Proceedings of Machine Learning Research 248:169–181, 2024 Conference on Health, Inference, and Learning (CHIL) 2024

A Machine Learning Approach for Predicting Upper Limb Motion Intentions with Multimodal Data in Virtual Reality

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Abstract

Over the last decade, there has been significant progress in the field of interactive virtual rehabilitation. Physical therapy (PT) stands as a highly effective approach for enhancing physical impairments. However, patient motivation and progress tracking in rehabilitation outcomes remain a challenge. This work addresses the gap through a machine learning-based approach to objectively measure outcomes of the upper limb virtual therapy system in a user study with non-clinical participants. In this study, we use virtual reality to perform several tracing tasks while collecting motion and movement data using a KinArm robot and a custom-made wearable sleeve sensor. We introduce a two-step machine learning architecture to predict the motion intention of participants. The first step predicts **reaching task segments** to which the participant-marked points belonged using gaze, while the second step employs a Long Short-Term Memory (LSTM) model to predict **directional movements** based on resistance change values from the wearable sensor and the KinArm. We specifically propose to transpose our raw resistance data to the time-domain which significantly improves the accuracy of the models by 34.6%. To evaluate the effectiveness of our model, we compared different classification techniques with various data configurations. The results show that our proposed computational method is exceptional at predicting participant's actions with accuracy values of 96.72% for diamond reaching task, and 97.44% for circle reaching task, which demonstrates the great promise of using multimodal data, including eye-tracking and resistance change, to objectively measure the performance and intention in virtual rehabilitation settings.

Data and Code Availability This paper uses two types of data: gaze data collected from the HTC Vive Pro Eye tracker and resistance data collected from a wearable sleeve sensor made of carbon nanotubes. Detailed explanations of the data collection process are provided in later sections. The data and code generated during the current study are publicly accessible via the following *GitHub repository link*.

Institutional Review Board (IRB) The research has been sanctioned by the Institutional Review Board (IRB) of the University of Delaware, ensuring compliance with all ethical norms concerning research with human participants. This encompasses the protection of participant confidentiality and the mitigation of any potential harm. Ethical approval was obtained on Feb 3, 2022 under protocol Number 1982585-1, and applies for the duration of the project.

1. Introduction

Over the past years, the use of virtual reality (VR) has increased significantly. VR involves various technologies that create an engaging, simulated digital world. Users can interact within this environment, which responds to their movements, fostering a sense of presence in the virtual environment. Moreover, there have been substantial developments in these interactive virtual settings specifically designed for the motor skills rehabilitation. These improvements are especially beneficial for patients with cognitive issues and those undergoing orthopedic rehabilitation.

In addition, technology advancements in robotics and artificial intelligence progress the rehabilitation process for upper extremity patients (Araújo et al., 2020). Patients impacted by from stroke need to perform reaching and stretching movements to regain mobility in the upper limb. The VR setup for the upper extremity offers benefits like an increase in patient engagement in therapy, easy setup for home, and no distraction and disturbance from the environment (Baron et al., 2021, 2023). Robotics rehabilitation also shows a huge improvement in terms of the recovery process. Despite its potential, the research on combining VR and the endpoint robot is limited (Mubin et al., 2019; Tarnita et al., 2022).

In this work, we utilized a framework for upper extremity rehabilitation that integrates both VR and endpoint robotics. The study involved 16 participants, each engaging in two distinct reaching tasks within the framework: drawing shapes such as a circle and a diamond. The participants were required to hit each of the 40 points arranged in the shapes of a diamond or circle.

This setup was crucial for evaluating their ability to execute planar movements across multiple joints, offering insights into the smoothness and precision of their reaching trajectories (Kwakkel et al., 2019). We have extracted two different types of data using this framework: gaze data and resistance values. The gaze data was collected from the VR headset which provides information about the visual focus throughout the task. The resistance data was captured from nano-composite sensors embedded in the wearable sleeve. These values were recorded during muscle flexion and extension while performing reaching tasks with the sensor effectively converting the physical energy exerted during muscle movement into measurable electrical signals (Saggio et al., 2015). The above-described framework used for data collection exhibits significant advancements in the field of rehabilitation and improvement of motor function.

In this study, we used these two types of data, gaze and resistance values, to predict the motion intentions of participants. To assess the effectiveness of our proposed approach, we applied different machine learning models with various data setups and compared the results with our proposed architecture. This comparative analysis provides insights into the performance and advantages of our proposed methodology over alternative approaches. The study on predicting the motion intentions of participants allows therapists to identify specific motor deviations. Therapists can use this information to tailor rehabilitation exercises, potentially leading to a more efficient and effective rehabilitation process.

