FOOD CLASSIFICATION USING CNN

PROJECT DOCUMENTATION

BY DEVATHI SRIJA

TITLE PAGE

Project Title : Food Classification using CNN

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Organization : Viharatech

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Technologies Used : Python, Flask, TensorFlow, Keras, HTML, OpenCV, CSS, JavaScript

Version : 1.0

1. ABSTRACT

In today's fast-paced world, automated food recognition has become increasingly significant in dietary monitoring, calorie tracking, and personalized nutrition systems. The Food Classification using CNN project is a web-based application that allows users to upload food images in JPG or PNG formats and identify the dish using deep learning models such as CNN, VGG16, and ResNet.

The system predicts the class of the uploaded image and provides nutritional information, including protein, fat, carbohydrate, and calorie content and the system also provides the accuracy score and classification report. The user-friendly web interface allows real-time image preview, model selection, and detailed result visualization. This project combines deep learning, computer vision, and web technologies to make food classification efficient and accessible.

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3. Introduction

3.1 Problem Statement

With the growing popularity of fitness tracking and personalized nutrition, there is an increasing need for systems that can automatically identify food items and estimate their nutritional composition. Traditional manual methods of food identification and calorie calculation are time-consuming, subjective, and prone to human error.

The lack of an automated, image-based food classification system makes it difficult for users to track their diet efficiently. Thus, there is a need for a deep learning–based web application that can accurately classify food images and instantly provide essential nutritional information such as protein, fat, carbohydrates, and calories.

3.2 Overview

The Food Classification Using CNN project is a deep learning-driven web application designed to classify food images using pre-trained and custom convolutional neural network models. The system enables users to upload food images in JPG or PNG format, preview the selected image, and choose one of three models — CNN, VGG16, or ResNet — for classification.

Once a model is selected, the backend processes the uploaded image, predicts its class, and displays the predicted food name along with the nutritional details retrieved from a corresponding JSON file. These details include the food's protein, carbohydrate, fat, and calorie content.

The web interface is built using Flask, HTML, CSS, and JavaScript, offering a seamless and interactive experience. This system

demonstrates the power of convolutional neural networks in computer vision and their practical application in health and nutrition domains.

3.3 Scope

The project provides a foundation for real-world applications in dietary management and food recognition. Its scope includes:

- Implementing multiple deep learning models (CNN, VGG16, ResNet) for food image classification.
- Building a user-friendly interface for image upload, preview, and model selection.
- Generating structured JSON data containing nutritional information for each predicted class.
- Also generating the metrics of a model.
- Providing flexibility for future integration with mobile apps or calorie-tracking systems.

In the future, this system can be enhanced to include multi-food recognition, portion estimation, and real-time camera-based classification, extending its usability to health-focused applications, diet tracking platforms, and restaurant menu analysis.

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4. Objectives

The primary objective of this project is to design and develop a deep learning–based web application capable of classifying food images accurately and providing their nutritional information. The system leverages Convolutional Neural Networks (CNN) and transfer learning models (VGG16 and ResNet) to identify food items and return detailed nutrient data in a structured JSON format.

The following are the key objectives of the project:

1. To develop an intelligent food classification system

    - Implement a deep learning model that can classify various food items based on their visual features.
    - Train and integrate multiple models (CNN, VGG16, and ResNet) for comparative performance analysis.

2. To create an interactive and user-friendly web interface

    - Enable users to upload images in JPG or PNG format.
    - Provide real-time image preview and allow users to name the uploaded image before classification.
    - Offer easy navigation and clear options for model selection and result viewing.

3. To integrate model-based prediction with nutritional information

    - Retrieve and display nutritional data (protein, fat, carbohydrates, calories) for the predicted food class from a structured JSON file.
    - Present both the predicted class and provided class name for better understanding and validation.
    - Present the metrics of a selected model.

4. To implement a robust backend for efficient processing

    - Use Flask as the web framework to handle file uploads, model execution, and data rendering.
    - Ensure smooth communication between the frontend and backend with minimal latency.

5. To enhance dietary awareness and digital nutrition tracking

    - Provide accurate, automated nutritional insights to assist users in tracking their food intake.
    - Demonstrate the potential of deep learning in real-world health and dietary applications.

6. To ensure scalability and future adaptability

    - Design the system architecture to support additional food classes and models.
    - Prepare the platform for future extensions such as mobile deployment, real-time camera classification, and integration with health apps.

5. System Requirements

This project, Food Classification Using Convolutional Neural Networks (CNN), is a deep learning-based application designed to classify various food items using trained CNN architectures such as VGG16, ResNet, and a custom-built CNN model. The system performs image preprocessing, feature extraction, and classification with visualization of predictions and JSON-based class details. The following hardware, software, and platform requirements ensure smooth development, training, and deployment of the model.

5.1 Hardware Requirements

5.1.1 Minimum Configuration

- **Processor:** Dual-core processor (2.0 GHz or higher)
- **RAM:** 4 GB
- **Storage:** At least 2 GB free disk space
- **Graphics:** Integrated graphics with OpenGL support
- **Display:** 1280 × 720 resolution

5.1.2 Recommended Configuration

- **Processor:** Intel i5 / AMD Ryzen 5 or higher
- **RAM:** 8 GB or higher
- **Storage:** 10 GB free disk space (for dataset and model files)
- **Graphics:** Dedicated GPU (e.g., NVIDIA GeForce GTX/RTX series) for faster model training
- **Display:** 1920 × 1080 resolution or higher

5.2 Software Requirements

5.2.1 Backend

- **Python:** 3.10.5 or higher
- **TensorFlow:** 2.12.0
- **Keras:** 2.12.0
- **NumPy:** 1.23.1
- **Matplotlib:** 3.6.0
- **OpenCV:** 4.6.0 (for image handling and visualization)
- **Pandas:** 1.5.0
- **Pickle:** For model serialization
- **JSON:** For storing and retrieving class details

5.2.2 Frontend

- **HTML5, CSS3, JavaScript**
- Flask Framework (for web integration and model inference)
- Modern browser support (Google Chrome, Mozilla Firefox, Microsoft Edge)

5.2.3 Development Environment

- **IDE:** Visual Studio Code or PyCharm
- **Version Control:** Git (optional but recommended)

5.3 Platform Requirements

- **Operating System:** Windows 10/11, macOS, or Linux
- **Browser:** Google Chrome 90+, Mozilla Firefox 88+, Microsoft Edge 90+
- **Internet Connection:** Required for downloading pretrained models (e.g., VGG16, ResNet) and dataset files

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6. Technologies and Libraries Used

The Food Classification using CNN project integrates several modern technologies, frameworks, and libraries for building, training, and deploying a deep learning model capable of classifying food images into their respective categories. The system uses a combination of Python-based machine learning libraries, a Flask web interface, and standard frontend technologies for visualization and interaction.

