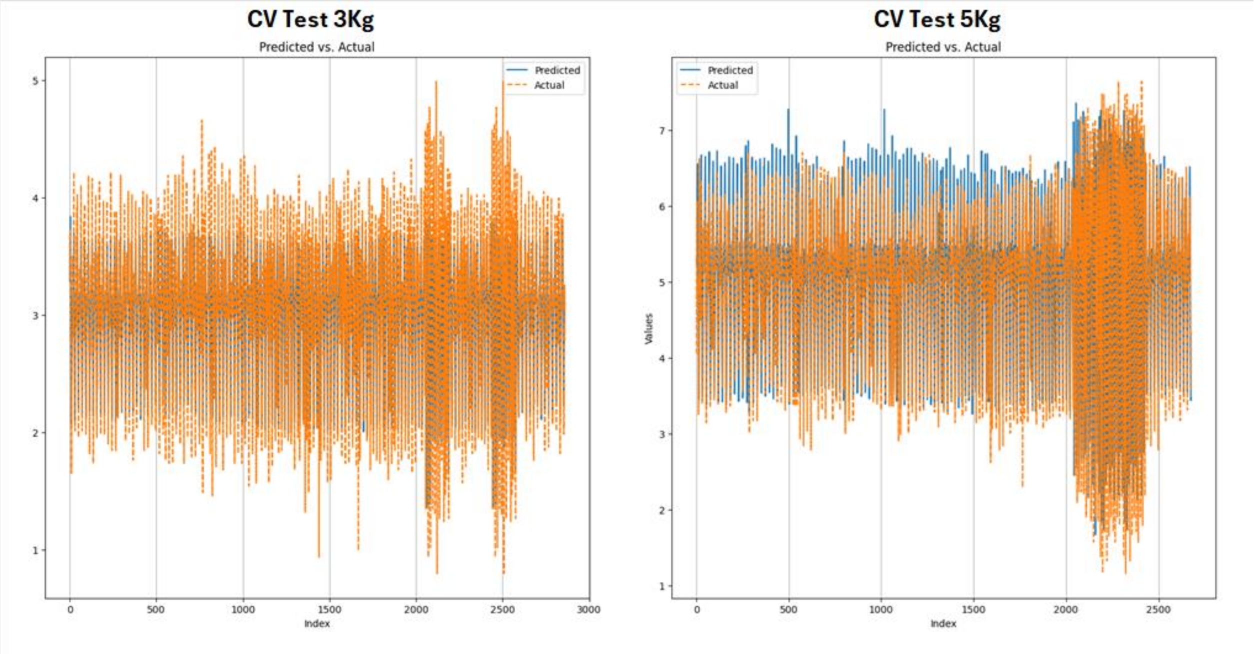
CV Test Repetition 3

CV Test Repetition 4

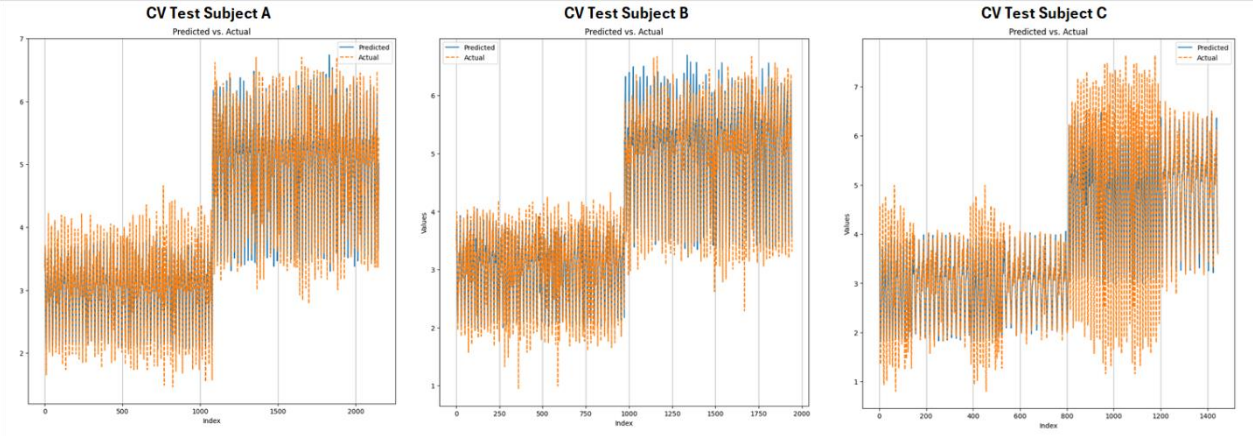
Appendix A.28: Graphics of the Set Repetition CV to predict the Force (Kg) for Exercise 2


Subject A - 3Kg - 1
Predicted vs. Actual
Subject A - 3Kg - 2
Predicted vs. Actual
Subject A - 3Kg - 3
Predicted vs. Actual
Subject A - 3Kg - 4
Predicted vs. Actual
Subject B - 3Kg - 1
Predicted vs. Actual
Subject B - 3Kg - 2
Predicted vs. Actual
Subject B - 3Kg - 3
Predicted vs. Actual
Subject B - 3Kg - 4
Predicted vs. Actual
Subject C - 3Kg - 1
Predicted vs. Actual
Subject C - 3Kg - 2
Predicted vs. Actual
Subject C - 3Kg - 3
Predicted vs. Actual
Subject C - 3Kg - 4
Predicted vs. Actual
Subject A - 5Kg - 1
Predicted vs. Actual
Subject A - 5Kg - 2
Predicted vs. Actual
Subject A - 5Kg - 3
Predicted vs. Actual
Subject A - 5Kg - 4
Predicted vs. Actual
Subject B - 5Kg - 1
Predicted vs. Actual
Subject B - 5Kg - 2
Predicted vs. Actual
Subject B - 5Kg - 3
Predicted vs. Actual
Subject B - 5Kg - 4
Predicted vs. Actual
Subject C - 5Kg - 1
Predicted vs. Actual
Subject C - 5Kg - 2
Predicted vs. Actual
Subject C - 5Kg - 3
Predicted vs. Actual
Subject C - 5Kg - 4
Predicted vs. Actual

Appendix A.29: Graphics of the Scene CV to predict the Force (Kg) for Exercise 2

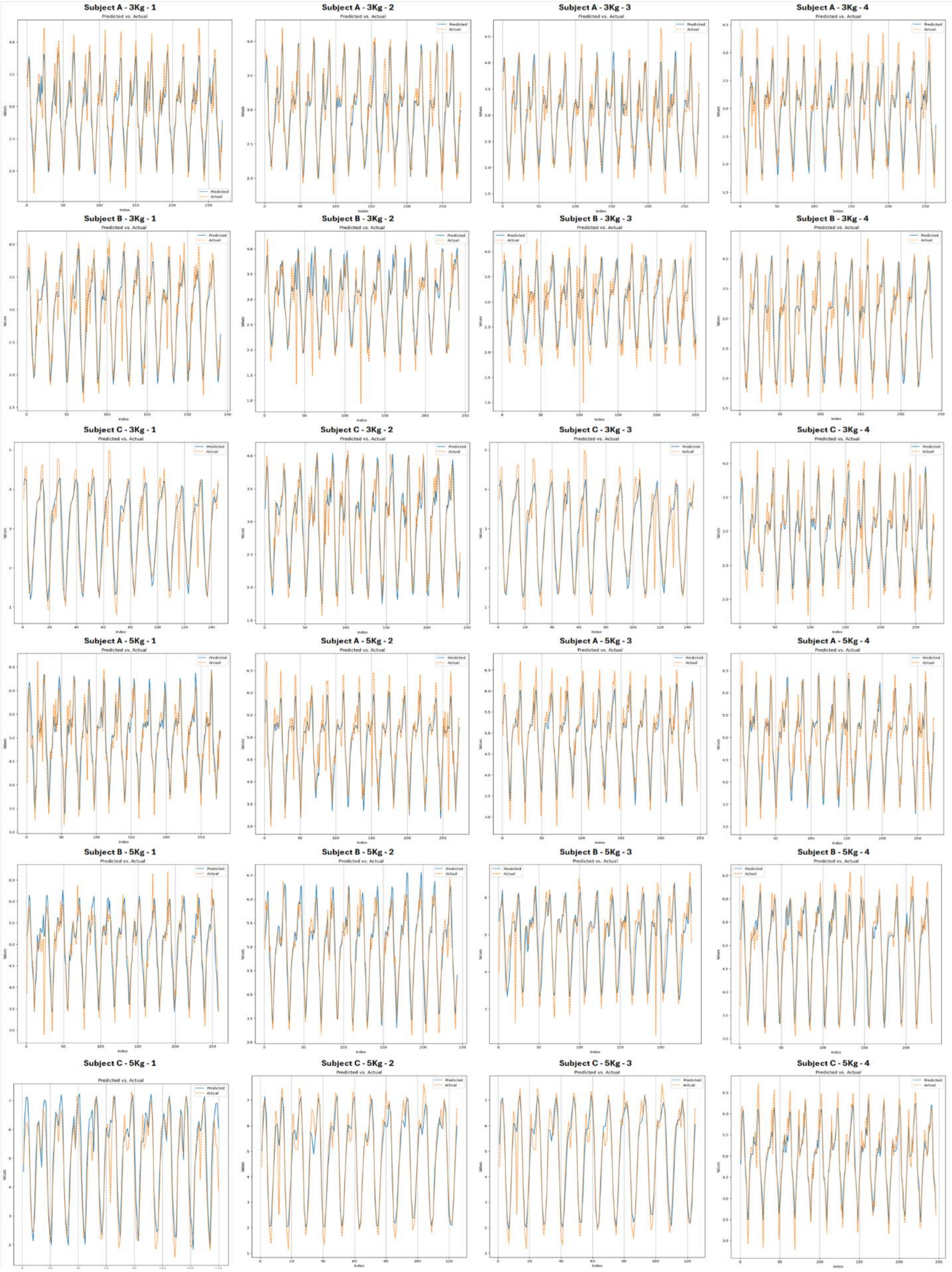


Appendix A.30: Graphics of the Weight CV to predict the Force (Kg) for Exercise 3

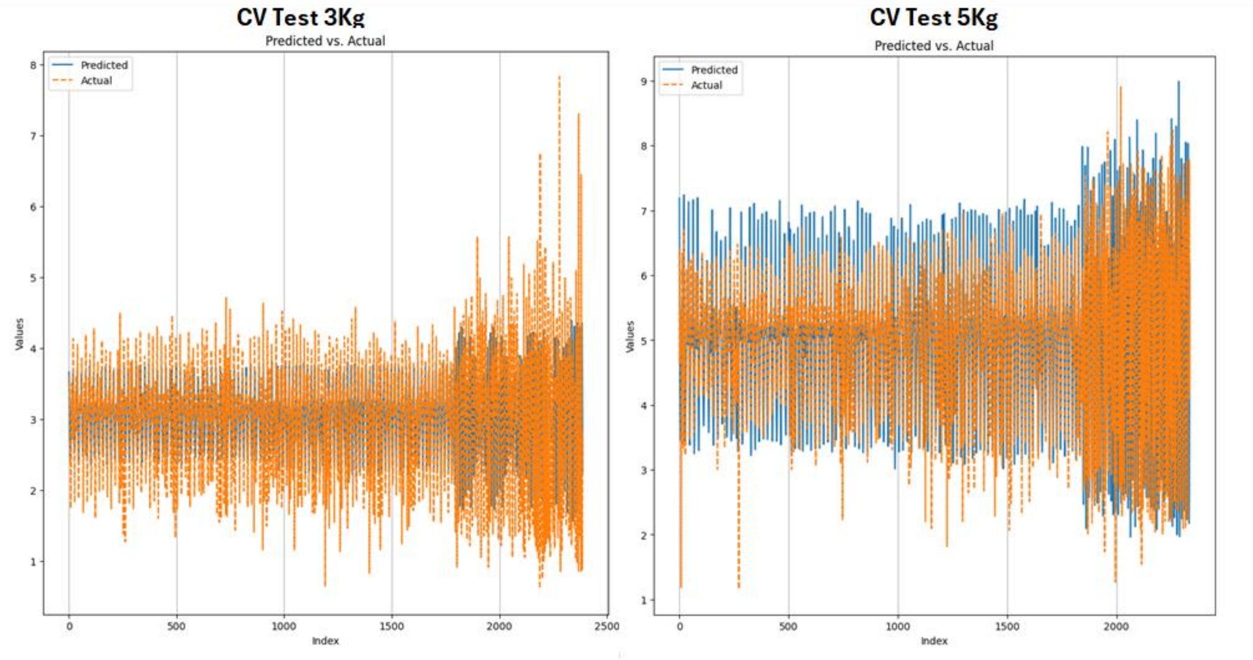


Appendix A.31: Graphics of the Subject CV to predict the Force (Kg) for Exercise 3

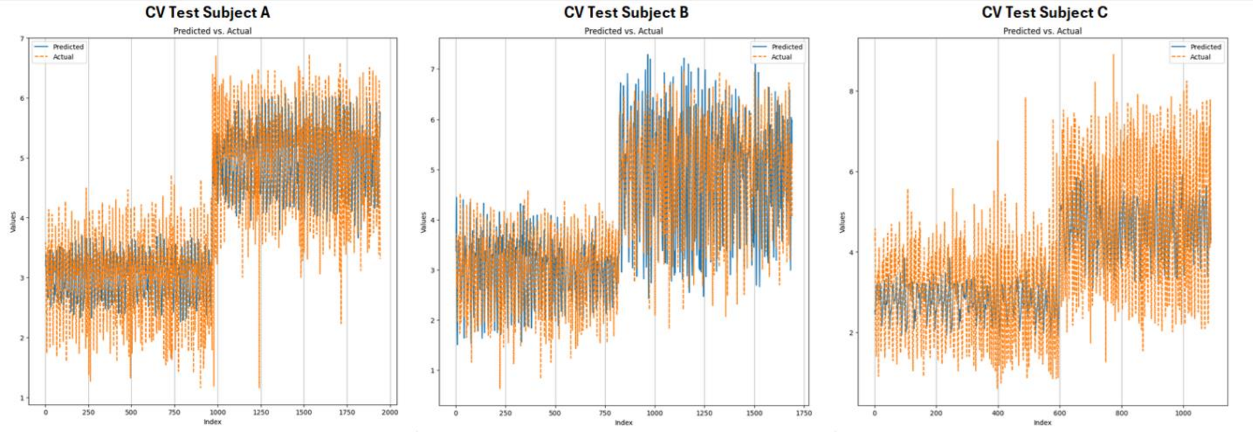
Appendix A.32: Graphics of the Set Repetition CV to predict the Force (Kg) for Exercise 3



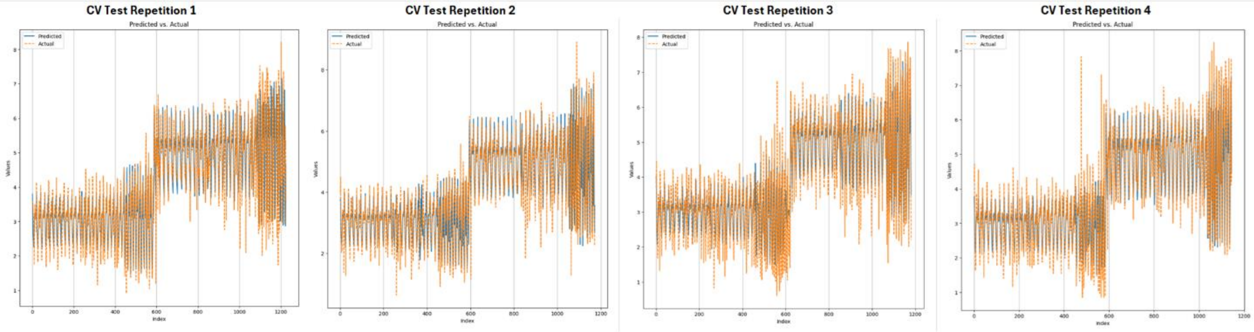
Appendix A. 33: Graphics of the Scene CV to predict the Force (Kg) for Exercise 3



