SMARTCARBS: AN INTELLIGENT MOBILE APPLICATION TO ASSIST DIET CONTROL USING ARTIFICIAL INTELLIGENCE AND COMPUTER VISION

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ABSTRACT

In today's society, Type 2 diabetes is a prevalent disease that affects hundreds of millions of people worldwide [11]. However, many people are unaware that they are diabetic or pre-diabetic, so they do not have access to the information to make better-informed nutritional choices that will suit their personal needs. In this paper, we designed an application that uses image classification to provide an estimate of the nutritional content of the selected food [12]. We applied our application to identify and list the nutritional content of multiple different foods, then conducted a qualitative evaluation of the approach. The results show that this application will facilitate healthy eating and allow users to utilize the image classification predictions to make diabetes-friendly nutritional choices.

KEYWORDS

Machine Learning, Nutrition, Flutter, Image Classification.

1. INTRODUCTION

Type 2 diabetes is when the body fails to properly regulate sugar (glucose) levels, resulting in an influx of glucose in the bloodstream [1]. Insulin is a type of hormone created in the pancreas to control glucose levels, and Type 2 Diabetes is caused by insufficient insulin production, which causes the cells to absorb less sugar. Type 2 diabetes is prevalent, especially in the United States. According to the Centers of Disease Control and Prevention (CDC), approximately 37 million suffer from diabetes [2]. Since Type 2 diabetes symptoms develop over the course of many years and the symptoms are often overlooked, those affected need a way to regulate their blood sugar levels.

One of the key factors in keeping blood sugar at a healthy level is following a proper diet. The consequences of not following a proper diet, such as low carb and low sugar, can lead to blood glucose constantly being high. If left unchecked for a period of time, a high blood glucose level can lead to serious health issues and complications, such as damaged body organs, heart attacks, and strokes, etc. [3]. Therefore, it is especially important for people to be educated in diabetes prevention methods, since diabetes comes with many health consequences, and in extreme cases, may lead to death. Unfortunately, "Population-based estimates of mortality are often derived from vital statistics. This method, again, may under represent the burden of diabetes since physicians commonly do not identify diabetes as the underlying cause of death on death certificates" [4]. As the consequences of diabetes are grossly underestimated, current diabetes prevention methods do not seem to be as effective.

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Some of the existing techniques and lifestyle changes that have been proposed to help a user regulate their blood sugar are maintaining a healthy diet and weight, as well as an active lifestyle. According to the Global Burden of Disease Study, which was carried out in 188 countries, diet is the leading contributor to worldwide obesity and death rates [5]. However, it is very difficult for an individual to implement a healthy diet due to most physicians not being trained in nutrition and the time-consuming aspect of talking to patients about nutrition [5]. As a result, dietary information is not sufficiently monitored, while it should be constantly monitored by doctors and hospital clinics.

Additionally, people could seek healthcare as an option to maintain their blood sugar levels. A paper titled "The burden of type 2 diabetes: Are we doing enough?" by Zimmet P. claims, "Diabetic patients are more than twice as costly to manage as non-diabetic patients..." [6]. The existing healthcare system is already under tremendous stress, and managing diabetic patients is overstraining the system. Because cost is a barrier for many patients, receiving the proper diabetic care can be daunting. Furthermore, " Controlling the type 2 diabetes epidemic will require changes [such as] effective coordination between all levels of government, health care agencies, multidisciplinary health care teams, professional organizations, and patient advocacy groups" [6]. Unfortunately, rigorous action is required by many authorities, and it may be difficult to implement such changes to the health care system due to cost and time-related issues. So, there must be a more efficient and cost-friendly approach in place to alleviate the effects of the epidemic.

Another existing technique is using mobile applications to educate diabetic patients on strategies to best suit their needs. A research article, "Mobile Intervention Design in Diabetes," by Mulvaney et al., discusses the potential limits: "Although mobile programs can lead to improvements in glycemic control, many aspects, such as the role of the diabetes clinician, real-time features, and patient engagement have not been documented" [7]. Integrating the proper diabetic intervention strategies along with clinical support has yet to be researched, so it is difficult to know the actual potential of the mobile application. Another limitation of this method is that "attempting to relate design features to patient engagement and outcomes was the actual lack of documentation of patient engagement with the systems and process outcomes". This method requires a lot of time and dedication from the patient, and thus mobile applications that target diabetes intervention or prevention need to focus more on user experience and retention. Since utilizing app-based methodologies can be an open-ended answer, there are a wide variety of shortcomings that can be fixed with the correct application implementation.

