FoodNet: Food Recognition Project Documentation

Executive Summary

FoodNet is a deep learning-powered web application that classifies food images into three categories: **Pizza**, **Steak**, and **Sushi**. Built with PyTorch and deployed via Streamlit, this project demonstrates end-to-end machine learning and AI implementation from model training to production deployment.

Key Features:

- Multi-model architecture support (LeNet64, TinyVGG, ResNet18)
- Real-time image classification with confidence scores
- Nutritional information lookup
- AI-generated food descriptions using Groq LLM
- YouTube cooking video recommendations
- Interactive web interface with visualizations

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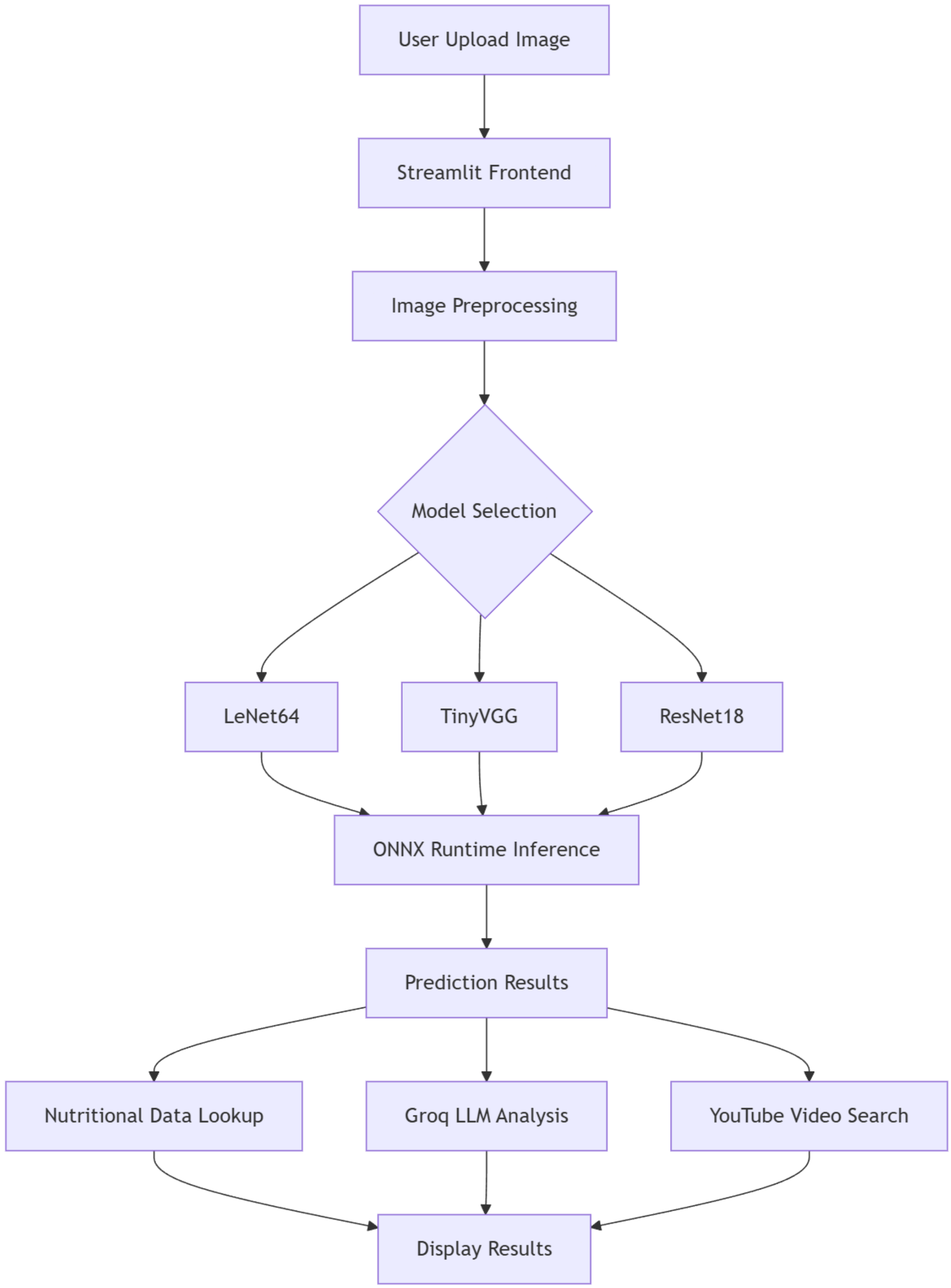
Project Architecture