The contributions of this paper include:

- Introducing a machine learning framework for prediction of the segmentation of trajectory shapes and directional movement.
- Integrating and leveraging multiple data modalities, such as gaze data and resistance measurements from sleeve sensors.
- Converting resistance measurements obtained from wearable sleeve sensors into time-domain features to attain higher accuracy.
- Incorporating KinArm robot data for analyzing motion intention, thereby enhancing the efficacy of predictive models for potential upper extremity rehabilitation tasks.

This study is organized as follows: Following the introduction, the related works are discussed in Section 2. The methodology of the work is explained in Section 3. The results are presented in Section 4. The discussion, including implications, limitations, and future research directions, is in Section 5. Lastly, the conclusion is presented in Section 6

2. Related Work

In this section, we review some previous work related to virtual reality and robotics for upper extremity rehabilitation and the use of machine learning for upper limb motion prediction.

2.1. VR Therapy and Robots

Recent technological advancements have significantly increased the demand for human-machine interaction, particularly in the realm of robotics. This surge in interest has notably impacted the field of rehabilitation, leading to a deeper understanding of motor control. This work focuses on developing a better machine learning algorithm that can precisely analyze the motion intentions. Robots can analyze the movement of limbs help in controlling the motions of the joint and provide precise motion direction for effective therapy (Durandau et al., 2019). When compared with normal physical therapy, assistive robots result in a more positive outcome in rehabilitation because patients can train for longer periods (Daunoraviciene et al., 2018). Robots can also assist in improving motor control and restoring neurological functions (Dixit and Tedla, 2019). Kim et al. (2023) developed an electromagnetic robot for the rehabilitation of the upper extremity in sub-acute stroke patients. Its real-time position tracking feature allows for active flexion and extension, irrespective of the hand's position. The researchers found that this robotic rehabilitation system aided stroke patients in improving their hand-motor function. This system also helps in tracking the motion in real-time and get feedback from it.

Virtual reality-based rehabilitation in stroke patients demonstrates improvements in patient motivation, functional recovery, motor function, and dual-task performance (Aderinto et al., 2023). Anwar et al. (2021) conducted a study on 68 stroke patients to compare VR training and physical therapy, revealing that VR was more effective in improving balance and lower limb function. Vibhuti et al. (2023) presented a systematic review of VR therapy for various neuromotor impairments such as stroke, cerebral palsy, spinal cord injury, and parkinson's disease reviewing forty-five studies. They reported that home-based VR therapy systems significantly improved the functional mobility of the patients. VR and gaming for upper extremity rehabilitation have also been shown to be effective in improving the motor recovery of the patients (Karamians et al., 2020).

Walker et al. (2023) specified the potential of robots and VR in improving the treatment procedure by using assistive robots. Wonsick and Padir (2020) proposed the increase in growth of technology, the integration of both robots and the VR interface has more potential to improve rehabilitation techniques for people suffering from motor impairments.

Wearable sensors provide continuous tracking and valuable clinical insights on physical activities such as the practice of diminished skills, thus playing an important role in rehabilitation systems (Dobkin and Dorsch, 2011). Caviedes et al. (2020) proposed a wearable sensor array design for monitoring spine posture during physical therapy exercises. The sensor array consists of stretch sensors integrated into a custom-made sports garment, forming a triangular pattern resembling spinal exercise. Their pilot study showcased the potential of the wearable sensor array in monitoring both the adherence and accuracy of therapeutic spinal exercises during unsupervised home-based programs. Luo et al. (2010) developed an interactive VR system for arm and hand rehabilitation that includes a wearable sensor system consisting of an arm suit with an Optical Linear Encoder, two Inertial Measurement Units for tracking arm motion, and a SmartGlove for tracking finger motion. They developed two VR games that increase patient motivation and enable objective evaluation of patient progress.

The VR environment integrated with eye tracking shows improvement to the rehabilitation process (Gavas et al., 2018). This data provides a clear understating of the participant's interaction with the VR environment; the eye tracking system provides proper data that can track the vision. This data is crucial in grasping and locomotion tasks (Desanghere and Marotta, 2015). Hence, gaze data can play a crucial role in rehabilitation and assistance of both upper and lower limb impairments (Cognolato et al., 2018). Gaze data helps to provide support to participants while doing rehabilitation tasks (Novak and Riener, 2013). Park et al. (2019) worked on integrating eye tracking with the VR environment for vestibular rehabilitation. The integration of eye tracking in rehabilitation parallels our approach of combining the VR environment integrated with eye tracking and end-point robotics. Park et al. observed a significant improvement in rehabilitation outcomes with the addition of eye tracking, motivating us to utilize eye tracking data in our work.