In this paper, we follow the same line of research by focusing on the diet aspect of regulating healthy blood glucose levels. Our proposed method is a mobile application that provides personalized information on the recommended foods for the user and the basic nutritional information for the selected food. The application requires user input in order to generate a personalized profile including the following pieces of information: the user's age, gender, weight, family health history, and underlying health conditions. Based on these pieces of information, the dashboard provides tips and recommendations on what foods the user should and should not consume. Many existing methods require systems to record and monitor diabetes process measures in medical records. However, such information is constantly neglected due to the difficulty of constantly collecting it. Our application uses self-reported health data and self-collected food images to predict a list of foods fit for the user. Since this application is available to the general public, anyone with a device can use it anywhere at any given time. Therefore, we believe that this application could help pre-diabetic or diabetic users to maintain healthy blood glucose levels by providing a list of recommended foods based on their personal health information and needs.

To test the effectiveness of our method, we will conduct an experiment in which we test the accuracy of our AI model when classifying different food types. In the experiment, we will use the flickr scraper to generate 25 new images for the same ten food types: apple, bread, chocolate, coffee, cooked chicken, ice cream, lettuce, milk, orange, and seafood. Then, we will test each of the 250 images in the AI model and note whether it classified it correctly or not. We will also note what the AI classified the food as, if it were categorized incorrectly. For each food, we will record the accuracy, minimum, highest and average confidence. After recording these four measures of data, we will create separate graphs for each of these measures per food type. Overall, we will note the average, lowest, and highest accuracies and confidences. The experiment is structured this way so we can observe what types of images the AI can classify correctly, and conclude why some foods yield higher accuracies or average confidences than others.

The rest of the paper is organized as follows: Section 2 gives the details of the challenges that we met during the experiment and designing the sample; Section 3 focuses on the details of our solutions corresponding to the challenges that we mentioned in Section 2; Section 4 presents the relevant details about the experiment we did, following by presenting the related work in Section 5. Finally, Section 6 gives the concluding remarks, as well as points out the future work of this project.

2. CHALLENGES

In order to build the project, a few challenges have been identified as follows.

2.1. Configuring and fitting the model

Our entire application revolves around the effectiveness and efficiency of the AI model that we create for it [13]. As such, there are several concerns that we have to address. When it comes to fitting and accuracy, one must make a compromise at some point between accurate predictions and development time spent. In addition, one must also determine at what point the AI is considered sufficiently accurate. There are also several concerns over how the data for such an AI would be collected. Based on the arbitrarily chosen level of accuracy, one must consider how many images need to be collected in order for the AI to be able to predict at the desired accuracy. In addition, one must also consider where to source these images from as well as how to access them for use in training. Lastly, in regards to scale, we had to consider how robust our AI should be. We have to make a compromise as to how many foods the AI could analyze with regards to development time. We also have to make sure that our AI can be easily expandable with new foods in the future.

2.2. Figuring out how to save data

Another challenge that may arise in the development of the mobile application is the storage of data. Such concerns include the type, location, and display of the data. For storage type, we must consider what type of data needs to be collected from the user. We must also make sure that the amount of data we collect from the user is not invasive and is only the minimum required data for our operations. Additionally, with regards to where the data would be stored, we must decide whether a backend server or a phone would be more reliable. We must determine how the AI stores data, its overall reliability, and any limitations in storage space. Finally, the method of display for the data must be considered, as the user has to understand the context presented by the application. Since the displayed data can vary from person to person based on their meal plans, there needs to be a way to personalize the information so it is tailored towards the user's specific experience.

2.3. User experience

A final challenge is user experience, as users may encounter issues with the application. Some common navigation issues are confusing content, difficult navigation, filling data repeatedly, and landscape compatibility. We must consider a method that will ensure that users can conveniently access the app's features, such as the pages and the navigation tools. Furthermore, we must also address the issue of reliability, such as the accuracy and consistency of the image classification system. Another thing to consider is the ideal use case for an application like this, which should be around several months of continued, everyday use at every meal. There must be a method in place to keep users consistently engaged and satisfied with the application. Additionally, we need to consider the elements of the application that may be frustrating and/or confusing to new users. Another issue that must be taken into consideration is repeated use such as the ideal amount of time the user should use the application everyday, keeping users engaged, and minimizing the chances of user dissatisfaction and uninstallment of the application. Content can be potentially confusing to users as they need to know how to navigate the application, how much control they have over their meals, and which information is necessary for them to view whilst using the app. In addition, we must consider whether the application should be put in a landscape mode, or portrait mode. Additionally, it may be frustrating for users to fill out personal information every time they open the application.

