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ORIGINAL ARTICLE

Shoulder rehabilitation: a neuro-fuzzy inference approach to recovery prediction

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Abstract

This study proposes a system for predicting the recovery status of patients with shoulder damage by estimating the results of the Disabilities of the Arm, Shoulder, and Hand (DASH) questionnaire using an Adaptive Neuro-Fuzzy Inference System (ANFIS). The study aimed to answer two primary research questions: First, is it possible to accurately predict the recovery status of patients with shoulder damage using the proposed system during treatment? Second, how does this estimation contribute to the treatment process? A literature review indicates that artificial intelligence is often used in rehabilitation to help patients perform exercises correctly. However, previous studies have typically focused solely on exercise execution, without addressing recovery prediction. In contrast, this study aims to predict the recovery status of patients and integrate it into a physiotherapy application, allowing for real-time observation of patient progress. To develop the recovery prediction model, we collected data on the treatment processes of 105 shoulder patients at Bilecik State Hospital and estimated the results of the DASH questionnaire using an ANFIS-based model. The developed model has a mean square error of 9.4E − 3 for the training data and a mean square error of 2.56E − 2 for the test data. The proposed model was integrated into a physiotherapy application using the best weight values from 1000 runs. In this way, it is ensured that successfully predicted recovery status can be observed in real-time. The findings of this study have important implications for shoulder injury rehabilitation. By integrating recovery prediction into a physiotherapy application, healthcare providers can monitor patient progress more effectively and make more informed decisions about the timing and intensity of rehabilitation exercises.

Keywords Artificial intelligence · Rehabilitation · Physiotherapy · ANFIS · DASH

1 Introduction

According to the World Health Organization (WHO) media center report, there are more than one billion disabled people in the world [1]. Some of these people need rehabilitation in some parts of their lives, whereas others need it throughout their lives. In the rehabilitation treatment of these patients, there are some important issues. One of the most important issues is that the patients perform rehabilitation exercises correctly.

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Despite the criticality of this problem, studies show that patients who do rehabilitation exercises by themselves can only do 31% of the exercises right, and 65% of them are not sure whether they are doing the exercises right or wrong [2]. Considering the fact that doing the exercises incorrectly is likely to cause the treatments to fail, patients who cannot complete their treatment continue their lives with disabilities [3–5].

In order to minimize such risks, different solutions have been proposed in physiotherapy with the developing technology. By using the internet and telecommunication networks, the provision of rehabilitation services can be described as telerehabilitation [6]. Studies show that, thanks to telerehabilitation, patients can perform their exercises as successfully as they do under the supervision of a physiotherapist [7–9].

Using this technology has allowed the development of many rehabilitation applications. Various systems have been proposed for patients with different injuries, including shoulder damage [10–12], anterior cruciate ligament [13], Parkinson's disease [14–16], and stroke [17]. Additionally, some studies have proposed systems suitable for daily rehabilitation exercises for individuals without injuries [18, 19] and online aerobics teaching [20].

In addition to telerehabilitation systems, Artificial Intelligence (AI) has also recently been used in health systems, as in many other fields such as data control [21], object recognizing [22]. AI methods such as Multi-Layer Perceptron (MLP), Adaptive Neuro-Fuzzy Inference System (ANFIS), and Convolutional Neural Network (CNN) are used to predict some issues such as heart attack and cancer risk [23–26]. There are also studies focusing on issues such as disease diagnosis from human bones, malaria diagnosis based on geographical conditions, abnormal bone growth detections, evaluation of body balance, and breast cancer diagnoses by using AI in health. AI studies in rehabilitation, however, generally focus on the detection of joint points through human images, and thus, by observing the patients. Studies have concluded that patients take more effective rehabilitation treatment with the help of these observations [27–31]. Another study shows that RNN-based body pose prediction can be reach 99.89% accuracy rate [32].

It is observed that most of the telerehabilitation studies focused on estimating the human body pose correctly. The results obtained in these studies provide an important contribution to making rehabilitation exercises correctly. However, this contribution is not sufficient to provide a clear result regarding the estimation of the patients' recovery processes. Knowing the patient's recovery status is critical for physiotherapists to be able to guide their patients properly. By knowing the patient's recovery status, physiotherapists can change the treatment method, modify the patient's exercises, or adjust the number of repetitions of the exercises, which can lead to faster and more effective treatment for patients. Therefore, observing the patient's recovery status is as important as accurately predicting human body pose for treatment purposes.

However, previous studies of rehabilitation by using AI have not dealt with the prediction of shoulder-damaged patients' recovery status. The recovery status of shoulder patients can be observed by the results of the Disabilities of the Arm, Shoulder, and Hand (DASH) questionnaire [33]. To the best of our knowledge, no studies to date have focused on DASH prediction by using AI, and no telerehabilitation system seems to have been developed that displays these predictions in real-time.

This study mainly focuses on recovery prediction for shoulder damage rehabilitation by proposing an ANFIS-based Recovery Prediction (ARP) system that estimates the results of the DASH questionnaire to determine the recovery status of patients with shoulder injuries. The other aim of this study is to integrate the proposed ARP system into a Kinect-based integrated physiotherapy mentor application for shoulder damage (PhyMen), which is a valid and reliable [34] telerehabilitation system used for shoulder damage patient's rehabilitation [10]. With the integration of these systems, it is intended that physiotherapists can better observe the real-time recovery processes of patients and plan the rehabilitation processes more effectively.

In the continuous parts of this study, which differs from other studies and whose main novelty is AI-based prediction of patient recovery statues and integration into an existing physical therapy application (i.e., PhyMen), methods, results and discussion, and conclusion sections are given, respectively.

2 Methods

Within the scope of this study, the rehabilitation process of 105 patients with shoulder damage treated with PhyMen in Bilecik State Hospital was investigated. Since Bilecik State Hospital is the only hospital in Bilecik that provides shoulder rehabilitation treatment, it is thought that the results obtained in this hospital will reflect the generality. All patients received treatment for 12 sessions and PhyMen was used for treatment in the hospital about 4 months. Before starting the treatment, the demographic information (i.e., height, age, weight, and gender) of the volunteers was obtained, and their ability to perform abduction, flexion, internal rotation, external rotation, and extension exercises was measured with a clinical goniometer. Apart from this information, the DASH questionnaire was applied to the volunteers, and their pre-treatment DASH scores were recorded. After the treatment was completed, the post-treatment DASH scores of the volunteers were calculated, and their ability to perform the exercises was measured again with a clinical goniometer.

