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Revolutionizing Culinary Experiences: AI-Driven Ingredient Recognition and Personalized Recipe Recommendation System

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ABSTRACT

The hectic world of working professionals often leaves them burnt out by the time they reach home. The very thought of planning and preparing a healthy meal can feel insurmountable. This challenge is further compounded by two factors: inventory invisibility and the recipe roadblock. Without a clear picture of what ingredients are actually sitting in their fridge and pantry, they struggle to take stock. The mental effort of rummaging through cabinets and drawers after a long day feels like another burden, leading to underestimates or overestimates of what they have available. Even if they could see everything clearly, they might still face the "recipe roadblock." Staring down a pantry full of possibilities can be overwhelming. They might not know what meals can be quickly and efficiently prepared with the specific ingredients they have on hand. Decision fatigue sets in, and the potential for creative and healthy meals gets lost. The consequences of these challenges create a vicious cycle. Uneaten food gets tossed, leading to wasted money and increased food waste. The mental strain of figuring out what to make eats into precious relaxation time, further draining their energy reserves. Exhausted and short on time, unhealthy take-out options become the path of least resistance. This reliance on convenience can have negative health consequences in the long term, creating a cycle that's difficult to break free from.

1. INTRODUCTION

This paper introduces a novel system designed to empower busy individuals with efficient cooking experiences. The system leverages advanced technologies in deep learning and recommendation systems: Ingredient Recognition Engine: A Convolutional Neural Network (CNN) with six convolution layers and four pooling layers, enhanced by a softmax activation function, efficiently analyzes and recognizes food ingredients captured through a smartphone camera.Recipe Recommendation Module: Collaborative and content-based recommendation algorithms work in tandem with the ingredient recognition engine. This combined approach suggests personalized recipes based on identified ingredients in your pantry and your personal taste preferences.

A new hybrid recipe model, trained on a diverse dataset of 6,000 recipes, is set to transform meal preparation. By combining deep learning with recommendation systems, this innovative solution offers several advantages. Users can quickly identify recipes that can be made with their existing ingredients, minimizing food waste and saving time. Additionally, the model suggests new recipe possibilities tailored to individual dietary needs and preferences, fostering culinary creativity. This empowers users to make healthier choices by reducing reliance on unhealthy takeout options. Overall, this user-friendly system aims to revolutionize meal prep, making it a more efficient, enjoyable, and healthy experience.

2. LITERATURE SURVEY:

This literature survey below explores the use of image recognition technology to address the problems identified. By recognizing fruits and vegetables, these systems aim to recommend recipes based on what users have on hand. This approach can not only reduce food waste but also inspire creativity by suggesting new dishes based on available produce. The model will recognize the effectiveness of image recognition in recipe recommendation, along with the strengths and limitations of current systems. The following research has been conducted:

Rodrigues et al. address the challenge of recipe selection based on available ingredients [1]. The proposed system, RecipeIS, utilizes image recognition to recommend recipes containing user-captured images of fruits and vegetables. A convolutional neural network (ResNet-50) achieves 96% accuracy in classifying these ingredients. However, the paper acknowledges limitations. The recommendation system currently relies on the Edamam API, potentially restricting recipe variety. Additionally, it focuses solely on fruits and vegetables, neglecting other essential recipe components. Future work is proposed to expand the ingredient library and explore more sophisticated recommendation techniques.

Li et al. (2020) propose a method for vegetable recognition and classification using an improved VGG deep learning model [2]. The approach builds upon the VGG architecture, incorporating modifications to enhance accuracy. The authors introduce two key modifications: 1) combining the output features from the first two fully-connected layers (VGG-M), and 2) adding Batch Normalization (BN) layers (VGG-M-BN) to accelerate convergence and improve accuracy. Tested on a dataset of 10 vegetables, their VGG-M approach achieved 95.8% accuracy, while VGG-M-BN reached 96.5%. The study also explores the influence of factors like dataset size and activation functions on recognition accuracy.

Morol et al. (2022) propose a food recipe recommendation system leveraging deep learning for ingredient detection [3]. The proposed paper addresses the challenge of recommending recipes based on detected ingredients, advancing the field of personalized culinary recommendation systems. By utilizing deep learning techniques, the authors enhance the accuracy of ingredient detection, thereby improving the quality of recipe recommendations. This study builds upon previous research in both deep learning and recommendation systems, highlighting the importance of incorporating advanced machine learning methodologies in the domain of food-related applications. The literature survey underscores the growing interest in utilizing deep learning for enhancing various aspects of food-related technologies, including recipe recommendation.

