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Artificial Intelligence based Recommender System for Fitness Assistance

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ABSTRACT

In recent years, there has been a growing awareness and emphasis on health and fitness. People are becoming more health-conscious, leading to an increased demand for personalized fitness guidance. Traditional fitness assistance systems typically involve generic workout plans, dietary guidelines, and limited interaction with users. Personal trainers, while providing personalized guidance, are expensive and may not be accessible to everyone. Generic fitness apps offer predefined workouts, but they lack the adaptability and personalization artificial intelligence (AI) can provide. These systems often do not consider individual preferences, past fitness experiences, or real-time feedback, leading to suboptimal results for users. The integration of AI in fitness assistance systems can be traced back to the early 2000s when researchers began exploring machine learning algorithms to analyze user behavior and preferences. Over the years, advancements in AI technologies, particularly in deep learning and natural language processing, have significantly improved the capabilities of these systems, enabling them to provide more accurate and personalized recommendations. Therefore, the need for AI-based recommender systems in fitness assistance arises from the diverse and unique requirements of individuals concerning their fitness goals, preferences, and health conditions. A personalized approach ensures that users receive tailored workout routines, nutrition plans, and lifestyle recommendations, leading to higher motivation, adherence, and ultimately, better fitness outcomes. Moreover, AI-based systems can continuously adapt and learn from user interactions, providing ongoing support and motivation. Therefore, this research aims to build AI-based recommender systems for fitness assistance to provide personalized and adaptive recommendations to users based on their unique fitness goals, preferences, and health conditions.

Keywords: Fitness Assistance, Recommender Systems, Nutrition Plans, Health-conscious, Workout Routines.

1.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. Currently, the RS has been upgraded with the several machine learning algorithms to provide users with the suggestion for their purposes in or build the framework for RS as shown in. 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. Moreover, RS has been approached for a runner, which is described in. 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 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 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.

2. LITERATURE SURVEY

In the past few decades, lots of clinical data have been collected across different sites. With the growth of information technology, these data provided a high value of digital information to integrate into the healthcare recommendation system [1]. These systems gave patients a personalized recommendation and improved understanding of their medical condition. Personalized diets, exercise routines, medications, disease diagnoses, and other healthcare services all belong to the domain of healthcare recommendation systems. In addition to health-related recommendation systems, various recommendation systems have been integrated into online retailers, streaming services, social networks, physical assistants, and e-commerce applications [2].

The current AI-driven global health interventions cover four categories relevant to global health researchers: (1) diagnosis, (2) patient morbidity or mortality risk assessment, (3) disease outbreak prediction and surveillance, and (4) health policy and planning [3]. Focus on health policy and planning of previous healthcare recommendation systems, collaborative filtering, content-based, knowledge-based and hybrid approaches are the basic recommendation techniques in health [4] recommender systems [5]. The preventive programs for therapy optimization, adherence and risk factor management including exercise training, are now recommended for patients with CVD to reduce disease recurrence by the 2016 European guidelines for CVD prevention [6]. The European Association of Preventive Cardiology developed a digital training and decision support system for optimized exercise prescription in CVD patients based on the definition and diagnostic criteria for diseases and risk factor [7].

On the other hand, up to 75% of the world's people are defined as belonging to the "sub-healthy group" according to the statistics from the World Health Organization. The health condition of this group is needed to be take care as well. In addition, high rest heart rate (rest HR) exists higher risk to suffer from CVD such as obesity, diabetes, dyslipidaemia and hypertension than low rest HR. Additionally, exercising with a period of time has been proved to decrease rest HR [8].

3. PROPOSED METHODOLOGY

The project comprises several modules, including admin, user, and fas (Fitness Assistance System), each serving distinct functionalities.

In the admin module, the code handles administrative tasks such as managing user registrations, viewing user data, and activating user accounts. The adminlogin function handles admin login authentication, while adminhome renders the admin dashboard. viewadminuserpage retrieves user data for admin viewing, and activateusers activates user accounts upon admin action. The uploadfile function facilitates file uploads, likely for data import or system configuration.

The user module primarily caters to registered users. The userregistration function manages user registration, while userlogincheck validates user login credentials and sets session variables upon successful login. userfitness retrieves exercise data tailored to the user's age and weight, likely providing personalized fitness recommendations. status allows users to update their daily fitness status, and viewuserdailystatus enables users to view their status history. UserPredections likely provides predictive analytics or recommendations based on user data.