3. SOLUTION

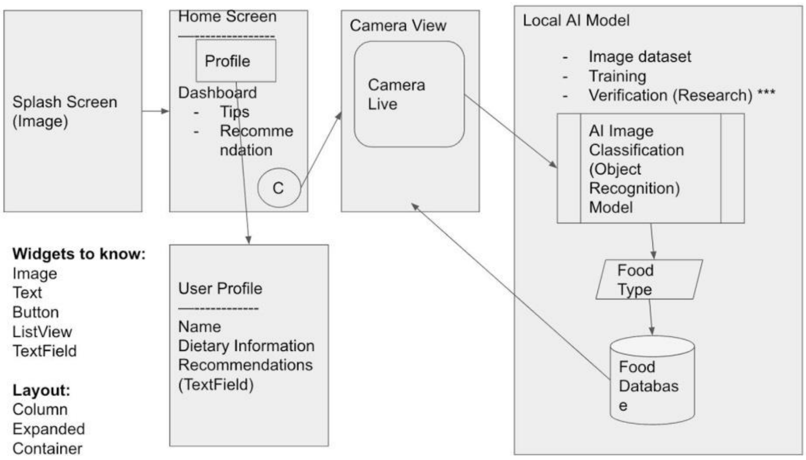

Figure 1. Overview of the solution

SmartCarbs is a mobile application written in Dart in Flutter that evaluates users' diets based on their eating preferences. It functions with 5 main components: the splash screen, home screen, user profile screen, camera view, and local AI model which includes AI Image classification to find the food type and store it into the food database. Users first interact with the splash screen, which is the loading page of the application. Then, they are directed to the home screen, which includes their profile page and the dashboard with tips and recommended foods. Users sign in after clicking into their profile, and are directed to a text field which allows them to enter and reset their name. There is a button with a camera icon in the bottom right part of the home screen, which allows the user to select their meal type, then brings them to a corresponding page with the meal type name and the same button. Once that button is clicked, the user is brought to the camera view page where they upload images of the food and confirm it using the left button with the image icon. Once they upload an image from their downloads, the local AI model uses image classification based on the image training to predict the food type and refers back to the food database to retrieve the 5 pieces of nutritional information for the piece of food. As the user confirms the food by clicking the check mark button on the bottom right corner, they are then brought to the meal type page where they can either add another food image using the camera icon button or confirm that their meal is complete. When they confirm that their meal is complete, then they are brought to the food result page which tells them the total number of calories consumed that day. On the bottom right of that meal result page, there is a home icon which brings the user back to the home page when clicked.