These data were used to compare volunteers' exercise abilities and DASH scores before and after the treatment. Then, the number of data points was increased with data augmentation methods, so a data set was created for the ARP. Using this dataset, ARP estimated the change in the DASH scores of the volunteers from the third day of the start of the treatment, thus predicting the recovery status of the patients upon the completion of the treatment. In order to make these predictions in real-time, ARP was integrated into the previously developed PhyMen, thus turning PhyMen into a treatment system that can predict the recovery status of patients.

The rest of this section provides detailed information about the DASH questionnaire, data set, ARP, and PhyMen.

2.1 Disabilities of the arm, shoulder and hand (DASH) questionnaire

The Disabilities of the Arm, Shoulder, and Hand questionnaire (DASH) was developed to evaluate disability and symptoms in single or multiple disorders of the upper body [33]. In DASH, there are 30 Likert-type questions with a five-point response scale (see Table 1). For the total DASH score to be calculated, at least 27 of these questions must be answered.

Turkish DASH questionnaire, the validity and reliability of which were demonstrated by Düger et al., (2006) [35], was applied to 105 patients before and after their treatment in Bilecik State Hospital. Using these patients' responses and Eq. (1), the total DASH score was calculated. If the DASH score is 0, it means no disability, and 100 means maximum disability. In Eq. (1) T_{D_S} denotes the total DASH score, Q_s defines each question score, and n represents the number of completed responses.

$$T_{D_S} = \left(\frac{\sum_{i=1}^{n} Q_s}{n} - 1 \right) \times 25 \quad (1)$$

2.2 Data set

The dataset used in this study comprised the demographic information of 105 patients who received treatment for shoulder injuries at Bilecik State Hospital, as well as the changes in angular measurement resulting from five types of exercises (abduction, flexion, internal rotation, external rotation, and extension exercises), and the changes in DASH scores before and after treatment. Through the application of data augmentation techniques, the number of patient data was increased to 232. In these data, there are four different injuries: proximal humerus fracture, adhesive capsulitis, rotator cuff, and impingement syndrome. Notably, each of these four injuries that require shoulder rehabilitation was represented equally within the data set, with 58 instances of each injury type being included. Table 2 gives the statistical properties of the data set.

2.3 ANFIS based recovery prediction (ARP) system

Artificial neural networks are one of the machine learning methods that can classify large amounts of data according to various output groups. On the other hand, Fuzzy inference systems can classify input values according to fuzzy memberships and produce clarified outputs according to defined coefficients. Adaptive network-based fuzzy logic inference system (ANFIS) is a hybrid model proposed by Jang (1993) that emerges by combining the learning ability of artificial neural networks with the human-like decision-making features of fuzzy logic [36, 37].

The ANFIS architecture consists of five layers: input layer, fuzzy layer, normalization layer, rule layer, and output layer. The input layer consists of the variables that are fed into the system, while the fuzzy layer generates fuzzy sets and membership functions based on these inputs. The normalization layer scales the outputs of the fuzzy layer, and the rule layer combines the fuzzy sets and generates fuzzy rules. Finally, the output layer performs the final computation and generates the system output. In Fig. 1, the general structure of ANFIS model is shown.

The first layer generates membership grades for each input variable based on a set of fuzzy if–then rules. The equations for this layer are:

$$\mu_{A_i}(x) = e^{\left(\frac{-(x-c_i)^2}{2\sigma_i^2} \right)}, i = 1,2 \quad (2)$$

$$\mu_{B_i}(y) = e^{\left(\frac{-(y-c_{i+2})^2}{2\sigma_{i+2}^2} \right)}, i = 1,2 \quad (3)$$

where $\mu_{A_i}(x), \mu_{B_i}(y)$ are the membership grades for inputs in fuzzy set A_i and B_i, c_i and σ_i represent the antecedent parameters. The second and third layers scale the output of the fuzzy layer so that the sum of the weights for each rule is equal to 1. The equations for these layers are:

Table 1 DASH questionnaire answer options

Question No	1	2	3	4	5
1–21	No difficulty	Mild difficulty	Moderate difficulty	Severe difficulty	Unable
22	Not at all	Slightly	Moderately	Quite a bit	Extremely
23	Not limited at all	Slightly limited	Moderately limited	Very limited	Unable
24–28	None	Mild	Moderate	Severe	Extreme
29	No difficulty	Mild difficulty	Moderate difficulty	Severe difficulty	So much difficulty that I can't sleep
30	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree

Table 2 Statistical properties of the data set

	Min	Max	Mean	Std
Height (cm)	150.00	190.00	165.16	7.05
Weight (kg)	50.00	110.00	74.70	7.71
Age (year)	25.00	81.00	54.82	10.56
Change in flexion (°)	0.00	70.00	30.62	13.13
Change in abduction (°)	0.00	82.00	35.51	14.02
Change in internal rotation (°)	− 10.00	42.00	18.34	7.90
Change in external rotation (°)	− 10.00	85.00	24.61	12.56
Change in extension (°)	− 5.00	20.00	4.78	4.01
Change in DASH (T_{D_S})	0.00	44.00	17.49	7.71

$$\overline{w}_i = \frac{\mu_{A_i}(x)\mu_{B_i}(y)}{\sum_i \mu_{A_i}(x)\mu_{B_i}(y)}, i = 1,2 \quad (4)$$

where $\overline{w}_i$ is the normalized weight for rule i. The rule layer combines the normalized weights with the consequents of the fuzzy if–then rules to generate a single output for the system. The equations for this layer are:

$$f_i = p_i x + q_i y + r_i, i = 1,2 \quad (5)$$

where p_i, q_i, r_i are the consequent parameters, and f_i denotes the output of rule i. The output layer sums the outputs of all the rules to generate the final output of the system. The equation for this layer is:

$$z = \sum_i \overline{w}_i f_i \quad (6)$$

where z is the output of the system. The ANFIS model involves a hybrid learning algorithm that uses a combination of gradient descent and least-squares methods to optimize the model's parameters. The learning algorithm involves two phases: a forward pass, which involves propagating the input through the network to produce an output, and a backward pass, which involves adjusting the model's parameters based on the error between the predicted and actual outputs.

In this study, the proposed hybrid model utilizing the ANFIS was employed for the prediction of recovery status. To estimate the DASH results using the ANFIS-based model, a total of 232 data points were collected, out of which 162 (70%) were utilized for training purposes and the remaining 70 (30%) for testing. The backpropagation algorithm was utilized for training the ANFIS, and several parameters were set for the training step size, step size reduction ratio, and step size increase ratio, with values of 0.01, 0.9, and 1.1, respectively.