Core Technologies

Component	Technology	Version/Details
Deep Learning	PyTorch	Neural network training & architecture
Inference	ONNX Runtime	Optimized model execution
Web Framework	Streamlit	Interactive UI
LLM Integration	Groq API	Food descriptions & recipes
Data Analysis	Pandas, NumPy	Data processing
Visualization	Plotly Express	Interactive charts
Video Search	YouTube Search	Recipe video recommendations

Dependencies

```
# Key Libraries
- streamlit
- torch
- onnxruntime
- Pillow (PIL)
- pandas
- numpy
- plotly
- groq
- youtube-search
- python-dotenv
```

Model Architectures

1. LeNet64

Architecture: Classic LeNet adapted for 64×64 RGB images

Specifications:

- **Input:** 64×64×3 (RGB images)

- **Output:** 3 classes (Pizza, Steak, Sushi)
- **Layers:**
  - Conv2D (6 filters, 5×5 kernel) + BatchNorm + ReLU
  - AvgPool (2×2)
  - Conv2D (16 filters, 5×5 kernel) + BatchNorm + ReLU
  - AvgPool (2×2)
  - Fully Connected (2704 → 120 → 84 → 3)

Key Features:

- Kaiming initialization for conv layers
- Xavier initialization for fully connected layers
- Batch normalization for training stability

```python
class Model(nn.Module):
    def __init__(self, in_channels=3, num_classes=3, pool_type="avg"):
        super().__init__()
        self.conv1 = nn.Conv2d(in_channels, 6, kernel_size=5)
        self.bn1 = nn.BatchNorm2d(6)
        self.conv2 = nn.Conv2d(6, 16, kernel_size=5)
        self.bn2 = nn.BatchNorm2d(16)
        self.pool = nn.AvgPool2d(2, 2)
        self.fc1 = nn.Linear(16 * 13 * 13, 120)
        self.fc2 = nn.Linear(120, 84)
        self.fc3 = nn.Linear(84, num_classes)
```

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2. TinyVGG

Architecture: Lightweight VGG-inspired convolutional network

Specifications:

- **Input:** 224×224×3 (RGB images)
- **Output:** 3 classes
- **Blocks:**
  - **Block 1:** 2× Conv2D + BatchNorm + ReLU + MaxPool + Dropout
  - **Block 2:** 2× Conv2D + BatchNorm + ReLU + MaxPool + Dropout
  - **Classifier:** Flatten + Linear

Key Features:

- Dropout (25%) for regularization
- Batch normalization
- Padding preservation (same convolutions)

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3. ResNet18

Architecture: Pre-trained ResNet18 (transfer learning)

Specifications:

- **Input:** 224×224×3
- **Output:** 3 classes (fine-tuned)
- **Parameters:** ~11M
- **Training:** Transfer learning from ImageNet

