Semi-Supervised Grocery Image Classification

A Machine Learning Mini-Project

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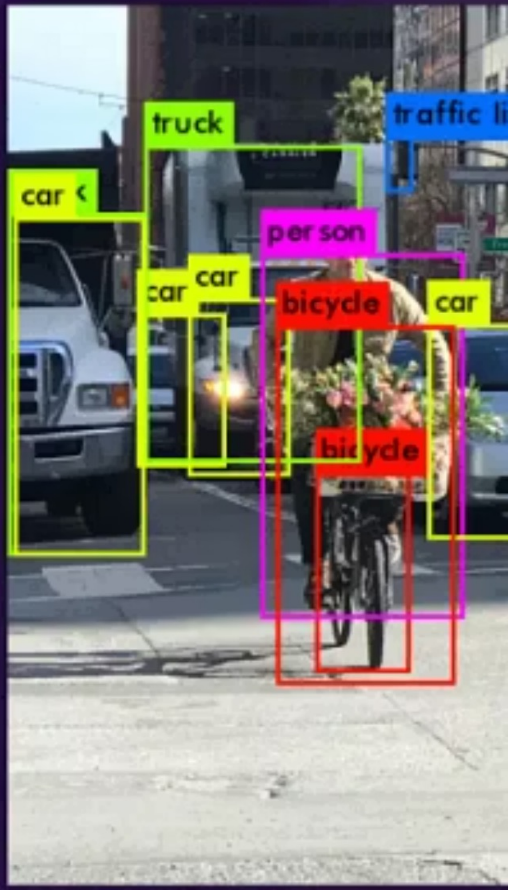


The High Cost of Labeling: A Real-World Problem

Expensive Manual Labeling

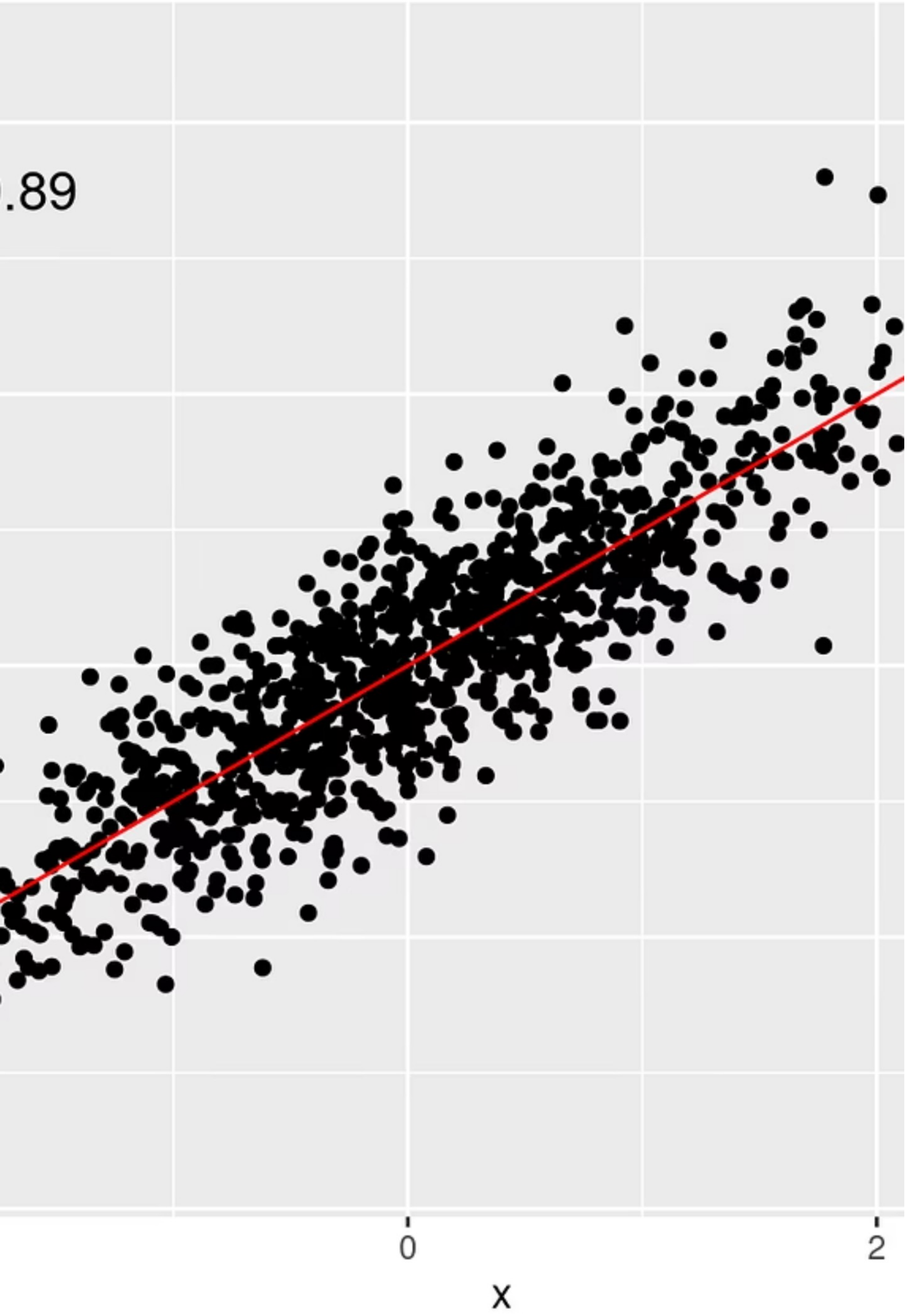
Manually labeling vast datasets of product images is a labor-intensive and costly process, especially for large e-commerce platforms.