Banerjee, Bansal, and Thomas (2022) present a comprehensive review of food detection and recognition techniques using deep learning [4]. The paper synthesizes existing research, providing insights into the latest advancements, methodologies, and challenges in this domain. By summarizing the key findings from a range of studies, the authors contribute to a better understanding of the current state-of-the-art in food-related deep learning applications. This review highlights the significance of deep learning in improving the accuracy and efficiency of food detection and recognition systems. It serves as a valuable resource for researchers and practitioners interested in exploring the intersection of deep learning and food technology.

In conclusion, the surveyed literature demonstrates the evolving landscape of recipe recommendation systems through the incorporation of fruit and vegetable recognition technologies. Leveraging advancements in machine learning and image processing, these systems offer personalized culinary suggestions, enhancing user experiences and promoting healthier dietary choice.

3. METHODOLOGY

The methodology for recipe recommendation through fruit and vegetable recognition involves a multi-faceted approach integrating image processing, machine learning algorithms, and culinary knowledge. By extracting features from images of fruits and vegetables, categorizing them, and correlating with recipe databases, personalized recommendations tailored to users' dietary preferences can be generated effectively.

The above Fig 3.1 shows an overview of a recipe recommendation system with an integrated ingredient recognition module. Here’s a breakdown of the components:

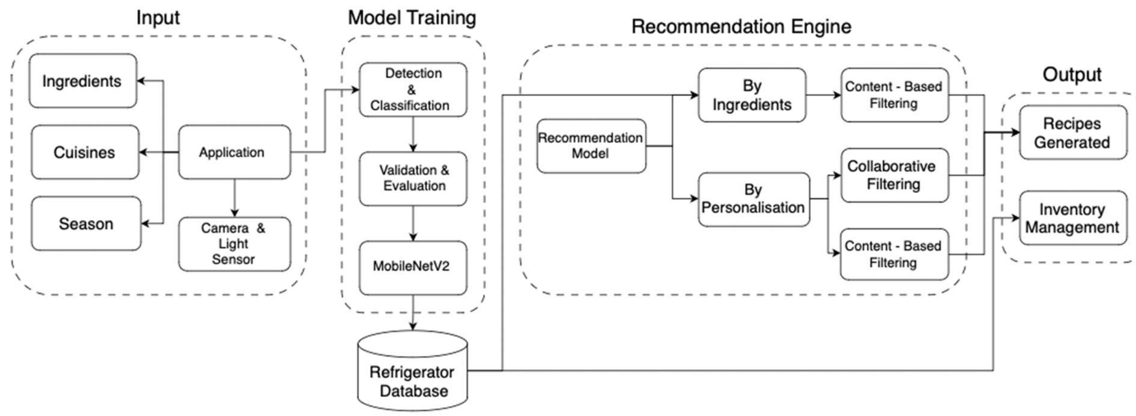


Fig 3.1 Architecture Diagram

1. Data Collection and Review

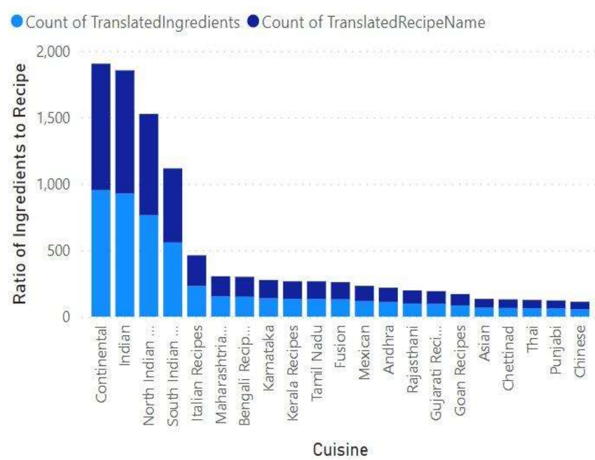
Camera & Light Sensor: This captures an image of the ingredients, possibly from a mobile device. **Season:** This could indicate that the system can account for seasonal ingredients when making recommendations.

Cuisines : This suggests a database of 6,000 different cuisines that the system references.

Data Cleaning: Since the dataset we had very less or near to no vacancy and hence not much cleaning was required.The recipes , way to do it and ingredients to make are very well presented in the data.

