Motion tracking and ML for rehabilitation

Shreevarsinii Balasekar
Graduate student of School of Artificial Intelligence
Amrita Vishwa Vidyapeetham, Coimbatore-641112,India.
shreevarsinii@gmail.com

Sanjay R.
Graduate student of School of Artificial Intelligence
Amrita Vishwa Vidyapeetham, Coimbatore-641112,India.
sanjayrajendran@gmail.com

Srijan Sivaram
Graduate student of School of Artificial Intelligence
Amrita Vishwa Vidyapeetham, Coimbatore-641112,India.
srijansivaram@gmail.com

Snendar M
Graduate student of School of Artificial Intelligence
Amrita Vishwa Vidyapeetham, Coimbatore-641112,India.
dawgsonstreet@gmail.com

Dr.Amrutha V*
Assistant Professor of School of Artificial Intelligence
Amrita Vishwa Vidyapeetham, Coimbatore-641112,India.
v_amrutha1@cb.amrita.edu

Dr. Snigdhatanu Acharya*
Assistant Professor of School of Artificial Intelligence
Amrita Vishwa Vidyapeetham, Coimbatore-641112,India.
s_acharya@cb.amrita.edu

***Abstract*—We present an innovative rehabilitation system that gamifies wrist physiotherapy. With the use of the MPU6050 motion sensor and LSTM (Long Short-Term Memory) deep learning, we accurately interpret wrist movements (rest, left, right) and translate these wrist movements into live game controls. Now patients are encouraged to do their daily rehabilitation exercises without the built-up dread of monotony. Healing enhanced by play!**

***Index Terms*—mpu 6050,3 axis accelerometer,3 axis gyroscope,game**

I. Introduction

Rehabilitation is an important component of recovery from injury, surgery, or other conditions involving the wrist. Patients with wrist fractures, ligament tears, nerve injuries, or post-surgical stiffness may enter a rehabilitation programme requiring ongoing physiotherapy. These rehabilitation exercises are usually repetitive and can easily become dull, frustrating, and boring for patients. Due to these sources of frustration, patients demonstrate decreased adherence to rehabilitation programmes, resulting in slower recovery progress, reduced recovery quality, or both. Consequently, this problem is the motivation for a new and exciting program that helps to develop motivation, attendance, and therapeutic adherence.

Recent advances in wearable devices and artificial intelligence offer opportunities to change the paradigm of rehabilitation. One such paradigm uses motion sensors and machine learning algorithms to track, record and evaluate movement of users. Our project fills this opportunity gap via the development of a wrist rehabilitation system using an MPU6050 sensor integrated with a Long Short-Term memory (LSTM) machine learning model to enable a game-action based rehabilitation therapy. The MPU6050 is a widely used inertial measurement unit (IMU) composed of a 3-axis accelerometer and a 3-axis gyroscope best used for wrist orientation and movement recording.

The main concept for this project is to gather motion data from users that are performing the wrist movements up, down, left, and right and to train a time-series deep learning model to classify the gestures. The LSTM learning architecture is well-suited because of its strengths in learning sequential data. The LSTM model is trained using labeled datasets of each of the specified movements. After training and validating the model, it is used in an interactive game in which the game action is controlled by wrist movements. Practicing potentially repetitive therapy in an immersive gaming environment, can motivate the user to participate in the rehabilitation process in a more engaged and willing manner. By collecting, preprocessing, and optimizing the necessary data, we trained the LSTM model to classify wrist movements with high accuracy. After training and validating multiple times, this method allowed us to obtain classification accuracy of 94%—an important metric of system robustness and future utilization in real-life rehabilitation situations in the setting of a wrist rehabilitation system. This accuracy means that each gesture formed by a given user will be accurately classified and will reliably interface with the game screen.Then, the classified wrist movements could be used as an input control for the interactive game and represent the potential to transition otherwise mundane exercise into a more enjoyable experience. For example, tilting your wrist to the left would move the user-character to the left, while lifting the wrist would cause the character to jump. This approach gamifies the experience of exercise, allowing them to play rather than just practice.

