Food Image To Recipe Converter

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***Abstract*—The project aims to generate food recipe by classifying the image present in the dataset and along with that shall also give calorie, degree of the food, based on the image using multiple machine learning models**

Keywords*— *food recipe, degree of food, calorie

I. Introduction

Food is indeed a very important aspect in the life of a human being. It helps us gain energy, help sustain living and also provides rich nutrients to help us do our day- to-day activities. Food is thus an essential component in a human's life. Tasty food adds more nutrients and interest to children especially in their growing ages. But due to lack of finding the proper recipe or taking the worst case not knowing the dish's name can cause mother's and many people limit their food exploration capacity, making them limit to their daily food, which would have bored them. When children and even teenagers lose interest in eating food, they tend to lose their appetite and thus effects their health and doesn't let them enjoy food anymore, thus it is a sheer necessity to eat proper food. To make proper food, modern age people seek for recipes in the internet which do not actually tell them the quantity to enjoy quality food. Health freaks who are very much concerned about their health often tend to analyze their daily intake of food based on the number of calories and the protein thus giving a health-conscious recipe. Thus, we have are introducing Recepto. Recpeto is a image classification model that gives the statistics of food and also its recipe for a healthy diet through machine learning models. We take different parameters since we are very much health conscious and believe in the ideology of "a fitter world, makes a better world", thus we use different machine learning models to classify the image of the food and give the recipe based on that.

II. LITERATURE SURVEY

Food computing is becoming a major area of research, with the ultimate goal of creating machine learning systems that can automatically generate recipes based on food images. Current methods rely on finding similar recipes in a database, which limits their success. This paper proposes approaches, which uses powerful language models to directly generate recipes from images. The classification works in three major steps : (1)**BLIP Model** : Bootstrapping Language-Image Pre-training, is a state-of-the-art model used in the FIRE system for generating titles for food images. Here's a breakdown of its key aspects: BLIP is a multimodal model, meaning it can process both visual information (images) and textual information (language).It's specifically trained on a large dataset of images and their corresponding captions. (2) **Vision transformer with a decoder** : To extract the proper ingredients that are required for the creation of the recipe we need a tool that extracts the ingredients. There are multiple approaches but the best approach is through Vision transformer that is specified to bring out the ingredients that are necessary for the food. (3) **T5 Model** : Well last but not the least, once we are ready with the ingredients it is time to cook the food, thus we use the T5 model that is used in generating the recipe of the food and make it feel tasty.**[1]**

We tend to create a web and a mobile application platform that can be useful in making the model. Thus, to implement it as a dual service we have planned to blend in machine learning models that shall suffice both the sources. To come up with that we have used the following approaches : (1)**Advanced Search**: Forget keyword limitations! Feast In's innovative search algorithm helps you refine your recipe search based on available ingredients, dietary restrictions, cooking time, and even cuisine. No more sifting through irrelevant recipes – find the perfect fit for your needs. (2)**Search by Image**: Ever seen a mouthwatering dish but don't know what it is or how to make it? Feast In's powerful image recognition technology comes to the rescue. Simply upload a picture, and Feast In will suggest similar recipes, unlocking a world of culinary possibilities.**[2]**

This paper, by Obaid et al. (2020), delves into the world of deep learning models for image classification. As the authors highlight, the "big data age" has fueled the development of increasingly complex deep learning algorithms, capable of surpassing traditional machine learning methods in feature learning and expression. This has led to significant advancements in image classification tasks within the field of computer vision. The paper provides a comprehensive overview, starting with an introduction to deep learning itself. It then delves into various deep learning models used for image classification, including: **Convolutional Neural Networks (CNNs):** These are the workhorses of image classification, adept at extracting spatial features from images. **Recurrent Neural Networks (RNNs):** While less common, RNNs can be useful for handling sequential data like image sequences. **Transformers:** Newer architectures like transformers are gaining traction, offering advantages in handling long-range dependencies within images. The authors compare and contrast these models based on their strengths and weaknesses, highlighting factors like accuracy, computational efficiency, and suitability for specific tasks. They also discuss the impact of factors like dataset size and diversity on model performance. Finally, the paper focuses on two popular benchmark datasets for image classification: CIFAR-10 and CIFAR-100. The authors compare the performance of various deep learning models on these datasets, providing insights into their relative effectiveness. Overall, this paper offers a valuable resource for anyone interested in understanding the current landscape of deep learning models for image classification. It provides a clear and concise overview of the key concepts and models, along with insights into their strengths, weaknesses, and practical considerations. **[3]**