E-commerce Scale

Platforms like Amazon deal with millions of diverse products, requiring efficient, scalable classification solutions that minimize human effort.

Need for Efficiency

Automated or semi-automated labeling is crucial to maintain competitive pricing and rapid product onboarding.

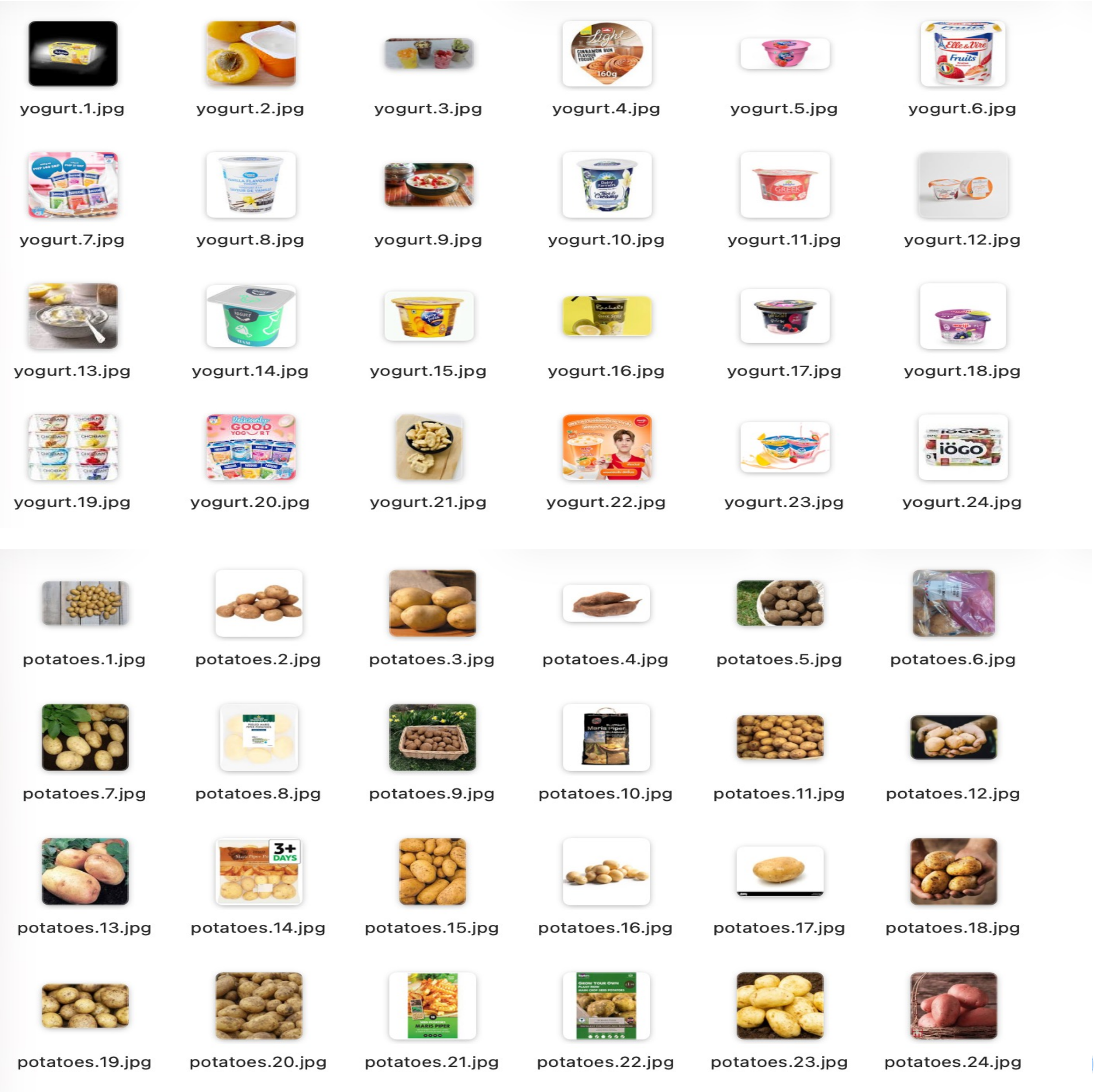


The Classification Challenge: Limited Labeled Data

- Large grocery image datasets are mostly **unlabeled**
- Manual image labeling is **expensive and time-consuming**
- Supervised learning requires **fully labeled data**
- Image classification alone does not provide **direct user value**
- Need to convert predictions into **useful recommendations**

Dataset Overview

We utilized a specialized dataset tailored for grocery product classification, reflecting the diversity found in typical retail environments.



Key Challenges

Classifying grocery images at large scale presents several technical challenges related to data size, labeling, and model scalability.

