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Recommender System with Artificial Intelligence for Fitness Assistance System*

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***Abstract*—This paper proposes a recommender system (RS) to support the fitness assistance system (FAS) with artificial intelligence. The RS is applied to make these suggestions for the beginners and existing users. The goal of the paper aims to develop an RS that has an ability to learn, analyze, predict, and make these suggestions as well as communicate to human through AI. Artificial Neural Network and Logistic Regression have been employed to predict the suitable workout for each beginner. In addition, the agent developed with reinforcement learning capability of Soar architecture help the members select their workout based on their condition. Through the experimental result, the effectiveness of utility application is validated.**

I. INTRODUCTION

The RS is known as a part of information filtering system which helps the users seek the prediction of rating or preference that users would give to an item or service recommendations [1]. Currently, the RS has been upgraded with the several machine learning algorithms to provide users with the suggestion for their purposes in [2] or build the framework for RS as shown in [3]. In the fitness field, recent studies have focused on developing the RS to user with a wearable device and recording data in real-time. A fitness assistant framework is developed to smartly track and identify user's activity based on contextual interpretation in [4-5]. Moreover, RS has been approached for a runner, which is described in [6].

The purpose of this study is to design the RS that will suggest personalized workout to the users and predict the plan for doing exercise in future. In the proposed RS, we use machine learning algorithms on activity data to build a predictive module in the basic training layer (BTL) that classify the user's activity in their workout. In addition, we also build the trainer agent (TA) with Soar architecture and machine learning algorithm to reflect the prediction of BTL for suggesting the several workouts to help users select the suitable workout fitting well with their exercise plan.

The rest of the paper is organized as follows. In Section II we introduce the overview of FAS and RS. In Section III we define the requirements based on the results of user survey and implement the methodology in details of RS to help the users to make the suggestions for their workout. Some preliminary experimental results are discussed in Section IV, and we conclude the present work with our plan for future work in Section V.

II. BACKGROUND OF RS WITH AI

A. The Fitness assistance system

The FAS is the system designed to support users doing exercise with two motors (called fitness assistance equipment, FAE) used to support lifting the weight of exercise instead of the traditional method. The structure of FAS is shown in Fig. 1. As shown in Fig. 1, in order to control the FAE, there is an embedded controller built with microcontroller to control the speed of two motors. In FAS, the proposed RS is added to predict appropriate suggestions for users and transfer a control commands to embedded controller conducting the FAE.

The proposed RS used in FAS is a system combined with artificial intelligence (AI) packages, which plays a role as a professional trainer to give the training instructions of workout for users based on predictability and data analysis to provide the appropriate suggestions according to user's condition. Machine learning algorithms help RS improve the ability of learning, identifying and acquiring knowledge from the real workout data. Particularly, it supports FAS to perform the simulation of exercise for each user's requirements.

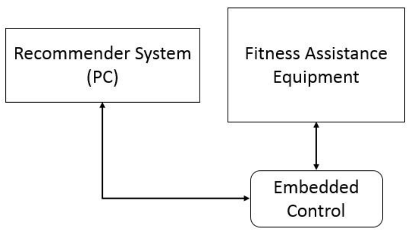

Figure 1. Structure of fitness assistance system.

B. RS architecture of fitness equipment

The structure of RS employed in FAS is illustrated in Fig. 2. In order to build the RS with AI, some machine learning

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algorithms have been applied to predict and give the workout recommendation. As shown in Fig 2, the structure of RS is composed of two modules: basic training layer (BTL) and trainer agent (TA), where BTL is built with Artificial Neural Network (ANN) and Logistic Regression (LR). Data classification is the core component of this module. In the current implementation, the main task of this module aims to predict and give the suggestions of workout for beginners based on their initial information.

