Sehat Co. - A Smart Food Recommendation System

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Abstract- Amidst Covid-19, nutrition has become a very important aspect of everyone's life since the major factor in helping us prevent this deadly virus is a person's own immunity. In addition, picturing food has become a major hobby now-a-day. Social media comes with a huge amount of food images posted each day. Most people will not be able to identify food, and to determine it directly will be very difficult. The system proposed helps to not only help to track the food details but also eliminate the chance of eating ingredients which are poor against covid. As a result, it uses image processing techniques to extract features and convolutional neural networks that can distinguish and label different features in the image, and then provide a cooking environment. Recipe1M provides the largest open access to recipe data, allowing high-quality models to be trained in targeted, multimodal data. In addition, by adding a high-level separation process, we show that doing so enhances the return of full functionality to humanity while enabling semantic vector calculations. The ingredients predicted then are matched with our sophisticated Covid-dataset which contains ingredients useful for fighting against covid and accordingly stats for a recipe are displayed with recipe recommendation as well with the same set of predicted ingredients.

***Keywords*—Food recommendation system, Diet, Recipe1M, Image processing, Nutrition, Health, Covid, Corona, Ingredient's prediction, Food against covid.**

INTRODUCTION

There are numerous aspects that have been identified as having an impact on an individual's health. Physical activity, sleep, nutrition, inheritance, and pollution are only a few examples of external variables. Considering that eating is one of the most adjustable aspects of our life, it's no surprise that minor differences can have large consequences. Because our food has a deep connection in its culture, we can spin around every sector to recognize food that surrounds them. The very common elements in an area are closely linked to local factors such as climate. This has a significant impact on the supply of ingredients used in local cooking.

Some chemicals have been shown to have a beneficial influence on health, specifically in the fight against Covid. Knowing which compounds have the highest amounts could aid in the treatment and prevention of the virus. Furthermore, by incorporating these products into delectable and economical meals, the population's dietary habits may be influenced. In a society where the consumption of fast food is on the rise, it's evident that, in addition to the two prior reasons, time in preparation is a key component.

Huge data is being added to the internet every day and is made accessible for various educational as well as commercial purposes and with this we have a better chance of developing complex recommendation models which not only take into account user interests but also other factors like molecule interaction in foods, disease or virus or bacteria resistant qualities, etc. This would enable the user to make more informed choices while purchasing or making his subsequent meal.

The website, "Sehat Co." would exhibit detailed information on exactly where and how we fall in to fix the problem and bring awareness to the users visiting our platform. The user would be able to upload their daily food images and our system would then predict the ingredients with the recipe as well for the food image along with another recipe recommendation. Besides that, there would be test images to help users try our platform and see for himself/herself how it works.

LACUNAS IN THE CURRENT SYSTEM

A) Non-existent automated models: -

The lack of a platform that can dynamically display the covid metrics for ingredients is a fundamental flaw in today's systems. The existing systems can just anticipate ingredients and display a recipe based on that prediction, with no participation of the covid beating factor whatsoever.

B) Proprietary existing systems: -

The second issue is the availability of proprietary systems which means most of the companies develop these systems as a business product rather than a platform that helps everyone.

C) Limited Access to People: -

Due to this business aspect of the current systems, the people cannot afford this software either due to very high costs or the system being developed for enterprises and is complex to understand for common people as such.

D) Biased on other forms of data: -

The emergence of content-based recommendation engines may occasionally result in incorrect results since users simply like or share without giving it much thought, which falls into the muddled category of data collecting with no useful results.

LITERATURE SURVEY

In the paper by M.B. Vivek, et al. findings include collaborative filtering approach work by collecting user interactions in the form of ratings or preferences for each of the items and identifying similarities amongst other users to determine how to recommend an item. Whereas in content-based, recommendations were given by comparing representations of content describing an item to representations of content that interest the user. A hybrid recommendation system was built by combining the collaborative filtering approach and the content-based approach [1].

In the paper by Dietrich Knorr, et al. findings include several foods and nutrition-related challenges encountered during the COVID-19 pandemic, including food and water safety, supply chain disruptions, food and water insecurity, consumer and food behavior, malnutrition and nutrient intakes, food surveillance technology, as well as potential post-COVID-19 strategies [2].

In a paper by Laura Di Renzo, et al. The findings include that it was a study aimed at investigating the immediate impact of the COVID-19 epidemic on diet and lifestyle changes among the Italian population. The study included a structured questionnaire that included demographic information, anthropometric data, dietary information, lifestyle habits. Weight gain has been observed in 48.6% of people [3].