High-dimensional images

Raw pixels are too large for ML

Limited labeled data

Few annotated samples available

Compact representation needed

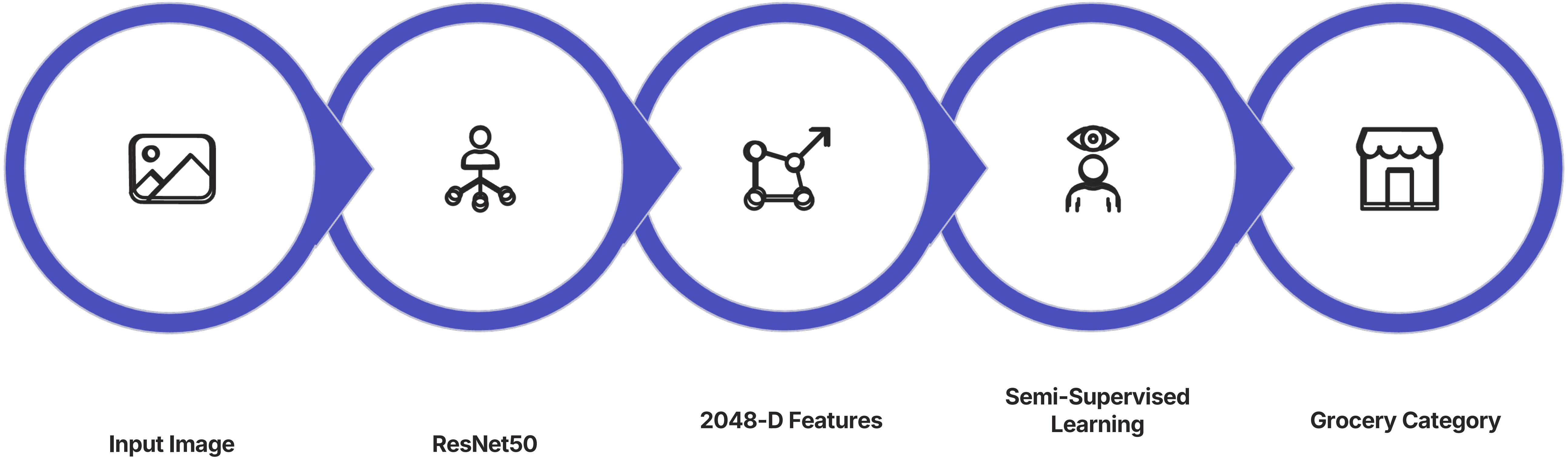
Images must be converted into vectors

Scalability

Method must handle large datasets efficiently

Our Proposed Classification Pipeline