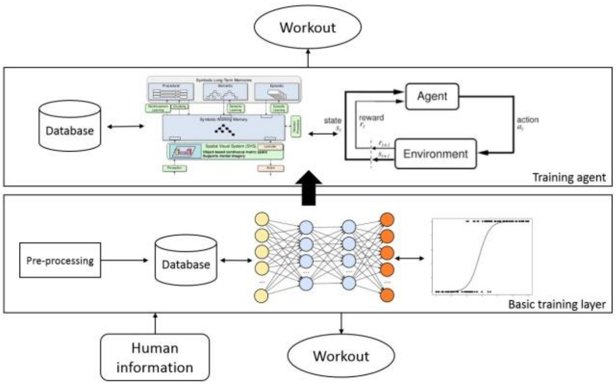

Figure 2. Recommender system architecture.

After then, the result of suggestions from the BTL will be stored and updated with the new data into the database. TA is the module integrated with Soar and Reinforcement Learning (RL) to suggest the several recommendations based on some supposed rules with the reference result from BTL. We define some rules with reference conditions in Table I for Soar agent and through RL algorithm to suggest the various recommendations at the same time. Hence, users select the appropriate workout based on the overall assessment given by this module. The profile of workout also changes to suit each specific user.

III. METHODOLOGY

In order to build the proposed RS, we proceed to collect individual data several volunteers to generate the dataset for training, including men and women. We assume that the patterns of volunteers are considered as standard data to predict and generate the suggestion for the beginner using the FAS to get the workout in the first time. To generate user's profile, format of user's input data includes gender, age, height, weight, type of exercise, and one-repetition maximum (1-RM). The output suggestions are exercise weight, repetition, and break time for each suggested set.

Furthermore, the important parameters of the input value are 1-RM index. In weight training, 1-RM is the maximum amount of force that can be generated in one maximal contraction [7]. It can be used for determining an individual's maximum force, or as an upper limit in order to figure out the desired "load" for an exercise.

A. Workout properties determination

As mentioned above, the RS needs user's profile as an input information of RS to compare with its database, then predict and generate the recommendation workouts that take following attributes

- *Gender:* man or woman who does exercise with FAS
- *Age:* from 20 to 60 years old
- *Height:* between 160 and 200 centimeters
- *Weight:* range of 40 to 120 kilograms
- *Type of exercise:* six types such as flat bench, incline bench, decline bench, squat, shoulder press and deadlift
- *1-RM:* maximum load for an exercise

On the other hand, we assume that the purpose of doing exercise, i.e., diet or muscle up, needs to be evaluated based on the 1-RM index by the supposed rules shown in Table I, as shown in [8]. The users will be checked for their 1-RM index before using the FAS for each workout. As can be seen from Table I, 1-RM indices are set up each purpose of doing exercise as below

TABLE I. GUIDELINE FOR 1-RM INDEX

Purpose	1-RM (%)	Repetition	Set	Break
Diet	<67	~ 20	1	<4mins
		~17	2	<4mins
		~15	3	<4mins
Muscle up	67~85	~15	1	<4mins
		~13	2	<4mins
		~11	3	<4mins

B. ANN and LR for training dataset

This module is responsible for training dataset to predict and suggest an appropriate type of workout for the beginner, which is ANN and LR. The combination between ANN and LR allows the implementation of the analysis and prediction of average result based on the sample patterns. With LR, hypothesis function *H(X)* is described as below.

$$H(X) = \frac{1}{1+e^{-W^T X}} \quad (1)$$

where X denotes the input matrix, and W is the weight. To calculate the error index on training process, the cost function of LR is written below

$$cost(W, b) = \frac{1}{m}\sum_{i=1}^{m}(H(x^{(i)}) - y^{(i)})^2 \quad (2)$$

where x is input value, y denotes output value, m expresses the number of values, including input and output, and b is bias.

In addition, from the cost function presented in (2), with the optimization in place, LR cost function can be rewritten as following

$$cost(W, b) = -\frac{1}{m}\sum_{i=1}^{m}[y^{(i)} log\left(H\left(x^{(i)}\right)\right) + \left(1 - y^{(i)}\right)\log(1 - H\left(x^{(i)}\right))] \quad (3)$$

To combine with ANN, Rectifier Linear Unit (ReLU) is applied to train the user profile data for better prediction and recommendations. We defined seven hidden layers to train the user profile data with each weight and bias for each hidden layer. Fig. 3 shows the training process with user's profile data.

