2023 IEEE International Conference on Pervasive Computing and Communications Workshops and other Affiliated Events (PerCom Workshops) | 978-1-6654-5381-3/23/$31.00 ©2023 IEEE | DOI: 10.1109/PERCOMWORKSHOPS56833.2023.10150359

CHARLIE: A Chatbot That Recommends Daily Fitness and Diet Plans

Deepanjali Chowdhury[‡†], Ahana Roy[‡], Sreenivasan Ramasamy Ramamurthy[§], Nirmalya Roy[†]
[‡†]*Department of Electrical and Computer Engineering, Texas A&M University, College Station, United States*
[‡]*Howard County Public School System, Maryland, United States*
[§]*Department of Computer Science, Bowie State University, Bowie, United States*
[†]*Department of Information Systems, University of Maryland, Baltimore County, Baltimore, United States*
deepachowdhury@tamu.edu, ahanarai2020@gmail.com, sramamurthy@bowiestate.edu, nroy@umbc.edu

***Abstract*—Managing a work-life balance has always been challenging, especially after the recent trend of working from home, which has made maintaining one's fitness and diet regime strenuous. Failing to adhere to a fitness and diet plan has been shown to cause long-term effects on a person's health including obesity and shortened lifespans. Currently, people plan their fitness and diet plans around their schedule, but these tasks are challenging to maintain. Users tend to give up these plans due to a lack of time and planning. To help with better planning for a fitness and diet regime, we propose, *CHARLIE*, a chatbot that works around a user's schedule to intelligently recommend diets and fitness goals based on their calendar. *CHARLIE* is a recommendation system that suggests the users' a certain meal and fitness activities based on the amount of time they have left in their day and the number of calories they lose.**

***Index Terms*—e-Health, Fitness, Diet, Deep Learning, Feed-Forward Neural Networks, Recommendation Systems**

I. Introduction

In 2018, roughly 42.4% of Americans were categorized as obese. Obesity is a very common disease in the US that can lead to "heart disease, strokes, type 2 diabetes, and certain cancers" [1]. The primary cause of obesity can be attributed to a massive 23% increase in caloric consumption in the last 50 years [2]. Although there are numerous ways to overcome obesity, most of the methods (especially involving professionals such as fitness coaches and dietitians to advice on workouts and nutrition, respectively) are both time consuming and expensive.

The current inexpensive solutions that people rely on to overcoming obesity and decreasing caloric consumption are mobile applications and websites. However, a study from UCLA found that many of these inexpensive applications and websites are ineffective and do not show any differences in weight loss. Besides, it was also reported that the application usage reduced drastically over time. During the first week, the users would check their application about five times per week, while in the fourth week, users would only check the application once a week [3]. For the applications and websites to be effective, it was required that the users be motivated, regular and committed towards achieving their fitness goals.

The next solution was to observe strict diet, especially, a diet with a balanced nutrition. Given that most young population fails to invest money and time to meet with the dietitian, it was imperative to search for a novel method to motivate users to follow diet and fitness plans. In this paper, we propose, ***CHARLIE***, that stands for Chatbot Health Assistant for a Robust Lifestyle and Ideal Eating. The novelty of ***CHARLIE*** is that it is capable of automatically help the users plan their fitness and diet goals around their schedule. We envision, that a person would use ***CHARLIE***, while working on their day job, where, ***CHARLIE*** would keep suggesting their fitness and diet goals dynamically as their schedule changes.

CHARLIE leverages Natural Language Processing (NLP) techniques to derive the context of the user input/request from the chatbot, combine them with the user's calendar/schedule, map it with calories burnt data, and recommend a fitness and diet plan. In this work, we have evaluated ***CHARLIE*** using a real calendar/schedule dataset collected from a population of students in conjunction with a publicly available dataset that tracks the number of calories a user loses doing certain activities. ***CHARLIE*** is essentially a recommender system that recommends the user certain meals and fitness activities based on various factors such as the amount of time they have left in their day and/or the number of calories they lose.

This paper is organized as follows. Section 2 discusses the background and Section 3 describes the overall architecture of ***CHARLIE***. In section 4, we describe the proposed methodology and the datasets used in this work. We then discuss our results, discussions and future work in Sections 5, 6, 7 respectively.