The ANFIS utilized in this study was designed to have nine inputs, each of which is characterized by four membership functions, namely disease type, volunteer's height, weight, age, as well as the changes observed in the highest angles attained by the volunteer during various exercises (including abduction, flexion, internal rotation, external rotation, and extension) before and after treatment. The output parameter was determined as the change in the DASH results of the individuals. Using these input parameters and associated rules, the ANFIS-based ARP was utilized as a system for predicting the recovery status of individuals with shoulder injuries.

2.4 Kinect-based integrated physiotherapy mentor application for shoulder damage (PhyMen)

PhyMen is a system developed to enable physiotherapy exercises of patients with shoulder joint, muscle, and tendon injuries to be performed correctly and effectively, to record the data generated during the treatment process, to provide instant information to physical therapists about the treatment processes of patients, and to enable physiotherapy specialists to update the treatment process. As shown

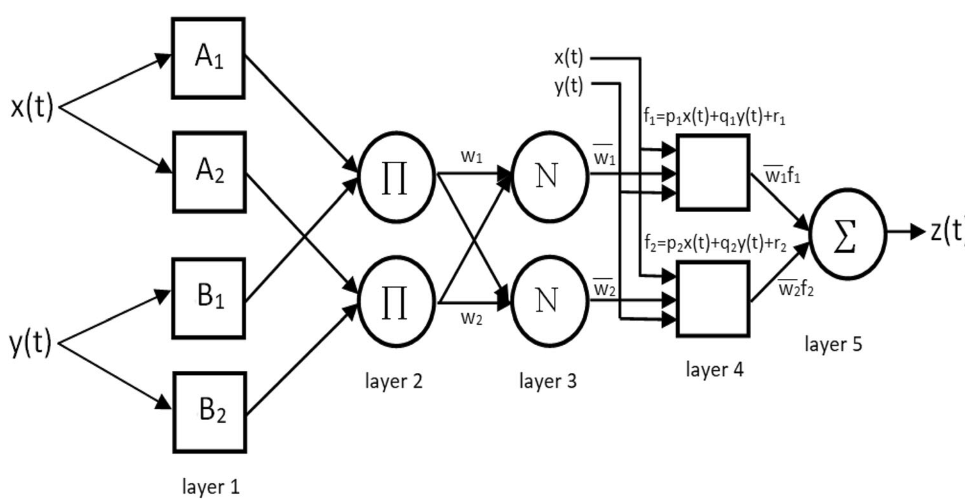


Fig. 1 The general structure of ANFIS model [38]

in Fig. 2, PhyMen consists of two basic components, a console application and a web application. Console application, called ISPA (Integrated Physiotherapy Mentor Application), allows patients with shoulder injuries to perform exercises correctly and record their exercise data. The web application provides telecommunication between patients and physiotherapists. PhyMen was established in Bilecik State Hospital and used in the treatment of shoulder patients. A room is reserved for the system in the hospital. With the guidance of PhyMen, patients can perform their exercises at a distance of 2 to 2.5 m from the system [10]. In this study, the data obtained from this system was used.

In Fig. 2, sections. 1 and 6 depict the communication between the physiotherapist and the web application, while sections. 2 and 5 illustrate the bidirectional data exchange between the Kinect-based Intelligent Shoulder Physiotherapy Assistant (ISPA) and the server. section 3 provides information and feedback to patients for the accurate execution of physical exercises, while section 4 calculates the joint angles of the patient during the exercise using the joint points detected by Kinect. Additional information about the PhyMen application can be found in the study conducted by [10].

PhyMen's real-time functioning capability is a significant advantage, as it allows the Adaptive Neuro-Fuzzy Inference System (ANFIS) for Recovery Prediction (ARP) to instantly predict the recovery status of patients. This feature provides healthcare professionals with an efficient and reliable tool to evaluate the effectiveness of the treatment provided and make adjustments if necessary. The accuracy of the ARP model was evaluated using a data set composed of information from the patients who received treatment for shoulder injuries at Bilecik State Hospital.

3 Results and discussion

Data from 232 volunteers in the dataset were used to develop the recovery prediction system. Figure 3 presents the demographic information of these volunteers, as well as the changes in the angular measurements of exercises and DASH scores. As elaborated in Sect. 2.3, the ARP system was designed to utilize nine input parameters, which include disease type, volunteer's height, weight, age, and the differences in the highest angles that the volunteer could perform in exercises such as abduction, flexion,