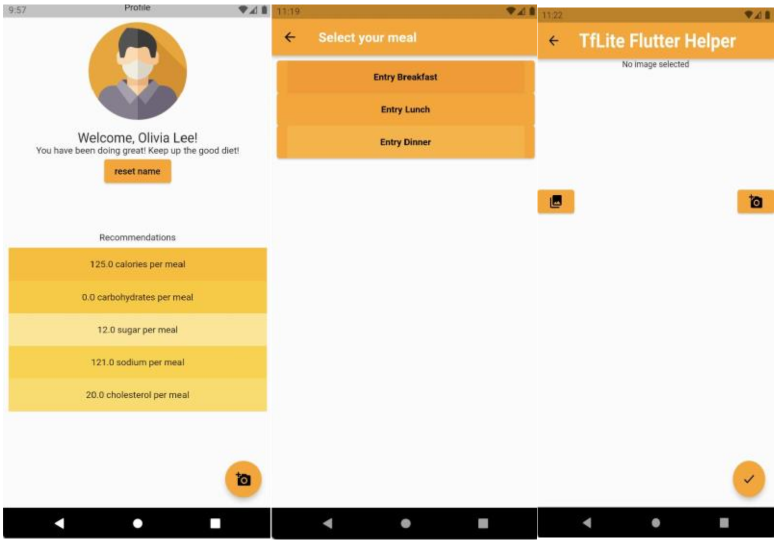

Figure 2. Home Screen, Meal Selection Page, and Camera View Page

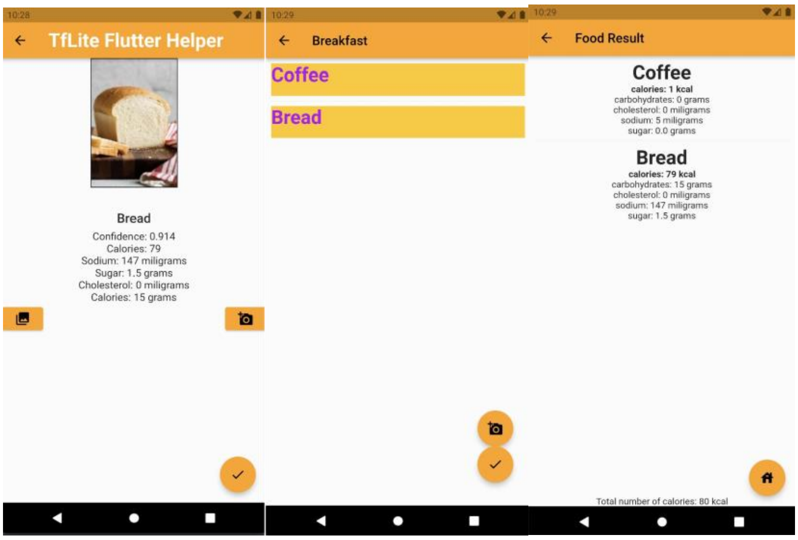

Figure 3. Local AI model, Meal Generation Page, and Food Result Page

This application was written on Dart and developed on Flutter, an open-source UI development kit used to build Android and iOS application versions. Here, the plugins present in all application components are the pubspec.yaml. Pubspec.yaml is a metadata file that includes the package name, version, author, etc. A variety of plugins, including tensorflow, image gallery, and Shared Preferences are required by the app to function properly.

In figure 3, the local AI model is shown. It is a computer vision AI which uses deep learning and a tensorflow training model. The model has been trained with 30 images of each of the 10 food types: Lettuce, Cooked Chicken, Milk, Bread, Ice cream, Apples, Chocolate, Fish, Orange, and Coffee to recognize the food type. Those specific foods were chosen because they are basic foods, are commonly consumed, and refer to all sections of the food pyramid. The purpose of the AI is to analyze the image and determine the type of food the image contains given an image containing a piece of food.

Regarding the process in developing the application, we used Google Colab, Flickr API, and Teachable Machines to train our model. Google Colab was used to test the AI and train it in earlier models during development, and the model was trained using 30 images per piece of food. The Flickr API was used to acquire training data and access images, using an image scraper algorithm in Colab. To accomplish this, we used a for loop to repeatedly grab multiple images for each specific type of food. Lastly, Teachable Machines was used to train the AI faster for future iterations and separate the foods into 10 different classes. Teachable Machines was an easy-to-use, more robust method of generating a trained Tensorflow model.

Figure 4. Save Food List and Meal Generation Data

This application uses code to record food data from the AI. The function requires key elements such as static and future data types, which allow the application to store data to be used in the future. In Figure 4, a snippet of the code is shown, and static is the keyword which allows data to be accessed freely from other screens without a direct reference. This goes for all data within RecordedData, which includes meal type and the names of foods eaten. The static functionnamed generateFoodNames generates a food list for each meal and converts the FoodInfo list into strings; it also records the meal type: breakfast, lunch, or dinner, and the date of the meal. RecordedData is referenced multiple times within the app due to it being static. RecordedData stores the type of meal (breakfast, lunch, or dinner), the list of foods of data type string eaten for each specific meal, and RecordedData clears when the meal is reset or submitted. Recorded data is an essential component of the application code because it is also called in other classes, such as the MealGenerationState class, in which the meal contents are saved.

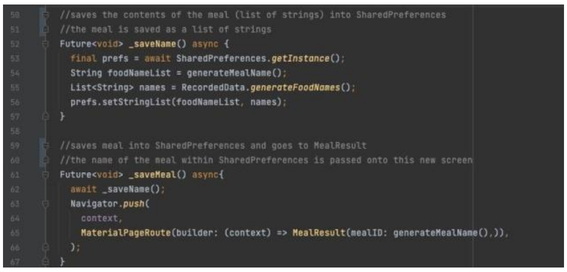

Figure 5. Snippet 2 of the application code

Shared Preferences is a plugin that allows the application to save a limited amount and type of information to the phone's memory. In Figure 5, the asynchronous and await function _saveMeal is used to save the meal name into Shared Preferences before the program transitions to the MealResult page. This is an asynchronous method, which are types of methods that run out of sync with the usual program execution. This method is asynchronous because it relies on Shared

Preferences, whose operations can take a significant amount of time. The use of await before these operations is done so that synchronous code that relies upon this method has the appropriate data in time. Otherwise the program would result in an error. Here, the saveName variable saves the user's name along with other essential pieces of information, such as the list of food names in string type. The saveMeal function saves the meal when a check mark button widget is pressed (not shown in Figure 5).

