Al-Powered Food Classification and Calorie Estimation Using the Food-101 Dataset

Abdallah Waked

Dr. Mohammed Yousefhussien

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Project Overview

- Goal: Classify food images and estimate caloric value
- Dataset: Food-101
- API Integration: Spoonacular API for recipe and nutrition details
- Output: Fast food classification and calorie estimation through web app



Why is this project valuable?

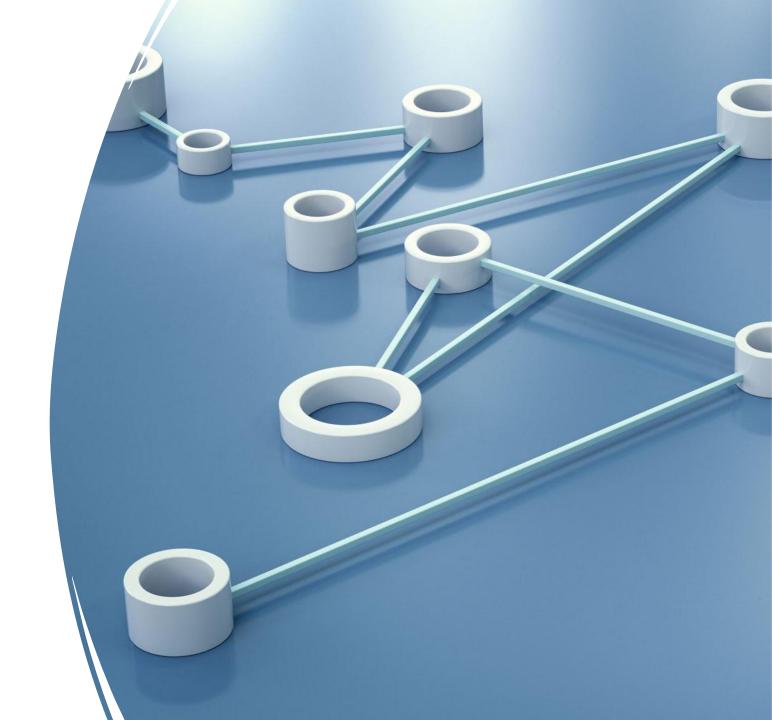
Simplifies food identification and calorie tracking

Useful for healthconscious users and diet tracking Provides instant results using image input

No manual search for nutritional info needed

Approach & Methodology

- Train a Convolutional Neural Network(CNN)
- •Use ResNet18 pretrained model to improve accuracy
- Integrate with JSON nutrition database and Spoonacular API
- Deploy model using Streamlit webapplication



Dataset

- Food-101 Dataset
- •Total images: 101,000 (101 categories)
- •Split:
 - •70% Training
 - •15% Validation
 - •15% Testing
- Preprocessing:
 - •Resize: 224×224
 - Augmentation: Horizontal flip, rotation
 - Normalization: ImageNet mean and std

Model Architecture (ResNet18)

- Pretrained on ImageNet
- •Frozen initial layers, fine-tuned Layer4 and FC
- Custom classifier for 101 food classes
- Efficient for small-to-medium datasets

Baseline Model Flowchart

Load Food-101 Dataset

Preprocess Images

Resize to 224x224

Normalize (ImageNet stats)

Split: Train / Val / Test

Build ResNet18 Model (Baseline)

- Random initialization
- No pretrained weights

Define Training Settings

Loss: CrossEntropy

• Optimizer: Adam

• LR: 0.001

Training Loop Forward pass Compute loss Backpropagation Update weights Validation Step Check Accuracy **Monitor Loss Checkpoint Saving** Save "Best Model" Save "Final Model"

Save training history (JSON)

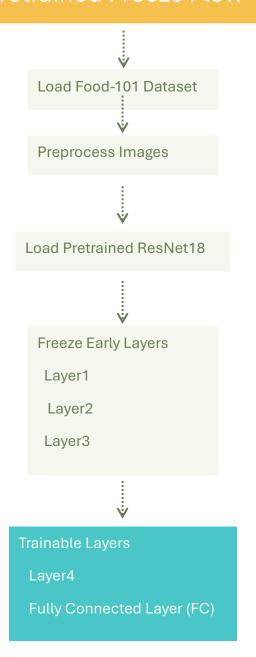
Test on Unseen Data

Use saved checkpoint

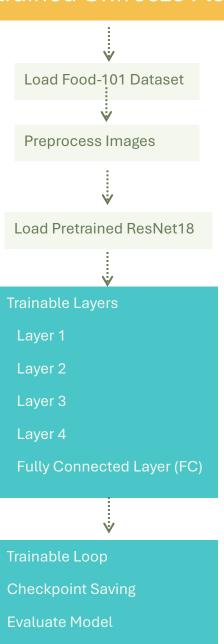
Evaluate Model

- Accuracy
- Classification Report
- Confusion Matrix

Pretrained Freeze Flow



Pretrained Unfreeze Flow



Training Process

- Device: GPU (if available), fallback to CPU
- Epochs: ~10 with early stopping
- •Batch Size: 32 → 8 (due to device limits)
- •Learning Rate:
 - •Started: 0.001
 - •Planned: 0.0003 (but limited by Colab quota and hardware)
- •Features:
 - Checkpoint saving
 - Best model saving
 - Training history logged

Hyperparameter Tuning

- •Experiments:
 - •Learning rates: 0.001, planned 0.0003
 - •Batch sizes: 32 → 8
 - •Model modes:
 - Pretrained Freeze
 - Pretrained Unfreeze
- Observations:
 - Pretrained models outperformed baseline
 - Freezing sped up training
 - Unfreezing all layers achieved higher accuracy

Deployment Application

- •Web App: Streamlit Link
- Auto-downloads model from Google Drive
- •User uploads image → Model predicts category
- •Click on prediction → Spoonacular API fetches:
 - Recipes
 - Nutritional information
- •Code available on GitHub: GitHub Repository

Challenges & Limitations

- Google Colab quota limits GPU usage
- Local device performance is limited
- Large model size (~5 GB) requires external storage
- •API rate limits from Spoonacular
- Time constraints limited fine-tuning
- Complex dataset with varied image conditions

Results & Evaluation

- Model accuracy: (Insert your number here)
- •Classification report: (Add sample screenshot or table)
- Confusion matrix visualization: (Optional screenshot)
- Efficient web deployment achieved

Conclusion

- Successfully classified food images and estimated calories
- Integrated external API for dynamic recipe and nutrition data
- •ResNet18 pretrained model improved accuracy and efficiency
- Deployed as an interactive Streamlit web application

Thank You!