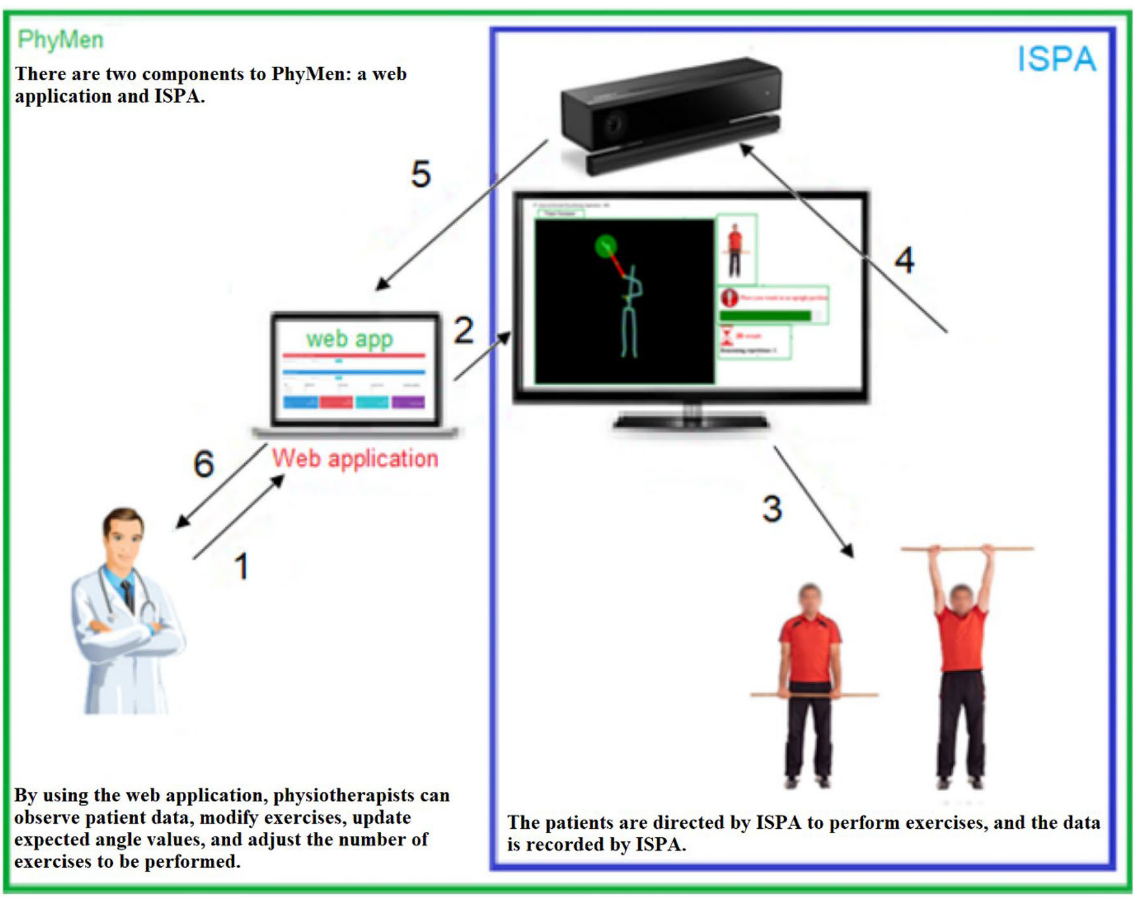
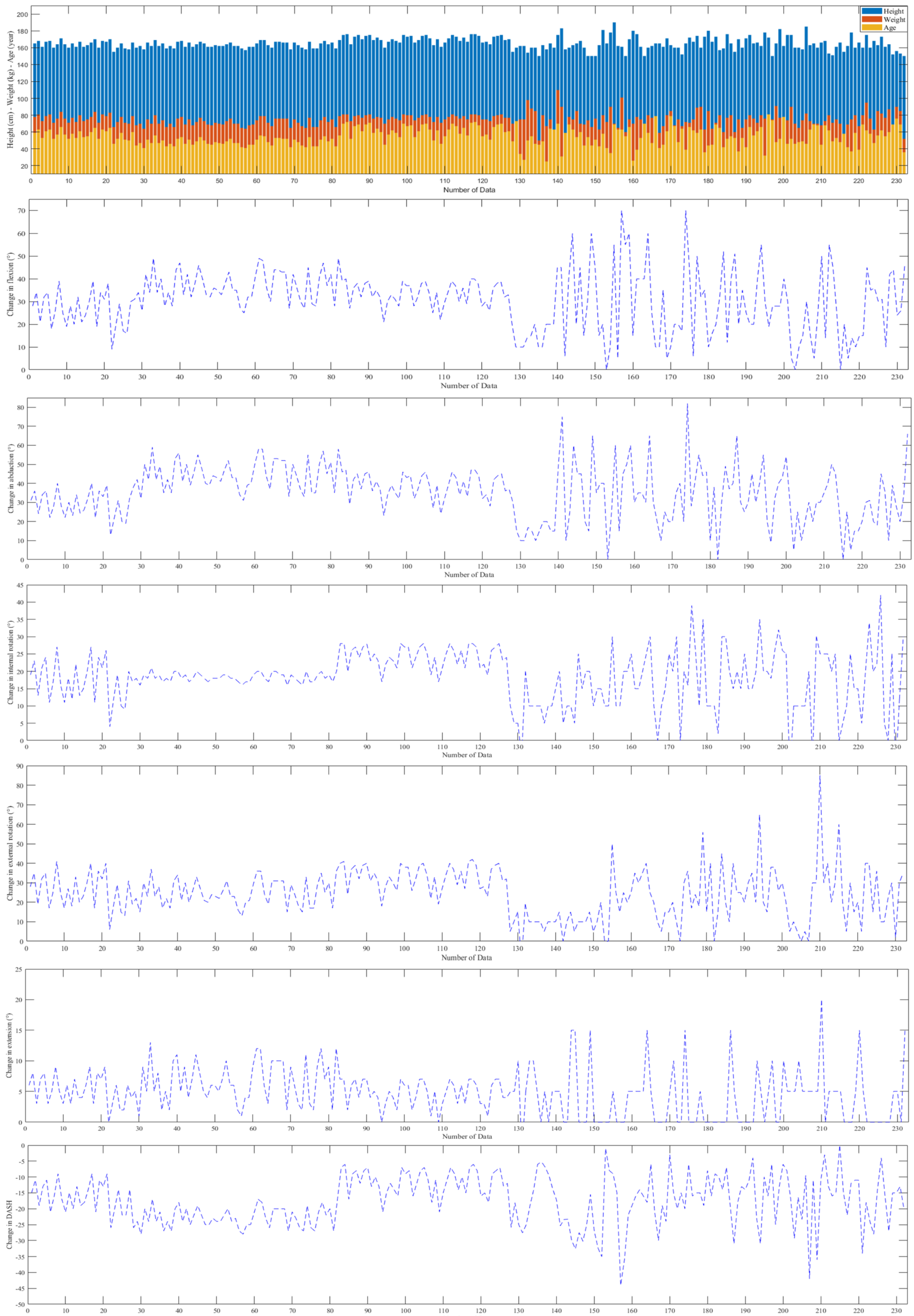


Fig. 2 Kinect-based integrated physiotherapy mentor application (PhyMen) [10]


Height
Weight
Age
Height (cm) - Weight (kg) - Age (year)
Number of Data
Change in flexion (°)
Number of Data
Change in abduction (°)
Number of Data
Change in internal rotation (°)
Number of Data
Change in external rotation (°)
Number of Data
Change in extension (°)
Number of Data
Change in DASH
Number of Data

◀ **Fig. 3** Data set **a** height, weight, age **b** change in flexion **c** change in abduction **d** change in internal rotation **e** change in external rotation **f** change in extension **g** change in DASH

internal rotation, external rotation, and extension after and before the treatment. Furthermore, the change in DASH results was determined as the output parameter for the ARP system.

The ANFIS model employed in the ARP system comprises nine inputs, each of which is associated with four Gaussian membership functions. The Gaussian function utilized in the model has two primary parameters, namely, mean and standard deviation. Initially, these two parameters are assigned randomly. Figure 4 depicts the input membership functions obtained before and after training for a single run.

At the fourth layer of the ANFIS model, there are four Sugeno rules. Throughout the training of the ARP system, a total of 112 model parameters were optimized, comprising 72 antecedent parameters (9 × 4x2) and 40 consequent parameters (4 × 10). In the training of the model, the data were normalized between 0–1 and applied to the ARP system.

In the single training result shown in Fig. 5, the mean squared error (MSE) was found to be 16.176, whereas the root mean squared error (RMSE) was found to be 4.022. The error values are provided at the lower left of Fig. 5, and the distributions of these errors are displayed at the lower right of Fig. 5. The mean of the error change for training data was − 0.033, and the standard deviation of the errors was 4.034. Analysis of the error graph revealed that the number of training samples with an error greater than 10 was 5, whereas the number of samples with an error between − 5 and 5 was 141.