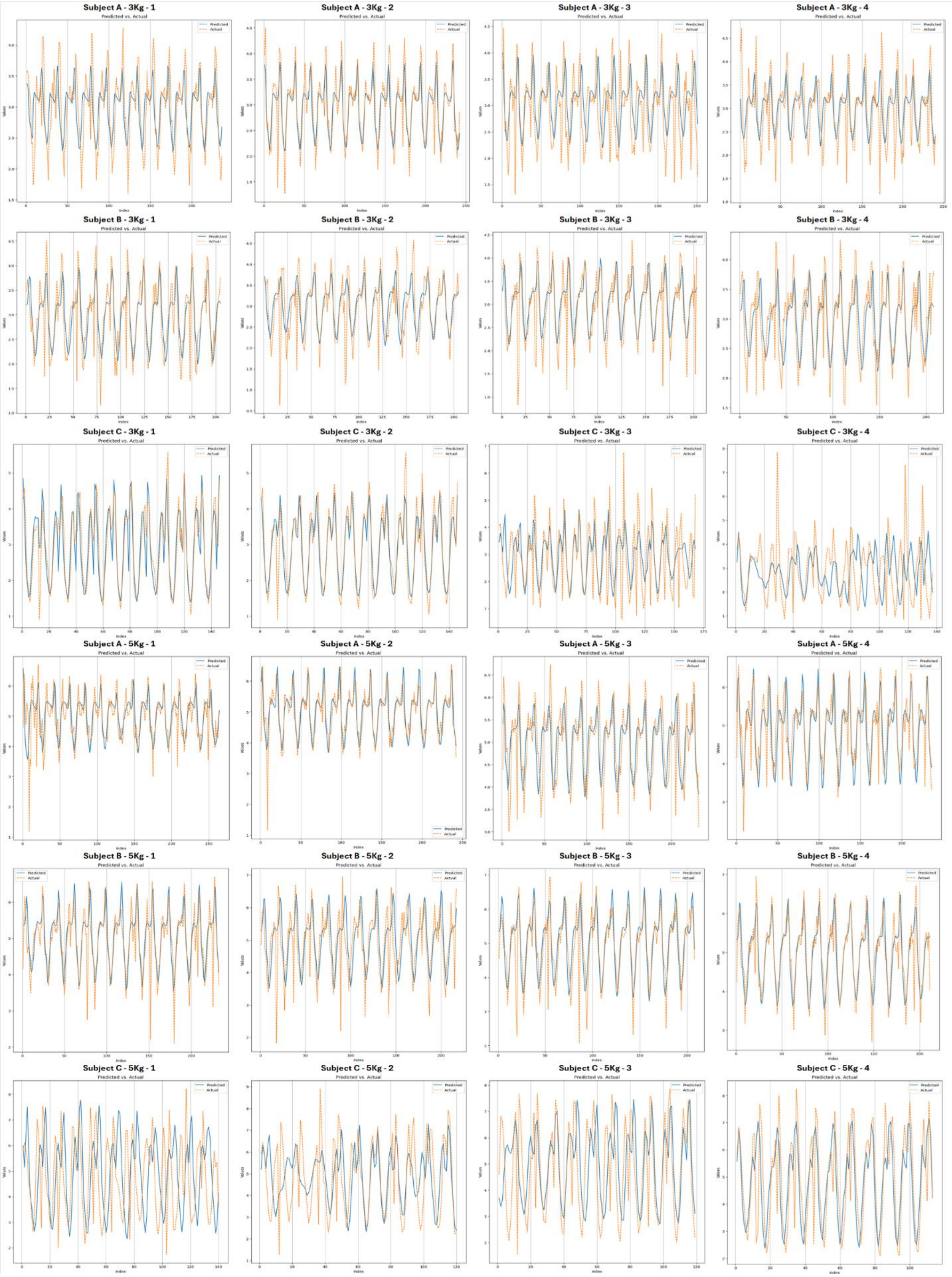
Appendix A.34: Graphics of the Weight CV to predict the Force (Kg) for Exercise 4



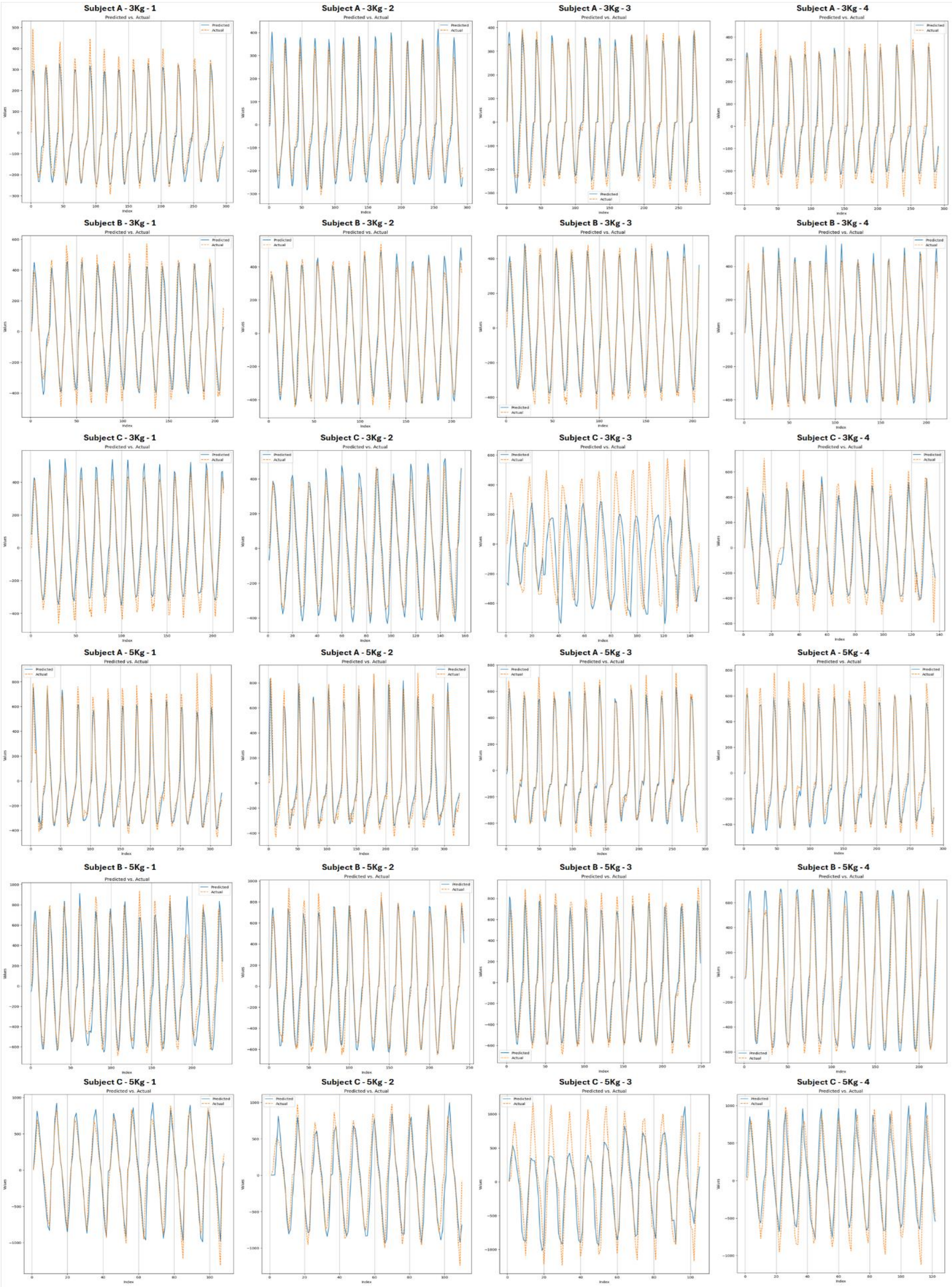
Appendix A.35: Graphics of the Subject CV to predict the Force (Kg) for Exercise 4



Appendix A.36: Graphics of the Set Repetition CV to predict the Force (Kg) for Exercise 4


Subject A - 3Kg - 1
Subject A - 3Kg - 2
Subject A - 3Kg - 3
Subject A - 3Kg - 4
Subject B - 3Kg - 1
Subject B - 3Kg - 2
Subject B - 3Kg - 3
Subject B - 3Kg - 4
Subject C - 3Kg - 1
Subject C - 3Kg - 2
Subject C - 3Kg - 3
Subject C - 3Kg - 4
Subject A - 5Kg - 1
Subject A - 5Kg - 2
Subject A - 5Kg - 3
Subject A - 5Kg - 4
Subject B - 5Kg - 1
Subject B - 5Kg - 2
Subject B - 5Kg - 3
Subject B - 5Kg - 4
Subject C - 5Kg - 1
Subject C - 5Kg - 2
Subject C - 5Kg - 3
Subject C - 5Kg - 4

Appendix A.37: Graphics of the Scene CV to predict the Force for (Kg) Exercise 4



Subject A - 3Kg - 1

Subject A - 3Kg - 2

Subject A - 3Kg - 3

Subject A - 3Kg - 4

Subject B - 3Kg - 1

Subject B - 3Kg - 2

Subject B - 3Kg - 3

Subject B - 3Kg - 4

Subject C - 3Kg - 1

Subject C - 3Kg - 2

Subject C - 3Kg - 3

Subject C - 3Kg - 4

Subject A - 5Kg - 1

Subject A - 5Kg - 2

Subject A - 5Kg - 3

Subject A - 5Kg - 4

Subject B - 5Kg - 1

Subject B - 5Kg - 2

Subject B - 5Kg - 3

Subject B - 5Kg - 4

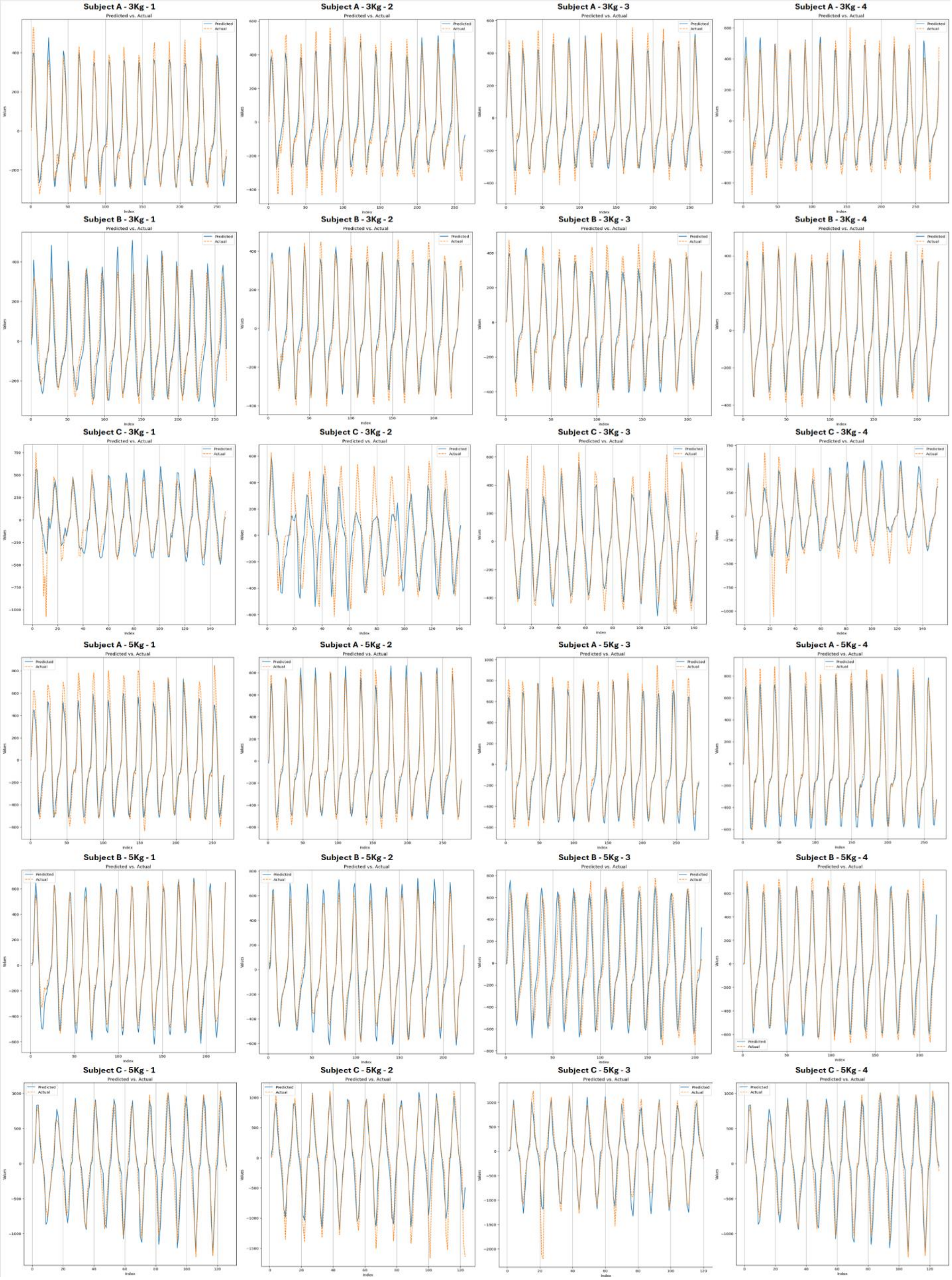
Subject C - 5Kg - 1

Subject C - 5Kg - 2

Subject C - 5Kg - 3

Subject C - 5Kg - 4

Appendix A.38: Graphics of the Scene CV to predict the Power (cm/s × Kg) for Exercise 1



Appendix A.39: Graphics of the Scene CV to predict the Power (cm/s × Kg) for Exercise 2

Appendix A.40: Graphics of the Scene CV to predict the Power (cm/s × Kg) for Exercise 3

Appendix A.41: Graphics of the Scene CV to predict the Power (cm/s × Kg) for Exercise 4

# A.2 – Complementary Tables

Appendix B.1: Exercise 1 - Number of samples and time for each scene and input – X and Y

| User \| Weight \| Sets | Input X Time (s) | Input X Number of Samples | Input X Time (s) | Input X Number of Samples |
|---|---|---|---|---|
| **Subject A \| 3 KG \| 1** | 37.525 | 3923 | 34.684 | 3469 |
| **Subject A \| 3 KG \| 2** | 37.574 | 3929 | 34.312 | 3431 |
| **Subject A \| 3 KG \| 3** | 36.143 | 3778 | 33.261 | 3326 |
| **Subject A \| 3 KG \| 4** | 37.149 | 3883 | 34.192 | 3420 |
| **Subject A \| 5 KG \| 1** | 43.670 | 4567 | 36.973 | 3697 |
| **Subject A \| 5 KG \| 2** | 42.173 | 4410 | 37.623 | 3762 |
| **Subject A \| 5 KG \| 3** | 37.498 | 3920 | 33.895 | 3389 |
| **Subject A \| 5 KG \| 4** | 37.692 | 3941 | 33.694 | 3370 |
| **Subject B \| 3 KG \| 1** | 28.364 | 2963 | 25.972 | 2598 |
| **Subject B \| 3 KG \| 2** | 28.011 | 2926 | 26.109 | 2611 |
| **Subject B \| 3 KG \| 3** | 27.403 | 2862 | 25.758 | 2576 |
| **Subject B \| 3 KG \| 4** | 27.761 | 2900 | 26.239 | 2624 |
| **Subject B \| 5 KG \| 1** | 31.208 | 3260 | 28.805 | 2881 |
| **Subject B \| 5 KG \| 2** | 31.438 | 3285 | 29.326 | 2933 |
| **Subject B \| 5 KG \| 3** | 32.414 | 3386 | 29.915 | 2992 |
| **Subject B \| 5 KG \| 4** | 29.251 | 3055 | 27.178 | 2718 |
| **Subject C \| 3 KG \| 1** | 27.761 | 2900 | 26.239 | 2624 |
| **Subject C \| 3 KG \| 2** | 23.402 | 2442 | 20.721 | 2072 |
| **Subject C \| 3 KG \| 3** | 22.63 | 2361 | 19.743 | 1975 |
| **Subject C \| 3 KG \| 4** | 21.785 | 2272 | 18.799 | 1880 |
| **Subject C \| 5 KG \| 1** | 19.648 | 2047 | 15.805 | 1580 |
| **Subject C \| 5 KG \| 2** | 19.976 | 2081 | 16.093 | 1609 |
| **Subject C \| 5 KG \| 3** | 17.862 | 1859 | 15.508 | 1551 |
| **Subject C \| 5 KG \| 4** | 20.748 | 2163 | 17.209 | 1721 |
| **Total** | 719.086 | 75113 | 648.053 | 64809 |

