A project report on

DEEP LEARNING BASED RECIPE GENERATOR

Submitted in partial fulfillment for the award of the degree of

M.Tech. (Integrated) Computer Science and Engineering with Specialization in Business Analytics

by

PRINCE (19MIA1079)

SCHOOL OF COMPUTER SCIENCE AND ENGINEERING

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Vellore Institute of Technology
(Deemed to be University under section 3 of UGC Act, 1956)
CHENNAI

DECLARATION

I here by declare that the thesis entitled "DEEP LEARNING BASED RECIPE GENERATOR" submitted by me, for the award of the degree of M.Tech.(Integrated) Computer Science and Engineering with Specialization in Business Analytics, Vellore Institute of Technology, Chennai, is a record of bonafide work carried out by me under the supervision of "Dr. Noel Jeygar Robert V".

I further declare that the work reported in this thesis has not been submitted and will not be submitted, either in part or in full, for the award of any other degree or diploma in this institute or any other institute or university.

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CERTIFICATE

This is to certify that the report entitled **“DEEP LEARNING BASED RECIPE GENERATOR”** is prepared and submitted by **Prince K (19MIA1079)** to Vellore Institute of Technology, Chennai, in partial fulfillment of the requirement for the award of the degree of **M.Tech. (Integrated) Computer Science and Engineering with Specialization in Business Analytics** programme is a bonafide record carried out under my guidance.The project fulfills the requirements as per the regulations of this University and in my opinion meets the necessary standards for submission. The contents of this report have not been submitted and will not be submitted either in part or in full, for the award of any other degree or diploma and the same is certified.

Signature of the Guide:

Name: Dr. Noel Jeygar Robert V Date:

Signature of the Examiner 1	Signature of the Examiner 2
Name: Dr. Joe Dhanith P R	Name: Dr. Amutha S
Date:	Date:

Approved by the Head of Department

ABSTRACT

Food identification is significant in choosing food and consumption, which is necessary for human well- being and health. It is therefore essential to computer vision and can also help with various food-related vision tasks, such as food categorization, recipe retrieval, and development. A common food classification job is to predict food names based on associated food images. New advances in deep learning improve food classification ability. Recipe generation is a more difficult challenge than food Classification and ingredient recognition since the evaluation of nutritious food depends not only on com ponents but also on the size, shape, and color of food owing to varied cooking methods.

Surprisingly, not much research work has been done on recipe generation. As a result of this research, we provide a deep learning-based recipe generation model that creates cooking instructions from food images. Our system predicts ingredients using a architecture which we had proposed as goes down,
Modelling their relationships without enforcing any order, followed by the creation of culinary instructions while paying attention to the image and its predicted components. Extensive experimental investigation on various food photos was performed to evaluate the performance of the suggested model.

On the large-scale Indian Food dataset, a well-known dataset in the field of recipe instructions generation, we thoroughly evaluate the entire system and demonstrated that high-quality recipes have been generated by combining images, ingredients, and instructions. From the results, we observed that our system can produce recipes that, in the opinion of a human, are more compelling than those produced by retrieval- based methods.

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LIST OF ACRONYMS

CNN	Convolutional Neural Network
ResNet	Residual Neural Networks
Conv2d	Convolution matrix with two dimensions
RNN	Recurrent Neural Network

Chapter 1
1. Introduction

1.1 INTRODUCTION:

Food is a source of survival, but in our culture, it is even more important because it defines and influences our lifestyle and health. The expression "we are what we eat" refers to how closely tied our eating habits are to our overall well-being. Although food has always been important in society, it has grown even more so with the increased use of social media. In this day and age, social media is flooded with attractive food photos and recipes for preparing at home, increasing our likelihood of cooking the dishes ourselves. The downside of this tendency is a desire to be authentic while displaying a perfect lifestyle.

Since the breakout of COVID-19, everyone has been staying at home and rekindling the taste for homemade food. People spend most of their time surfing through gorgeous images of exquisite dishes on the internet but do not have the time or money to buy it. They therefore attempt to cook in some primitive or unprepared manner without training in cooking. This shift creates a new demand for easily accessible tools that can take the consumer from a simple food image to an all-inclusive recipe.

While these dishes are available to be purchased, it's not always easy or possible, and cooking them requires some instruction and skill in the home. Therefore, the demand is for cooking aids that are more than just a recipe search, but rather intuitive and image-driven to create recipes. Photograph any dish you would like to try, and then obtain a customized recipe with ingredients and instructions-a tool that easily ridges the gap between inspiration and execution in the kitchen.

A system for creating a recipe from an image that may recognize food is extremely challenging; food itself presents such extensive patterns of different ingredients and plating styles, textures, and colors that make the image difficult to detect as representing one kind of dish. Most other research efforts on food try to recognize specific types of food or classify them into labeled descriptions only, not at all trying to venture more into the complexity to bring out step-by-step instruction for preparation.

In response to these challenges, our project has proposed an end-to-end recipe generator based on deep learning, breaking away from simple recognition.

Our system is capable of detecting food items in images and providing comprehensive recipes of Indian cuisine. We trained this model on the Indian Food Images Dataset, which contains diverse Indian dishes with their accompanying recipes. Using a CNN, it classifies visual clues, predicts the ingredients that will be included, and generates structured recipes. Beyond just naming the dish from an image, the system supplies an ingredient list and the detailed cooking instructions, proving particularly useful for a home cooking amateur. The model was trained in the Indian Food Images Dataset generally for detecting the characteristic colors, textures, and serving modes of Indian food items.

So far, our system has effectively produced accurate recipes through a vast number of trials and tests on diversified images of food items after wide training. Also, recipes produced from our model contain richer and easier directions than any basic search-based system because they produce step-by-step tailor-made guidance. This project is being built for ordinary people to bring restaurant-style Indian dishes into their own homes with the least amount of effort.

Moving beyond personalized cooking, it creates new avenues for smart kitchen applications towards immersive and interactive culinary experiences that reflect actual user needs in real-time. The design aim is to access, enjoy, and personalize cooking for individuals to cook in the manner they love it, thus opening up the possibilities for innovations into AI-driven culinary assistance and the future of home cooking in a first digital world.

However, food recognition poses challenges due to its variability and complex composition. Overcoming these obstacles requires advanced computer vision and prior knowledge. Previous efforts have focused on categorization, but deeper analysis is needed to provide accurate food preparation descriptions.

1.2 MOTIVATION:

1.2.1 THE IMPACT OF COVID-19 ON HOME COOKING:

The COVID-19 pandemic drastically altered the course of ordinary life, with the home culinary sector experiencing the most severe impact. Lockdowns and restrictions on going-out services prompted most people to turn to home cooking as a means of assuring food security, diet management, and reducing the hazards connected with eating from outside sources.

It became a source of self-control instead of just a need, in a place where they could prepare and eat what they wanted to. A consequence of the adaptation of remote work is extra time spent at home and fewer opportunities or desires to eat out.

Therefore, for most people, cooking became a new focus either because of necessity, creativity, or an interest in exploring new cuisines. With interest rising in food, there was now a need for tools that could make cooking easier to access through easy recipes or guidance for those without formal training.

1.2.2 CHALLENGES IN FOOD RECOGNITION AND RECIPE GENERATION:

Some of the intrinsic intricacies in food, such as variation in appearance based on cooking methods, presentation styles, and even portion sizes, make it difficult to identify food from photos and then generate appropriate recipes. The same cuisine prepared by different persons will seem, taste, and feel differently.

Food may also be made up of a variety of ingredients that appear identical or change appearance when cooked. For example, before cooking, different spices, veggies, or meats may appear extremely similar, making it difficult for a system to distinguish between them.

Cooking also alters food and vegetables wilt, meats brown, and sauces thicken so that is not as recognizable by just the image. Once again, the plating and presentation aspect of visual recognition is also challenging because of vast cultural differences and individual preferences.

The lighting utilized, the amount size, and the type of serving dish used to serve the food can all have an impact on how a picture of the food appears, adding to the difficulty of constant recognition.

1.2.3 TRADITIONAL FOOD RECOGNITION SYSTEMS HAVE LIMITATIONS:

The classic food recognition system helps identify different types of food, such as pizza, spaghetti, and salad.

Although such classification systems of food are valuable for classifying food, they are not accurate for generating full recipes. Typically, food classification simply identifies a particular dish from a fixed list of categories and does not consider the real ingredients or detailed steps that go into preparing a dish.

Generating a recipe would require understanding not just the food item but its ingredients, quantities, the steps of cooking, and relations among them. Current systems are not generally deep enough to generate full instructions for cooking or even to offer ingredient substitutions that are central to creating good, actionable recipes. Gaps along these lines make it very difficult for users to draw reliable, actionable guidance directly from food recognition systems alone.

1.3 PURPOSE OF OUR PROJECT:

The challenge our project was based upon the image classification of food, particularly generating recipes for food preparation using these images. Inspiration drew from this was developing a system connecting food recognition with recipe generation.

We would like to design a deep learning model that recognizes the food present in the given images. Not only would it provide identification but also generate very accurate recipes in an easy- to-follow format.

This system should identify the ingredients in a dish and give a structured recipe including lists of ingredients, their quantities, and step-by-step instructions.

It will be the innovative solution where a user can upload a picture of a dish, and there will be a complete recipe for it. It should make cooking in front of anyone from the freshest novice to the grizzled veteran smooth, then finish with dishes that might intimidate even them or be intimidating for anyone to produce.

Our system will inform users step by step with customizable advice, no matter whether a first timer is trying to prepare a simple dish or an expert who wants to explore their appetite for new cuisines.

Our goal in this project is to make cooking at home easier, enjoyable, and personalized. We aim to make cooking so accessible and engaging that everyone can just cook with the feel of ease and fun while in the comfort of their home.

The system also opens doors to future innovations in smart kitchens and AI-driven culinary tools, making the kitchen interactive and efficient for the casual cook as well as the professional.

1.4 PROBLEM STATEMENT

Food, being one of the most important parts of our lives because of how fast-paced our world is at present, has greatly influenced health, lifestyle, and even culture. Social media and online food culture have fueled interest more: nowadays, a lot of people want to see new ideas for dinner meals and recipes based on images posted online. While, of course, very exciting, it leaves a vast chasm between food inspiration and the ability to recreate those dishes at home for cooks without professional culinary knowledge.

Generating the right cooking recipe from food images remains an open challenge despite the advances in computer vision and machine learning. Currently, food recognition systems are more focused on showing the category of food and rarely give out specific recipes or instructions on how to cook.

The variation in ingredients, cooking methods, and plating styles makes food visuals very challenging to predict the ingredient quantities, portions, or steps for cooking accurately using the current systems.

Specifically, our project aims to fix the following problems:

1.4.1 Lack of Recipe Generation from Food Images: Current systems can correctly identify food items from images but fail to generate complete, detailed recipes. This leaves a huge gap in offering users actionable cooking instructions to build a specific dish they are looking to prepare.