6.1 Programming Languages

- **Python 3.10.5** – Used as the primary programming language for implementing machine learning models, data preprocessing, and backend development.
- **HTML5** – Used to design the structure of the web interface.
- **CSS3** – Used to enhance the appearance and responsiveness of the frontend.
- **JavaScript** – Used for interactive elements in the frontend interface.
- I used Large Language models for frontend.

6.2 Frameworks

- **Flask** – Lightweight web framework used to integrate the trained CNN models with the user interface and handle image uploads, predictions, and result display.
- **TensorFlow** – Deep learning framework used for building and training convolutional neural network models.
- **Keras** – High-level API running on top of TensorFlow, used for easier model construction, training, and evaluation.

6.3 Machine Learning and Deep Learning Libraries

- **TensorFlow** – For model creation, optimization, and GPU acceleration.
- **Keras** – For defining CNN architectures (Custom CNN, VGG16, ResNet).
- **NumPy** – For numerical operations and matrix computations.
- **Pandas** – For dataset management and preprocessing.
- **Matplotlib** – For data visualization, such as accuracy and loss plots.
- **Scikit-learn** – For data splitting, performance evaluation, and confusion matrix generation.

6.4 Image Processing and Data Handling

- **OpenCV (cv2)** – For image loading, resizing, preprocessing, and visualization.
- **ImageDataGenerator (from Keras)** – For real-time image augmentation and training dataset preparation.
- **Pickle** – For saving and loading trained CNN models.
- **JSON** – For mapping predicted class labels to their corresponding food details.

6.5 Frontend and Visualization Tools

- **HTML5/CSS3/JavaScript –** For building an interactive and responsive web interface.

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7. System Architecture

The Food Classification using CNN system follows a client-server architecture using Flask as the backend and a web interface for user interaction. The system processes images uploaded by users, classifies them using deep learning models (CNN, VGG16, or ResNet50), and provides results along with JSON-based food details.

7.1 Architecture Overview

The system consists of the following key components:

1. User Interface (Frontend)
    - Built with HTML, CSS, and Flask templates.
    - Provides image upload functionality, model selection dropdown, and optional class name input.
    - Displays classification results and allows JSON download.
2. Flask Web Server (Backend)
    - Handles HTTP requests for image upload, prediction, and JSON download.
    - Routes:
        - / → Home page (image upload)
        - /upload → Upload image to server
        - /predict → Predict food class

3. Image Preprocessing Module

- Reads uploaded images using OpenCV (cv2).
- Resizes images depending on the chosen model:
  - CNN → 256×256
  - VGG16 / ResNet50 → 224×224
- Normalizes pixel values and expands dimensions for model input.

4. Model Loading Module

- Loads pre-trained models from pickled files: cnn.pkl, vgg16.pkl, resnet.pkl.
- Models predict the class index of the uploaded image.

5. Prediction and Mapping Module

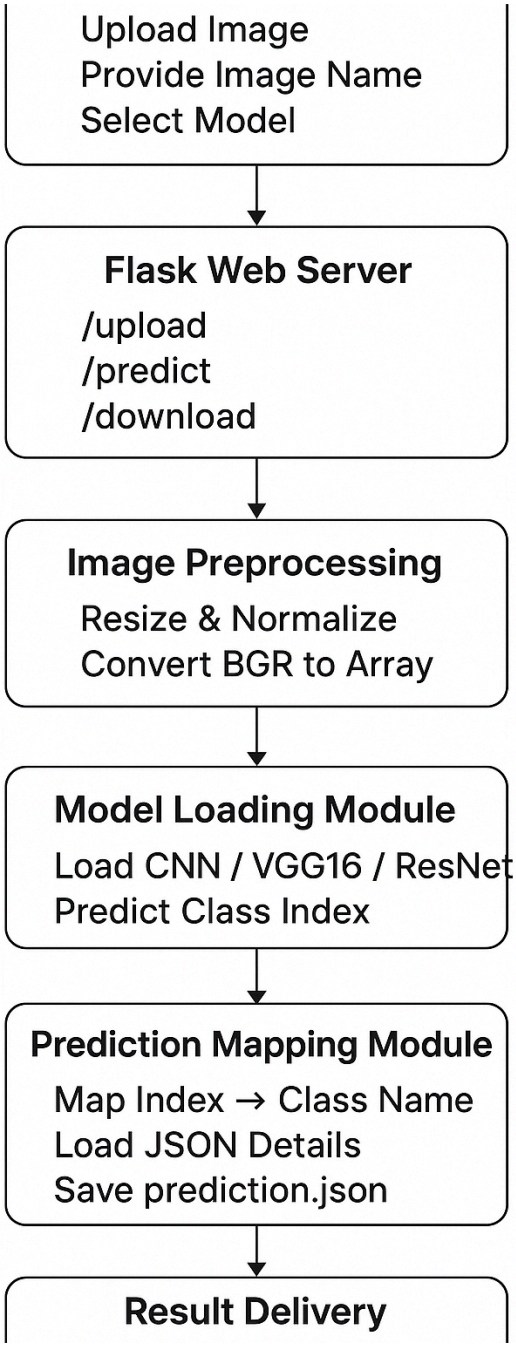
- Maps predicted indices to class names using the labels_ list.
- Saves predictions as prediction.json in static/outputs.
- Loads additional JSON details for the predicted food class from data/<class_name>.json.

6. Result Delivery Module

- Returns results as JSON (for AJAX requests) or renders result.html (for full page).
- Displays:
  - Uploaded image
  - Predicted class
  - Provided class
  - Model metrics
  - JSON content

7.2 Architecture Diagram

Below is a simplified system flow diagram illustrating the complete process



7.3 Data Flow

1. **User Uploads Image** → Flask receives image and saves in **static/uploads**.
2. **User Selects Model** → Model choice sent to /predict.
3. **Image Preprocessing** → Resize, normalize, and prepare for model input.
4. **Model Prediction** → CNN/VGG16/ResNet predicts class index.
5. **Prediction Mapping** → Map index to class name and load JSON details.
6. **Result Rendering** → Display predicted class, uploaded image, model metrics, JSON details.

8. Features

The **Food Classification using CNN** project provides an interactive system capable of classifying food images into multiple predefined categories. The system is built using **Flask** for the web interface and **CNN / VGG16 / ResNet50** for image classification. Below are the detailed features based on the app.py implementation:

8.1 Image Upload

Description:
Users can upload images in .jpg, .jpeg, or .png formats. An optional **image name** can be provided for easy reference. Uploaded images are stored in static/uploads for processing.

