FOOD INSIGHTS AND ANALYSIS BASED RECOMMENDATIONS

Project ID - 21_22-J-058

Final Project Group Report(Draft)

B.Sc. (Hons) Degree in Information Technology

Specialization in Information Technology

Department of Information Technology

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Supervising by

Ms.Anjali Gamage

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DECLARATION

We declare that this is our work and this proposal does not incorporate without acknowledgment any material previously submitted for a degree or diploma in any other university or institute of higher learning and to the best of our knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgment is made in the text.

Name	Student ID	Signature
Prakash A	IT17111652	
T.Abishek	IT18234930	
J. A. Prashanthan	IT18228618	

The supervisor/s should certify the proposal report with the following declaration.

The above candidates are researching the undergraduate dissertation under my supervision.

……………………………..... …../…../….

Signature of the supervisor Date

ABSTRACT

Due to the obvious great variety of products, cuisines, and personal tastes available, making food decisions plays an important role in our daily lives. Choosing the appropriate food for a given type of person appears to be a challenging task almost exclusively for dietitians in the majority of circumstances. Adding to the fact this generation of people are living in a fast-paced lifestyle: most are reluctant to change their food eating habits when it comes to cooking regardless of their health concerns. Hence we propose a research project to identify a food suggestion system that will assist people in preparing their own meals in an acceptable way and provide proper food based knowledge to the people. Firstly this application will use image-to-recipe technology, takes a food image as input and produces a recipe with a title, ingredients, and cooking directions. The other component will generate meals based on the user's preferences as well as the image uploaded to the app. This allows the user to keep track of the various components that have been incorporated into his meals. The system will generate a recipe based on the user's choices as well as the image that has been uploaded to the application. In this way, the user may keep track of the many types of components that have been incorporated into their meals and eliminate the need of the personal dietician. Finally there is a component which suggests food recipes that will assist people in preparing their own meals in an acceptable way based on their preference details and a feedback system to identify feedback given to recipe.

This report focuses on all the procedures followed by all members towards the development of the application along with individual and the common objectives associated with the product.

Tags : Convolutional Neural Network, Image Processing, Machine Learning, Food Detection, Sentiment Analysis

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1.0 INTRODUCTION

1.1 Background and Literature Survey

Food is necessary for human survival. It not only gives us energy, but it also defines our identity and culture [10]. We are what we eat, as the old adage goes, and food-related activities like cooking, eating, and talking about it occupy a big portion of our daily lives. Food culture has spread faster than ever in the digital age, with many people posting photos of food they're consuming on social media [11]. Searching for #food on Instagram yields at least 300 million results, while searching for #foodie yields at least 100 million results, demonstrating the undeniable value of food in our society. Furthermore, eating habits and cooking culture have changed over time. Food was traditionally produced at home, however nowadays we regularly consume food prepared by others (e.g. takeaways, catering and restaurants). As a result, access to specific information regarding prepared foods is limited, making it difficult to determine exactly what we eat. As a result, we believe that inverse cooking systems, which can infer components and cooking directions from a prepared meal, are required.

Visual recognition tasks such as natural image classification, object detection, and semantic segmentation have seen significant advancements in recent years [12]. Food identification, however, presents extra hurdles as compared to natural picture interpretation, because food and its components have substantial intraclass variability and severe deformations that occur throughout the cooking process. In a cooked food, ingredients are frequently hidden and come in a variety of colors, shapes, and textures. Visual ingredient detection also necessitates advanced reasoning and prior knowledge (e.g. cake will likely contain sugar and not salt, while croissant will presumably include butter). As a result, food recognition forces current computer vision systems to think beyond the obvious and utilize prior knowledge in order to provide high-quality structured food preparation descriptions. Previous efforts to better comprehend food have primarily focused on categorizing foods and ingredients. A system for comprehensive visual food recognition, on the other hand, 2 should be able to recognize not only the type of meal or its ingredients, but also the process of preparation. The picture-to-recipe problem has traditionally been framed as a retrieval job [3], in which a recipe is recovered from a fixed dataset using an embedding space image similarity score. The amount and diversity of the dataset, as well as the quality of the learnt embedding, have a significant impact on the performance of such systems. When a matching recipe for the picture query does not exist in the static dataset, these systems fail.

The image-to-recipe problem can be reformulated as a conditional generation problem to get around retrieval systems' dataset limits. As a result, we propose a system in this work that creates a cooking recipe from an image, complete with a title, ingredients, and cooking directions. Which generates cooking directions by first predicting ingredients from an image and then applying conditions to both the image and the ingredients. Our method is the first to produce culinary recipes directly from food photos, as far as we know. The instruction generation problem is modeled as a sequence generation problem with two modalities, namely an image and its expected constituents. We use their underlying structure to express the ingredient prediction problem as a set prediction. We represent ingredient dependencies without penalizing prediction order, reopening the debate over whether or not order matters. We tested our approach extensively on the large-scale Recipe1M dataset [13], which contains photos, ingredients, and cooking directions, and found it to be satisfactory. More specifically, we show that our inverse cooking system surpasses previously introduced image-to-recipe retrieval systems by a considerable margin in a human evaluation study. Furthermore, we demonstrate that food image-to-ingredient prediction is a difficult problem for humans, and that our approach is capable of outperforming them using a small amount of images.

An organism consumes a material that is digested by the organism's cells to provide energy, preserve life, or promote growth. Food selection is an important part of our daily activities due to the enormous variety of ingredients, foods, and personal tastes. Many people appear to find it difficult to choose the right food at the right time. With so many options, selecting food is a daily chore. We can't tell how something was made just by looking at it. However, with the help of image processing, we were able to achieve something that humans could not. People are still unaware of the nutritional value, benefits, and drawbacks of their food choices when making healthcare decisions.

Food has a calorie nevertheless, in most meals, the consumer has no idea how many calories are in the food being provided. It is necessary to identify food. In a food picture, there are usually multiple varieties of food served, and it is possible to tell what food is served from just one picture. Food selection is essential for specific purposes, such as a diet grading system, to prevent obesity, diabetes and others. Food references can be found through the food classification. Image classification is a challenge because the food image dataset is not linear; for example, There is a food which has more similarities in look and taste, which is not the same, and there is also a food with another food which has similarities in types and forms of food.

A doctor, a dietitian, or a nutritionist are all knowledgeable about these topics and highly recommended. [11] However, how many of us seek professional advice and have the financial means to hire them? Numerous studies have found that diet has a significant impact on our life span. Diabetes, which is caused by a high carbohydrate intake, affects the majority of the Asian continent's population. A doctor suggests a diet, but only after we make an appointment with them. So, how about we have a caregiver with us every day, making suggestions and informing us by reading and analyzing our medical statistics on a daily basis, as well as keeping track of everything we're going through?

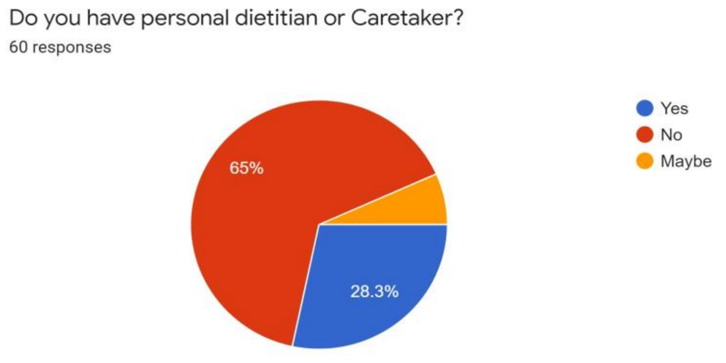

Figure 1.1 : People interested in a caregiver or personal dietitian

According to [Figure 1.1], the majority of us lack a personal caregiver or nutritionist who can monitor our health and well-being. This is another factor that no one gives much thought to.

They would prefer, however, to have someone look after them.

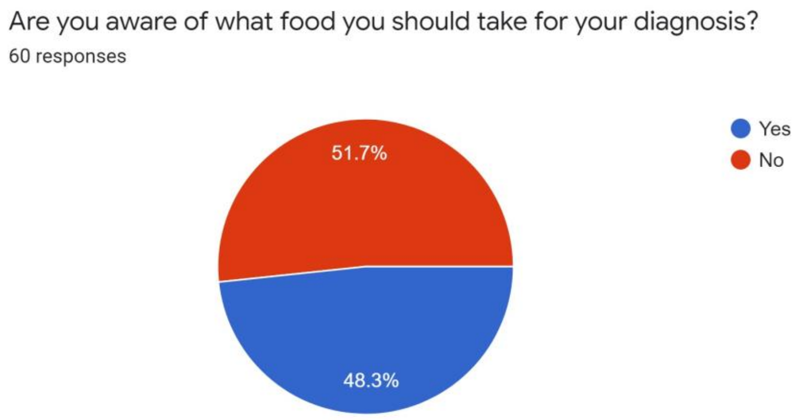

Figure 1.2 : People's interest in food consumption based on diagnosis

Despite the fact that many of us are afflicted with various diseases. We do not take care of those the majority of the time. We are concerned about maintaining our mental and physical health. Individuals are completely unaware of the foods they consume. Some people eat because they are hungry, while others eat because they enjoy it or because they like it. This graph shows that they have adequate guidance and understanding of food and related topics, with a near 50-50 chance of being correct.

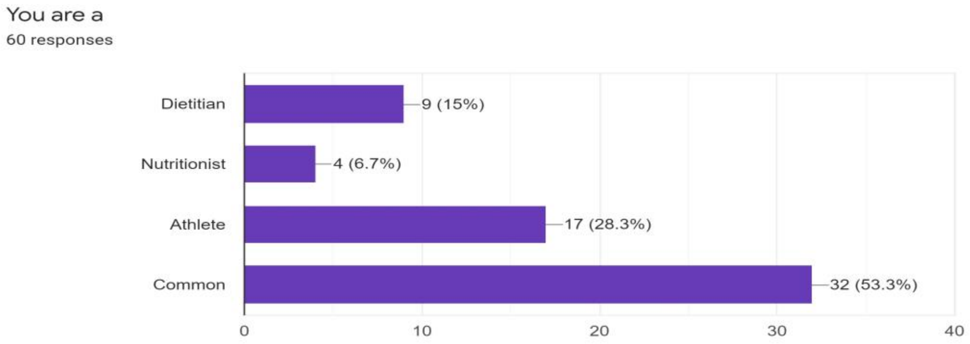

Figure 1.3 : who seek food-related statistics and information

This graph demonstrates that 53.3 percent of the population is interested in learning about food-related topics. Athletes like to be as precise as possible with their nutrition and fitness measurements. Dietitians and nutritionists need precise findings in order to be successful in their careers. Many of us are intrigued by the prospect of discovering what is contained within a specific object. As a result, this piqued interest will lead to the realization that this application will be beneficial to many people in the near future.

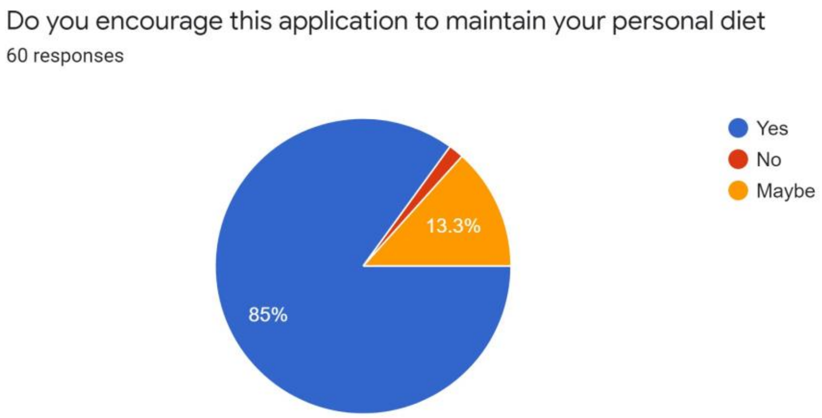

Figure 1.4 : Absolutely liked understanding their personal diet.