2.2. Machine Learning for Upper Limb Motion Prediction

The integration of machine learning techniques with wearable sensor technology can enhance the efficacy of rehabilitation procedures for patients suffering from conditions requiring prolonged recovery periods, such as stroke (Wei and Wu, 2023). García-Vellisca et al. (2021) introduced a method for predicting hand kinematics for prosthesis control using high-density Electromyography (EMG) data. The actual hand kinematics were collected using the 18 sensors of CyberGlove II by CyberGlove Systems LLC. They employed artificial neural networks, which effectively predicted joint trajectories over 13 key hand movements. Trigili et al. (2019) introduced a novel concept of using the signals by analyzing the behaviors of participants doing the reaching task. They then converted the sEMG signals into 14 time-domain features and used these features to train the machine learning algorithm to predict reaching tasks, go-forward, and go-backward movements. There research focused on basic task prediction without considering the motion trajectory or directional components. However, in our study, we focused on developing multimodal analysis to predict the motion intention.

Little et al. worked on the application of neural network in predicting the elbow motion trajectory focuses on dealing with different key elements for the model training process. Their work emphasised more on algorithm, which is rigid in individual variances (Little et al., 2021). Sibo Yand et al, did similar research on the topic of motion intention prediction; they proposed a machine learning model to predict the hand positions. This work suggests that modern machine learning algorithms can effectively predict the motion intention by taking the data in a sequence type (Yang et al., 2023).

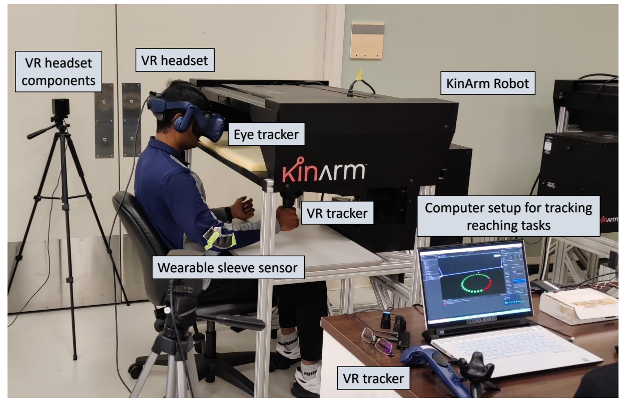


Figure 1: The upper extremity rehabilitation framework setup for data collection. The participant completes the circle task by holding the KinArm robot handle.

3. Materials and Methods

The research project was approved by the Institutional Review Board (IRB). In this upcoming session, we describe briefly the participants, equipment used, data collection procedures, data preprocessing methods, and the study procedure.

3.1. Participants

The dataset consists of data from 16 healthy participants from the university of Delaware, with 16 participants (eight males), aged between 22 and 37 years (M=27.38, SD=4.13). The participants volunteered for the study and were not provided any financial compensation. Nine participants reported familiarity with video games, varying from several times a year to daily engagement, while seven had previous virtual reality experience. All participants self-reported as right-handed.

3.2. Apparatus

In this section, we explain the upper extremity rehabilitation system utilized for our experiments (Chheang et al., 2023). The details of the setup can be found in Figure 1. The virtual environment was developed using Unity game engine (version 2021.3.10f1).

Gaze data was collected at each hit point using the advanced eye-tracking technology of the HTC Vive Pro Eye tracker, providing detailed information on eye and head movements (Baron et al., 2023)

The KinArm robot, featuring six degrees of freedom with a cylindrical handle for horizontal movement, was integrated into the VR setup. The KinArm model was constructed in the virtual environment with the HTC Vive tracker capturing the handle's position and inverse kinematics calculated through simulation. The KinArm robot does not provide assistive support for the participants, and in this study we didn't focus on analysis of the data from the KinArm robot. Instead, it is used for consistent hand movement of participants in 2-Dimensional space, supporting and understand the motor functions in individuals (Thostenson et al., 2019). KinArm also helps to provide a controlled space for motor tasks (Mochizuki et al., 2019).

Elbow movement data was obtained using a wearable sleeve sensor made of a carbon nanotube. The sensor is incorporated into a knit fabric sleeve. Due to the piezo-resistive nature of the sensor, the resistance of the electrode changes due to the strain generated in the sensor during elbow flexion/extension. Participants used this sensor during reaching tasks. Data on resistance values were recorded using an Arduino-based voltage divider circuit, and data transmission occurred through Microsoft Excel. Each participant engaged in two study conditions: reaching tasks in the geometry of a circle and a diamond.