Appendix B.2: Exercise 2 - Number of samples and time for each scene and input – X and Y

| User \| Weight \| Sets | Input X Time (s) | Input X Number of Samples | Input X Time (s) | Input X Number of Samples |
|---|---|---|---|---|
| **Subject A \| 3 KG \| 1** | 34.313 | 3585 | 31.324 | 3133 |
| **Subject A \| 3 KG \| 2** | 33.962 | 3550 | 31.488 | 3148 |
| **Subject A \| 3 KG \| 3** | 34.138 | 3568 | 31.713 | 3172 |
| **Subject A \| 3 KG \| 4** | 37.628 | 3929 | 33.479 | 3348 |
| **Subject A \| 5 KG \| 1** | 34.507 | 3605 | 31.642 | 3164 |
| **Subject A \| 5 KG \| 2** | 35.681 | 3729 | 32.742 | 3274 |
| **Subject A \| 5 KG \| 3** | 35.544 | 3715 | 33.34 | 3334 |
| **Subject A \| 5 KG \| 4** | 34.275 | 3583 | 31.778 | 3178 |
| **Subject B \| 3 KG \| 1** | 34.752 | 3633 | 31.698 | 3170 |
| **Subject B \| 3 KG \| 2** | 30.874 | 3226 | 28.562 | 2857 |
| **Subject B \| 3 KG \| 3** | 28.497 | 2976 | 26.529 | 2653 |
| **Subject B \| 3 KG \| 4** | 29.548 | 3086 | 27.561 | 2756 |
| **Subject B \| 5 KG \| 1** | 29.182 | 3048 | 27.201 | 2720 |
| **Subject B \| 5 KG \| 2** | 29.575 | 3090 | 27.447 | 2745 |
| **Subject B \| 5 KG \| 3** | 27.865 | 2909 | 25.793 | 2580 |
| **Subject B \| 5 KG \| 4** | 28.973 | 3026 | 26.918 | 2691 |
| **Subject C \| 3 KG \| 1** | 22.798 | 2378 | 20.296 | 2030 |
| **Subject C \| 3 KG \| 2** | 23.39 | 2440 | 19.101 | 1910 |
| **Subject C \| 3 KG \| 3** | 24.011 | 2505 | 19.242 | 1924 |
| **Subject C \| 3 KG \| 4** | 23.501 | 2452 | 20.283 | 2028 |
| **Subject C \| 5 KG \| 1** | 22.95 | 2395 | 19.495 | 1950 |
| **Subject C \| 5 KG \| 2** | 20.999 | 2189 | 17.685 | 1769 |
| **Subject C \| 5 KG \| 3** | 20.21 | 2106 | 17.366 | 1736 |
| **Subject C \| 5 KG \| 4** | 20.923 | 2182 | 17.006 | 1701 |
| **Total** | 698.096 | 72905 | 629.689 | 62971 |

Appendix B.3: Exercise 3 - Number of samples and time for each scene and input – X and Y

| User \| Weight \| Sets | Input X Time (s) | Input X Number of Samples | Input X Time (s) | Input X Number of Samples |
|---|---|---|---|---|
| **Subject A \| 3 KG \| 1** | 35.499 | 3711 | 31.994 | 3200 |
| **Subject A \| 3 KG \| 2** | 35.611 | 3722 | 32.667 | 3267 |
| **Subject A \| 3 KG \| 3** | 35.192 | 3678 | 32.097 | 3210 |
| **Subject A \| 3 KG \| 4** | 34.395 | 3595 | 31.422 | 3142 |
| **Subject A \| 5 KG \| 1** | 36.94 | 3861 | 32.807 | 3281 |
| **Subject A \| 5 KG \| 2** | 36.032 | 3766 | 32.382 | 3238 |
| **Subject A \| 5 KG \| 3** | 35.588 | 3719 | 29.693 | 2970 |
| **Subject A \| 5 KG \| 4** | 36.016 | 3761 | 33.532 | 3353 |
| **Subject B \| 3 KG \| 1** | 31.16 | 3255 | 29.148 | 2915 |
| **Subject B \| 3 KG \| 2** | 31.338 | 3274 | 29.286 | 2928 |
| **Subject B \| 3 KG \| 3** | 31.637 | 3306 | 30.123 | 3012 |
| **Subject B \| 3 KG \| 4** | 30.218 | 3156 | 28.928 | 2893 |
| **Subject B \| 5 KG \| 1** | 33.222 | 3472 | 30.844 | 3084 |
| **Subject B \| 5 KG \| 2** | 31.795 | 3322 | 29.326 | 2933 |
| **Subject B \| 5 KG \| 3** | 30.601 | 3197 | 28.886 | 2889 |
| **Subject B \| 5 KG \| 4** | 30.721 | 3208 | 28.152 | 2816 |
| **Subject C \| 3 KG \| 1** | 22.797 | 2378 | 19.593 | 1959 |
| **Subject C \| 3 KG \| 2** | 31.16 | 3255 | 29.148 | 2915 |
| **Subject C \| 3 KG \| 3** | 22.797 | 2378 | 19.593 | 1959 |
| **Subject C \| 3 KG \| 4** | 35.611 | 3722 | 32.667 | 3267 |
| **Subject C \| 5 KG \| 1** | 23.818 | 2485 | 19.021 | 1903 |
| **Subject C \| 5 KG \| 2** | 30.273 | 3243 | 17.579 | 1758 |
| **Subject C \| 5 KG \| 3** | 30.065 | 3141 | 17.239 | 1752 |
| **Subject C \| 5 KG \| 4** | 31.034 | 3199 | 29.699 | 2970 |
| **Total** | **767.882** | **80227** | **675.01** | **67505** |

Appendix B.4: Exercise 4 - Number of samples and time for each scene and input – X and Y

| User \| Weight \| Sets | Input X Time (s) | Input X Number of Samples | Input X Time (s) | Input X Number of Samples |
|---|---|---|---|---|
| **Subject A \| 3 KG \| 1** | 31.686 | 3311 | 28.64 | 2864 |
| **Subject A \| 3 KG \| 2** | 32.775 | 3425 | 29.216 | 2922 |
| **Subject A \| 3 KG \| 3** | 34.811 | 3638 | 30.183 | 3019 |
| **Subject A \| 3 KG \| 4** | 31.612 | 3303 | 29.076 | 2908 |
| **Subject A \| 5 KG \| 1** | 36.246 | 3790 | 31.493 | 3149 |
| **Subject A \| 5 KG \| 2** | 37.132 | 3882 | 29.27 | 2927 |
| **Subject A \| 5 KG \| 3** | 32.608 | 3407 | 28.257 | 2825 |
| **Subject A \| 5 KG \| 4** | 31.825 | 3325 | 28.653 | 2866 |
| **Subject B \| 3 KG \| 1** | 27.208 | 2841 | 25.55 | 2555 |
| **Subject B \| 3 KG \| 2** | 27.378 | 2858 | 25.563 | 2556 |
| **Subject B \| 3 KG \| 3** | 28.234 | 2949 | 25.315 | 2531 |
| **Subject B \| 3 KG \| 4** | 27.89 | 2913 | 25.874 | 2587 |
| **Subject B \| 5 KG \| 1** | 30.501 | 3186 | 28.341 | 2834 |
| **Subject B \| 5 KG \| 2** | 29.051 | 3033 | 26.778 | 2678 |
| **Subject B \| 5 KG \| 3** | 27.691 | 2892 | 25.9 | 2590 |
| **Subject B \| 5 KG \| 4** | 29.245 | 3054 | 26.135 | 2614 |
| **Subject C \| 3 KG \| 1** | 21.949 | 2289 | 19.69 | 1969 |
| **Subject C \| 3 KG \| 2** | 21.899 | 2249 | 19.31 | 1931 |
| **Subject C \| 3 KG \| 3** | 24.994 | 2609 | 21.816 | 2181 |
| **Subject C \| 3 KG \| 4** | 20.724 | 2160 | 18.786 | 1878 |
| **Subject C \| 5 KG \| 1** | 23.01 | 2400 | 19.017 | 1902 |
| **Subject C \| 5 KG \| 2** | 20.544 | 2142 | 17.03 | 1703 |
| **Subject C \| 5 KG \| 3** | 20.199 | 2105 | 16.973 | 1698 |
| **Subject C \| 5 KG \| 4** | 18.593 | 1937 | 16.356 | 1636 |
| **Total** | **667.855** | **69738** | **593.602** | **59361** |

Appendix B.5: Pearson Correlation Coefficient for each pair of files of every exercise

| **User \| Weight \| Sets** | **Exercise 1** | **Exercise 2** | **Exercise 3** | **Exercise 4** |
|---|---|---|---|---|
| **Subject A \| 3 KG \| 1** | -0.975 | 0.984 | 0.959 | -0.977 |
| **Subject A \| 3 KG \| 2** | -0.963 | 0.985 | 0.959 | -0.975 |
| **Subject A \| 3 KG \| 3** | -0.961 | 0.986 | 0.966 | -0.968 |
| **Subject A \| 3 KG \| 4** | -0.970 | 0.985 | 0.960 | -0.974 |
| **Subject A \| 5 KG \| 1** | -0.977 | 0.987 | 0.974 | -0.934 |
| **Subject A \| 5 KG \| 2** | -0.960 | 0.990 | 0.982 | -0.973 |
| **Subject A \| 5 KG \| 3** | -0.973 | 0.987 | 0.967 | -0.975 |
| **Subject A \| 5 KG \| 4** | -0.971 | 0.985 | 0.982 | -0.967 |
| **Subject B \| 3 KG \| 1** | -0.946 | 0.969 | 0.981 | -0.931 |
| **Subject B \| 3 KG \| 2** | -0.962 | 0.977 | 0.983 | -0.950 |
| **Subject B \| 3 KG \| 3** | -0.958 | 0.972 | 0.978 | -0.931 |
| **Subject B \| 3 KG \| 4** | -0.955 | 0.972 | 0.986 | -0.966 |
| **Subject B \| 5 KG \| 1** | -0.956 | 0.975 | 0.974 | -0.930 |
| **Subject B \| 5 KG \| 2** | -0.958 | 0.979 | 0.973 | -0.933 |
| **Subject B \| 5 KG \| 3** | -0.953 | 0.974 | 0.979 | -0.958 |
| **Subject B \| 5 KG \| 4** | -0.977 | 0.981 | 0.988 | -0.955 |
| **Subject C \| 3 KG \| 1** | -0.955 | 0.973 | 0.973 | -0.962 |
| **Subject C \| 3 KG \| 2** | -0.961 | 0.982 | 0.981 | -0.962 |
| **Subject C \| 3 KG \| 3** | -0.982 | 0.977 | 0.973 | -0.952 |
| **Subject C \| 3 KG \| 4** | -0.961 | 0.977 | 0.959 | -0.938 |
| **Subject C \| 5 KG \| 1** | -0.968 | 0.983 | 0.976 | -0.972 |
| **Subject C \| 5 KG \| 2** | -0.947 | 0.990 | 0.976 | -0.962 |
| **Subject C \| 5 KG \| 3** | -0.980 | 0.977 | 0.976 | -0.957 |
| **Subject C \| 5 KG \| 4** | -0.966 | 0.967 | 0.967 | -0.962 |
| **Mean** | **-0.964** | **0.980** | **0.974** | **-0.957** |

Appendix B.6: Initial offset for each .txt file (input X) of every exercise

| User \| Weight \| Sets | Exercise 1 (s) | Exercise 2 (s) | Exercise 3 (s) | Exercise 4 (s) |
|---|---|---|---|---|
| **Subject A \| 3 KG \| 1** | 1.40 | 1.35 | 2.30 | 1.85 |
| **Subject A \| 3 KG \| 2** | 1.70 | 1.50 | 1.85 | 1.95 |
| **Subject A \| 3 KG \| 3** | 1.40 | 1.05 | 1.80 | 1.65 |
| **Subject A \| 3 KG \| 4** | 1.30 | 1.60 | 1.75 | 1.40 |
| **Subject A \| 5 KG \| 1** | 3.90 | 1.40 | 2.50 | 2.30 |
| **Subject A \| 5 KG \| 2** | 2.60 | 1.50 | 2.10 | 2.05 |
| **Subject A \| 5 KG \| 3** | 1.80 | 1.00 | 3.40 | 1.95 |
| **Subject A \| 5 KG \| 4** | 2.30 | 1.25 | 2.10 | 1.95 |
| **Subject B \| 3 KG \| 1** | 0.80 | 1.20 | 0.70 | 0.60 |
| **Subject B \| 3 KG \| 2** | 0.90 | 1.10 | 0.90 | 0.85 |
| **Subject B \| 3 KG \| 3** | 0.80 | 0.95 | 0.45 | 0.95 |
| **Subject B \| 3 KG \| 4** | 0.70 | 1.00 | 0.55 | 0.95 |
| **Subject B \| 5 KG \| 1** | 1.40 | 1.00 | 1.10 | 0.95 |
| **Subject B \| 5 KG \| 2** | 1.20 | 1.20 | 0.75 | 0.80 |
| **Subject B \| 5 KG \| 3** | 1.10 | 1.20 | 0.75 | 0.80 |
| **Subject B \| 5 KG \| 4** | 1.10 | 0.90 | 1.25 | 1.00 |
| **Subject C \| 3 KG \| 1** | 0.70 | 1.60 | 1.90 | 1.00 |
| **Subject C \| 3 KG \| 2** | 1.50 | 1.50 | 0.70 | 1.00 |
| **Subject C \| 3 KG \| 3** | 1.70 | 2.05 | 1.90 | 1.80 |
| **Subject C \| 3 KG \| 4** | 1.70 | 1.35 | 1.85 | 0.85 |
| **Subject C \| 5 KG \| 1** | 1.50 | 1.50 | 1.40 | 1.00 |
| **Subject C \| 5 KG \| 2** | 2.60 | 2.05 | 1.60 | 2.40 |
| **Subject C \| 5 KG \| 3** | 1.20 | 1.25 | 1.60 | 1.65 |
| **Subject C \| 5 KG \| 4** | 1.40 | 1.95 | 3.40 | 1.05 |
| **Mean** | **1.529** | **1.352** | **1.608** | **1.365** |

## Appendix B.7: Summary of metrics performance for Scene CV for Exercise 1

| Ex | Prec | Rec | F1-S |
|---|---|---|---|
| 1 | 1.00 | 1.00 | 1.00 |
| 2 | 0.00 | 0.00 | 0.00 |
| 3 | 0.00 | 0.00 | 0.00 |
| 4 | 0.00 | 0.00 | 0.00 |

**3Kg - Subject A – 1**

| Ex | Prec | Rec | F1-S |
|---|---|---|---|
| 1 | 1.00 | 1.00 | 1.00 |
| 2 | 0.00 | 0.00 | 0.00 |
| 3 | 0.00 | 0.00 | 0.00 |
| 4 | 0.00 | 0.00 | 0.00 |

**3Kg - Subject A - 2**

| Ex | Prec | Rec | F1-S |
|---|---|---|---|
| 1 | 1.00 | 1.00 | 1.00 |
| 2 | 0.00 | 0.00 | 0.00 |
| 3 | 0.00 | 0.00 | 0.00 |
| 4 | 0.00 | 0.00 | 0.00 |

**3Kg - Subject A - 3**

| Ex | Prec | Rec | F1-S |
|---|---|---|---|
| 1 | 1.00 | 1.00 | 1.00 |
| 2 | 0.00 | 0.00 | 0.00 |
| 3 | 0.00 | 0.00 | 0.00 |
| 4 | 0.00 | 0.00 | 0.00 |