The fas module seems to target advanced fitness assistance, possibly for professionals. faslogin and fasloginaction handle login functionalities, while fashome renders the fas dashboard. faspredection seems to leverage machine learning models for fitness predictions or recommendations, utilizing both artificial neural networks and logistic regression algorithms.

In practice, this project aims to provide a comprehensive fitness assistance system, encompassing user registration, personalized recommendations, daily status tracking, administrative functionalities, and advanced analytics, leveraging machine learning algorithms for enhanced fitness guidance.

3.2 Settings

This project has the settings file for a Django project named "recommendersystem", which configures various aspects of the Django project, including database connection, middleware, template engine, static and media files handling, internationalization, and more. These configurations ensure that the Django project operates correctly and securely according to its requirements. Here is an overview of its structure and functionality:

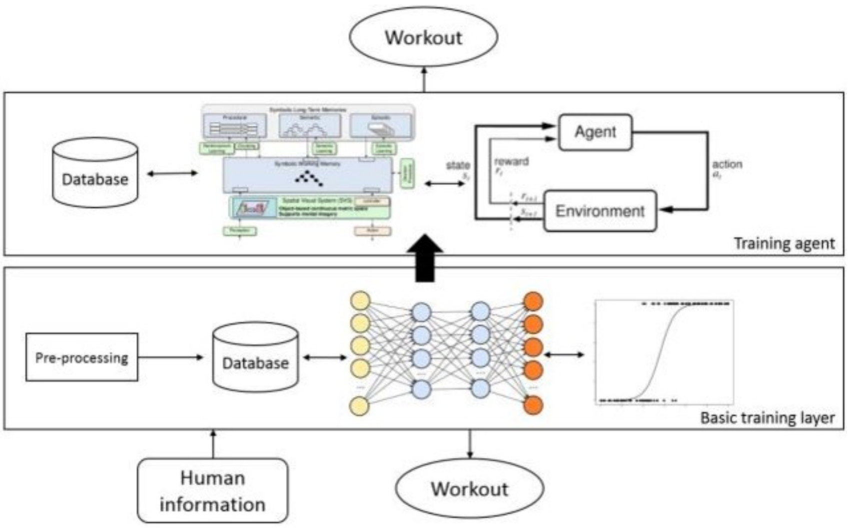


Fig. 1: Overall architecture of proposed AI-based fitness recommendation system.

3.3 Importing Libraries: To perform data preprocessing using Python, we need to import some predefined Python libraries. These libraries are used to perform some specific jobs. There are three specific libraries that we will use for data preprocessing.

3.4 Data Preprocessing

Data pre-processing is a process of preparing the raw data and making it suitable for a machine learning model. It is the first and crucial step while creating a machine learning model. When creating a machine learning project, it is not always a case that we come across the clean and formatted data. And while doing any operation with data, it is mandatory to clean it and put in a formatted way. So, for this, we use data pre-processing task. A real-world data generally contains noises, missing values, and maybe in an unusable format which cannot be directly used for machine learning models. Data pre-processing is required tasks for cleaning the data and making it suitable for a machine learning model which also increases the accuracy and efficiency of a machine learning model.

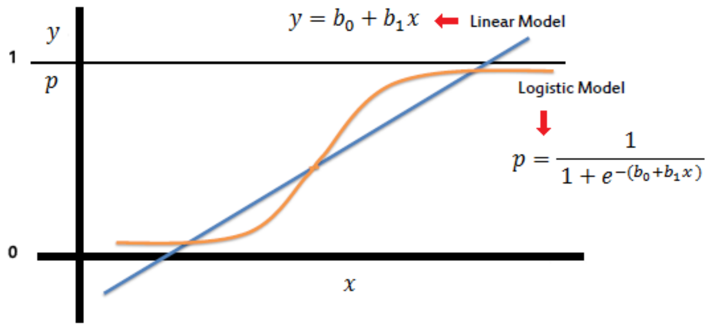
3.5 ML Model Building

3.5.1 Logistic Regression

Logistic regression predicts the probability of an outcome that can only have two values (i.e. a dichotomy). Predictions are based on the use of one or several predictors (numerical and categorical). A linear regression is not appropriate for predicting the value of a binary variable for two reasons:

- A linear regression will predict values outside the acceptable range (e.g. predicting probabilities
- outside the range 0 to 1)
- Since the dichotomous experiments can only have one of two possible values for each experiment, the residuals will not be normally distributed about the predicted line.