Project Structure

```
Food_Recognition_Project/
├── app.py                      # Main Streamlit application
├── config.py                   # Configuration & settings
├── __init__.py                 # Package initializer
│
├── architecture/               # Model definitions
│   ├── lenet64.py             # LeNet64 architecture
│   └── tinyvgg.py             # TinyVGG architectures
│
├── models/                     # Trained models
│   ├── onnx/                  # ONNX format models
│   │   ├── lenet64.onnx
│   │   ├── tinyvgg.onnx
│   │   └── resnet18.onnx
│   └── torch/                 # PyTorch format models
│
├── utils/                      # Utility modules
│   ├── preprocessing.py       # Image preprocessing
│   ├── inference.py           # Model inference logic
│   ├── nutrients.py           # Nutritional data lookup
│   ├── groq_analysis.py       # LLM-based food analysis
│   └── youtube_service.py     # Video search integration
│
├── data/                       # Data files
│   └── nutrients.csv          # Nutritional information (101 foods)
│
└── notebooks/                  # Jupyter notebooks
    ├── 001_eda.ipynb          # Exploratory Data Analysis
    ├── 002_lenet.ipynb        # LeNet training
    ├── 004_tinyvgg.ipynb      # TinyVGG training
    ├── 005_resnet.ipynb       # ResNet training
    └── 006-onnx_conversion.ipynb  # Model conversion
```

Core Components

1. Configuration Management: config.py

Central configuration class managing paths and settings:

```
class Config:
    APP_NAME = "FoodVision: Food Classification using PyTorch and Groq"
    GROQ_API_KEY = os.getenv("PUBLIC_GROQ_API_KEY")

    ONNX_PATH = {
        "lenet64": "models/onnx/lenet64.onnx",
        "tinyvgg": "models/onnx/tinyvgg.onnx",
        "resnet18": "models/onnx/resnet18.onnx"
    }

    CLASS_NAMES = ["pizza", "steak", "sushi"]
    DEVICE = "cuda" if torch.cuda.is_available() else "cpu"
```

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2. Image Preprocessing: utils/preprocessing.py

Handles image normalization and transformation:

Process:

1. Resize image (64×64 for LeNet, 224×224 for others)
2. Convert to NumPy array
3. Normalize pixel values to [0,1]
4. Apply ImageNet normalization (mean/std)
5. Transpose to channel-first format (C,H,W)
6. Add batch dimension

```
def preprocess(image: Image.Image, model_name: str = "resnet18") ->
np.ndarray:
    # Resize based on model
    size = (64, 64) if model_name == "lenet64" else (224, 224)
    image = image.resize(size)

    # Normalize with ImageNet stats
    img_array = np.array(image).astype(np.float32) / 255.0
    mean = np.array([0.485, 0.456, 0.406])
    std = np.array([0.229, 0.224, 0.225])
    img_array = (img_array - mean) / std

    # Format for PyTorch (B, C, H, W)
    img_array = img_array.transpose(2, 0, 1)
    return np.expand_dims(img_array, axis=0)
```

---

3. Model Inference: utils/inference.py

Executes ONNX model predictions:

Features:

- Numerically stable softmax implementation
- ONNX Runtime with CUDA support
- Returns class index and probability distribution

```
def run_inference(session: ort.InferenceSession, input_array: np.ndarray):
    input_name = session.get_inputs()[0].name
    outputs = session.run(None, {input_name: input_array})

    logits = outputs[0]
    probs = softmax(logits)
    pred_index = int(np.argmax(probs, axis=1)[0])

    return pred_index, probs[0]
```

---

4. Nutritional Data Lookup: utils/nutrients.py

Searches nutritional database for food items:

Data Fields (per 100g):

- Calories
- Protein
- Carbohydrates
- Fat
- Fiber
- Sugar

Implementation:

```
def filter_csv_by_label(label_value):
    df = pd.read_csv(settings.NUTRIENTS_PATH)
    return df[df['label'].str.lower() == label_value.lower()]
```

---

5. LLM-Powered Food Analysis: utils/groq_analysis.py

Generates AI-powered food descriptions using Groq's LLaMA 3.3 70B:

Capabilities:

- Food descriptions
- Recipe details

- Cooking tips

```python
def get_food_description(food_name: str, model="llama-3.3-70b-versatile"):
    client = Groq(api_key=settings.GROQ_API_KEY)
    response = client.chat.completions.create(
        model=model,
        messages=[{
            "role": "user",
            "content": f"Give a small description, recipe details and some
cooking tips for {food_name}?"
        }]
    )
    return response.choices[0].message.content
```