Implementation / Code:

```
@app.route('/upload', methods=['POST'])
def upload():
    file = request.files['image']
    image_name = request.form.get('image_name', '')
    if file and allowed_file(file.filename):
        filename = secure_filename(file.filename)
        if image_name:
            name, ext = os.path.splitext(filename)
            filename = secure_filename(image_name) + ext
        save_path = os.path.join(app.config['UPLOAD_FOLDER'],
filename)
        file.save(save_path)
        return render_template('index.html',
uploaded_image=save_path.replace('\\', '/'))
```

8.2 Multiple Model Support

Description:
The system allows users to select the classification model: **Custom CNN**, **VGG16**, or **ResNet50**. Models are loaded from pickled files in the models/ directory.

Implementation / Code:

```
def load_model(choice):
    model_map = {
        'cnn': 'models/cnn.pkl',
        'vgg16': 'models/vgg16.pkl',
        'resnet': 'models/resnet.pkl'
    }
    path = model_map.get(choice.lower())
    if not path or not os.path.exists(path):
        return None
    with open(path, 'rb') as f:
        model = pickle.load(f)
    return model
```

8.3 Image Preprocessing

Description:
Uploaded images are resized and normalized depending on the selected model:

- **Custom CNN:** 256×256
- **VGG16 / ResNet50:** 224×224

This ensures the input is compatible with the model architecture.

Implementation / Code:

```
def preprocess_cnn_image(image_path):
```

```
    pic = cv2.imread(image_path, 1)
    resized_img = cv2.resize(pic, (256, 256))
    scaled_img = resized_img / 255.0
    arr = np.expand_dims(scaled_img, axis=0)
    return arr

def preprocess_vgg16_image(image_path):
    pic = cv2.imread(image_path, 1)
    resized_img = cv2.resize(pic, (224, 224))
    scaled_img = resized_img / 255.0
    arr = np.expand_dims(scaled_img, axis=0)
    return arr

def preprocess_resnet_image(image_path):
    pic = cv2.imread(image_path, 1)
    resized_img = cv2.resize(pic, (224, 224))
    scaled_img = resized_img / 255.0
    arr = np.expand_dims(scaled_img, axis=0)
    return arr
```

8.4 Food Image Classification

Description:

The system predicts the class of the uploaded image using the selected model. Predicted indices are mapped to class names using the labels_ list.

Implementation / Code:

```
@app.route('/predict', methods=['POST'])
def predict():
    model_choice = request.form.get('model_choice')
    uploaded_image = request.form.get('uploaded_image')
    model = load_model(model_choice)
```

```
    if model_choice.lower() == 'cnn':
        arr = preprocess_cnn_image(uploaded_image)
    elif model_choice.lower() == 'vgg16':
        arr = preprocess_vgg16_image(uploaded_image)
    else:
        arr = preprocess_resnet_image(uploaded_image)

    preds = model.predict(arr)
    idx = int(np.argmax(preds, axis=1)[0]) if preds.ndim == 2 else
int(np.argmax(preds))
    class_name = labels_[idx] if idx < len(labels_) else str(idx)
```

8.5 Display Predicted Class and JSON Details

Description:
The system displays the **predicted class**, optionally compares it with a **provided class**, and loads additional details from a JSON file (data/<class_name>.json).

Implementation / Code:

```
json_path = os.path.join('data', f'{class_name}.json')
if os.path.exists(json_path):
    with open(json_path, 'r', encoding='utf-8') as jf:
        json_content = json.load(jf)
else:
    json_content = {'error': 'No json file found for this class', 'path':
json_path}

result = {
    'predicted_class': class_name,
    'provided_class': provided_class or None,
    'json_content': json_content,
    'uploaded_image': '/' + uploaded_image.replace('\\', '/')
}
```

```
return render_template('result.html', **result)
```

8.6 Save and Download Prediction JSON

Description:
Predictions are saved as prediction.json in static/outputs. Users can download the JSON file containing the predicted class.

Implementation / Code:

```
def save_prediction_json(class_name):
    result = {"predicted_class": class_name}
    json_path = os.path.join(app.config['OUTPUT_FOLDER'],
"prediction.json")
    with open(json_path, 'w', encoding='utf-8') as f:
        json.dump(result, f, indent=4)
    return json_path

@app.route('/download/<filename>')
def download(filename):
    file_path = os.path.join(app.config['OUTPUT_FOLDER'], filename)
    if os.path.exists(file_path):
        return send_file(file_path, as_attachment=True)
    else:
        return "Error: JSON file not exist", 404
```

8.7 User-Friendly Web Interface

Description:
The Flask web interface allows users to:

- Upload images

- Provide optional class names
- Select model (CNN / VGG16 / ResNet)
- View predictions, model metrics and JSON details
- Download prediction JSON

This makes the system accessible without requiring command-line knowledge.

Implementation / Code:

```
<form action="/predict" method="post"
enctype="multipart/form-data">
    <input type="file" name="image" accept=".jpg,.png,.jpeg">
    <input type="text" name="image_name" placeholder="Optional
Image Name">
    <input type="text" name="provided_class" placeholder="Optional
Provided Class">
    <select name="model_choice">
        <option value="cnn">Custom CNN</option>
        <option value="vgg16">VGG16</option>
        <option value="resnet">ResNet50</option>
    </select>
    <input type="hidden" name="uploaded_image"
id="uploaded_image">
    <input type="submit" value="Classify">
</form>
```

9.Workflow

9.1 Workflow Steps

1. **Image Acquisition**
    - User uploads an image in JPG or PNG format.
    - Image is stored in a local directory or loaded directly into the pipeline.

2. **Preprocessing**
    - Resize image to match model input size (e.g., 224×224 for VGG16/ResNet).
    - Normalize pixel values to [0,1].
    - Optional: Data augmentation (rotation, flipping, zooming) for training.