**3Kg - Subject A – 4**

| Ex | Prec | Rec | F1-S |
|---|---|---|---|
| 1 | 1.00 | 1.00 | 1.00 |
| 2 | 0.00 | 0.00 | 0.00 |
| 3 | 0.00 | 0.00 | 0.00 |
| 4 | 0.00 | 0.00 | 0.00 |

**3Kg - Subject B - 1**

| Ex | Prec | Rec | F1-S |
|---|---|---|---|
| 1 | 1.00 | 1.00 | 1.00 |
| 2 | 0.00 | 0.00 | 0.00 |
| 3 | 0.00 | 0.00 | 0.00 |
| 4 | 0.00 | 0.00 | 0.00 |

**3Kg - Subject B - 2**

| Ex | Prec | Rec | F1-S |
|---|---|---|---|
| 1 | 1.00 | 1.00 | 1.00 |
| 2 | 0.00 | 0.00 | 0.00 |
| 3 | 0.00 | 0.00 | 0.00 |
| 4 | 0.00 | 0.00 | 0.00 |

**3Kg - Subject B - 3**

| Ex | Prec | Rec | F1-S |
|---|---|---|---|
| 1 | 1.00 | 1.00 | 1.00 |
| 2 | 0.00 | 0.00 | 0.00 |
| 3 | 0.00 | 0.00 | 0.00 |
| 4 | 0.00 | 0.00 | 0.00 |

**3Kg - Subject B – 4**

| Ex | Prec | Rec | F1-S |
|---|---|---|---|
| 1 | 1.00 | 1.00 | 1.00 |
| 2 | 0.00 | 0.00 | 0.00 |
| 3 | 0.00 | 0.00 | 0.00 |
| 4 | 0.00 | 0.00 | 0.00 |

**3Kg - Subject C - 1**

| Ex | Prec | Rec | F1-S |
|---|---|---|---|
| 1 | 1.00 | 1.00 | 1.00 |
| 2 | 0.00 | 0.00 | 0.00 |
| 3 | 0.00 | 0.00 | 0.00 |
| 4 | 0.00 | 0.00 | 0.00 |

**3Kg - Subject C - 2**

| Ex | Prec | Rec | F1-S |
|---|---|---|---|
| 1 | 1.00 | 1.00 | 1.00 |
| 2 | 0.00 | 0.00 | 0.00 |
| 3 | 0.00 | 0.00 | 0.00 |
| 4 | 0.00 | 0.00 | 0.00 |

**3Kg - Subject C - 3**

| Ex | Prec | Rec | F1-S |
|---|---|---|---|
| 1 | 1.00 | 1.00 | 1.00 |
| 2 | 0.00 | 0.00 | 0.00 |
| 3 | 0.00 | 0.00 | 0.00 |
| 4 | 0.00 | 0.00 | 0.00 |

**3Kg - Subject C – 4**

| Ex | Prec | Rec | F1-S |
|---|---|---|---|
| 1 | 1.00 | 1.00 | 1.00 |
| 2 | 0.00 | 0.00 | 0.00 |
| 3 | 0.00 | 0.00 | 0.00 |
| 4 | 0.00 | 0.00 | 0.00 |

**5Kg - Subject A - 1**

| Ex | Prec | Rec | F1-S |
|---|---|---|---|
| 1 | 1.00 | 1.00 | 1.00 |
| 2 | 0.00 | 0.00 | 0.00 |
| 3 | 0.00 | 0.00 | 0.00 |
| 4 | 0.00 | 0.00 | 0.00 |

**5Kg - Subject A - 2**

| Ex | Prec | Rec | F1-S |
|---|---|---|---|
| 1 | 1.00 | 1.00 | 1.00 |
| 2 | 0.00 | 0.00 | 0.00 |
| 3 | 0.00 | 0.00 | 0.00 |
| 4 | 0.00 | 0.00 | 0.00 |

**5Kg - Subject A - 3**

| Ex | Prec | Rec | F1-S |
|---|---|---|---|
| 1 | 1.00 | 1.00 | 1.00 |
| 2 | 0.00 | 0.00 | 0.00 |
| 3 | 0.00 | 0.00 | 0.00 |
| 4 | 0.00 | 0.00 | 0.00 |

**5Kg - Subject A – 4**

| Ex | Prec | Rec | F1-S |
|---|---|---|---|
| 1 | 1.00 | 1.00 | 1.00 |
| 2 | 0.00 | 0.00 | 0.00 |
| 3 | 0.00 | 0.00 | 0.00 |
| 4 | 0.00 | 0.00 | 0.00 |

**5Kg - Subject B - 1**

| Ex | Prec | Rec | F1-S |
|---|---|---|---|
| 1 | 1.00 | 1.00 | 1.00 |
| 2 | 0.00 | 0.00 | 0.00 |
| 3 | 0.00 | 0.00 | 0.00 |
| 4 | 0.00 | 0.00 | 0.00 |

**5Kg - Subject B - 2**

| Ex | Prec | Rec | F1-S |
|---|---|---|---|
| 1 | 1.00 | 1.00 | 1.00 |
| 2 | 0.00 | 0.00 | 0.00 |
| 3 | 0.00 | 0.00 | 0.00 |
| 4 | 0.00 | 0.00 | 0.00 |

**5Kg - Subject B – 3**

| Ex | Prec | Rec | F1-S |
|---|---|---|---|
| 1 | 1.00 | 1.00 | 1.00 |
| 2 | 0.00 | 0.00 | 0.00 |
| 3 | 0.00 | 0.00 | 0.00 |
| 4 | 0.00 | 0.00 | 0.00 |

**5Kg - Subject B – 4**

| Ex | Prec | Rec | F1-S |
|---|---|---|---|
| 1 | 1.00 | 1.00 | 1.00 |
| 2 | 0.00 | 0.00 | 0.00 |
| 3 | 0.00 | 0.00 | 0.00 |
| 4 | 0.00 | 0.00 | 0.00 |

**5Kg – Subject C – 1**

| Ex | Prec | Rec | F1-S |
|---|---|---|---|
| 1 | 1.00 | 1.00 | 1.00 |
| 2 | 0.00 | 0.00 | 0.00 |
| 3 | 0.00 | 0.00 | 0.00 |
| 4 | 0.00 | 0.00 | 0.00 |

**5Kg – Subject C – 2**

| Ex | Prec | Rec | F1-S |
|---|---|---|---|
| 1 | 1.00 | 1.00 | 1.00 |
| 2 | 0.00 | 0.00 | 0.00 |
| 3 | 0.00 | 0.00 | 0.00 |
| 4 | 0.00 | 0.00 | 0.00 |

**5Kg – Subject C – 3**

| Ex | Prec | Rec | F1-S |
|---|---|---|---|
| 1 | 1.00 | 1.00 | 1.00 |
| 2 | 0.00 | 0.00 | 0.00 |
| 3 | 0.00 | 0.00 | 0.00 |
| 4 | 0.00 | 0.00 | 0.00 |

**5Kg – Subject – 4**

Appendix B.8: Summary of metrics performance for Scene CV for Exercise 2

| Exe | Prec | Rec | F1-S |
|---|---|---|---|
| 1 | 0.00 | 0.00 | 0.00 |
| 2 | 1.00 | 1.00 | 1.00 |
| 3 | 0.00 | 0.00 | 0.00 |
| 4 | 0.00 | 0.00 | 0.00 |

**3Kg - Subject A - 1**

| Exe | Pre | Rec | F1-S |
|---|---|---|---|
| 1 | 0.00 | 0.00 | 0.00 |
| 2 | 1.00 | 1.00 | 1.00 |
| 3 | 0.00 | 0.00 | 0.00 |
| 4 | 0.00 | 0.00 | 0.00 |

**3Kg - Subject A - 2**

| Exe | Prec | Rec | F1-S |
|---|---|---|---|
| 1 | 0.00 | 0.00 | 0.00 |
| 2 | 1.00 | 1.00 | 1.00 |
| 3 | 0.00 | 0.00 | 0.00 |
| 4 | 0.00 | 0.00 | 0.00 |

**3Kg - Subject A - 3**

| Exe | Prec | Rec | F1-S |
|---|---|---|---|
| 1 | 0.00 | 0.00 | 0.00 |
| 2 | 1.00 | 1.00 | 1.00 |
| 3 | 0.00 | 0.00 | 0.00 |
| 4 | 0.00 | 0.00 | 0.00 |

**3Kg - Subject A – 4**

| Exe | Prec | Rec | F1-S |
|---|---|---|---|
| 1 | 0.00 | 0.00 | 0.00 |
| 2 | 1.00 | 1.00 | 1.00 |
| 3 | 0.00 | 0.00 | 0.00 |
| 4 | 0.00 | 0.00 | 0.00 |

**3Kg - Subject B - 1**

| Exe | Prec | Rec | F1-S |
|---|---|---|---|
| 1 | 0.00 | 0.00 | 0.00 |
| 2 | 1.00 | 1.00 | 1.00 |
| 3 | 0.00 | 0.00 | 0.00 |
| 4 | 0.00 | 0.00 | 0.00 |

**3Kg - Subject B - 2**

| Exe | Prec | Rec | F1-S |
|---|---|---|---|
| 1 | 0.00 | 0.00 | 0.00 |
| 2 | 1.00 | 1.00 | 1.00 |
| 3 | 0.00 | 0.00 | 0.00 |
| 4 | 0.00 | 0.00 | 0.00 |

**3Kg - Subject B - 3**

| Exe | Prec | Rec | F1-S |
|---|---|---|---|
| 1 | 0.00 | 0.00 | 0.00 |
| 2 | 1.00 | 1.00 | 1.00 |
| 3 | 0.00 | 0.00 | 0.00 |
| 4 | 0.00 | 0.00 | 0.00 |

**3Kg - Subject B – 4**

| Exe | Pre | Rec | F1-S |
|---|---|---|---|
| 1 | 0.00 | 0.00 | 0.00 |
| 2 | 1.00 | 1.00 | 1.00 |
| 3 | 0.00 | 0.00 | 0.00 |
| 4 | 0.00 | 0.00 | 0.00 |

**3Kg - Subject C - 1**

| Exe | Prec | Rec | F1-S |
|---|---|---|---|
| 1 | 0.00 | 0.00 | 0.00 |
| 2 | 1.00 | 1.00 | 1.00 |
| 3 | 0.00 | 0.00 | 0.00 |
| 4 | 0.00 | 0.00 | 0.00 |

**3Kg - Subject C - 2**

| Exe | Prec | Rec | F1-S |
|---|---|---|---|
| 1 | 0.00 | 0.00 | 0.00 |
| 2 | 1.00 | 1.00 | 1.00 |
| 3 | 0.00 | 0.00 | 0.00 |
| 4 | 0.00 | 0.00 | 0.00 |

**3Kg - Subject C - 3**

| Exe | Prec | Rec | F1-S |
|---|---|---|---|
| 1 | 0.00 | 0.00 | 0.00 |
| 2 | 1.00 | 1.00 | 1.00 |
| 3 | 0.00 | 0.00 | 0.00 |
| 4 | 0.00 | 0.00 | 0.00 |

**3Kg - Subject C – 4**

| Exe | Pre | Rec | F1-S |
|---|---|---|---|
| 1 | 0.00 | 0.00 | 0.00 |
| 2 | 1.00 | 1.00 | 1.00 |
| 3 | 0.00 | 0.00 | 0.00 |
| 4 | 0.00 | 0.00 | 0.00 |

**5Kg - Subject A - 1**

| Exe | Prec | Rec | F1-S |
|---|---|---|---|
| 1 | 0.00 | 0.00 | 0.00 |
| 2 | 1.00 | 1.00 | 1.00 |
| 3 | 0.00 | 0.00 | 0.00 |
| 4 | 0.00 | 0.00 | 0.00 |

**5Kg - Subject A - 2**

| Exe | Prec | Rec | F1-S |
|---|---|---|---|
| 1 | 0.00 | 0.00 | 0.00 |
| 2 | 1.00 | 1.00 | 1.00 |
| 3 | 0.00 | 0.00 | 0.00 |
| 4 | 0.00 | 0.00 | 0.00 |

**5Kg - Subject A - 3**

| Exe | Prec | Rec | F1-S |
|---|---|---|---|
| 1 | 0.00 | 0.00 | 0.00 |
| 2 | 1.00 | 1.00 | 1.00 |
| 3 | 0.00 | 0.00 | 0.00 |
| 4 | 0.00 | 0.00 | 0.00 |

**5Kg - Subject A – 4**

| Exe | Pre | Rec | F1-S |
|---|---|---|---|
| 1 | 0.00 | 0.00 | 0.00 |
| 2 | 1.00 | 1.00 | 1.00 |
| 3 | 0.00 | 0.00 | 0.00 |
| 4 | 0.00 | 0.00 | 0.00 |

**5Kg - Subject B - 1**

| Exe | Prec | Rec | F1-S |
|---|---|---|---|
| 1 | 0.00 | 0.00 | 0.00 |
| 2 | 1.00 | 1.00 | 1.00 |
| 3 | 0.00 | 0.00 | 0.00 |
| 4 | 0.00 | 0.00 | 0.00 |

**5Kg - Subject B - 2**

| Exe | Prec | Rec | F1-S |
|---|---|---|---|
| 1 | 0.00 | 0.00 | 0.00 |
| 2 | 1.00 | 1.00 | 1.00 |
| 3 | 0.00 | 0.00 | 0.00 |
| 4 | 0.00 | 0.00 | 0.00 |

**5Kg - Subject B - 3**

| Exe | Prec | Rec | F1-S |
|---|---|---|---|
| 1 | 0.00 | 0.00 | 0.00 |
| 2 | 1.00 | 1.00 | 1.00 |
| 3 | 0.00 | 0.00 | 0.00 |
| 4 | 0.00 | 0.00 | 0.00 |

**5Kg - Subject B – 4**

| Exe | Pre | Rec | F1-S |
|---|---|---|---|
| 1 | 0.00 | 0.00 | 0.00 |
| 2 | 1.00 | 1.00 | 1.00 |
| 3 | 0.00 | 0.00 | 0.00 |
| 4 | 0.00 | 0.00 | 0.00 |

**5Kg – Subject C – 1**

| Exe | Pre | Rec | F1-S |
|---|---|---|---|
| 1 | 0.00 | 0.00 | 0.00 |
| 2 | 1.00 | 1.00 | 1.00 |
| 3 | 0.00 | 0.00 | 0.00 |
| 4 | 0.00 | 0.00 | 0.00 |

**5Kg – Subject C – 2**

| Exe | Prec | Rec | F1-S |
|---|---|---|---|
| 1 | 0.00 | 0.00 | 0.00 |
| 2 | 1.00 | 1.00 | 1.00 |
| 3 | 0.00 | 0.00 | 0.00 |
| 4 | 0.00 | 0.00 | 0.00 |

**5Kg – Subject C – 3**

| Exe | Prec | Rec | F1-S |
|---|---|---|---|
| 1 | 0.00 | 0.00 | 0.00 |
| 2 | 1.00 | 1.00 | 1.00 |
| 3 | 0.00 | 0.00 | 0.00 |
| 4 | 0.00 | 0.00 | 0.00 |

**5Kg – Subject – 4**

Appendix B.9: Summary of metrics performance for Scene CV for Exercise 3

| **Exe** | **Prec** | **Rec** | **F1-S** |
|---|---|---|---|
| **1** | 0.00 | 0.00 | 0.00 |
| **2** | 0.00 | 0.00 | 0.00 |
| **3** | 1.00 | 1.00 | 1.00 |
| **4** | 0.00 | 0.00 | 0.00 |

**3Kg - Subject A - 1**

| **Exe** | **Pre** | **Rec** | **F1-S** |
|---|---|---|---|
| **1** | 0.00 | 0.00 | 0.00 |
| **2** | 0.00 | 0.00 | 0.00 |
| **3** | 1.00 | 1.00 | 1.00 |
| **4** | 0.00 | 0.00 | 0.00 |

**3Kg - Subject A - 2**

| **Exe** | **Prec** | **Rec** | **F1-S** |
|---|---|---|---|
| **1** | 0.00 | 0.00 | 0.00 |
| **2** | 0.00 | 0.00 | 0.00 |
| **3** | 1.00 | 1.00 | 1.00 |
| **4** | 0.00 | 0.00 | 0.00 |