Figure 6 depicts the predicted DASH score change values for the 70-test data of the proposed ARP system, along with the corresponding error variations and error histogram. In a single run, the test results showed that the mean squared error (MSE) was 68.8689 and the root mean squared error (RMSE) was 8.2987, as presented in Fig. 6.

The mean of error change for the test data was calculated as − 0.8709, and the standard deviation of the errors was found to be 8.3125. Notably, the number of test samples with an error greater than 10 was 14, while the number of samples with an error between − 5 and 5 was 48. As expected, the training results showed lower error values than the test results. However, both stages exhibited a positive correlation between the predicted and observed data, as shown in Fig. 7. These findings demonstrate the potential of the ARP model in predicting recovery status based on the nine input parameters and the change in DASH scores.

To evaluate the performance of the ARP system, it was run 1000 times with shuffled test and training datasets in each run. The Mean Squared Error (MSE) and Sum of Squared Errors (SSE) were separately calculated for training and test sets. The results, including statistical

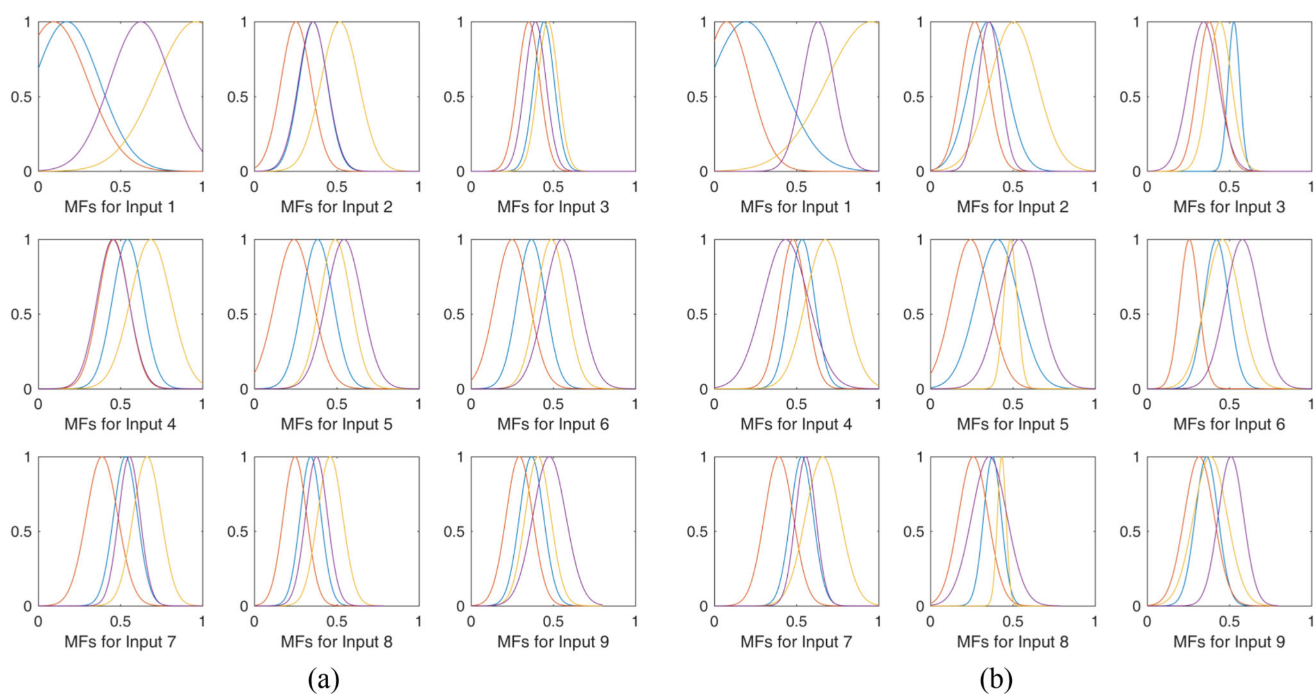


Fig. 4 Membership functions of each input in ARP system. **a** Before training and **b** After training