II. Background

There are several chatbots that can help people monitor their diet plans. For instance, PAOLA [4] is a chatbot that helps users meet their diet plans. Besides, the authors of PAOLA showed that the participants enjoyed using a chatbot to design their diet for a healthier life. Another promising chatbot, Step Up Life [5] relies on artificial intelligence to suggest daily fitness plans to users. Step Up Life is a smartphone application that reminds users to perform physical activity daily based on user location, personal preferences, calendar events, time of the day, and the weather. Reviewers of Step Up Life describe the system as an application that "generates notifications and reminders when the user is physically inactive for a predefined period". The reality is that the app only notifies the user

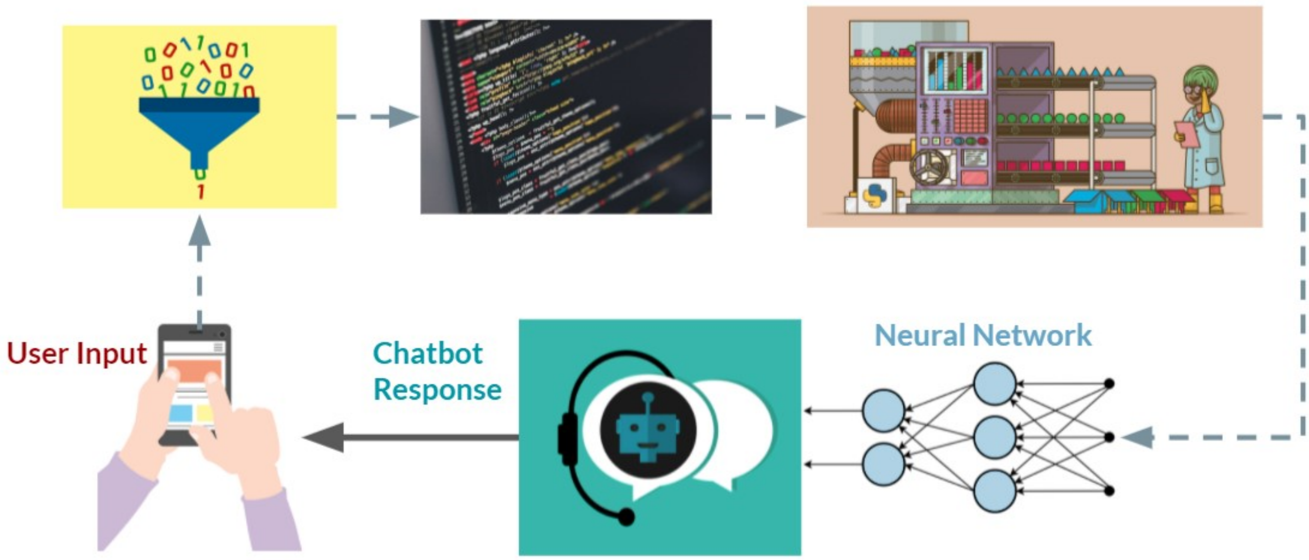

Fig. 1. Overview of CHARLIE

and doesn't actually help the user with implementing exercise into their daily life [6]. Through both these applications, the research found a strong participation rate of about 60% and that it was possible to build a chatbot with similar uses that utilized creating a diet and fitness plan by looking at a user's calendar. The proposed chatbot, ***CHARLIE***, differs from both these chatbots. ***CHARLIE*** is capable of integrating with a calendar, that eventually can work around a user's schedule to recommend diet and fitness plans.

III. Overall Architecture

Figure 1 shows the high-level overview of ***CHARLIE***. ***CHARLIE*** operates in an iterative manner, where the sequence of operations involve acquiring user input, perform pre-processing to compute features necessary from various datasets, feed them to the respective neural networks to generate both diet/fitness plans and a chatbot response to communicate the users about their diet and fitness plans created based on the user's calendars and answer questions about ***CHARLIE***, diets, and workouts.