**3Kg - Subject A - 3**

| **Exe** | **Prec** | **Rec** | **F1-S** |
|---|---|---|---|
| **1** | 0.00 | 0.00 | 0.00 |
| **2** | 0.00 | 0.00 | 0.00 |
| **3** | 1.00 | 1.00 | 1.00 |
| **4** | 0.00 | 0.00 | 0.00 |

**3Kg - Subject A – 4**

| **Exe** | **Prec** | **Rec** | **F1-S** |
|---|---|---|---|
| **1** | 0.00 | 0.00 | 0.00 |
| **2** | 0.00 | 0.00 | 0.00 |
| **3** | 1.00 | 1.00 | 1.00 |
| **4** | 0.00 | 0.00 | 0.00 |

**3Kg - Subject B - 1**

| **Exe** | **Prec** | **Rec** | **F1-S** |
|---|---|---|---|
| **1** | 0.00 | 0.00 | 0.00 |
| **2** | 0.00 | 0.00 | 0.00 |
| **3** | 1.00 | 1.00 | 1.00 |
| **4** | 0.00 | 0.00 | 0.00 |

**3Kg - Subject B - 2**

| **Exe** | **Prec** | **Rec** | **F1-S** |
|---|---|---|---|
| **1** | 0.00 | 0.00 | 0.00 |
| **2** | 0.00 | 0.00 | 0.00 |
| **3** | 1.00 | 1.00 | 1.00 |
| **4** | 0.00 | 0.00 | 0.00 |

**3Kg - Subject B - 3**

| **Exe** | **Prec** | **Rec** | **F1-S** |
|---|---|---|---|
| **1** | 0.00 | 0.00 | 0.00 |
| **2** | 0.00 | 0.00 | 0.00 |
| **3** | 1.00 | 1.00 | 1.00 |
| **4** | 0.00 | 0.00 | 0.00 |

**3Kg - Subject B – 4**

| **Exe** | **Pre** | **Rec** | **F1-S** |
|---|---|---|---|
| **1** | 0.00 | 0.00 | 0.00 |
| **2** | 0.00 | 0.00 | 0.00 |
| **3** | 1.00 | 1.00 | 1.00 |
| **4** | 0.00 | 0.00 | 0.00 |

**3Kg - Subject C - 1**

| **Exe** | **Prec** | **Rec** | **F1-S** |
|---|---|---|---|
| **1** | 0.00 | 0.00 | 0.00 |
| **2** | 0.00 | 0.00 | 0.00 |
| **3** | 1.00 | 1.00 | 1.00 |
| **4** | 0.00 | 0.00 | 0.00 |

**3Kg - Subject C - 2**

| **Exe** | **Prec** | **Rec** | **F1-S** |
|---|---|---|---|
| **1** | 0.00 | 0.00 | 0.00 |
| **2** | 0.00 | 0.00 | 0.00 |
| **3** | 1.00 | 1.00 | 1.00 |
| **4** | 0.00 | 0.00 | 0.00 |

**3Kg - Subject C - 3**

| **Exe** | **Prec** | **Rec** | **F1-S** |
|---|---|---|---|
| **1** | 0.00 | 0.00 | 0.00 |
| **2** | 0.00 | 0.00 | 0.00 |
| **3** | 1.00 | 1.00 | 1.00 |
| **4** | 0.00 | 0.00 | 0.00 |

**3Kg - Subject C – 4**

| **Exe** | **Pre** | **Rec** | **F1-S** |
|---|---|---|---|
| **1** | 0.00 | 0.00 | 0.00 |
| **2** | 0.00 | 0.00 | 0.00 |
| **3** | 1.00 | 1.00 | 1.00 |
| **4** | 0.00 | 0.00 | 0.00 |

**5Kg - Subject A - 1**

| **Exe** | **Prec** | **Rec** | **F1-S** |
|---|---|---|---|
| **1** | 0.00 | 0.00 | 0.00 |
| **2** | 0.00 | 0.00 | 0.00 |
| **3** | 1.00 | 1.00 | 1.00 |
| **4** | 0.00 | 0.00 | 0.00 |

**5Kg - Subject A - 2**

| **Exe** | **Prec** | **Rec** | **F1-S** |
|---|---|---|---|
| **1** | 0.00 | 0.00 | 0.00 |
| **2** | 0.00 | 0.00 | 0.00 |
| **3** | 1.00 | 1.00 | 1.00 |
| **4** | 0.00 | 0.00 | 0.00 |

**5Kg - Subject A - 3**

| **Exe** | **Prec** | **Rec** | **F1-S** |
|---|---|---|---|
| **1** | 0.00 | 0.00 | 0.00 |
| **2** | 0.00 | 0.00 | 0.00 |
| **3** | 1.00 | 1.00 | 1.00 |
| **4** | 0.00 | 0.00 | 0.00 |

**5Kg - Subject A – 4**

| **Exe** | **Pre** | **Rec** | **F1-S** |
|---|---|---|---|
| **1** | 0.00 | 0.00 | 0.00 |
| **2** | 0.00 | 0.00 | 0.00 |
| **3** | 1.00 | 1.00 | 1.00 |
| **4** | 0.00 | 0.00 | 0.00 |

**5Kg - Subject B - 1**

| **Exe** | **Prec** | **Rec** | **F1-S** |
|---|---|---|---|
| **1** | 0.00 | 0.00 | 0.00 |
| **2** | 0.00 | 0.00 | 0.00 |
| **3** | 1.00 | 1.00 | 1.00 |
| **4** | 0.00 | 0.00 | 0.00 |

**5Kg - Subject B - 2**

| **Exe** | **Prec** | **Rec** | **F1-S** |
|---|---|---|---|
| **1** | 0.00 | 0.00 | 0.00 |
| **2** | 0.00 | 0.00 | 0.00 |
| **3** | 1.00 | 1.00 | 1.00 |
| **4** | 0.00 | 0.00 | 0.00 |

**5Kg - Subject B - 3**

| **Exe** | **Prec** | **Rec** | **F1-S** |
|---|---|---|---|
| **1** | 0.00 | 0.00 | 0.00 |
| **2** | 0.00 | 0.00 | 0.00 |
| **3** | 1.00 | 1.00 | 1.00 |
| **4** | 0.00 | 0.00 | 0.00 |

**5Kg - Subject B – 4**

| **Exe** | **Pre** | **Rec** | **F1-S** |
|---|---|---|---|
| **1** | 0.00 | 0.00 | 0.00 |
| **2** | 0.00 | 0.00 | 0.00 |
| **3** | 1.00 | 1.00 | 1.00 |
| **4** | 0.00 | 0.00 | 0.00 |

**5Kg – Subject C – 1**

| **Exe** | **Pre** | **Rec** | **F1-S** |
|---|---|---|---|
| **1** | 0.00 | 0.00 | 0.00 |
| **2** | 0.00 | 0.00 | 0.00 |
| **3** | 1.00 | 1.00 | 1.00 |
| **4** | 0.00 | 0.00 | 0.00 |

**5Kg – Subject C – 2**

| **Exe** | **Prec** | **Rec** | **F1-S** |
|---|---|---|---|
| **1** | 0.00 | 0.00 | 0.00 |
| **2** | 0.00 | 0.00 | 0.00 |
| **3** | 1.00 | 1.00 | 1.00 |
| **4** | 0.00 | 0.00 | 0.00 |

**5Kg – Subject C – 3**

| **Exe** | **Prec** | **Rec** | **F1-S** |
|---|---|---|---|
| **1** | 0.00 | 0.00 | 0.00 |
| **2** | 0.00 | 0.00 | 0.00 |
| **3** | 1.00 | 1.00 | 1.00 |
| **4** | 0.00 | 0.00 | 0.00 |

**5Kg – Subject – 4**

Appendix B.10: Summary of metrics performance for Scene CV for Exercise 4

| Exe | Prec | Rec | F1-S |
|---|---|---|---|
| **1** | 0.00 | 0.00 | 0.00 |
| **2** | 0.00 | 0.00 | 0.00 |
| **3** | 0.00 | 0.00 | 0.00 |
| **4** | 1.00 | 1.00 | 1.00 |

**3Kg - Subject A - 1**

| Exe | Pre | Rec | F1-S |
|---|---|---|---|
| **1** | 0.00 | 0.00 | 0.00 |
| **2** | 0.00 | 0.00 | 0.00 |
| **3** | 0.00 | 0.00 | 0.00 |
| **4** | 1.00 | 1.00 | 1.00 |

**3Kg - Subject A - 2**

| Exe | Prec | Rec | F1-S |
|---|---|---|---|
| **1** | 0.00 | 0.00 | 0.00 |
| **2** | 0.00 | 0.00 | 0.00 |
| **3** | 0.00 | 0.00 | 0.00 |
| **4** | 1.00 | 1.00 | 1.00 |

**3Kg - Subject A - 3**

| Exe | Prec | Rec | F1-S |
|---|---|---|---|
| **1** | 0.00 | 0.00 | 0.00 |
| **2** | 0.00 | 0.00 | 0.00 |
| **3** | 0.00 | 0.00 | 0.00 |
| **4** | 1.00 | 1.00 | 1.00 |

**3Kg - Subject A – 4**

| Exe | Prec | Rec | F1-S |
|---|---|---|---|
| **1** | 0.00 | 0.00 | 0.00 |
| **2** | 0.00 | 0.00 | 0.00 |
| **3** | 0.00 | 0.00 | 0.00 |
| **4** | 1.00 | 1.00 | 1.00 |

**3Kg - Subject B - 1**

| Exe | Prec | Rec | F1-S |
|---|---|---|---|
| **1** | 0.00 | 0.00 | 0.00 |
| **2** | 0.00 | 0.00 | 0.00 |
| **3** | 0.00 | 0.00 | 0.00 |
| **4** | 1.00 | 1.00 | 1.00 |

**3Kg - Subject B - 2**

| Exe | Prec | Rec | F1-S |
|---|---|---|---|
| **1** | 0.00 | 0.00 | 0.00 |
| **2** | 0.00 | 0.00 | 0.00 |
| **3** | 0.00 | 0.00 | 0.00 |
| **4** | 1.00 | 1.00 | 1.00 |

**3Kg - Subject B - 3**

| Exe | Prec | Rec | F1-S |
|---|---|---|---|
| **1** | 0.00 | 0.00 | 0.00 |
| **2** | 0.00 | 0.00 | 0.00 |
| **3** | 0.00 | 0.00 | 0.00 |
| **4** | 1.00 | 1.00 | 1.00 |

**3Kg - Subject B – 4**

| Exe | Pre | Rec | F1-S |
|---|---|---|---|
| **1** | 0.00 | 0.00 | 0.00 |
| **2** | 0.00 | 0.00 | 0.00 |
| **3** | 0.00 | 0.00 | 0.00 |
| **4** | 1.00 | 1.00 | 1.00 |

**3Kg - Subject C - 1**

| Exe | Prec | Rec | F1-S |
|---|---|---|---|
| **1** | 0.00 | 0.00 | 0.00 |
| **2** | 0.00 | 0.00 | 0.00 |
| **3** | 0.00 | 0.00 | 0.00 |
| **4** | 1.00 | 1.00 | 1.00 |

**3Kg - Subject C - 2**

| Exe | Prec | Rec | F1-S |
|---|---|---|---|
| **1** | 0.00 | 0.00 | 0.00 |
| **2** | 0.00 | 0.00 | 0.00 |
| **3** | 0.00 | 0.00 | 0.00 |
| **4** | 1.00 | 0.86 | 0.92 |

**3Kg - Subject C - 3**

| Exe | Prec | Rec | F1-S |
|---|---|---|---|
| **1** | 0.00 | 0.00 | 0.00 |
| **2** | 0.00 | 0.00 | 0.00 |
| **3** | 0.00 | 0.00 | 0.00 |
| **4** | 1.00 | 1.00 | 1.00 |

**3Kg - Subject C – 4**

| Exe | Pre | Rec | F1-S |
|---|---|---|---|
| **1** | 0.00 | 0.00 | 0.00 |
| **2** | 0.00 | 0.00 | 0.00 |
| **3** | 0.00 | 0.00 | 0.00 |
| **4** | 1.00 | 1.00 | 1.00 |

**5Kg - Subject A - 1**

| Exe | Prec | Rec | F1-S |
|---|---|---|---|
| **1** | 0.00 | 0.00 | 0.00 |
| **2** | 0.00 | 0.00 | 0.00 |
| **3** | 0.00 | 0.00 | 0.00 |
| **4** | 1.00 | 1.00 | 1.00 |

**5Kg - Subject A - 2**

| Exe | Prec | Rec | F1-S |
|---|---|---|---|
| **1** | 0.00 | 0.00 | 0.00 |
| **2** | 0.00 | 0.00 | 0.00 |
| **3** | 0.00 | 0.00 | 0.00 |
| **4** | 1.00 | 1.00 | 1.00 |

**5Kg - Subject A - 3**

| Exe | Prec | Rec | F1-S |
|---|---|---|---|
| **1** | 0.00 | 0.00 | 0.00 |
| **2** | 0.00 | 0.00 | 0.00 |
| **3** | 0.00 | 0.00 | 0.00 |
| **4** | 1.00 | 1.00 | 1.00 |

**5Kg - Subject A – 4**

| Exe | Pre | Rec | F1-S |
|---|---|---|---|
| **1** | 0.00 | 0.00 | 0.00 |
| **2** | 0.00 | 0.00 | 0.00 |
| **3** | 0.00 | 0.00 | 0.00 |
| **4** | 1.00 | 1.00 | 1.00 |

**5Kg - Subject B - 1**

| Exe | Prec | Rec | F1-S |
|---|---|---|---|
| **1** | 0.00 | 0.00 | 0.00 |
| **2** | 0.00 | 0.00 | 0.00 |
| **3** | 0.00 | 0.00 | 0.00 |
| **4** | 1.00 | 1.00 | 1.00 |

**5Kg - Subject B - 2**

| Exe | Prec | Rec | F1-S |
|---|---|---|---|
| **1** | 0.00 | 0.00 | 0.00 |
| **2** | 0.00 | 0.00 | 0.00 |
| **3** | 0.00 | 0.00 | 0.00 |
| **4** | 1.00 | 1.00 | 1.00 |

**5Kg - Subject B - 3**

| Exe | Prec | Rec | F1-S |
|---|---|---|---|
| **1** | 0.00 | 0.00 | 0.00 |
| **2** | 0.00 | 0.00 | 0.00 |
| **3** | 0.00 | 0.00 | 0.00 |
| **4** | 1.00 | 1.00 | 1.00 |

**5Kg - Subject B – 4**

| Exe | Pre | Rec | F1-S |
|---|---|---|---|
| **1** | 0.00 | 0.00 | 0.00 |
| **2** | 0.00 | 0.00 | 0.00 |
| **3** | 0.00 | 0.00 | 0.00 |
| **4** | 1.00 | 1.00 | 1.00 |

**5Kg – Subject C – 1**

| Exe | Pre | Rec | F1-S |
|---|---|---|---|
| **1** | 0.00 | 0.00 | 0.00 |
| **2** | 0.00 | 0.00 | 0.00 |
| **3** | 0.00 | 0.00 | 0.00 |
| **4** | 1.00 | 1.00 | 1.00 |

**5Kg – Subject C – 2**

| Exe | Prec | Rec | F1-S |
|---|---|---|---|
| **1** | 0.00 | 0.00 | 0.00 |
| **2** | 0.00 | 0.00 | 0.00 |
| **3** | 0.00 | 0.00 | 0.00 |
| **4** | 1.00 | 1.00 | 1.00 |

**5Kg – Subject C – 3**

| Exe | Prec | Rec | F1-S |
|---|---|---|---|
| **1** | 0.00 | 0.00 | 0.00 |
| **2** | 0.00 | 0.00 | 0.00 |
| **3** | 0.00 | 0.00 | 0.00 |
| **4** | 1.00 | 1.00 | 1.00 |