3.3. Data Collection

Participants were equipped with a sleeve sensor and a VR headset, and seated in front of the KinArm robot. Subsequently, participants engaged in two distinct reaching tasks: following the outline of a diamond shape and a circle. Each shape was composed of 40 points along its circumference, and participants were

Table 1: The list of 11 time-domain features and their explanations.

Name of the Feature	Equation	Explanation
Integrated Absolute Value	$IAV = \sum_{n=1}^{N} \lvert x_n \rvert$	the summation of the absolute values of the resistance values between two hit positions
Mean Absolute Value	$MAV = \frac{1}{N} \sum_{n=1}^{N} \lvert x_n \rvert$	the average resistance values
Modified Mean Absolute Value 1	$MMAV1 = \frac{1}{N} \sum_{n=1}^{N} w_n \lvert x_n \rvert$	a modified version of MAV with a weight component (w_n) in the equation $w_n = \begin{cases} 1, & \text{if } 0.25N \leq n \leq 0.75N \\ 0.5, & \text{otherwise} \end{cases}$
Modified Mean Absolute Value 2	$MMAV2 = \frac{1}{N} \sum_{n=1}^{N} \lvert x_n \rvert$	a modified version of MMAV1 with a different weight function $w_n = \begin{cases} 1, & \text{if } 0.25N \leq n \leq 0.75N \\ 4n/N, & \text{if } 0.25N > n \\ 4(n-N)/N, & \text{if } 0.75N < n \end{cases}$
Simple Square Integral	$SSI = \sum_{n=1}^{N} x_n^2$	the energy of the signal
Variance	$VAR = \frac{1}{N-1} \sum_{n=1}^{N} (x_n - \mu)^2$	the variance of the resistance values, where μ is the mean value of the resistance
Root Mean Square	$RMS = \sqrt{\frac{1}{N} \sum_{n=1}^{N} x_n^2}$	the root mean square of the resistance values
Waveform Length	$WL = \sum_{n=1}^{N} \lvert x_{n+1} - x_n \rvert$	the summation of the length of the waveform of the resistance signal
Logarithm	$LOG = \frac{1}{N} \sum_{n=1}^{N} \log_{10}(\lvert x_n \rvert)$	the average of the total summation logarithm of resistance values between consecutive hit positions
Skewness	$SKEW = \frac{\frac{1}{N} \sum_{n=1}^{N} (x_n - \mu)^3}{(\frac{1}{N} \sum_{n=1}^{N} (x_n - \mu)^2)^{3/2}}$	a measure of imbalance in the resistance data
Kurtosis	$KURT = \frac{\frac{1}{N} \sum_{n=1}^{N} (x_n - \mu)^4}{(\frac{1}{N-1} \sum_{n=1}^{N} (x_n - \mu)^2)^2}$	a statistical equation which is used to compare the general profile of data, it reveals the outlier frequency

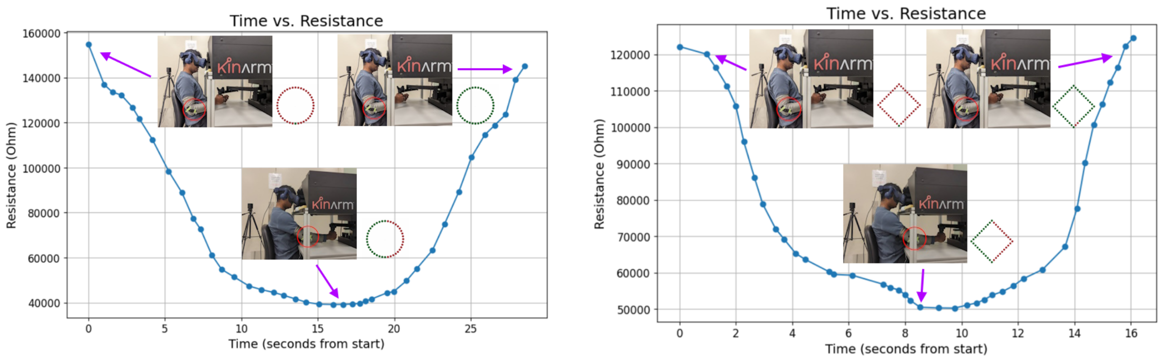
N: the number of sensor values generated between two hitting points.

tasked with hitting the points sequentially. Backtracking was disallowed if a point was missed, and participants were expected to trace the shape in both clockwise and counterclockwise directions. Participants were instructed based on their group, with eight participants performing counterclockwise motions and the others executing clockwise motions.

