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RESEARCH ARTICLE

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Virtual Analysis for Spinal Cord Injury Rehabilitation

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Abstract:

Background: Spinal cord injuries (SCI) are debilitating conditions affecting individuals worldwide annually, leading to physical, emotional, and cognitive challenges. Effective rehabilitation for SCI patients is crucial for restoring motor function and enhancing their overall quality of life. Advances in technology, including machine learning (ML) and computer vision, offer promising avenues for personalized SCI treatment.

Aims: This paper aimed to propose an automated and cost-effective system for spinal cord injury (SCI) rehabilitation using machine learning techniques, leveraging data from the Toronto Rehab Pose dataset and Mediapipe for real-time tracking.

Objective: The objective is to develop a system that predicts rehabilitation outcomes for upper body movements, highlighting the transformative role of ML in personalized SCI treatment and offering tailored strategies for improved outcomes.

Methods: The proposed system utilized data from the Toronto Rehab Pose dataset and Mediapipe for real-time tracking. Machine learning models, including Support Vector Machines (SVM), Logistic Regression, Naive Bayes, and XGBoost, were employed for outcome prediction. Features such as joint positions, angles, velocities, and accelerations were extracted from movement data to train the models.

Results: Statistical analysis revealed the ability of the system to accurately classify rehabilitation outcomes, with an average accuracy of 98.5%. XGBoost emerged as the top-performing algorithm, demonstrating superior accuracy and precision scores across all exercises.

Conclusion: This paper emphasizes the importance of continuous monitoring and adjustment of rehabilitation plans based on real-time progress data, highlighting the dynamic nature of SCI rehabilitation and the need for adaptive treatment strategies. By predicting rehabilitation outcomes with high accuracy, the system enables clinicians to devise targeted interventions, optimizing the efficacy of the rehabilitation process.

Keywords: Spinal cord injury, Rehabilitation, Classification, Mediapipe, Xgboost, SVM.

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1. INTRODUCTION

The spinal cord is a vital part of the human's central nervous system, carrying signals between the brain and the rest of the body. When damaged, it can disrupt the flow of these signals, leading to a wide range of symptoms. It occurs when the spinal cord is damaged, which can produce a wide range of physical, emotional, and cognitive challenges. Spinal cord injury (SCI) is a debilitating condition that can result in the loss of motor function and sensation in the limbs. Rehabilitation for SCI patients often involves the use of physical therapy to help regain movement and strength in the affected limbs. One important aspect of SCI rehabilitation is tracking the movement of the joints in the hand and upper body, as this can provide valuable information about the progress of the patient and help guide therapy. It is estimated that every year, around 250,000 to 500,000 patients suffer from spinal cord injury. The strictness of an SCI depends on the degree and extent of the damage, with some individuals suffering complete palsy while others may have only partial palsy. Common symptoms include loss of sensation or movement, habitual pain, and difficulty with bowel and bladder control. SCI treatment generally involves a combination of medical care, physical therapy, and recuperation to help individuals regain important functions and upgrade their overall quality of life. Advances in technology and new treatments analogous, such as stem cell therapy and nerve-stimulating bias are being probed as implicit ways to help individuals with SCI recover. With the right treatment and support, multitudinous individuals are able to make significant progress in their recovery and ameliorate their overall quality of life.

Rehabilitation for individuals with SCI is a crucial aspect of the recovery process. The idea of SCI recuperation is to help individuals reclaim important function and mobility, as well as to upgrade their overall quality of life. Rehabilitation generally includes a combination of medical care, physical therapy, and occupational remedy. Physical therapy aims to improve strength, flexibility, and coordination through exercises targeting muscle tone, range of motion, and cardiovascular fitness.

Occupational therapy, on the other hand, focuses on helping individuals regain the capability to perform day-to-day living exercises. Recent advancements in technology have introduced new tools for SCI rehabilitation, such as virtual reality and robotics, which aid in restoring movement and enhancing physical capabilities. Additionally, ongoing research is exploring innovative treatments like stem cell therapy and nerve-stimulating techniques to further facilitate the recovery process for individuals with SCI.