In simple terms, ***CHARLIE*** takes user input and then extracts all necessary information from the user input using a neural network. The user's response is first turned into phrases and words that the computer can understand. These phrases and words then go through the code to determine which words and phrases are necessary for the algorithm. After figuring out the necessary phrases and words, the algorithm then goes into a sorting system that sorts the user response into a category. Examples of categories could be Nutritional and Diet Questions, Food and Diet Recommendations, and jokes. After being sorted into certain categories, the chatbot then goes into a neural network that determines the best chatbot response based on user input. There were a few chosen varieties of specific methods in order to make CHARLIE more efficient and user-friendly. The first was utilizing a neural network simply because this would increase the efficiency of CHARLIE and allow for future works to make things more user-specific. Additionally, it was decided to use a python based system as it will allow for efficient coding and comes with packages such as Pytorch that utilize deep learning very efficiently. The main concepts that were planned to be utilized are a recommender system [7], chatbots, and nutritional values.

IV. Proposed Methodology

In order for ***CHARLIE*** to gain access to the user's data and to tailor the health plans towards each specific user, as shown in Figure 2 the first step is to start extracting the data.

A. Datasets

The first step was gathering datasets by extracting calendar data. Students and faculty from the UMBC-REU in Smart Computing were asked to give a "dummy calendar" of their schedules and google calendars.

To better understand caloric and nutritional goals of a person, it is important to understand the daily caloric intake of a person. Several recipes uses Food Standards Agency (FSA) lights, which are essentially traffic light colors, that notify the user if a food is healthy; the healthier the food, the more green lights present on the FSA labels. [1] This system of utilizing FSA lights will help the chatbot determine if the user has met the nutritional goals of the day.

Next, the goal was to indentify a mechanism to suggest the best diet plan. For this aspect, we relied on the Recipes 1M+ dataset. The Recipes 1M+ dataset was created by the students at the Massachusetts Institute of Technology where the original