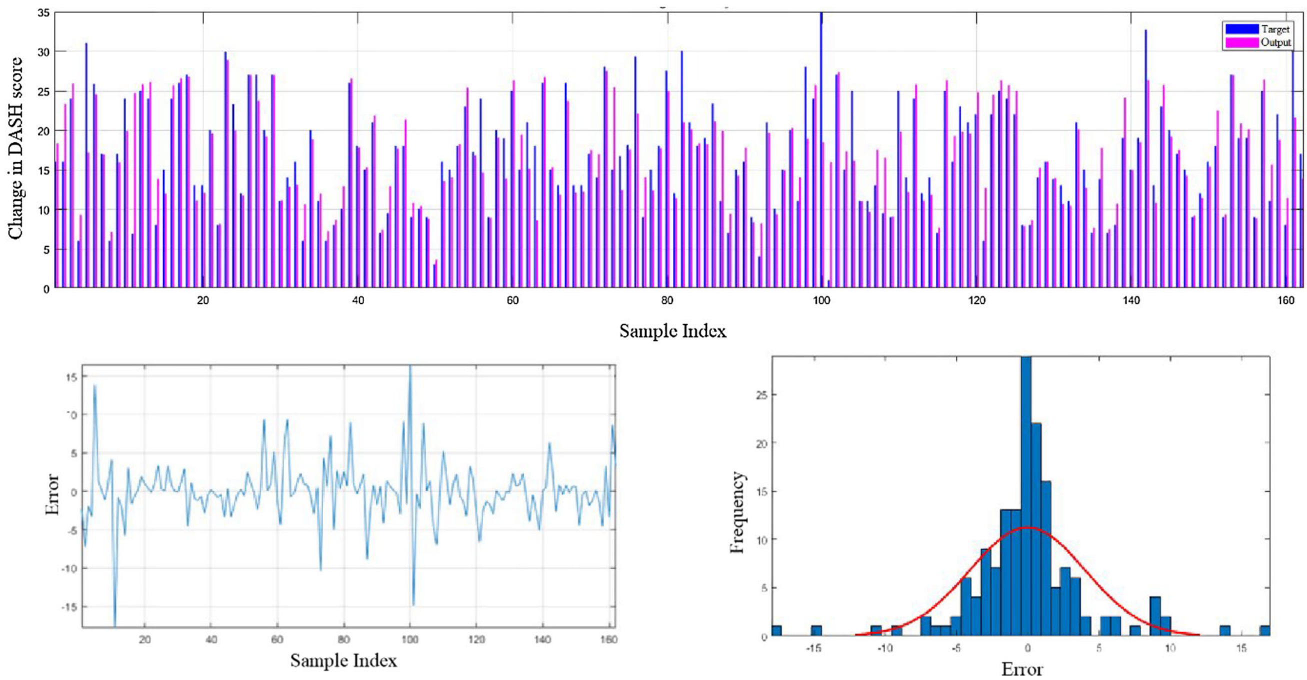


Fig. 5 The training results of ARP system

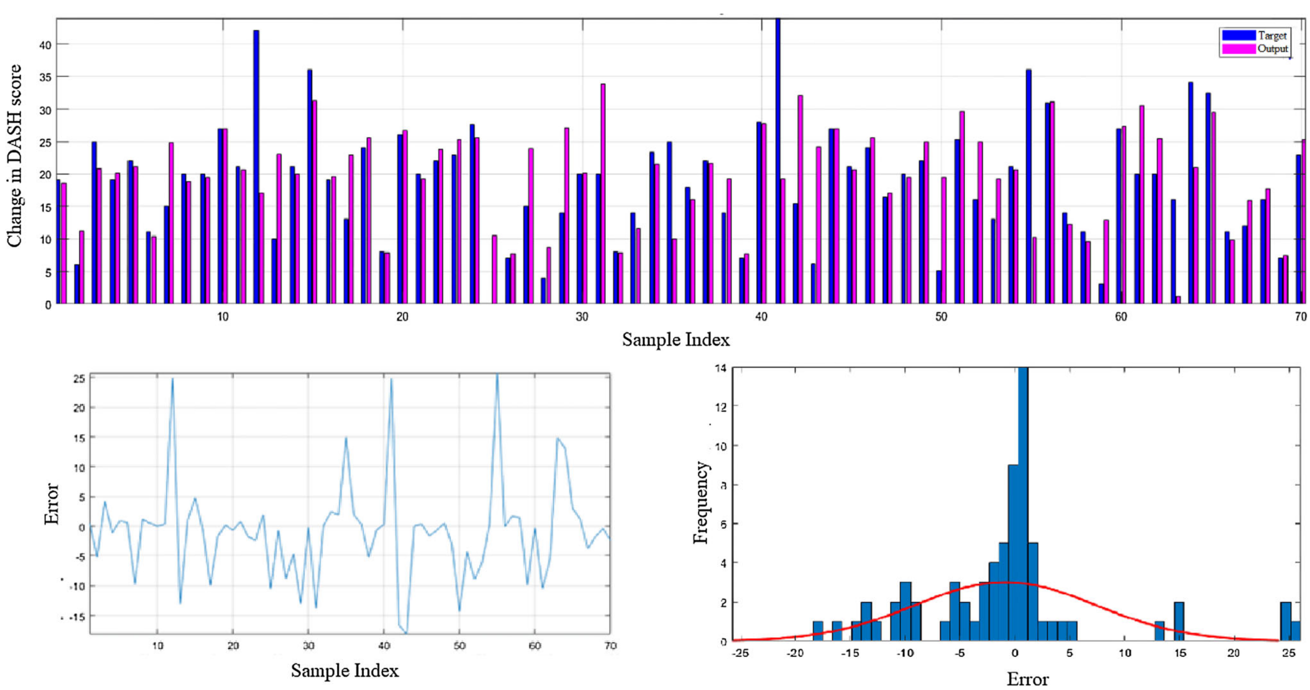


Fig. 6 The test results of ARP system

metrics such as the best, mean, worst, and standard deviation, are presented in Table 3 to provide a comprehensive assessment of the system's performance.

It is seen in Table 3 that the training results are more successful than the test results after 1000 different runs. While there is approximately three times difference between the best and worst results in the training results, this rate increases to about five times in the test results. Looking at the best of these test results, the error is low. This low error indicates that the DASH change estimates are promising.

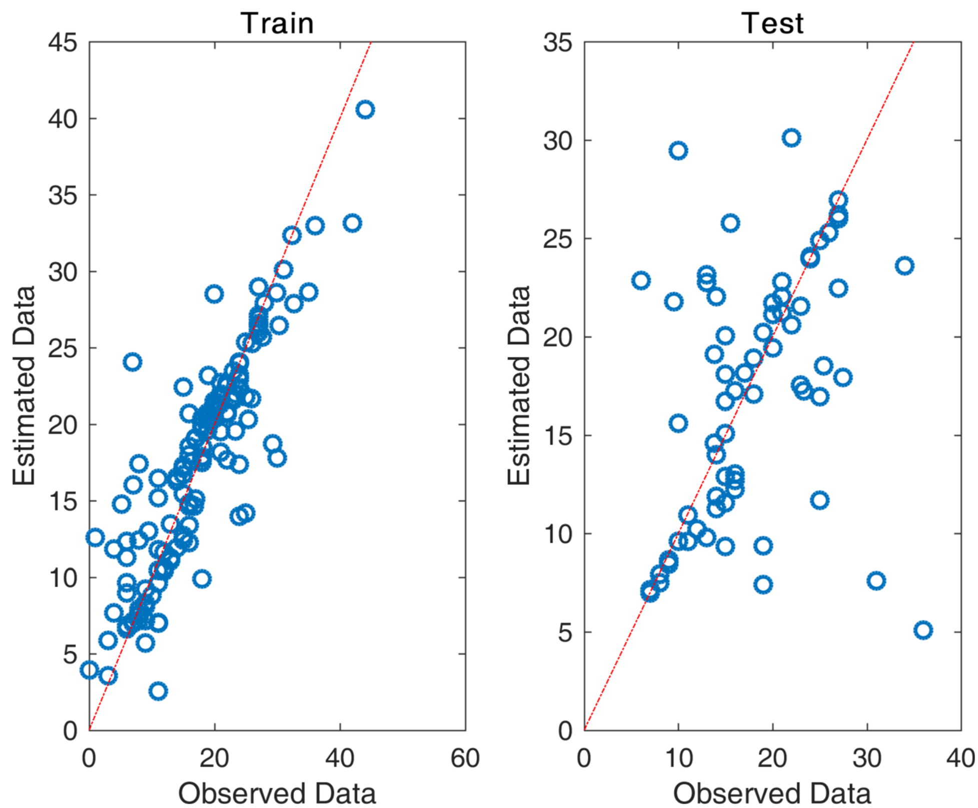


Fig. 7 Training and test results of ARP system

Table 3 Statistical results of ARP system

Metric	Test MSE	Test SSE	Train MSE	Train SSE
Best	9.419E − 03	6.593E − 01	4.228E − 03	6.849E − 01
Mean	2.556E − 02	1.789E + 00	9.388E − 03	1.521E + 00
Worst	5.090E − 02	3.563E + 00	1.393E − 02	2.257E + 00
Standard Dev.	6.085E − 03	4.259E − 01	1.629E − 03	2.639E − 01

Since the best results obtained in the test results are considered promising, the parameters here are precisely transferred to the PhyMen system so that the DASH change estimates are real-time. By integrating the ARP system into PhyMen, predictions of patients' recovery status can be seen in real-time. Figure 8 displays the screen of the PhyMen page where real-time predictions are made. Figure 9 presents a screenshot of the system during a volunteer's use of PhyMen while exercising, and Fig. 10 illustrates the screen used by physiotherapists to view the results of exercise conducted by patients on the web. A detailed explanation of PhyMen is available in the study of [10].