1.4.2 Complexity in Food Identification: Some conditions which make food identification complex include variations of ingredients and, of course, the differences between meals when prepared and presented because of regional differences. The models also often fail to identify the individual ingredients or understand how they relate.

1.4.3 Personalized and Correct Recipe Suggestions: Besides detection of the dish, a system must suggest personalized recipes that contain exact ingredients detected in the image. The user may need more than a name: he should know the exact amount of ingredients, techniques of preparation, and the time to cook so that the dish could be copied successfully.

1.4.4 Customization to Specific Cuisines-for example, Indian Cuisine Various cuisines present challenges in ingredient identification and generation. Older models might not perform well with region-specific dishes or complex spice-ingredient combinations mixed with cooking techniques. Our system aims for specialization in recipe generation for Indian cuisine, understanding intricate regional ingredients and cooking processes.

Hence, our system's problem statement will be to design a deep learning-based food image recognition and recipe generation system that correctly identifies the dishes, predicts the ingredients, and gives an adequately structured step-by-step cooking instructions for the same.

This should do the following:

- Identify Food Items: It will recognize the different food items from images with an emphasis on Indian cuisine.
- Generate Recipes: It will give a detailed recipe by providing lists, amounts, and cooking instruction about the found dish.
- Tackle Problems Arising from Food Complexity: Cooking Techniques, Presentation, Regional Specialties
- Personalized Recipes: Offer users a recipe according to the food picture, giving them the opportunity for cooking experiences tailored to their preferences.

In addressing these concerns, we aim to deliver an accessible interface that will enable users to cook with greater confidence and creativity and turn a simple food image into the realization of a recipe.

1.5 OBJECTIVES

The purpose of this project is to develop an object recognition-based deep learning-driven recipe generator, able to identify food items in an image and generate correct, detailed cooking recipes. This can be achieved through the design of a model that may accurately classify and identify food items - with a focus on the realm of Indian cuisine - using CNNs.

This would be a system capable of not only identifying the dish but also predicting the ingredients involved in the recipe, including consideration for the complex interrelations between the ingredients even though they could be represented in a myriad of ways or styles of preparation. Other than food identification, the model will create ready recipes, including amounts and how to prepare the ingredients and their cooking times as well as serving instructions using identified foods and ingredients.

It challenges the model to recognize different variations and complexities in images of food, be it how food is cooked differently or the variety of presentations through different ingredients and arrangements of the plating of dishes. Special attention will be given to Indian cuisine with developing a model that is able to identify large numbers of traditional and regional dishes, taking into account specific ingredients, spices, and cooking methods utilized in Indian cooking. The system will give access to a user-friendly interface through which users will be able to upload images of food items with receiving detailed recipes in return, accessible even to those not experienced in cooking.

The model will be performance-evaluated to perfect the model in regards to precision and efficiency, such that predictions made are of high quality. Finally, the project aims at developing an application that will be deployed for wide usage, wherein any user can generate recipes using instant images of food for connecting food inspiration with food execution and enabling people to serve authentic Indian dishes with relative ease.

1.6 SCOPE OF THE PROJECT

This project scope encompasses the development of a deep learning-based system that can recognize food items based on images taken and produces detailed and accurate recipes over Indian cuisine. It includes several key areas:

1.6.1 FOOD IMAGE RECOGNITION AND CLASSIFICATION:

The system will be based on identifying food items from images and will make use of deep models, essentially CNNs. The food items covered would include all sorts of Indian cuisines, regional dishes, and popular meals.

1.6.2 INGREDIENT DETECTION AND PREDICTION:

The system can predict, for example, the ingredients of a dish in the food image. This feature requires detecting individual ingredients with their quantities even though the food is presented in complicated forms or mixed states.

1.6.3 RECIPE GENERATION:

Based on the dish and the items I selected, the model's output would be structured recipes with detailed preparation methods, cooking advice, ingredient proportions, and other particular serving suggestions. Authentic, simple dishes for a variety of users will be covered, with a focus on Indian cuisine.

1.6.4 FOCUS OF THE DATASET INDIAN CUISINE:

This project will employ the Indian Food Images Dataset, which provides a mix of images and recipes of various Indian cuisine. This means that the model is to pay attention to the peculiar characteristics of Indian food features, from the spices applied, cooking techniques, and regional variations that define Indian dishes.

1.6.5 DEALING WITH VISUAL VARIABILITY IN FOOD IMAGES:

This is a project in which image recognition is going to be based on variations in angle, lighting, style, and methods of cooking. Therefore, the main challenge for this project is image recognition. This would be in terms of scope because it involves training the system in a way that the model would deliver real results in real application scenarios where conditions for representing images are not standardized.

1.6.6 DESIGN OF USER INTERFACE:

This project will involve developing a straightforward interface to upload food images and retrieve elaborate recipes on how to prepare that food. In this regard, the user will be able to prepare dishes with their fingers because there is no need to type in the first place, knowing their culinary ability.

1.6.7 PERFORMANCE EVALUATION:

System's correctness, speed, and ability to produce meaningful recipes will be measured and optimized. The project will assess the performance of the model through measurements of accuracy in food recognition, the relevancy, quality of the generated recipe, as well as user experience.

LIMITATIONS:

Although the prototype is going to mainly focus on Indian cuisine, diversity in datasets will form a base for further expansions. Further, the system is going to be reliant on the quality and diversity of the dataset that is used to train the model to generate recipes from images.

Overall, the project aims at bridging the inspiration gap from a visual perspective and bring them to an act of culinary execution where one can easily recreate authentic dishes from India, in addition to demonstrating potential applications by combining deep learning with culinary application, applicable to daily life.

1.7 PRELIMINARIES:

Our proposed model has been implemented on CNN. In this section we discussed the fundamental concepts that used to understand the proposed model. Each CNN model that is used to train our proposed model has been discussed below:

1.7.1 AUTOENCODERS CNN (KERAS AND TORCH

Autoencoders is a type of neural network, that is used for data compression and the reconstruction of the same. The encoder compresses the input and the decoder tries to reconstruct it from the compressed version. An autoencoder is actually learning how to group data together. CNN stands for a kind of neural network that extracts features from data using the convolution operator, generally 2D convolution when used for applications in image processing.

1.7.2 CNN WITH 2 FULLY CONNECTED LAYERS

The CNN is a deep-learning model for image categorization. This system has fully connected layers that follow the convolutional layers. Fully connected layers have each neuron from the previous layer connected to the next, while the convolutional layers make use of filters to extract local characteristics from input images. Fully connected layers extract higher-level features and transform them into class labels, thus enabling the network to forecast using the learned features earlier. Usually, at the end of a CNN design, these appear and play an important role in converting the extracted features into class probabilities or regression results.

1.7.3 RESNET

Residual Neural Network is a CNN model with 50 layers. This network requires an input image of size 224*224. There are 64 different kernels that have a kernel size of 7*7 in a convolution and with a stride of size 2. Then there is a max pooling layer that contains a stride size of 2. Now kernel dimension increases in the subsequent layers. Then comes average pooling and finally softmax function is used in the final layer.

Chapter 2

2. Background

2.1 LITERATURE SURVEY

From the Literature we observed that different approaches related to recipe generation have been proposed like recipe categorization, ingredient recognition etc. A brief description of all these studies has been discussed in this section.

2.1.1 FOOD-101–MINING DISCRIMINATIVE COMPONENTS WITH RANDOM FORESTS:

The Authors Bossard et al. [1] explored the challenge of automatically recognizing food items in their study they suggested a new Random Forests-based technique to mine discriminative components and simultaneously transfer data between classes. To improve mining and representation capabilities, they evaluated patches aligned with image superpixels.

The authors also introduced a comprehensive dataset with 101 food categories and 101 '000 images to test their rf component mining approach for food identification.

Their model achieved an average accuracy of 50.76%, outperforming previous component-based classification algorithms on the challenging mit-Indoor dataset and other classification techniques except for CNN. Specifically, their solution improved accuracy by 11.88% and 8.13% compared to Improved Fisher Vectors and SVM classification, respectively.

2.1.2 DEEP-BASED INGREDIENT RECOGNITION FOR COOKING RECIPE RETRIEVAL:

The Authors Jing-Jing Chen et al. [3] explored the problem of recognizing ingredients in food images and its relevance to cooking recipe retrieval in their study the authors argued that obtaining recipes that match the given food pictures can improve the computation of nutrition information, which is essential for various health-related applications. They highlighted the primary focus of current methods on classifying food categories based on the appearance of global dishes, with little attention paid to the composition of the ingredients.

The authors also noted the potential issue of zero-shot retrieval, which arises when retrieving recipes that contain unidentified dietary groups, rendering the current approach inadequate. In addition, they pointed out that achieving adequate performance in content-based retrieval without knowledge of food categories is equally challenging due to significant visual differences in food appearance and component composition.

Since the number of ingredients is significantly lower than the number of food categories, the authors proposed that ingredient identification is ideal for zero-shot retrieval because it is more scalable than distinguishing each food category. However, they acknowledged that ingredient identification is significantly more challenging than food classification, raising questions about their use for retrieval.

The authors presented deep architectures for concurrent constituent identification and food classification learning to tackle these challenges, utilizing their mutual but ambiguous relationship. They applied the learned deep features and ingredient semantic labels cleverly to zero-shot recipe retrieval, demonstrating the practicality of their approach and illuminating the zero-shot issue in recovering culinary recipes. The authors evaluated their method on a large dataset of highly complex dishes photos and provided insights into fixing recognizable proof.

2.1.3 CHINESEFOODNET: A LARGE-SCALE IMAGE DATASET FOR CHINESE FOOD RECOGNITION:

The Authors Xin Chen et al. [6] present in this study their work on "ChineseFoodNet," a large-scale food image dataset that enables automatic recognition of Chinese cuisine images. This novel and the challenging dataset include approximately 180,000 images of Chinese food divided into 208 categories, containing numerous examples of the same dish. The authors explain how they chose the culinary categories, obtained and cleaned the data, and labeled it for machine-learning purposes to make human labeling less expensive and time-consuming.

The authors gave a thorough analysis of different state-of-the-art deep convolutional neural networks (CNNs) using the ChineseFoodNet dataset in their paper. They also introduce "TastyNet," a novel two-step data fusion method that combines CNN prediction results with a voting procedure. The proposed approach accomplishes top-1 accuracy rates of 81.43 and 81.55 percent on the validation and test sets, respectively. This study contributes to the advancement of computer vision and machine learning techniques in the field of food image recognition and classification, specifically for Chinese cuisine.

2.1.4 EXISTING WORK

Previous attempts at food comprehension have primarily focused on food and ingredient classification. On the other hand, a comprehensive visual food identification system ought to be able to differentiate not only the components that make it up but also how it was prepared. An embedding space-based image similarity score is used to obtain a recipe from a given dataset the image-to-recipe problem is also known as a retrieval problem. The quantity and variety of the dataset, in addition to the learned embedding's quality, are crucial factors in determining these systems' success. When there is no recipe in the static data that corresponds to the image query, it should not come as a surprise that these systems fail.