Throughout the reaching tasks, data on resistance values were collected for each time instance, capturing the flexion/extension of muscles. Additionally, gaze data, encompassing the position and orientation of participants' heads and eyes at the moment of dot contact, was systematically recorded.

Synchronization among all the system components was ensured using packages from the Lab Streaming Layer (LSL) (Kothe et al., 2024) for the collection of synchronized data among the sensors. LSL is an open-source system designed for the collection of time series in research experiments. Besides using LSL, manual checking of the data was necessary to ensure identical start and end times for accurate data synchronization.

Figure 2 provides visual examples of the data collected during the experiments. Figure 2(a) and Figure 2(b) illustrate the variation in resistance values recorded by the sleeve sensor throughout the reaching task for one participant, showing data for both the



(a) (b)

Figure 2: Example plots of the measurements. The variation in resistance values captured by the sleeve sensor over time (a) for the circle task and (b) for the diamond tasks. The lowest values are observed in elbow extension and higher values for the flexion.

circle and diamond tasks, respectively. Additionally, technical setups displaying the angle of flexion and conceptual views of the task progress are included for better illustration.

3.4. Data Preprocessing

We utilized two distinct types of data collected from the framework: gaze data for the first model and resistance data for the second model. In this section, we detail the preprocessing steps applied to the resistance data collected through carbon nanotube sensors. The objective is to transform raw resistance values into 11 time-domain features, each serving a specific purpose in characterizing upper extremity movements (Trigili et al., 2019). For instance, the absolute value reflects overall muscle activation levels, and the root mean square relates to the force of muscle contractions. Combining all these features provides a refined overview of muscle behavior, offering a more comprehensive analysis than a single sensor value. These features are crucial for obtaining a detailed pattern of muscle behaviors and understanding the subtle aspects of human movement. Encompassing a wide range of characteristics, from the mean to the rate of signal variations, these features enhance the accuracy and robustness of analysis using machine learning. The comprehensive list of these features and their explanations are provided in Table 1.

We divided the dataset into two subsets: 80% for training and 20% for testing. This split was applied to ensure that the model was trained on a sufficiently large portion of the data while also having an independent set for evaluating its performance. Furthermore, to ensure consistency and comparability across different features, we applied regular min-max normalization to both the training and testing data. This standardized data was then used as input for subsequent machine learning models.

3.5. Study Procedure

In this study, we propose a two-step machine learning framework designed to predict both the specific segment to which participant-marked points belong and the participant's intention to move either in a clockwise or counterclockwise direction. Figure 3 provides an overview of our two-step machine learning architecture. In this section, we provide the details about our two models that use the data explained in Section 3.4. Our approach integrates traditional machine learning and deep learning approaches for a comprehensive understanding of motion intention.

3.5.1. Neural Network for Segment Prediction

The neural network model is designed to predict segments, which takes gaze data as input. The architec-

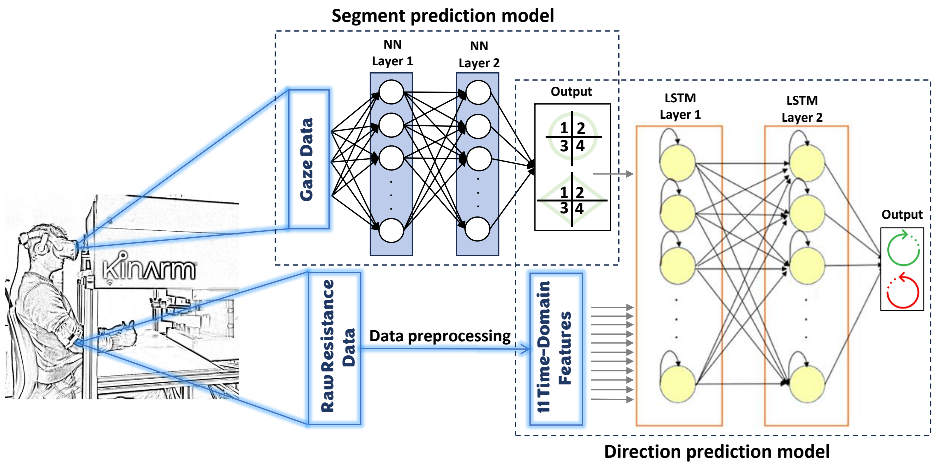


Figure 3: Overview of the two-step machine learning architecture. In the first step, we proposed a network for predicting segments using a neural network and gaze data. In the second step, we trained a model for predicting movement direction using an LSTM model with the output of the first model and 11 time-domain features.

ture of the neural network consists of four layers: one input layer, two hidden layers with 64 and 32 neurons, and one output layer. We used the ReLU activation function, chosen for its efficiency compared to other activation functions (Sharma et al., 2017). The neural network was trained using the Adam optimizer with a learning rate of 0.001, 50 epochs, and a batch size of 32. We trained the input layer of the neural network by gaze data for predicting the four segments of reaching task shapes.