The integration of an ANFIS-based method for estimating changes in DASH scores into PhyMen has enabled the software to instantly predict DASH results for users of the system. The flowchart of the systems as a result of this integration is shown in Fig. 11. The software uses the patient's disease type, height, weight and age in the database as input parameters. To further improve the accuracy of the predictions and minimize the risk of incorrect results, PhyMen also considers changes in certain exercise measurements (such as abduction, flexion, internal rotation, external rotation, and extension) by using the difference between the highest measurement from the first two sessions and the highest measurement from the last two sessions as input parameters.

It is clear that with the developed ARP system and its integration into PhyMen, the recovery status of patients can be better observed throughout the treatment period. Before the ARP system was added to PhyMen, patients could do their exercises with PhyMen. However, there was no reliable data, such as DASH, where physiotherapists could observe the recovery status of patients. This is one of the situations in Turkey where all patients in State Hospitals are rehabilitated for 12 days, and many of them do the

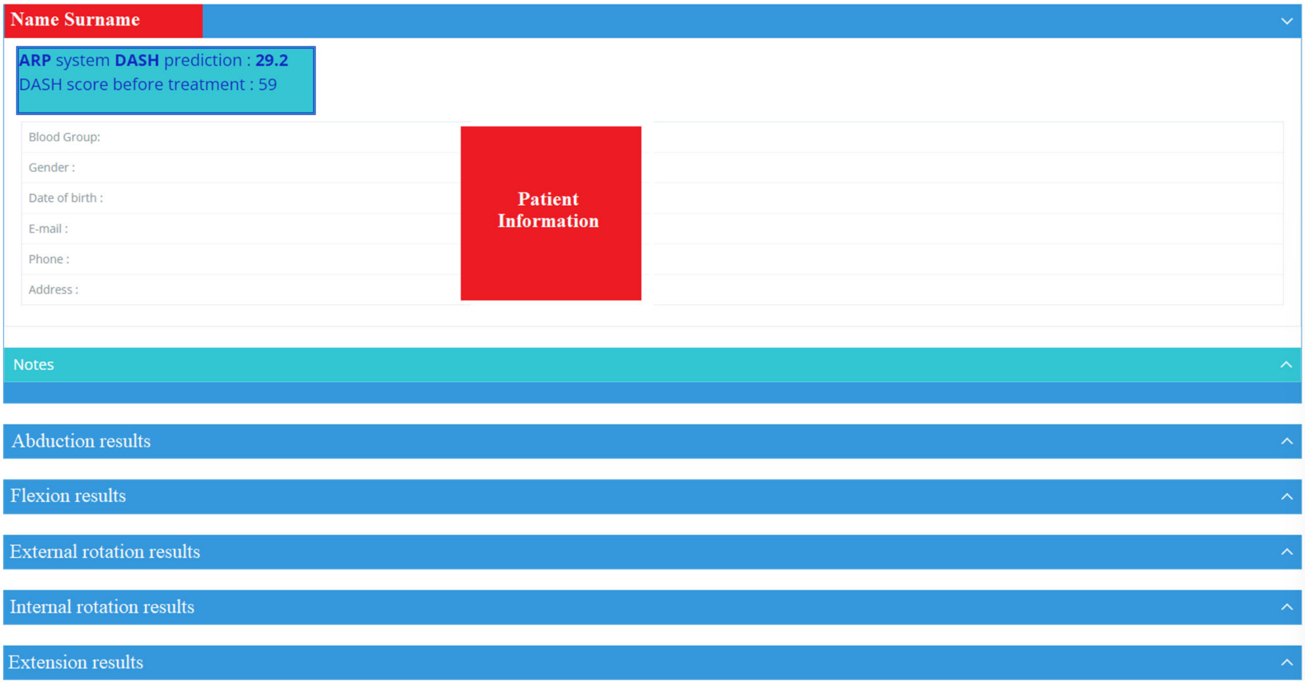


Fig. 8 Screen of DASH estimation on PhyMen

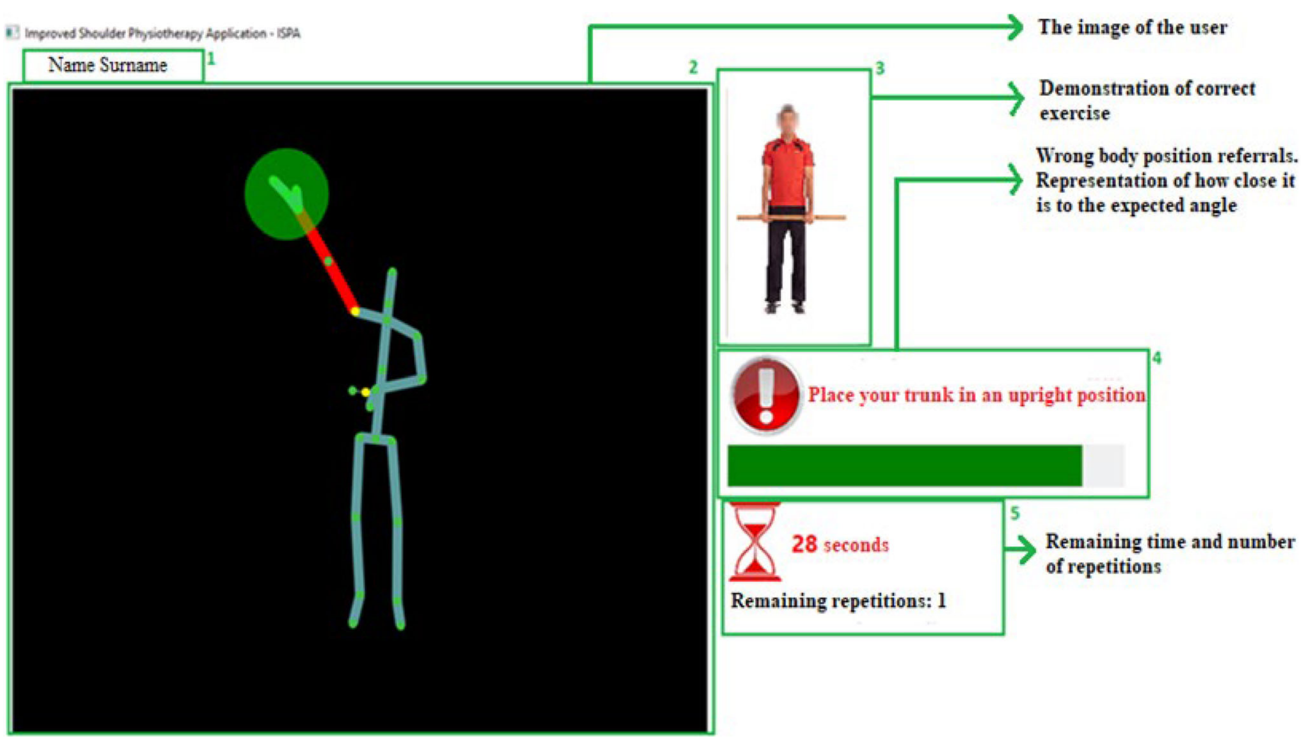


Fig. 9 A screen of the PhyMen while a volunteer is exercising [10]

same exercises the same number of times. Thanks to PhyMen, which is powered by the ARP system, physiotherapists can perform actions such as updating the number of exercises a patient is required to do or extending the total duration of the treatment before their treatment ends.

Compared to other studies such as telerehabilitation systems developed for Parkinson's [15], which use robotics for telerehabilitation [39], aim to provide remote exercise [40], aim to increase the effectiveness of game-based rehabilitation [41], it is considered that the main innovation

Fig. 10 PhyMen exercise result screen

of the proposed system is the prediction of the recovery status of the patient while the treatment continues. The recovery prediction results made by ARP are considered promising, with the best MSE results $4.228E-03$ for training data and $9.419E-03$ for test data. To the best of our knowledge, no studies to date have focused on DASH prediction by using AI, so it is not possible to compare the estimation accuracy with other studies.