Data Processing: The dataset contain nearly 6000 diverse recipes sourced from various culinary traditions and cuisines . Firstly the dataset had many features but to make the model to be efficient accurate , the necessary features are Recipe_Name, Ingredients, Total_Time, Cuisines, Ingredient_Count, Instructions.

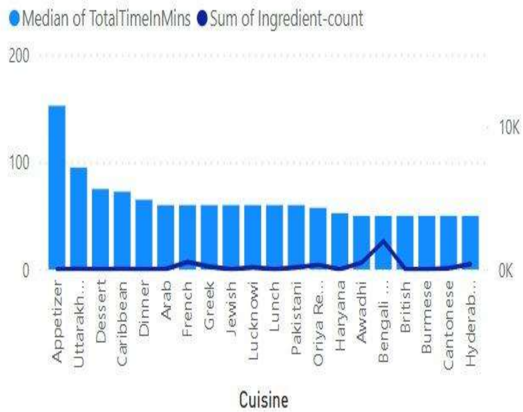
Fig 3.1.1 Graph for ratio between ingredients and recipe



The figure 3.1.1 shows the x-axis shows the number of cuisines, while the y-axis shows the number of translated recipe names. Each data point on the graph represents a particular cuisine, and the height of the data point shows how many translated recipe names there are for that cuisine relative to the number of cuisines in total .The most common ratio of ingredients to the food cuisine is 'Continental' which has the value around 1900 and it tapers towards the end to chinese. The next most common ratio for the same is 'Indian' with the rating of around 1800. Some people prefer 'Continental Indian','North Indian ','South Indian' in that order while the others are sparsely distributed towards Italian Mexican, and other Indian Regional Cuisines.The data point for "Continental" cuisine is the highest on the graph, which means that there are more translated recipe names for Continental cuisine than for any other cuisine. The data point for "Chettinad" cuisine is the lowest on the graph, which means that there are fewer translated recipe names for Chettinad cuisine than for any other cuisine.Overall, the graph shows that there is a wide variation in the number of translated recipe names for different cuisines. This could be due to a number of factors, such as the popularity of the cuisine, the ease of translating recipes for that cuisine, and the availability of resources for translating recipes.

The figure 3.1.2 shows the median total cooking time in minutes for various cuisines. The x-axis (horizontal) lists the cuisines, while the y-axis (vertical) shows the median cooking time in minutes. Each bar in the chart represents a particular cuisine, and the length of the bar shows the median cooking time for that cuisine. The bar for "Appetizers" is the shortest on the chart, which means that the median cooking time for appetizers is shorter than the median cooking time for any other cuisine on the chart.

Fig 3.1.2 Graph between type of meal and total number of ingredients



The bar for "Dinner" is the longest on the chart, which means that the median cooking time for dinner is longer than the median cooking time for any other cuisine on the chart.Overall, the chart shows that there is a wide variation in the median cooking time for different cuisines. This could be due to a number of factors, such as the complexity of the dishes, the number of ingredients, and the cooking methods used.

Fig 3.1.3 Graph between cuisine and sum of ingredients

The figure 3.1.3 is a continuation of the figure 3.1.2 , that shows the median total cooking time in minutes for various cuisines. The x-axis lists the cuisines, while the y-axis shows the median cooking time in minutes. Each data point on the line represents a particular cuisine, and the position of the data point on the y-axis shows the median cooking time for that cuisine.The data point for "Kashmiri" cuisine is near the bottom of the graph, which means that the median cooking time for Kashmiri cuisine is shorter than the median cooking time for many other cuisines on the chart. The data point for "Continental" cuisine is near the top of the chart, which means that the median cooking time for Continental cuisine is longer than the median cooking time for many other cuisines on the chart.Overall, the chart shows that there is a wide variation in the median cooking time for different cuisines. This could be due to a number of factors, such as the complexity of the dishes, the number of ingredients, and the cooking methods used.

2. Model Training

Detection & Classification: Detection and classification in the context of an AI system that recognizes and classifies ingredients involve several critical components. This process begins with detecting objects (in this case, ingredients like fruits and vegetables) in an image and then classifying them into specific categories.