[1] https://www.food.gov.uk/safety-hygiene/check-the-label

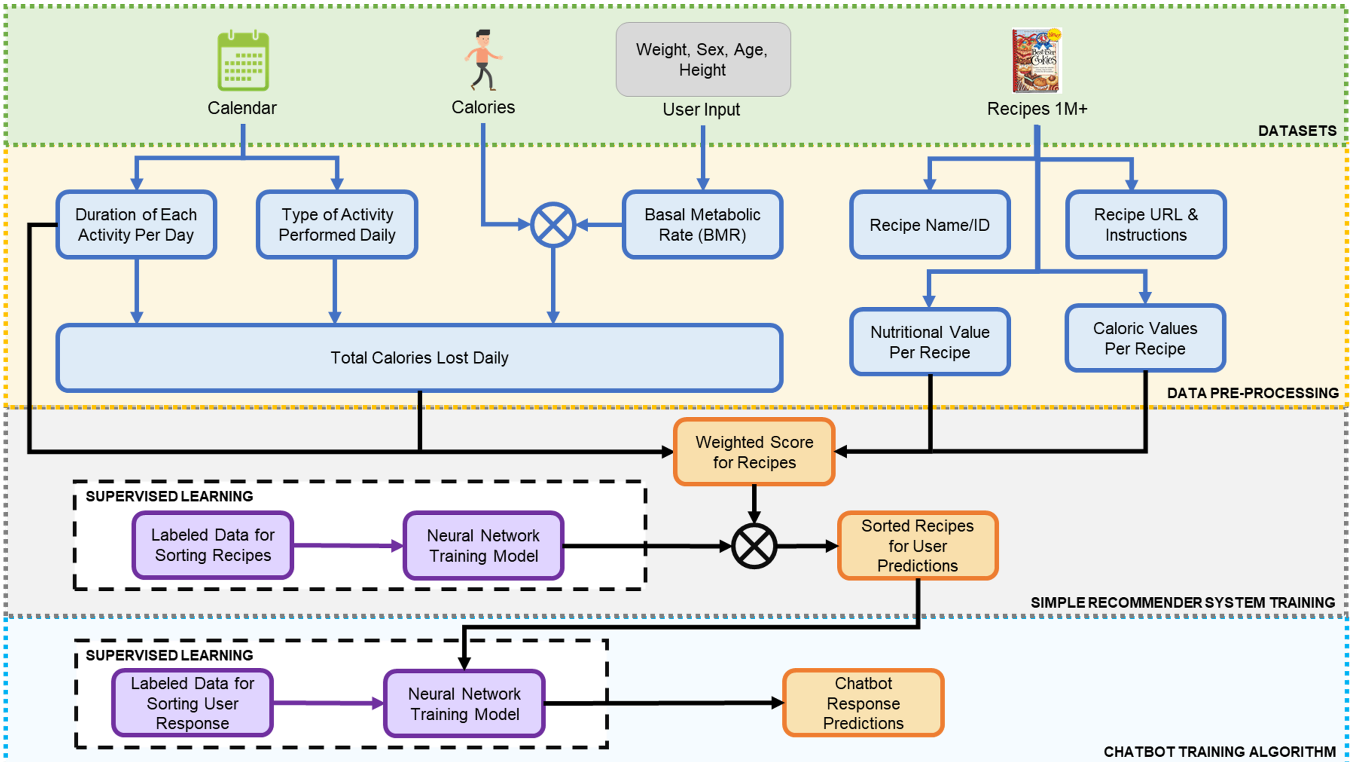

Fig. 2. Flowchart of CHARLIE Processes

paper utilized a neural network to ”learn a joint embedding of recipes and images that yields impressive results on an image-recipe retrieval task” [8]. The Recipes 1M+ dataset has recipes with nutritional information in a .json file that has roughly 50,000 recipes with their nutritional and caloric information. Additional data was gathered on the number of calories burned for certain activities per hour using NutriStrategy [9], a website that contains information about health and fitness.

Using both the recipes' information to find nutritional and caloric consumption as well as the calories lost per exercise that the user accomplishes, causes a caloric deficit. This information and the user's calendar are used to determine the best diet and fitness plan for the user's schedule.

The reason behind choosing a dummy calendar is that it was needed to initialize certain parameters in the first version of ***CHARLIE*** in order to be able to recognize the variables from similar calendars later. Then, it was important to move on to gathering a file that has a list of around 150-200 exercises where each activity is associated with calories lost per hour per exercise dependent on the user's weight. This file was found in Kaggle, where this information was gathered and contained in a .csv file that was created from a website called NutriStrategy [9]. Another piece of data that was needed was user information, more specifically the weight, sex, age, and height of the user using the chatbot. This would be used to calculate the Basal Metabolic Rate (BMR)[2] which will be explained in the next section. Lastly, information had to be gathered from the Recipes 1M+ Dataset, which is a dataset created by students at MIT for identifying food images with recipe names. In this project, the dataset is used to give us 50,000 recipe options and their nutritional values.

[2]https://www.healthline.com/health/what-is-basal-metabolic-rate#estimating-bmr

B. Pre-Processing Data

After gathering the calendar data and utilizing the .csv file for calories lost per exercise per hour, it was utilized in a .ics package to gather information from the calendars, specifically the duration of each activity and the type of activities performed daily. After taking both of these types of data, the total calories lost daily for activities and the duration of time the user has available to make recipes and workout were found. It was also important to account for the BMR in the total calories lost daily. The BMR is an equation used to determine the calories lost from basic daily functions. Equations 1 and 2 show how to find the BMR of a person, which is dependent on the weight (kg), age (years) , sex, and height (cm) of a person. Weight is defined as W, age is defined as A, and height is defined as H. For other sexes, there is an assumption that the algorithm will be using Equation 2. After pre-processing the caloric and calendar data, the next step was to pre-process the recipe data. The code utilized a pandas data frame to gather the Recipe Name, ID, and URL, the instructions and ingredients per recipe, and the nutritional values per recipe.

$$BMR_{women} = 655 + (9.6 \cdot W) + (1.8 \cdot H) - (4.7 \cdot A) \quad (1)$$

$$BMR_{men} = 66 + (13.7 \cdot W) + (5 \cdot H) - (6.8 \cdot A) \tag{2}$$

C. Simple Recommender System

After pre-processing the data, the next step was to move on to setting up the simple recommender system training model. The weighted scores system is set up to where the scores are all using Equation 5 to determine the best recipe for each meal. Each recipe has the option of three different serving sizes to maximize options, 1 serving size, 1/2 of a serving size, and 1/3 of a serving size. After utilizing the best-weighted score for a recipe, which is between 30 and 40% (since the main goal is to make sure all three meals reach the 100% caloric and nutritional value marks as described above). It is then time to narrow down the recipe options to only the ones that fit the weighted scores necessary. Fats are defined as *F*, Proteins are defined as *P*, Sodium is defined as *Na*, Saturates are defined as *S*, Sugars are defined as *T*, and calories per recipe are defined as *C*.