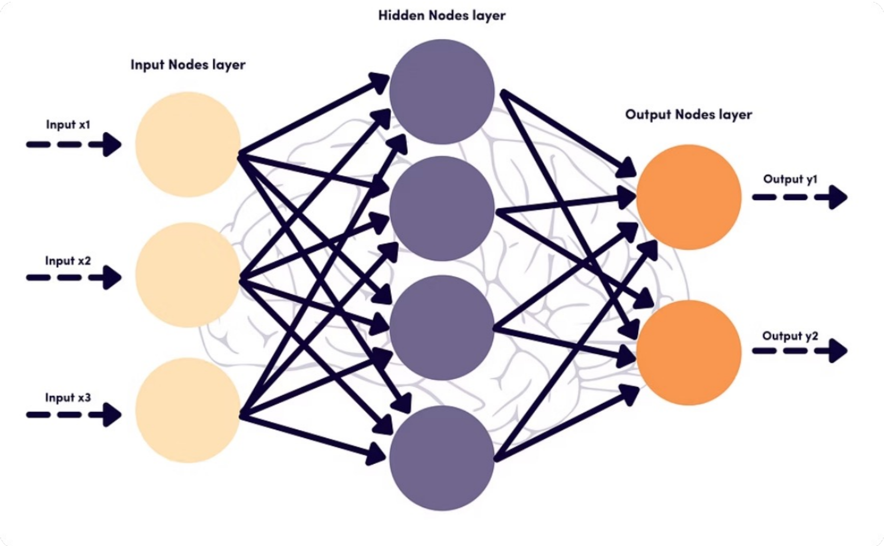
This simplified diagram illustrates the flow from a raw grocery image to its final classified category using our semi-supervised approach.

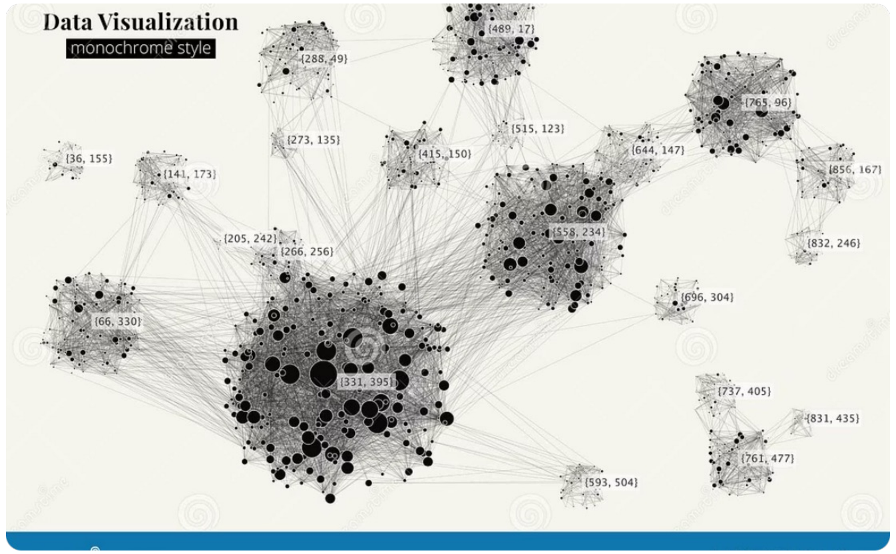


Each stage plays a crucial role in transforming complex visual data into an understandable classification.

