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Machine Learning for Upper Limb Flexion Movement Classification[1]

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Abstract

Introduction: This paper introduces the development and validation of a Machine Learning (ML) program aimed at discerning smooth and jittery arm movements during flexion/extension exercises. **Objective:** The study compares the efficacy of three classification algorithms—K-Nearest Neighbors (KNN), Support Vector Machine (SVM), and Logistic Regression—in differentiating flexion/extension movements with and without added weight. **Method:** Using a quasi-experimental design, participants voluntarily performed the exercise under two conditions: with and without a 5-kilogram dumbbell. Meticulous frame-by-frame extraction of movement parameters informed the data collection process. **Results:** Biomechanical analysis identified key features (minAngle, coefTrajectory, maxJerk, avgAcceleration, and frames) relevant for algorithm training. Post-normalization, KNN, Logistic Regression, and SVM demonstrated robust validation performance through metrics and confusion matrices. Detection of a user-dependent data leak prompted a user-specific validation approach. **Conclusion:** This research amalgamates biomechanics and ML, yielding insights into algorithmic performance for detecting weighted exercises. Robust validation is crucial for ensuring the generalizability of classification models in real-world scenarios.

***Keywords*:** Machine Learning, Medical technology, Medical Rehabilitation, Upper limb, Motor Assessment.

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Aprendizaje automático para la clasificación de movimientos de flexión del miembro superior

Resumen

Introducción. Este artículo presenta el desarrollo y validación de un programa de aprendizaje automático (ML, por sus siglas en inglés) diseñado para distinguir movimientos regulares y temblorosos del brazo durante ejercicios de flexión/extensión. **Objetivo**. El estudio compara la eficacia de tres algoritmos de clasificación: K-Nearest Neighbors (KNN), Support Vector Machine (SVM) y Regresión Logística, en la diferenciación de movimientos de flexión/extensión con y sin peso adicional. **Método**. Utilizando un diseño cuasiexperimental, los participantes realizaron voluntariamente el ejercicio en dos condiciones: con y sin una mancuerna de 5 kilogramos. Un meticuloso proceso de extracción de parámetros de movimiento, cuadro por cuadro, informó el proceso de recopilación de datos. **Resultados**. El análisis biomecánico identificó características clave (minAngle, coefTrajectory, maxJerk, avgAcceleration y frames) relevantes para el entrenamiento del algoritmo. Después de la normalización, KNN, Regresión Logística y SVM demostraron una sólida actuación de validación mediante métricas y matrices de confusión. La detección de una fuga de datos dependiente del usuario llevó a un enfoque de validación específico para el usuario. **Conclusión**. Esta investigación amalgama la biomecánica y el ML, proporcionando información sobre el rendimiento algorítmico para detectar ejercicios con peso. La validación sólida es crucial para garantizar la generalización de modelos de clasificación en escenarios del mundo real.

Palabras clave: aprendizaje de máquina, tecnología médica, rehabilitación médica, miembro superior, evaluación motora.

Aprendizado de Máquina para Classificação de Movimentos de Flexão do Membro Superior

Resumo

Introdução: Este artigo apresenta o desenvolvimento e validação de um programa de Aprendizado de Máquina (ML, em inglês) projetado para distinguir movimentos suaves e tremidos do braço durante exercícios de flexão/extensão. **Objetivo:** O estudo compara a eficácia de três algoritmos de classificação–K-Nearest Neighbors (KNN), Support Vector Machine (SVM) e Regressão Logística–na diferenciação de movimentos de flexão/extensão com e sem peso adicional. **Método:** Utilizando um design quase experimental, os participantes realizaram voluntariamente o exercício em duas condições: com e sem um haltere de 5 quilogramas. Um meticuloso processo de extração de parâmetros de movimento, quadro a quadro, informou o processo de coleta de dados. **Resultados:** A análise biomecânica identificou características-chave (minAngle, coefTrajectory, maxJerk, avgAcceleration e frames) relevantes para o treinamento do algoritmo. Após a normalização, KNN, Regressão Logística e SVM demonstraram uma sólida performance de validação por meio de métricas e matrizes de confusão. A detecção de um vazamento de dados dependente do usuário levou a uma abordagem de validação específica para o usuário. **Conclusão:** Esta pesquisa combina biomecânica e ML, fornecendo insights sobre o desempenho algorítmico na detecção de exercícios com peso. A validação robusta é crucial para garantir a generalização de modelos de classificação em cenários do mundo real.