$$W_{Calories} = (\frac{C}{2000}) * (serving\ size) \tag{3}$$

$$W_{Nutrition} = \frac{(\frac{F}{60.5}) + (\frac{P}{50}) + (\frac{Na}{2.3}) + (\frac{S}{20}) + (\frac{T}{50})}{serving\ size} \tag{4}$$

$$W_{simple-score} = \frac{(W_{Nutrition} + W_{Calories})}{2} * 100 \tag{5}$$

Another way to think about the weighted score is to treat it as if it is a quiz each recipe has to take. As shown in Figure 3, a woman is taking a quiz to determine the best type of career for her. She is checking off the things she is interested in and in this case, the algorithm is ”checking” the recipes that fit the nutritional and caloric values the user would need. After checking off the things she is interested in, the quiz will give her a recommended career. In the chatbot's case, this quiz is done for every recipe, and after all the recipes go through the quiz there is a narrowed-down list of recipes for the chatbot to give to a user.

When all the recipes fit the weighted score (depending on the user's necessary nutrition that can be found through the user's inputs), the recipes are narrowed down further to determine which recipes will be able to be made with the time the user has available in their day, based on their calendar. This will update the weighted score list that is further narrowed down to include all recipe options that fit the nutritional and time needs of the user. All of these updated recipes then go through a Feed-Forward Neural Network. A feed-forward neural network is similar to a recurrent neural network except for the fact that it continuously goes forward and has no backward propagation, as shown in Figure 4. The specific use of the feed-forward neural network, in this case, is to sort recipes into breakfast, lunch, dinner, snack, and dessert options. It is trained using an intents file that has a list of words categorized into typically breakfast, lunch, dinner, snack, and dessert options. An example would be that salmon is categorized as dinner and bacon is categorized as a snack or breakfast item. Depending on the words and combinations

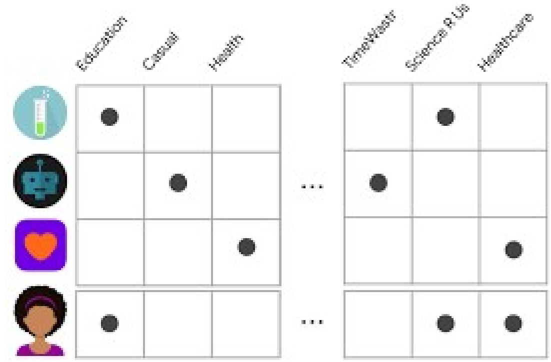

Fig. 3. Example of Weighted Score in Different Scenario

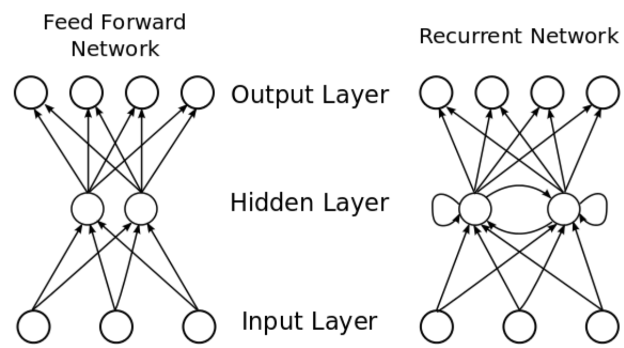

Fig. 4. Comparison of Feed Forward and Recurrent Neural Network

of words in each recipe name, the recipes will be sorted into their specific category. After the recipes are sorted, it is now time to move on to how the chatbot will respond to user input. Additionally, after determining the amount of time available after recipes are made, a fitness plan is added to the system. Since this is a preliminary version, the fitness plan only includes the recommended amount of exercise a person needs daily, either 30 min/per day of rigorous activity or 60 min/per day of moderate activity. [10]

D. Chatbot Response System

The chatbot response system is also a feed-forward neural network that works exactly like the feed-forward neural network for sorted recipes. There is an intents file that has phrases a user may ask and the chatbot will respond with a pre-determined response. The model is trained through the intents file and that trained model is used to determine the chatbot response in real time. If the response triggers the recommender system algorithm, then the algorithm will run to determine the best recommendations for a daily fitness and diet plan.