In order to train the user's profile data with ReLU, the hypothesis function $H(x)$ can be attained by calculating with weight and bias for each layer, as presented in the following

$$H(x) = W_j x_j + b_j \quad (4)$$

where x is input value, W is weight, and b denotes the bias at the j-th layer.

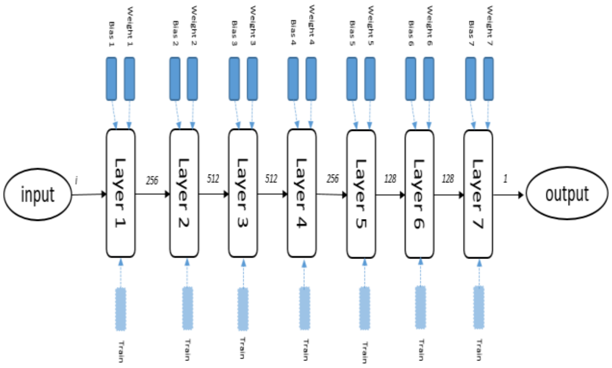

Figure 3. ANN structure with ReLu.

In BTL, ANN creates the neural network with several hidden layers with the input values as mentioned in Section III. It converts the inputs for the next layers. Then the outputs are the workout parameters, including weight of exercise, repetition, and break time for three sets. LR is applied to classifying the suggestion result based on the relationship between input and output.

C. Soar agent and RL to setup the workout plan

Soar agent with RL is applied to suggest the workout plan recommendation to user based on the reference result from the BTL as mentioned above. With the predictive recommendation from BTL, features of Soar agent aims to recommend the several particular workouts for the existing member that can select the exercise time, type of exercies, repetition and set. Soar agent plays a role of the professinoal trainer for users. To provide the recommendations, we designed the trainer agent with RL algorithm based on epsilon value in order to compare the highest epsilon score in the epsilon-greedy method [9]. The final recommendation will be selected by the highest epsilon score corresponding to a suggestion.

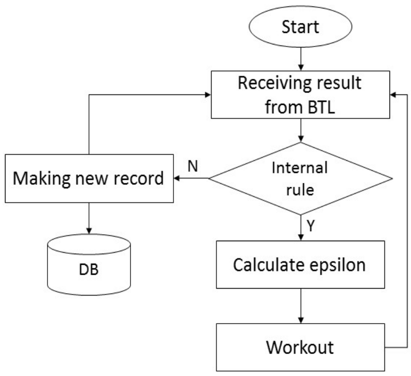

Figure 4. Block diagram of TA to suggest the workout

To perform a suggestion of workout plan, based on the first workout from BTL, TA implements the comparison with the assumed rules that we build for Soar architecture. Fig. 4 shows a process of using TA for making a workout evaluation for each user with its accuracy and suitability.

IV. Experiment Result

For validating the performance of the proposed RS that is discussed in this paper, we experimentally evaluated with four volunteers as the beginners of FAS. Since the present FAS has not been completely finished its functions, we have just implemented the experiment with the BTL for predicting and suggesting the workout plan for four new beginners. The experimental evaluation of TA in our proposed RS will be discussed in future work.

A. Experimental setup

Before using the proposed RS, we collect the 1-RM indices of each volunteer to determine their maximum power. For our experiments, we used the dataset collected by the several volunteers mentioned in Section III. The data were collected with some information format, i.e., gender, age, height, weight, type of exercise, and 1-RM, and purpose of diet or muscle up.

The 1-RM index is calculated for the experimental users with their purpose. Once the 1-RM is calculated and stored as input to the BTL, experiments were carried out for the sample records of dataset to create the database for training with AI algorithm. Also, the supposed rules in Table I will be used with TA for evaluation of workout.

TABLE II. The input information of user for experiment

	User1	**User2**	**User1**	**User2**
Purpose	Diet	Diet	Muscle up	Muscle up
Age	30	26	31	24
Gender	Male	Male	Male	Female
Weight	57	70	75	59
Height	162	175	175	167
1-RM	30	50	50	30
Type	1	1	1	1

As can be seen in Table II, the input private information of four experimental users will be used to validate the accuracy of algorithm applied to BTL. These experimental users are people who use the FAS for the first time.