This research, by Gulzar (2023), investigates the use of MobileNetV2 with deep transfer learning for classifying fruit images. This approach leverages pre-trained models to improve accuracy and efficiency in tasks with limited data. The study focuses on a dataset of 40 different fruits and utilizes MobileNetV2, a lightweight and efficient CNN architecture. By applying transfer learning, the pre-trained weights of MobileNetV2 are fine-tuned on the fruit image dataset, allowing the model to learn fruit-specific features. **[4]**

A new study uses machine learning to predict the degree of processing in any food, revealing that over 73% of the US food supply is ultra-processed. This has concerning health implications, with increased reliance on ultra-processed food linked to higher risks of metabolic syndrome, diabetes, and other issues. Replacing these foods with less processed alternatives could significantly improve health outcomes, highlighting the importance of better informing consumers about processing levels.**[5]**

This paper provides a conceptual and technical foundation for building a food image to recipe converter using machine learning. This paper, mentions that the system outputs the recipe names of the food, ingredients, and cooking procedures using machine learning datasets. This paper, mentions using the convolutional Neutral networks (CNN) to categorize food images into various categories and output matched recipes. this paper helps our project to how to offering insights into model architecture using CNN, dataset considerations, and output structures, enhancing the practical applicability and performance of our project**.[6]**

This paper is on automatic food recognition and nutrient estimation from food images using some datasets and computer versions which is relevant to our food image to recipe converter project. It tells the state-of-the-art methods for processing food images, including classification, segmentation, and volume estimation. The systematic review of these methods, along with insights into the strengths and limitations, can inform the design of our model. By this paper, we can enhance the accuracy and effectiveness of our food image to the recipe converter project**.[7]**

This paper provides the use of a subset of the 1M+ dataset and it involves using a mobile application with an approach to search encodings of food images generated through a DenseNet-121 CNN. This approach simplifies the model and uses CNN directly for mapping, it calculates the similarity index for input food image and image in the dataset. It uses DenseNet-121, a deep CNN for processing the food images. It also tells the use of distance metrics and the KNN algorithm to find the closest matching result. Finally, this paper informs and guides various aspects of our project covering dataset selection, model architecture, nutritional value integration, and similarity index calculation. **[8]**

This paper provides the limitations of existing food-logging tools and aims to improve precision and convenience. this paper uses leveraging advanced machine learning techniques for food recognition to potentially improve the accuracy of recipe conversion. In their paper, these optimized models are integrated into an Android app named Food Insight. finally, this paper can assist our food image to recipe converter project by providing insights into addressing challenges, leveraging advanced machine learning techniques, integrating knowledge bases, handling contextual information, and offering a practical example of Android app implementation**. [9]**

This paper provides creating standardized recipe datasets for machine learning is tough because recipes come in various formats and languages. In this study, we collected recipe datasets available publicly and made them consistent using dictionary and rule-based methods. We also used specific resources to convert measurements. This gave us two sets of data—one with ingredient embeddings and the other with recipe embeddings. When we tested a machine learning system to predict nutrients using these datasets, we found that combining embeddings using domain knowledge worked better than the usual methods**.[10]**

III. METHODOLOGY

A1. Finding inter and intraclass for the dataset

The above A1 deals with the findings of the inter and intraclass for the dataset that we have given. the dataset has multiple classes, so we considered only two classes. the classes present in our dataset are as follows:

1. Title
2. Ingredients
3. Instructions
4. Image Name
5. Cleaned Ingredients

here we considered two classes: Instructions and titles. The name intraclass is the distance from classes and intraclass is the distance within the classes. Thus, to finds the distances we find the distances we first drop the missing values present in our dataset to make it easy to read the data and later filters the data for classes. we use only two classes A and B to filter the data.

A2. Observing the density pattern

In the A2 code, it reads the dataset containing the ingredients and recipes from our dataset drop the rows with missing values in the instruction, and prints it. after extracting the instructions from the dataset, it calculates the length of every instruction in the form of several words finds the mean and variance of the instruction's lengths and prints these statistics. Also, it prints the histogram to find and print the distribution of the instruction length, using 20 bins and plots the frequency of instruction lengths to find the number of words. the result histogram provides the distribution and frequency of instructions length from the dataset.