3.5.2. Long Short-Term Memory (LSTM) Model for Direction Prediction

The output of our neural network model, representing the predicted segments, and 11 time-domain features of resistance data are utilized to create a specialized LSTM model. The LSTM model predicts the intended direction of movement of the participant, whether it is clockwise or counterclockwise. We chose the LSTM model for its ability to capture the temporal dependencies and patterns in the data, which are crucial in determining the direction of motion. The architecture of the LSTM model is designed as a sequential model. It consists of 40 data points arranged in sequence. The input layer takes the outputs of the neural network model and 11 time-domain features. The architecture further includes two hidden layers, each containing 50 neurons, and an output layer. We applied L2 regularization with a factor of 0.01 and used the ReLU activation function. We trained the LSTM model using the Adam optimizer with a learning rate of 0.001, 50 epochs, and a batch size of 32.

4. Experiments and Results

In this section, we present the results of our experiments aimed at understanding the effect of different dataset setups on the performance of our two-step machine learning architecture. Our study focused on predicting four segments of reaching tasks in the first model and predicting the direction of movement in the second model. We explored various combinations of raw resistance data—11 time-domain features extracted from the raw resistance value, and gaze data—and investigated different machine learning models to identify the most effective approaches. We used all the data except raw resistance data as consecutive pairs of values sequentially. This sequential process involved deriving features from consecutive pairs of data points. We present the details of all these different setups in Table 2. The size listed in the table represents the number of samples and features in each dataset, with size (samples x features). For the raw resistance data (D1), we included all 40 data points per participant, resulting in a dataset size of 640×1 ($640 = 40$ data points $\times$ 16 participants). For the remaining, due to the sequential feature extraction process, the 40 data points per participant were reduced to 39. This resulted in a total of 624 (39 data points × 16 participants) combined data points (samples) across all participants.

Table 2: Specifications of data setups used in the experiments.

Used data	Name	Size
Raw resistance data	D1	640x1
11 time-domain features	D2	624x11
Gaze data	D3	624x24
Output of the first model	D4	624x4
The combination of D2&D3	D5	624x35
The combination of D2&D4	D6	624x15
The combination of D3&D4	D7	624x28
The combination of D2&D3&D4	D8	624x39

4.1. Segment Prediction Experiments

We examined various data setups (D1, D2, D3, and D5) and machine learning techniques in our first set of experiments focusing on predicting four segments of the reaching tasks. We trained models using four different machine learning methods, namely Neural Network (NN), k-Nearest Neighbors (KNN), Support Vector Machine (SVM), and Logistic Regression (LR). We used four different data setups, to explore their impact on the models' performance.

For two reaching task shapes, diamond and circle, we listed the accuracy results and F1 scores of the trained four different machine learning models obtained with the different data setups in Table 3 and Table 4, respectively. All entities in these tables are presented in the format "Accuracy [F1 Score]", where the F1 Score is a metric that offers a balanced measure of a model's performance. We also compared our results with a random guess baseline. The random guess accuracy for segment prediction tasks, as shown in Table 5, is around 25% for both the Diamond and Circle. In addition to our selected NN model, the other machine learning models we experimented with also achieved better results than the baseline in most data setups. This further indicates the suitability of this problem for machine learning approaches.

After analyzing the accuracy and F1 score results presented in Tables 3 and 4, we chose the NN model trained with gaze data. The NN model trained with gaze data demonstrated higher accuracy and F1 scores for both the diamond and circle reaching tasks, achieving 92.31% [0.987] and 94.87% [0.884], respectively. These results show the critical role of gaze data, as it consistently contributed to the models' best performance. Incorporating gaze data in D3 and D5 provides supplementary cues that enhance the models' predictive abilities, thus resulting in improved performance compared to setups lacking gaze data (D1 and D2). The differences in performance between D3 and D5 highlight the possibility that integrating features from different modalities could introduce complexities or redundancies, potentially affecting the overall performance of the models.