In the paper by Faisal Rehman, et al. findings include a model that generates an optimal diet list using an ant colony algorithm and recommends appropriate meals based on the values of pathology reports. Dietary changes can help to control a variety of disorders. The testing results reveal that, as compared to single-node execution, parallel execution on the cloud has a 12 times faster convergence time [4].

In the paper by Mansura A Khan, et al. findings include when individualized recommendations are offered with health-aware smart-nudging services, the user receives more support and encouragement for healthy eating. Furthermore, these smart-nudging devices can successfully influence consumers' eating choices [5].

In the paper by Pratiksha N., et al. the findings include their system delivers recommendations to users based on their likeness, as well as custom recommendations for users with hereditary concerns such as heart disease, diabetes, hypertension, and so on. This can be expanded to include more product categories in order to provide recommendations to a wider range of users who choose products with distinct nutrition gainers [6].

In the paper by S.R. Chavare, et al. the findings include that their system takes into account the past and present relationships between objects and users. The focus was on creating end-to-end neural networks that take into account previous behavior. It was projected that deep learning would be used in a certain way [7].

Early attempts to produce a food recipe include comparisons and evaluations of popular and theoretically based programs using the largest database containing approximately 101k recipes corresponding to 101k food categories [8]. They have suggested a real-world app for identifying recipes for everyday users. This app is a search engine that allows any mobile user to upload a query image and restore relevant recipes to their website.

Efforts have been made [9] to promote the deeper structures of continuous ingredient recognition and study of food categories for ingredient recognition and meal planning, based on the links that exist between the two. Semantic labels for items were acquired, which they subsequently used to retrieve recipes using deep features. To do this, a multi-task deep learning model was used. They have developed a neural network considering a huge dataset of around 800k images and more than 1M recipes to build integrated image embeddings that help in providing subsequent learning in image to recipe obtaining tasks.

PROPOSED SYSTEM

The proposed system is used to predict ingredients from the input image and then include the ingredients with features of the image; the recipe of the image is also generated. The system also recommends a second recipe with the ingredients predicted. The predicted ingredients are also used to check the covid stats present in them as they are searched in the ingredient table in Mysql which consists of ingredients consisting of anti-covid molecules. A percentage of ingredients with anti-covid molecules among all the predicted ingredients is displayed with them having a green background. The percentage displays the effectiveness of the food in increasing the immunity of the consumer against covid-19.

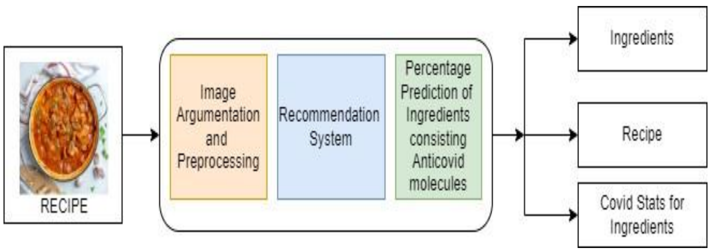

Fig.1. Block Diagram

According to the above block diagram, our system takes the food image as input from the user. After image augmentation and processing, the ingredients for the required recipe are predicted. This is then used with the given image to generate the recipe that we see in recipe1.

Recipe2 is also recommended based on the predicted ingredients. Finally using the ingredients, the percentage of ingredients consisting of anti-covid molecules is found which represents the effectiveness of overall food in increasing the immunity against covid. These ingredients are displayed with a green background and others are with a red background while displayed.

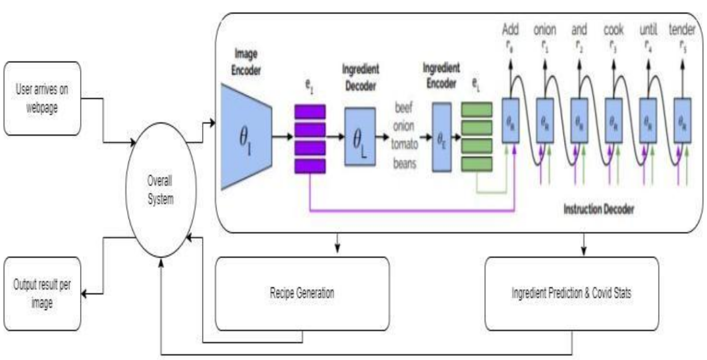

Fig.2. Modular Diagram

The major goal which is accomplished by the help of this method is the improved accuracy of an average person while trying to predict the ingredients from the image. In this system the inverse cooking algorithm has been successfully incorporated into the recommendation system which is developed for this project. As soon as the ingredients are predicted in the web application, based on that rest all the ingredients are then searched in the ingredient table in SQL containing ingredients that contain anti covid molecules and if found the same ingredients are introduced in a green background otherwise red. background color.