Freund *et al*. [1] in 2013 conducted a review of spinal cord changes, including both anatomical changes and changes in the brain, through neuroimaging studies. Kemal Nas *et al*. [2] in 2015 aimed to deliver comprehensive information on treatments offered by various rehabilitation disciplines and formulated guidelines for clinical decision-making grounded on the result. Grabher *et al*. [3] in 2015 used advanced magnetic resonance imaging to estimate progressive changes in the sensors and to determine how the sensory result of neuropathic pain below the injury degree gets cured due to rehabilitation. Huang *et al*. [4] in 2015 introduced a rehabilitation robot named Amadeo, which provides position-based passive training and interactive games with visual and audio feedback for finger extension and flexion. The Reinforcement Learning Neural Network controller can control the Amadeo robot but has the limitation of providing constant assistive force intensity, regardless of the actual needs of the patient. Dolatabadi *et al*. [5] in 2017 utilized the Microsoft Kinect sensor to collect accurate data on the motion of upper limb rehabilitation in 10 healthy individuals and 9 stroke survivors considering 3 types of upper body exercises but ignoring the lower body.

The use of machine learning (ML) in spinal cord injury (SCI) rehabilitation is getting increasingly popular as it can be used to analyze large quantities of data from various sources, similar to 3D tracking of joint movement, wearable bias, and clinical assessments. The data can be utilized to identify patterns and trends and forecast the progress of cases, showcasing one of the key advantages of ML in SCI rehabilitation.

This can help healthcare professionals make further informed decisions about patient care and treatment and optimize treatment plans. Zhi *et al*. [6], in 2017, developed a computer vision system to improve robotic rehabilitation therapy by automatically detecting compensatory motions using the Kinect sensor and SVM. Dalkilic *et al*., in 2018 [7], investigated the ability of the cerebrospinal fluid (CSF) and magnetic resonance imaging (MRI) biomarkers to classify injury severity and predict neurological recovery in acute cervical SCI patients. CSF inflammatory biomarkers demonstrated strong predictive power for Association Impairment Scale (AIS) grade conversion, while structural MRI biomarkers excelled in predicting motor score improvement, highlighting their complementary roles in assessing SCI prognosis.

Khan *et al*. [8], in 2019, applied K-Nearest Neighbor (KNN) and Support Vector Machines (SVM) to analyze imaging data and predict outcomes in large epidemiological datasets. The training set was annotated by board-certified radiologists in the axial spinal magnetic resonance images.

Inoue *et al*. [9], in 2020, performed prediction for the recovery of patients using XGBoost, logistic regression (LR), and Random Forest (RF), showing improvements in functional motor status, achieving an accuracy of 81% on average. Jiang *et al*. [10], in 2020, proposed a CNN model combined with the Common Space model for recognizing the Electroencephalography (EEG) signals related to unilateral hand movements. The average recognition rate was 78% for 10 patients with spinal cord injury, with the optimal subject recognition rate at 82% and an accuracy of 82.4% for the offline EEG recognition and control system. DeVries *et al*. [11], in 2020, introduced a new model for predicting lower body recovery for spinal cord injury patients using unsupervised learning, with Logistic Regression and K-mean models to predict if SCI patients can walk after rehabilitation. This work highlights the poor AUC for imbalanced data sets. Ahammad *et al*. [12], in 2020, presented a CNN-deep segmentation-based boosting classifier applied to sensor spinal cord injury image data using a wearable sensor for data collection and a filtering algorithm for feature extraction with 98.5% accuracy. In 2020, Haber *et al*. [13] evaluated the accuracy of clinical prediction rules for independent ambulation post-spinal cord injury, especially with age modifications from 65 to 50. Findings confirmed strong prognostic accuracy for combined AIS subgroups but suggested lower accuracy for separate AIS groups, emphasizing the importance of age, with a potential cutoff at 50 for improved prognostication.