4. EXPERIMENT

4.1. Experiment 1

A potential concern about the application is that the AI included with it cannot make sufficiently accurate classifications for food. This is potentially detrimental because if the app is inaccurate, then users will be misled by the health advice that this app suggests. So, our experiment addresses the concern by determining which foods the AI can and cannot analyze correctly. From the data in this experiment, the AI can be improved through retraining weak spots, or incorrectly classified images. To set up the experiment, we used the Flickr API by creating a non-commercial key and secret to generate images from the Flickr scraper. Then, we used the flutter application to store the recorded data and categorize the food images through using a sample size of 25 images for each of the 10 foods. In total, there are 250 images used to test out the AI in this experiment.

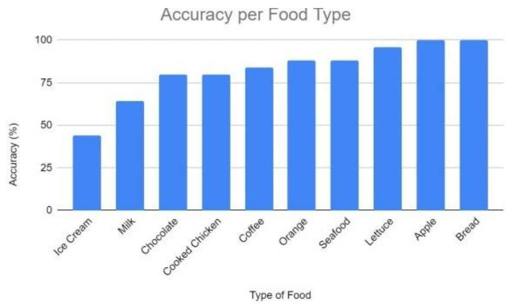

Figure 6. Accuracy per food type

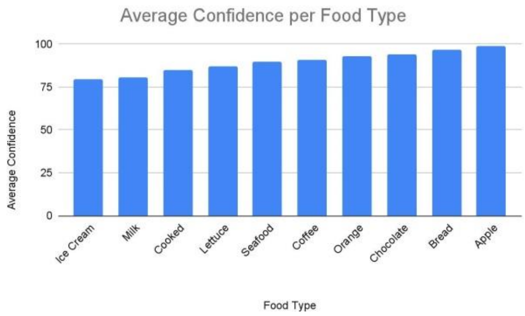

Figure 7. Average confidence per food type

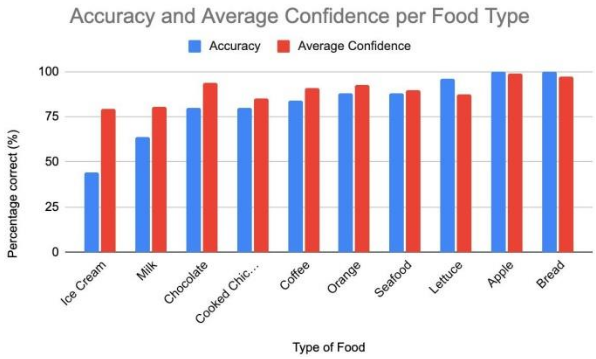

Figure 8. Accuracy and average confidence per food type

In our results, the lowest average accuracy for a given food group was ice cream at 44%. Conversely, the maximum recorded average accuracy for a given food type was 100% for apple and bread. When it comes to the AI's accuracy in general, it was able to predict 82.40% of all given images correctly, and its average confidence was 89.63%. The images tested for seafood yielded the average confidence of 89.84%, which was the closest out of all food types to the AI's average confidence level during the experiment session. Chocolate, cooked chicken, and coffee were closest to the average accuracy, at 80%, 80%, and 84% respectively. The lowest recorded average confidence for a given food type was 28%, a tie between lettuce and milk. Among all the food types, the maximum recorded confidence during testing was 100%. There appears to be no correlation between accuracy and average confidence for any given food type.

Our average accuracy for the food classification algorithm was 82.40%. All foods tested in this experiment yielded an average accuracy above 75%, but ice cream and milk had accuracies below (44% and 64%, respectively). The low classification percentages among ice cream and milk could be attributed to the possibility that the AI confused these two foods, because of the similar colors and textures. Ice cream had the lowest accuracy, likely due to the variance at which ice cream can be prepared, in both size, shape, toppings, and color, all of which can easily throw off the AI's pattern recognition. Additionally, the foods with the three lowest accuracies were ice cream, milk, and chocolate; this could ' ve been because these three foods are all dessert items and commonly associated with each other. In contrast, the foods with the three highest accuracies and average confidences were lettuce, apple, and bread. It is likely that the AI responded the best to those foods because the flickr scraper generated clean and easily-identifiable images of bread and apple. The top scoring foods are also " basic" foods in that they have very little ways of preparation or presentation compared to foods such as ice cream.