The "Inverse Cooking: Recipe Generation from Food Images"[11] paper introduces a novel approach that converts food images into corresponding cooking instructions using deep learning techniques. It leverages convolutional neural networks (CNNs) and recurrent neural networks (RNNs) to capture visual features and generate coherent recipes.

"DeepRecipes: Investigating Massive Online Recipe Collections and Recovering Food Ingredient Amounts"[12] focuses on recovering accurate ingredient amounts from unstructured text data and provides valuable insights into ingredient recognition and quantity estimation.

"Learning Recipe Generation and Food Retrieval Structural Representations" [13] presents a deep learning-based approach that combines text-based representations with graph neural networks to capture the hierarchical relationships between ingredients and cooking steps.

"Sequential Learning for Image-Based Ingredient Recognition" [14] proposes a sequential learning framework for ingredient recognition in food images. To recognise ingredients in complex recipes, it employs convolutional neural networks (CNNs) and long short-term memory (LSTM) networks.

"Large Scale Visual Food Recognition"[15] proposes a deep learning-based approach for accurately classifying a wide range of food items from images. It utilizes convolutional neural networks (CNNs) and hierarchical fine-tuning to improve recognition performance.

From the approaches we observed that all the approaches use deep learning models to either recognize ingredients or generate recipes but one of the drawbacks we found is that a comprehensive visual food identification system, on the other hand, should be able to distinguish not only the kind of dish or its components but also how the food was prepared.

2.2 RESEARCH GAP:

The literature survey reveals several notable research gaps in the domain of Recipe prediction using deep learning. These gaps pose challenges and opportunities for future investigations, impacting the development and implementation of effective prediction models.

The identified research gaps include:

2.2.1 LIMITED DATASET:

Our dataset, with 10,000 food images, might not be diverse enough to accurately identify and generate recipes. Its limited size could also prevent the model from covering the full range of Indian cuisines, including regional variations and lesser-known dishes. If the dataset expands with even more diverse food products, as well as a wider variety of variances in cooking methods and image quality variations, then the model's performance, robustness, and flexibility across different culinary contexts will increase.

2.2.2 VOICE INTEGRATION:

The incorporation of speech functionality to the recipe creation system will bring more problems. To begin with, a perfect transcription of ingredients and stages of cooking would be tough because of pronunciation differences, noise in the background, and imprecise voice in terms of producing recipes. This would require much more advanced speech recognition systems that are very accurate and reliable across different accents and languages. Voice means doing a lot more work in trying to solve such a problem, as it offers voice-enabling precise cooking instructions.

2.2.3 INSTRUCTIONAL COMPLEXITY LEVEL:

The system is only capable of generating relatively simple cooking procedures from food images; it could not retrieve the more complex culinary techniques, for example, recipes that demand expert expertise.

Some examples are dishes that would involve multi-step processes, require high accuracy with specific techniques, or include niche ingredients that a system might not learn thoroughly from images. In other words, the present model may seem to lack comprehension of why things are the way they are: a complexity level it currently falls short of.

A general or incomplete description of the instructions is most likely to result due to this lacuna. Further, the following sets of contextual understandings, such as video-based recipes for a better understanding, ingredient relationships, and advanced culinary knowledge, will be used further to create more accurate and quality instructions.

Rather than just involving these external resources, expert knowledge, and user feedback from outside will be sourced to generate recipes, which would be based on a much higher degree of accuracy and contextual awareness.

The filling of these research gaps will make the proposed system more powerful and all-inclusive for food recognition and recipe generation. A proposed system with a stronger back-end database, capable of handling a wide variety of cuisines, integral multimedia features, and improvements upon sophisticated cooking guidance may provide better information to it.

2.3 SOFTWARE USED:

2.3.1 GOOGLE COLABORATORY:

1. Purpose: Employed for the analysis, preprocessing, model building, and evaluation stages.

2. Description: Google Colaboratory provides a collaborative and cloud-based environment for Python programming and data analysis. Its seamless integration with Google Drive facilitates efficient collaboration and resource sharing.

2.3.2 VISUAL STUDIO CODE:

1. Purpose: Employed for building the API.

2. Description: Visual Studio Code is a lightweight yet feature-rich code editor. It supports various programming languages and offers extensions for additional functionalities. Its versatility makes it a popular choice for software development, including API creation.

Category	Description
Domain	Deep Learning
Programming Language	Python, HTML, CSS, Sqlite3
Tools & Libraries	Numpy, Pandas, Mathplotlib, Keras, Tensorflow, OpenCV, Flask
IDE	Anaconda prompt, Jupyter Notebook
Operating System	Windows 11

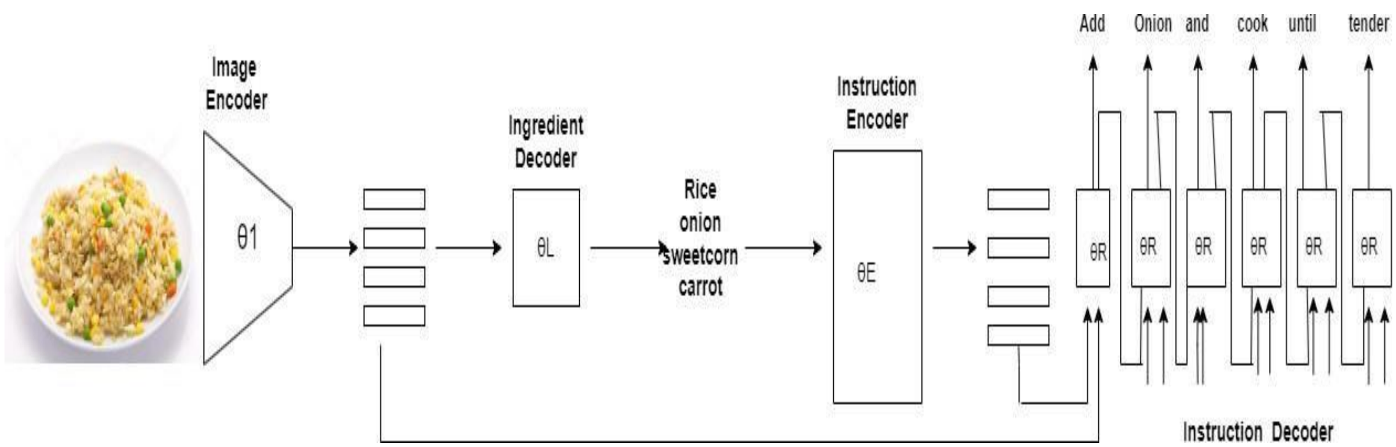
Table 1: Software Requirements

CHAPTER 3

3. Methodology:

3.1 ARCHITECTURE OF THE PROPOSED SYSTEM

3.1.1 USING GEMINI API KEY:



- User Uploads Food Image:

  The system starts with the user uploading a food image to the platform. This image serves as the primary input for the recipe generation process.

- Analyze Image using Gemini Pro Vision API:

  The uploaded image is sent to the Gemini Pro Vision API for image analysis. This API is tasked with visually identifying key elements within the image, particularly focusing on recognizing individual ingredients or general food items.

- Identify Ingredients from Image:

Based on its analysis, the Gemini Pro Vision API detects and lists ingredients visible in the image. This list of ingredients is then sent back to the system, forming the core data required to generate a recipe.

- Generate Culinary Prompt using Identified Ingredients:

Using the identified ingredients, the system crafts a culinary prompt that is detailed enough to convey the necessary cooking context. This prompt incorporates both the recognized ingredients and any relevant information that could guide the recipe generation, such as potential dish type (if detectable) or cooking style suggestions.

- Generate Recipe using Google GenerativeAI API:

The culinary prompt is sent to the Google GenerativeAI API, which processes it to produce a comprehensive recipe. This recipe includes specific quantities, step-by-step instructions, and other details tailored to the identified ingredients. The AI interprets the prompt in a culinary context to create a recipe that is as accurate and user-friendly as possible.

- Display Personalized Recipe to User:

Once generated, the recipe is displayed to the user in a clear, accessible format. The recipe is personalized, based on the ingredients identified in the uploaded image, giving the user a detailed guide to recreate the dish they captured.

- End:

The system completes the interaction by delivering a customized recipe, tailored to the user's uploaded image and ingredients, which can then be used for cooking.

3.1.2 USING DEEP LEARNING MODELS:

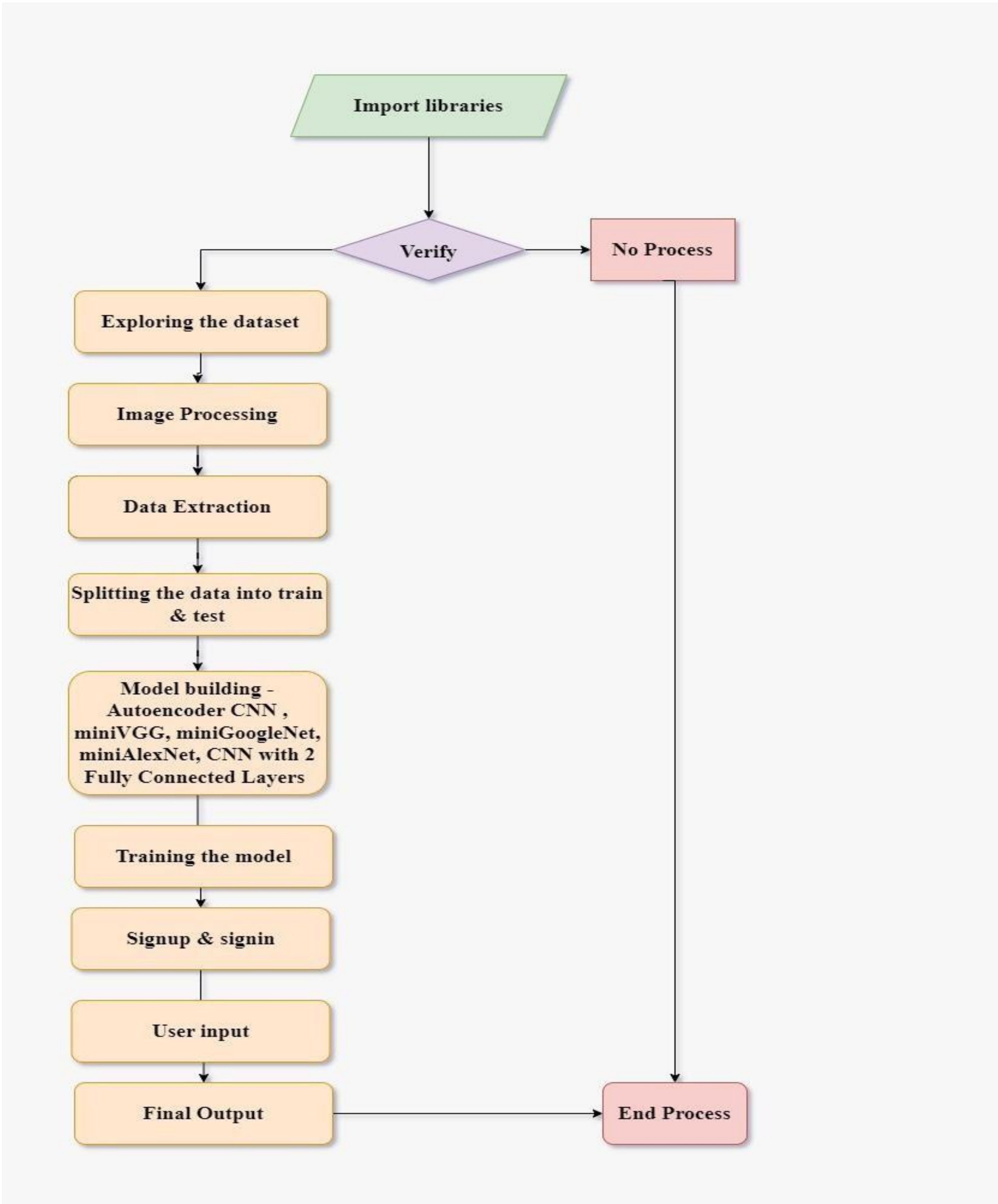


Figure 1.1: Data Flow Diagram

The figure 1.1 flow chart shows the execution flow of the proposed recipe generation system. The proposed system is trained on different CNN models.