**5Kg – Subject – 4**

Appendix B.11: Metric values of the Scene CV for Exercise 1 – Velocity

| User \| Weight \| Sets | MSE | MAE | RMSE | R-squared |
|---|---|---|---|---|
| **Subject A \| 3 KG \| 1** | 0.0006 | 0.0189 | 0.0246 | 0.9768 |
| **Subject A \| 3 KG \| 2** | 0.0017 | 0.0317 | 0.0410 | 0.9317 |
| **Subject A \| 3 KG \| 3** | 0.0018 | 0.0336 | 0.0422 | 0.9380 |
| **Subject A \| 3 KG \| 4** | 0.0011 | 0.0278 | 0.0332 | 0.9601 |
| **Subject A \| 5 KG \| 1** | 0.0025 | 0.0426 | 0.0503 | 0.9550 |
| **Subject A \| 5 KG \| 2** | 0.0044 | 0.0570 | 0.0664 | 0.9177 |
| **Subject A \| 5 KG \| 3** | 0.0032 | 0.0461 | 0.0565 | 0.9438 |
| **Subject A \| 5 KG \| 4** | 0.0007 | 0.0215 | 0.0265 | 0.9870 |
| **Subject B \| 3 KG \| 1** | 0.0010 | 0.0262 | 0.0312 | 0.9821 |
| **Subject B \| 3 KG \| 2** | 0.0033 | 0.0495 | 0.0573 | 0.9340 |
| **Subject B \| 3 KG \| 3** | 0.0026 | 0.0405 | 0.0508 | 0.9585 |
| **Subject B \| 3 KG \| 4** | 0.0037 | 0.0454 | 0.0609 | 0.9500 |
| **Subject B \| 5 KG \| 1** | 0.0009 | 0.0214 | 0.0307 | 0.9690 |
| **Subject B \| 5 KG \| 2** | 0.0019 | 0.0359 | 0.0440 | 0.9390 |
| **Subject B \| 5 KG \| 3** | 0.0009 | 0.0238 | 0.0295 | 0.9701 |
| **Subject B \| 5 KG \| 4** | 0.0007 | 0.0203 | 0.0274 | 0.9752 |
| **Subject C \| 3 KG \| 1** | 0.0030 | 0.0419 | 0.0550 | 0.9421 |
| **Subject C \| 3 KG \| 2** | 0.0063 | 0.0634 | 0.0792 | 0.8805 |
| **Subject C \| 3 KG \| 3** | 0.0014 | 0.0286 | 0.0375 | 0.9735 |
| **Subject C \| 3 KG \| 4** | 0.0017 | 0.0324 | 0.0408 | 0.9621 |
| **Subject C \| 5 KG \| 1** | 0.0027 | 0.0407 | 0.0522 | 0.9637 |
| **Subject C \| 5 KG \| 2** | 0.0058 | 0.0594 | 0.0759 | 0.9230 |
| **Subject C \| 5 KG \| 3** | 0.0174 | 0.1105 | 0.1318 | 0.8503 |
| **Subject C \| 5 KG \| 4** | 0.0171 | 0.1106 | 0.1309 | 0.7876 |
| **Mean** | **0.0036** | **0.0429** | **0.0532** | **0.9404** |

Appendix B.12: Metric values of the Weight CV for Exercise 2 – Velocity

| CV Method Weight | MSE | MAE | RMSE | R-squared |
|---|---|---|---|---|
| **3 Kg** | 0.0039 | 0.0439 | 0.0628 | 0.8742 |
| **5 Kg** | 0.0034 | 0.0438 | 0.0583 | 0.9283 |
| **Mean** | **0.0037** | **0.0439** | **0.0605** | **0.9013** |

Appendix B.13: Metric values of the Subject CV for Exercise 2 – Velocity

| CV Method Subject | MSE | MAE | RMSE | R-squared |
|---|---|---|---|---|
| **Subject A** | 0.0023 | 0.0348 | 0.0624 | 0.9102 |
| **Subject B** | 0.0031 | 0.0404 | 0.0555 | 0.8833 |
| **Subject C** | 0.0246 | 0.1289 | 0.1570 | 0.7846 |
| **Mean** | **0.0100** | **0.0680** | **0.0916** | **0.8594** |

Appendix B.14: Metric values of the Set Repetition CV for Exercise 2 – Velocity

| CV Method Set Repetition | MSE | MAE | RMSE | R-squared |
|---|---|---|---|---|
| **Repetition 1** | 0.0020 | 0.0336 | 0.0443 | 0.9360 |
| **Repetition 2** | 0.0019 | 0.0326 | 0.0432 | 0.9432 |
| **Repetition 3** | 0.0011 | 0.0241 | 0.0327 | 0.9716 |
| **Repetition 4** | 0.0015 | 0.0278 | 0.0383 | 0.9654 |
| **Mean** | **0.0016** | **0.0295** | **0.0396** | **0.9541** |

Appendix B.15: Metric values of the Scene CV for Exercise 2 – Velocity

| User \| Weight \| Sets | MSE | MAE | RMSE | R-squared |
|---|---|---|---|---|
| **Subject A \| 3 KG \| 1** | 0.0008 | 0.0218 | 0.0278 | 0.9697 |
| **Subject A \| 3 KG \| 2** | 0.0010 | 0.0254 | 0.0316 | 0.9665 |
| **Subject A \| 3 KG \| 3** | 0.0005 | 0.0166 | 0.0229 | 0.9830 |
| **Subject A \| 3 KG \| 4** | 0.0004 | 0.0159 | 0.0207 | 0.9859 |
| **Subject A \| 5 KG \| 1** | 0.0011 | 0.0236 | 0.0325 | 0.9496 |
| **Subject A \| 5 KG \| 2** | 0.0007 | 0.0210 | 0.0272 | 0.9726 |
| **Subject A \| 5 KG \| 3** | 0.0004 | 0.0156 | 0.0201 | 0.9863 |
| **Subject A \| 5 KG \| 4** | 0.0011 | 0.0254 | 0.0327 | 0.9640 |
| **Subject B \| 3 KG \| 1** | 0.0029 | 0.0393 | 0.0534 | 0.9302 |
| **Subject B \| 3 KG \| 2** | 0.0013 | 0.0280 | 0.0361 | 0.9707 |
| **Subject B \| 3 KG \| 3** | 0.0016 | 0.0296 | 0.0394 | 0.9660 |
| **Subject B \| 3 KG \| 4** | 0.0022 | 0.0367 | 0.0473 | 0.9462 |
| **Subject B \| 5 KG \| 1** | 0.0017 | 0.0309 | 0.0406 | 0.9468 |
| **Subject B \| 5 KG \| 2** | 0.0005 | 0.0171 | 0.0217 | 0.9848 |
| **Subject B \| 5 KG \| 3** | 0.0005 | 0.0169 | 0.0217 | 0.9856 |
| **Subject B \| 5 KG \| 4** | 0.0004 | 0.0140 | 0.0189 | 0.9893 |
| **Subject C \| 3 KG \| 1** | 0.0012 | 0.0273 | 0.0340 | 0.9495 |
| **Subject C \| 3 KG \| 2** | 0.0009 | 0.0245 | 0.0301 | 0.9598 |
| **Subject C \| 3 KG \| 3** | 0.0029 | 0.0443 | 0.0539 | 0.9025 |
| **Subject C \| 3 KG \| 4** | 0.0010 | 0.0244 | 0.0312 | 0.9677 |
| **Subject C \| 5 KG \| 1** | 0.0045 | 0.0512 | 0.0667 | 0.9233 |
| **Subject C \| 5 KG \| 2** | 0.0024 | 0.0364 | 0.0486 | 0.9606 |
| **Subject C \| 5 KG \| 3** | 0.0061 | 0.0606 | 0.0779 | 0.9258 |
| **Subject C \| 5 KG \| 4** | 0.0033 | 0.0410 | 0.0571 | 0.9640 |
| **Mean** | **0.0016** | **0.0286** | **0.0373** | **0.9604** |

Appendix B.16: Metric values of the Weight CV for Exercise 3 – Velocity

| CV Method Weight | MSE | MAE | RMSE | R-squared |
|---|---|---|---|---|
| **3 Kg** | 0.0014 | 0.0307 | 0.0381 | 0.9699 |
| **5 Kg** | 0.0046 | 0.0482 | 0.0675 | 0.9335 |
| **Mean** | **0.0030** | **0.0395** | **0.0528** | **0.9517** |

Appendix B.17: Metric values of the Subject CV for Exercise 3 – Velocity

| CV Method Subject | MSE | MAE | RMSE | R-squared |
|---|---|---|---|---|
| **Subject A** | 0.0015 | 0.0315 | 0.0389 | 0.9651 |
| **Subject B** | 0.0008 | 0.0226 | 0.0283 | 0.9826 |
| **Subject C** | 0.0153 | 0.0830 | 0.1235 | 0.8429 |
| **Mean** | **0.0059** | **0.0457** | **0.0636** | **0.9302** |

Appendix B.18: Metric values of the Set Repetition CV for Exercise 3 – Velocity

| CV Method Set Repetition | MSE | MAE | RMSE | R-squared |
|---|---|---|---|---|
| **Repetition 1** | 0.0013 | 0.0275 | 0.0355 | 0.9766 |
| **Repetition 2** | 0.0008 | 0.0225 | 0.0282 | 0.9834 |
| **Repetition 3** | 0.0013 | 0.0283 | 0.0356 | 0.9772 |
| **Repetition 4** | 0.0006 | 0.0197 | 0.0244 | 0.9870 |
| **Mean** | **0.0010** | **0.0245** | **0.0310** | **0.9811** |

Appendix B.19: Metric values of the Scene CV for Exercise 3 – Velocity

| User \| Weight \| Sets | MSE | MAE | RMSE | R-squared |
|---|---|---|---|---|
| **Subject A \| 3 KG \| 1** | 0.0007 | 0.0210 | 0.0265 | 0.9829 |
| **Subject A \| 3 KG \| 2** | 0.0011 | 0.0274 | 0.0333 | 0.9722 |
| **Subject A \| 3 KG \| 3** | 0.0012 | 0.0273 | 0.0342 | 0.9745 |
| **Subject A \| 3 KG \| 4** | 0.0008 | 0.0222 | 0.0285 | 0.9826 |
| **Subject A \| 5 KG \| 1** | 0.0022 | 0.0379 | 0.0464 | 0.9543 |
| **Subject A \| 5 KG \| 2** | 0.0013 | 0.0282 | 0.0358 | 0.9713 |
| **Subject A \| 5 KG \| 3** | 0.0006 | 0.0195 | 0.0243 | 0.9878 |
| **Subject A \| 5 KG \| 4** | 0.0010 | 0.0256 | 0.0318 | 0.9806 |
| **Subject B \| 3 KG \| 1** | 0.0015 | 0.0300 | 0.0387 | 0.9801 |
| **Subject B \| 3 KG \| 2** | 0.0007 | 0.0201 | 0.0259 | 0.9857 |
| **Subject B \| 3 KG \| 3** | 0.0026 | 0.0407 | 0.0514 | 0.9649 |
| **Subject B \| 3 KG \| 4** | 0.0114 | 0.0807 | 0.1069 | 0.7136 |
| **Subject B \| 5 KG \| 1** | 0.0020 | 0.0374 | 0.0448 | 0.9527 |
| **Subject B \| 5 KG \| 2** | 0.0008 | 0.0232 | 0.0283 | 0.9807 |
| **Subject B \| 5 KG \| 3** | 0.0010 | 0.0247 | 0.0321 | 0.9789 |
| **Subject B \| 5 KG \| 4** | 0.0005 | 0.0172 | 0.0222 | 0.9882 |
| **Subject C \| 3 KG \| 1** | 0.0011 | 0.0276 | 0.0335 | 0.9732 |
| **Subject C \| 3 KG \| 2** | 0.0006 | 0.0189 | 0.0240 | 0.9862 |
| **Subject C \| 3 KG \| 3** | 0.0006 | 0.0185 | 0.0235 | 0.9881 |
| **Subject C \| 3 KG \| 4** | 0.0021 | 0.0363 | 0.0453 | 0.9571 |
| **Subject C \| 5 KG \| 1** | 0.0056 | 0.0566 | 0.0749 | 0.9392 |
| **Subject C \| 5 KG \| 2** | 0.0012 | 0.0261 | 0.0340 | 0.9885 |
| **Subject C \| 5 KG \| 3** | 0.0013 | 0.0277 | 0.0355 | 0.9874 |
| **Subject C \| 5 KG \| 4** | 0.0010 | 0.0241 | 0.0318 | 0.9793 |
| **Mean** | **0.0018** | **0.0300** | **0.0381** | **0.9646** |

Appendix B.20: Metric values of the Weight CV for Exercise 4 – Velocity

| CV Method Weight | MSE | MAE | RMSE | R-squared |
|---|---|---|---|---|
| **3 Kg** | 0.0034 | 0.0436 | 0.0584 | 0.9354 |
| **5 Kg** | 0.0058 | 0.0529 | 0.0761 | 0.8922 |
| **Mean** | **0.0034** | **0.0436** | **0.0584** | **0.9354** |

Appendix B.21: Metric values of the Subject CV for Exercise 4 – Velocity

| CV Method Subject | MSE | MAE | RMSE | R-squared |
|---|---|---|---|---|
| **Subject A** | 0.0027 | 0.0408 | 0.0524 | 0.0959 |
| **Subject B** | 0.0034 | 0.0449 | 0.0585 | 0.9219 |
| **Subject C** | 0.0249 | 0.1313 | 0.1579 | 0.7346 |
| **Mean** | **0.0104** | **0.0723** | **0.0896** | **0.5841** |

Appendix B.22: Metric values of the Set Repetition CV for Exercise 4 – Velocity

| CV Method Set Repetition | MSE | MAE | RMSE | R-squared |
|---|---|---|---|---|
| **Repetition 1** | 0.0021 | 0.0345 | 0.0454 | 0.9552 |
| **Repetition 2** | 0.0028 | 0.0404 | 0.0528 | 0.9416 |
| **Repetition 3** | 0.0025 | 0.0375 | 0.0503 | 0.9482 |
| **Repetition 4** | 0.0020 | 0.0334 | 0.0450 | 0.9591 |
| **Mean** | **0.0024** | **0.0365** | **0.0484** | **0.9510** |

Appendix B.23: Metric values of the Scene CV for Exercise 4 – Velocity

| **User \| Weight \| Sets** | **MSE** | **MAE** | **RMSE** | **R-squared** |
|---|---|---|---|---|
| **Subject A \| 3 KG \| 1** | 0.0010 | 0.0258 | 0.0322 | 0.9720 |
| **Subject A \| 3 KG \| 2** | 0.0021 | 0.0367 | 0.0462 | 0.9431 |
| **Subject A \| 3 KG \| 3** | 0.0033 | 0.0479 | 0.0577 | 0.9094 |
| **Subject A \| 3 KG \| 4** | 0.0013 | 0.0257 | 0.0358 | 0.9672 |
| **Subject A \| 5 KG \| 1** | 0.0016 | 0.0310 | 0.0394 | 0.9667 |
| **Subject A \| 5 KG \| 2** | 0.0088 | 0.0780 | 0.0937 | 0.8112 |
| **Subject A \| 5 KG \| 3** | 0.0057 | 0.0580 | 0.0753 | 0.8729 |
| **Subject A \| 5 KG \| 4** | 0.0019 | 0.0353 | 0.0441 | 0.9562 |
| **Subject B \| 3 KG \| 1** | 0.0033 | 0.0462 | 0.0572 | 0.9531 |
| **Subject B \| 3 KG \| 2** | 0.0042 | 0.0496 | 0.0651 | 0.9393 |
| **Subject B \| 3 KG \| 3** | 0.0048 | 0.0554 | 0.0694 | 0.9230 |
| **Subject B \| 3 KG \| 4** | 0.0063 | 0.0644 | 0.0791 | 0.9151 |
| **Subject B \| 5 KG \| 1** | 0.0023 | 0.0353 | 0.0477 | 0.9285 |
| **Subject B \| 5 KG \| 2** | 0.0016 | 0.0297 | 0.0399 | 0.9532 |
| **Subject B \| 5 KG \| 3** | 0.0018 | 0.0330 | 0.0422 | 0.9527 |
| **Subject B \| 5 KG \| 4** | 0.0014 | 0.0293 | 0.0372 | 0.9621 |
| **Subject C \| 3 KG \| 1** | 0.0013 | 0.0277 | 0.0354 | 0.9677 |
| **Subject C \| 3 KG \| 2** | 0.0018 | 0.0325 | 0.0421 | 0.9585 |
| **Subject C \| 3 KG \| 3** | 0.0031 | 0.0438 | 0.0554 | 0.9326 |
| **Subject C \| 3 KG \| 4** | 0.0012 | 0.0278 | 0.0348 | 0.9717 |
| **Subject C \| 5 KG \| 1** | 0.0038 | 0.0462 | 0.0614 | 0.9486 |
| **Subject C \| 5 KG \| 2** | 0.0050 | 0.0593 | 0.0705 | 0.9386 |
| **Subject C \| 5 KG \| 3** | 0.0023 | 0.0377 | 0.0484 | 0.9740 |
| **Subject C \| 5 KG \| 4** | 0.0034 | 0.0456 | 0.0587 | 0.9600 |
| **Mean** | **0.0030** | **0.0417** | **0.0529** | **0.9407** |