B. Experiment evaluation

The experiment results for purposes of diet and muscle up are shown in Table III, which illustrates the workout parameters suggestions, i.e., exercise weight (kg), repeat (time), and break time (min) to user.

TABLE III. Suggesstion for diet and muscle up with user's profile

	Set 1		**Set 2**		**Set 3**	
	User1	**User2**	**User1**	**User2**	**User1**	**User2**
			Diet			
Weight	12	20	14	23	14	24
Repetition	17	19	17	15	13	13
Break	2	2	2	2	2	1
			Muscle up			
Weight	33	20	36	21	39	24
Repetition	14	14	11	9	7	6
Break	2	2	3	3	3	3

As can be seen in Table III, the output workout type of BTL includes weight, number of repetition, and break time. We observe that the workout for purposes of diet and muscle up matches well with the guideline as shown in Table I. With the purposes of muscle up and diet, there are two users who use the FAS to do exercise.

According to Section III, the recommendation workout type for each user is predicted by BTL. We observe the comparison of different workout parameter as the weight between the purposes of diet and muscle up. It depends on the 1-RM index, and the workout recommendation is validated in terms of prediction accuracy.

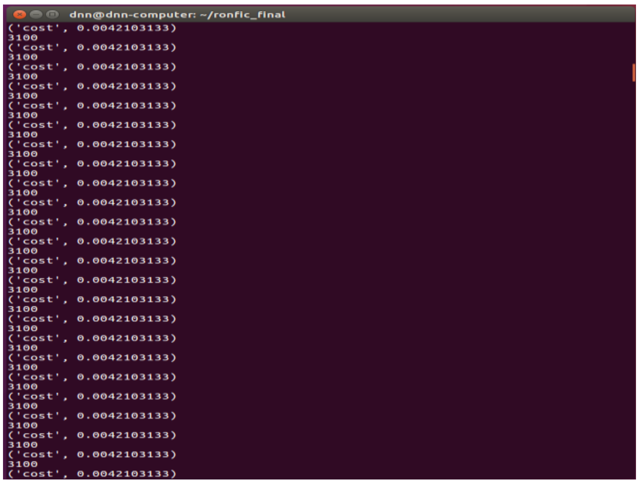

Figure 5. Accuracry of cost value for workout parameter.

On the other hand, in order to prove the accuracy of prediction with BTL of the proposed RS in this paper, we show the result of cost values when training the dataset with the output parameters of workout such as weight, number of repetition, and break time, as shown in Fig. 5. In Fig. 5, the cost value is very low, which means the training dataset gets the high accuracy.

V. Conclusion and Future Work

In this study, we proposed RS for fitness assistance system and a novel method for fitness workout recommendation with artificial intelligence algorithms. We developed a system with several machine learning algorithms to predict and train data to give the suggestion for the fitness workout. The ANN with LR implements the prediction of workout parameters with the best accuracy. The proposed RS is expected to give better recommendation for user to do exercise.

Table IV illustrates the result of User#1 with the purpose of muscle up between suggested workout and the supposed rules. As can be seen in Table IV, the exercise weight for User #1 is in the range of the supposed rule. In the meanwhile, the repetition and break time also approach the values within the range of the assumed rule as shown in Table I.

As future work of this study, we plan to focus on improving the TA module in the proposed RS with Soar agent by designing the RL algorithm to recommend several workouts for existing member's average selection. TA will be developed in future work for improving its features to calculate the epsilon value of epsilon-greedy method, and validate the suggested workout for approaching the stuitable workout plan to the users. Consequently, the proposed RS will play a role of the professional trainer for user in future.

TABLE IV. The suggestion result of user #1 with purpose of muscle up

	Weight	**Repetition**	**Break time**
Set 1	33	14	2
Set 2	36	11	3
Set 3	39	7	3
Supposed rule	33.5 ~ 42.5	<15	<4

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