Advancements of Deep Learning Model-Based Rehabilitation Training System

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Abstract. Traditional therapies for rehabilitation training in modern society are difficult to track patients dynamically, so this paper introduces a rehabilitation training evaluation system under deep learning modeling to help assess the effectiveness of rehabilitation training. In this paper, one of the studies proposed the concept of posture-guided matching based on paired Siamese Convolutional Neural Networks (SCNN), abbreviated as ST-AMCNN, on a dataset of the traditional Chinese rehabilitation training Baduanjin. Another study classified the output layers of shoulder pain rehabilitation using IMU sensors with multiple training programs for different patients wearing IMUs. IMU sensors for rehabilitation training that requires some time to analyze data and feedback data, there are more efficient studies that promote finger movement by giving patients robotic gloves to wear and propose a hand rehabilitation system thus helping stroke survivors with active rehabilitation. In addition, it was suggested to use a Smart Movement and Rehabilitation Monitoring System (SMRMS) to focus more on the participants' training precision and recuperation. The experimental results show that there is still room for the development of rehabilitation training assessment systems in terms of privacy, interpretation ability, and application scenarios, and that researchers can address the above issues by using federated learning, developing an expert system, and using transfer learning domain adaptation, respectively.

1 Introduction

Rehabilitation, as used in modern medicine, refers mainly to the restoration of physical and mental functioning, occupational ability, and ability to lead a social life. As population ageing progresses, the probability of stroke and other diseases in the elderly increases, so an increasing number of people need rehabilitation training. Rehabilitation training process has a high demand for quality, if the quality is too low, the minor just did not reach the requirements of rehabilitation, or even serious damage to the body. Moreover, it is impractical for medical professionals to oversee and rectify every patient's posture, particularly when there are a lot of patients [1]. So, it is possible to introduce some advanced methods such as deep learning to assist traditional physician-guided rehabilitation, such as recognizing a patient's posture and scoring rehabilitation.

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Deep learning has several applications in other aspects of medicine, such as in cancer diagnosis, prognosis and treatment selection [2], or use a novel segmentation approach that leverages dendritic neurons to tackle the challenges of medical imaging segmentation [3]. Another important direction for deep learning in medicine is in the field of rehabilitation training, and there have been studies using algorithms that enable the evaluation of rehabilitation training. One of the studies proposed a concept of pose-guided matching based on Siamese Convolutional Neural Networks in pairs, on a data set of eight-section brocade, among China's most exemplary traditional rehabilitation exercises [1]. Another study classified the output layer for shoulder pain rehabilitation training utilizing IMU sensors by employing Rectified Linear Units and Soft Max as the activation function of the hidden layer. Exercise regimens for the rehabilitation of shoulder discomfort were created, and each exercise was performed ten times during each session while the IMU sensor was worn [4]. For stroke survivors, reduced hand function limits their ability to perform activities of daily living (ADLs), therefore, one investigation made advantage of the study also proposed a hand rehabilitation system that consists of an 8-degree-of-freedom soft robotic glove and a vision-based intention detection framework. Soft robotic gloves help stroke survivors engage in active rehabilitation by facilitating finger movements based on intentions expressed by bio-signals (e.g., EMG and EEG). To facilitate active rehabilitation, their suggested system, the Deep Augmented Hand Posture Intent Network, predicts the intent of various hand postures by analyzing picture and depth data, observing the user's arm movement, and observing interactions between the user and hand objects [5]. A Smart Movement and Rehabilitation Monitoring System (SMRMS) was designed to capture multi-channel sensing data from subjects in real time while they were engaging in exercise and rehabilitation training. Another study suggested a porous PDMS-based TENG sensor for tracking and assessing whole-body exercise and rehabilitation training [6]. Since many different deep learning algorithms for rehabilitation have been proposed, so there is a great need to do a comprehensive study of deep learning algorithms for rehabilitation.

The rest of the paper is organized as follows: In the second section, this paper will focus on the methods used in rehabilitation studies and how other studies have used different algorithms, such as the algorithms used to score a patient's posture to predict the outcome of rehabilitation. In the third section, this paper will focus on some of the shortcomings and challenges of utilizing deep learning to implement rehabilitation training and compare different deep learning approaches to implement rehabilitation training. The fourth section summarizes the whole paper to deepen the understanding of deep learning approaches to rehabilitation training.