Consequently, the design would encourage practice, promote user engagement, and ultimately facilitate consistent therapy. This system also has potential for remote dissemination, where doctors and physiotherapists could track user performance scores and logs.In summary, we implemented integration of LSTM-powered classification into a real-time gaming dynamic that modernizes these exercises and also personalizes the experience. By creating an interactive gaming interface for exercises for wrist rehabilitation, this becomes easily accessible and engaging for various users. We believe this method is an important step towards creating smart healthcare solutions that better develop AI that align with human needs—so that therapy becomes something that is anticipated—not avoided.

The following sections in the paper explains about the related works ,information about the dataset,proposed work of the project,results,conclusion and future works

II. Related Works

Seung-Ji Hong et al. investigated the effects of combining grip-strengthening exercises with wrist stability training in patients with non-specific chronic wrist pain. Thirty-one participants were split into an experimental group and a control group. The experimental group underwent combined grip and stability exercises, while the control group received only massage and conservative therapy. After four weeks, the study found significant improvements in pain reduction, grip strength, muscle strength, and wrist function in the experimental group. This confirms the clinical relevance of incorporating targeted wrist exercises to treat chronic wrist discomfort effectively [1].

Fabíola Costa et al. evaluated a fully remote Digital Care Program (DCP) for patients with wrist and hand pain, aiming to reduce healthcare barriers and improve therapy accessibility. The study involved a single-arm, prospective longitudinal design with participants undergoing telerehabilitation using digital devices, exercise guidance, and virtual consultations. High engagement levels and significant clinical improvements in pain, function, and mental health were reported. The study confirms that digital rehabilitation is a feasible, scalable, and effective alternative for managing musculoskeletal wrist conditions, especially in remote or underserved populations [2].

This paper reviews recent insights on wrist proprioception and provides a four-stage rehabilitation protocol for clinicians managing patients post wrist trauma or surgery. The authors emphasize structured progression through sensory reeducation, stability training, resistance work, and return to function. Proprioceptive impairments in wrist injuries can delay recovery; thus, the paper highlights proprioceptive training's crucial role in restoring neuromuscular control and wrist functionality [3].

The study evaluates FEPSim, a new hand and wrist rehabilitation device, for patients recovering from upper extremity injuries. It integrates resistance-based training and range-of-motion features into a single tool. When added to standard care, FEPSim improved hand dexterity, grip strength, and forearm control. The device is promising for scalable, affordable upper-limb rehabilitation across various clinical settings [4].

A systematic review and meta-analysis examined the impact of rehabilitation on pain and function following wrist fracture. The review found that early active rehabilitation significantly improves short-term pain and range of motion. Patient-specific factors (age, injury type) can moderate outcomes. The paper suggests personalized rehab plans to maximize recovery after wrist fractures [5].

This comprehensive review explores various robotic devices for wrist rehabilitation and identifies gaps in affordability, adaptability, and gamification. It recommends integrating simplified designs with serious games to improve engagement and outcomes. The paper concludes that future wrist rehab robots should prioritize user feedback, low cost, and customizable therapy plans [6].

Focused on sports-related wrist and hand injuries, this review outlines therapeutic approaches like immobilization, progressive loading, manual therapy, and sport-specific retraining. The authors emphasize individualized rehab programs and gradual return-to-play protocols. The study also highlights the importance of proprioceptive and neuromuscular training in preventing reinjury [7].

This paper presents a two-degree-of-freedom wrist exoskeleton designed for range of motion therapy in carpal tunnel syndrome patients. The cable-driven mechanism allows smooth wrist flexion-extension and radial-ulnar deviation. Clinical tests showed significant improvement in wrist flexibility and reduced discomfort, indicating the effectiveness of robot-assisted therapy for nerve-related wrist conditions [8].

A randomized controlled trial investigated the use of robotic wrist therapy versus traditional therapy. Participants using a robotic system showed equal or greater improvements in range of motion and hand function. The robot provided adaptive resistance and consistent guidance, making it a valuable tool for structured rehabilitation in orthopedic settings [9].

This paper developed an IoT-enabled robotic system for remote wrist and forearm rehabilitation. The system offers real-time motion tracking, adjustable resistance, and therapist monitoring. Results from pilot testing revealed high compliance, ease of use, and clinical benefit, especially for tele-rehab in post-stroke and orthopedic recovery patients [10].