Alhammad *et al*. [14], in 2021, developed a systematic activity recognition method using a wrist-worn accelerometer to track physical activities during rehabilitation for spinal cord injury and achieved 94.86%, 94.15%, 96%, and 94% accuracy for SVM, KNN, Decision Tree (DT), and Gaussian Naïve Bayes, respectively, in recognizing physical activities. Dietz *et al*. [15], in 2022, focused on MRI evaluation and segmentation for improved diagnostic accuracy and prognosis, prediction of mobility, functional ability, prevention of long-term complications, and assessment of psychological quality of life. Yang *et al*. [16], in 2022, proposed a prediction model for the discharge score of daily living activities and constructed a more comprehensive dataset combining ML, AI, and optimized algorithms to predict the daily living score. Fallah *et al*. [17], in 2022, developed a simple and easy-to-use mortality risk assessment tool that uses machine learning for pattern recognition to predict in-hospital and one-year mortality following spinal cord injury, with a predicted mortality Area Under a Receiver Operating Characteristic curve (AUC) value of 85% and 86%, reducing the bias in estimating parameters.

Buri et.al., in 2022 [18], evaluated the robustness of unbiased recursive partitioning with conditional inference trees in identifying homogeneous subgroups and compared its predictive performance with traditional statistical methods and machine learning techniques. URP-CTREE demonstrated replicable and robust subgroup identification and comparable prognostic accuracy to machine learning, supporting its robustness and practicality in clinical settings. In the study outlined by Fallah *et al*. [17] (2022), the process involved selecting variables associated with outcomes in a cohort of 1245 traumatic spinal cord injury (tSCI) patients and creating the Spinal Cord Injury Risk Score (SCIRS) through a two-step variable selection approach, comprising bivariate analysis and a LASSO model. The SCIRS was statistically and clinically validated using 10-fold cross-validation and comparison with the Injury Severity Score (ISS), demonstrating its predictive accuracy for in-hospital and 1-year mortality following tSCI. Machine learning techniques, including neural networks and decision trees, were utilized to determine variable weighting and develop the SCIRS algorithm.

Several studies attempted to substitute traditional rehabilitation with a modern approach using Virtual Reality (VR) devices for better movement tracking. Kizony *et al*. [19], in 2005, provided a VR system that gives users natural control of movements, the ability to use as many body parts as desired, and the flexibility to adapt to specific therapy tasks. Krutli *et al*. [20], in 2018, used a VR game gesture chair to enhance recovery through rehabilitation in individuals with spinal cord injuries and compared the effects on movement performance between the two groups (with and without SCI), focusing on the upper limb movement. B. Chi *et al*. [21], in 2019, investigated the efficacy of VR therapy in spinal cord injury neuropathic pain, categorizing it into “at level” and “below level,” and examining the use of VR with immersive and non-immersive mirror visual feedback for pain reduction. Palaniappan *et al*. [22], in 2020, also used VR for rehabilitation by developing a pilot/adaptive exergame using commercial VR systems with customizable parameters for gameplay interface and observed the effects on the motor performance of patients. In the medical field, machine learning (ML) and deep learning (DL) algorithms play a crucial role in revolutionizing rehabilitation practices [23, 24]. By harnessing the power of data analysis and pattern recognition, these algorithms aid in customizing treatment plans, predicting patient responses, and refining therapeutic approaches [25-27]. Their application facilitates personalized care delivery, leading to improved patient outcomes and enhanced efficiency in rehabilitation processes.

While prior research has laid the groundwork for utilizing technology in rehabilitation, there is a clear need for more comprehensive datasets, advanced tracking capabilities, and improved predictive modeling techniques to enhance the effectiveness of rehabilitation strategies for spinal cord injury patients. Previous works have overlooked the importance of capturing subtle movements and variations in motion patterns of the patients, which are crucial for developing accurate predictive models.

For this paper, the main contributions are as follows:

1.1. Proposing an Automated Rehabilitation System

This system leverages machine learning models to offer a cost-effective solution for rehabilitation exercises.