To solve the picture-to-recipe problem, a recipe is typically derived from a fixed dataset using the image similarity score in an embedding space. The number and diversity of the datasets, as well as the quality of the learned embedding, all have a substantial impact on the success of these systems.

It should come as no surprise that these systems fail if the static dataset lacks a recipe that corresponds to the image query. To address retrieval systems' dataset limits, the image-to-recipe problem could be recast as a conditional generation problem.

We employed two methods in this project. One is a pre-trained dataset, and the other one is we have trained the dataset using different models.

We, therefore, developed a method in this work that converts an image into a instructions food recipe that generates title, ingredients, and cooking instructions.

3.2 DATASET:

The dataset for this project was obtained from Kaggle, which happens to be the most popular scientific dataset platform used by many practitioners in deep learning. Food has always played a pivotal role in the culture and society of human beings.

Today, in this increasingly interlinked world, such high volumes of information related to food exist to show an interest in understanding what cuisine trends and dietary patterns along with recipes are recommended.

At the heart of our goal, then, is our comprehension of combination and interaction of compound s and cooking methods. We will call this core-data_recipe, this set of information with which we will train and test our recipe generation system.

It consists of paths or urls to the image files and lists of ingredients and extensive step-by-step instructions on how to cook, spread across multiple columns in this table-formatted CSV.

Every row in this dataset contains all the information such as an ID for the recipe, a name, an image, ingredients used, and how to cook. The column of cooking_directions has estimated preparation time and recommended temperatures for cooking. Nutrition column contains nutritional information of each recipe. In the dataset, there are about 45,000 recipes in total.

All these come under a total of 80 categories, and this dataset plus another set of 10,000 images of Indian food represents the rich varieties of flavors across India. This cuisine can be characterized as region-specific and traditional flavors due to the varied soils, climates, cultures, and religious influences of the country.

Centuries of culinary development, fueled by trade, historical invasions, and cross-cultural exchange, have transformed Indian food into the rich tradition of global cuisines-from Europe and the Middle East to North America and Oceania-that it is today.

3.3 DATA PREPARATION:

Data preparation is a critical phase in readying the dataset for model training. This process involves:

3.3.1 VISUALIZING DATA AND EXPLORING CORRELATIONS:

1. Examining the dataset through visualization tools to understand its structure.
2. Exploring correlations between various attributes to identify potential patterns or relationships.

3.3.2 FEATURE SELECTION:

1. Addressing missing values and incomplete records to ensure data completeness.
2. Improving overall data quality by resolving discrepancies and outliers.

3.3.3 AGGREGATION, AUGMENTATION, NORMALIZATION, AND STRUCTURING:

1. Aggregating data when necessary for a more comprehensive view.
2. Augmenting the dataset to increase its size or diversity.
3. Normalizing data to bring it to a consistent scale.
4. Structuring data to align with the model's requirements.

3.3.4 TRANSFORMING NON-NUMERICAL DATA:

Converting non-numerical data into numerical values, ensuring compatibility with machine learning algorithms.

3.3.5 FEATURE SELECTION:

Selecting relevant features to enhance model performance by focusing on the most impactful attributes. This meticulous data preparation lays the foundation for a robust and effective machine learning model, improving its ability to learn patterns.

3.4 DATA CLEANING:

Finding and fixing inaccurate, incomplete, or missing data items is the process of "data cleaning." This work is successfully completed using popular Python packages like Pandas and NumPy.

3.5 DATA EXPLORATION:

Data exploration for Recipe generator involves a thorough analysis of the dataset using bar graph and word cloud for effective visualization. Key steps include:

3.5.1 Understanding Structure:

- Grasping the dataset's composition, variable types, and overall size.

3.5.2 Variable Analysis:

- Examining individual recipe-related variables with statistical measures and visualizations.

3.5.3 Correlation Examination:

- Investigating relationships and patterns between different attributes through visualizations.

3.5.4 Distribution Inspection:

- Analysing the frequency and variability of essential variables using histograms and box plots.

3.5.5 Pattern Recognition:

- Identifying trends or patterns indicative of recipe-related factors.

3.5.6 Outlier Detection:

- Using visualizations to spot potential outliers or anomalies in the data.

This process enhances understanding, aids decision-making, and provides valuable insights into recipe generator-related factors.

3.6 FEATURE SELECTION

Feature selection aims to identify and choose the most relevant attributes from the extensive dataset for predicting recipe.

3.7 DATA MODELING

The data is ready for modeling once it has been organized, categorized, and cleansed. We use a variety of machine learning strategies to build the model in this study. The selected algorithms include: CNN

```
base_model = ResNet152(weights='imagenet', include_top=False,
 ↪input_shape=(im_shape[0], im_shape[1], 3))
model = Sequential()
model.add(base_model)
model.add(GlobalAveragePooling2D())
model.add(Dense(512, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(num_classes, activation='softmax'))
```

Figure 1.2: CNN architecture

This CNN model leverages ResNet152 for feature extraction, followed by custom dense layers for classification.

It combines powerful pre-trained knowledge with layers optimized for the specific task, allowing it to adapt to new image classification problems efficiently. Fine-tuning ResNet152 also enables the model to learn task-specific details, providing a good balance of generalization and accuracy.

Here's a breakdown of how each component contributes to the model:

3.7.1 BASE MODEL - RESNET152:

- The base_model is initialized using ResNet152 with weights pre-trained on the ImageNet dataset (weights='imagenet'). This model has already learned a rich set of visual features across a large dataset, making it highly effective for various image classification tasks.

- include_top=False excludes the top fully connected layers of ResNet152, as they are specific to ImageNet classes. By removing these layers, the model retains only the convolutional feature extraction layers, which can be fine-tuned for a new task.

- input_shape=(im_shape[0], im_shape[1], 3) specifies the input dimensions for images, which allows for flexibility in adapting the model to images of a particular size as defined by im_shape.

3.7.2 SEQUENTIAL MODEL:

- A Sequential model is created to stack additional layers on top of the base_model, forming a custom classifier for the desired task.

3.7.3 GLOBAL AVERAGE POOLING LAYER:

- GlobalAveragePooling2D() takes the output feature map from ResNet152 and reduces it to a single feature vector.
- This pooling layer simplifies the feature map, providing a compact representation of the image, which reduces the model complexity and helps prevent overfitting.

3.7.4 DENSE LAYER WITH RELU ACTIVATION:

- A dense, fully connected layer with 512 units and ReLU activation (Dense(512, activation='relu')) learns higher-level patterns from the pooled features.

- This layer introduces a non-linearity and learns meaningful combinations of features to aid classification.

- Dropout Layer:

  Dropout(0.5) randomly drops 50% of the units in the dense layer during each training iteration. This reduces overfitting by ensuring that the model does not rely too heavily on any single feature.

- Output Dense Layer with Softmax Activation:

  The final dense layer, Dense(num_classes, activation='softmax'), produces num_classes outputs, with each output representing the probability of belonging to a particular class.

  The softmax activation function ensures the output probabilities sum to 1, making it suitable for multiclass classification tasks.

3.8 MODEL EVALUTAION & VALIDATION\

After developing a model, it's crucial to assess its performance through evaluation and validation. This process involves:

a. Evaluation Metrics:

- Accuracy: Measures the overall correctness of the model's predictions.
- Precision: Gauges the accuracy of positive predictions among all predicted positives.
- Recall: Measures the model's ability to capture all actual positives.
- F1-score: Balances precision and recall, providing a harmonic mean of the two.
- Area Under the ROC Curve (AUROC): Evaluates the model's ability to distinguish between classes.
- Assessing Model Accuracy: Using accuracy to determine the proportion of correct predictions out of the total.

b. Precision and Recall Analysis:

- Precision assesses the model's precision in positive predictions.
- Recall evaluates how well the model captures positive instances.
- AUROC Curve: Constructing and analysing the AUROC curve to understand the model's discrimination ability.

c. Cross-Validation:

- Employing cross-validation techniques to validate the model's generalizability and performance across different datasets.

This comprehensive evaluation and validation process ensure a thorough understanding of the model's strengths and weaknesses, guiding further refinement and optimization.

Chapter 4

4 RESULTS:

4.1 RESULTS AND DISCUSSION:

Our image-to-recipe generation system, built using a Convolutional Neural Network (CNN) based on ResNet152, demonstrated significant accuracy in recognizing and classifying food items from images, allowing for the generation of detailed recipes.

During testing, the model was able to:

- Identify Key Ingredients:

With high accuracy, it could recognize the primary ingredients, essential for creating precise recipes.

- Generate Recipe Steps:

By leveraging ingredient-based prompts, it generated recipe steps that matched traditional cooking instructions for a wide range of dishes.

The model was evaluated against other architectures, including standard CNN model and showed superior accuracy and performance.

This comparison highlighted ResNet152's ability to generalize across various food images, largely due to its deep feature extraction layers, which capture complex textures and colors characteristic of specific dishes.

4.1.1 COMPARISON OF MODELS

We compared our ResNet152-based CNN with simpler architectures, observing:

- Higher Accuracy:

  ResNet152 consistently outperformed simpler models in ingredient recognition and recipe generation accuracy.

- Better Generalization:

  Due to its greater depth, ResNet152 captured intricate details that are often essential for accurately identifying ingredients and dish types, particularly for Indian cuisine, which often has visually complex dishes.