A3. *Minkowski Distance*

In the A3 code reads a dataset which contains food ingredients and the recipes from the CSV file and extract the cleaned vectors. (++) then it processes the first two vectors to calculate their numeric representation which are the count of observations.(++) these numeric representation are used to find the Minkowski distance between the two vectors for different values of the parameter (r) ranging from 1 to 10.(++)The resulting distances are plotted against the (r) values, generates a line plot to visualizes the relationship between the Minkowski distance and the parameter (r).++ this provides the insight how the minkowski distance changes as parameter (r) varies ,and allows for the observation of any patterns in the distance matrix.

A4. *Testing and Training*

In the A4 code starts with importing the 'pandas' library and then 'train_test_split' function from the sklearn model selection module. It reads a dataset from a CSV file named 'Food Ingredients and Recipe Dataset with Image Name Mapping.csv' into a pandas data frame. The columns of the data frame are printed using the columns attribute.The code then defines the target variable y as 'Instructions'. Two classes, class1 and class2, are assigned the values 0 and 1, respectively.And then subset of the DataFrame is created, containing only rows where the 'Instructions' column is equal to either class1 or class2. The 'train_test_split' function is used to split the data into training and testing sets. The 'Ingredients' column is used as the feature vector (X) and the 'Instructions' column is used as the target variable (y). The 'test_size parameter' is set to 0.3, indicating that 30% of the data will be used for testing. Additionally, the random_state parameter is set to 42 for reproducibility.The sizes of the training and testing sets are printed.

A5. *Testing the KNN classifier*

For this question the value of K is set to 3. The target variable is set to Title class and the feature vector is set to the Cleaned Ingredients. If there are two valid classes that are found in the dataset after taking out the unique titles a subset dataset is formed. The dataset is then split into training and testing sets using the train_test_split module and we have given 50% or 0.5 for testing in this case. After the model is trained, it is used to predict the labels for the testing data, through which the accuracy is found using the special function called **accuracy score** in sklearn.metric. Through this we find the accuracy of the KNN classifier.

A6. *Testing the KNN classifier from the above test cases*

We have used pandas, sci-kit learn libraries of python for this code, where the train_test_split module is used to train and test the data by splitting some of the element of the dataset for testing. The TfidVectorizer has been used to convert test into a numerical value that is present in the dataset. We have used a target variable y_column_name which is set to the instructions class. Similarly, we have set the feature vector X to Cleaned Ingredients class. The text values in the Cleaned Ingredients class are converted into numerical and the dataset is split into training nad testing where 0.3 or 30% is given for testing.

A7. *Predicting the behavior of the dataset*

We have usedmodules like sci-kit learn which includes train_test_split for splitting the dataset and the KNeighbourClassifier for classification. We have initialized A TfidVectorizer convert the text data in the ingredients class that is present in our dataset to numerical values. We have also implemented feature vectors that have a variable name feature_vector X and they are assigned to Cleaned Ingredients class. The dataset is split into training and testinf sets using train_test_split, where 0.5 or 50% of the data is for testing. For a vaue of k=3 is used for training the data. we have made a test vector that is used to match the expected form of KNeightboutsClassifer.

A8. *Testing KNN for k = 1*

In the code we have used **make_classification** function that makes classification in the code . Our dataset has 1000 samples with 20 features divided into2 classes. We have used the **train_test_split** function that is used for training and testing, where we have given 0.2 or 20% for testing. As per the question we have to find the generate the classification report for k = 1 value. Thus, for that we have used the KNNClassifier functionality in python.

A9. Generating Confusion Matrix, Accuracy, Precision and f1 score

The code makes sure that there is pre-processing done to the data and selects three groups. The value of K is set to 3 and then the dataset is split into training and testing for further classification. We got the confusion matrix by using the matplotlib library in python that gives us a heatmap between true value and predicted value thus generating the accuracy, precision, f1 score and recall. We have used KNN classifier to evaluate the confusion matrix as well where it plays a crucial role in making the confusion matrix.

IV. RESULT

The project is currently under development and we are still under exploration to blend in as much as functionality required to make it a user-friendly application. The insight on machine learning is indeed a very helpful aspect in the complete project since that shall help users determine what they shall be eating and exploring. The project aims to provide an insight of the food quality and quantity of the user. It helps the user give detailed insights of what ingredients were used for making the food.

Below, we can see the results or output we can get by running the codes A1 to A9 in the codes we have done the testing and training and we calculate the accuracy, f1 score, recall, and precision for the question asked accordingly using our dataset which we are going to use in our project. we printed the confusion matrix and classification report as asked in some of the questions.