METHODOLOGY

A) Dataset: -

To train our model, we used a 1M recipe data set to obtain food photos and recipes. The recipes were collected from various well-known cooking websites and run in the process of retrieving important text in raw HTML, retrieved linked images, and editing data in a short JSON format. Too much white space, HTML elements, and non-ASCII characters have been removed from the recipe text during the extraction phase. All the ingredients in this database are important contributions to make it machine-learning friendly.

Starting with the scraping part, around 1M images with 5 images related to a particular recipe given as a search query param were downloaded from the internet using various publicly available web crawling tools and python scripts programmed by us. Filtering out images that were not related to the recipe properly or were blurred or distorted was done following the previous task.

To sum up the duplicate ones, a total of 0.3 percent are found, and approximately 15% of recipes have topics that are not distinct but separated by a median of sixteen elements. The simplest of them which occupied 0.15 percent of the recipes consisted of the same ingredients with a median of six. In the first collection of data from recipe websites, about half of the recipes did not contain related images. Around 2% of the recipes are left missing associated photos after the data extension phase. Upon researching a lot with utmost care, the exact copy/duplicate was pulled out using ResNet18 as a feature extractor.

About 80% of the data is used for training while the remaining data is evenly divided between both test and validation sets. A joint data set was created while working on the data expansion phase to allow for valid testing of test results in both major and extended versions of the database.

Database content can be divided into two categories. The first layer includes basic information in text formats, such as title, list of ingredients, and a series of recipes. The second layer builds on the first by incorporating all of the related JPEG photos.

Nine ingredients are transformed throughout the course of 10 instructions in the average recipe in the dataset. The densities of data are heavy-tailed, as can be shown. For example, only 4,000 of the 16000 items were recognized as a separate individual account for 95% of all events. At the lower end of the frequency of instructions, one will encounter the command 'Combine all ingredients'. Subsequently long recipes which contain nested short recipes can add to the number of recipes even more.

One more frequently faced issue was of outliers as several recipe collections were stored on the basis of user images due to which sweet recipes like desserts. have more recipes than the usual ones. In the early stages of the data gathering process, there were 333K distinct recipes with associated food photos. This unit increased to around a million which was quite significant during the data expansion phase. Recipe1M + has 13 images per recipe, while Recipe1M has less than one image per recipe. Therefore, we decided to move forward with the expanded dataset.

B) Machine learning model: -

i. Implementation

The neural network models were trained with the help of Tensorflow2 which is an open-source machine learning framework developed by Google researchers. For training, we measured images into 256 pixels and took a random yield of 224x224 pixels. We select 224x224 pixels from the center for testing. As for the instruction decoder, we used a 16-block transformer and 8 headers, each with its own 64-bit size. We use a four-block transformer and two multihead attention, each with a size of 256, on the component decoder. To get embeddings of the image, we used the final ResNet-150 layer. Image size and ingredient embedding is 512 pixels. The highest number of ingredients per recipe is limited to 20, and the directions are limited to 150 words. Models are trained with Adam optimizer [11] and meet the premise condition of 50 patience as well as monitoring of loss of validation.

ii. Recipe Generation

We have discussed the multi-layered structures and different attention-grabbing techniques. In the validation database, Table 1 shows the complexity of the model for each attention strategy Model. We can deduce from the table that the outcome of independent attention is poorer and that sequential attention comes in second. This demonstrates the techniques' inability to forecast the predicted outcome. However, discussing concatenated attention, with a score of 8.50, achieves a very good result as it adapts to give value to each approach, while independent attention as such ought to inherit value from both model encoders. As a result, we used a concatenated attention model to provide appropriate results in our test database.

Our system has been compared to two other models. One is an image sequence command (I2R) system, which generates direct sequence instructions on the image element, while the other model removes visual elements and predicts sequence instructions from ingredients (E2R). In the test database, our system detected 8.51 confusion by upgrading both the I2R and E2R baseline. It has defeated the other two models, which had perplexities of 8.67 (L2R) and 9.66 (I2R), respectively, from which we can deduce the significance of ingredients in anticipating instructions. Finally, we trained and assessed our model's output.