On the other hand, a logistic regression produces a logistic curve, which is limited to values between 0 and 1. Logistic regression is similar to a linear regression, but the curve is constructed using the natural logarithm of the "odds" of the target variable, rather than the probability. Moreover, the predictors do not have to be normally distributed or have equal variance in each group.



In the logistic regression the constant (b0) moves the curve left and right and the slope (b1) defines the steepness of the curve. By simple transformation, the logistic regression equation can be written in terms of an odds ratio.

$$\frac{p}{1-p} = \exp(b_0 + b_1 x)$$

Finally, taking the natural log of both sides, we can write the equation in terms of log-odds (logit) which is a linear function of the predictors. The coefficient (b_1) is the amount the logit (log-odds) changes with a one unit change in x.

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$$ln\left(\frac{p}{1-p}\right) = b_0 + b_1 x$$

As mentioned before, logistic regression can handle any number of numerical and/or categorical variables.

$$p = \frac{1}{1 + e^{-(b_0 + b_1 x_1 + b_2 x_2 + \cdots + b_p x_p)}}$$

There are several analogies between linear regression and logistic regression. Just as ordinary least square regression is the method used to estimate coefficients for the best fit line in linear regression, logistic regression uses maximum likelihood estimation (MLE) to obtain the model coefficients that relate predictors to the target. After this initial function is estimated, the process is repeated until LL (Log Likelihood) does not change significantly.

$$\boldsymbol{\beta}^1 = \boldsymbol{\beta}^0 + [\boldsymbol{X}^T \boldsymbol{W} \boldsymbol{X}]^{-1}.\boldsymbol{X}^T(\boldsymbol{y} - \boldsymbol{\mu})$$

$\boldsymbol{\beta}$ is a vector of the logistic regression coefficients.

$\boldsymbol{W}$ is a square matrix of order N with elements $n_i \pi_i (1 - \pi_i)$ on the diagonal and zeros everywhere else.

$\boldsymbol{\mu}$ is a vector of length N with elements $\mu_i = n_i \pi_i$.

A pseudo R^2 value is also available to indicate the adequacy of the regression model. The likelihood ratio test is a test of the significance of the difference between the likelihood ratio for the baseline model minus the likelihood ratio for a reduced model. This difference is called "model chi-square“. Wald test is used to test the statistical significance of each coefficient (b) in the model (i.e., predictors contribution).

Pseudo R2

There are several measures intended to mimic the R2 analysis to evaluate the goodness-of-fit of logistic models, but they cannot be interpreted as one would interpret an R2 and different pseudo R2 can arrive at very different values. Here we discuss three pseudo R2measures.

Pseudo R^2	Equation	Description
Efron's	$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - p_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$	$'p'$ is the logistic model predicted probability. The model residuals are squared, summed, and divided by the total variability in the dependent variable.

McFadden's	$R^2 = 1 - \frac{LL_{full\ model}}{LL_{intercept}}$	The ratio of the log-likelihoods suggests the level of improvement over the intercept model offered by the full model.
Count	$R^2 = \frac{\#\ Corrects}{Total\ Count}$	The number of records correctly predicted, given a cutoff point of .5 divided by the total count of cases. This is equal to the accuracy of a classification model.

Likelihood Ratio Test

The likelihood ratio test provides the means for comparing the likelihood of the data under one model (e.g., full model) against the likelihood of the data under another, more restricted model (e.g., intercept model).

$$LL = \sum_{i=1}^{n} y_i ln(p_i) + (1 - y_i) ln(1 - p_i)$$

where 'p' is the logistic model predicted probability. The next step is to calculate the difference between these two log-likelihoods.

$$2(LL_1 - LL_2)$$

The difference between two likelihoods is multiplied by a factor of 2 in order to be assessed for statistical significance using standard significance levels (Chi^2 test). The degrees of freedom for the test will equal the difference in the number of parameters being estimated under the models (e.g., full and intercept).

3.5.2 ANN model

It determines weighted total is passed as an input to an activation function to produce the output. Activation functions choose whether a node should fire or not. Only those who are fired make it to the output layer. There are distinctive activation functions available that can be applied upon the sort of task we are performing.