This graph clearly shows that consumers value innovative technology that meets their needs in an efficient and cost-effective manner. They are curious about the variety of meals available around the world, as well as the quality of those meals, and they want to sample every morsel of that goodness. A healthy way of life is something that modern society prioritizes above all else.

Diabetes is a long-term health condition that affects how your body converts food into energy. [2] The majority of the food you eat is converted into sugar (also known as glucose) and released into your bloodstream. When your blood sugar rises, your pancreas sends a signal to release insulin. Insulin functions as a key, allowing blood sugar to enter cells and be used as energy. [12] Diabetes can be divided into several types. Diabetes is classified into three types: type 1 diabetes, type 2 diabetes, and gestational diabetes. Type 1 diabetes is most commonly diagnosed in children and adolescents. Because type 1 diabetes can run in families (Genetics). Experts recommend routine testing for type 2 diabetes if you are 45 or older, between the ages of 19 and 44, overweight or obese, and have one or more other diabetes risk factors, or if you are a woman who has had gestational diabetes. Type 2 diabetes is most common in adults, but it can also affect children. Experts recommend testing children aged 10 to 18 who are overweight or obese and have at least two other diabetes risk factors.

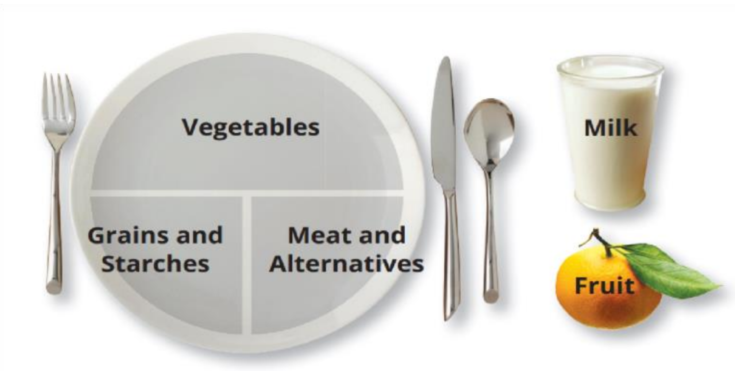

Figure 1. 5 : The Plate Method. Using standard dinner plate

Some carbohydrate-containing foods and beverages contain so little carbohydrate that they lack a GI value. [8] This does not preclude them from being a part of a healthy diet. Green vegetables, lemons, and some low-carbohydrate drinks are examples. Diabetes Canada refers to these foods and beverages as "free" because they have no effect on the blood sugar of diabetics. You can put free foods in the green category, but they don't have a GI and aren't on the food lists.

The A1C test, also known as the hemoglobin A1C or HbA1c test, is a straightforward blood test that measures your average blood sugar levels over the previous three months. It is one of the most commonly used tests for diagnosing prediabetes and diabetes, as well as the primary test for assisting you and your health care team in managing your diabetes. Higher A1C levels have been linked to diabetes complications, so achieving and maintaining your personal A1C goal is critical if you have diabetes.

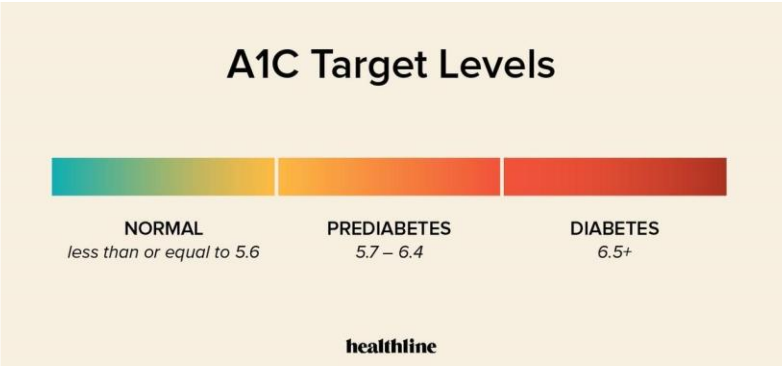

Figure 1. 6 : A1C Target Levels

According to the International Diabetes Federation (IDF), the prevalence of diabetes among adults in Sri Lanka is 8.5 percent. Diabetes affects one in every twelve adults in the country, a total of 1.16 million people.

People with diabetes can manage their blood sugar levels by eating certain foods and avoiding others. A diet high in vegetables, fruits, and lean proteins can provide significant health benefits. Blood sugar levels can be raised by both sugary and starchy carbohydrates. However, in the right amounts, these foods can contribute to a well-balanced diet. Many factors, including a person's activity level and medications, such as insulin, can influence the appropriate amount and type of carbohydrates.

In the recommendation systems there are three types of techniques are used extensively for filtering.

1. Content Based Filtering (CBF)
2. Collaborating Filtering (CBF)
3. Demographic Filtering (DF)

The content based filtering technique [1] uses similarities in features to make decisions. For instance, text recommendation systems which are used in the newsgroup system uses the words of their texts as features. This content-based recommender learns from the characteristics of the objects that the user has rated, a profile of user interest, known as "itemto-item correlation," and derives the type of user profile. In the collaborative filtering technique uses similarities between users and items simultaneously to make recommendation decisions. The main characteristic of this model is that it allowed generating recommendations based on a combination of ideas from the contributions of many other users. Instead of filtering items by content, make recommendations based on like-minded users' reviews. Finally in demographic filtering it aims to classify the user based on personal characteristics and make recommendations based on demographic classes. For our research demographic filtering technique would be helpful rather than the other two techniques which are CBF and CF because this technique doesn't require collecting complex data like user activities and don't have to suffer from high computational power issues. Adding to that content filtering technique also often suffer from a main problem

Cold start issues – Need bulky data from already created systems in order to provide precise recommendation.

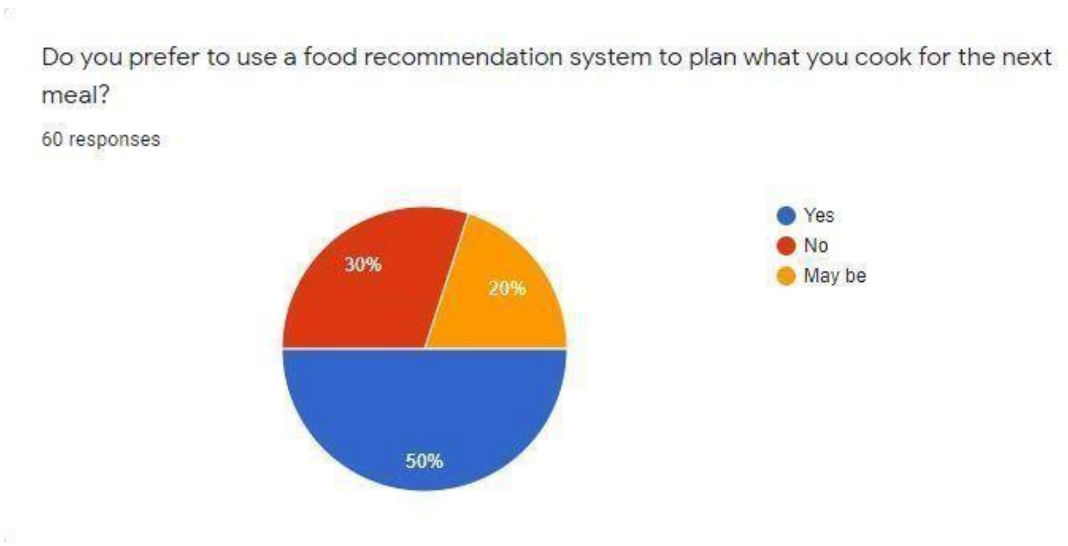

Figure 1. 7: Users Likeliness of Having Guide

From the figure 1.1.7, it shows that most people prefer to have a recommendation system to prepare a meal. However, the lack of accuracy in predicting food choices moves people from not relying on the existing food application systems.

The main reason could be the recommended recipe is not compatible to the users' preferences. For instance, recommending a hard recipe for an average cooking skilled user is not applicable. Since the recipe recommendations are unrealistic to the users' cooking expertise, the user might stick to his own way of cooking.

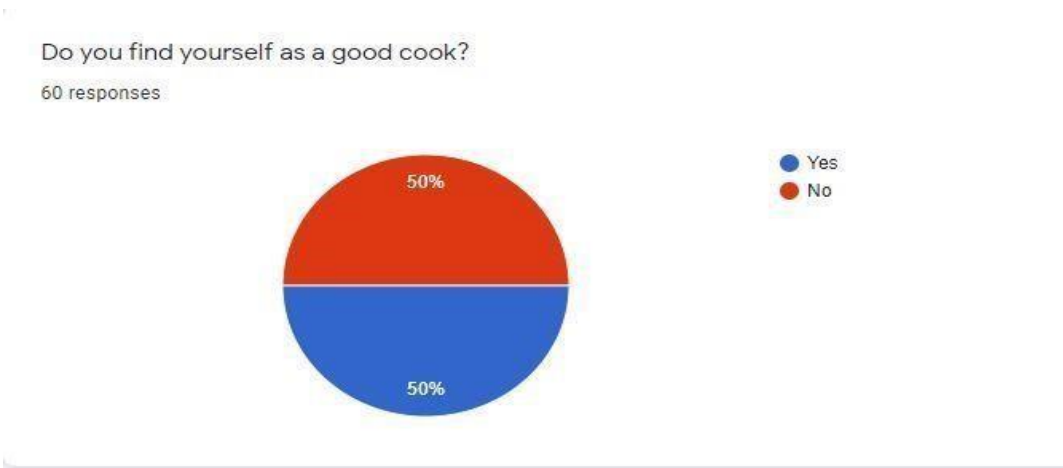

Figure 1. 8 : Users Cooking Skill Level

1.2 Research Gap

Large-scale food datasets, such as Food-101 and Recipe1M [13], have enabled considerable gains in visual food recognition by providing reference benchmarks for training and comparing machine learning algorithms. As a result, there is already a large body of work in computer vision dealing with a wide range of food-related problems, with a particular emphasis on image classification [6], [14]. Following studies tackle more difficult tasks including estimating the number of calories in a given food image, estimating food quantities, predicting the list of present ingredients [3, 4], and determining the recipe for a given image [13]. [10] also gives an extensive cross-region analysis of culinary recipes, taking into account visuals, features (such as style and course), and recipe ingredients. Recipe generation has been studied in the context of creating procedural text from either flow graphs or ingredients' checklists in the natural language processing literature [15].

Deep neural networks for multi-label classification have received a lot of attention in the literature, with models [16] and loss functions that are ideally adapted for this job. Early approaches relied on single-label classification models with binary logistic loss [3], assuming label independence and discarding potentially relevant data. Label powersets are one method of capturing label dependencies. For large-scale issues, powersets evaluate all possible label combinations, making them unsolvable. Another expensive option is to calculate the labels' combined probability. To address this problem, probabilistic classifier chains and their recurrent neural network-based [16] counterparts propose decomposing the joint distribution into conditionals at the cost of intrinsic ordering. It's worth noting that most of these models ask you to forecast each of the possible labels. In addition, to preserve correlations and predict label sets, joint input and label embeddings have been established. Researchers have attempted to forecast the cardinality of a set of labels as an alternative, assuming label independence. Binary logistic loss [3], target distribution crossentropy [17], target distribution mean squared error, and ranking-based losses have all been explored and

4 contrasted when it comes to multi-label classification objectives. The potential of the target distribution loss has been highlighted by recent results on large scale datasets [17].

In the literature, both text-based and image-based conditionings have been used to study conditional text generation with auto-regressive models. Different architecture designs, such as recurrent neural networks, convolutional models, and attention-based techniques, have been researched in neural machine translation, where the goal is to anticipate the translation for a given source text into another language. Sequenceto-sequence models have lately been used in more open-ended generation tasks like poetry and tale generation. Autoregressive models have shown promising performance in picture captioning, where the goal is to provide a brief explanation of the image contents, opening the door to less limited issues like creating descriptive paragraphs [18] or visual storytelling.