***Palavras-chave*:** Aprendizado de máquina, tecnologia médica, reabilitação médica, membro superior, avaliação motora.

Introduction

The dynamic landscape of healthcare finds itself intricately woven with the threads of technological innovation, ushering in a transformative era in the analysis of human movement (Dindorf *et al*., 2022; Roggio *et al*., 2021). Recent years have witnessed the convergence of technology and healthcare, giving birth to novel methodologies that hold profound implications for the realms of rehabilitation and motor skill assessment (Kim *et al*., 2023; Sarhan *et al*., 2023). This paper embarks on a journey into this dynamic intersection, offering a meticulous exploration of a Machine Learning (ML) program crafted to distinguish between the fluidity of smooth arm movements and the jitteriness that may accompany them. Beyond its immediate impact on the assessment of upper limb exercises, this research embodies a broader endeavor aimed at reshaping our understanding and evaluation of human motion.

At the heart of this study lie arm flexion exercises, fundamental to daily motor activities. Participants engage in both unweighted and weighted iterations of these exercises, contributing to a nuanced dataset ripe for analysis. The attributes under scrutiny extend beyond conventional metrics like total trajectory, time to complete the task, velocity, acceleration, and jitter. Instead, they delve into intricate parameters that encapsulate the quality inherent in each movement. This comprehensive approach seeks to unravel the multifaceted nature of arm flexion, transcending simplistic classifications to offer a nuanced comprehension of the dynamics at play.

Against the backdrop of this exploration stand three prominent classification algorithms: K-Nearest Neighbors (KNN) (Zhang, 2016), Support Vector Machine (SVM) (Gholami and Fakhari, 2017), and Logistic Regression. Chosen for their diverse methodologies, these algorithms serve as the lens through which the study navigates the classification of flexion/extension movements, both with and without added weight. The goal extends beyond mere categorization; it aims to distill meaningful insights capable of reshaping the landscape of movement analysis within healthcare.

As the narrative unfolds, the paper not only delves into the intricacies of algorithmic classification but meticulously details the design and execution of the experiment. Ten voluntary participants form the core of this study, engaging in a crafted experiment that involves the performance of arm flexions under varying conditions. The manual extraction of 2D coordinates from the shoulder, elbow, and wrist, coupled with sophisticated data processing techniques, paints a vivid picture of the intricacies inherent in human movement. This approach transcends the conventional, capturing both quantitative metrics and qualitative nuances, such as trembling, especially pertinent in individuals with spinal cord injuries.

In essence, this research surpasses the confines of a singular study; it embodies a transformative exploration at the nexus of healthcare and machine learning. Beyond its immediate applications in movement analysis, the findings stimulate contemplation on the broader integration of ML in healthcare. The potential for real-time feedback systems, personalized rehabilitation programs, and advancements in motor skill assessment opens up a realm of possibilities. As we navigate this juncture of innovation, the outcomes of this study not only contribute to the scientific discourse on movement analysis but also pave the way for a future where technology becomes an integral ally in our pursuit of enhanced healthcare methodologies.

Related Work

Movement analysis has been integral in various treatments aimed at restoring mobility in patients grappling with motor difficulties arising from trauma or central nervous system disorders. The term "quality of movement" is defined in this context as an individual's capacity to perform a movement in comparison to a predefined reference model, outlining the normal range for a specific movement or characteristic (Tao *et al.*, 2016). This article explores a research endeavor wherein four distinct postures (Sitting, Standing, walking on flat surfaces, Gait on Stairs) are scrutinized. The objective is to evaluate functional mobility differentials between Parkinson and stroke patients, employing depth sensors for the precise capture of 3D joint positions.