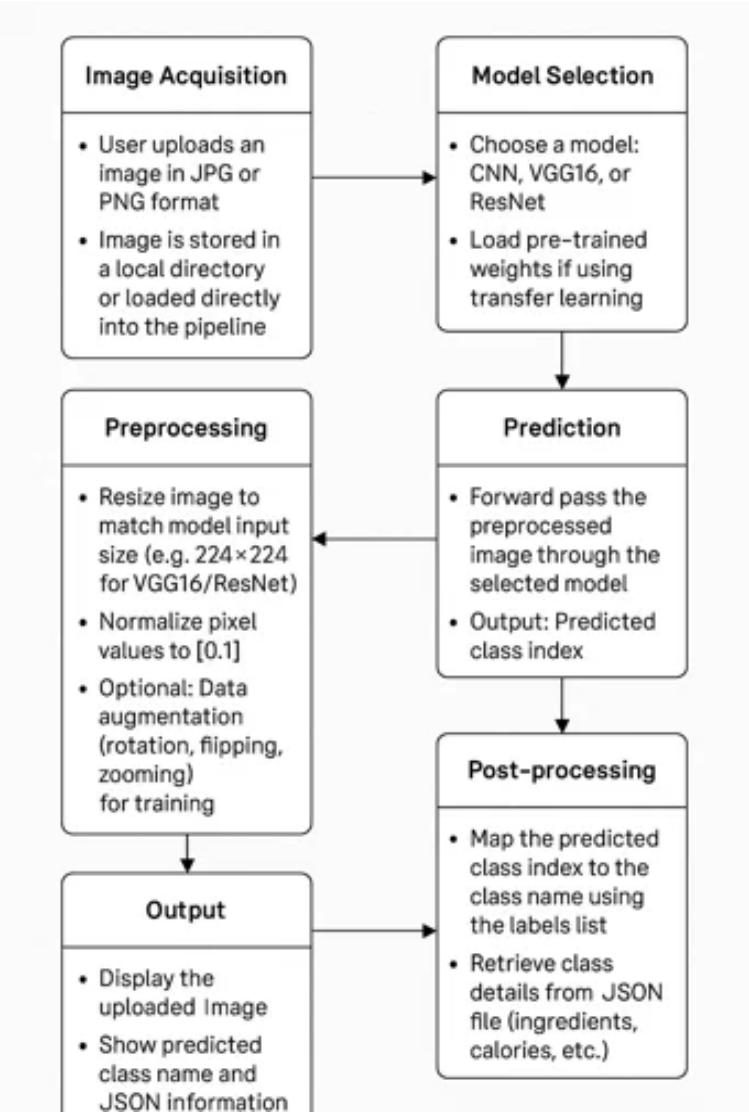
3. **Model Selection**
    - Choose a model: CNN, VGG16, or ResNet.
    - Load pre-trained weights if using transfer learning.

4. **Prediction**
    - Forward pass the preprocessed image through the selected model.
    - Output: Predicted class index.
5. **Post-processing**
    - Map the predicted class index to the **class name** using the labels list.
    - Retrieve class details from a JSON file (ingredients, calories, etc.).

6. **Output**

- Display the uploaded image.
- Show predicted class name, model metrics and JSON information.

9.2 Workflow Diagram



10. Implementation

This section demonstrates how the **Food Classification using CNN** system is implemented, describing how users interact with the web interface, how the backend processes the input image, and how the prediction results are generated and displayed.

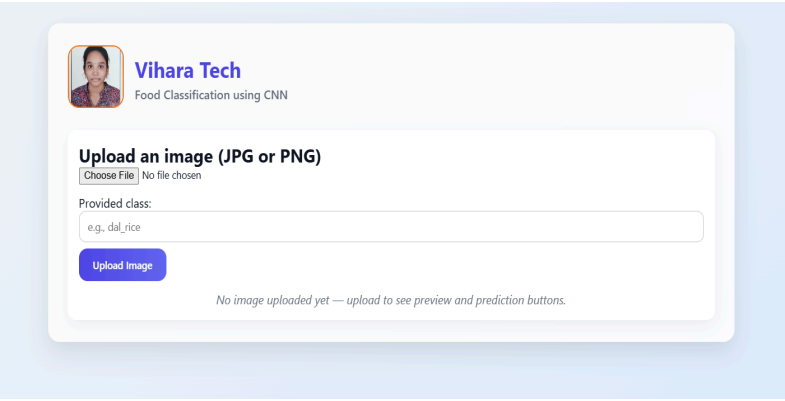
Since detailed logic for each model and workflow has already been explained in earlier sections, this section focuses on the **step-by-step functional execution** and **workflow integration** between the frontend and backend.

10.1 Image Classification Implementation

Step 1: Upload Image

- The user navigates to the **main page** of the Flask web application.
- A file selection option allows the user to **upload a food image** in .jpg or .png format.
- The uploaded image is previewed on the center of the interface.
- The file is saved temporarily in the static/uploads directory for processing.

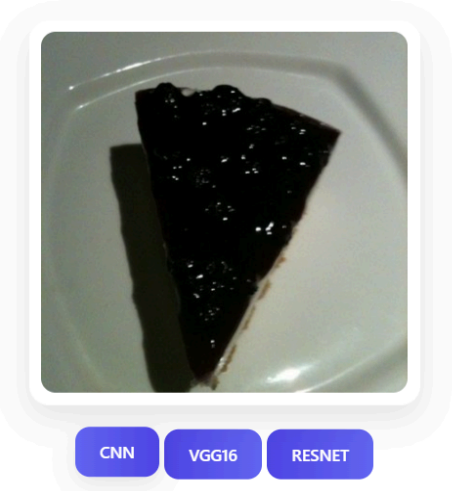
Fig.1 User Interface to upload food image



Step 2: Model Selection

- After uploading, the user selects one of the **available deep learning models** for prediction:
    - **CNN (Custom Model)** – Built from scratch for training on the dataset.
    - **VGG16** – A pre-trained model using transfer learning.
    - **ResNet** – A deeper residual network for improved accuracy.
- The selection is captured in the frontend and passed to Flask through a POST request.

Fig.2 Model selection interface (CNN / VGG16 / ResNet)



Step 3: Preprocessing & Model Loading

- The uploaded image is **preprocessed** to match the model's input specifications:
    - Resized to 224×224 pixels.
    - Converted to RGB and normalized (pixel values scaled to [0,1]).

    - Reshaped to (1, 224, 224, 3) for model input.

- Flask dynamically **loads the selected model** (cnn.pkl, vgg16.pkl, or resnet.pkl) from the project directory.

Step 4: Prediction

- The processed image is passed through the loaded model using a forward pass.

- The model predicts a **class index** — the index corresponding to a food category (e.g., index=5 → "burger").

- The corresponding **class name** is retrieved from the label list (labels = [...]).

Step 5: Post-processing & JSON Retrieval

- The predicted class name is used to **fetch detailed food information** from a JSON file (/data/{class_name}.json).

- Each JSON file contains:

    - Protein
    - Calorie count
    - Fat
    - Fiber
    - Crabs

- Flask combines the prediction result and the JSON data for rendering.