There are several methods and applications for keeping track of what you consume, but in most cases, this information must be entered manually each time. Some programs suggest foods that the user dislikes and that are also out of reach for the majority of people. In our case, however, we recommend foods that the user has selected. When a user selects the wrong food for their meal, This program will suggest meal options based on the user's grade level; however, the user will have complete control over which food to select from the suggested options. Using this application, they will be given recommendations for more beneficial ingredients. There are numerous technologies available for detecting and obtaining information about objects. Image processing will be essential for identifying and segmenting components. In addition, we will use machine learning technology to analyze those elements and recommend meal plans, as well as evaluate and process medical report data.

There are several researches have been conducted in the food recommendation domain in the past [2] [3]. Most of the researches have been conducted either in user preference based recommendation or by predicting the best recipe based on user comments. However, in the researches where user preference based recommendations have been done, aspect of the users' cooking skill knowledge has been highly neglected. Measuring the cooking skill level and knowledge could allow the system to predict more accurate recommendation to the user. This could be highly beneficial to the end user.

Approach	User Preference Model	Real Time Sentiment Analysis on Recipe Feedbacks	Sentimental analysis on food recipe dataset.
Research A [2]	✓	X	X
Research B [3]	X	X	✓
Proposed Research	✓	✓	✓

Table 1: Research Gap Analysis

Research based on analyzing food Recipe Comments [3] has been conducted and this approach can be more aligned to general perspective than the model based user preference. However, this can be applied as a component to the user based research model. The benefit of having this component is by applying sentimental analysis (LEXICON) the dataset can be rearranged

Sentiment analysis [3] which is a popular technique for text analysis was adapted to the recipe recommendation. For instance, the recipe dataset can be categorized into three subset which can be easy, medium, hard recipes. By segregating the dataset users with the low cooking skill could be directed to the easy recipes. Appling a lexicon-based would be appropriable in case of avoiding the need to generate a labelled training set. This can eliminate the major disadvantage of relying heavily on machine learning models.

1.3 Research Problem

1) People enjoys food photography because they appreciate food**. Behind each meal there is a story described in a complex recipe and, unfortunately, by**

simply looking at a food image we do not have access to its preparation process [1]. Therefore, in this application we introduce a function that recreates cooking recipes and ingredients given food images.

2) Although food is an essential part of our life choosing what to eat repeatedly is a boring thing, it would be helpful to have someone picking our next dish.

3) Existing apps are designed to recommend personalized recipes for only single users [2]. Thus, this system could provide a personalized recipe guide to a group of users with a change in ingredients quantity.

4) A Beginner cook may not have much knowledge to cook the recipe from scratch to end on their own. they lack in choosing the ingredients and also mix and match them. Some entry level cooks don't know the correct portions for a meal.

5) Lots of food waste occurs due to bad choice of raw materials for the food [3]preparation and amateur cuts in vegetables.

6) There is insufficient personalized counseling or meal recommendations based on the user's diagnosis. For a long time, some were considered myths. No precise measures have been taken to assist users based on their diagnosis.

7) Image processing was useful in calculating preprocessing and segmentation level items in order to conduct fundamental research. However, no practical application existed that enabled users to combine recipes based on their inputs.

8) User preference based recommendation system highly neglecting the users' domain knowledge when recommending items/content.

9) User based recommendation accuracy level could be improved further.

10) Users lack proper awareness when using the recommendation system by providing inaccurate information to the system

1.4 Research Objectives

1.4.1 Main Objective

The main objective of this research is to provide food based knowledge to a user and tackle problems caused by food selection by providing suggestion that will assist people in preparing their own meals in an acceptable way and generating a recipe based on the user's choices as well as collecting food image as an input and in return catering information about the particular food that has been uploaded to the application. In this way, the user may keep track of the many types of components that have been incorporated into their meals and eliminate the need of the personal dietician.

1.4.2 Sub Objectives

<u>Objective 1</u>
Identifying more efficient and suitable algorithm for each component and getting the dataset which is more cleaner and reliable than the others.

<u>Objective 2</u>
Providing more accurate suggestions and information to user by extracting real user data from their medical reports.

<u>Objective 3</u>
Minimizing the food waste issue faced by people.

2.0 METHODOLOGY

2.1 Food Analyzer using Image Processing.

According to human assessment, our system proposes a new technique to generate recipes directly from food photos that delivers more engaging recipes than retrieval-based approaches. This technique increases ingredient prediction performance over previous baselines when tested on the large-scale Recipe1M dataset. We hope that by submitting a food photograph, we will be able to enable access to meal preparation.

Our image-to-recipe technology takes a food image as input and produces a recipe with a title, ingredients, and cooking directions. Our solution begins with pretraining an image encoder and an ingredients decoder, which uses visual features extracted from the input image and ingredient co-occurrences to predict a set of ingredients. Then we train the ingredient encoder and instruction decoder, which create title and instructions by feeding visual cues from the image and expected ingredients into a state-of-the-art sequence creation model.

Food recognition pushes today's computer vision systems to think beyond the obvious. Visual ingredient prediction necessitates higher-level thinking and prior knowledge when compared to natural image understanding (e.g., that croissants likely contain butter). Food components have substantial intra-class variability, heavy deformations occur during cooking, and elements are commonly occluded in a cooked dish, posing further complications. Our method is a first step toward a more comprehensive understanding of food.

The result of our research will be an Android application with three key capabilities or subsystems. Image processing and other machine learning, optimization, and visualization algorithms were used to create my component.

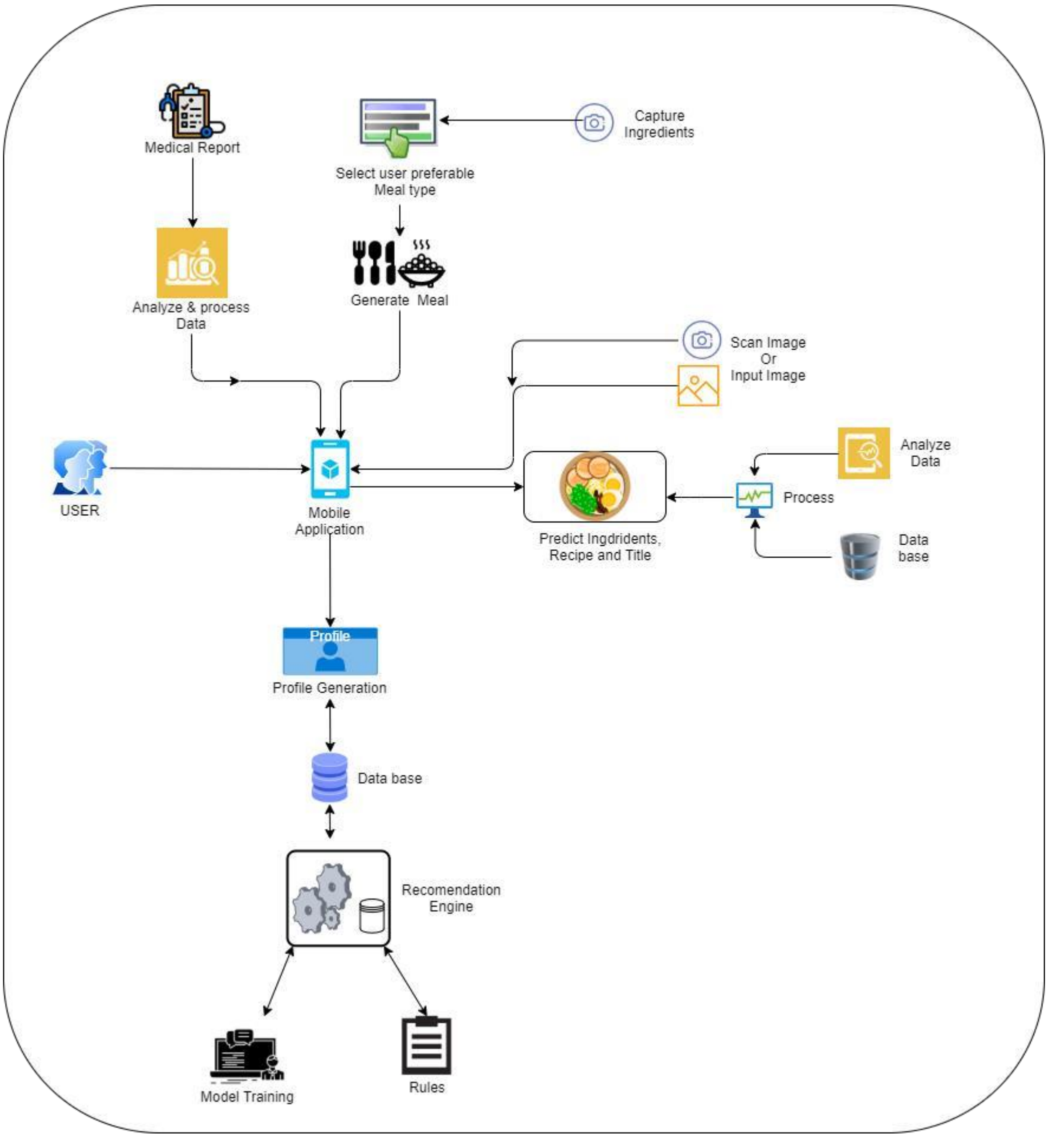

Figure 9 : Food Identifier System Diagram

2.2 Meal Planner Generator According to User's Medical Condition.

The user must first provide [5] medical data to this system, which will then analyze and process the data to determine the user's ailment or diagnosis. [3] Based on the information they have provided, it will then generate some meal alternatives. [6] Users of this program have complete control over the ingredients they use in their meals. It will generate a healthy meal plan for the user based on the food components and preparation techniques gathered, as well as the user's medical conditions. It will also keep tabs on their health. The general public, as well as athletes, dietitians, and nutritionists, will benefit from this.

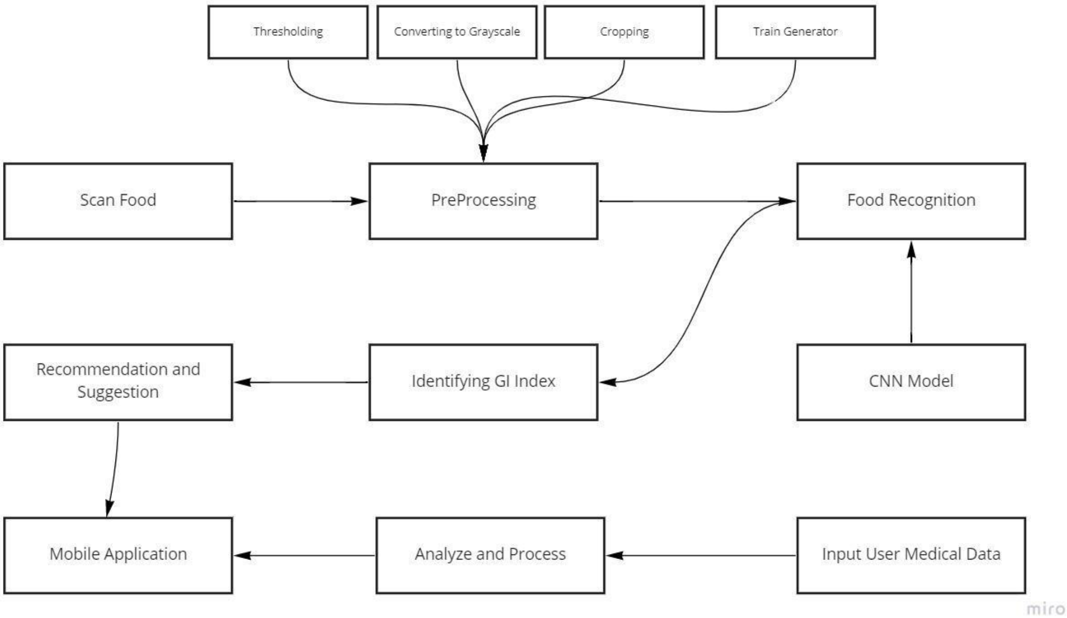

Figure 10 : Individual Meal Predictor System Architecture

The glycemic index (GI) [1] is a scale that ranks carbohydrate-containing foods and beverages based on how much they raise blood sugar levels after consumption. High GI foods raise blood sugar levels higher and faster than low GI foods.