The application of movement quality assessment extends beyond clinical contexts and rehabilitation; it is also a pivotal tool in optimizing athletic performance. Young and Reinkensmeyer (2014) exemplify this by investigating specialized posture movements in diving athletes, using human judges' scores as benchmarks. Athletes benefit from a computer model during training sessions, which provides insights into areas of improvement for enhancing their scores. Furthermore, health professionals leverage movement quality assessments to gauge motor ability, functional capacity, and sensory functions through a diverse array of assessment tools.

In a specific study concentrating on upper limb assessments (Wang *et al.*, 2018), seventeen distinct assessments were scrutinized to discern those specifically measuring the quality of movement. The findings revealed that only six assessments—ARAT, AMULA, AMAT, CAHAI, MESUPES, and MSS—yielded scores relevant to movement quality.

Optimizing patient rehabilitation demands precise progress measurement. Despite relying on subjective observation, a common challenge arises from potential variations in medical opinions among health professionals (Spooren *et al.*, 2009). A preceding study by Duque *et al.* (2020)spinal cord or others nervous system injuries, must face different challenges for a complete recovery of physical functional impairment. An accurate and recurrent assessment of the patient rehabilitation progress is very important. So far, wearable sensors (e.g. accelerometers, gyroscopes addressed this by introducing quantitative elements into evaluations, particularly for those with upper limb difficulties. Leveraging noninvasive electronic devices and statistical or machine learning techniques, the study aimed to objectively assess patient status, mitigating the inherent subjectivity in qualitative assessments. This shift towards quantitative measures provides a standardized and data-driven approach for health professionals, enhancing the precision and consistency of rehabilitation evaluations.

The increasing use of sensors and machine learning in movement analysis opens avenues for innovative rehabilitation approaches, emphasizing caution in data interpretation and predictions (Halilaj *et al.*, 2018). For instance, Linkel *et al.* (2015) employed IMUs to model and compare movement quality between healthy individuals and those with upper limb disabilities due to stroke. Similarly, Van Kordelaar *et al.* (2014) discovered that, within the initial 8 weeks post-stroke, smoothness in movements improves, highlighting the significant impact of early-stage therapies on movement recovery. Contrarily, Huang and Patton (2016) revealed diverse movement patterns among patients, emphasizing the need for detailed insights, including distribution analysis using linear discriminant analysis, beyond mere summarized properties like total trajectory.

While the cited works predominantly focus on stroke-related movement analysis, there exists a broader spectrum of research encompassing various motor disabilities. Notable examples include the use of depth sensors for Multiple Sclerosis patients (Kontschieder *et al.*, 2014), grippers for Spinal Cord Injury patients (Lee *et al.*, 2016), and investigations into movement patterns in Parkinson's disease (Ferraris *et al.*, 2018), Huntington's disease (Bennasar *et al.*, 2018), Cerebral Palsy (Iwasaki and Hirotomi, 2015), and even in healthy children (Alsamour *et al.*, 2018).

Classification Algorithms

This experiment aims to assess three key classification algorithms, evaluating their efficacy in distinguishing between flexion/extension movements performed with and without weight.

K-Nearest Neighbors (KNN).

KNN is a non-parametric, instance-based learning algorithm applicable for classification or regression. It involves a training phase, where instances of arm flexion exercises and their corresponding class labels (indicating whether the exercise is done correctly or not) are stored. In the classification phase, new samples are categorized based on their proximity to these labeled instances. The algorithm identifies the k nearest neighbors, and the class assignment for a new element is determined by the most frequent class in this list. Proximity between instances is measured using the Euclidean distance between multidimensional vectors.

Support Vector Machine (SVM).

SVM, a supervised learning algorithm for classification or regression, operates in a binary classification framework. Like KNN, the algorithm requires a set of labeled training instances, each associated with one of the two classes. It constructs a hyperplane, dividing the multidimensional space into two sub-spaces, one for each data cluster. During classification, SVM determines the side of the hyperplane on which a new instance lies, assigning it to the corresponding class in the binary classification.