4.2. Direction Prediction Experiments

In this section, we present the results of our experiments focused on predicting the direction of movements, as clockwise or counterclockwise direction. We explored all data combinations shown in Table 2, and applied multiple machine learning techniques to determine the one with the highest accuracy. We trained models with four different machine learning methods: LSTM, KNN, SVM, and LR.

Tables 6 and 7 present both the accuracy and F1 score results of the machine learning models for predicting the direction of movements in the diamond and circle reaching tasks, respectively. These tables provide the accuracy and F1 scores achieved by each model for different data setups. The highest accuracy and F1 score values, highlighted in bold, identify the most successful models for predicting tasks.

Analysis of the results shows that the LSTM model trained with the combination of D2&D4 data is the optimal choice. This model demonstrated superior accuracy and F1 score, reaching 96.72% [0.946] in the diamond reaching task and 97.44% [0.923] in the Circle reaching task. The incorporation of both 11 time-domain-specific resistance features and the output of the previous segment prediction model (D2&D4) significantly improved the accuracy and F1 scores of direction predictions for both task shapes.

Similar to the segment prediction problem, in this context, machine learning results were compared with a random guess baseline. The random guess accuracy for direction prediction tasks, presented in Table 5, is approximately 50% for both diamond and circle tasks. Similar to the segment prediction experiments, the machine learning models for direction prediction

Table 3: The accuracy and F1 score results of the machine learning models for predicting segments in *Diamond reaching task*

	D1	**D2**	**D3**	**D5**
NN	39.67 [0.325]	49.37 [0.402]	**92.31 [0.987]**	91.03 [0.857]
KNN	32.50 [0.308]	41.00 [0.365]	88.60 [0.897]	85.90 [0.859]
SVM	38.40 [0.350]	42.70 [0.346]	87.20 [0.870]	83.34 [0.830]
LR	31.25 [0.254]	41.00 [0.344]	87.12 [0.911]	84.20 [0.935]

All entities are in the format: Accuracy (%) [F1 Score]. A higher Accuracy/F1 score indicates a better performance.
*D*1: Raw resistance data, *D*2: 11 time-domain features, *D*3: Gaze data, *D*5: D2&D3

Table 4: The accuracy and F1 score results of the machine learning models for predicting segments in *Circle reaching task*

	D1	**D2**	**D3**	**D5**
NN	38.05 [0.258]	47.25 [0.451]	**94.87 [0.884]**	85.06 [0.854]
KNN	36.25 [0.349]	37.80 [0.577]	87.10 [0.946]	76.92 [0.894]
SVM	25.76 [0.317]	33.57 [0.570]	87.55 [0.797]	84.28 [0.922]
LR	36.25 [0.230]	23.08 [0.422]	86.76 [0.823]	84.61 [0.962]

All entities are in the format: Accuracy (%) [F1 Score]. A higher Accuracy/F1 score indicates a better performance.
*D*1: Raw resistance data, *D*2: 11 time-domain features, *D*3: Gaze data, *D*5: D2&D3

Table 5: Random Guess Prediction Results - Baseline for Task Segmentation and Direction Prediction

Prediction problem	**Accuracy (%)**
Segment prediction for diamond	26.44
Segment prediction for circle	25.77
Direction prediction for diamond	50.71
Direction prediction for circle	51.90

outperformed the random guess baseline in most data setups.

5. Discussion

In this study, we propose a novel two-step machine learning architecture for predicting the motion intention of participants engaged in upper extremity rehabilitation tasks. The framework we used for extracting data integrated VR with the KinArm robot, and we utilized gaze data and resistance values to enhance the precision of motion intention predictions. The KinArm robot is primarily utilized for support in the rehabilitation, playing a role in improving the process without directly contributing to prediction analysis.

Our first model, based on a neural network, successfully predicted the four reaching task segments. Our experiments demonstrate the importance of incorporating gaze data for accurate predictions. Eye movement information significantly improved the model's performance, highlighting the relevance of multi-modal data integration in rehabilitation studies.

Our second model, an LSTM model, accurately determined the participant's intention to move in a clockwise or counterclockwise direction. The integration of 11 time-domain features extracted from resistance data, combined with the output of the first model, achieved high accuracy in predicting bidirectional rotational behavior. The 11 time-domain features carry a wide range of statistical and temporal properties that capture the dynamic nature of resistance over time.