Figure 11 : Shows how GI index vary and works

Foods in the high GI category can be substituted for foods in the medium and/or low GI categories to reduce GI.

A convolutional neural network (CNN) is a type of artificial neural network that is specifically designed to process pixel data in image recognition and processing. CNNs are powerful image processing, artificial intelligence (AI) systems that use deep learning to perform both generative and descriptive tasks, frequently utilizing machine vision, which includes image and video recognition, recommender systems, and natural language processing. A CNN employs a system similar to a multilayer perceptron that has been optimized for low processing requirements. A CNN has three layers: an input layer, an output layer, and a hidden layer with multiple convolutional layers, pooling layers, fully connected layers, and normalization layers. The removal of constraints and increased efficiency for image processing results in a system that is far more effective, simpler to train, and more efficient for image processing and natural language processing.

Transfer learning is a machine learning research subject that focuses on storing and transferring knowledge learned while addressing one problem to a different but related problem. For instance, skills learned when learning to recognize vehicles could be applied to recognizing trucks.

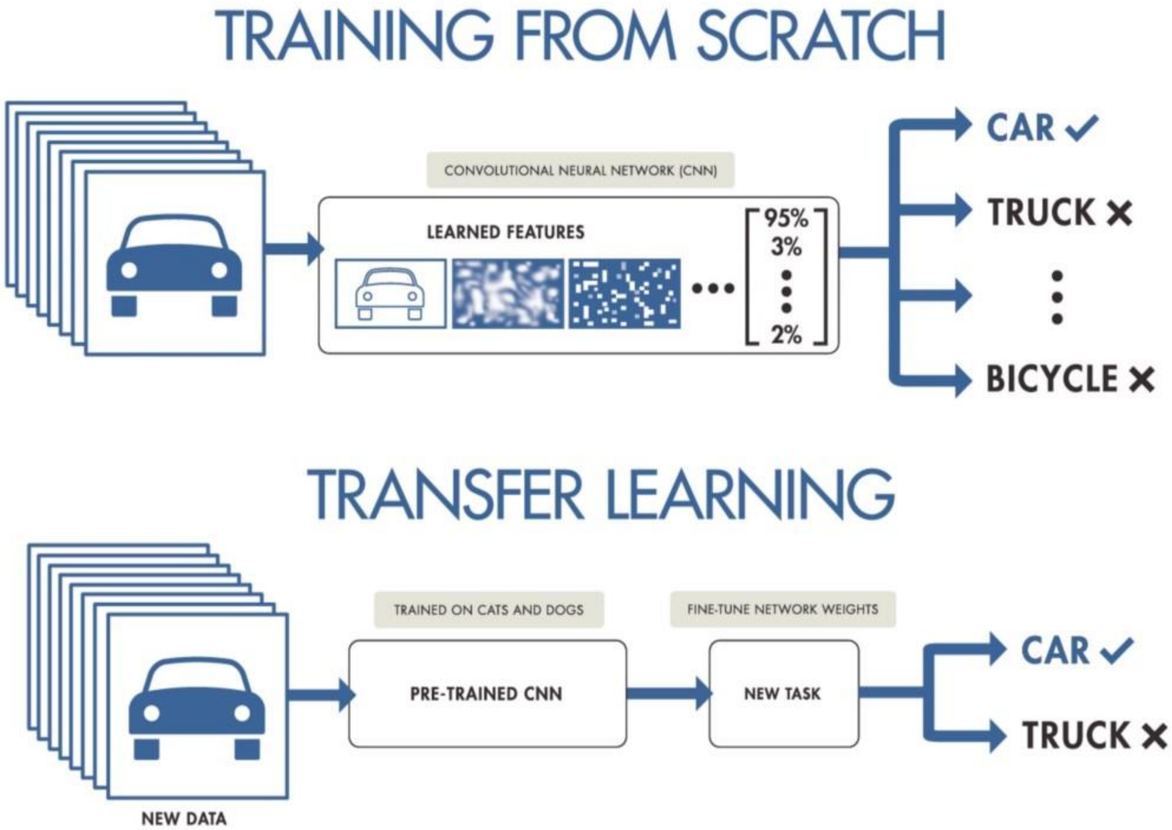

Figure 12 : Transfer learning Architecture

Keras is a Python interface for artificial neural networks that is open-source software. Keras serves as a front end for the TensorFlow library.

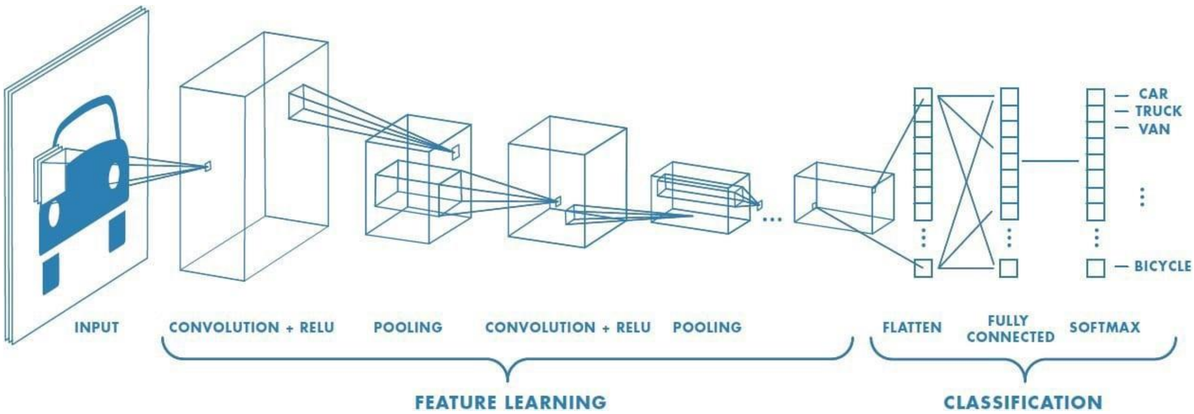

Figure 13 : Convolutional Neural network architecture

CNN operates by extracting features from images. [4] A grayscale image serves as the input layer. [9] The output layer consists of binary or multi-class labels. [7] Convolution layers[10] , ReLU (rectified linear unit) layers, pooling layers, and a fully connected Neural Network comprise the hidden layers.

The Conv2D parameter specifies the number of filters from which convolutional layers will learn. It is an integer value that also determines the number of convolution output filters.

The max pool layer is similar to the convolution layer, but instead of performing convolution operations, we select the maximum values in the input's receptive fields.

Every negative value in the filtered image is removed and replaced with zero in the ReLU layer. This function is only activated when the node input exceeds a certain threshold. As a result, when the input is less than zero, the output is zero. Dense Layer is used to classify images based on convolutional layer output. A single neuron at work. In neural network models that predict a multinomial probability, the softmax function is used as the activation function in the output layer.

2.3 Personalized Recipe Recommender and Recipe Feedback Predictor using Sentiment Analysis.

This component predicts the best recipe recommendation based on user preferences. Firstly, the system asks the user to provide his/her demographic related data when registering [Physical activity level]. With provided data, a personalized user model would be created by using the Demographic Filtering technique - hard rule based and considered to be as a technique used for a single person based on that particular user's data. Demographic Filtering (DF) Technique uses the demographic data of a user to determine which recipe may be appropriate for the food recipe recommendation.

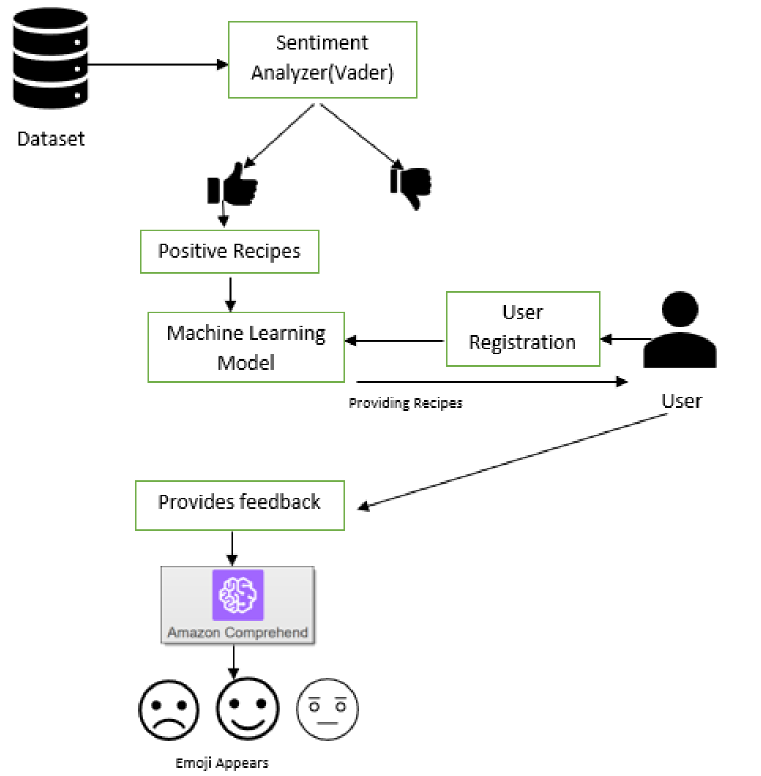

Figure 14 : Architecture of Recipe Recommender & Feedback analyzer

Meanwhile, the dataset of the recipe would be refined using Vader sentimental analysis which is considered to be as a lexicon and rule-based sentiment analysis tool, using this tool only positively commented recipes having positive score are saved in the server. This allows the system to redirect the user to only tryout the best recipes available in the recipe dataset. It also provides a feedback field for each recipes to find the sentiment level of the users given feedback. Once the users feedback entered into the feedback field, based on the feedback given by the user, a positive/negative/neutral emoji gets appeared; this is built using NLP service provided by amazon called Amazon Comprehend document analysis.