2 Method

2.1 Traditional machine learning-based pose evaluation

2.1.1 A view-invariant technique to rate human movement quality

To gather data on dynamic motion in their investigation, video frames were taken. In the study, a comparable method of breaking the video up into frames to assess motion can also be used [7]. They unveiled a methodology for learning from user poses in videos in order to assess their impact. It maps these representations to quality scores by using poses as features and learning Support Vector Regression. By concentrating on certain Olympic sports, it can hire experts to evaluate scores and provide unbiased assessments of quality. Nevertheless, alignment and comparability between learner poses and standard postures are not considered in this suggestion. By altering the feature representations and use the tandem approximation entropy of the postures rather than the Discrete Cosine Transform (DCT) of the poses, Venkataraman et al. expand on this work. Performance improved by 4% as a result of this improved coding method [8], but the issues mentioned above (inability to handle fluctuations in motion data) still exist [1].

2.1.2 Machine learning-assisted SMRMS

The eight PP-TENG and four RS-TENG sensors, the Micro Controller Unit (MCU), the Bluetooth transmitter module, the Analog-to-Digital Converter (ADC) with multi-channel data acquisition, and these components make up the SMRMS.For whole-body motion monitoring, tracking, and recognition, the TENG sensor array adjusts to strain fluctuations in various body areas and accurately records body motion data. For whole-body motion monitoring, a single TENG sensor is unable to reliably gather body motion information. An array of eight TENG sensors must be used to gather electrical signals of whole-body movement in order to avoid the volunteer's movement not being able to be tracked in all directions and to determine whether or not his movement is balanced.By monitoring TENG output signals from eight sites in volunteers—left/right triceps brachii, left/right biceps brachii, left/right tibialis anterior, and left/right gastrocnemius—an eight-channel signal collecting and processing system was designed and put together [6].

2.2 Deep learning-based pose evaluation

2.2.1 ST-AMCNN

Based on two identical CNNs with the same weights, the Siamese Neural Network serves as its model. The input is an unaligned pose image that is sent to the STN module for initial alignment. In order to obtain a matched outcome, they subsequently forward propagate both the aligned position and the standard pose through the AMCNN module. The eight-part Brocade dataset provides the pair of input poses, one of which is the learner's posture and the other of which is the standard pose. Training ST-AMCNN is still possible even with the little size of the gathered eight-part Brocade data set. This is because the pose features extracted by Open Pose consist only of relatively uncomplicated poly lines. Additionally, because of its highly nonlinear feature extraction capacity, the suggested model can be applied to the test dataset. [1].

2.2.2 IMU sensor-based DNN

Motion data can be collected during rehabilitation activities using Inertial Measurement Unit (IMU) sensors, which integrate accelerometers, gyroscopes, and magnetometers. These sensors have shown promise in this regard. With the ability to precisely monitor motion, orientation, and position in three dimensions, these sensors offer comprehensive data regarding motor performance [4]. It is feasible to keep an eye on the patient's movements while they are exercising by employing IMU sensors [4].

Preprocessing was done on the gathered IMU sensor data before deep neural network models were trained. In order to segregate the workout data from the rest intervals and enable AI system to concentrate on pertinent and copious amounts of data, this preprocessing involved multiple processes. First, they established the start and end times of the workouts. Using filters to find and process any irregularities in the sensor readings, any inaccurate or noisy data points were eliminated from the dataset [4].

Deep Neural Networks (DNNs) can intimately determine the elements that influence 3D localization and learn complex data patterns. Using preprocessed IMU sensor data, a DNN was built to categorize shoulder pain rehabilitation workouts. The model has five hidden layers—each with 8, 16, 32, 64, and 128 nodes—and an input layer with 24 characteristics. This allows the model to understand intricate relationships and patterns in the data. The activation function for the hidden layers is the modified linear unit, and Softmax is utilized for the output layers [9]. A trained DNN model was fed preprocessed test set acceleration and angular velocity data to predict the kinds of 11 shoulder rehabilitation activities. Using the accuracy score function in the scikit-learn package, the predicted exercises were compared to the real patient data to determine their correctness [4].

