A Classification Tool for Dietary Restrictions

Final Project Report

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Problem and Motivation

The intake of food is one of the most natural actions for a human being. Ever since we are born, we crave for food for survival. Despite all the variety of food that is available on Earth, a universal problem is that not all foods are suitable for everyone to eat. Every person in the world has their own specific choice of food. It could be innate, such as a food allergy, where an individual's health would be affected when having a specific food. Or it could be a personal choice, such as from religion or belief, that an individual would specifically avoid a certain type of food. The food choice for one person could be so different from another that for places such as a canteen in school or assisted living places, it could be hard for one to distinct whether a meal would be suitable for an individual. For this purpose, we decided to create an application named Mega-Bite, to use the techniques of machine learning to help the user distinct whether a meal is proper for their diet restrictions.

In settings such as retirement home, the meals are often offered from a set menu to all the residents in the home. However, with the different health conditions, a meal may be suitable for the majority, but not for some individuals. For example, toasted bread is a breakfast choice that is acceptable by most of the people. However, for the individuals who have celiac disease, they would not be able to have it due to the gluten ingredients in the bread [1]. For this purpose, they would need to be offered gluten free products or their health condition would be threatened. It might seem too obvious that, "of course breads contain gluten, why should be bother to use machine learning?" but often it is not as easy to avoid the foods that has the specific ingredient. Again, with the example of gluten, it may seem plain that wheat in the bread should be avoided, but there are many hidden traps. Other foods such as noodles or doughnuts, cookies, and waffles, even beer and prepared lunch meat could have gluten in them [2]. Thus, instead of keeping the extensive list in the head of the patient and all the members close to the patient, it could be more convenient if an artificial intelligence can keep track of the list and analyze the ingredients in the foods right away, to tell the user whether the food is suitable for them to have. With machine learning, the information can be updated and become more correct as time pass and more training done, eventually it can become more reliable than human to analyze whether a certain food is fitting in one's eating habits.

In addition, not only the foods with clear distinct features, but the foods having the macronutrients such as protein and glucose, or minerals such as potassium or sodium, can be hard to distinct by human eyes. People suffering from diabetes or renal problems, are sensitive to the level of the intakes of these. Currently, the most effective way is to remember the list of foods that has or do not have these ingredients, and make sure to follow the list properly. This can create lots of burden especially that the intake of food is a reoccurring action that cannot be omitted. Again, it would be made very convenient if all the lists of forbidden ingredients could be kept on track by an application, and any time when preparing a meal, one can simply just consult the app to make sure the foods prepared will not cause a burden to the health of the individual.

As the food restrictions can be an overly broad topic, in this project, with the limited timeframe and availability of resources, we are focusing on three main groups of special diets. These are the renal diet, dysphagia soft diet and non-mixed consistencies foods. Renal diets are for people with compromised kidney, thus the amount of minerals and macronutrients, such as sodium, potassium, phosphorus, and protein intake should be considered [3]. Dysphagia soft diets are for people who have a tough time chewing their foods, for example, patients who just recovered from a major illness or surgery [4]. Non-mixed consistencies foods that release liquid when chewing such as watermelon [5], these are usually for people with choking hazard. In the end, our goal is to use deep learning to build a system that can ease the life for the special diet needs people.

Methodology

Approach

Research into diet and machine learning has led to a decision to build a preliminary model that can recognize different food types. Initially, this type of image classification problem has been solved by using Convolutional Neural Network for features learning and Fully Connected Neural Network for classifications using Keras/TensorFlow which is very complicated to design the model, number of filters and layers, finding the best learning rate e.t.c. However, while optimising the system using above mentioned models, we experienced some unwanted slower training times and the accuracy was not up to the mark. Next, we have designed this system more effectively using transfer learning with VGG16 model to avoid unknown extra training times. But still we couldn't get the efficient accuracy and the process was time consuming since we had to design every steps in details manually. Finally, we decided to use Fastai packages to solve this image classification problem with feedback to compare with Keras/TensorFlow. Moreover, Foods have been classified and mapped according to each diet's requirements & saved as a csv file and then returned whether a particular food falls under a specific diet with significant accuracy.