Overall, this is currently a preliminary system, hence why there are many directions and ideas that are in their beginning phases. As discussed in future works, there is a hope to utilize more advanced deep learning models in the system to make it more user-friendly.

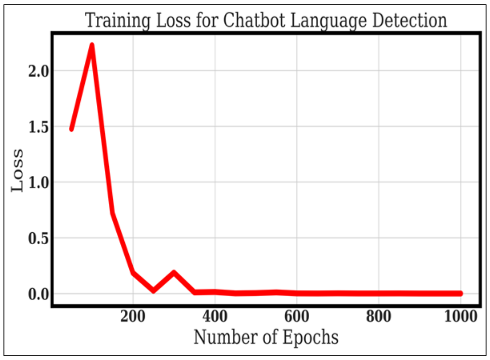

Fig. 5. Training loss for Chatbot Response

Fig. 6. Training loss for Recipe Sorting

TABLE I
TRAINING LOSS FOR EACH MODEL

Model Name	Final Loss
Training Loss for Sorting Recipes	0.1037
Training Loss for Chatbot Language Detection	0.001

V. RESULTS

All the algorithms in this paper were written using Python and all datasets were publicly available. Additionally, the calendar data was created by gathering from fellow REU students and faculty at UMBC. All calendars were dummy calendars that were sent anonymously for confidentiality.

The results found that the training models have a good loss pattern with the final loss for the chatbot response mode being about 0.001 and the final loss for the recipe sorting model being about 0.1037, as shown in Table I and Figures 5 and 6.

In figure 7, we show the window of the chatbox with a few example queries. We show that ***CHARLIE*** is capable of showing both general information about dietary needs and also answer specific question. We can see that for a query, the user input needs to be in a certain format. It is understandable that it is difficult for the users to remember the format. Therefore, we have enabled ***CHARLIE*** to let the user know of the format with just a simple query. Besides, we can also notice that ***CHARLIE*** is capable of replying a diet plan, recipe links, serving size for breakfast, lunch and dinner. If the user were to check back at a later time, and let us assume that the user's

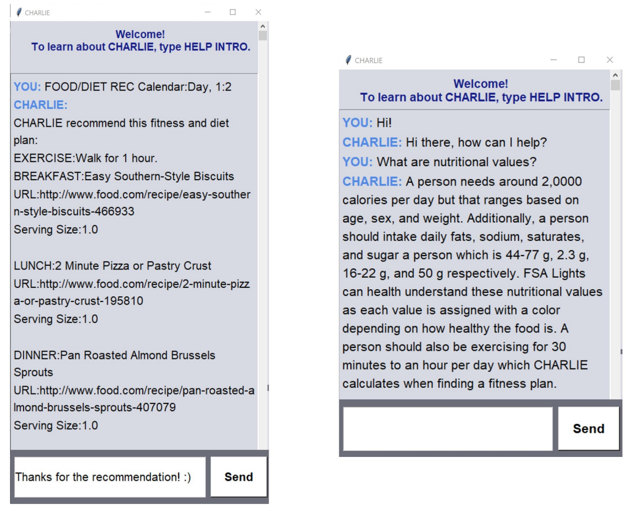

Fig. 7. Examples of Chatbot Window in Use

scheduled has changed, ***CHARLIE*** is capable of devising a new exercise and diet plan for the remainder of the day.

VI. DISCUSSION

Throughout the project, there were a few ideas that we used to make the processes and algorithms more efficient. The first idea was to set up a system of weighted scoring as our first version. This would make it so time would be spent focusing on the chatbot and other parts of the algorithm while also recommending foods and workouts. The reason Python was chosen as the coding language for this project was because it had a lot of packages, such as the .ics, pytorch, and pandas packages, that would make gathering and utilizing data very efficient.