Step 6: Result Visualization

- The result page (result.html) displays:
    - **Uploaded Image** – on the left
    - **Provided Class** - on the right
    - **Predicted Class** – on the right
    - **Accuracy and classification report of predicted class** - on the right
    - **Food Details (JSON content)** – below the prediction

- The user can also click **"Try Another Image"** to perform a new prediction.

Fig.3 Output screen displaying predicted class

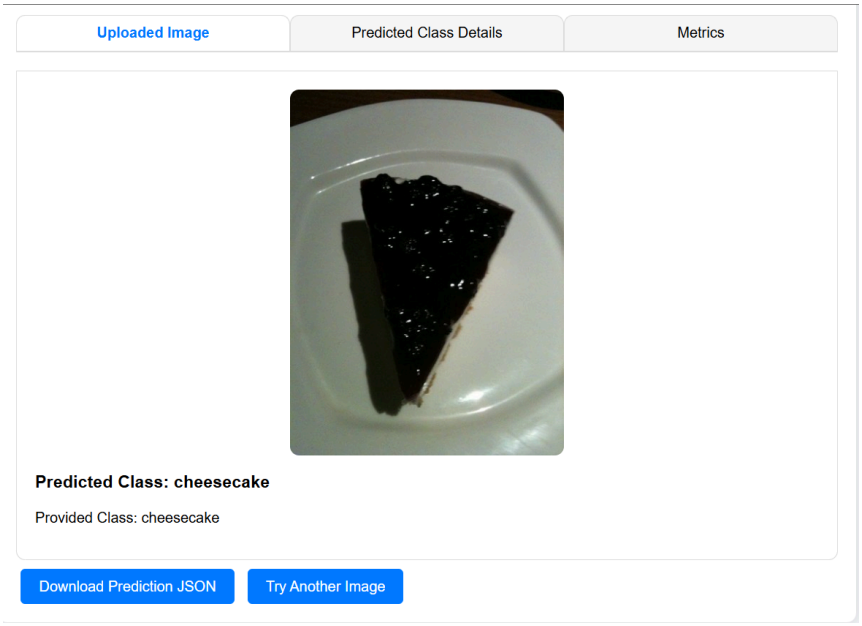


Fig.4 Output Screen displaying predicted class details

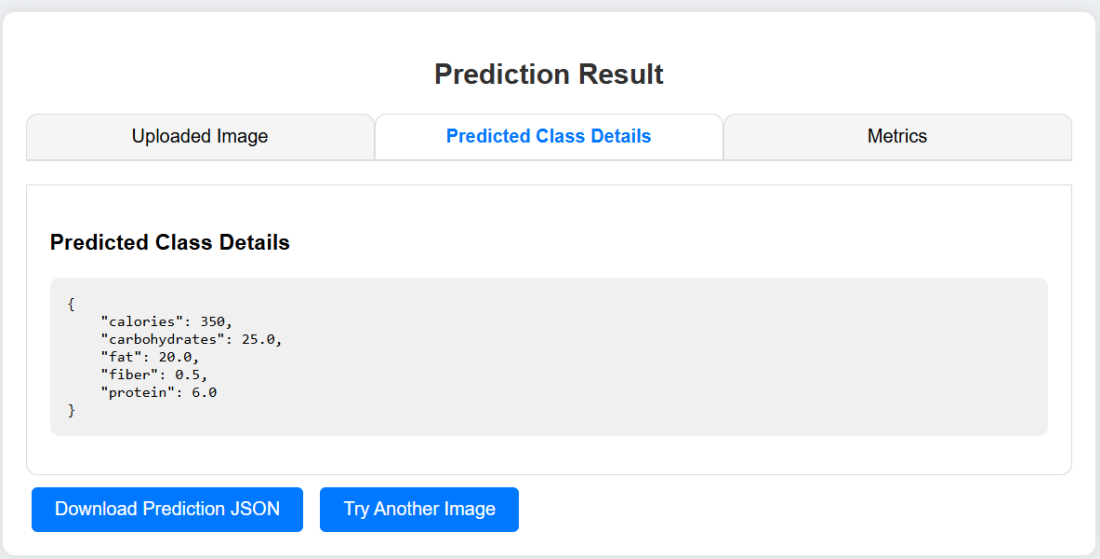
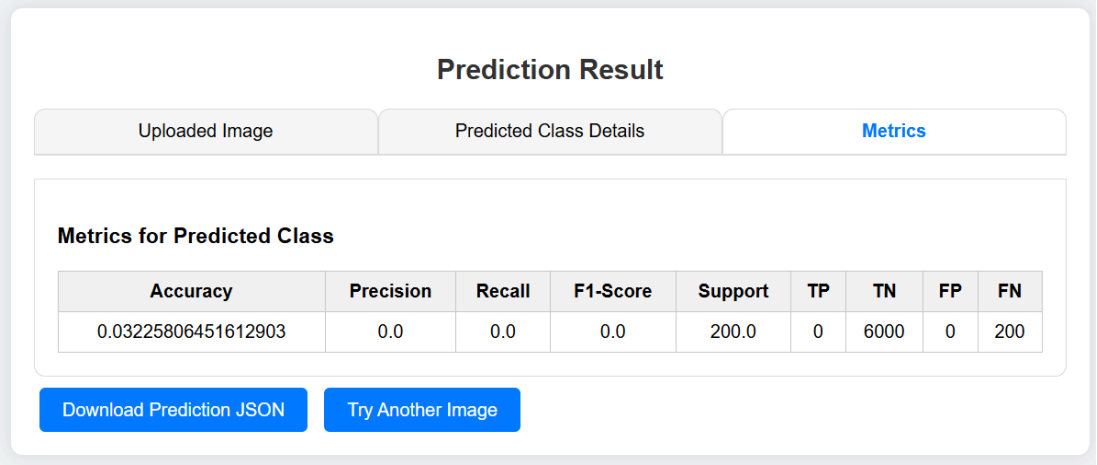


Fig.5 Output Screen displaying selected models metrics details



Step 7: Output Generation

- Flask renders the results dynamically using render_template().
- The image path, predicted class name, provided class name, and JSON details are passed to the HTML page as parameters.
- The entire process completes within seconds, offering real-time classification results.