Detection

Object detection involves identifying the presence and location of objects within an image. Techniques like bounding boxes or segmentation masks can be used to pinpoint these objects.
Bounding Boxes: Typically used in object detection, bounding boxes encompass the detected object, providing information about its position and size. This is useful for distinguishing individual items in an image that may contain multiple ingredients.
Feature Extraction: The system extracts features from the image that are useful for classification. This involves using convolutional neural networks (CNNs) to capture patterns and characteristics that differentiate one object from another.

Classification

Classification involves assigning a detected object to one or more predefined categories. This typically follows object detection, where the system has already identified what part of the image contains an object.
Convolution Layers: These layers apply convolution operations to the input data, typically the image, to extract features. Each convolution layer applies a set of filters (or kernels) to identify patterns, such as edges, corners, or textures. In MobileNetV2, these layers are designed to be lightweight and efficient, using depth wise separable convolutions.
Pooling Layers: Pooling layers reduce the spatial dimensions of the feature maps, effectively condensing the information and reducing the computational load. The most common types of pooling are max pooling and average pooling. Max pooling selects the maximum value from a set of pixels, while average pooling calculates the average. In MobileNetV2, these layers contribute to the model's efficiency by reducing the dimensionality while preserving important features.
Fully Connected (Dense) Layers: After the convolutional and pooling layers, the data is usually flattened into a 1D array and passed through fully connected (dense) layers. These layers connect every node to every other node, allowing for complex interactions that help with classification. The final dense layer typically uses a softmax activation function to output probabilities for each class, indicating the likelihood that the object belongs to a specific category.

MobileNetV2

When using MobileNetV2 for multi-class recognition of fruits and vegetables, the following steps are typically involved:

1. Preprocessing: Images are resized and normalized to match the input requirements of MobileNetV2. This ensures consistent input data for the model.
2. Feature Extraction: The convolution layers extract features that are characteristic of different fruits and vegetables.
3. Classification: The fully connected layers classify the extracted features into one of the predefined classes, indicating which fruit or vegetable is present in the image. This output can be used to label the ingredients for further processing or user feedback.
4. Training and Fine-tuning: To achieve high accuracy, the model can be fine-tuned with a dataset of labeled images of fruits and vegetables. This allows it to adapt to the specific task and improve performance.

Overall, MobileNetV2 provides an efficient and robust solution for image classification tasks, making it well-suited for applications where computational resources are limited, such as mobile devices or embedded systems.

Recognition: The image represents a concept for a system that uses a camera to recognize and record ingredients on a refrigerator shelf. There isn't enough information to say for sure how it works, but it likely connects to a system that creates and maintains a list of the ingredients.

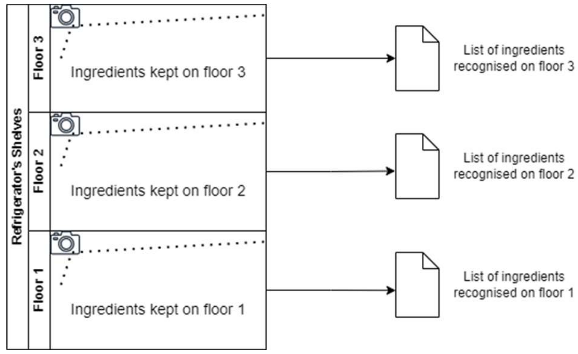


Fig 3.2.1 Visual Refrigerator Map

Refrigerator Database: This component is likely referencing a database that stores information about the contents of a refrigerator.

3. Recommendation Engine

Recipe recommendation model: This can be a combination of:

Hybrid Approach: This approach combines the strengths of both collaborative filtering and content-based filtering to provide more personalized recommendations. Here's how it works:

The diagram 3.2.2 depicts a hybrid approach for recipe recommendation that combines collaborative filtering and content-based filtering. Here's a breakdown of the components focused on how these two techniques work together:

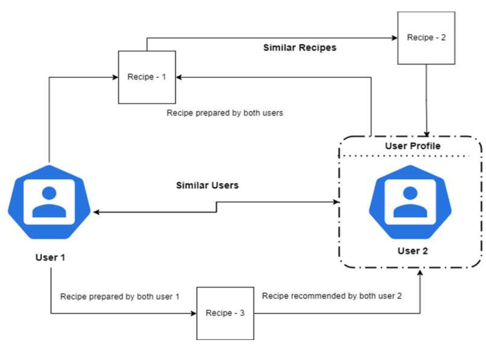


Fig 3.2.2 Hybrid Approach of Recommendation System

Collaborative Filtering

Similar Users: This refers to the system finding users with similar taste preferences to the active user.