1.2. Streamlining Data Collection

Movement during exercises is captured using a camera, and the system automatically extracts joint positions and angles from the images.

1.3. Enhancing Data Capture with 3D Fingertip Tracking

The system goes beyond basic movement by incorporating 3D tracking of fingertips, allowing for more precise exercise classification (*e.g*., reach-forward/back, reach-side/side). These enriched data are used to predict rehabilitation outcomes.

1.4. Multi-Level Outcome Prediction

The system employs various machine learning models (SVM, Logistic Regression, *etc*.) to classify rehabilitation outcomes into different levels, providing valuable insights for personalized rehabilitation plans.

2. PROPOSED METHODOLOGY

In proposing an automated rehabilitation system, a cost-effective solution is introduced, leveraging image processing and machine learning techniques for effective rehabilitation exercises. Through streamlined data collection, the system captures movement during exercises using a camera, automatically extracting joint positions and angles from the images. Features such as joint angles, velocities, and accelerations are extracted, incorporating additional features derived from clinical assessment scores or annotations of compensatory motions provided in the dataset. These features provide valuable insights into the motion patterns and aid in training the machine learning model. To enhance data capture, the system integrates 3D fingertip tracking, surpassing basic movement tracking capabilities. This advanced feature enables precise exercise classification, distinguishing between reach-forward/back and reach-side/side movements. By incorporating this enriched data, the system predicts rehabilitation outcomes with greater accuracy and granularity, contributing to more effective rehabilitation plans. Fig. (**1**) depicts the architecture or workflow of the system.

This approach employs a multi-level outcome prediction strategy. Machine learning models, such as Support Vector Machine (SVM), Logistic Regression, Naive Bayes, and XGboost, are used to categorize potential rehabilitation outcomes into different levels. This multi-level classification provides valuable insights for tailoring personalized rehabilitation plans to individual needs, ultimately optimizing the efficacy of the rehabilitation process. The detailed algorithm for the proposed method is shown in Algorithm 1.

Algorithm1: Automated Rehabilitation System

1. Initialize:
- Load Toronto Rehab Pose dataset
- Set machine learning models: SVM, Logistic Regression, Naive Bayes, XGBoost
2. Data Collection and Preprocessing:
- Capture movement during exercises using a camera
- Extract joint positions and angles from images
- Incorporate additional features from clinical assessment scores or compensatory motion annotations
- Integrate 3D fingertip tracking for enhanced data capture
3. Feature Extraction:
- Extract features, such as joint angles, velocities, and accelerations
4. Model Training:
- Train machine learning models using the extracted features
- Employ a multi-level outcome prediction strategy
5. Evaluation:
- Evaluate the trained models using the dataset

2.1. Dataset

The proposed study utilized the Toronto Rehab Pose dataset [28, 29] and a dataset generated using Mediapipe. The Toronto Rehab Pose dataset, captured with a Microsoft Kinect sensor, included two groups of participants: 10 healthy individuals and 9 SCI survivors. These participants performed a series of seated motions using an upper-limb rehabilitation robot, with healthy subjects executing additional sets of scripted motions to simulate common compensatory movements post-SCI. Each recorded data frame was assigned to one of four labels: “no compensation,” “lean-forward,” “shoulder elevation,” or “trunk rotation.” Stroke survivors engaged in two specific exercises, namely reach-forward-backward and reach-side-to-side, using both their left and right hands. Concurrently, healthy participants performed the same exercises and additionally mimicked common compensatory movements observed in stroke patients. The dataset also incorporated common clinical assessment scores, with compensatory motions annotated by two experts for both healthy and SCI participants.

2.2. Data Generated Using Upper-body Module

Upper body movement tracking was recorded with Mediapipe, which captured and analyzed the position and motion of the upper body of an individual. This tool processed video feeds from a camera, detecting and tracking the upper body and outputting positional data in the x, y, and z directions, as illustrated in Fig. (**2**).

Fig. (2). Samples of upper body tracking.