- Improved Robustness with Dropout Layers:

  Adding dropout layers helped reduce overfitting, enabling the model to perform better on unseen data.

4.1.2 CHALLENGES AND LIMITATIONS

- Dataset Constraints:

  Our dataset, although extensive with 10,000 images, still posed some limitations. Certain regional dishes or variations may not be well-represented, impacting the model’s ability to generalize across the full diversity of Indian cuisine. Expanding the dataset would improve the model's accuracy for lesser-known dishes.

- Complex Recipe Instructions:

Some intricate cooking techniques were not fully captured due to the basic instruction format used. Enhancing the text generation with more context-specific instructions could improve usability for complex recipes.

- Ambiguity in Ingredient Quantities:

While the model was successful in identifying ingredients, determining the exact quantity for each ingredient was challenging due to the variability in dish presentations.

Using the Gemini API Key to generate the recipe Application

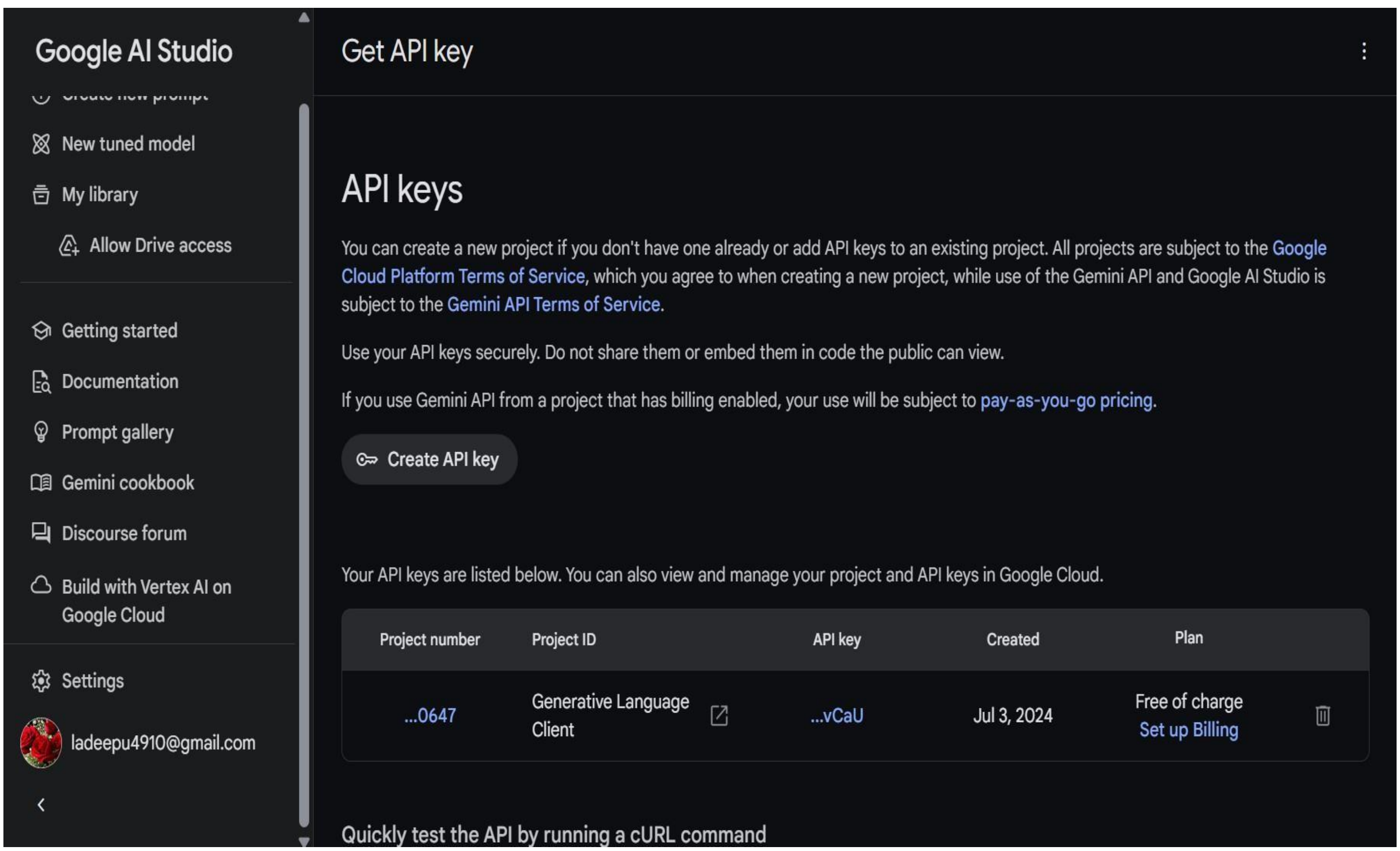
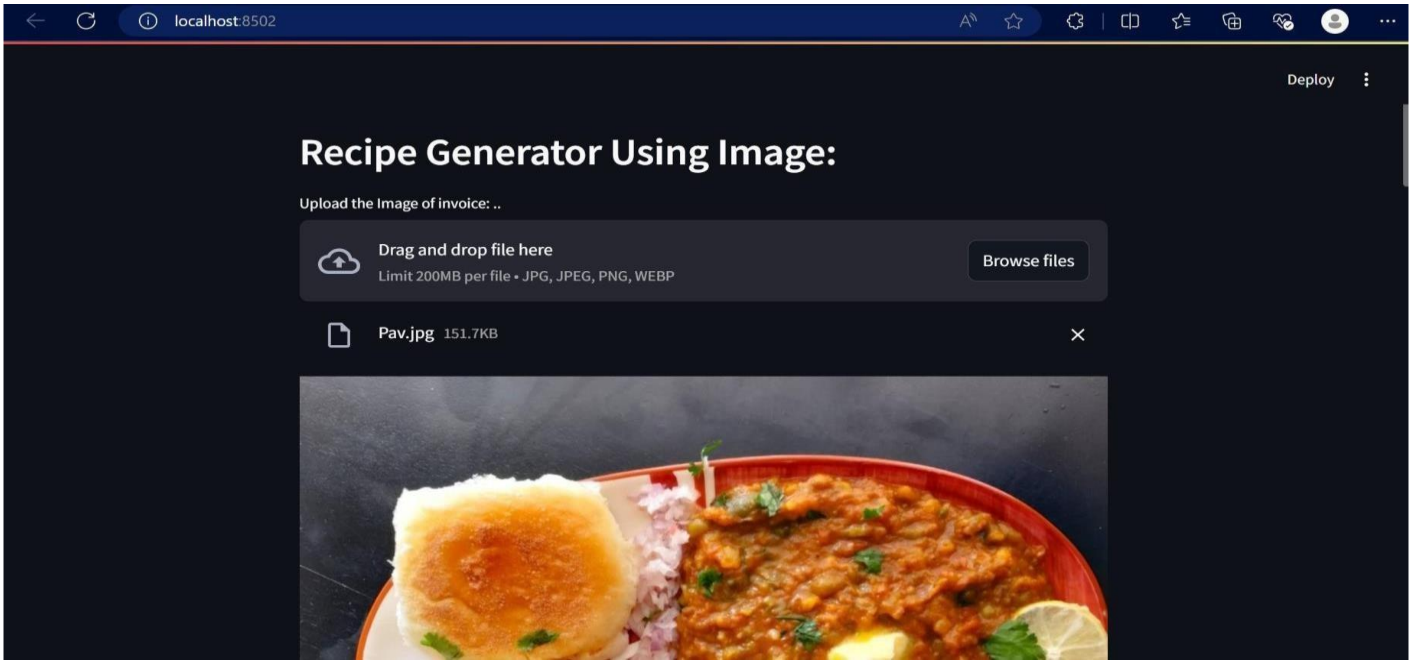


Figure 1.3: Create gemini api key



The image above is a screenshot of a web application interface for a "Recipe Generator Using Image." The interface includes the following sections:

1. Title: "Recipe Generator Using Image"

2. Upload Section:
   - Prompt text: "Upload the Image of invoice: .."

   - A drag-and-drop area for uploading files, with a note specifying a file size limit of 200MB and supported formats (JPG, JPEG, PNG, WEBP).

   - A "Browse files" button for selecting files from the system.

3. Uploaded Image Preview:

   - Shows the file named "Pav.jpg" with a size of 151.7KB, indicating that an image has been uploaded.

   - Below the file name, there is a preview of the image itself, showing an Indian dish called Pav Bhaji, consisting of a buttered pav (bread roll) alongside a bowl of bhaji (spiced mashed vegetables).

4. UI Styling: The interface has a dark theme, with light-colored text and buttons, creating a high-contrast, user-friendly experience.

The page also has a "Deploy" button in the top right corner, suggesting it might be a development or testing environment for the web app.

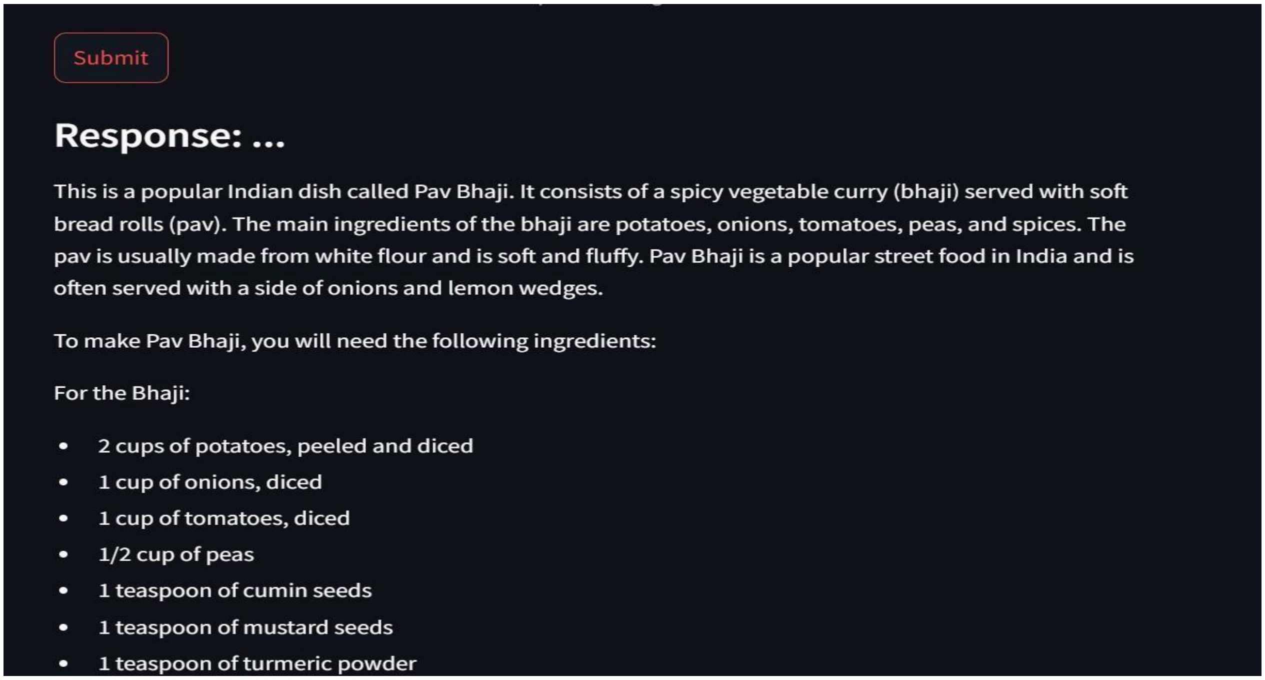


Figure 1.4: Recipe generator output

This image shows the response output of the image uploaded.