Appendix B.24: Metric values of the Weight CV for Exercise 1 – Force

| CV Method Weight | MSE | MAE | RMSE | R-squared |
|---|---|---|---|---|
| **3 Kg** | 0.0180 | 0.0895 | 0.1340 | 0.1188 |
| **5 Kg** | 0.0249 | 0.1174 | 0.1577 | 0.7251 |
| **Mean** | **0.0214** | **0.1034** | **0.1458** | **0.4219** |

Appendix B.25: Metric values of the Subject CV for Exercise 1 – Force

| CV Method Subject | MSE | MAE | RMSE | R-squared |
|---|---|---|---|---|
| **Subject A** | 0.0140 | 0.0990 | 0.1183 | 0.8861 |
| **Subject B** | 0.0036 | 0.0435 | 0.0597 | 0.7583 |
| **Subject C** | 0.0611 | 0.1869 | 0.2472 | 0.4358 |
| **Mean** | **0.0262** | **0.1098** | **0.1417** | **0.6934** |

Appendix B.26: Metric values of the Set Repetition CV for Exercise 1 – Force

| CV Method Set Repetition | MSE | MAE | RMSE | R-squared |
|---|---|---|---|---|
| **Repetition 1** | 0.0027 | 0.0355 | 0.0524 | 0.7995 |
| **Repetition 2** | 0.0034 | 0.0379 | 0.0584 | 0.7722 |
| **Repetition 3** | 0.0044 | 0.0464 | 0.0666 | 0.7618 |
| **Repetition 4** | 0.0186 | 0.0838 | 0.1364 | 0.3357 |
| **Mean** | **0.0073** | **0.0509** | **0.0785** | **0.6673** |

Appendix B.27: Metric values of the Scene CV for Exercise 1 – Force

| User \| Weight \| Sets | MSE | MAE | RMSE | R-squared |
|---|---|---|---|---|
| **Subject A \| 3 KG \| 1** | 0.0016 | 0.0293 | 0.0395 | 0.8064 |
| **Subject A \| 3 KG \| 2** | 0.0024 | 0.0324 | 0.0493 | 0.6726 |
| **Subject A \| 3 KG \| 3** | 0.0023 | 0.0371 | 0.0485 | 0.7523 |
| **Subject A \| 3 KG \| 4** | 0.0033 | 0.0406 | 0.0573 | 0.6644 |
| **Subject A \| 5 KG \| 1** | 0.0040 | 0.0395 | 0.0635 | 0.8086 |
| **Subject A \| 5 KG \| 2** | 0.0029 | 0.0425 | 0.0536 | 0.8396 |
| **Subject A \| 5 KG \| 3** | 0.0020 | 0.0349 | 0.0449 | 0.8942 |
| **Subject A \| 5 KG \| 4** | 0.0025 | 0.0328 | 0.0501 | 0.8629 |
| **Subject B \| 3 KG \| 1** | 0.0019 | 0.0287 | 0.0436 | 0.8964 |
| **Subject B \| 3 KG \| 2** | 0.0117 | 0.0685 | 0.1080 | 0.5765 |
| **Subject B \| 3 KG \| 3** | 0.0068 | 0.0611 | 0.0826 | 0.8120 |
| **Subject B \| 3 KG \| 4** | 0.0835 | 0.2394 | 0.2889 | 0.4617 |
| **Subject B \| 5 KG \| 1** | 0.0014 | 0.0268 | 0.0376 | 0.7535 |
| **Subject B \| 5 KG \| 2** | 0.0015 | 0.0268 | 0.0391 | 0.7512 |
| **Subject B \| 5 KG \| 3** | 0.0010 | 0.0212 | 0.0318 | 0.8313 |
| **Subject B \| 5 KG \| 4** | 0.0010 | 0.0232 | 0.0320 | 0.8513 |
| **Subject C \| 3 KG \| 1** | 0.0049 | 0.0555 | 0.0701 | 0.5493 |
| **Subject C \| 3 KG \| 2** | 0.0024 | 0.0400 | 0.0495 | 0.7666 |
| **Subject C \| 3 KG \| 3** | 0.0033 | 0.0426 | 0.0572 | 0.7328 |
| **Subject C \| 3 KG \| 4** | 0.0024 | 0.0346 | 0.0486 | 0.7612 |
| **Subject C \| 5 KG \| 1** | 0.0088 | 0.0664 | 0.0936 | 0.7428 |
| **Subject C \| 5 KG \| 2** | 0.0106 | 0.0830 | 0.1029 | 0.7174 |
| **Subject C \| 5 KG \| 3** | 0.0641 | 0.1947 | 0.2532 | 0.3554 |
| **Subject C \| 5 KG \| 4** | 0.0343 | 0.1425 | 0.1853 | 0.2716 |
| **Mean** | **0.0109** | **0.0602** | **0.0805** | **0.7138** |

Appendix B.28: Metric values of the Weight CV for Exercise 2 – Force

| CV Method Weight | MSE | MAE | RMSE | R-squared |
|---|---|---|---|---|
| **3 Kg** | 0.0176 | 0.0830 | 0.1272 | 0.2666 |
| **5 Kg** | 0.0162 | 0.0902 | 0.1327 | 0.3063 |
| **Mean** | **0.0169** | **0.0866** | **0.1299** | **0.2865** |

Appendix B.29: Metric values of the Subject CV for Exercise 2 – Force

| CV Method Subject | MSE | MAE | RMSE | R-squared |
|---|---|---|---|---|
| **Subject A** | 0.0103 | 0.0784 | 0.1013 | 0.1847 |
| **Subject B** | 0.0047 | 0.0531 | 0.0689 | 0.5246 |
| **Subject C** | 0.0756 | 0.2266 | 0.2750 | 0.3704 |
| **Mean** | **0.0302** | **0.1194** | **0.1484** | **0.3599** |

Appendix B.30: Metric values of the Set Repetition CV for Exercise 2 – Force

| CV Method Set Repetition | MSE | MAE | RMSE | R-squared |
|---|---|---|---|---|
| **Repetition 1** | 0.0098 | 0.0646 | 0.0988 | 0.4801 |
| **Repetition 2** | 0.0081 | 0.0567 | 0.0898 | 0.4578 |
| **Repetition 3** | 0.0040 | 0.0444 | 0.0635 | 0.7775 |
| **Repetition 4** | 0.0092 | 0.0563 | 0.0957 | 0.4665 |
| **Mean** | **0.0078** | **0.0555** | **0.0869** | **0.5455** |

Appendix B.31: Metric values of the Scene CV for Exercise 2 – Force

| User \| Weight \| Sets | MSE | MAE | RMSE | R-squared |
|---|---|---|---|---|
| **Subject A \| 3 KG \| 1** | 0.0016 | 0.0308 | 0.0399 | 0.8410 |
| **Subject A \| 3 KG \| 2** | 0.1536 | 0.3765 | 0.3919 | 0.2345 |
| **Subject A \| 3 KG \| 3** | 0.0044 | 0.0520 | 0.0663 | 0.6356 |
| **Subject A \| 3 KG \| 4** | 0.0016 | 0.0282 | 0.0404 | 0.8556 |
| **Subject A \| 5 KG \| 1** | 0.0027 | 0.0391 | 0.0518 | 0.6407 |
| **Subject A \| 5 KG \| 2** | 0.0020 | 0.0302 | 0.0447 | 0.8324 |
| **Subject A \| 5 KG \| 3** | 0.0054 | 0.0554 | 0.0734 | 0.6278 |
| **Subject A \| 5 KG \| 4** | 0.0038 | 0.0459 | 0.0619 | 0.7233 |
| **Subject B \| 3 KG \| 1** | 0.0144 | 0.0833 | 0.1199 | 0.6960 |
| **Subject B \| 3 KG \| 2** | 0.0391 | 0.1565 | 0.1979 | 0.0621 |
| **Subject B \| 3 KG \| 3** | 0.0279 | 0.1246 | 0.1671 | 0.2671 |
| **Subject B \| 3 KG \| 4** | 0.0070 | 0.0620 | 0.0840 | 0.7847 |
| **Subject B \| 5 KG \| 1** | 0.0035 | 0.0450 | 0.0588 | 0.5382 |
| **Subject B \| 5 KG \| 2** | 0.0007 | 0.0190 | 0.0270 | 0.9018 |
| **Subject B \| 5 KG \| 3** | 0.0022 | 0.0324 | 0.0464 | 0.7181 |
| **Subject B \| 5 KG \| 4** | 0.0007 | 0.0203 | 0.0265 | 0.9114 |
| **Subject C \| 3 KG \| 1** | 0.0012 | 0.0264 | 0.0341 | 0.8249 |
| **Subject C \| 3 KG \| 2** | 0.0016 | 0.0298 | 0.0403 | 0.7569 |
| **Subject C \| 3 KG \| 3** | 0.0039 | 0.0500 | 0.0626 | 0.6094 |
| **Subject C \| 3 KG \| 4** | 0.0027 | 0.0392 | 0.0524 | 0.7053 |
| **Subject C \| 5 KG \| 1** | 0.0044 | 0.0494 | 0.0667 | 0.8431 |
| **Subject C \| 5 KG \| 2** | 0.0087 | 0.0661 | 0.0930 | 0.7303 |
| **Subject C \| 5 KG \| 3** | 0.0186 | 0.1005 | 0.1363 | 0.6331 |
| **Subject C \| 5 KG \| 4** | 0.0214 | 0.1113 | 0.1463 | 0.5888 |
| **Mean** | **0.0139** | **0.0698** | **0.0887** | **0.6651** |

Appendix B.32: Metric values of the Weight CV for Exercise 3 – Force

| CV Method Weight | MSE | MAE | RMSE | R-squared |
|---|---|---|---|---|
| **3 Kg** | 0.0075 | 0.0650 | 0.0867 | 0.7493 |
| **5 Kg** | 0.0279 | 0.1031 | 0.1671 | 0.3456 |
| **Mean** | **0.0177** | **0.0840** | **0.1269** | **0.5474** |

Appendix B.33: Metric values of the Subject CV for Exercise 3 – Force

| CV Method Subject | MSE | MAE | RMSE | R-squared |
|---|---|---|---|---|
| **Subject A** | 0.0046 | 0.0512 | 0.0679 | 0.6969 |
| **Subject B** | 0.0073 | 0.0628 | 0.0857 | 0.5882 |
| **Subject C** | 0.0145 | 0.0831 | 0.1204 | 0.7174 |
| **Mean** | **0.0088** | **0.0657** | **0.0914** | **0.6675** |

Appendix B.34: Metric values of the Set Repetition CV for Exercise 3 – Force

| CV Method Set Repetition | MSE | MAE | RMSE | R-squared |
|---|---|---|---|---|
| **Repetition 1** | 0.0034 | 0.0409 | 0.0585 | 0.8552 |
| **Repetition 2** | 0.0034 | 0.0395 | 0.0581 | 0.8406 |
| **Repetition 3** | 0.0039 | 0.0419 | 0.0628 | 0.8599 |
| **Repetition 4** | 0.0023 | 0.0336 | 0.0476 | 0.8669 |
| **Mean** | **0.0033** | **0.0390** | **0.0567** | **0.8557** |

Appendix B.35: Metric values of the Scene CV for Exercise 3 – Force

| User \| Weight \| Sets | MSE | MAE | RMSE | R-squared |
|---|---|---|---|---|
| **Subject A \| 3 KG \| 1** | 0.0018 | 0.0328 | 0.0427 | 0.8864 |
| **Subject A \| 3 KG \| 2** | 0.0019 | 0.0320 | 0.0438 | 0.8804 |
| **Subject A \| 3 KG \| 3** | 0.0031 | 0.0439 | 0.0559 | 0.8518 |
| **Subject A \| 3 KG \| 4** | 0.0027 | 0.0410 | 0.0524 | 0.8782 |
| **Subject A \| 5 KG \| 1** | 0.0030 | 0.0392 | 0.0544 | 0.8637 |
| **Subject A \| 5 KG \| 2** | 0.0056 | 0.0434 | 0.0750 | 0.7514 |
| **Subject A \| 5 KG \| 3** | 0.0054 | 0.0552 | 0.0735 | 0.7625 |
| **Subject A \| 5 KG \| 4** | 0.0035 | 0.0403 | 0.0595 | 0.8513 |
| **Subject B \| 3 KG \| 1** | 0.0700 | 0.0700 | 0.0984 | 0.8438 |
| **Subject B \| 3 KG \| 2** | 0.0025 | 0.0373 | 0.0496 | 0.8869 |
| **Subject B \| 3 KG \| 3** | 0.0087 | 0.0621 | 0.0933 | 0.8596 |
| **Subject B \| 3 KG \| 4** | 0.0022 | 0.0352 | 0.0472 | 0.8611 |
| **Subject B \| 5 KG \| 1** | 0.0017 | 0.0302 | 0.0416 | 0.8258 |
| **Subject B \| 5 KG \| 2** | 0.0019 | 0.0302 | 0.0438 | 0.8276 |
| **Subject B \| 5 KG \| 3** | 0.0015 | 0.0301 | 0.0392 | 0.8912 |
| **Subject B \| 5 KG \| 4** | 0.0016 | 0.0259 | 0.0396 | 0.8592 |
| **Subject C \| 3 KG \| 1** | 0.0021 | 0.0330 | 0.0463 | 0.7989 |
| **Subject C \| 3 KG \| 2** | 0.0013 | 0.0275 | 0.0357 | 0.8926 |
| **Subject C \| 3 KG \| 3** | 0.0042 | 0.0462 | 0.0645 | 0.7162 |
| **Subject C \| 3 KG \| 4** | 0.0015 | 0.0290 | 0.0385 | 0.8997 |
| **Subject C \| 5 KG \| 1** | 0.0088 | 0.0692 | 0.0939 | 0.8323 |
| **Subject C \| 5 KG \| 2** | 0.0053 | 0.0526 | 0.0726 | 0.9227 |
| **Subject C \| 5 KG \| 3** | 0.0053 | 0.0511 | 0.0727 | 0.9224 |
| **Subject C \| 5 KG \| 4** | 0.0010 | 0.0244 | 0.0323 | 0.9259 |
| **Mean** | **0.0061** | **0.0409** | **0.0569** | **0.8538** |

Appendix B.36: Metric values of the Weight CV for Exercise 4 – Force

| CV Method Weight | MSE | MAE | RMSE | R-squared |
|---|---|---|---|---|
| **3 Kg** | 0.0347 | 0.1307 | 0.1864 | 0.2003 |
| **5 Kg** | 0.0139 | 0.0784 | 0.1177 | 0.4376 |
| **Mean** | **0.0243** | **0.1045** | **0.1520** | **0.3189** |

Appendix B.37: Metric values of the Subject CV for Exercise 4 – Force

| CV Method Subject | MSE | MAE | RMSE | R-squared |
|---|---|---|---|---|
| **Subject A** | 0.0091 | 0.0813 | 0.0952 | 0.6636 |
| **Subject B** | 0.0121 | 0.0846 | 0.1101 | 0.3002 |
| **Subject C** | 0.0722 | 0.2269 | 0.2686 | 0.2300 |
| **Mean** | **0.0311** | **0.1309** | **0.1580** | **0.3979** |