The exercises could be tailored to focus on traditional rehabilitation exercises aimed at analyzing the movement patterns of the upper body during side-to-side reaching in both left and right directions, as well as forward-reaching movements in both left and right directions.

Table **1a-d** displays the data obtained from upper body tracking *via* camera for the movements of reaching forward in the left and right directions and reaching side-to-side in the left and right directions.

This data can be used to analyze the movement patterns of the upper body during each exercise and compare them to understand the effects of the different exercises on the upper body.

3. RESULTS AND DISCUSSIONS

The proposed model for Tracking joint movement was implemented on a system with Windows 11 64-bit OS with 16GB RAM and Python 3.10.2 released by Python Software Foundation located in Wilmington, DE, USA, installed. The

Table 1a. Joint positions generated data *from* upper body tracking. Reaching_Forward_Left.

x	Y	Z
0.449627	0.574429	-0.47363
0.45624	0.574263	-0.2808
0.459044	0.574364	-0.28252
0.458826	0.574343	-0.31139
0.459098	0.574036	-0.23481
0.459962	0.574003	-0.16854
0.460518	0.573819	-0.17459
0.463594	0.579377	-0.20323
0.46451	0.580061	-0.20247
0.46578	0.582335	-0.21579
0.468393	0.587084	-0.23068

Table 1b. Reaching_Forward_Right.

X	y	z
0.102073	0.643169	-0.15064
0.101888	0.64439	-0.17574
0.100787	0.645382	-0.20663
0.100754	0.645859	-0.23288
0.099918	0.64601	-0.25194
0.099816	0.644662	-0.20773
0.099739	0.64468	-0.20612
0.100518	0.644724	-0.20368
0.10117	0.644752	-0.23822
0.101126	0.6457	-0.23243
0.101012	0.646707	-0.22812

Table 1c. Reaching_Side_to_Side_Left

x	Y	Z
0.474478	0.636219	-0.17169
0.474697	0.63096	-0.34395
0.474799	0.6279	-0.34451
0.474847	0.625656	-0.34255
0.474889	0.624523	-0.35377
0.474915	0.623283	-0.33485
0.474906	0.62327	-0.32298
0.474751	0.622386	-0.31379
0.474663	0.621883	-0.30888
0.474661	0.62154	-0.30536
0.474645	0.621086	-0.30428

Table 1d. Reaching_Side_to_Side_Right.

X	y	z
0.101072	0.62521	-0.37415
0.10125	0.625326	-0.49774
0.101282	0.62549	-0.4998
0.101295	0.625729	-0.50438
0.101273	0.625708	-0.5078

(Table 1) contd.....

X	y	z
0.101257	0.625677	-0.50129
0.103645	0.625513	-0.43759
0.107271	0.624578	-0.29902
0.10934	0.623977	-0.31615
0.110335	0.623602	-0.28044
0.110976	0.623411	-0.29095

Table 2. Accuracy of 3D tracking.

Modules	Scores
Hand	0.95-0.99
Upper Body	0.99

Table 3. Accuracy of four exercise with ML models.

Algorithm	Reaching Forward_L	Reaching Forward_R	Reaching Side_to_Side_L	Reaching Side_to_Side_R
SVM	99.84	99.79	99.63	99.82
Logistic Regression	99.72	99.58	99.75	99.76
Naive Bayes	97.05	96.49	97.89	96.11
MLPClassifier	99.7	99.51	98.64	99.85
SGDClassifier	96.93	94.41	98.64	97.29
Xgboost	99.87	99.92	99.78	99.79

Table 4. Performance comparison with existing works.

Algorithm / Avg Accuracy	[8]	[14]	[9]	[11]	[6]	[28]	Proposed Method
SVM	89.80	94.80	-	-	86.00	93.30	99.60
Logistic Regression	-	-	80.60	87.54	-	-	99.66
Naive Bayes	-	94.00	-	-	-	-	96.84
XGboost	-	-	81.10	-	-	-	99.64

widely used and open-source Visual Studio Code was used for implementation purposes. The libraries OpenCV 4.6.0.66, Numpy 1.23.3, TensorFlow, Pandas, Mediapipe 0.9.2.1, and Sklearn were installed and used along with the Jupyter extension present in it.