Here’s a breakdown of the content:

1. Submit Button: A red button labeled "Submit" is located at the top left.

2. Response Section:

- Title: "Response: ..." with ellipses, suggesting it’s the output area.

- Description: The response provides details about Pav Bhaji, a popular Indian street food. It describes the dish as a spicy vegetable curry (bhaji) served with soft bread rolls (pav), made from potatoes, onions, tomatoes, peas, and spices. Additional information is given about its texture, flavor, and typical accompaniments like onions and lemon wedges.

3. Ingredients List:

- The response continues with an ingredients section titled "For the Bhaji:".

The UI design has a dark background with light-colored text, maintaining readability and consistency with the previous screen's dark theme. This output appears to provide users with a brief description of Pav Bhaji and a basic ingredients list for cooking it.

4.2 USING THE CNN MODEL DATA VISUALIZATION:

4.2.1 BAR GRAPH:

- The recipe.csv file contains data structured into four columns: Name, Ingredients, Procedure, and Serving.
- From the bar graph, we see the top 10 most frequent ingredients used in the cooking the recipe.

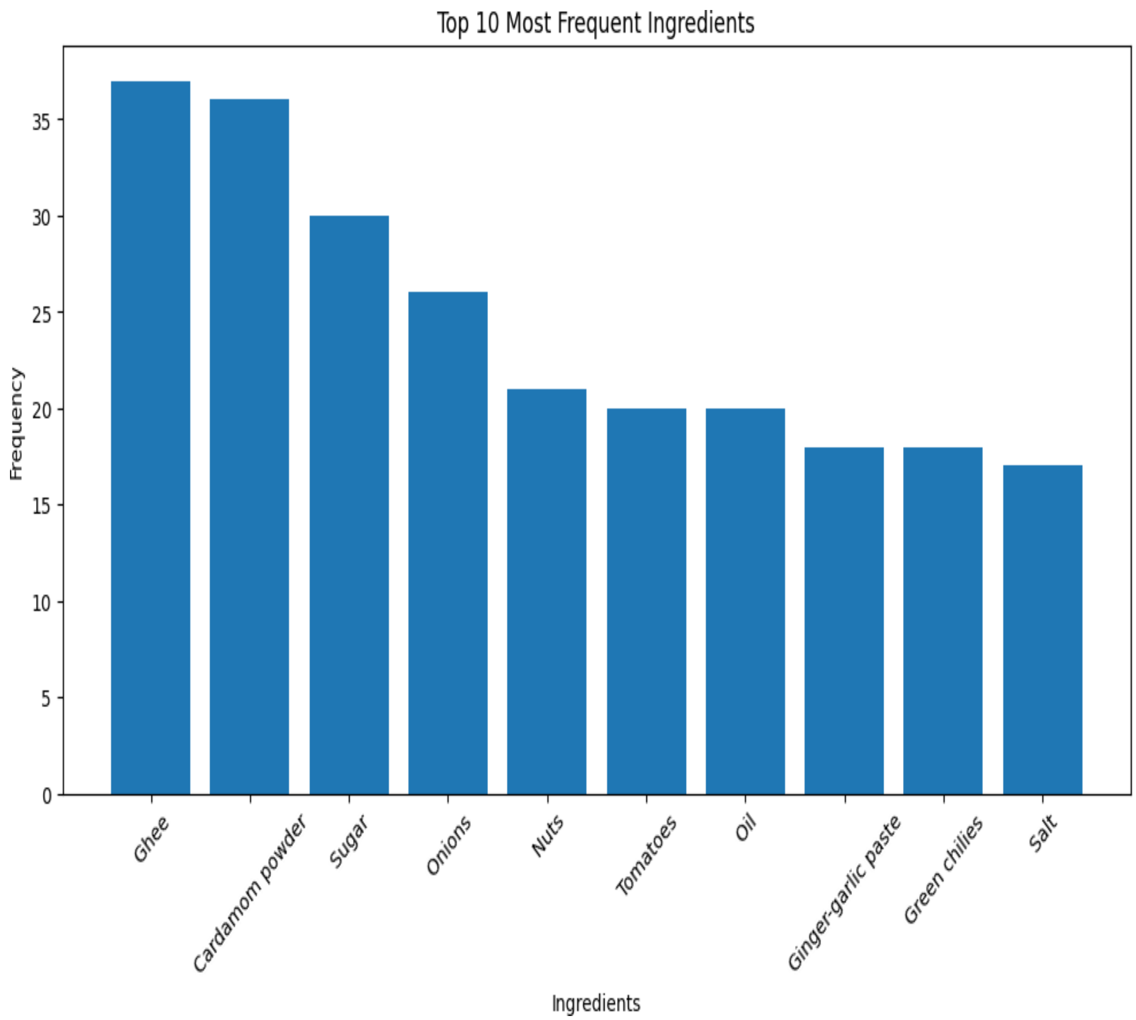


Figure 1.5: Most frequent ingredients Bar Graph

4.2.2 WORD CLOUD:

To provide a visual summary of the recipe data, we generated a Word Cloud that displays the most frequent ingredients and dish names in our dataset.

This visual representation helps highlight the most common ingredients across recipes, emphasizing trends and popular items in our dataset. Larger, bolder words represent ingredients and dish names that appear most frequently, allowing users and researchers to quickly grasp the essential components in the recipe collection.

The Word Cloud was generated using:

- Recipe Names and Ingredients: The dataset was parsed to extract all unique ingredients and recipe names, with each item's frequency determining its prominence in the Word Cloud.

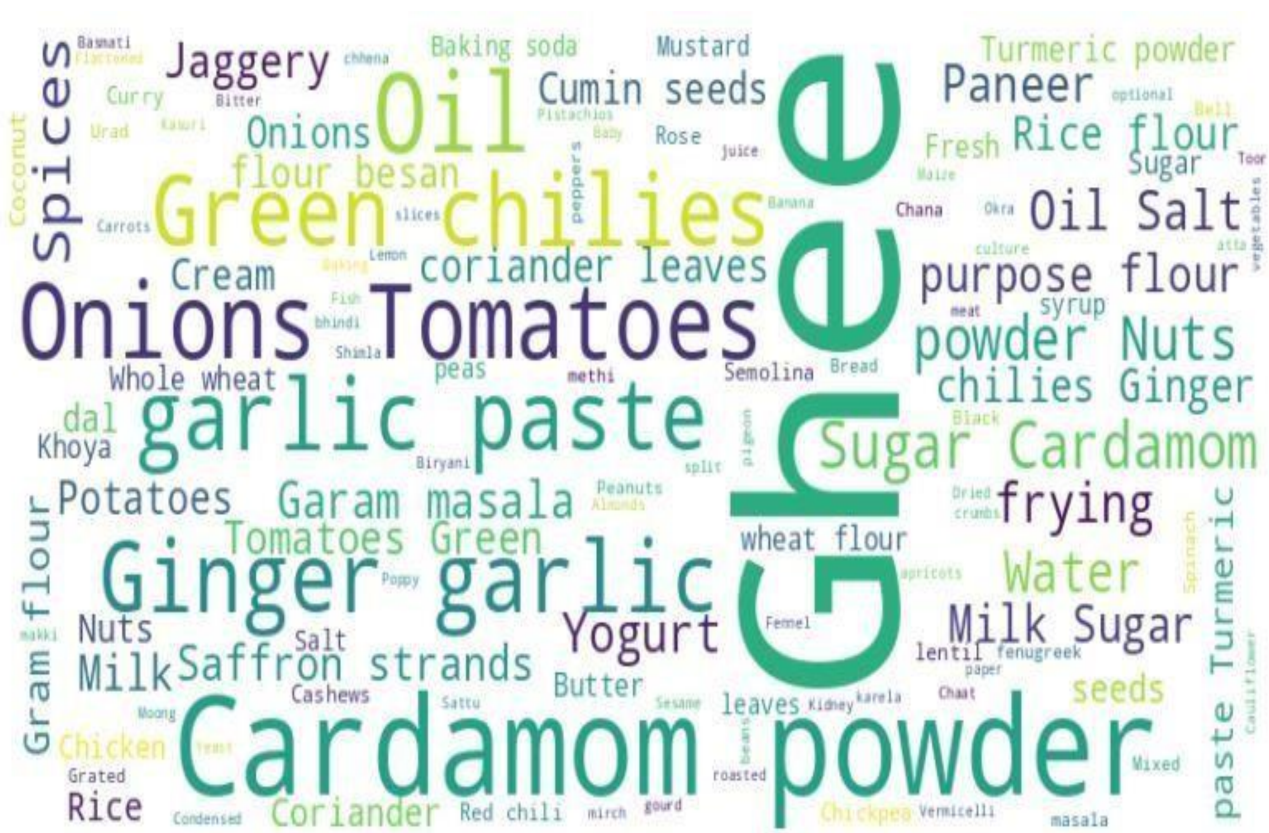


Figure 1.6: Frequency-Based Visualization word cloud 1

The figure 1.6 is Frequency-Based Visualization: Ingredients like spices, vegetables, and common Indian ingredients (e.g., rice, turmeric, cumin) appear prominently, showcasing common elements in the recipes.