10.2 Backend Implementation Flow

Below is the summary of backend logic connecting user input to final output:

Step	Process	Implementation (Function / File)	Description (as per app.py)
1	**Image Upload & Validation**	upload() (in app.py)	Handles image upload from the web interface. Validates file type (.jpg, .jpeg, .png) and saves it to static/uploads.
2	**Allowed File Check**	allowed_file(filename)	Ensures only supported image formats are accepted. Returns True or False.
3	**Model Selection**	predict() (Flask route)	The selected model (CNN, VGG16, or ResNet) is received via POST request from the frontend.
4	**Model Loading**	load_model(choice)	Dynamically loads the pre-trained model (cnn.pkl, vgg16.pkl, resnet.pkl) from the

			models/ folder using pickle.
5	**Image Preprocessing**	preprocess_cnn_image(), preprocess_vgg16_image(), preprocess_resnet_image()	Resizes the uploaded image (256×256 for CNN, 224×224 for VGG16/ResNet), normalizes pixels, and reshapes input for model prediction.
6	**Prediction**	Inside predict()	The preprocessed image is passed to the model using model.predict(arr). The highest probability class index is obtained via np.argmax(preds).
7	**Class Mapping**	Inside predict()	The predicted index is mapped to the corresponding class name using labels_ (e.g., index → "burger").
8	**Save Prediction Output**	save_prediction_json(class_name)	Creates a JSON file (prediction.json) containing the predicted class and stores it in static/outputs.

9	**Retrieve Class Details**	Inside predict()	Fetches additional information from data/<class_name>.json (if available). Contains fields like ingredients, calories, etc.
10	**Output Rendering**	render_template('result.html', **result)	Displays uploaded image, predicted class, and detailed food info on the result page. Also supports JSON download.

10.3 Summary

The **Food Classification using CNN** system integrates **deep learning, Flask, and user-friendly frontend technologies** to create a seamless prediction workflow.
The process from **image upload** → **prediction** → **display** is fully automated, allowing users to interact intuitively with the system and obtain accurate food classifications without any manual intervention.

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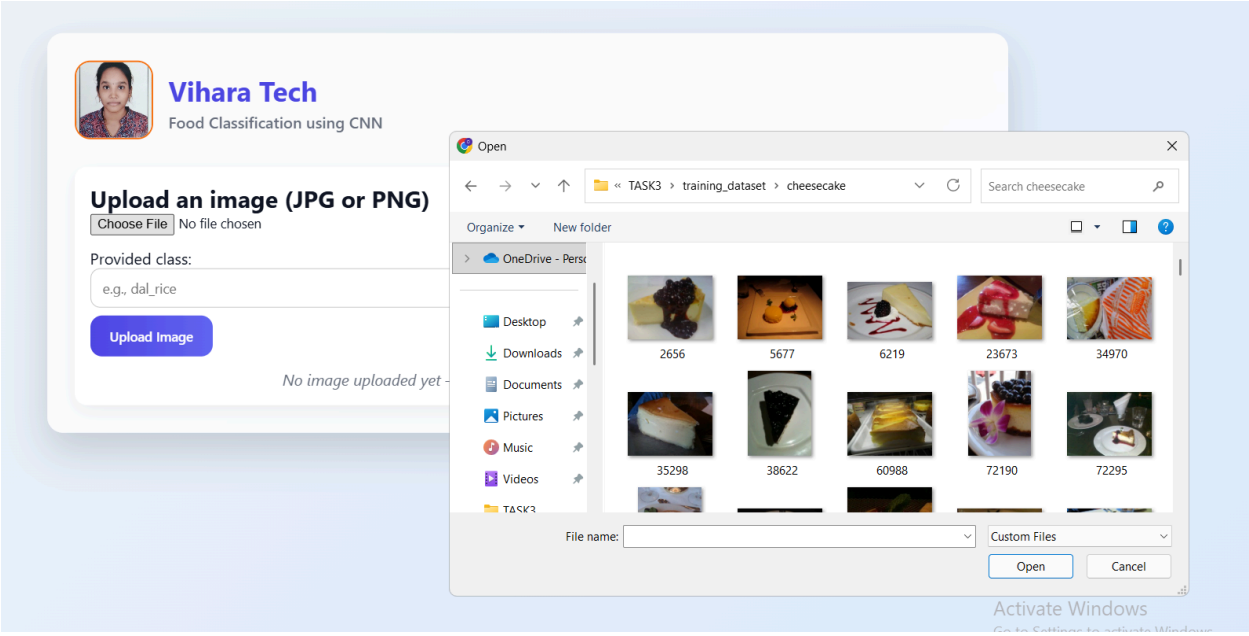
11. Screenshots