4 Conclusion

Shoulder injuries are frequently observed among patients who require physical therapy. To evaluate the patient's disability status, physiotherapists commonly employ the Disabilities of the Arm, Shoulder and Hand (DASH) questionnaire. However, the DASH score is usually assessed at the conclusion of treatment, posing difficulties in monitoring the patient's recovery progress during the treatment process.

In this study, we developed an artificial intelligence-based (ANFIS) system to predict the recovery progress of shoulder injury patients using the Disabilities of the Arm, Shoulder and Hand (DASH) questionnaire during treatment. The system was integrated into Kinect-based integrated physiotherapy mentor application for shoulder damage (PhyMen), which enables real-time DASH score predictions. Our results suggest that the ANFIS-based system accurately predicts patient progress. The utilization of this system by physiotherapists may aid in monitoring patient conditions and predicting treatment outcomes.

As there are no systems focused on recovery prediction, the performance of the proposed system's prediction results accuracy cannot be compared. Therefore, future studies

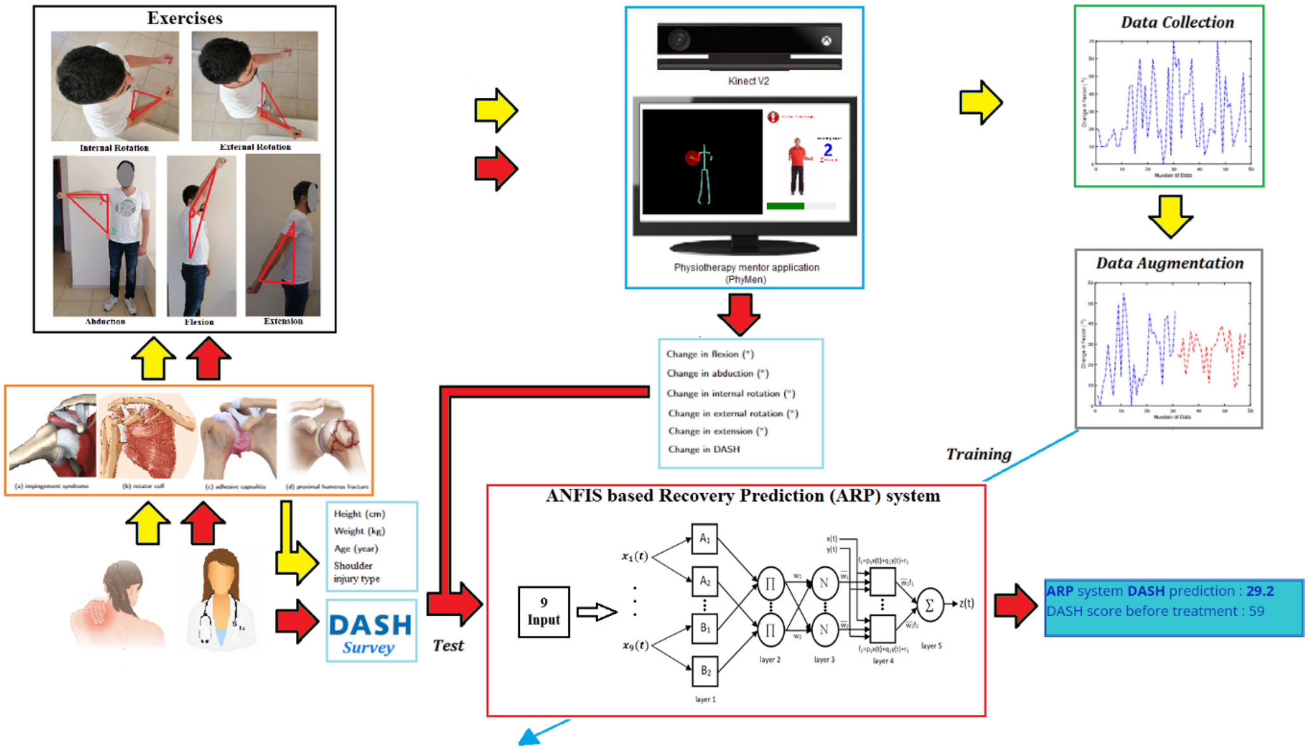


Fig. 11 Flowchart of the real-time recovery prediction system

aim to use various artificial intelligence methods such as multilayer perceptron and long short-term memory to make recovery predictions. Additionally, PhyMen is currently a system used only for shoulder damage patients' treatment; however, it is intended to be developed for patient's damage in other body parts with the guidance of expert opinions.

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Author contributions BC: Conceptualization, Methodology, Software, Data preparation, Writing. UY: Conceptualization, Methodology, Supervision, Writing, Review, Editing.

Data availability Since the dataset used in the study was obtained from patients, is not openly available, and is available from the corresponding author upon reasonable request for sharing.

Declarations

Conflict of interest The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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