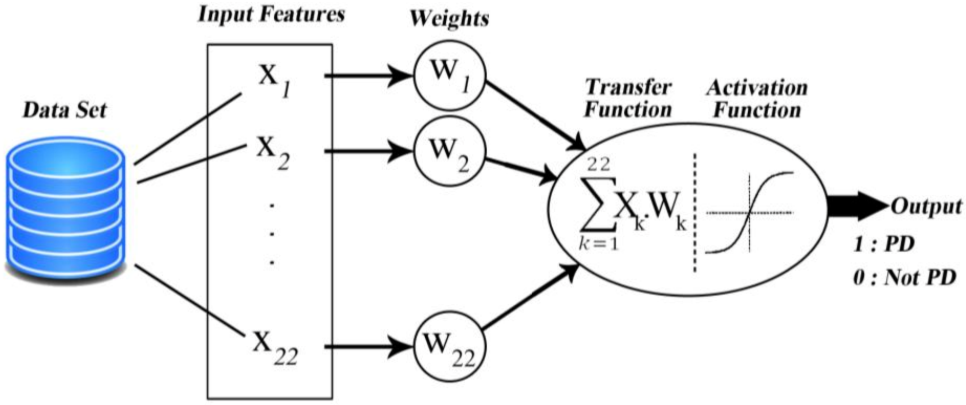

Fig. 2: Architecture of ANN-based prediction system.

To define a neural network that consists of many artificial neurons, which are termed units arranged in a sequence of layers. Let's us look at various types of layers available in an artificial neural network. Artificial Neural Network primarily consists of three layers:

Input Layer: As the name suggests, it accepts inputs in several different formats provided by the programmer.

Hidden Layer: The hidden layer presents in-between input and output layers. It performs all the calculations to find hidden features and patterns.

Output Layer: The input goes through a series of transformations using the hidden layer, which finally results in output that is conveyed using this layer.

$$\sum_{i=1}^{n} Wi * Xi + b$$

The artificial neural network takes input and computes the weighted sum of the inputs and includes a bias. This computation is represented in the form of a transfer function.

It determines weighted total is passed as an input to an activation function to produce the output. Activation functions choose whether a node should fire or not. Only those who are fired make it to the output layer. There are distinctive activation functions available that can be applied upon the sort of task we are performing.

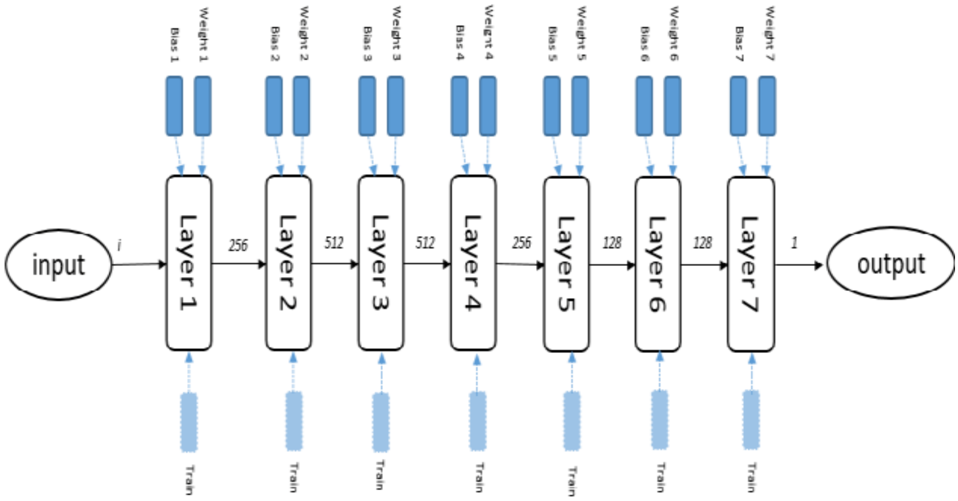

Fig. 3: Proposed architecture of ANN with ReLU.

4. RESULTS AND DISCUSSION

4.1 Dataset description

The dataset contains information related to individuals and their fitness activities, including age, weight, exercise routines, and dietary habits. Analyzing this data could help identify patterns, correlations, and trends related to fitness and lifestyle choices. Here's an explanation of each column:

Age: This column represents the age of each individual in the dataset. Age can be an important factor in determining fitness levels and exercise routines, as the nutritional and physical requirements of individuals can vary based on their age.

Weight: This column represents the weight of each individual. Weight is a crucial metric in assessing fitness and health status. It influences the type and intensity of exercises recommended for an individual, as well as their dietary requirements.

Exercise1: This column represents the first exercise performed by each individual. It could include activities such as running, weightlifting, swimming, etc. Different exercises target different muscle groups and have varying effects on overall fitness.