3.0 RESULTS AND DISCUSSION

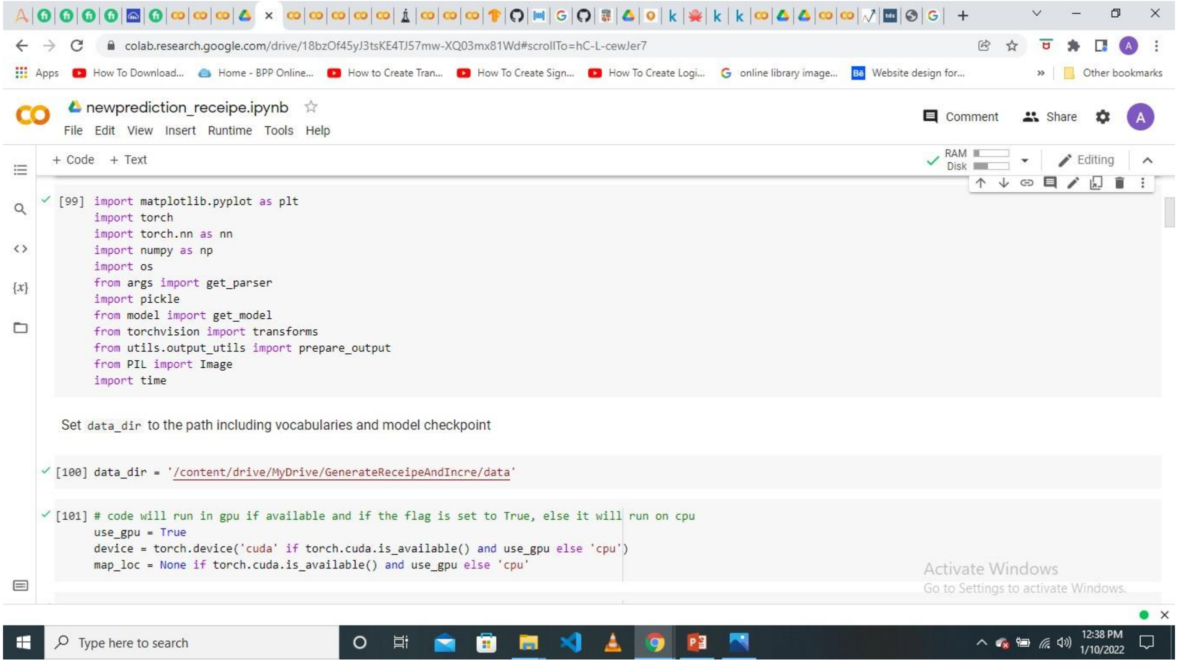

Figure 15

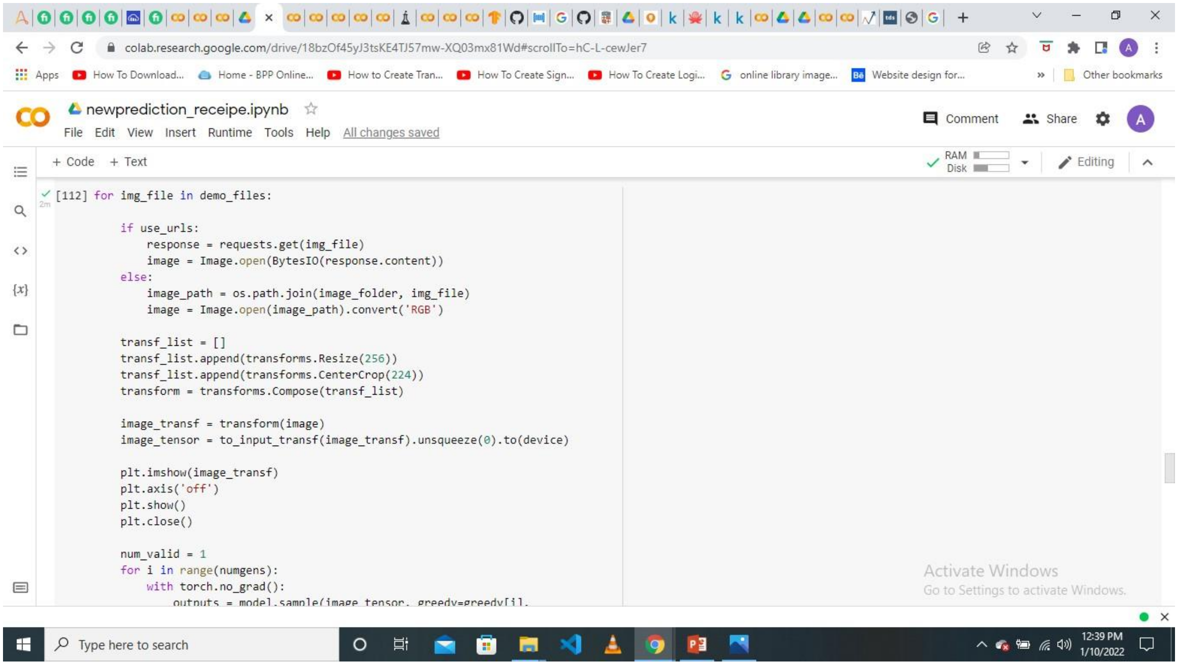

Figure 16

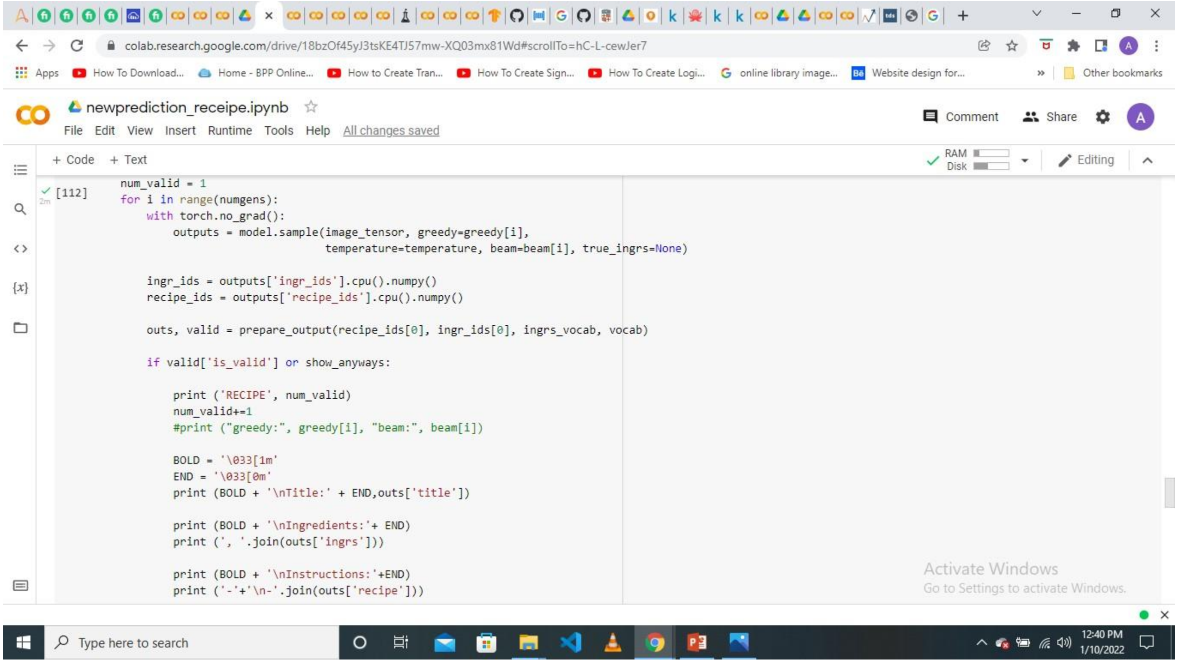

Figure 17

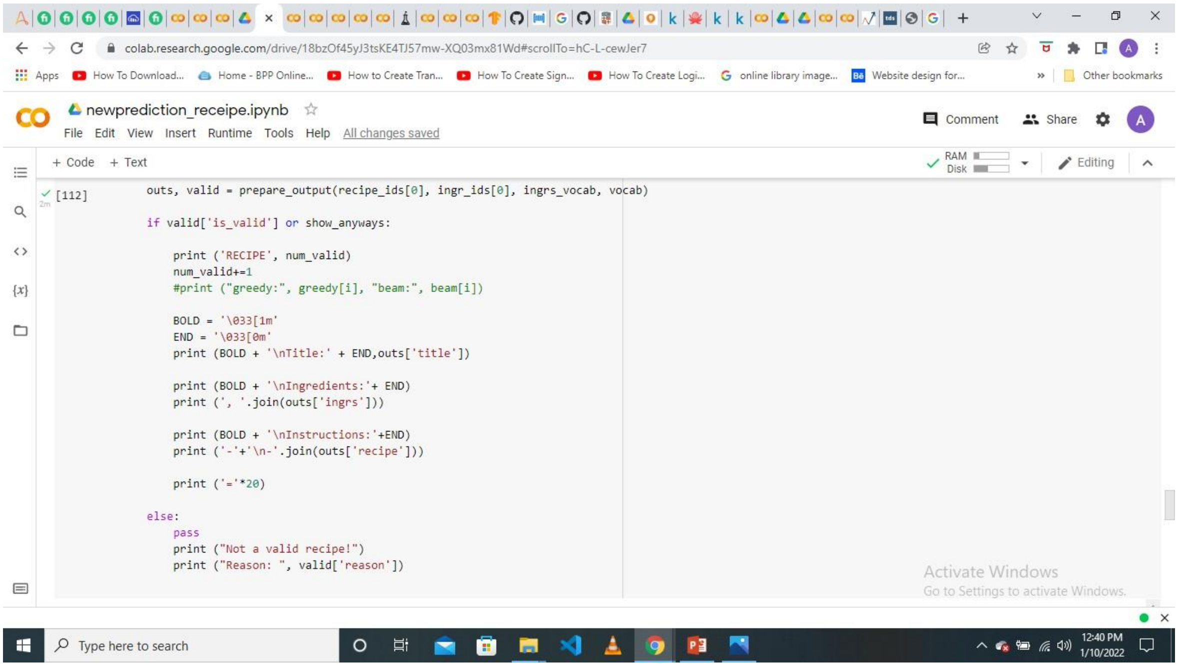

Figure 18

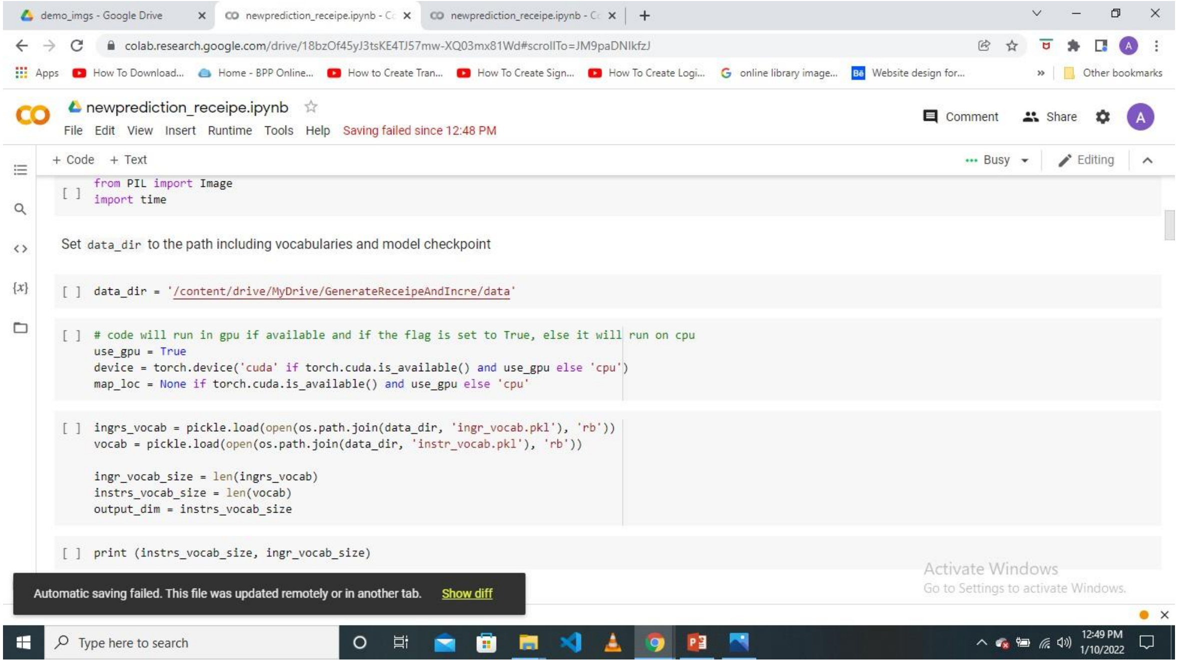

Figure 19

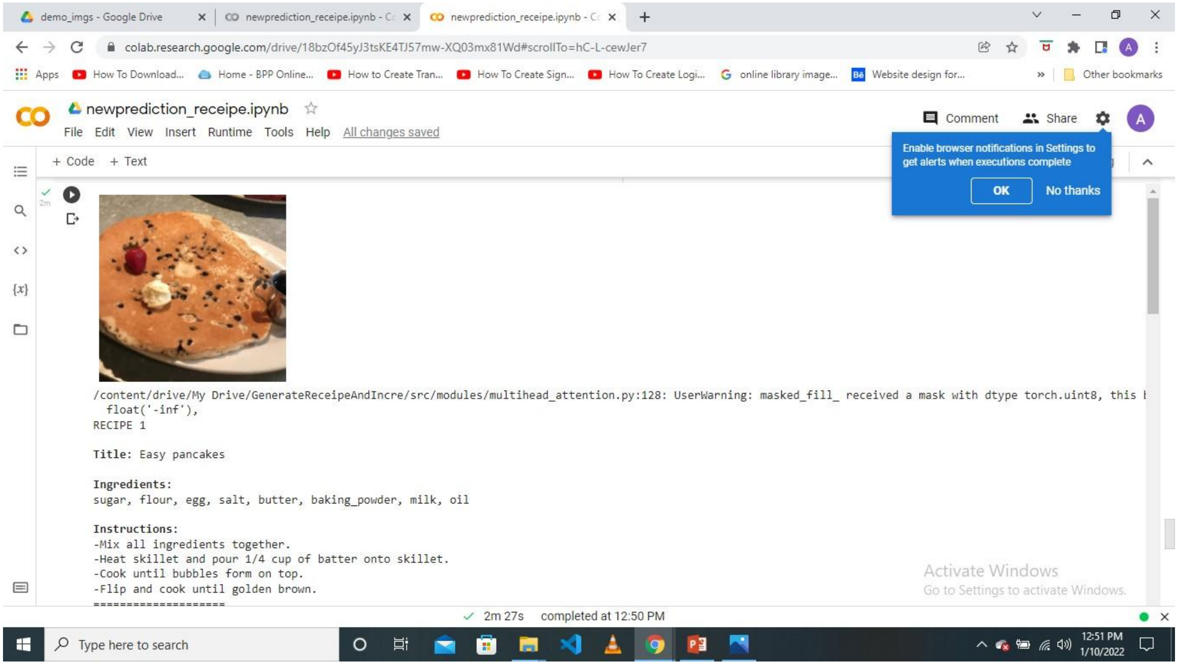

Figure 20

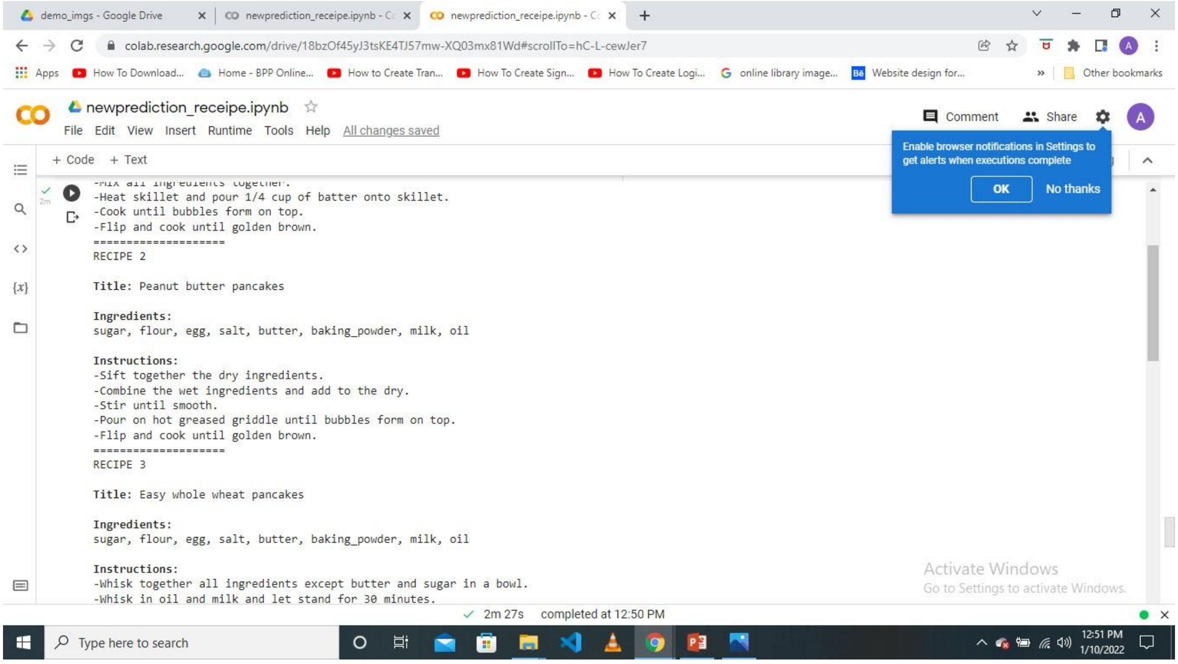

Figure 21

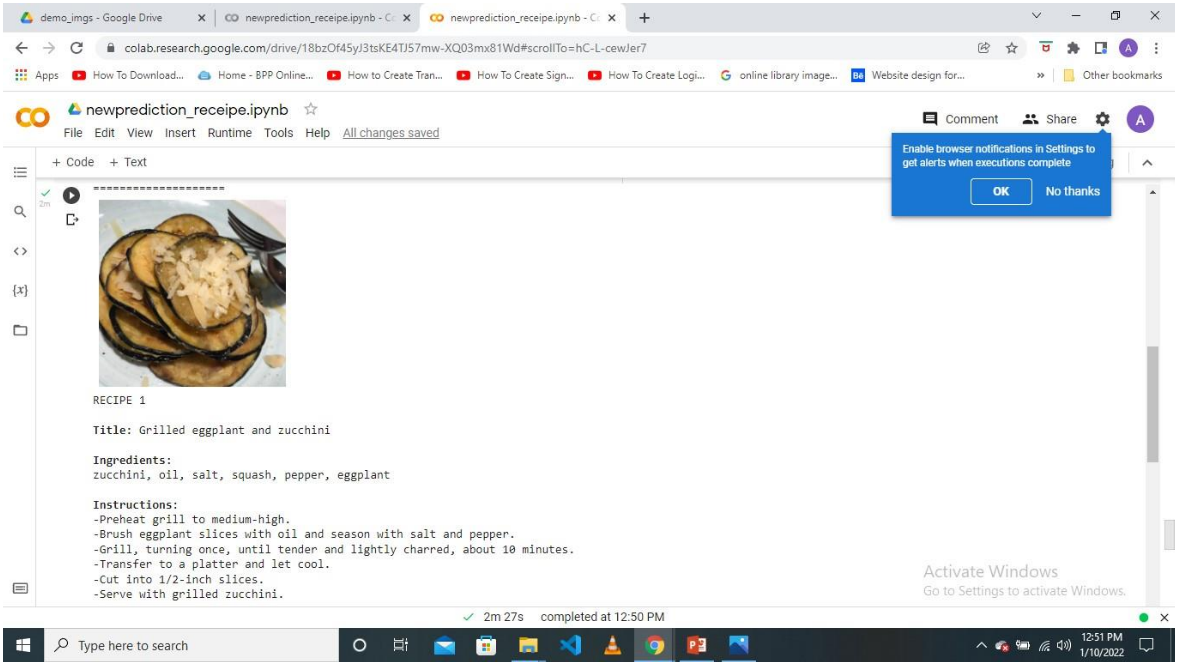

Figure 22

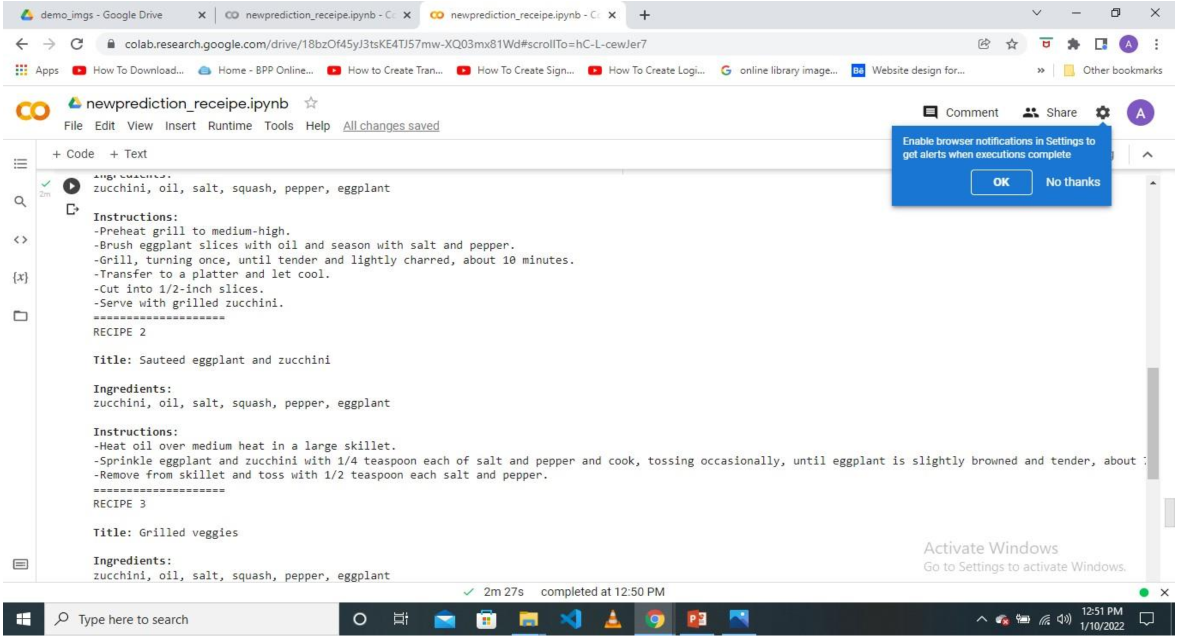

Figure 23

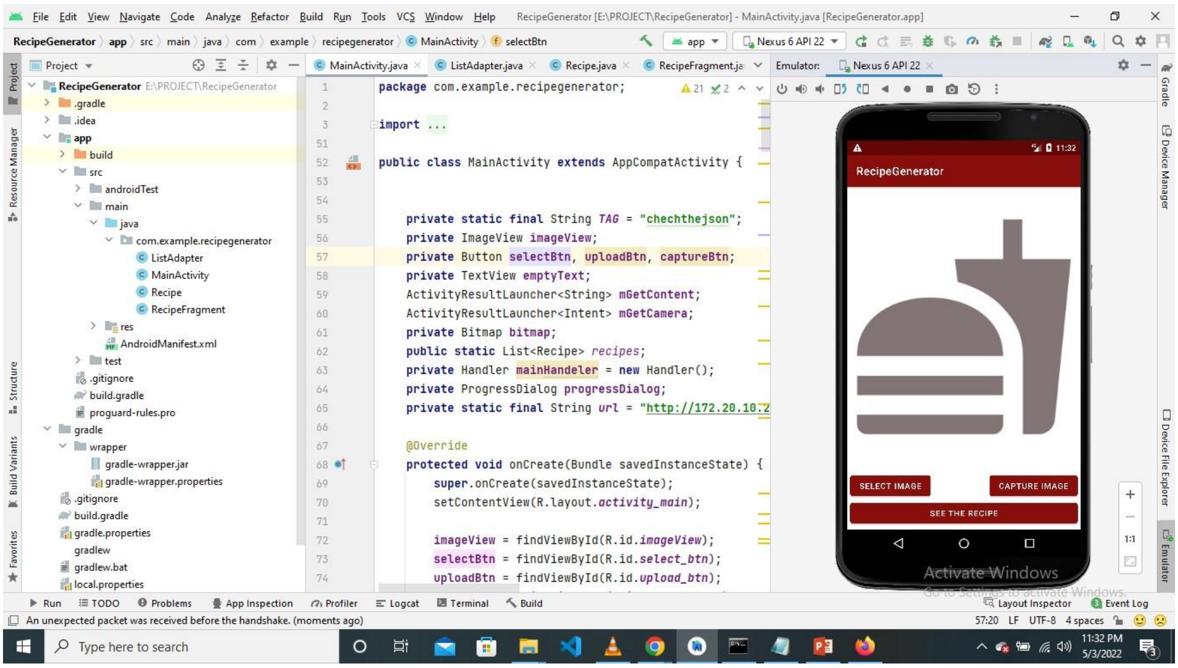

Figure 24

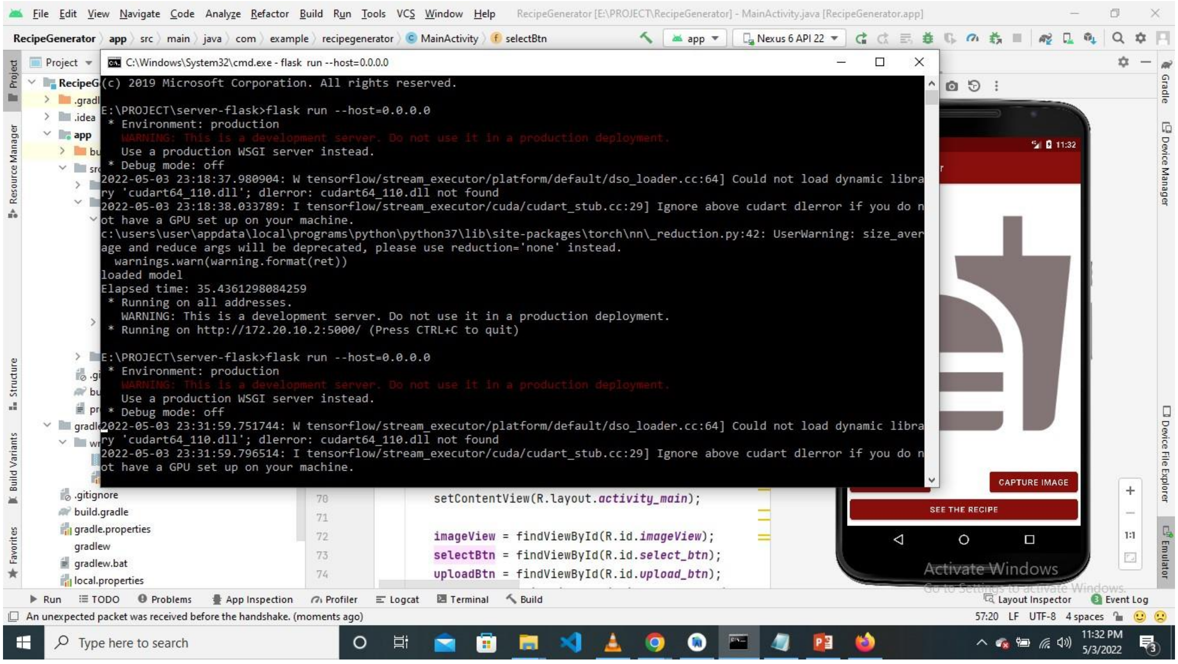

Figure 25

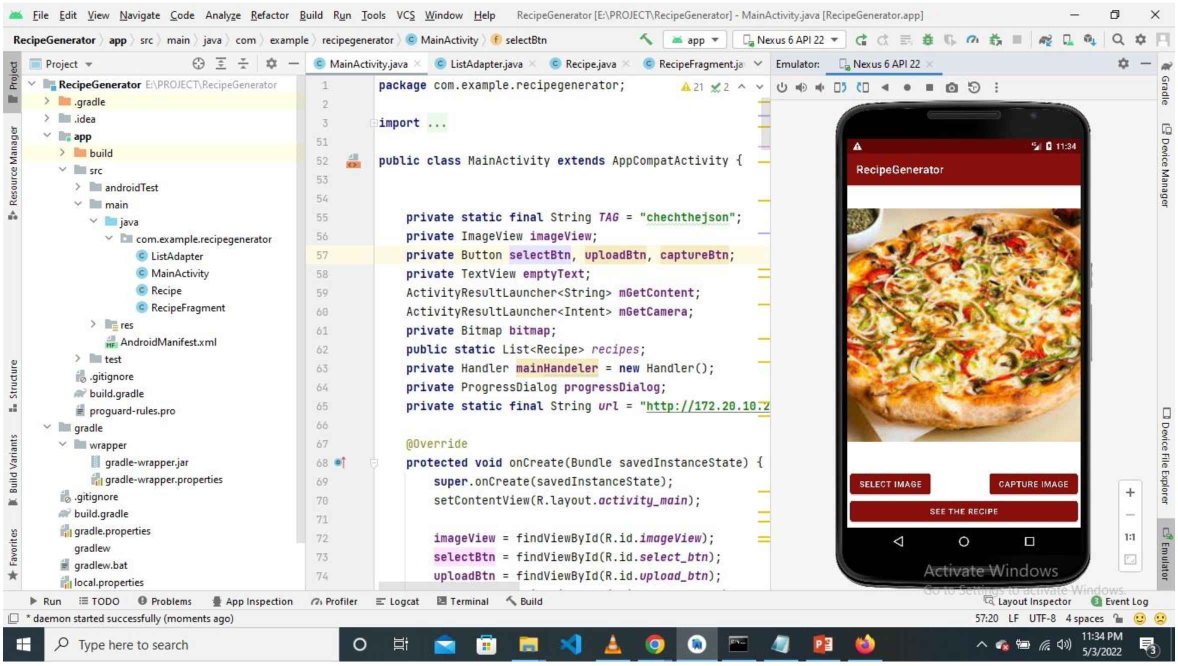

Figure 26

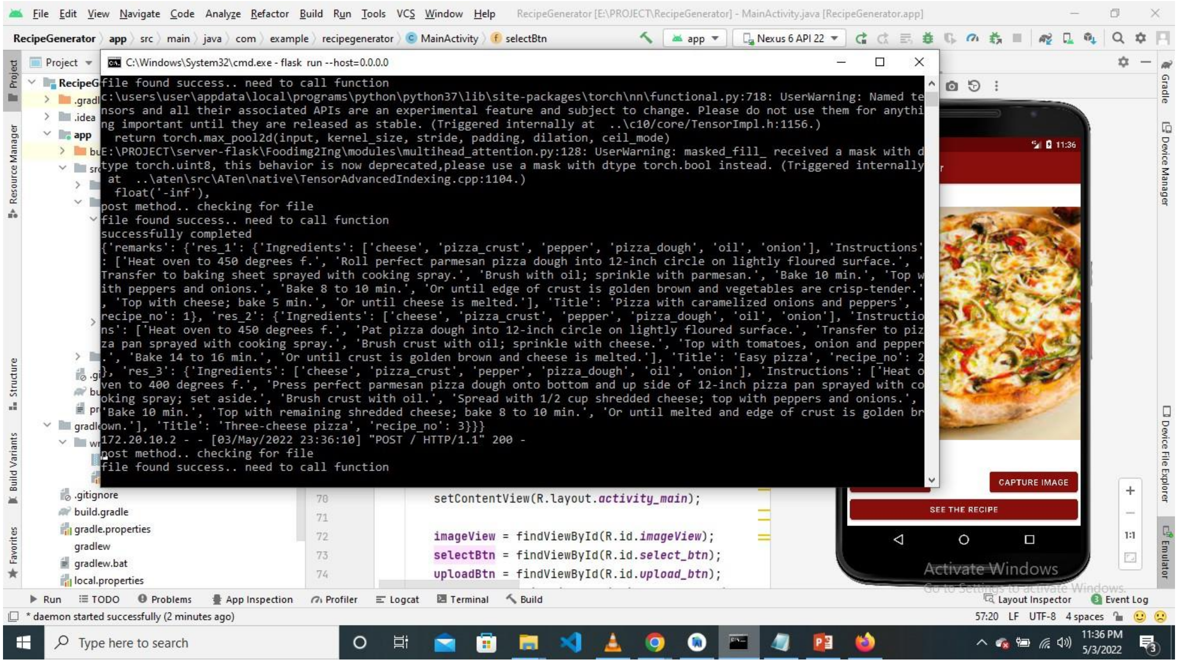

Figure 27

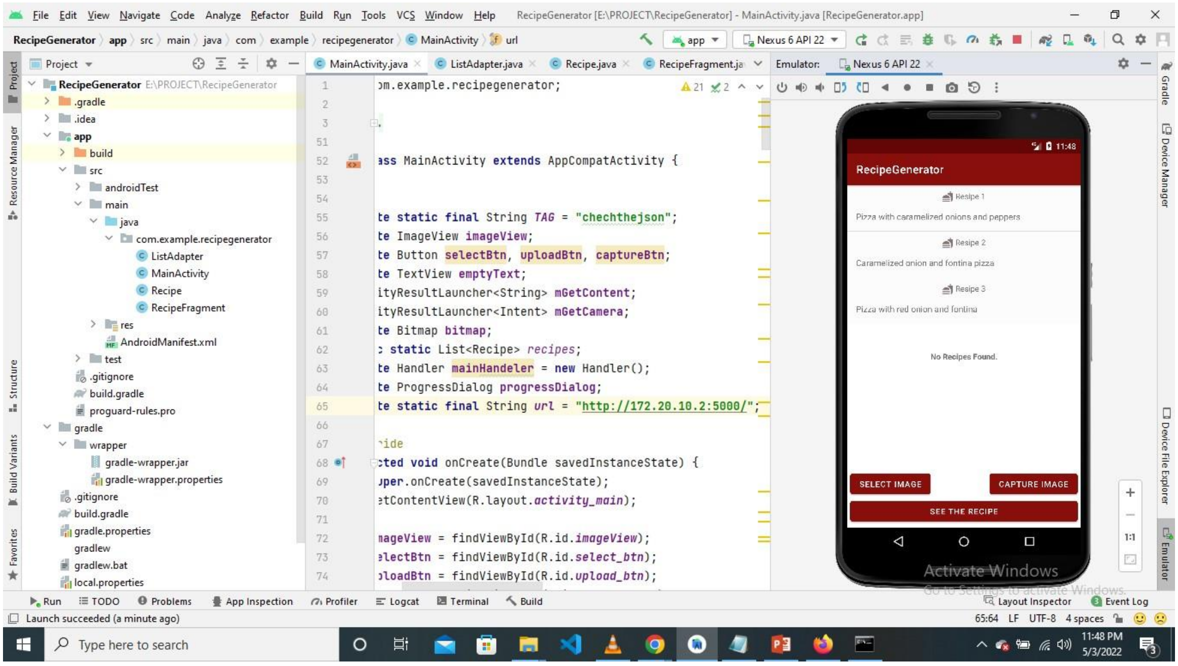

Figure 28

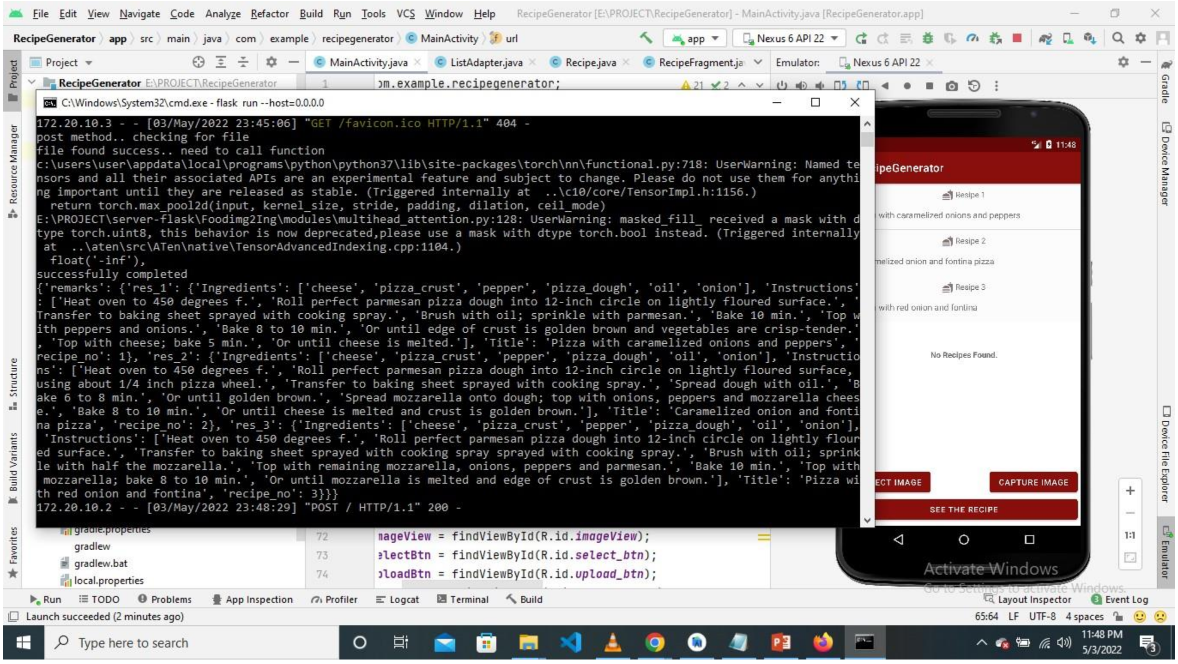

Figure 29

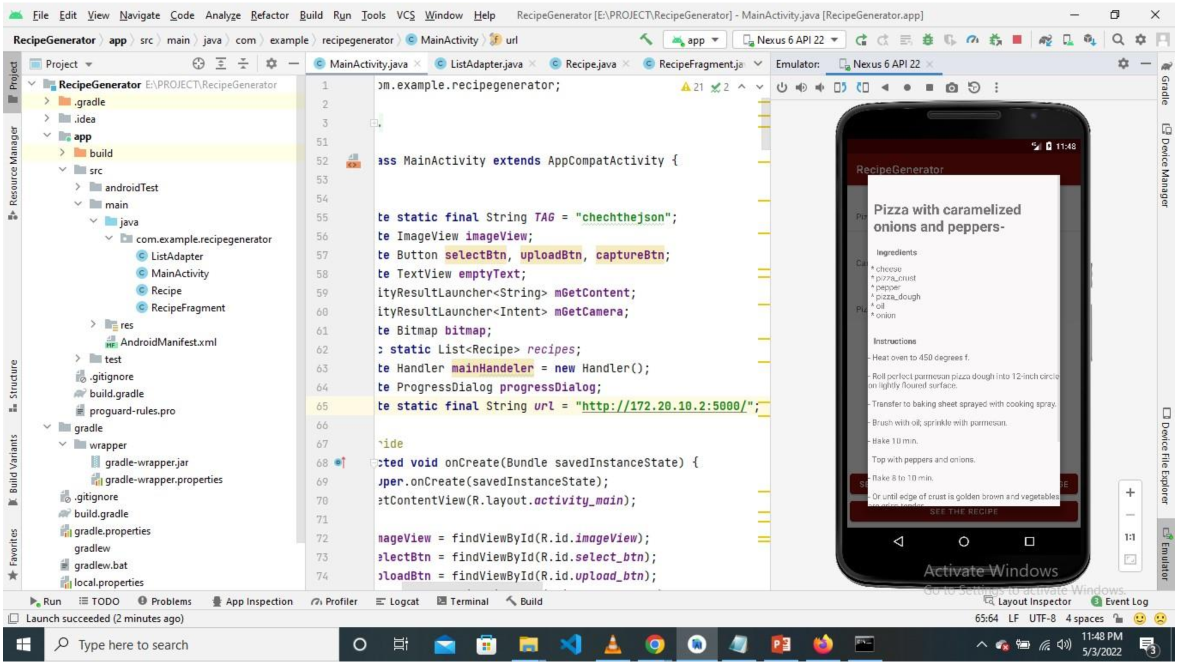

Figure 30

Food Prediction

```python
import warnings
warnings.filterwarnings('ignore', category=FutureWarning)
import tensorflow as tf
classifierLoad = tf.keras.models.load_model('Food_model.h5')

import numpy as np
import pandas as pd
from keras.preprocessing import image

test_image = image.load_img('TestFood/Pitu/p2.jpg', target_size=(200, 200))
# test_image = image.img_to_array(test_image)
test_image = np.expand_dims(test_image, axis=0)
result = classifierLoad.predict(test_image)
print(result)