Logistic Regression.

Logistic regression, a statistical model, utilizes a logistic function to estimate the probability of a binary dependent variable belonging to one of two classes. The logistic function scales the odds of the outcome linearly with the multiplicatively increased independent variables. Each independent variable has its own parameter (beta). Classification involves defining a cutoff value 'c,' segregating probabilities into the two classes [0, c] and (c, 1].

Experiment: Materials and Methods

Incorporating a quasi-experimental design (Lazar *et al.*, 2010), this research delves into the impact of added weight on upper limb flexion/extension movements. Participants voluntarily engage in two conditions: executing the exercise without added weight and with a 5-kilogram dumbbell. This quasi-experimental approach, lacking random assignment, allows for a pragmatic exploration of real-world scenarios. Through data collection and analysis, the study aims to unveil critical insights into the biomechanics of these movements, providing valuable implications for exercise performance.

To address research goals, ten (10) volunteers willingly participated in an experiment involving flexion/extension movements with and without added weight. Employing a 720p HD video recording at 30 frames per second from the user's side (**figure 1**), the researcher strategically placed squared

(10cm x 10cm) black targets at the shoulder, elbow, and wrist positions. These targets facilitate precise detection of limb positions during the arm flexion exercise, enhancing the quality of data collection.

Figure 1.

Target placement at each position for detection

*Source***.** Author's own work.

For each participant, two videos captured repetitions of the flexion and extension movement. A repetition involves moving the wrist from the hip to the shoulder while keeping the elbow fixed to the torso. In the first video, participants performed five repetitions without added weight, while in the second video, a 5-kilogram dumbbell was introduced, allowing participants to perform N repetitions based on their capability. However, for movement analysis, only the initial five repetitions and the final five repetitions from each video were considered.

The manual processing of each video involves extracting 2D coordinates from the shoulder, elbow, and wrist by manually selecting the center of each target within the frame. To expedite this process, shoulder and elbow movements are not extracted for every frame, as they are nearly indistinguishable when the exercise is performed correctly. Instead, elbow coordinates are extracted every 3 frames, and shoulder coordinates every 6 frames. The coordinates between these frame jumps are calculated by dividing the difference between the previously extracted coordinates and the current ones by the number of omitted frames. The omitted frames' coordinates are then generated by sequentially adding this difference to the previously calculated coordinates. In essence, the movement between omitted frames is assumed to follow a linear path with constant speed, and the missing coordinates are filled in accordingly.

Due to the significant movement of the wrist, its coordinates are extracted for each frame without omitting any frames. This process yields a nx3 matrix of x-y coordinate pairs, where each row contains the shoulder, elbow, and wrist coordinates in that order, and n represents the number of frames from the original video.

Data Processing

The first variable we calculate is the internal angle formed by the shoulder, elbow and wrist at each frame. This is obtained by calculating the dot product of the vectors elbow-wrist and elbow-shoulder. This variable itself is not used for the classification, but for calculating other significant variables. For example, we use the minimal and the maximal angle for each repetition. We also calculate the angular speed, taking a discrete approximation of the derivative of the angle respect to the time, with the delta of the angle and the delta of the time between consecutive frames.

The delta of time is very small, and is constant for each repetition, so this approximation of the angular speed is very precise. We use the angular speed to estimate the average angular speed and the maximal angular speed, which we use for the classification. The minimal angular speed is not considered since it is very similar for every instance, mostly around 0, which happens at the moment of the change of direction when the wrist reaches its maximum height.

Another significant variable is the tremble coefficient. First, we define the Angular range of a repetition as the difference between the maximal angle and the minimal angle. This is a normalized measure for the total trajectory, since it does not depend on the anatomy of the person nor on the position/orientation of the camera. It only depends on how low the person started the repetition and how high the wrist went during it. Second, we define the total angular trajectory as the total angle traveled during the repetition. The difference when comparing this to the angular range, is that for the total angular trajectory, we also consider short movements caused by trembling (very common in people with a spinal cord injury). If the person does not tremble at all, both variables would have the same value.