Exercise2: Similar to Exercise1, this column represents the second exercise performed by each individual. Including multiple exercises allows for a more comprehensive understanding of an individual's fitness routine.

Diet: This column indicates the dietary habits or nutritional intake of each individual. Diet plays a crucial role in fitness and overall health. It impacts energy levels, muscle recovery, and body composition. The diet column contains information about dietary patterns, such as salads, brown rice, vegetarian, vegan, low-carb, etc., or specific dietary items consumed.

4.2 Results analysis

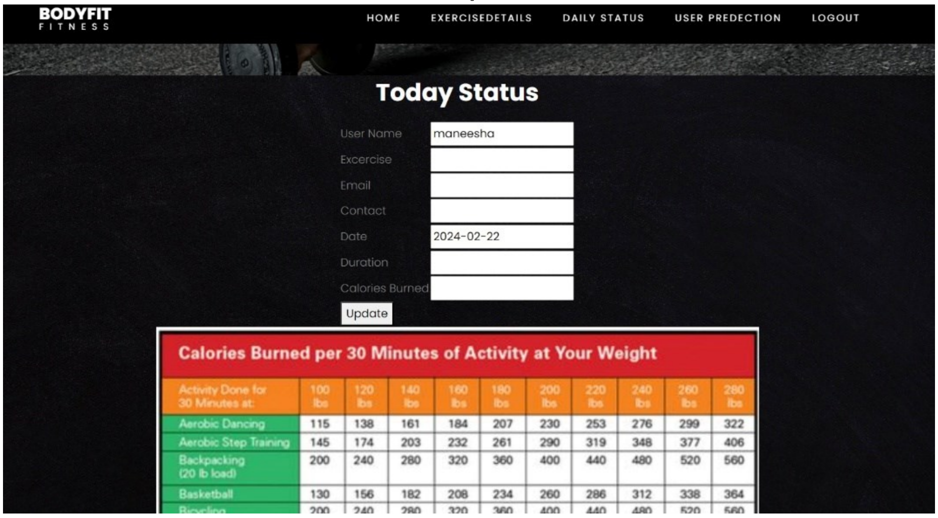

Fig. 4: Daily status update.

Figure 4 is the daily status update interface allows users to input their daily fitness activities, dietary habits, mood, etc.

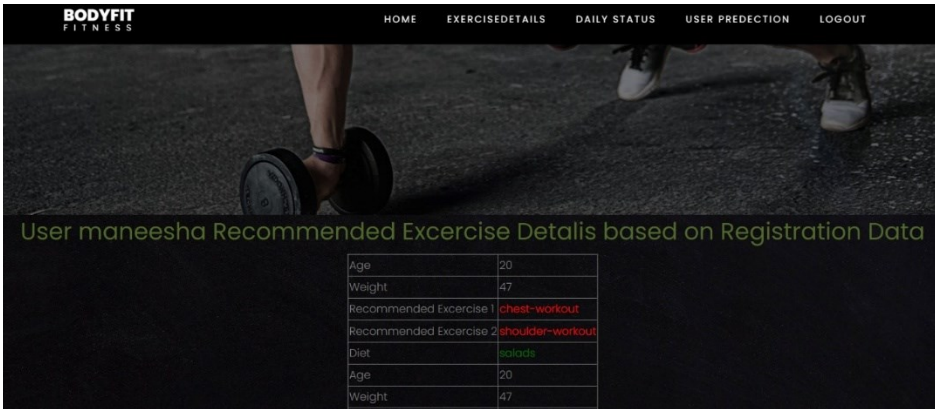

Fig. 5: Recommendations based on user daily status update.

Figure 5 demonstrate the recommendations based on user daily status update provide users with personalized fitness recommendations and suggestions based on their input

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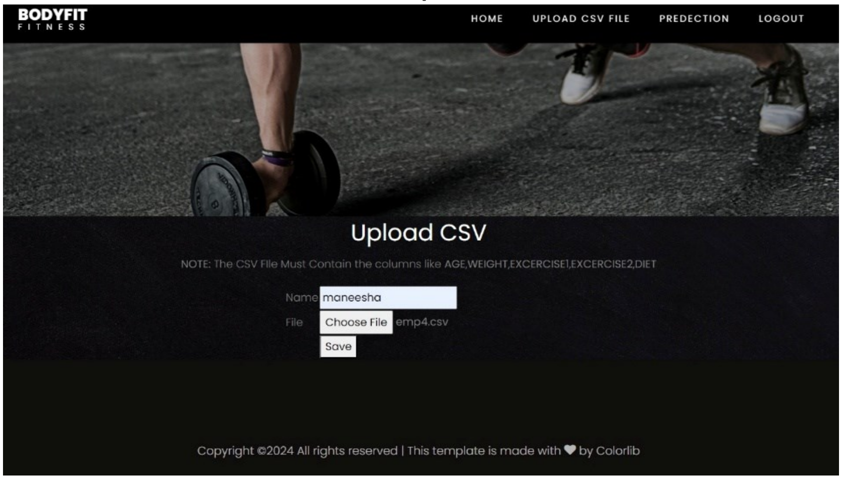