print("------------------ Predicted Food ------------------")
if result[0][0] == 1:
    print("French Fries")
    Predicted_Food = "French Fries"
elif result[0][1] == 1:
    print("Fried Rice")
    Predicted_Food = "Fried Rice"
elif result[0][2] == 1:
    print("Pittu")
    Predicted_Food = "Pittu"
elif result[0][3] == 1:
    print("White Bread")
    Predicted_Food = "White Bread"

print("------------------ Predicted Ingredients ------------------")
```

Figure 31

```python

ingredientsData = pd.read_csv('DataSet/ingredients.csv', skipinitialspace=True)
ingredients_Value = ingredientsData[(ingredientsData["foodName"] == Predicted_Food ).tolist() ]


print(ingredients_Value['ingredients'].loc[ingredients_Value.index[0]])

print("------------------ Predicted sugarLevel (Glycemic Index) ------------------")

print(ingredients_Value['sugarLevel (Glycemic Index)'].loc[ingredients_Value.index[0]])

print(ingredients_Value['GI Index Range'].loc[ingredients_Value.index[0]])



print("------------------ Summary ------------------")

S_Value = (ingredients_Value['sugarLevel (Glycemic Index)'].loc[ingredients_Value.index[0]])


if (S_Value > 50):
    print("This food has more than 50% sugar! Prevent it!")
else:
    print("This food has less than 50% sugar! you have have it!")

# disbts stus

```

Figure 32

CNN Model

```python
from keras.models import Sequential