The more the person trembles, the higher the difference between the total angular trajectory and the angular range will be. Based on this, we define the tremble coefficient as the ratio between the total angular trajectory and the angular range. Finally, there are other variables that we take that are not related to the angles between the shoulder, the elbow and the wrist such as time of completion by detecting the number of frames a user took to perform the complete exercise; other variables are derivatives like velocity, acceleration and jerkiness.

Results and Discussion

After all the data aggregation process where we calculate repetition movements by extracting frame by frame data and summarizing them to get minAngle, maxAngle, MeanAngle, number of frames required to reach a repetition, minSpeed, maxSpeed, avgSpeed, min Acceleration, maxAcceleration, avgAcceleration, minJerk, maxJerk, avgJerk, angRange, totalAng, and a coefficient trajectory explained in previous section as tremble coefficient.

Figure 2.

The p-values of each feature

	Feature	Statistic	P-value
0	coefTrajectory	0.600000	4.147459e-07
1	minAngle	0.600000	4.147459e-07
2	maxJerk	0.583333	1.022538e-06
3	avgAcceleration	0.566667	2.437855e-06
4	frames	0.550000	5.625816e-06
5	maxAcceleration	0.533333	1.257759e-05
6	avgJerk	0.500000	5.734701e-05
7	avgSpeed	0.466667	2.324133e-04
8	meanAngle	0.450000	4.483668e-04
9	maxAngle	0.416667	1.536634e-03
10	totalAng	0.283333	7.527115e-02
11	minSpeed	0.283333	7.527115e-02
12	maxSpeed	0.200000	3.871305e-01
13	angRange	0.183333	4.976110e-01
14	minAcceleration	0.183333	4.976110e-01
15	minJerk	0.150000	7.456284e-01

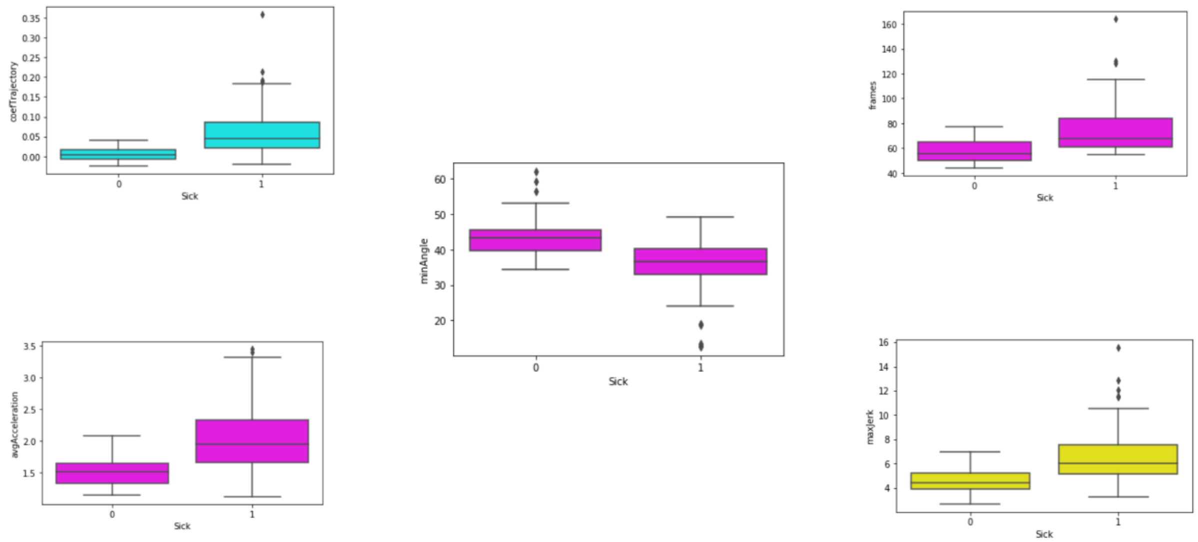
Source. Author's own work.