Fig. 6: Upload the dataset for model training.

Figure 6 disclose the upload dataset interface enables administrators to upload datasets for model training and updating.

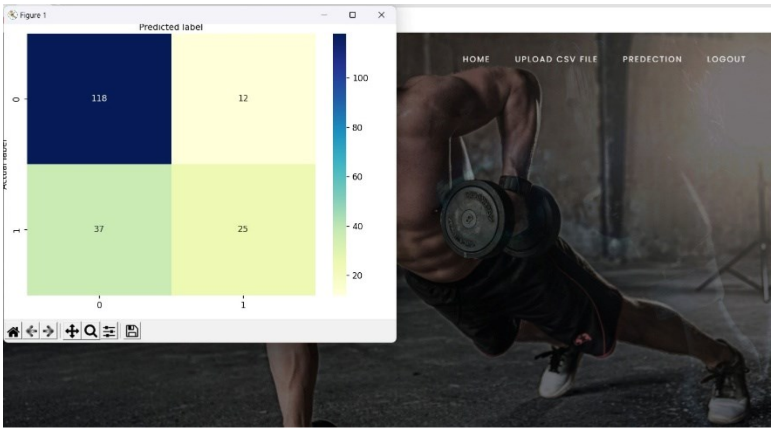

Fig. 7: Displaying confusion matrix of proposed ANN model.

Figure 7 is displaying confusion matrix of proposed ANN model visualizes the performance of the artificial neural network model used in the system, helping administrators and users understand its accuracy and effectiveness.

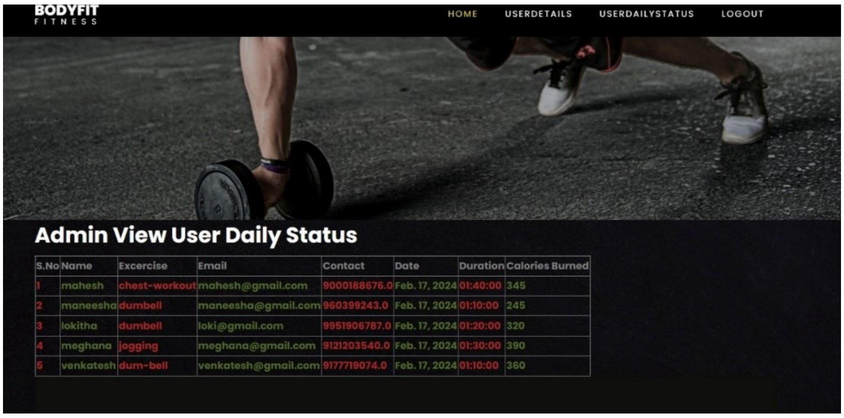

Fig. 8: View of user details with daily status.

Figure 8 is a view of user details with daily status provides administrators with insights into individual user profiles, including their daily fitness status updates, allowing for better monitoring and management.

5. CONCLUSION

The AI-based recommender system for fitness assistance project is designed to revolutionize the fitness industry by offering personalized recommendations and guidance to users based on their unique profiles and goals. Leveraging machine learning algorithms like artificial neural networks and logistic regression, the system analyzes user data, including age, weight, exercise preferences, and dietary habits, to generate tailored exercise and diet plans. This personalized approach enhances the effectiveness and efficiency of fitness programs, providing users with targeted strategies to achieve their fitness objectives. In conclusion, the project showcases the potential of integrating AI technologies into fitness assistance, offering users a more personalized and effective means of reaching their fitness goals. However, there are opportunities for future enhancement and expansion. Refining recommendation algorithms, integrating wearable devices for real-time data tracking, and collaborating with healthcare professionals are just a few avenues to further improve the system's effectiveness and user experience. Overall, the project represents a significant step forward in leveraging technology to promote health and wellness.

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