Inspired by Kresling origami patterns, this study proposed a wearable wrist orthosis capable of six motion modes. The design integrates tendons and actuation for dynamic movement support. It allows customization for individual joint needs and holds promise for lightweight, adjustable wrist supports in active rehab programs [11].

Researchers developed a mobile app that uses phone sensors to classify wrist movements in real time. Designed for children with motor impairments, the app adapts based on detected motion quality. Classification accuracy was high, and the system proved useful for remote, personalized rehab programs in pediatric care [12]. This paper proposed a machine learning system that uses wrist-worn sensors to evaluate patient movement during stroke rehab. It predicts assessment scores and tracks recovery trends over time. The compact feature extraction method allows clinicians to assess motion objectively without in-person evaluations A novel emulator was created to assess the biomechanics of wrist-driven orthotics using the tenodesis effect. The study examined how users adapted their movements to maximize control. The system

Raw ax Value Range	Mapped data (0–255)	Action / Movement	Label
ax < -11500	data < 90	Left Hit	2
-11500≤ ax ≤ 11500	90 ≤ data ≤ 160	Idle / No Action	0
ax > 11500	data > 160	Right Hit	1

Fig. 1. Dataset of the mpu6050 with the target values ranges to calculate

could guide the development of hybrid control strategies that blend human and robotic interaction for users with partial wrist control [13].. This systematic review evaluated three types of FES therapies for upper limb rehab, including wrist movement restoration. FES improved active range of motion and muscle reactivation in stroke patients. The paper concludes that FES can enhance neuroplasticity and functional gains, especially when integrated with voluntary movement tasks [14].

III. Dataset

The dataset that we use for the model was collected directly from the sensor the accelerometer and gyroscope values are collected in each direction using the Arduino uno , mpu6050 like rest ,left ,right and marked unlabled dataset with the target values as 0,1,2 in the csv format, these are done with the help of the Arduino uno code and the python code

The completed dataset was separated into training, validation, and test datasets (usually 70/15/15%). This dataset was used as input for the LSTM model to learn the temporal patterns related to each motion. Using real wearable sensor data instead of synthetic samples facilitates the model's generalizability to real-world users and rehabilitation contexts.

Fig 1. explains the combined rest,left and right dataset with the target column

IV. Proposed work

With the proposed system, a combination of motion sensing, deep learning, and gamification will be used to create a fun, interactive wrist rehabilitation tool. The main idea will be to use the MPU6050 sensor to detect wrist movements, and then classify those movements into four categories (up, down, left, and right) using a machine learning model. Then these movements would control the game, allowing users to do their rehab exercises through game play. The main goals is to reduce boredom and create engagement in the rehabilitation process, particularly for individuals requiring long term physiotherapy. The system will be low-cost, portable, and quick to launch in clinical and home environments.

The data acquisition phase is the initial step, wherein the MPU6050 sensor will continuously monitor accelerometer and gyroscope measurements from the user's wrist. The sensor module is connected to a microcontroller, such as Arduino or ESP32, and it captures six-axis motion data in real-time.

19	127	0
270	130	0
1856	148	0
2458	154	0
-242	124	0
3735	168	1
592	134	0
1388	142	0
523	133	0
-3966	83	2
-1834	107	0
1490	144	0
3068	161	1
-361	123	0
-28	127	0
3618	167	1
-620	120	0
1476	143	0
3543	166	1
2971	160	0
-824	118	0

Fig. 2. Dataset of the mpu6050 with the target values

During the data collection, the user will repeat pre-defined wrist motions several times and send the data to a computer or mobile device through either serial or wireless communication. Each sensor reading will be time-stamped, which ensures that the durations of each motion are of complete duration as time-series samples. The time-series data samples, along with their labels, will comprise the training dataset for the model.

Following this, during the preprocessing and training of the models, the data that has been gathered is filtered to remove noise, normalized for consistency, and each stream of data is truncated into fixed-size time windows compatible with LSTM input. Subsequently, the LSTM model is trained on this data through supervised learning. The architecture of the model is a series of stacked LSTM layers with dense layers that have softmax output for classifying gestures. The models were optimized using Adam optimizer and categorical cross-entropy loss. Upon completion of the training, the trained model is saved and made ready for real-time inference to guarantee that it will evaluate and respond to user input correctly.