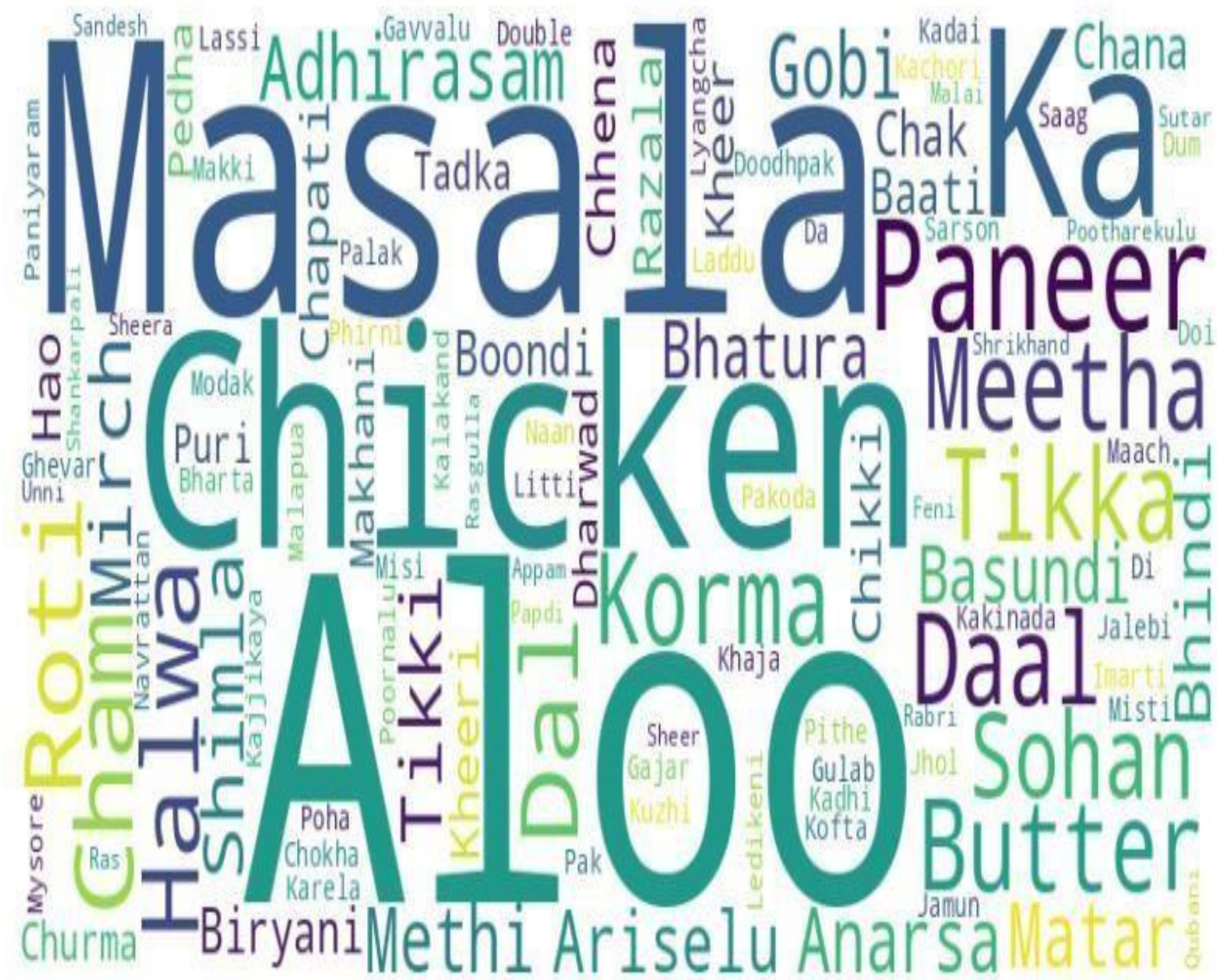


Figure 1.7: Frequency-Based Visualization word cloud 2

This figure 1.7 is a word cloud visualization which helpful not only for understanding the composition of the dataset but also for identifying popular and frequently used ingredients

4.3 TRAINING AND VALIDATION LOSS GRAPH:

4.3.1. AXES OF THE GRAPH:

The x-axis represents the epochs (iterations over the training dataset).

The y-axis is for the loss values. Loss determines how well (or badly) the model's predictions match the actual data.

4.3.2. TRAINING LOSS CURVE:

Tells whether the model is learning or not from the training data. It starts very high, but the value should reduce with time as it improves the model. It is hoped that there is a steady decline of the training loss. If it too early becomes flat or remains at high levels, there could be an indication that the model isn't learning very well from the data.

4.3.3. VALIDATION LOSS CURVE:

This describes how well the model generalizes to new, unseen data, i.e., the validation dataset.

It tends to initially go down with the training loss. If it appears that the validation loss begins rising at some point but the training loss just keeps going down, it is an indication of overfitting in which the model does all right on training data, but fails to generalize to new data

4.3.4. COMBINING THE CURVES TO INTERPRET THEM:

Good Fit: a model which generalizes well is indicated by both curves which will decline and stabilize around comparable values.

Overfitting: Validation loss starts to rise while training loss continues to drop. At this stage, introducing dropout layers, regularization, or early stopping would be helpful. The training and validation losses are both high and do not improve much because there is underfitting. This may suggest that one needs to manipulate the learning rate or data preparation, or that the model is too simple (say, not enough layers or capacity).

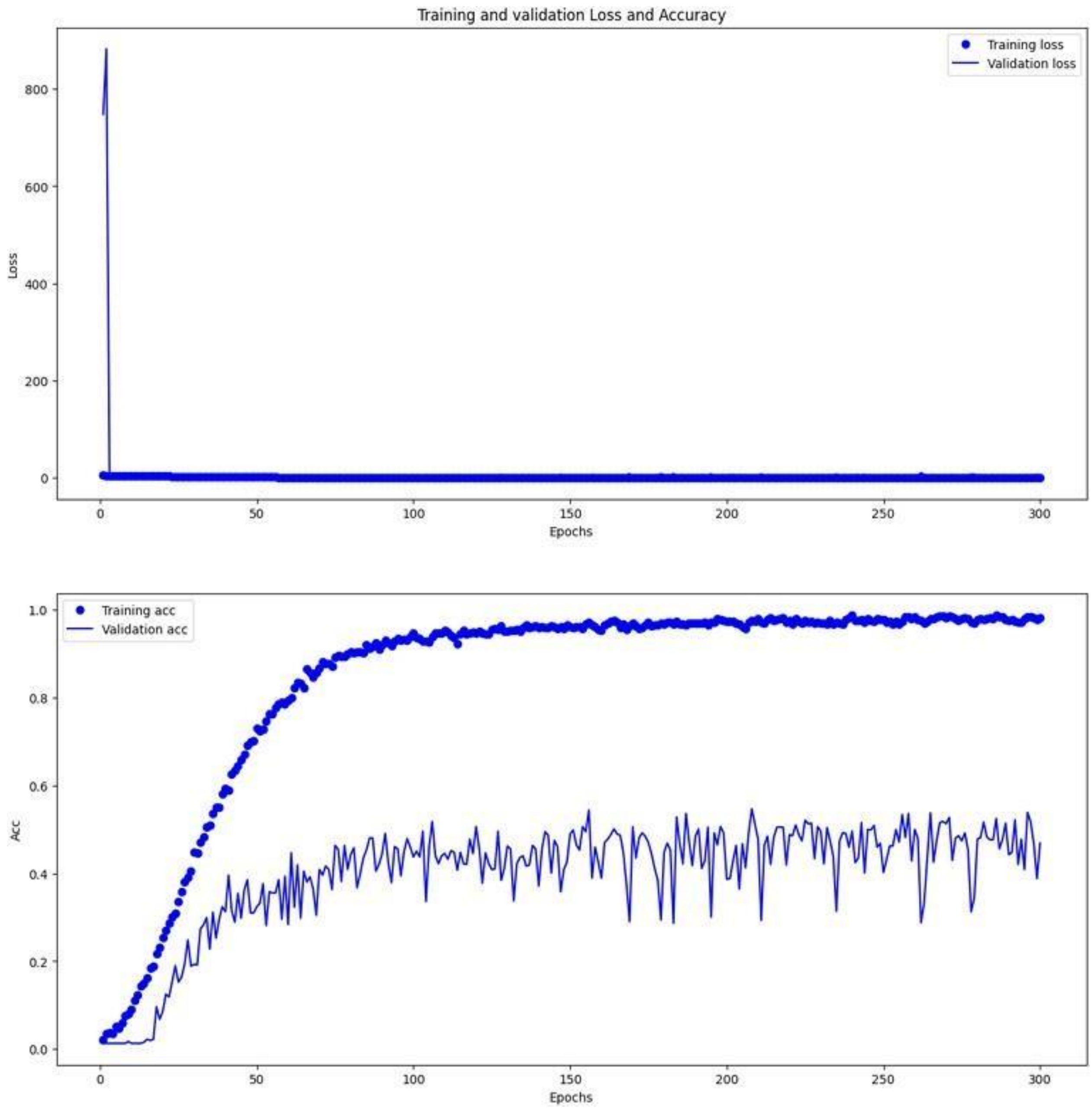


Figure 1.7: training and validation loss and accuracy graph

The training and validation loss graph is an essential tool for monitoring the performance of a machine learning model during the training phase.

4.3.5. INTERPRETATION

Validation Loss: 3.57. Pretty steep it might be, but it might also mean that there is still some room for improvement. It could be that the model has not fully learned all of the intricacies in the validation data during training, and that it would be due to either the size and diversity of the dataset or some model tweaking.

Validation Accuracy: 55.26%. This validation accuracy shows that the model can capture trends but fails with some validation samples, either due to overfitting or an insufficiency of representative validation data

Test Loss: 0.99 — Much lower test loss than the validation loss signifies that the model generalizes effectively on new data, thus showing that it has learned good features from the training set.

Test Accuracy: 86. 95%

By this test accuracy, it is evident that the model performs pretty well on unseen data with excellent prediction properties.

RESULT:

The model could predict recipes from food images with a test accuracy of around 87%. So, the model is looking forward to some real-world application. It can be suited with further optimization by filling the gap between validation and test performance. There are scopes to upgrade the model as:

- INCREASE THE DATASET: Potentially, more images and higher diversity could make the model generalise better.

- HYPERPARAMETERS OPTIMIZATION: Increasing/decreasing the learning rates, epochs, or number of regularization algorithms tends to decrease the overfitting.

- VALIDATION DATA: More balanced or diversified validation data may be closer to the test scenario. Summarizing: These results demonstrate usefulness in image-based recipe creation but still leave much room for improvement with an expanded dataset and fine-tuning.

Figure 1.8: performance of a CNN model in predicting food categories

The image shows a grid of food images along with their predicted and true labels.

The title suggests this is an example of the performance of a CNN model in predicting food categories. Each image has a label indicating what the model predicted and the actual (true) label.

Here’s a breakdown of the predictions:

1. **Top Row**:
    - The first three images show *Bhindi Masala*, with both predicted and true labels as "Bhindi Masala," indicating correct predictions.
2. **Middle Row**:
    - The first image is *Biryani* but was incorrectly predicted as "Chikki."
    - The remaining images in this row show *Biryani*, with correct predictions (both predicted and true labels as "Biryani").
3. **Bottom Row**:
    - All images depict *Biryani*, and the model has correctly identified each as "Biryani."

Overall, this figure shows that the CNN model has high accuracy in predicting *Biryani* but might occasionally misclassify similar-looking dishes, as seen with the single misclassification as "Chikki."

4.4 CNN MODEL PERFORMANCE IN FOOD CATEGORY

4.4.1 MODEL ACCURACY AND DEPENDABILITY EXAMPLES OF CORRECT CLASSIFICATION

The CNN model would correctly classify 86.5% of the test samples, thereby displaying a high degree of dependability in its predictions.