Recipes prepared by both User 1 & User 2: This indicates that the system considers recipes that both the active user and similar users have interacted with (prepared or possibly rated). This helps identify recipes that align with the active user's preferences based on the similar users' choices.

Content-Based Filtering

Recipe-1, Recipe-2, Recipe-3: These represent recipes in the system.

Recipe prepared by both users: This section combines collaborative filtering with content-based filtering. Here, it shows recipes that have been prepared by both similar users (collaborative filtering) and also by the active user themselves (content-based filtering), indicating a strong recommendation for the active user.

Similar Recipes: This refers to recipes that are similar to the recipes the user has interacted with in the past. This similarity could be based on ingredients, cuisine, or other factors.

User Profile

This likely stores information about the user's past interactions with the system, such as recipes they have prepared, rated, or searched for. This information is used for both collaborative and content-based filtering techniques.

Therefore the system leverages the strengths of both collaborative and content-based filtering to provide personalized recipe recommendations. Collaborative filtering helps identify recipes that users with similar tastes have enjoyed, while content-based filtering recommends recipes based on the user's own past preferences and the ingredients the user has on hand.

Recommendation and Personalization:

Recipe Retrieval: Technical Aspects

1. Recipe Retrieval Based on User Input:

To retrieve candidate recipes based on user input, you need to design a system capable of understanding and processing different types of inputs and then matching them with a large database of recipes. Key technical aspects are:

1.1 Image-based Input: This involves using computer vision techniques to extract meaningful information from images. MobilenetV2 are typically used for this purpose. An image of a dish or ingredient list can be processed to detect specific objects or text, and then used to search for matching recipes.

1.2 Ingredient List Input: Text processing and Natural Language Processing (NLP) techniques are required to understand and extract key information from ingredient lists. The system can then use these extracted ingredients to query a database of recipes.

1.3 Preference-based Input: This involves capturing user preferences, which might include ingredients, dietary restrictions, or cultural preferences, and applying them to the recipe retrieval process. Machine learning models such as collaborative filtering or content-based filtering can be used to personalize recommendations based on user history and preferences.

2. Personalization Filters

Personalization filters allow for more refined recommendations based on user-specific information. The following are key technical considerations for each type of personalization:

2.1 Ingredient Preferences: Prioritizing Liked Ingredients: Use a scoring system to rank recipes based on the presence of liked ingredients. This can involve a simple count of matches between user preferences and recipe ingredients, or a more complex model that considers ingredient combinations.

Avoiding Disliked Ingredients: Similar to prioritizing liked ingredients, but with a negative scoring system. This can involve flagging recipes with specific ingredients or removing them from the candidate list.Custom Ingredient Sets: Allow users to create custom sets of liked or disliked ingredients, and then apply these sets as filters to the recipe retrieval process.

2.2 Dietary Choices: Allergies and Intolerances: Implement a filter to remove recipes that contain known allergens or intolerances. This requires a well-labeled recipe database with clear ingredient listings.Specific Diets: Support various dietary requirements like vegan, vegetarian, gluten-free, etc. This can involve categorizing recipes based on their suitability for different diets and then filtering results accordingly.

2.3 Cultural Preferences: Preferred Cuisines: Categorize recipes by cuisine and apply a filter based on user preferences. This might involve text-based analysis of recipe metadata to determine the cuisine type.Cooking Styles: Identify and categorize recipes by cooking styles (e.g., grilling, baking, stir-frying). This information can be used to align recommendations with user preferences for specific cooking techniques.

2.4 Mood-Based Recommendations : Emotional State Analysis: Use NLP techniques to analyze text input from users about their current mood or emotional state. This could involve sentiment analysis to determine the overall tone of the input. Mapping Moods to Recipe Types: Establish a mapping between emotional states and types of recipes. For example, comfort food for sadness, celebratory dishes for happiness, etc. This can involve pre-classifying recipes by mood type.Dynamic Suggestions: Based on the identified mood, dynamically adjust the recipe recommendations to align with the emotional context. This can involve a scoring system that boosts recipes most closely aligned with the detected mood.

Each of these personalization filters can be implemented as part of a broader recommendation system that integrates multiple data sources, uses various machine learning techniques, and interacts with a large, well-organized recipe database. The combination of these technical aspects enables a comprehensive and adaptable recipe recommendation system.