Data Selection

There are many image datasets readily available on the internet. Fastai also offers many varieties like TensorFlow including a few that are food based. While other image datasets are available from research studies, Fastai's food101 provides a ready built dataset that cover a wide variety of food types. The dataset is also scaled to a maximum side length of 512 pixels and is already broken into training and test sets. Food101 has 101,000 images with 101 categories. These are further broken into 250 test images and 750 training images per food type. Noise, such as bright colours that stand out are kept in the images of food101 to provide realistic data where ideal conditions do not exist. A potential issue with food101 is that Tensorflow has left some images intentionally mislabeled. This may contradict the model as it begins to distinguish food, but this may lead to a more robust model. For our convenient, we further modified the dataset by reducing the number of images/class and number of classes as well. We have used only 1000 images and 10 classes to build and train our model.

Model Selection

As the number of samples in our model is limited it makes sense to use a pre-trained model and hence, we investigate Resnet18 of CNN model in Fastai which has 18 layers deep.

We want a model that gives us the highest accuracy on validation data since it can make sound predictions. The model should be able to train and predict as efficiently as possible. In production, we may need to produce hundreds or thousands of predictions every second. Using a Fully Connected Neural Network would not be appropriate here, as the number of parameters to train would take an unreasonable amount of time, even with using a GPU. In comparison, a CNN would have dramatically less trainable parameters, thus also reducing the training time. Hence, we would be using a pre-trained Resnet18 CNN model as it matches the criteria for our project.

Metrics and Validation

Evaluating a model is a major and crucial part of building an effective machine learning model. The most frequent classification evaluation metric that we use for deep learning is 'Accuracy' because of its simplicity and interpretation. The higher the accuracy, the more efficient the model is. It's therefore essential to increase the accuracy by optimizing the model.

As we already know, accuracy works best for generic and uncomplicated datasets when classes are balanced because it is just the percentage of the made predictions. Accuracy does an excellent job of blending specificity/true negative rate (TNR) and sensitivity/true positive rate (TPR), recall and precision [9]. However, sometimes accuracy can be misleading in some situations. To get the overall scenario and to relate the ratios between predictions vs actual test data predictions, confusion matrix is best.

Findings

The accuracy of the current model is of course not ideal for production or public use, but is a good starting point and is a good proof of concept. The final results (I.e., the conversion of food types to applicable diets) are also affected since they depend on the accuracy of the model prediction. Table 1 below compares a sample of the predictions that the model made to the expected results and the diets associated with the food types.

Actual			Predicted		
	Food	Diet	Label	Food	Diet
25	club_sandwich	Renal	88	seaweed_salad	None
71	paella	None	64	miso_soup	Renal, soft, mixed
72	pancakes	Renal, Soft, mixed	12	cannoli	Renal, soft
68	onion_ring	None	68	onion_ring	None
16	cheesecake	Renal, soft mixed	12	cannoli	Renal, soft
37	filet_mignon	Renal, mixed	50	grilled_salmon	Soft, mixed
99	tuna_tartare	Soft	37	filet_mignon	Renal, mixed

Table 1: Summary of the model predictions and associated diets.

After that, we have developed the app using Voila and Ipython widgets. Finally, we deployed the app using Binder. (Here is the link- https://github.com/sonia-UoC/Diet_Classification_Fastai.git)

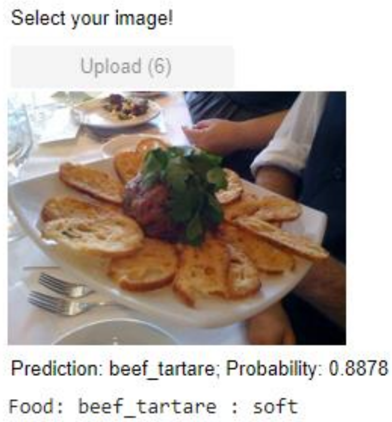

Figure: Food image recognition and Prediction of diet classification

From the above figure, we see that the model could correctly recognize one food image. These results are expected since the training of the model only resulted in approximately 80% accuracy. In the future, we would like to continue training the Resnet18 model to produce a more reliable and accurate product and to help those with restricted diets in compliance with medical advice.

Discussion

In comparison with Keras/TensorFlow packages, Fastai packages are more simple, less sophisticated and user friendly. To solve this image classification problem using Keras/TensorFlow, we had to define every step such as loading and splitting the dataset, training model's number of layers and filters, parameters, loss function, optimizer e.t.c manually. Whereas to solve the same problem using Fastai, it was so easier that we don't need to define and design anything. We just need to call the built in functions such as DataLoaders to load and split the data, cnn_learner to train and define the pretrained model e.t.c.; no need to define the loss function, optimizer and number of layers or filters of a model. Fastai libraries are user friendly and easy to understand for new coders.

Future Scopes

i. We can run the model with full dataset.
ii. We can fine tune the model and increase the accuracy by increasing the deep layer numbers.

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