Finally, in the deployment phase, the learned LSTM model is implemented into a game setup created using Python (Pygame or Unity to ensure cross-platform compatibility). The model is constantly fed with real-time sensor input and infers the user's current wrist gesture. These inferences are translated to respective game actions, like moving a character or picking up objects. This real-time feedback loop guarantees that the rehabilitation exercises have a direct influence on the gameplay, providing a smooth and enjoyable experience. The game can further record performance statistics, like accuracy, movement frequency, and time to complete, which can be used by therapists to measure progress. The entire pipeline from sensing to game interaction reflects the intended system's aim: making therapy fun, personalized digital rehab.

A. Pre-processing

Subsequently, we applied normalization to the sensor data onto a common scale (typically 0 to 1) since we wanted to eliminate any influence due to differences in signal level across users. We performed this normalization step, followed by different lengths of the input data converted to fixed-length sequences, again establishing homogeneous input samples, which would be fed into the LSTM network. Gesture sequences longer than the length we selected, were truncated; gesture sequences shorter than our set length, were zero-padded. We subsequently labeled each of those sequences by movement type: 1 for up, 2 for down, 3 for left, and 4 for right. Finally, the dataset was split into training data, validation data, and testing data to allow for model evaluation and alleviate overfitting. These preprocessing steps provided a clean, normalized dataset corresponding to time-series based deep learning.

Then, we normalized the sensor readings to a standard scale (usually 0 to 1) to avoid bias due to different signal strengths associated with the user experience. Following that, we divided the data into fixed-length sequences to create uniform input samples for LSTM network training. If a gesture sequence was too long, we truncated it, and if it was too short, we padded it with zeros. Each sequence received a class label based on the type of movement: 1 for up, 2 for down, 3 for left, and 4 for right. Finally, we split the dataset into training, validation and test sets to assist in model evaluation and to avoid overfitting. These preprocessing steps helped create a clean, consistent dataset for time-series analysis using deep learning.

B. LSTM-Long short term Memory

At the heart of our classification approach is a Long Short-Term Memory (LSTM) neural network, which is purpose-built for sequential data processing and learning. This is a significant advantage over standard neural networks which do not include an internal memory unit and gates for long-term dependencies in time-series data. This gives LSTM an edge transporting wrist gestures where the ordering and timing of the wrist gesture is crucial to the classification. In our case, the model received sensor input in the form of sequenced data from the four movements so the model learned to classify each

Fig. 3. Sensor and Arduino uno

sequenced data as belonging to of the four movement types that were predetermined.

We designed a multi-layer LSTM model comprising an input layer to accept six-axis sensor data, followed by one or more LSTM layers for development of the temporal relationships between consecutive samples. To overcome potential overfitting, a dropout layer was included, followed by a dense (fully connected) layer with softmax activation, in order to yield the probability of each output class. During the model training, we adopted the categorical cross-entropy loss value, and the Adam function for an efficient learning process. The model was trained using a tunable batch size over several epochs to maximize the GPU utilization capabilities of the underlying architecture. Overall, this multi-layer architecture was able to generalize well for different users, through different wrist motion scenarios, whilst also maintaining accuracy.

V. Result

Having successfully trained the LSTM model on our pre-processed dataset of wrist movement, we evaluated its performance by a held-out test set. The model performed with an overall accuracy of 94% which is a strong ability to distinguish among the four major wrist movement modes: up, down, left, and right. The training curve revealed a fairly consistent decrease in loss and increase in accuracy across each epoch, which demonstrated good learning without overfitting. Additionally, we were able to trust the results of cross-validation as reflective of the model's reliability and stability even when tested on unseen data from a set of new users.

We also assessed model performance based on other metrics including precision, recall, and F1-score. All movement classes achieved F1-scores greater than 0.92, validating the strength of prediction for all classes as balanced. Misclassifications were found to be minimal from confusion matrix analysis with very little overlap between left and right, which are easily confused because they are similar in the direction of the gesture. These measures indicate the ability of the model to track fine changes in wrist movement even when the users gesture at varied speeds or orientations.