User Feedback:

Ranking and presentation: Rank the retrieved recipes based on the combined score from the recommendation model and personalization filters. Present the top recommendations to the user in an appealing and informative way.

Overall, the diagram depicts a system that can recommend recipes to users based on a combination of factors, including ingredient recognition, user preferences, and the dietary restrictions.

4. RESULTS

Recognition Model:

Training Accuracy:

The training accuracy represents the model's performance on the training data. The graph shows that the training accuracy increases steadily throughout the training epochs, which is approximately 93%. This indicates that the model is effectively learning from the training data and improving its ability to identify and classify the image captured of a particular ingredient identified.

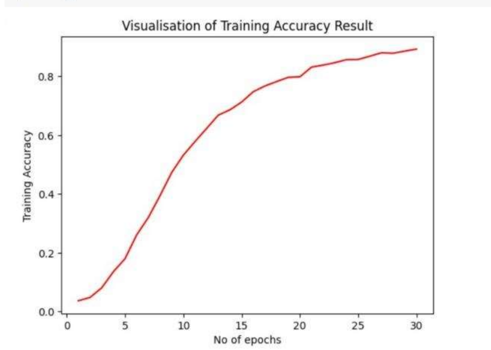


Fig 4.1 Training Accuracy (Recognition)

Validation Accuracy:

The validation accuracy represents the model's performance on unseen data. The graph shows that the validation accuracy also increases throughout the training epochs, reaching a peak of approximately 0.94 (94%). This indicates that the model is generalizing well and can accurately identify and classify ingredients in new data.

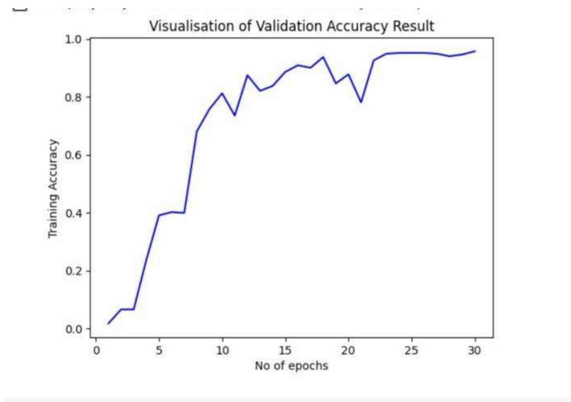


Fig 4.2 Validation Accuracy (Recognition)

Recommendation Model:
Training Accuracy:
The training accuracy represents the model's performance on the training data. The graph shows that the training accuracy increases steadily throughout the training epochs, which is approximately 95%. This indicates that the model is effectively learning from the training data and improving its ability to identify and classify recipes.

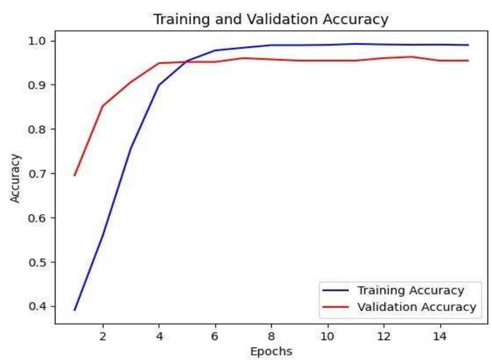


Fig 4.3 Training and Validation Accuracy (Recommendation)

Validation Accuracy:
The validation accuracy represents the model's performance on unseen data. The graph shows that the validation accuracy also increases throughout the training epochs, reaching a peak of approximately 0.9 (90%). This indicates that the model is generalizing well and can accurately identify and classify recipes in new data.
Interpreting the Graph:
The gap between training and validation accuracy is relatively small, suggesting that the model is not overfitting the training data. In this case, the model is effectively learning from the training data and can accurately identify and classify ingredients in both training and validation datasets.

Recommendation Accuracy:
While the graph directly measures the accuracy of ingredient identification, it indirectly relates to the accuracy of recipe recommendations. Accurate ingredient identification is crucial for effective recipe recommendations. As the model's accuracy improves, the likelihood of generating relevant and personalized recipe recommendations based on the identified ingredients also increases.The validation loss is typically lower than the training loss, because the model has been trained on the training data and has therefore learned to fit in training data as well.