2.2.3 Vision-based system used DEEPOSE-Net

The activation function for the hidden layers is the modified linear unit, and Softmax is utilized for the output layers [9]. A trained DNN model was fed preprocessed test set acceleration and angular velocity data to predict the kinds of 11 shoulder rehabilitation activities. Using the accuracy score function in the scikit-learn package, the predicted exercises were compared to the real patient data to determine their correctness. The five hand poses that are most frequently employed in ADL are Medium Wrap, Lateral Pinch, Thumb-2-Finger, Power Sphere, and Tripod. DEEPOSE-Net predicts the aim of these poses by analyzing top-view photos and depth sequences obtained from an RGB-D camera positioned in front of the user. DEEPOSE-Net learns the depth and picture segment that are important for predicting the intended hand position by means of an attention mechanism. This enables DEEPOSE-Net to classify intents for aesthetically comparable poses (e.g., tripod and power ball) by emphasizing distinctive characteristics of various hand poses, such as the fingers involved. The 8-DOF soft robotic glove assists the user in achieving the appropriate hand attitude by facilitating their fingers based on the identified intent [5].

3 Discussion

3.1 Limitations and challenges

3.1.1 Interpretability

The above study's still face the problem of interpretability, in these studies utilizing deep learning for rehabilitation training may be difficult to explain the match and rationality of the patient's symptoms and performing the associated exercises, the following provides an example of a study that faced the associated challenges. The study uses RS-TENG to monitor the force applied by the human arm and leg in the machine learning-assisted SMRMS approach. The sensor data is sent to an endpoint computing device where the machine learning model can process the data, identify movement patterns, and monitor movement. But in the end, it takes a professional to analyze the data to understand muscle health and offer precise, impartial, quantifiable, and trustworthy assistance for programs involving exercise and rehabilitation. These data are connected to a computer through sensors to form multiple line graphs based on different movement patterns, but the lack of UI on the computer line graphs does not allow users to understand the meaning behind the line graphs, which is not intuitive enough, and the explanatory nature of the graphs still needs to be improved [6]. The decision-making process of machine learning models is often complex and difficult to understand, and users may not be able to trace the exact basis of the model's judgment, leading to less trust in the results.

3.1.2 Applicability

There are significant limitations in the applicability of rehabilitation training models that utilize deep learning to analyze data, with specific challenges that can be demonstrated in the following examples. Rehabilitative workouts for shoulder discomfort were studied utilizing deep learning modeling and IMU sensors., patients will be able to wear the sensors to exercise at home and the patient's exercise records will be accessible to professionals. The DNN model for this study was trained and validated using a certain percentage of segmentations in the same dataset, and therefore needed to be validated against data collected in a new environment. And only patients with shoulder problems were included in the subject group, who suffered from shoulder pain; the sensor did not include data on all shoulder disorders, so that would limit the practical application of the model [4].

3.1.3 Privacy

Deep learning and machine learning model-assisted rehabilitation training evaluation systems have certain privacy drawbacks, which is also due to the uploading of model-trained data to the cloud or training the data in the cloud and giving feedback, which may lead to violation of the patient's privacy, as the following example faces such a challenge.To prepare for training deep neural network models, preprocessing was done on the gathered IMU sensor data. This preprocessing involved a number of actions:In order to isolate the workout data from the rest periods and enable the study's AI system to concentrate on pertinent and copious amounts of data, the researchers established the start and end times of the exercise.Patients will be able to wear the sensors and work out at home thanks to the development of an in-home training service using this deep learning model in conjunction with a TV or smartphone app.The patient's workout records will be accessible to medical specialists. They can offer patients encouragement and feedback to keep up their fitness regimen based on these facts [4]. Future patient research may also make use of the recorded data. However, such a deep learning system would save the patient's symptoms to the web, which could violate the patient's privacy if the database is compromised, so it would be better to save the data from it for local analysis rather than uploading it to a cloud-based platform for analysis.

3.2 Future prospects

3.2.1 Expert systems

Deep learning-assisted rehab can introduce expert systems or similar models and systems that analyze the cause of the disease and the antecedents and consequences of actually performing each step of rehab in a way and from a perspective that is easily understood by the patient, a vision expressed in the following study. In a machine learning-assisted SMRMS approach [6], an expert system can be utilized to develop a system that uses explicit rules for interpreting data on a line graph, ideally so that the patient can see how decisions are derived from specific conditions. Additionally, the development of the expert system should be analogous to the thought process of a human expert to make it easier for the patient to understand and accept the logic. The expert system can be combined with SHAP to provide personalized explanations for each patient's different predicted outcomes and rehab scores, to see what factors influenced their rehab scores, to understand the future direction of improvement and their current status, and SHAP can give visual charts and graphs to help the patient intuitively understand the effects and changes of their rehab.