We performed the non-parametric Kolmogorov-Smirnoff test to check if there is a significant difference between performing the exercise with weight versus without weight. Given that the null hypothesis is that both datasets come from the same distribution, we can check if the p-value is smaller than 0.01, in that case, the null hypothesis is rejected, which means that the two datasets come from different distributions. In **figure 2** it is shown the p-values of each feature ordered from smallest to largest where the only variable that doesn't deny that both datasets come from the same distribution is maxSpeed, because of this, it will be dropped from the data frame. We can also see that the variables with the lowest p-value are minAngle, coefTrajectory, frames, maxJerk and avgAcceleration.

Therefore, the first five features: coefTrajectory, minAngle, maxJerk, avgAcceleration, and frames; are taken as most relevant to train the algorithms. In fact, in **figure 3** a box plot is used to see their distribution behavior where variable sick equals to zero means repetition without weight and sick equals to one a repetition with weight. The box plots suggest that adding weight affects the distribution of the measured movement quality metrics, possibly indicating a change in the patients' ability to perform the movements or the strategy they use to do so.

Figure 3.

Distribution of repetitions with and without weight

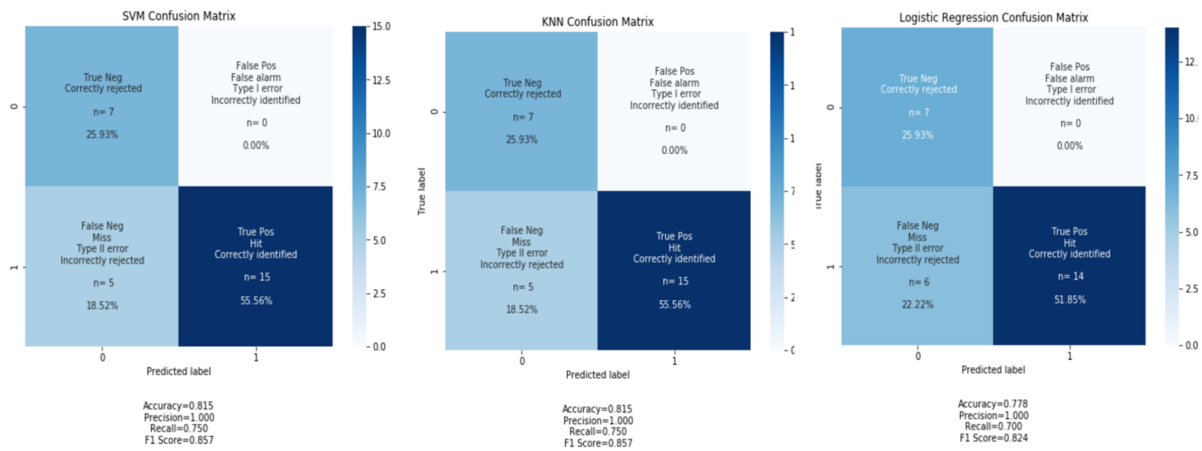


Source. Author's own work.

After this, resulting variables were normalized, trained and validated using KNN, Logistic Regression and Support Vector Machine algorithms. Three algorithms perform well in the validation throwing metrics performance and confusion matrix behaving as **figure 4** shows. All three models exhibit high accuracy and no false positives, indicating a strong ability to correctly identify normal movements. However, SVM and KNN show marginally superior performance over Logistic Regression in recognizing abnormal movements, as evidenced by their higher recall and F1 scores.

Figure 4.