from keras.layers import Convolution2D
from keras.layers import MaxPooling2D
from keras.layers import Flatten
from keras.layers import Dense
from keras.models import model_from_json
from keras.optimizers import adam_v2

from keras.preprocessing.image import ImageDataGenerator
import tensorflow as tf
from tensorflow.keras.optimizers import RMSprop

batch_size = 48

# All images will be rescaled by 1./255
train_datagen = ImageDataGenerator(rescale=1 / 255)

# Flow training images in batches of 128 using train_datagen generator
train_generator = train_datagen.flow_from_directory(
    'DataSet/train/',  # This is the source directory for training images
    target_size=(200, 200),  # All images will be resized to 200 x 200
    batch_size=batch_size,
    # Specify the classes explicitly
    classes=['French Fries', 'Fried Rice', 'Pitu','White Bread'],
    # Since we use categorical_crossentropy loss, we need categorical labels
    class_mode='categorical')
```

Figure 33

```python
model = tf.keras.models.Sequential([
    # Note the input shape is the desired size of the image 200x 200 with 3 bytes color
    # The first convolution
    tf.keras.layers.Conv2D(16, (3, 3), activation='relu', input_shape=(200, 200, 3)),
    tf.keras.layers.MaxPooling2D(2, 2),
    # The second convolution
    tf.keras.layers.Conv2D(32, (3, 3), activation='relu'),
    tf.keras.layers.MaxPooling2D(2, 2),