5. RELATED WORK

Sowah, Robert, et al. describes creating a management system that uses many AI algorithms to measure the multiple factors that affect diabetes in people [8]. The food recommendation system mainly uses the K-Nearest Neighbor (KNN) algorithm to recommend meals by setting reminders for diabetic patients to take their medication, tracking their blood glucose levels, and giving them a visual explanation of their diabetic results. The food recognition and classification model achieved over 95% accuracy levels for specific calorie intakes. Our application also allows users to input their meal choices and returns the total calories; however, it does not recommend the user to consume or avoid any of the entered foods and has a lower food classification accuracy. Although our application is a simpler version of the aforementioned application, both are convenient and beneficial for users by providing them with a diabetic-friendly diet, as long the users have their devices with them.

Shroff, G. et al. proposes Diawear, a Neural Network-Based Food Recognition and Calorie Calculation for Diabetes Patients [9]. Diawear is a wearable food image classification system that monitors the patients' calorie intake and amount of calories burnt, then gives the user a recommended daily calorie consumption by displaying it on a mobile device. This is similar to our application since both consider calorie consumption and food type. Our application also presents the meal results as a convenient visual form for the user through technology. In contrast, Diawear is different as it is a wearable device and uses various machine learning algorithms to address the issue, including Support Vector Machines (SVM) and Neural Networks.

Anthimopoulos, M. et al. explore how the carbohydrate content of a meal can be calculated using image-based food recognition systems [10]. The experiment involved organizing 4868 food images into 11 classes and, through extensive k-means clustering, reached a classification accuracy of 78%. According to Figure 12 from the study, the image classification algorithm was not 100% accurate, which was similar to our application. Additionally, this application resembled ours as it used multiple food types for training, and the accuracy was positively correlated with the number of trained images. On the other hand, this study uses k-mean clusters and support vector machines to predict a wide range of foods, which differs from our application, which only predicts ten foods.

6. CONCLUSIONS

There are many different resources that guide consumers on following a diabetic-friendly diet, and this is a mobile-based approach that offers diabetes nutritional advice for individuals to benefit from personalized food data. In this research paper, we built an AI model to generally classify 10 commonly-consumed foods by training it through machine learning platforms such as Tenserflow, Google Colab, and Teachable Machines. These foods are apple, bread, chocolate, coffee, cooked chicken, ice cream, lettuce, milk, orange, and seafood. For each piece of entered food, five pieces of nutritional data: carbohydrates, cholesterol, sugar, sodium, and calories are displayed. The average and total number of calories consumed per day is tracked. As seen in the experiment, the mobile application AI had a relatively high accuracy of 82.40%, indicating that it’s quite reliable. Since the AI is reliable, users may have a better understanding of what foods they should keep or remove from their diet. This mobile application also addresses the issues of the traditional approach of the time-consuming and expensive process of having physicians assign proper diabetic-friendly diets. Therefore, as long as users have their mobile devices with them, they can conveniently use the application to scan individual pieces of foods and meals for quick nutritional information. With this app, diabetic users can be more equipped with the proper resources needed to improve their dietary lifestyle. The results of the research can be used by anyone, especially those who are diabetic or pre-diabetic for an effective and enriching experience in the future [14].

Currently, while we consider our AI image classification model to be sufficiently accurate, there are still improvements that could be done to it in order for it to be more accurate [15]. There are also only 10 foods that are present within the AI model for it to classify, and more should be implemented. As users can not adjust the serving size per food, the application should bemodified so that specific serving sizes can be added. Additionally, in terms of the application the AI is housed in, it could be better formatted and structured to ensure quality use and good user experience. In terms of optimization of the AI model, some changes could be made so that the AI operates with less resources when run on lightweight mobile devices.

The experiment conducted in this paper was done in an isolated environment to test only the accuracy of the model, but consideration should also be put forth for practical environments. Future work for this AI will involve running another experiment in real-world scenarios to gauge whether or not the AI responds well to photographs of a variety of foods in a variety of conditions.

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