Algorithm Performance and Confusion Matrix Analysis

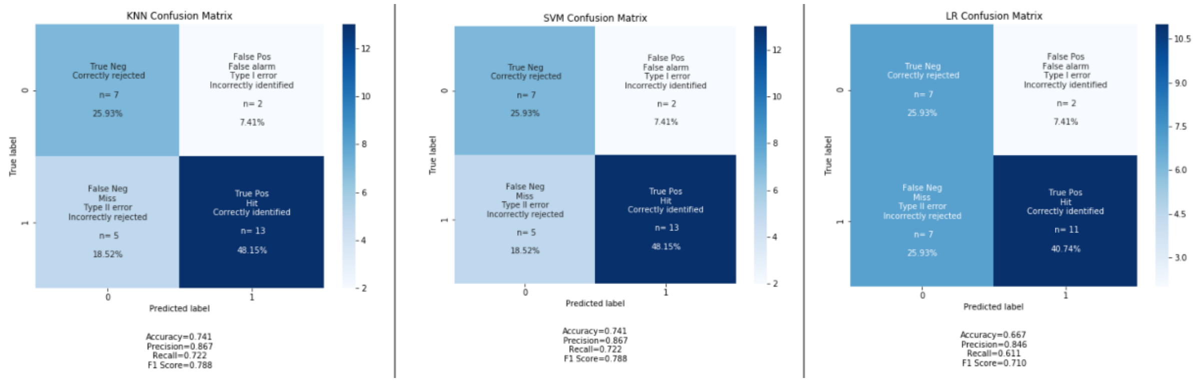


Source. Author's own work.

Again, we can see that the three algorithms perform really well in the validation, which makes some sense because all of its variables were proved to be significant, but even considering this fact, there might be some data leak when the same user's repetitions are on the training and validation datasets, since their variables behave very similarly. To test this idea, we will perform a similar procedure but instead of randomly selecting the training and validation data, we will pick some users' repetitions to be in the validation dataset and the rest to be on the training dataset. **Figure 5** shows results after this procedure.

Figure 5.

Robustness assessment: user-based training and validation split



Source. Author's own work.

It is clear that this was indeed affecting the results from the previous test, meaning that the accuracy obtained only meant that if a repetition of a person who was part of the training data was classified, there was that high of a chance to get it right, however, when trying to classify a repetition from a person who was not part of the training data, there is this smaller chance of it being correct. In both ways of testing the accuracy of the training, we found the accuracy was heavily dependent on the data picked for training, in order to avoid that, a cross validation will be performed.

Conclusion And Future Work

In drawing conclusions from this study, it becomes evident that the application of machine learning algorithms, specifically K-Nearest Neighbors (KNN), Support Vector Machine (SVM), and Logistic Regression, presents a promising avenue for discerning the subtleties in arm movements during flexion and extension exercises. The robust performance of these algorithms in accurately classifying movements with and without added weight underscores their potential utility in evaluating the quality of upper limb exercises. The selection of features such as coefTrajectory, minAngle, maxJerk, avgAcceleration, and frames emerges as pivotal, reflecting their significance in capturing the nuanced variations inherent in arm flexion.

The experiment's design, involving ten voluntary participants engaged in both weighted and unweighted arm flexion movements, lays the foundation for a nuanced understanding of motor activities. The manual extraction of 2D coordinates from the shoulder, elbow, and wrist, coupled with a sophisticated data processing approach, reveals the intricacies of arm movements beyond traditional metrics. The calculated variables, including internal angles, angular speed, and the innovative tremble coefficient, contribute to a comprehensive dataset that reflects not only the quantitative aspects of movement but also the qualitative nuances such as trembling in individuals with spinal cord injuries.

The results, validated through rigorous statistical tests and visualized in figures, provide compelling insights into the significance of the chosen features. The Kolmogorov-Smirnoff test elucidates the impact of added weight on various movement attributes, with maxSpeed being the sole variable that doesn't differentiate between exercises with and without weight. The emphasis on cross-validation acknowledges and addresses potential data leak issues, ensuring the generalizability of the classification models beyond the confines of the training dataset.

As we navigate the intersection of healthcare and technology, the findings of this research not only contribute to the specific domain of movement analysis but also open avenues for broader applications in rehabilitation methodologies. The success of the machine learning models in accurately classifying arm movements encourages further exploration, prompting considerations for real-time feedback systems and personalized rehabilitation programs tailored to individual motor abilities. Ultimately, this study underscores the transformative potential of integrating machine learning into healthcare, offering nuanced insights that extend far beyond the realm of arm flexion analysis.

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