3.2.2 Transfer learning domain adaptation

Transfer learning reduces the reliance on large amounts of data by pre-training models in similar domains and then applying them to new tasks [10]. Domain Adaptation allows models to switch between different data distributions. When training data and test data come from different distributions, domain adaptive techniques help the model overcome this distributional difference. Transfer learning can greatly reduce the time and computational resources required for model training by reusing the weights of pre-trained models. In some cases, where the amount of data for a particular task is small or noisy, the performance of the model for the new task can be improved by transferring knowledge from similar domains, utilizing data from different domains to enhance the robustness of the model.

3.2.3 Federated learning

Addressing the privacy concerns of deep learning-assisted rehab requires utilizing federated learning or similar approaches to allow data retention to complete training and analysis locally, here are some detailed objectives. To address privacy concerns, data obtained from IMU sensors should be processed locally: collect and process IMU sensor data locally on each patient's device [1], rather than sending raw data to a centralized server. And it is best to train AI models locally to ensure that personal data does not leave the device. Each device should only keep the model parameters, not the raw parameters, and periodically train the model to update the local model with the parameters or weights in it, and then the cloud will pass the updated data to each patient locally for updating.

4 Conclusion

In this analytical review work, deep learning has been studied in the medical field using algorithms to evaluate rehabilitation training. The study analyzes a pose-guided matching based on paired Siamese Convolutional Neural Networks (SCNN), as well as classifying the output layer of a shoulder pain rehabilitation training using IMU sensors, and an eight-degree-of-freedom soft robotic glove as part of a hand rehabilitation system. The intention detection framework is based on vision. The methodologies of these experiments and studies are analyzed in the study and their strengths and weaknesses are summarized. In the analysis, it is shown that there is still room for development of the rehabilitation training assessment system in terms of privacy, interpret ability, and application scenarios. In the future, researchers should plan to utilize federated learning and expert systems to remedy these shortcomings.

References

1. Y. Qiu, J. Wang, Z. Jin, H. Chen, M. Zhang, & L. Guo, Pose-guided matching based on deep learning for assessing quality of action on rehabilitation training. Biomedical Signal Processing and Control, 72, 103323 (2022).
2. K. A. Tran, O. Kondrashova, A. Bradley, E. D. Williams, J. V. Pearson & N. Waddell Deep learning in cancer diagnosis, prognosis and treatment selection. Genome Medicine, 13, 1-17 (2021).
3. Z. Liu, Z. Zhang, Z. Lei, M. Omura, R. L. Wang & S. Gao, Dendritic deep learning for medical segmentation. IEEE/CAA Journal of Automatica Sinica, 11(3), 803-805 (2024).

4. K. Lee, J. H. Kim, H. Hong, Y. Jeong, H. Ryu, H. Kim & S. U. Lee, Deep learning model for classifying shoulder pain rehabilitation exercises using IMU sensor. Journal of NeuroEngineering and Rehabilitation, 21(1), 42 (2024).
5. E. Rho, H. Lee, Y. Lee, K. D. Lee, J. Mun, M. Kim, ... & S. Jo, Multiple hand posture rehabilitation system using vision-based intention detection and soft-robotic glove. IEEE Transactions on Industrial Informatics (2024).
6. L. Liu, J. Li, Z. Tian, X. Hu, H. Wu, X. Chen, ... & W. Ou-Yang, Self-powered porous polymer sensors with high sensitivity for machine learning-assisted motion and rehabilitation monitoring. Nano Energy, 128, 109817 (2024).
7. V. Venkataraman, I. Vlachos & P. K. Turaga, Dynamical Regularity for Action Analysis. In BMVC (Vol. 67, pp. 1-12) (2015).
8. O. Giggins, D. Kelly & B. Caulfield, Evaluating rehabilitation exercise performance using a single inertial measurement unit. In 2013 7th International Conference on Pervasive Computing Technologies for Healthcare and Workshops (pp. 49-56). IEEE (2013).
9. T. Szandała, Review and comparison of commonly used activation functions for deep neural networks. Bio-inspired neurocomputing, 203-224 (2021).
10. K. Weiss, T. M. Khoshgoftaar, & D. Wang. A survey of transfer learning. Journal of Big data, 3, 1-40 (2016).