---

6. YouTube Video Integration: utils/youtube_service.py

Fetches cooking tutorials from YouTube:

Features:

- Searches for detailed cooking videos
- Filters by minimum duration (10+ minutes)
- Randomly selects from valid results

```python
def get_cooking_videos(food_name: str, min_minutes: int = 10):
    query = f"how to cook {food_name} in detail"
    results = YoutubeSearch(query, max_results=10).to_dict()

    # Filter by duration
    valid_videos = [
        video for video in results
        if parse_duration_to_minutes(video["duration"]) >= min_minutes
    ]

    video = random.choice(valid_videos)
    return {
        "title": video["title"],
        "url": f"https://www.youtube.com/watch?v={video['id']}",
        "thumbnail": video["thumbnails"][0],
        "duration": video["duration"]
    }
```

Features

1. Multi-Model Support

Users can select from three different architectures:

- **LeNet64:** Lightweight, fast inference
- **TinyVGG:** Balanced accuracy/speed
- **ResNet18:** Highest accuracy (transfer learning)

2. Real-Time Classification

- Upload images in JPG, JPEG, or PNG formats
- Instant predictions with confidence scores
- Interactive probability visualization (pie chart)

3. Nutritional Information

Displays comprehensive nutritional data per 100g:

- **Pizza:** 266 calories, 11g protein, 33g carbs, 10g fat
- **Steak:** 271 calories, 25g protein, 0g carbs, 18g fat
- **Sushi:** 200 calories, 8g protein, 28g carbs, 5g fat

4. AI-Generated Insights

Uses Groq's LLaMA 3.3 to provide:

- Food descriptions
- Recipe instructions
- Cooking tips and techniques

5. Video Recommendations

Automatically finds relevant cooking tutorials on YouTube with:

- Video title and duration
- Direct playback in app
- Minimum 10-minute detailed tutorials

Data Pipeline

Training Data

- **Dataset:** Food-101 subset (Pizza, Steak, Sushi)
- **Notebooks:** 5 Jupyter notebooks documenting the ML pipeline

Pipeline Stages

1. **EDA**: 001_eda.ipynb
   - Data exploration
   - Class distribution analysis
   - Image statistics
2. **Model Training**

- 002_lenet.ipynb: LeNet64 experiments
- 004_tinyvgg.ipynb: TinyVGG variants
- 005_resnet.ipynb: Transfer learning

3. **Model Conversion** (006-onnx_conversion.ipynb)
    - PyTorch → ONNX export
    - Model optimization
    - Validation

Deployment

Application Stack

Framework: Streamlit
Inference Engine: ONNX Runtime
Execution Providers: CUDA (GPU) / CPU fallback

Running the Application

```
# Install dependencies
pip install -r requirements.txt

# Set environment variables
echo "PUBLIC_GROQ_API_KEY=your_api_key" > .env

# Launch application
streamlit run app.py
```