While some may question whether more complex models could offer better alternatives for this predic-

Table 6: The accuracy and F1 score results of the machine learning models for predicting the direction in *Diamond reaching task*

	LSTM	KNN	SVM	LR
D1	52.50 [0.665]	62.50 [0.576]	50.00 [0.666]	50.00 [0.667]
D2	87.18 [0.796]	94.44 [0.939]	71.79 [0.731]	74.36 [0.750]
D3	76.92 [0.698]	47.44 [0.782]	58.97 [0.620]	62.82 [0.701]
D4	56.25 [0.674]	57.50 [0.512]	50.00 [0.666]	50.00 [0.667]
D5	73.08 [0.887]	78.21 [0.798]	79.49 [0.789]	71.79 [0.755]
D6	**96.72 [0.946]**	76.92 [0.833]	75.64 [0.769]	74.36 [0.725]
D7	94.44 [0.939]	43.59 [0.435]	60.26 [0.629]	67.95 [0.721]
D8	96.15 [0.896]	70.51 [0.794]	65.38 [0.761]	71.79 [0.769]

All entities are in the format: Accuracy (%) [F1 Score]. A higher Accuracy/F1 score indicates a better performance.
$D1$: Raw resistance data, $D2$: 11 time-domain features, $D3$: Gaze data, $D4$: Output of the first model,
$D5$: D2&D3, $D6$: D2&D4, $D7$: D3&D4, $D8$: D2&D3&D4

Table 7: The accuracy and F1 score results of the machine learning models for predicting the direction in *Circle reaching task*

	LSTM	KNN	SVM	LR
D1	64.7 [0.529]	44.75 [0.473]	52.80 [0.570]	53.75 [0.539]
D2	89.74 [0.720]	51.28 [0.538]	76.19 [0.712]	56.41 [0.727]
D3	61.54 [0.602]	51.28 [0.525]	61.53 [0.646]	46.15 [0.502]
D4	57.67 [0.678]	48.75 [0.518]	51.34 [0.472]	51.21 [0.460]
D5	89.74 [0.917]	67.94 [0.679]	42.37 [0.377]	35.90 [0.307]
D6	**97.44 [0.923]**	53.84 [0.577]	74.35 [0.739]	58.97 [0.725]
D7	91.03 [0.894]	61.53 [0.602]	71.79 [0.741]	56.41 [0.733]
D8	96.15 [0.894]	66.67 [0.699]	51.28 [0.458]	46.15 [0.337]

All entities are in the format: Accuracy (%) [F1 Score]. A higher Accuracy/F1 score indicates a better performance.
$D1$: Raw resistance data, $D2$: 11 time-domain features, $D3$: Gaze data, $D4$: Output of the first model,
$D5$: D2&D3, $D6$: D2&D4, $D7$: D3&D4, $D8$: D2&D3&D4

tion problem, our approach highlights that, despite its simplicity, basic machine learning techniques can reveal valuable insights. By leveraging features, our models effectively capture essential information for prediction motion intentions in upper extremity rehabilitation tasks.

Limitations and Future Directions While our study provides useful insights into upper extremity movements using the proposed machine learning architecture, we must acknowledge some limitations. Firstly, the performance of our models depends on the quality and quantity of the data used, which may be impacted by sensor noise or data collection errors. Secondly, our study was focused on healthy, non-clinical participants. So, our future work will include validation with clinical populations to assess the applicability and generalizability of our approach in rehabilitation settings.

6. Conclusion

This study presents a comprehensive approach for personalized and effective rehabilitation practices, contributing to improvements in integrating robotics, VR, and biomechanical data analysis. Our study and findings demonstrate the potential of incorporating machine learning techniques to improve the effectiveness of virtual rehabilitation assessment. For instance, our NN model achieved an impressive accuracy of 92.31% in predicting segment tasks for the

Diamond reaching task and 94.87% for the Circle reaching task when trained with gaze data. Furthermore, our LSTM model, when trained with a combination of 11 time-domain features and the output of the segment prediction model, achieved accuracy rates of 96.72% and 97.44% for the Diamond and Circle reaching tasks, respectively. There are exciting possibilities for our research to explore. This research introduces an attractive application for real-time predictions, enabling robotic arms to obtain feedback from our proposed two-step model to guide participants accurately based on their motion intentions without diverting from the actual task.

7. Acknowledgments

We wish to acknowledge the support from our sponsors, the National Science Foundation (2222663), and the National Institute of General Medical Sciences of the National Institutes of Health (P20 GM103446 and P20 GM103446E). We also express our gratitude to Drs. Vuthea Chheang, Joshua Cashback, and Erik Thostenson for their invaluable efforts in ideation, data collection, and resource sharing. We also extend our sincere appreciation to the entire research team and the study participants for their contributions. Any opinions, findings, conclusions, or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the sponsors.

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