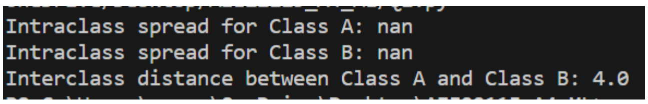
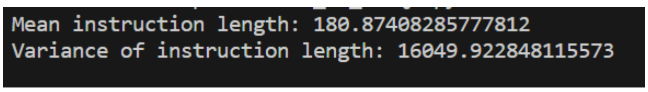


Fig A1



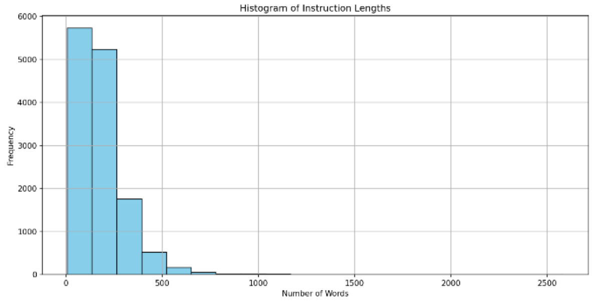


Fig A2

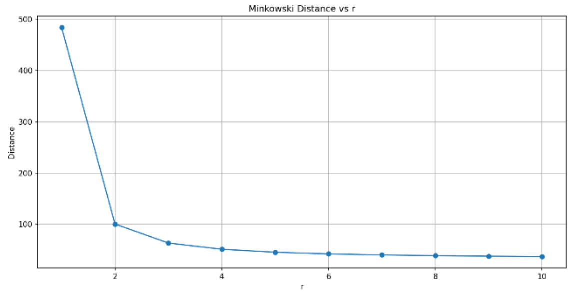


Fig A3

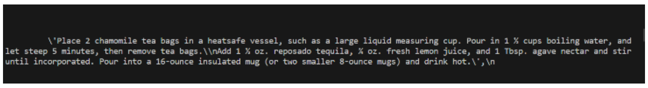


Fig A4

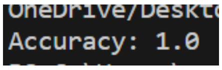


Fig A5

Fig A6

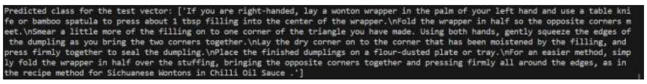


Fig A7

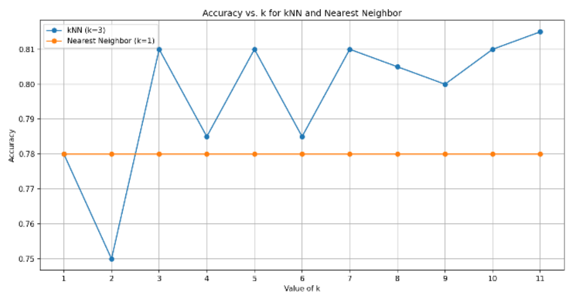


Fig A8

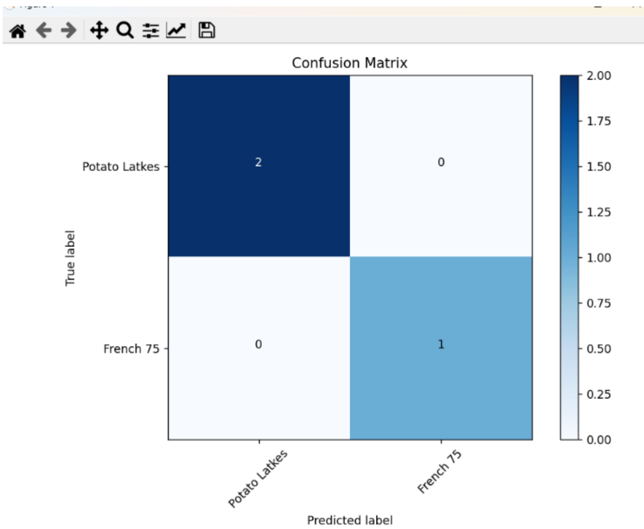


Fig A9

Observations : Each cell shows the number of images that were classified as a certain label, given their actual label. For example, the top-left cell shows that 2 images were correctly classified as potato latkes. The diagonal cells (highlighted in blue) represent the number of correctly classified images. In this case, the model correctly classified 2 potato latkes and 75 French fries. The off-diagonal cells (highlighted in orange) represent the number of misclassified images. In this case, the model misclassified 1 potato latke as a French fry and 0 French fries as potato latkes.

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