Model	**Perplexity**
Independent	8.59
Sequence Image First	8.53
Sequence Ingredient First	8.61
Concatenated	8.50

Table 1: Recipe perplexity

iii. Ingredient Prediction

We evaluate our ingredient prediction methods for models already established in this section, with the aim of determining whether ingredients should be considered as lists or sets. To start with, we implemented models of multilabel classification architecture, which we subsequently fine-tuned for our needs. Feedforward network models are trained to anticipate ingredient sets in compliance after the first step.

We performed experiments that considered different losses, including binary cross-entropy, soft intersection over the union, and cross-entropy targeted distribution. Consequently, we found sequential models predict ingredients as a series by increasing order and using dependence. Towards the end, we used the newly developed models where set predictions are combined with cardinal predictions to assess which features should be included in the set [12] because models using dependencies continuously increase ingredient F1 units and strengthen the modeling correlation of ingredient circumstances.

Model	IoU	F1
ResNet18	17.88	30.32
InceptionV2	26.28	41.59
ResNet50	27.25	42.83
ResNet150	28.85	44.14
TFlist	29.51	45.56
TFlist + shuffle	27.87	43.60
TFset	31.82	48.29

Table 2: IoU and F1 of Ingredient models

C) Website:-

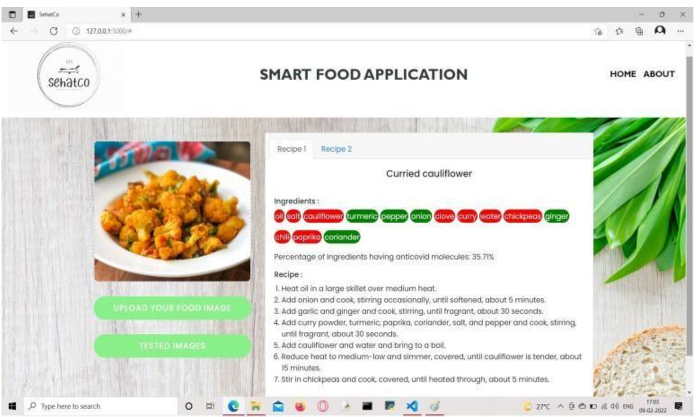

Fig.3. Recipe 1 for Curried Cauliflower

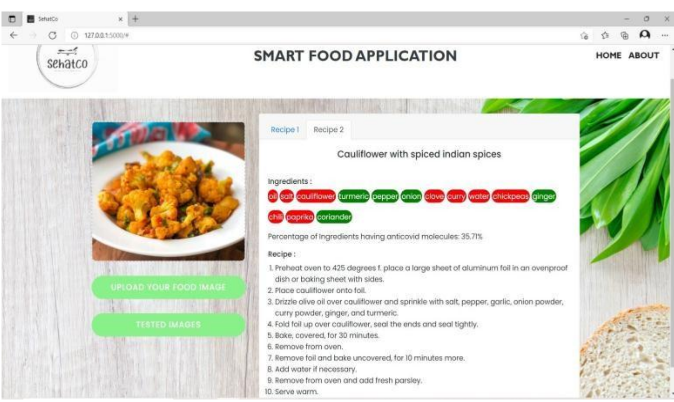

Fig.4. Recipe 2 for Curried Cauliflower

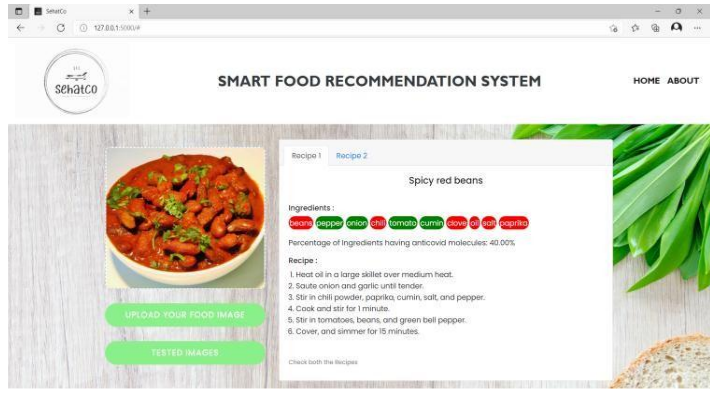

Fig.5. Recipe for Spicy Red Beans

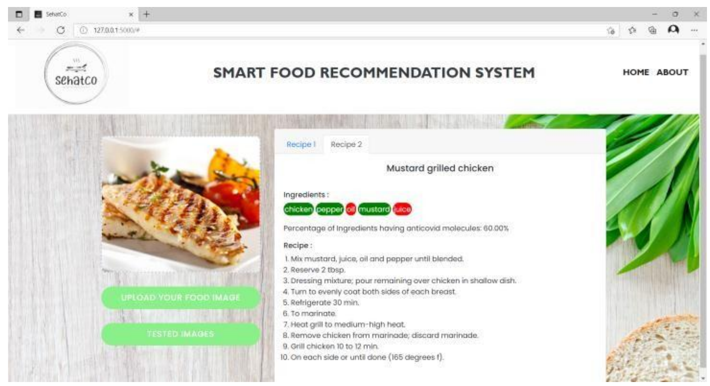

Fig.6. Recipe for Mustard Grilled Chicken.

RESULTS

i. Ingredient Prediction:-

Recipe Recovery Model from [10] serves as a basis for comparing our best prediction models, ResNet-150 and TFset. Ri2lr is a retrieval model trained using integrated image embedding and recipes (title, ingredients, and instructions). As a result, we used image embedding to find a recipe that was closer to the output metrics of the recipes for a predictive task in a particular container. We are also investigating Ri2l, another acquisition system trained using integrated image embedding and a list of ingredients (without considering account title and command). The acquired findings on the Recipe1M test dataset are shown in Table3. The Ri2lr model outperforms the Ri2l model, demonstrating the significance of complementary information in the ingredient's dataset. In spite of that, the system we propose exceeds both the retrieval-based model and the Ri2lr recovery base by a large margin (TFset exceeds the Ri2lr recovery base by 12.26 points in IoU and 15.48 F1 school points), indicating that our models are superior.