4.4.2 EXAMPLES OF CORRECT CLASSIFICATION

The CNN model classified some food categories that are visually distinguishable; these include Bhindi Masala and Biryani.

4.4.3 OVERALL MODEL EFFECTIVENESS:

With an accuracy of 86.5%, the CNN model is shown to perform very promisingly in tasks for food image classification, and shows reliable prediction capabilities of a variety of food items.

The ability of this model towards categorization of food item indicates its use towards automated food recognition, dietary tracking, or restaurant menu systems.

4.4.4 MODEL PERFORMANCE IMPLICATIONS

This is a very high accuracy rate of the model; hence it is capable of learning and generalization for different features acquired from other types of food that might make it useful in practical application.

This performance may be increased further with more data or fine-tuning the model and should give rise to better accuracy of classification.

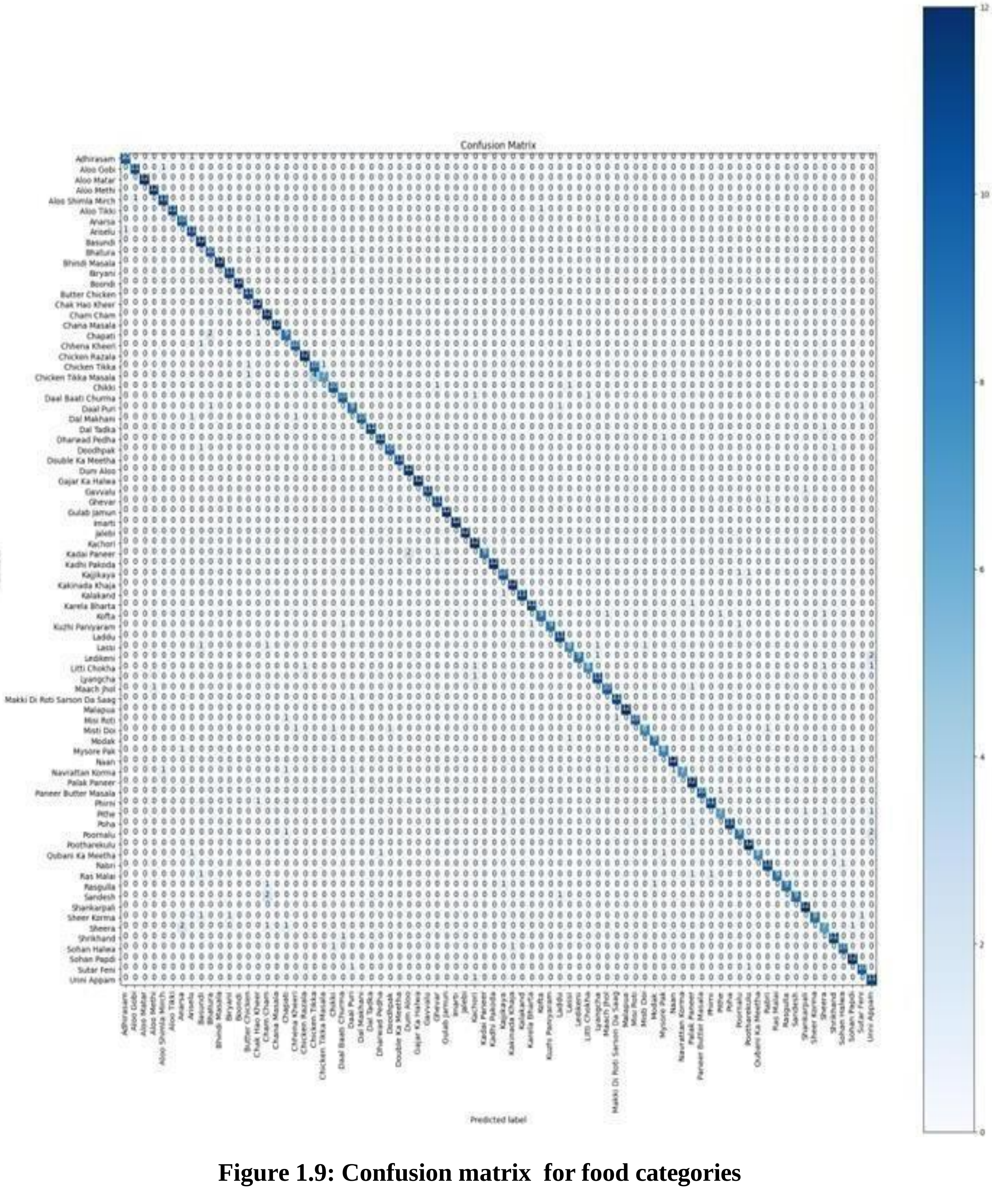


Figure 1.9: Confusion matrix for food categories

Figure 2.0: classification report of detailed performance of CNN model

Classification Report

	precision	recall	f1-score	support
Adhirasam	0.91	0.91	0.91	11
Aloo Gobi	0.92	0.92	0.92	12
Aloo Matar	1.00	1.00	1.00	12
Aloo Methi	0.92	1.00	0.96	12
Aloo Shimla Mirch	0.85	0.92	0.88	12
Aloo Tikki	1.00	0.92	0.96	12
Anarsa	0.77	0.83	0.80	12
Ariselu	0.79	0.92	0.85	12
Basundi	0.71	1.00	0.83	12
Bhatura	0.77	0.83	0.80	12
Bhindi Masala	1.00	1.00	1.00	12
Biryani	0.92	0.92	0.92	12
Boondi	1.00	1.00	1.00	12
Butter Chicken	0.85	0.92	0.88	12
Chak Hao Kheer	0.75	1.00	0.86	12
Cham Cham	0.71	1.00	0.83	12
Chana Masala	1.00	1.00	1.00	12
Chapati	0.69	0.75	0.72	12
Chhena Kheeri	0.83	0.83	0.83	12
Chicken Razala	0.92	1.00	0.96	12
Chicken Tikka	0.71	0.83	0.77	12
Chicken Tikka Masala	0.88	0.58	0.70	12
...				
accuracy			0.87	958
macro avg	0.88	0.87	0.87	958
weighted avg	0.88	0.87	0.87	958

Output is truncated. View as a scrollable element or open in a text editor. Adjust cell output settings...

Figure 2.0: classification report of detailed performance of CNN model

This CNN model was subjected to the task of training pictures depicting food commodities into respective categories. In order to estimate the output's correctness, some important parameters like precision, recall, and F1-score were computed for each food item.

The overall accuracy of 86.5% by the model reflects the reliability in identifying multiple food products.

High precision and recall scores are reported by categories such as Biryani and Bhindi Masala, high strength categorization performance. Besides providing good classification, the model is able to produce recipes from food images that are well classified and thus demonstrates abilities beyond recognition.

Indeed, the proposed model can be applied in automation processes for food recognition and recipe generation.

Predicted Class: Chana Masala

Recipe for Chana Masala

Ingredients : Chickpeas, Onions, Tomatoes, Ginger-garlic paste, Green chilies, Coriander powder, Cumin seeds, Garam masala, Oil, Salt

Procedure : Cook chickpeas and sauté with onions, tomatoes, and spices. Garnish with fresh coriander leaves.

Serving : Serve hot with rice or naan.

Figure 2.1: food image and output of recipe generator

Predicted Class: Gulab Jamun

Recipe for Gulab Jamun

Ingredients : Khoya, Paneer, All-purpose flour, Milk powder, Ghee, Milk, Sugar, Cardamom powder, Oil for frying

Procedure : Mix khoya, paneer, all-purpose flour, and milk powder to form a dough. Shape into balls and deep fry until golden brown. Soak in sugar syrup.

Serving : Serve as a sweet dessert.

Figure 2.2: food image and output of recipe generator

Chapter 5

5. CONCLUSION & FUTUREWORK

5.1 CONCLUSION

This project introduced a novel image-to-recipe generation system that would make cooking much easier for people because it can generate a whole recipe from any food image. Our model gives a recipe consisting of the dish name, a list of ingredients, and step- by-step cooking instructions. Several approaches were compared, and the algorithm with consistency in achieving the highest accuracy was carefully selected through rigorous training and evaluation.

Our method extends much beyond the typical food image classification to recipes; it generates a rich recipe by first inferring ingredients from images, which underlines the value of modeling relationships within the ingredient set. Additionally, the system includes an advanced instruction generation phase that makes use of both visual cues and inferred ingredients to create relevant and contextually accurate recipes. The system delivers a holistic cooking experience that closely matches the respective food image by jointly reasoning about visual and textual data.

User research is evidence to the model's power as our system has proven to be easily operated and accurate. Users responded that our system is more superior than the current image-to-recipe retrieval approaches especially when it came to depth within both ingredient prediction and instruction generation, which consistently posed challenges due to ingredient differences, regional differences in dishes, and lower quality images. Such endorsement by users testifies to real-world utility and capability by the system to fulfill the needs of the people and home cooks seeking simple and easy to find guidance to their recipes.

5.2 FUTUREWORK:

Although several milestones have been reached by our system, much work needs to be targeted toward the enhancement of its functionality and usability.

5.2.1. ADDING VOICES TO RECIPES:

Add voice-over to every recipe to provide audio guidance enhancing accessibility and ease of preparation.

This will provide hands-free cooking as the user goes through the preparation process with oral guidance-a perfect feature for those who are more comfortable listening with their ears rather than visually assessing.

The development will require improving the voice-to-text transcription and pronunciation to make it fit culinary terms and instruction.

5.2.2. DATA ENRICHMENT AND MODEL FINE-TUNING:

The dataset of 10,000 images about food is limited in its extent.
If the dataset had more diversified and regionally varied food images, it would make the system generalize effectively across cuisines of India and worldwide.

An enhanced dataset will enable the model to handle unique ingredients and complex dishes presented in various styles. We will constantly retrain and optimize our model on this enlarged dataset for better adaptability and precision.

5.2.3 INCORPORATION OF EXTERNAL RESOURCES:

Future versions of the system will include multimedia references from video links or detailed cooking guides that will be incorporated into the system, allowing users to access instruction videos or step-by-step visuals of the generated recipe.

5.2.4. BETTER INSTRUCTION GENERATION:

The existing system function will be able to provide simple cooking instructions. It will improve the module to handle complex cooking techniques and nuances in a recipe. This knowledge, concerning any relevant information related to different cooking methods and handling ingredients, means the generated recipes could carry finer details and authenticity.

5.2.5. MULTI-LANGUAGE AND CULTURAL CUSTOMIZATION:

As users grow in numbers, we would intend to support multiple languages and regional customization to give recipes in native language and ingredients and techniques tailored to regions having different traditional cooking practices, thus giving accessibility and satisfaction to the maximum extent.

Based on these improvements, our vision is to create a strong, accessible cooking assistant that is highly intuitive in helping people cook all the varieties of dishes easily. It will have true potential to revolutionize how people approach the cooking space, bridging the gap between visual inspiration and culinary execution.

Chapter 6

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