Appendix B.38: Metric values of the Set Repetition CV for Exercise 4 – Force

| CV Method Set Repetition | MSE | MAE | RMSE | R-squared |
|---|---|---|---|---|
| **Repetition 1** | 0.0064 | 0.0523 | 0.0800 | 0.2548 |
| **Repetition 2** | 0.0060 | 0.0477 | 0.0774 | 0.3608 |
| **Repetition 3** | 0.0067 | 0.0536 | 0.0818 | 0.3888 |
| **Repetition 4** | 0.0096 | 0.0605 | 0.0978 | 0.3279 |
| **Mean** | **0.0072** | **0.0535** | **0.0843** | **0.3331** |

Appendix B.39: Metric values of the Scene CV for Exercise 4 – Force

| User \| Weight \| Sets | MSE | MAE | RMSE | R-squared |
|---|---|---|---|---|
| **Subject A \| 3 KG \| 1** | 0.0037 | 0.0431 | 0.0605 | 0.3966 |
| **Subject A \| 3 KG \| 2** | 0.0018 | 0.0281 | 0.0423 | 0.7412 |
| **Subject A \| 3 KG \| 3** | 0.0064 | 0.0628 | 0.0799 | 0.1418 |
| **Subject A \| 3 KG \| 4** | 0.0062 | 0.0534 | 0.0786 | 0.2202 |
| **Subject A \| 5 KG \| 1** | 0.0032 | 0.0418 | 0.0568 | 0.6406 |
| **Subject A \| 5 KG \| 2** | 0.0059 | 0.0471 | 0.0767 | 0.3408 |
| **Subject A \| 5 KG \| 3** | 0.0040 | 0.0386 | 0.0633 | 0.5492 |
| **Subject A \| 5 KG \| 4** | 0.0031 | 0.0432 | 0.0558 | 0.5753 |
| **Subject B \| 3 KG \| 1** | 0.0055 | 0.0529 | 0.0743 | 0.7356 |
| **Subject B \| 3 KG \| 2** | 0.0032 | 0.0401 | 0.0566 | 0.8465 |
| **Subject B \| 3 KG \| 3** | 0.0212 | 0.1039 | 0.1455 | 0.2004 |
| **Subject B \| 3 KG \| 4** | 0.0554 | 0.1770 | 0.2353 | 0.3301 |
| **Subject B \| 5 KG \| 1** | 0.0023 | 0.0332 | 0.0477 | 0.3782 |
| **Subject B \| 5 KG \| 2** | 0.0011 | 0.0221 | 0.0326 | 0.6966 |
| **Subject B \| 5 KG \| 3** | 0.0024 | 0.0361 | 0.0485 | 0.4189 |
| **Subject B \| 5 KG \| 4** | 0.0017 | 0.0307 | 0.0417 | 0.5729 |
| **Subject C \| 3 KG \| 1** | 0.0018 | 0.0274 | 0.0422 | 0.5819 |
| **Subject C \| 3 KG \| 2** | 0.0040 | 0.0476 | 0.0630 | 0.2887 |
| **Subject C \| 3 KG \| 3** | 0.0026 | 0.0333 | 0.0512 | 0.5544 |
| **Subject C \| 3 KG \| 4** | 0.0011 | 0.0238 | 0.0337 | 0.7436 |
| **Subject C \| 5 KG \| 1** | 0.0296 | 0.1421 | 0.1721 | 0.1632 |
| **Subject C \| 5 KG \| 2** | 0.0158 | 0.0978 | 0.1256 | 0.1969 |
| **Subject C \| 5 KG \| 3** | 0.0186 | 0.1078 | 0.1364 | 0.1289 |
| **Subject C \| 5 KG \| 4** | 0.0113 | 0.0822 | 0.1064 | 0.4516 |
| **Mean** | **0.0088** | **0.0590** | **0.0803** | **0.4539** |

Appendix B.40: Metric values of the Scene CV for Exercise 1 – Power

| **User \| Weight \| Sets** | **MSE** | **MAE** | **RMSE** | **R-squared** |
|---|---|---|---|---|
| **Subject A \| 3 KG \| 1** | 0.0009 | 0.0182 | 0.0298 | 0.8955 |
| **Subject A \| 3 KG \| 2** | 0.0007 | 0.0232 | 0.0281 | 0.8979 |
| **Subject A \| 3 KG \| 3** | 0.0006 | 0.0199 | 0.0253 | 0.9326 |
| **Subject A \| 3 KG \| 4** | 0.0006 | 0.0174 | 0.0238 | 0.9380 |
| **Subject A \| 5 KG \| 1** | 0.0015 | 0.0278 | 0.0391 | 0.9203 |
| **Subject A \| 5 KG \| 2** | 0.0008 | 0.0209 | 0.0294 | 0.9509 |
| **Subject A \| 5 KG \| 3** | 0.0005 | 0.0181 | 0.0236 | 0.9704 |
| **Subject A \| 5 KG \| 4** | 0.0009 | 0.0209 | 0.0311 | 0.9464 |
| **Subject B \| 3 KG \| 1** | 0.0013 | 0.0278 | 0.0364 | 0.9269 |
| **Subject B \| 3 KG \| 2** | 0.0027 | 0.0382 | 0.0521 | 0.8610 |
| **Subject B \| 3 KG \| 3** | 0.0172 | 0.0950 | 0.1310 | 0.3268 |
| **Subject B \| 3 KG \| 4** | 0.0044 | 0.0483 | 0.0663 | 0.8793 |
| **Subject B \| 5 KG \| 1** | 0.0007 | 0.0164 | 0.0256 | 0.9263 |
| **Subject B \| 5 KG \| 2** | 0.0007 | 0.0186 | 0.0265 | 0.9260 |
| **Subject B \| 5 KG \| 3** | 0.0004 | 0.0144 | 0.0207 | 0.9506 |
| **Subject B \| 5 KG \| 4** | 0.0008 | 0.0208 | 0.0283 | 0.9127 |
| **Subject C \| 3 KG \| 1** | 0.0023 | 0.0390 | 0.0485 | 0.8505 |
| **Subject C \| 3 KG \| 2** | 0.0008 | 0.0199 | 0.0275 | 0.9513 |
| **Subject C \| 3 KG \| 3** | 0.0014 | 0.0265 | 0.0370 | 0.9159 |
| **Subject C \| 3 KG \| 4** | 0.0031 | 0.0467 | 0.0558 | 0.7653 |
| **Subject C \| 5 KG \| 1** | 0.0014 | 0.0280 | 0.0378 | 0.9485 |
| **Subject C \| 5 KG \| 2** | 0.0061 | 0.0581 | 0.0779 | 0.7868 |
| **Subject C \| 5 KG \| 3** | 0.0230 | 0.1152 | 0.1517 | 0.5298 |
| **Subject C \| 5 KG \| 4** | 0.0076 | 0.0637 | 0.0869 | 0.7516 |
| **Mean** | **0.0033** | **0.0351** | **0.0475** | **0.8609** |

Appendix B.41: Metric values of the Scene CV for Exercise 2 – Power

| User \| Weight \| Sets | MSE | MAE | RMSE | R-squared |
|---|---|---|---|---|
| **Subject A \| 3 KG \| 1** | 0.0007 | 0.0180 | 0.0257 | 0.9028 |
| **Subject A \| 3 KG \| 2** | 0.0007 | 0.0200 | 0.0272 | 0.9089 |
| **Subject A \| 3 KG \| 3** | 0.0005 | 0.0164 | 0.0234 | 0.9340 |
| **Subject A \| 3 KG \| 4** | 0.0006 | 0.0166 | 0.0245 | 0.9274 |
| **Subject A \| 5 KG \| 1** | 0.0012 | 0.0240 | 0.0340 | 0.7773 |
| **Subject A \| 5 KG \| 2** | 0.0009 | 0.0215 | 0.0303 | 0.8751 |
| **Subject A \| 5 KG \| 3** | 0.0021 | 0.0335 | 0.0458 | 0.7466 |
| **Subject A \| 5 KG \| 4** | 0.0008 | 0.0205 | 0.0290 | 0.8995 |
| **Subject B \| 3 KG \| 1** | 0.0041 | 0.0491 | 0.0637 | 0.8164 |
| **Subject B \| 3 KG \| 2** | 0.0190 | 0.1060 | 0.1379 | 0.2674 |
| **Subject B \| 3 KG \| 3** | 0.0056 | 0.0511 | 0.0747 | 0.7017 |
| **Subject B \| 3 KG \| 4** | 0.0052 | 0.0485 | 0.0722 | 0.6771 |
| **Subject B \| 5 KG \| 1** | 0.0033 | 0.0407 | 0.0571 | 0.5142 |
| **Subject B \| 5 KG \| 2** | 0.0005 | 0.0148 | 0.0213 | 0.9325 |
| **Subject B \| 5 KG \| 3** | 0.0004 | 0.0141 | 0.0194 | 0.9463 |
| **Subject B \| 5 KG \| 4** | 0.0007 | 0.0185 | 0.0273 | 0.8988 |
| **Subject C \| 3 KG \| 1** | 0.0003 | 0.0135 | 0.0172 | 0.9448 |
| **Subject C \| 3 KG \| 2** | 0.0005 | 0.0155 | 0.0216 | 0.9087 |
| **Subject C \| 3 KG \| 3** | 0.0025 | 0.0374 | 0.0499 | 0.6449 |
| **Subject C \| 3 KG \| 4** | 0.0005 | 0.0156 | 0.0223 | 0.9272 |
| **Subject C \| 5 KG \| 1** | 0.0026 | 0.0384 | 0.0510 | 0.8568 |
| **Subject C \| 5 KG \| 2** | 0.0041 | 0.0521 | 0.0223 | 0.8289 |
| **Subject C \| 5 KG \| 3** | 0.0014 | 0.0283 | 0.0376 | 0.9421 |
| **Subject C \| 5 KG \| 4** | 0.0026 | 0.0327 | 0.0513 | 0.9049 |
| **Mean** | **0.0025** | **0.0311** | **0.0411** | **0.8202** |

Appendix B.42: Metric values of the Scene CV for Exercise 3 – Power

| User \| Weight \| Sets | MSE | MAE | RMSE | R-squared |
|---|---|---|---|---|
| **Subject A \| 3 KG \| 1** | 0.0005 | 0.0167 | 0.0228 | 0.9668 |
| **Subject A \| 3 KG \| 2** | 0.0006 | 0.0188 | 0.0241 | 0.9619 |
| **Subject A \| 3 KG \| 3** | 0.0011 | 0.0251 | 0.0330 | 0.9415 |
| **Subject A \| 3 KG \| 4** | 0.0012 | 0.0250 | 0.0349 | 0.9361 |
| **Subject A \| 5 KG \| 1** | 0.0006 | 0.0193 | 0.0251 | 0.9662 |
| **Subject A \| 5 KG \| 2** | 0.0036 | 0.0381 | 0.0596 | 0.8029 |
| **Subject A \| 5 KG \| 3** | 0.0014 | 0.0277 | 0.0373 | 0.9279 |
| **Subject A \| 5 KG \| 4** | 0.0012 | 0.0269 | 0.0346 | 0.9434 |
| **Subject B \| 3 KG \| 1** | 0.0023 | 0.0324 | 0.0477 | 0.9411 |
| **Subject B \| 3 KG \| 2** | 0.0006 | 0.0175 | 0.0240 | 0.9691 |
| **Subject B \| 3 KG \| 3** | 0.0040 | 0.0449 | 0.0630 | 0.8972 |
| **Subject B \| 3 KG \| 4** | 0.0006 | 0.0167 | 0.0240 | 0.9622 |
| **Subject B \| 5 KG \| 1** | 0.0009 | 0.0210 | 0.0305 | 0.9331 |
| **Subject B \| 5 KG \| 2** | 0.0004 | 0.0146 | 0.0202 | 0.9719 |
| **Subject B \| 5 KG \| 3** | 0.0005 | 0.0194 | 0.0231 | 0.9684 |
| **Subject B \| 5 KG \| 4** | 0.0005 | 0.0171 | 0.0233 | 0.9624 |
| **Subject C \| 3 KG \| 1** | 0.0008 | 0.0212 | 0.0274 | 0.9467 |
| **Subject C \| 3 KG \| 2** | 0.0004 | 0.0153 | 0.0201 | 0.9719 |
| **Subject C \| 3 KG \| 3** | 0.0007 | 0.0200 | 0.0271 | 0.9559 |
| **Subject C \| 3 KG \| 4** | 0.0013 | 0.0267 | 0.0365 | 0.9219 |
| **Subject C \| 5 KG \| 1** | 0.0019 | 0.0333 | 0.0436 | 0.9546 |
| **Subject C \| 5 KG \| 2** | 0.0017 | 0.0294 | 0.0409 | 0.9646 |
| **Subject C \| 5 KG \| 3** | 0.0016 | 0.0294 | 0.0395 | 0.9670 |
| **Subject C \| 5 KG \| 4** | 0.0005 | 0.0184 | 0.0232 | 0.9683 |
| **Mean** | **0.0012** | **0.0240** | **0.0327** | **0.9460** |

Appendix B.43: Metric values of the Scene CV for Exercise 4 – Power

| User \| Weight \| Sets | MSE | MAE | RMSE | R-squared |
|---|---|---|---|---|
| **Subject A \| 3 KG \| 1** | 0.0009 | 0.0195 | 0.0296 | 0.8359 |
| **Subject A \| 3 KG \| 2** | 0.0009 | 0.0209 | 0.0295 | 0.8477 |
| **Subject A \| 3 KG \| 3** | 0.0016 | 0.0294 | 0.0402 | 0.7135 |
| **Subject A \| 3 KG \| 4** | 0.0013 | 0.0262 | 0.0362 | 0.7856 |
| **Subject A \| 5 KG \| 1** | 0.0010 | 0.0207 | 0.0316 | 0.8601 |
| **Subject A \| 5 KG \| 2** | 0.0016 | 0.0235 | 0.0399 | 0.7760 |
| **Subject A \| 5 KG \| 3** | 0.0009 | 0.0195 | 0.0307 | 0.8591 |
| **Subject A \| 5 KG \| 4** | 0.0012 | 0.0243 | 0.0340 | 0.8209 |
| **Subject B \| 3 KG \| 1** | 0.0018 | 0.0284 | 0.0424 | 0.8584 |
| **Subject B \| 3 KG \| 2** | 0.0008 | 0.0193 | 0.0280 | 0.9382 |
| **Subject B \| 3 KG \| 3** | 0.0058 | 0.0535 | 0.0761 | 0.5312 |
| **Subject B \| 3 KG \| 4** | 0.0083 | 0.0636 | 0.0910 | 0.6086 |
| **Subject B \| 5 KG \| 1** | 0.0013 | 0.0243 | 0.0364 | 0.6838 |
| **Subject B \| 5 KG \| 2** | 0.0003 | 0.0117 | 0.0166 | 0.9376 |
| **Subject B \| 5 KG \| 3** | 0.0004 | 0.0145 | 0.0194 | 0.9230 |
| **Subject B \| 5 KG \| 4** | 0.0006 | 0.0180 | 0.0239 | 0.8816 |
| **Subject C \| 3 KG \| 1** | 0.0009 | 0.0216 | 0.0298 | 0.8221 |
| **Subject C \| 3 KG \| 2** | 0.0006 | 0.0161 | 0.0249 | 0.8920 |
| **Subject C \| 3 KG \| 3** | 0.0006 | 0.0166 | 0.0252 | 0.8975 |
| **Subject C \| 3 KG \| 4** | 0.0005 | 0.0160 | 0.0213 | 0.9183 |
| **Subject C \| 5 KG \| 1** | 0.0091 | 0.0688 | 0.0953 | 0.1622 |
| **Subject C \| 5 KG \| 2** | 0.0036 | 0.0413 | 0.0597 | 0.7280 |
| **Subject C \| 5 KG \| 3** | 0.0046 | 0.0471 | 0.0681 | 0.6840 |
| **Subject C \| 5 KG \| 4** | 0.0046 | 0.0517 | 0.0680 | 0.6772 |
| **Mean** | **0.0022** | **0.0290** | **0.0416** | **0.7768** |