Model	**IoU**	**F1**
Ri2l [10]	18.92	31.83
Ri2lr [10]	19.85	33.13
ResNet150 (us)	29.89	45.99
TFset (us)	32.52	48.68

Table 3: Comparison of IoU and F1 scores

Input Image	**Predicted**	**Real**
	Oil, Salt, Cauliflower, Turmeric, pepper, onion, clove, curry, water, chickpeas, ginger, chili, paprika, coriander.	Oil, ginger, chili, coriander, cumin, Turmeric, Cauliflower, GaramMasala.
	beans, pepper, onion, chili, tomato, cumin, clove, oil, salt, paprika	bean, garam masala, onion, tomato, cumin, chili pepper, garlic, coriander, salt, dhaniya powder, chili powder
	chicken, pepper,oil, mustard, juice	chicken breast, mustard, oregano, paprika, salt

Table 4: Ingredient Prediction Examples

ii. Recipe Generation: -

The decoder that we propose has been evaluated with a retrieval model that takes images as an input given ingredients. We redesigned the recovery model to obtain recipes using both ingredients and images to provide a neutral comparison. We have used the ingredients of the basic truth as a measure in our analysis and reconsideration of precision depending upon the ingredients in the instructions received. The recall actually calculates how many of the actual positives our model captures through labeling it as positive and the accuracy is a metric that generally, describes how the model performs across all classes including positives and negatives. A comparison of our model with the retrieval method is shown in Table 3. Ingredients that we propose in our suggested generated instructions beat the recall and precision scores of ingredients in retrieved instructions, according to the results generated.

Model	**Recall**	**Precision**	**Accuracy**
Ril2r	31.93	28.96	30.36%
Inverse Cooking	75.50	77.10	76.31%
Ours	78.44	79.57	78.96%

Table 5: Precision and Recall of Ingredients Model

FUTURE SCOPE

The application has been developed as an academic project and hopefully, it gets to many NGOS or non-profit organizations. The future scope mainly includes refining the machine learning model to fit local needs delivered by the patients, their taste preferences, etc. since the majority have their sense of taste weakened or lost as well and developing a better UI along with some informative blogs to support it.

CONCLUSION

Food has been one of three main basic needs of life and being able to control what we eat or at least have knowledge about what we are eating can majorly restrict the consequences of getting diseases or even getting cured properly and as quickly as possible. Through this project, we think we can educate or create an awareness of those who have their family members affected due to covid a better chance of curing fast as well as preventive food measures if not already affected and post-covid too.

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