    # The third convolution
    tf.keras.layers.Conv2D(64, (3, 3), activation='relu'),
    tf.keras.layers.MaxPooling2D(2, 2),
    # The fourth convolution
    tf.keras.layers.Conv2D(64, (3, 3), activation='relu'),
    tf.keras.layers.MaxPooling2D(2, 2),
    # The fifth convolution
    tf.keras.layers.Conv2D(64, (3, 3), activation='relu'),
    tf.keras.layers.MaxPooling2D(2, 2),
    # Flatten the results to feed into a dense layer
    tf.keras.layers.Flatten(),
    # 128 neuron in the fully-connected layer
    tf.keras.layers.Dense(128, activation='relu'),
    # 5 output neurons for 5 classes with the softmax activation
    tf.keras.layers.Dense(4, activation='softmax')
])
```

```python
model.summary()

model.compile(loss='categorical_crossentropy',
              optimizer=RMSprop(lr=0.001),
              metrics=['acc'])

total_sample = train_generator.n
print(total_sample)
n_epochs = 30

history = model.fit(
    train_generator,
    steps_per_epoch=int(total_sample / batch_size),
    epochs=n_epochs,
    verbose=1)


model.save('Food_model.h5')
print("------------------ Disease Model Saved ------------------")

```

Figure 34

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Appendix – A

Gantt Chart

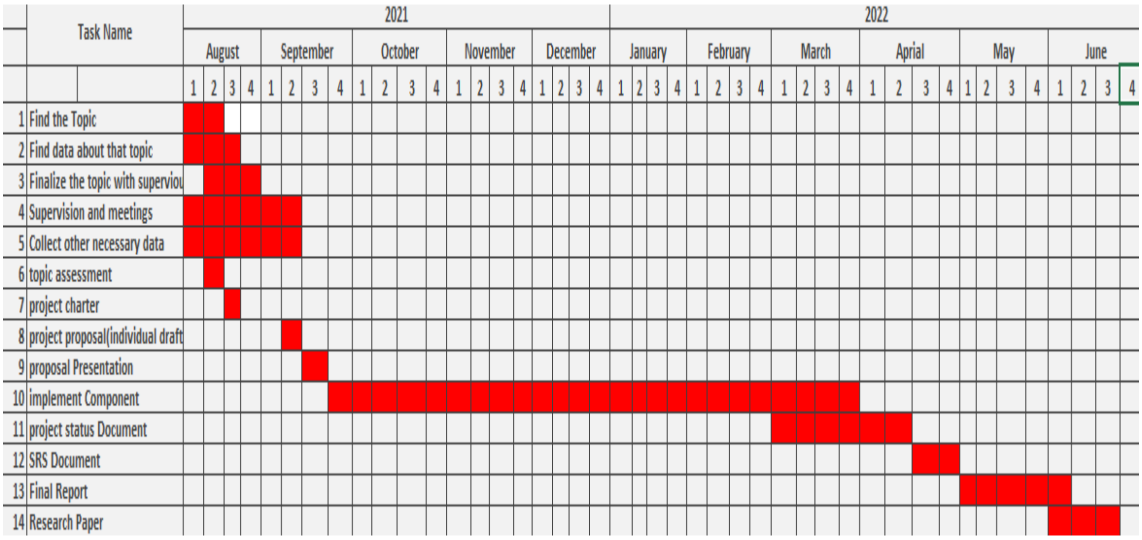

Figure 35

Appendix – B

WBS – Work Break Down Structure

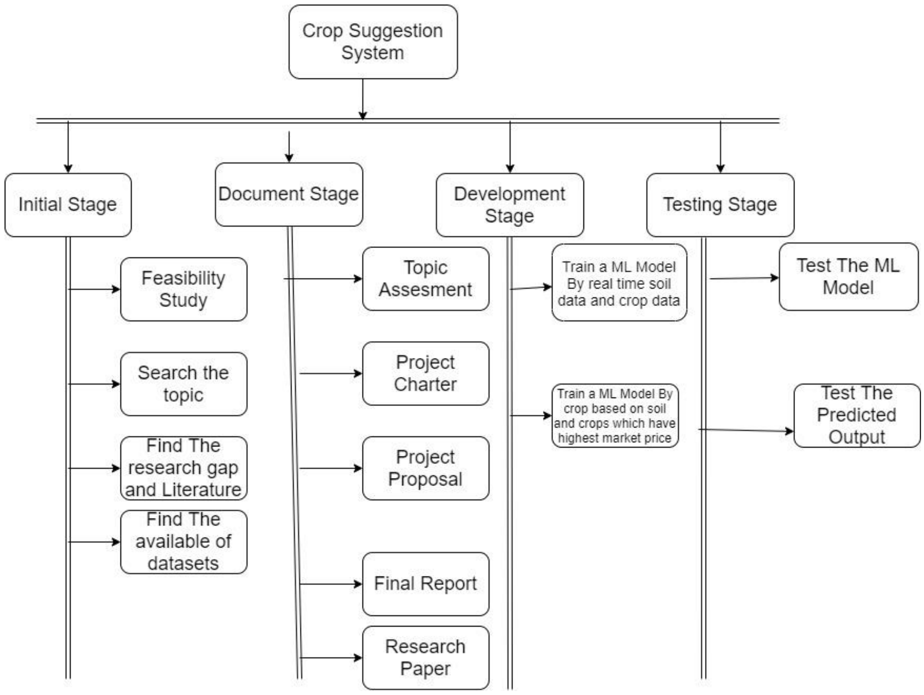

Figure 36