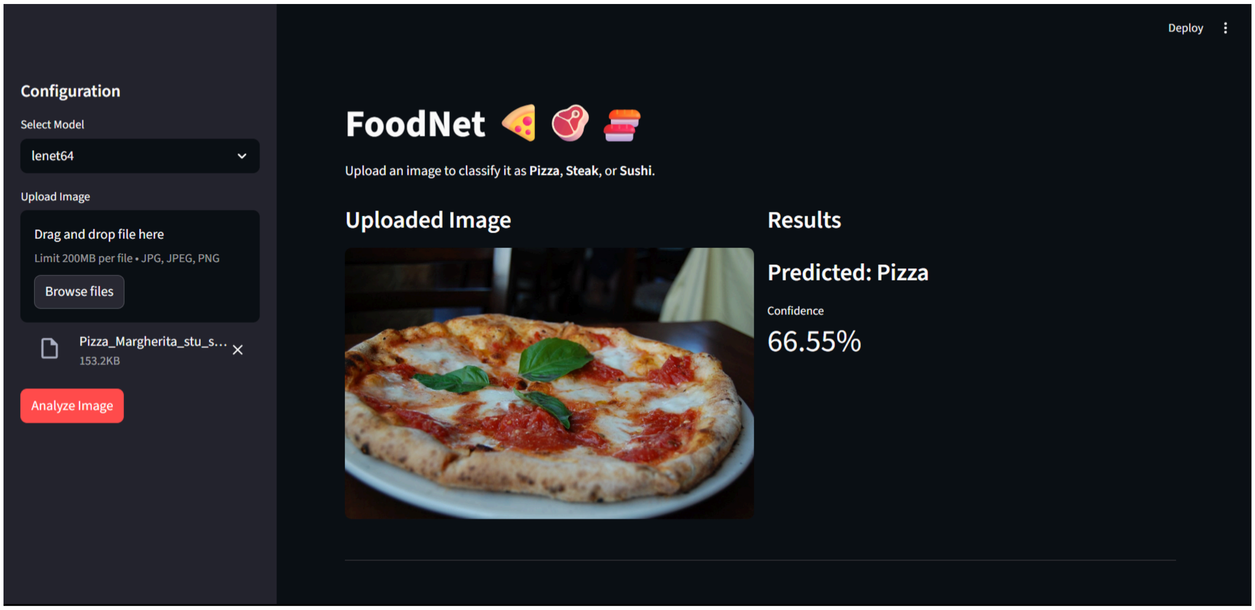
Session State Management

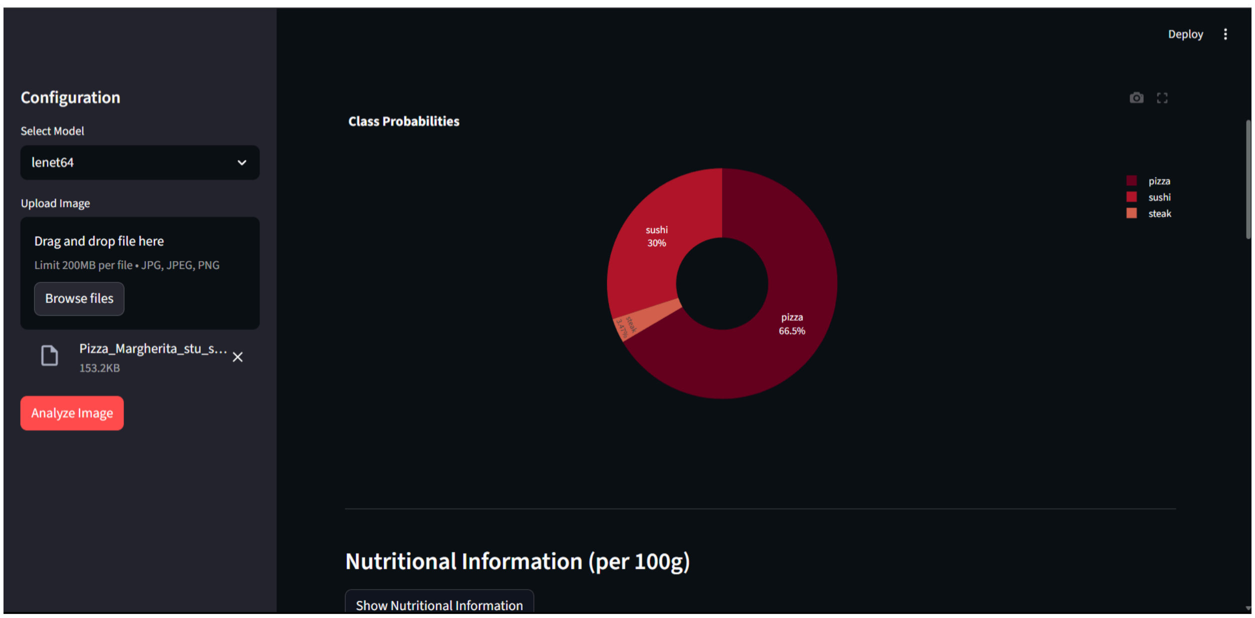
The app uses Streamlit's session state to persist:

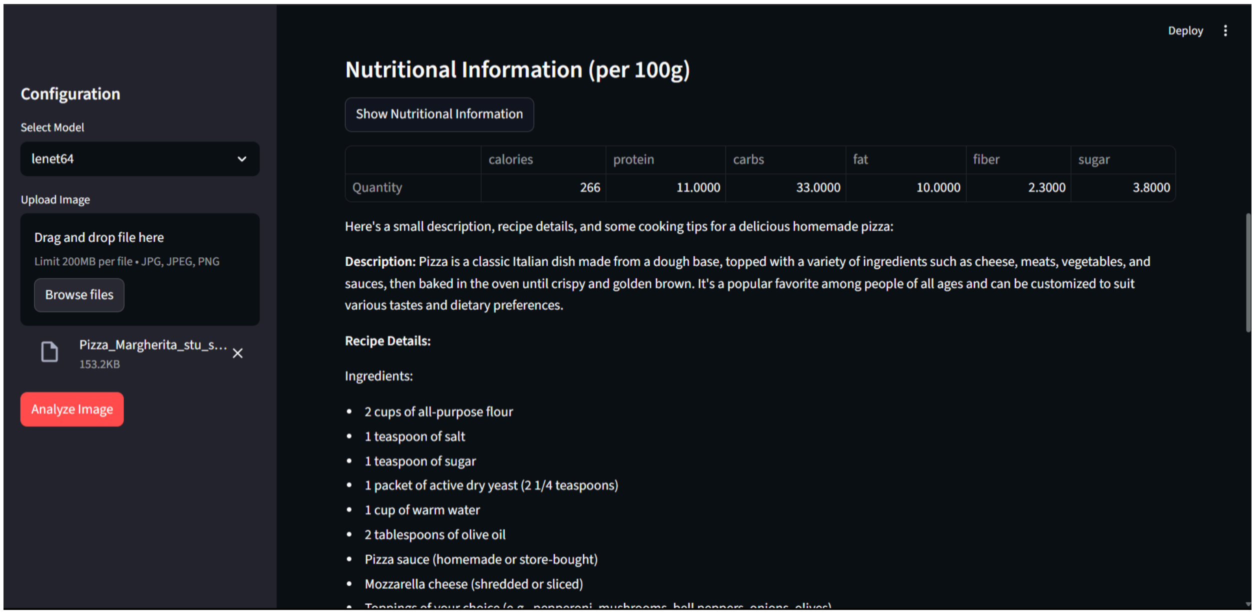
- Prediction results
- Confidence scores
- Probability distributions
- Video data
- UI state (nutrient display toggle)