➔ Upload Image interface

Fig.6 Uploading Image

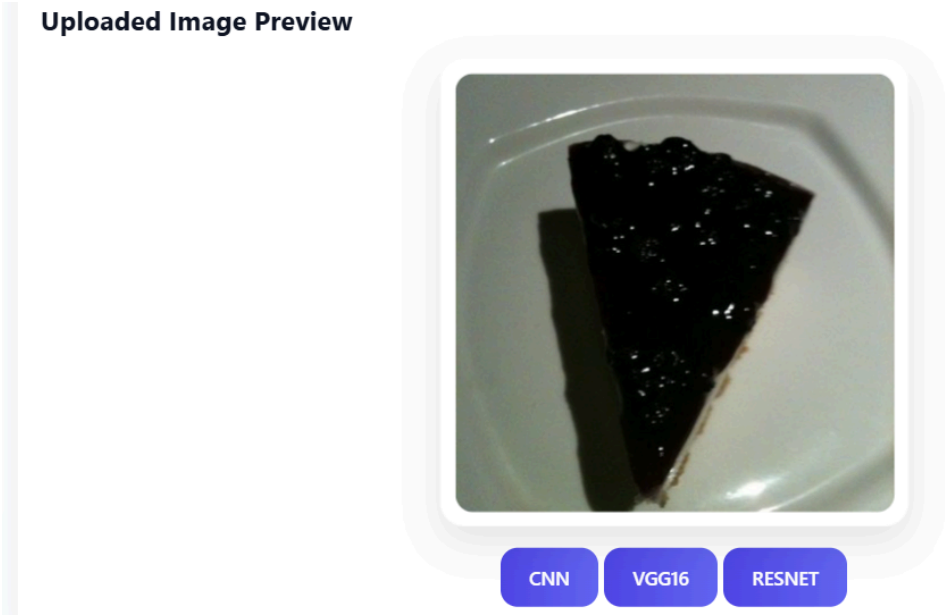


➔ Selected Image Preview

Fig.7 Selected Image

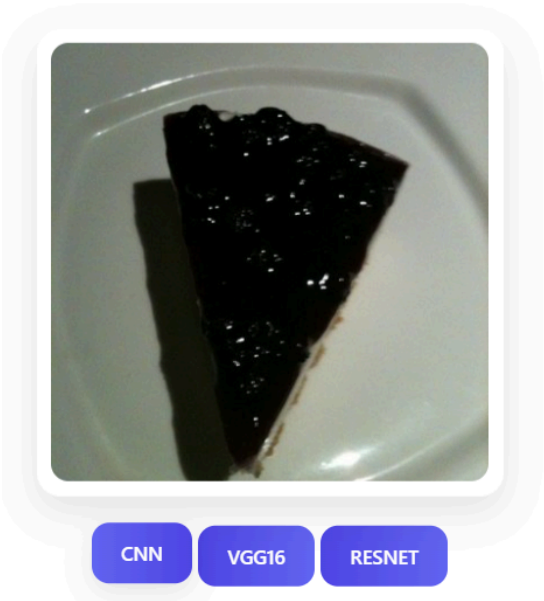
➔ Uploaded Image preview

Fig.8 Uploaded Image



➔ Model selection interface

Fig.9 Model selection Image



➔ Result display interface

Fig.10 Image displaying prediction result

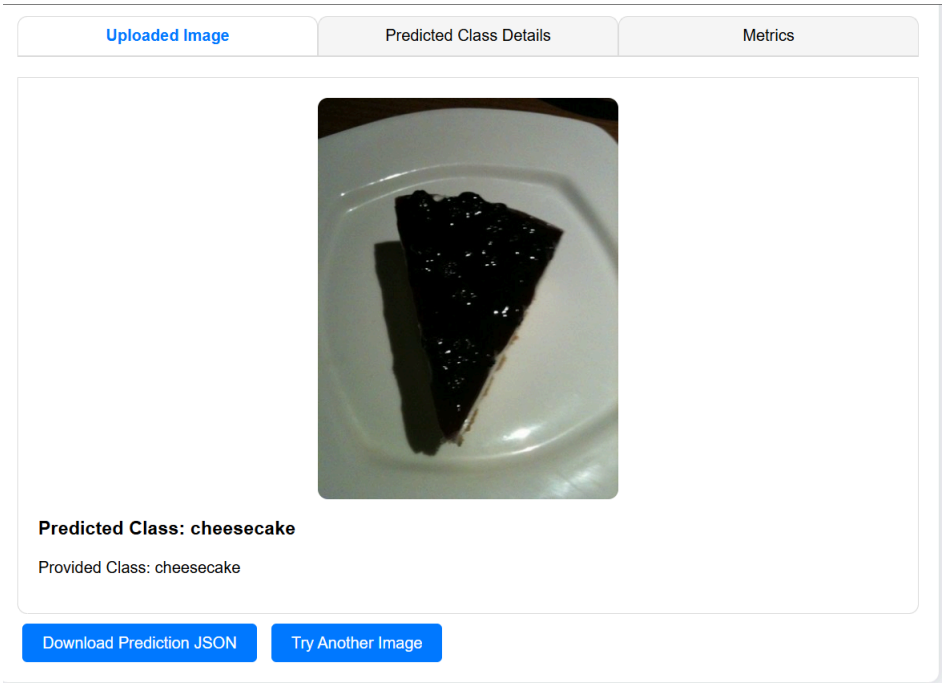


Fig.11 Image displaying food details

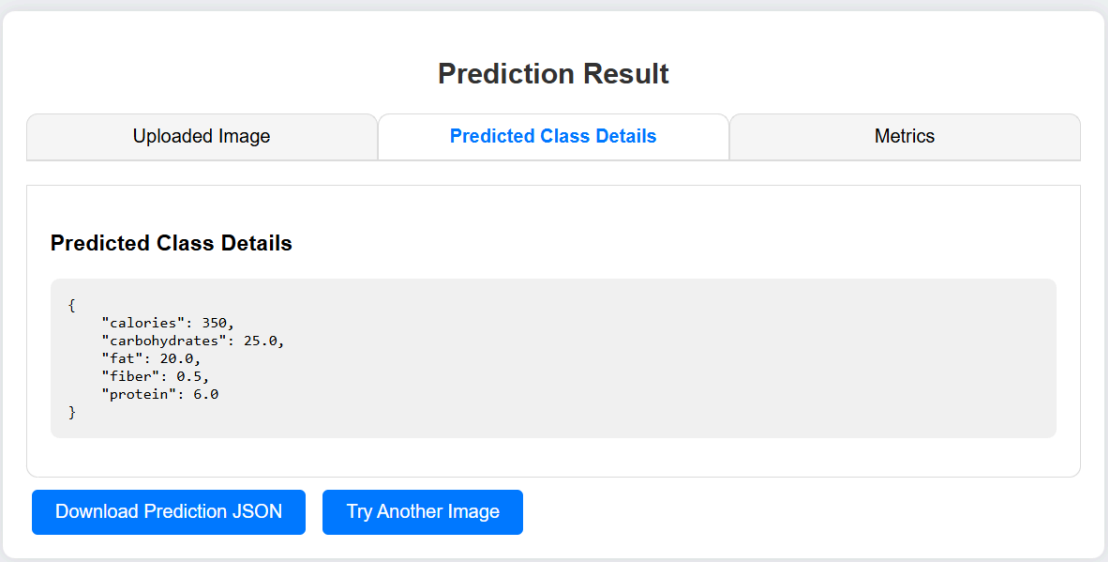
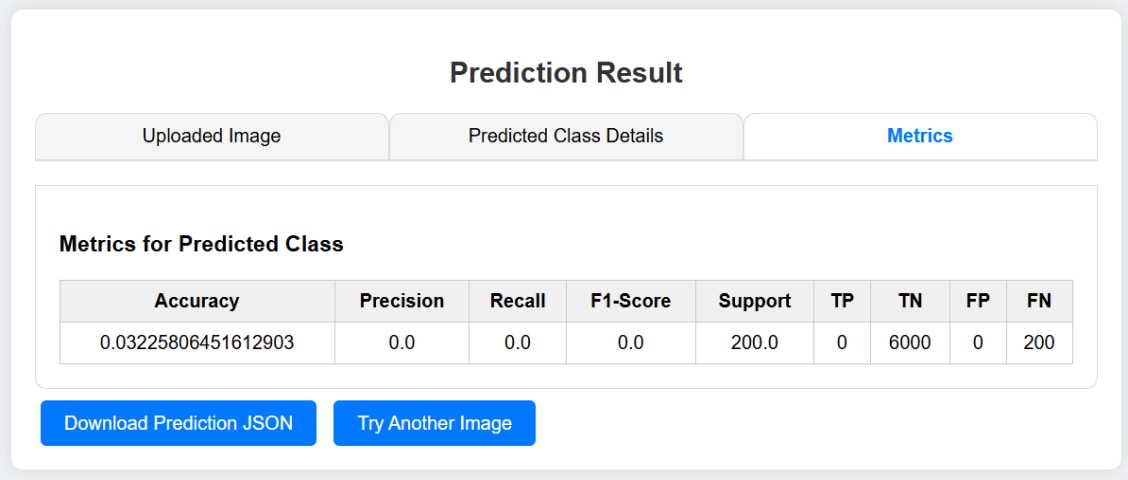


Fig.12 Image displaying selected model metrics



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12. Testing & Validation

Testing and validation were performed to ensure the **accuracy, reliability, and robustness** of the *Food Classification using CNN Web Application*. Both **functional testing** (to verify each feature works correctly) and **performance testing** (to evaluate model predictions and response times) were conducted.