In the context, the validation loss is the loss of the model on a set of images of dishes from different cuisines. The model is trying to learn to identify the cuisine of each dish. The validation loss is decreasing, which means that the model is learning to identify the cuisines of the dishes more accurately.

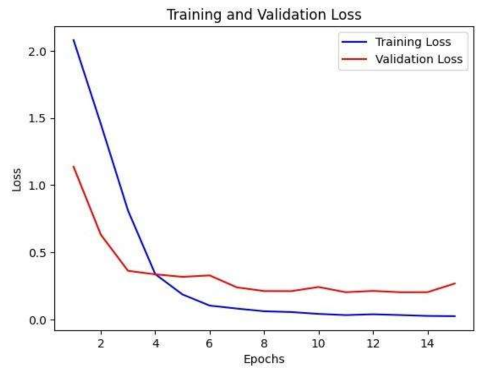


Fig 4.4 Training and Validation Loss (Recommendation)

The figure 4.5 shows the level of user engagement with different cuisines and ingredients. It is helpful for understanding which combinations of cuisines and ingredients are most popular with users.
The chart lists eleven different cuisines along the left side: Vegan, Mediterranean, Korean, Greek, French, Japanese, Chinese, Thai, Indian, Mexican, and Italian.

Thirteen ingredients are listed across the top of the chart: Cuishes, Tomato, Chicken, Pepper, Curry powder, Roe, Coconut milk, Cheese, Olive oil, Vegetables, Bears, Tortillas, Kimchi, Tofu, Noodles, Neam nead, Soy sauce, Rice paper, and Olives.

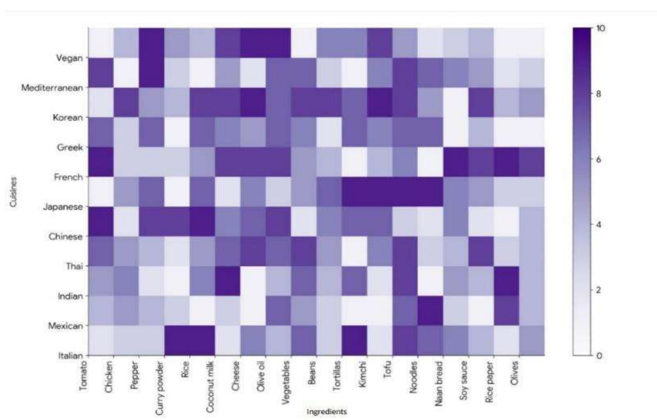


Fig 4.5 Heat Map of Cuisines and Ingredients

Each box in the chart is filled in with either a "yes" or "no" to indicate whether that particular ingredient is commonly used in that particular cuisine. For example, the chart indicates that tomatoes are commonly used in Mediterranean, Korean, Greek, French, Italian, and Mexican cuisine, but not commonly used in Vegan, Japanese, Chinese, Thai, or Indian cuisine. Overall, this provides
a visual representation of how users engage with different cuisines and ingredients.

The figure 4.6 in the context of recipe recommendation, a high precision would mean that the system is good at recommending recipes that the user will actually like. A high accuracy would mean that the system is good at making correct predictions about the recipes that the user will like. A high recall would mean that the system is good at recommending all of the recipes that the user might like. The table shows that the Faster CNN model has the highest precision, accuracy, and recall. This means that it is the best model in the table at recommending recipes to users.

Metric	Yolo	CNN	MobileNetV2
Accuracy	0.81	0.77	0.91
Precision	0.83	0.79	0.93
Recall	0.86	0.84	0.89

Fig 4.6 Comparative Analysis of different models

5.CONCLUSION:

Hence, the faster CNN model is much more robust and accurate than yolo and CNN models. The Recipe Recommendation using Hybrid Model is convenient, time and energy saving also you can access your kitchen anywhere else in the world. The integration of machine learning algorithms in Recipe Recommendation using Hybrid Model system allows it to process vast amount of culinary data, user preferences, dietary restrictions and ingredient availability to provide personalised meal plans and recipe suggestions. The project recipe recommendation engine and automated meal planning capabilities streamline the cooking process saving users time and effort while ensuring a balanced and nutritious diet. As the project continuous to gather user feedback and interactions its adaptive learning capabilities will fine tune recipe recommendations improving the systems accuracy and effectiveness over time. Recipe Recommendation using Hybrid Model is a luxury but it has its own disadvantages in terms of internet dependencies and privacy interruption.

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