Aside from accuracy-based testing, we incorporated the trained LSTM model into a wrist-based game programmed

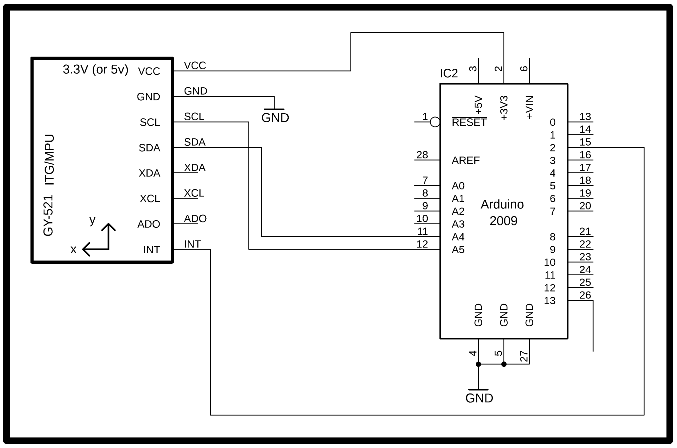

Fig. 4. A schematic diagram of the Sensor and Arduino uno image

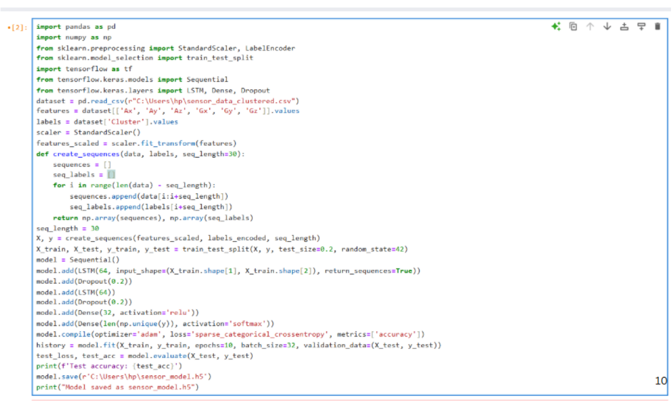

Fig. 5. code of the LSTM

using Python to verify the real-time prediction ability of the system. The game reacted near-instantaneously to wrist movements, with zero discernible latency. The users were able to move the character by just moving their wrist in the desired direction. During several sessions, the system was responsive and accurate, including when movement was rapid or somewhat jumpy. This real-time capability attests to the system's potential as an interactive tool for interactive rehabilitation.