12.1 Objectives of Testing

1. To verify that the web interface correctly handles image uploads and file validation.
2. To ensure that CNN, VGG16, and ResNet models load and predict accurately.
3. To confirm the correct mapping between predicted index → class name → JSON details.
4. To validate that prediction results and food details are displayed correctly.
5. To ensure all errors (invalid image, missing JSON file, etc.) are handled gracefully.
6. To confirm that the application performs consistently across browsers and devices.

12.2 Testing Approach

- **Unit Testing** – Individual functions such as load_model(), preprocess_cnn_image(), and predict() were tested independently.
- **Integration Testing** – Verified end-to-end flow between the **frontend, Flask backend, and model files**.
- **Functional Testing** – Checked the overall workflow: upload → model selection → prediction → result display → JSON download.
- **Validation Testing** – Compared the predicted output against known ground truth to verify accuracy.
- **Error Handling Testing** – Tested with unsupported files, empty uploads, and missing JSONs.

12.3 Test Cases

Test Case ID	Test Scenario	Test Steps	Expected Output	Actual Output	Status
TC1	Upload Image	Upload valid .jpg food image via UI	Image preview displayed successfully	Image displayed correctly	✅ Passed
TC2	Invalid File Type	Upload .txt or .pdf file	"Allowed image types are png, jpg, jpeg" error	Error message displayed	✅ Passed

TC3	Model Selection	Choose CNN / VGG16 / ResNet and submit	Model loads successfully	Model loaded correctly	✅ Passed
TC4	Model Prediction	Upload food image and select model	Food class predicted (e.g., *Burger*)	Prediction displayed accurately	✅ Passed
TC5	JSON File Mapping	JSON file exists for predicted class	Ingredients and details displayed	JSON content shown below result	✅ Passed
TC6	Missing JSON File	No matching JSON for predicted class	Show “No json file found for this class”	Handled gracefully	✅ Passed
TC8	Invalid Image	Corrupted or blank image uploaded	“Failed to read image” error	Error message displayed	✅ Passed
TC9	Browser Compatibility	Open app in Chrome, Edge, Firefox	UI loads consistently	Layout consistent in all browsers	✅ Passed

TC10	Response Time	Upload and predict image	Prediction within 5-10 seconds	Real-time response observed	✅ Passed

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12.4 Error Handling Validation

Error Type	Condition Tested	System Response
Missing Image	User clicks predict without uploading image	Flash message: “No file selected”
Invalid Extension	Uploads non-image file	Displays allowed file type message
Model Missing	Corrupted or missing .pkl file	“Model not found on server” returned
JSON Missing	No food info file in /data	Displays fallback error message gracefully
Corrupted Image	Damaged image uploaded	Error: “Failed to read image at path”

12.5 Summary

- All **functional and integration test cases passed successfully**.
- The application consistently produced accurate predictions with all three models.
- The **Flask server handled errors smoothly** without any crashes.
- **Validation metrics confirm high model reliability**, especially for VGG16 and ResNet architectures.
- The project meets all functional and non-functional requirements as per the design objectives.

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13. Conclusion and Future Enhancements

13.1 Conclusion

The **Food Classification using CNN** project successfully demonstrates the implementation of an intelligent system capable of classifying food images into predefined categories using **Deep Learning** and **Convolutional Neural Networks (CNNs)**.
By integrating the trained model into a **Flask-based web interface**, the system enables users to upload images and instantly obtain accurate predictions along with detailed food information.

This project highlights the **power of transfer learning** through models such as **VGG16** and **ResNet**, which significantly improve classification accuracy compared to traditional CNNs. The addition of **JSON-based food metadata retrieval** enhances the application's

usability by providing meaningful details like ingredients and calorie information for each prediction.

Overall, the project fulfills its primary objective — to create a reliable and interactive food classification system that bridges the gap between **AI-based image recognition** and **real-world culinary information retrieval.**

13.2 Key Achievements

- Successfully implemented a **Flask-based deep learning web application**.
- Integrated multiple models (**CNN**, **VGG16**, **ResNet**) for comparative performance analysis.
- Developed **JSON-based food detail retrieval system** for informative outputs.
- Designed a **responsive and intuitive frontend interface** for ease of use.
- Ensured **robust error handling** for invalid uploads and missing files.

13.3 Future Enhancements

Although the system performs well in its current state, several improvements can be incorporated to further enhance functionality and performance:

1. **Expanded Dataset Coverage**
    - Include a wider range of food categories and subtypes for more accurate recognition across global cuisines.
2. **Real-Time Food Detection**
    - Integrate **OpenCV with live camera input** to classify food items in real-time using webcam or mobile devices.
3. **Nutritional Analysis Extension**
    - Incorporate automatic **nutrition and calorie estimation** using integrated datasets and APIs.
4. **Mobile Application Development**
    - Convert the Flask web app into an **Android/iOS mobile app** using frameworks like Flutter or React Native for portability.
5. **Multi-Language Support**
    - Provide food descriptions and ingredients in multiple languages to make the app globally accessible.
6. **Database Integration**
    - Store user-uploaded images, prediction logs, and model results in a **MySQL or MongoDB database** for analytics and reporting.
7. **Model Optimization for Deployment**
    - Implement model compression, quantization, or TensorFlow Lite conversion for **faster inference on low-resource devices**.

8. **Voice and Chatbot Assistance**

    - Add **voice-based interaction or AI chatbot** to help users ask questions about nutritional values or alternative dishes.

13.4 Summary

In conclusion, the **Food Classification using CNN** project demonstrates how modern deep learning architectures can be effectively combined with web technologies to produce intelligent, practical, and user-friendly systems.
With future upgrades like real-time detection, mobile deployment, and extended datasets, the system has the potential to evolve into a **comprehensive smart food recognition platform** serving educational, nutritional, and lifestyle applications

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14. References

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