Additionally, the reason behind using a training model was that will help the model learn and figure out the best types of recipes a user can get. The model can also be remade to have specific health goals by changing the caloric and nutritional amounts a user has to reach daily. Examples of this being in action would be soldiers using ***CHARLIE*** to track their diets and fitness schedule to improve their physical health and older people using ***CHARLIE*** to make sure they are getting their necessary nutrition and exercise.

VII. FUTURE WORKS

In the future, there is a hope to expand CHARLIE's deep learning algorithm by utilizing an AI-based recommender system and more deep learning, There is also a plan to improve the implementation of the user's calendar and add more variety to diet and diet plan for users by including a user's diet and fitness preference as well as health goals. Lastly, another goal is to improve the system of updating specific parts of recipes and calendar data, such as making sure the algorithm can accurately update times instead of using the user's input for time updates per recipe.

Additionally, there is also a goal of having more detailed and defined variables. In many parts of CHARLIE, foods or workouts are described as ”moderately healthy” or ”moderate or high intensity”. While the current system utilizes the data to determine if an exercise is moderate, in the future, there is a hope to utilize a numerical system that uses calories burnt or gained during exercise. Additionally, while the current system uses equations to determine if the person is eating enough sugars, fats, etc., there is no way of determining if a food is healthy or not. Thus, this is also something that will be worked on in the future through numerical values or another system (such as another training model).

VIII. Conclusion

In conclusion, the algorithm was successfully able to score and sort recipes and exercises that would work with the user's schedule. The chatbot successfully was able to use a simple recommender system with a weighted score to find a daily recipe and fitness plan a user could use to track their weight and be healthy while not having to spend extra time to plan it. Through more development and experimentation, the chatbot could be used for various uses that will benefit people and allow people the time to focus on things they truly enjoy instead of planning when to eat and exercise.

IX. Acknowledgements

This research is supported by the NSF REU Site grant #2050999 and NSF CAREER grant #1750936.

References

[1] “Cdc: Adult obesity factds,” www.cdc.gov/obesity/data/adult.html, accessed: 2020.

[2] “Healthline: Obesity facts,” https://www.healthline.com/health/obesity-facts, accessed: 2020.

[3] “Harvard health blog: Can an app help you lose weight?” www.health.harvard.edu/blog/can-app-help-lose-weight-201411207537, accessed: 2020.

[4] C. R. Davis, K. J. Murphy, R. G. Curtis, and C. A. Maher, “A process evaluation examining the performance, adherence, and acceptability of a physical activity and diet artificial intelligence virtual health assistant,” *International journal of environmental research and public health*, vol. 17, no. 23, p. 9137, 2020.

[5] V. Rajanna, R. Lara-Garduno, D. J. Behera, K. Madanagopal, D. Goldberg, and T. Hammond, “Step up life: a context aware health assistant,” in *Proceedings of the Third ACM SIGSPATIAL International Workshop on the Use of GIS in Public Health*, 2014, pp. 21–30.

[6] S. Preum, S. Munir, M. Ma, M. Yasar, D. Stone, R. Williams, H. Alemzadeh, and J. Stankovic, “A review of cognitive assistants for healthcare: Trends, prospects, and future directions,” *ACM Computing Surveys*, vol. 53, pp. 1–37, 02 2021.

[7] D. Mudigere, M. Naumov, J. Spisak, G. Chauhan, N. Kokhlikyan, A. Singh, and V. Goswami, “Building recommender systems with pytorch,” in *Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, 2020, pp. 3525–3526.

[8] J. Marin, A. Biswas, F. Ofli, N. Hynes, A. Salvador, Y. Aytar, I. Weber, and A. Torralba, “Recipe1m+: A dataset for learning cross-modal embeddings for cooking recipes and food images,” *IEEE transactions on pattern analysis and machine intelligence*, vol. 43, no. 1, pp. 187–203, 2019.

[9] “Nutristrategy calories burned,” https://www.nutristrategy.com/ calories-burned.htm, accessed: 2020.

[10] “Cdc: How much physical activity do adults need?” https://www.cdc.gov/physicalactivity/basics/adults/index.htm, accessed: 2020.