The mediapipe library demonstrated high accuracy in tracking, with an overall accuracy rate of 95-99%, as shown in Table **2**. This indicated the capability to capture subtle movements and variations in the subjects' movements with precision.

Once data were collected using the tracking data, the coordinates were converted into a useful dataset using a variety of data processing techniques like scaling and normalization. Features, such as joint angles, joint velocities, and joint accelerations, were extracted and utilized as input to the machine learning algorithms. The accuracy of several popular machine learning algorithms, including Support Vector Machines (SVM), k-nearest Neighbors (KNN), Logistic Regression, Naive Bayes, Multi-Layer Perceptron (MLP) Classifier, Stochastic Gradient Descent (SGD) Classifier, and XGBoost, in predicting patient outcomes using the upper body module and hand module was compared. Each algorithm was trained and tested utilizing a 70/30 split, with 70% of the data allocated for training and the remaining 30% for testing. Additionally, performance evaluation of each algorithm was conducted using accuracy metrics.

As Table **3** shows, XGBoost outperformed the other algorithms in terms of accuracy in almost every exercise, with an accuracy score of 0.987-0.992, followed by SVM with an accuracy score of 0.9963-0.9984. Furthermore, XGBoost had the highest precision scores, indicating that it performs better at identifying true positives and minimizing false positives and false negatives.

A comparative analysis was conducted with existing research works, as shown in Table **4**. Findings indicated that the proposed methodology demonstrates superior accuracy compared to existing approaches. Specifically, XGBoost exhibited the highest degree of accuracy with an average of 99.64%, followed closely by logistic regression at 99.63%.

CONCLUSION

The proposed automated rehabilitation system presents a cost-effective solution for spinal cord injury rehabilitation. Leveraging advanced technologies, such as

3D fingertip tracking, the system facilitates precise exercise classification and outcome prediction, surpassing conventional approaches. The system streamlines data collection by capturing movement during exercises using a camera and automatically extracting joint positions and angles. This approach enhances the granularity of data analysis, incorporating features, such as joint angles, velocities, and accelerations, along with clinical assessment scores or annotations of compensatory motions. Through a multi-level outcome prediction strategy employing various machine learning models, potential rehabilitation outcomes are categorized with remarkable accuracy.

Further, XGBoost emerges as the top-performing algorithm, demonstrating superior accuracy and precision scores across all exercises. Comparative analysis with existing research highlights the efficacy of the proposed methodology, showcasing significantly higher accuracy rates. By predicting rehabilitation outcomes with high accuracy, the system enables clinicians to devise targeted interventions, optimizing the efficacy of the rehabilitation process. Moreover, the dataset of this study is limited primarily to upper-limb rehabilitation exercises, potentially constraining the generalizability of the proposed methodology to broader rehabilitation contexts and diverse patient populations. To address this limitation, future research should focus on expanding the dataset to include a more comprehensive range of rehabilitation exercises, patient demographics, and clinical conditions beyond spinal cord injury. By diversifying the dataset, the robustness and applicability of the proposed methodology can be enhanced, ensuring its effectiveness across a wider spectrum of rehabilitation scenarios.

LIST OF ABBREVIATIONS

SCI	=	Spinal cord injuries
ML	=	Machine Learning
SVM	=	Support Vector Machines
LR	=	Logistic Regression
RF	=	Random Forest
EEG	=	Electroencephalography

ETHICS APPROVAL AND CONSENT TO PARTICIPATE

Not applicable.

HUMAN AND ANIMAL RIGHTS

No animals/humans were used in this research.

CONSENT FOR PUBLICATION

Not applicable.

AVAILABILITY OF DATA AND MATERIALS

The data and supportive information are available within the article.

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CONFLICT OF INTEREST

The authors declare no conflict of interest, financial or otherwise.

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