Fig 2.Displays the sensor and Arduino uno or the prototype

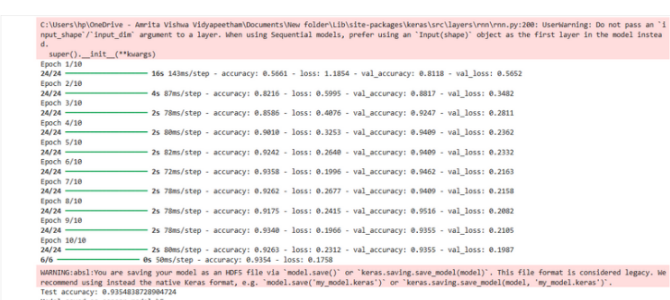

Fig. 6. Accuracy of the model

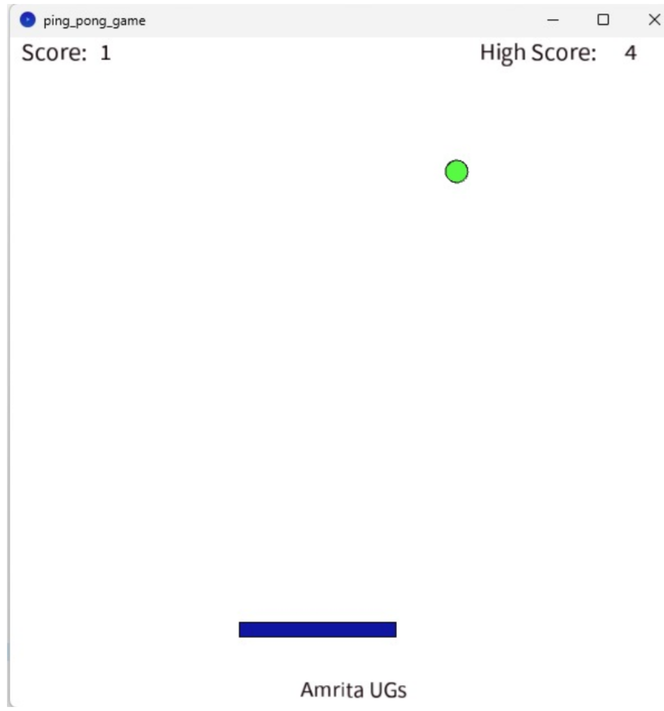

Fig. 7. Deployment of the ping-pong game

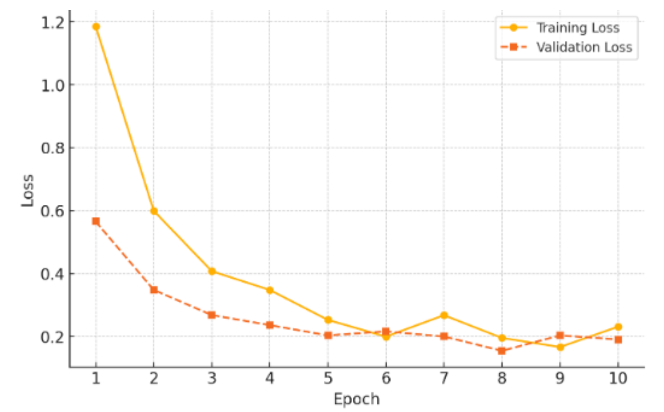

Fig. 8. Learning Curve of the Model

of the project. Fig 3.Displays the schematic diagram of the Sensor and Arduino uno. Fig 4.Displays the code of the LSTM. Fig 5.Displays the Accuracy of the model. Fig 6.Displays the deployment of the game. Fig 7.Learning Curve of the Model.

TABLE I
PERFORMANCE METRICS OF THE DATA

Model	Accuracy	Precision	Recall	F1-Score
LSTM	94%	0.93	0.95	0.94
SVM	87%	0.86	0.88	0.87
LogisticRegression	91%	0.90	0.92	0.91
Decision Tree	90%	0.89	0.91	0.90

Table 1 compares the performance of different models such as SVM, Logistic Regression, Decision Tree and LSTM on the first dataset using raw input features. LSTM achieves the highest accuracy of 94%, indicating it is the most effective model for this classification task.

We also made a comparison with other standard machine learning classifiers such as Support Vector Machines (SVM) and Random Forest (RF), which were both trained using the same data. Although they had moderate accuracy (80–85%), they could not learn from sequential patterns, and as a result, misclassified more overlapping or quick gestures. The LSTM model, on the other hand, remained stable and accurate throughout the sequence, reiterating its effectiveness for time-series data such as motion signals. These results confirm the adoption of LSTM as the primary classifier in our suggested rehabilitation framework.

VI. Future works and conclusion

This project demonstrates a full AI-powered rehabilitation system that incorporates motion sensing, deep learning, and gaming to encourage more engaging wrist therapy. Using the MPU6050 sensor and an LSTM model, we were able to capture and classify wrist movements in real time and convert them into actionable inputs for an interactive game. The model's 94% accuracy and high responsiveness emphasize the efficiency in employing time-series-based deep learning for wearable purposes. The system not only serves functional rehabilitation purposes but also deals with motivational issues that patients encounter in undergoing repetitive therapy.

The application of game mechanics provides a new paradigm for physical therapy through making the process engaging and autonomous. The ease of hardware needs (only a sensor and microcontroller) and real-time classification feature make this system viable for implementation in clinical and home settings. Additionally, because the system maps progress implicitly based on game scores and movements, therapists can monitor remotely and tailor rehabilitation programs. Successful comparison with the standard ML models is yet again the highlight of LSTM's potential for grasping sophisticated motion patterns.

To implement in the future, we project to enhance the system's abilities to incorporate more movements such as finger gestures, wrist rotation, and circular motion. This would broaden the scope of possible rehabilitations to any type of hand injury. We are also considering creating a web or smartphone application platform for remote login, synchronization, and multi-player rehabilitative games. Besides, advanced feedback systems like voice messages, vibration motors, and adjustable complexity levels would also be incorporated for enhanced user involvement. With development in AI and wearable technology, this project has a foundation on which the future digital therapeutics in physiotherapy will emerge.