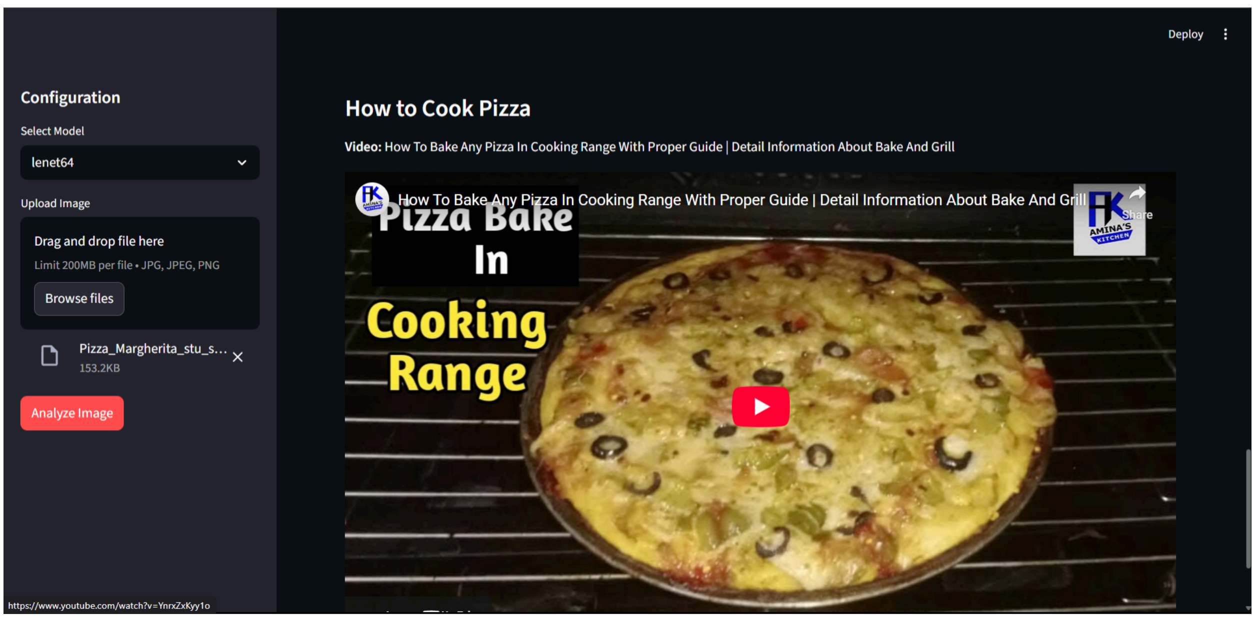
```
# Initialize session state
if "prediction" not in st.session_state:
    st.session_state.prediction = None
if "probabilities" not in st.session_state:
    st.session_state.probabilities = None
```

User Interface









Future Enhancements

Model Improvements

- Expand to 101 food classes (full Food-101 dataset)
- Implement ensemble predictions
- Add model explainability (Grad-CAM)
- Support for multi-food detection

Feature Additions

- User authentication and history tracking
- Calorie calculator based on portion size
- Allergen warnings and dietary restrictions
- Recipe recommendations based on ingredients
- Mobile app deployment (iOS/Android)

Technical Optimizations

- Model quantization for faster inference
- Batch processing for multiple images
- Cloud deployment (AWS/GCP/Azure)
- API endpoint for external integrations
- Docker containerization

Data Enhancements

- Expand nutritional database
- Add regional cuisine variations
- User-contributed food images
- Data augmentation pipeline

Key Technical Achievements

Production-Ready Features

- Multi-model architecture support with seamless switching
- ONNX optimization for cross-platform deployment
- GPU acceleration with automatic CPU fallback
- Comprehensive error handling and logging
- Modular codebase with clear separation of concerns

Performance Optimization

- ImageNet normalization for transfer learning compatibility
- Batch normalization for training stability
- Dropout regularization to prevent overfitting
- Efficient session state management in Streamlit

Difficulties Faced

The project encountered several technical and logistical challenges:

- **Computational and Time Constraints:**
    - Model training was limited to only three classes due to the excessive time required, even when using Google Colab.

    - The original plan to implement and validate a wider range of models was curtailed by both time and computational resource limitations.
- **Deployment and Scaling:**
    - While successful, the deployment phase was unable to achieve full scaling capabilities due to hardware restrictions.
- **Software and Version Compatibility:**
    - Converting the model to the ONNX (Open Neural Network Exchange) format proved challenging. This necessitated the use of multiple Python versions (3.11 and 3.14) because the ONNX library did not support Python 3.14 at the time.

Conclusion

FoodNet demonstrates a complete end-to-end deep learning application combining:

- **Computer Vision:** Multi-architecture food classification
- **Natural Language Processing:** AI-generated food insights
- **Data Integration:** Nutritional database and video recommendations
- **Web Deployment:** Interactive Streamlit interface

The project showcases modern AI engineering practices including model optimization (ONNX), transfer learning, and API integrations, making it a robust foundation for food recognition applications.