References

[1] S.-J. Hong, M.-Y. Lee, and B.-H. Lee, "Effects of wrist stability training combined with grip strength exercise on pain and function in patients with nonspecific chronic wrist pain," *Medicina*, vol. 60, no. 7, p. 1144, 2024.

[2] E. Hagert and S. Rein, "Wrist proprioception—an update on scientific insights and clinical implications in rehabilitation of the wrist," *Journal of Hand Therapy*, vol. 37, no. 2, pp. 257–268, 2024.

[3] A. M. Ríos Rincón, C. Guptill, Y. Liubaoerjijin, M. Figeys, F. Koubasi, G. Gregson, and A. Miguel Cruz, "Effectiveness of a new device for hand, wrist, and forearm rehabilitation: Feasibility randomized controlled trial," *JMIR Rehabilitation and Assistive Technologies*, vol. 12, p. e62809, 2025.

[4] S. Pradhan, S. Chiu, C. Burton, J. Forsyth, N. Corp, Z. Paskins, D. A. van der Windt, and O. O. Babatunde, "Overall effects and moderators of rehabilitation in patients with wrist fracture: a systematic review," *Physical Therapy*, vol. 102, no. 6, p. pzac032, 2022.

[5] G. F. Garcia, R. S. Gonçalves, and G. Carbone, "A review of wrist rehabilitation robots and highlights needed for new devices," *Machines*, vol. 12, no. 5, p. 315, 2024.

[6] C. A. Jaworski, M. Krause, and J. Brown, "Rehabilitation of the wrist and hand following sports injury." *Clinics in sports medicine*, vol. 29, no. 1, pp. 61–80, 2010.

[7] G. Karunasena, H. Herath, and L. M. Goyal, "Robotic-assisted wrist rehabilitation therapy for carpal tunnel syndrome," *International Journal of Advanced Robotic Systems*, vol. 22, no. 1, p. 17298806251313938, 2025.

[8] G. A. Albanese, E. Taglione, C. Gasparini, S. Grandi, F. Pettinelli, C. Sardelli, P. Catitti, G. Sandini, L. Masia, and J. Zenzeri, "Efficacy of wrist robot-aided orthopedic rehabilitation: a randomized controlled trial," *Journal of neuroengineering and rehabilitation*, vol. 18, no. 1, p. 130, 2021.

[9] ——, "Efficacy of wrist robot-aided orthopedic rehabilitation: a randomized controlled trial," *Journal of neuroengineering and rehabilitation*, vol. 18, no. 1, p. 130, 2021.

[10] C. Liu, S. Mao, Y. Lei, and L. He, "Designing kresling origami for personalised wrist orthosis," *arXiv preprint arXiv:2501.18796*, 2025.

[11] A. Karime, M. Eid, J. M. Alja'Am, A. El Saddik, and W. Gueaieb, "A fuzzy-based adaptive rehabilitation framework for home-based wrist training," *IEEE Transactions on Instrumentation and Measurement*, vol. 63, no. 1, pp. 135–144, 2013.

[12] S. Halloran, L. Tang, Y. Guan, J. Q. Shi, and J. Eyre, "Remote monitoring of stroke patients' rehabilitation using wearable accelerometers," in *Proceedings of the 2019 ACM International Symposium on Wearable Computers*, 2019, pp. 72–77.

[13] E. Y. Chang, R. Mardini, A. I. McPherson, Y. Gloumakov, and H. S. Stuart, "Tenodesis grasp emulator: Kinematic assessment of wrist-driven orthotic control," in *2022 International Conference on Robotics and Automation (ICRA)*. IEEE, 2022, pp. 5679–5685.

[14] A. S. Sousa, J. Moreira, C. Silva, I. Mesquita, R. Macedo, A. Silva, and R. Santos, "Usability of functional electrical stimulation in upper limb rehabilitation in post-stroke patients: a narrative review," *Sensors*, vol. 22, no. 4, p. 1409, 2022.