CNN Embeddings: Transforming Pixels into Insight

Convolutional Neural Networks (CNNs) serve as powerful feature extractors, converting complex raw images into compact, meaningful numerical representations known as embeddings.





Feature Extraction

CNNs learn hierarchical features, from edges and textures to complex object parts, effectively capturing visual essence.

Dimensionality Reduction

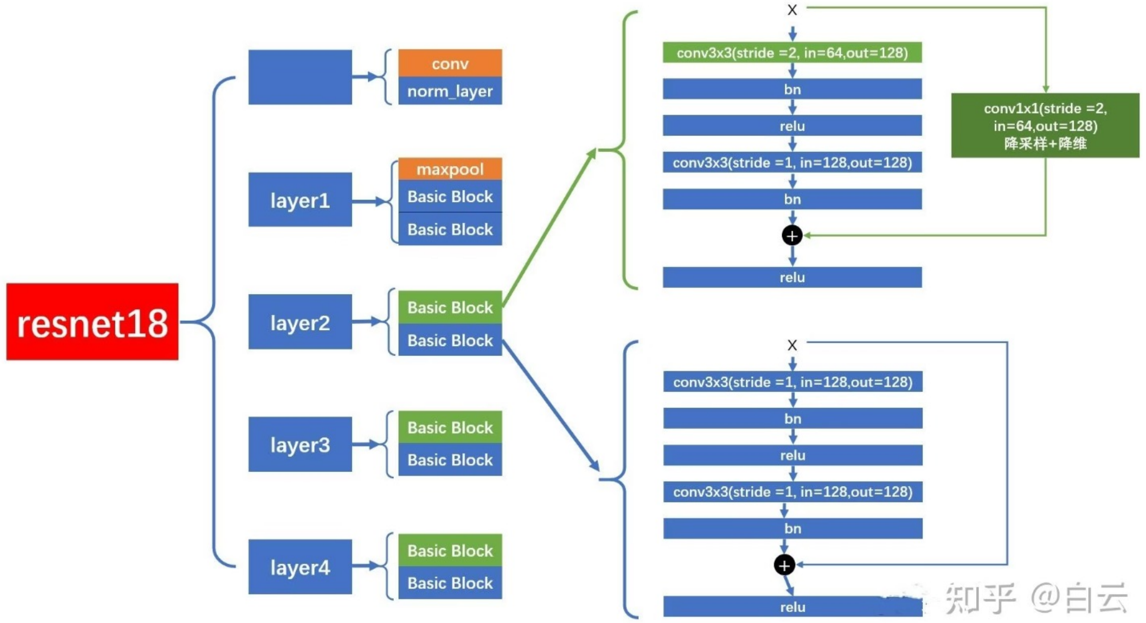
This process significantly reduces the data's dimensionality while preserving crucial information, making it tractable for subsequent ML tasks.

Compact Numerical Vectors

Each image is transformed into a fixed-size vector, representing its semantic content in a lower-dimensional space.

ResNet50: Our Chosen Feature Extractor

For our project, we selected ResNet50, a well-established convolutional neural network architecture, due to its strong balance between representational depth and computational efficiency.



- Architecture: ResNet50 is a deeper variant of the Residual Network architecture, utilizing *skip connections* to mitigate the vanishing gradient problem and enable effective training of deep networks.
- Pre-trained Advantage: We leverage a ResNet50 model pre-trained on ImageNet, allowing it to capture rich and diverse visual features learned from large-scale image data.
- Output: The final convolutional layer of ResNet50 produces a **2048-dimensional feature vector** for each input image.
- Purpose: These **2048-D feature vectors** serve as robust CNN embeddings, capturing essential visual information while remaining suitable for downstream semi-supervised learning algorithms.

The Semi-Supervised Learning

Semi-supervised learning is a paradigm that bridges the gap between supervised and unsupervised methods, making it ideal for scenarios with limited labeled data.

Label Propagation

Graph-based method that propagates lables from labled samples to unlabeled ones based on similarity

Label Spreading

An improved version of label propagation that uses soft labeling and regularization for better stability.

Self-Training (Pseudo-Labeling)

Iterative approach where a model trained on labeled data generates high-confidence labels for unlabeled samples and retrains itself.

Output :

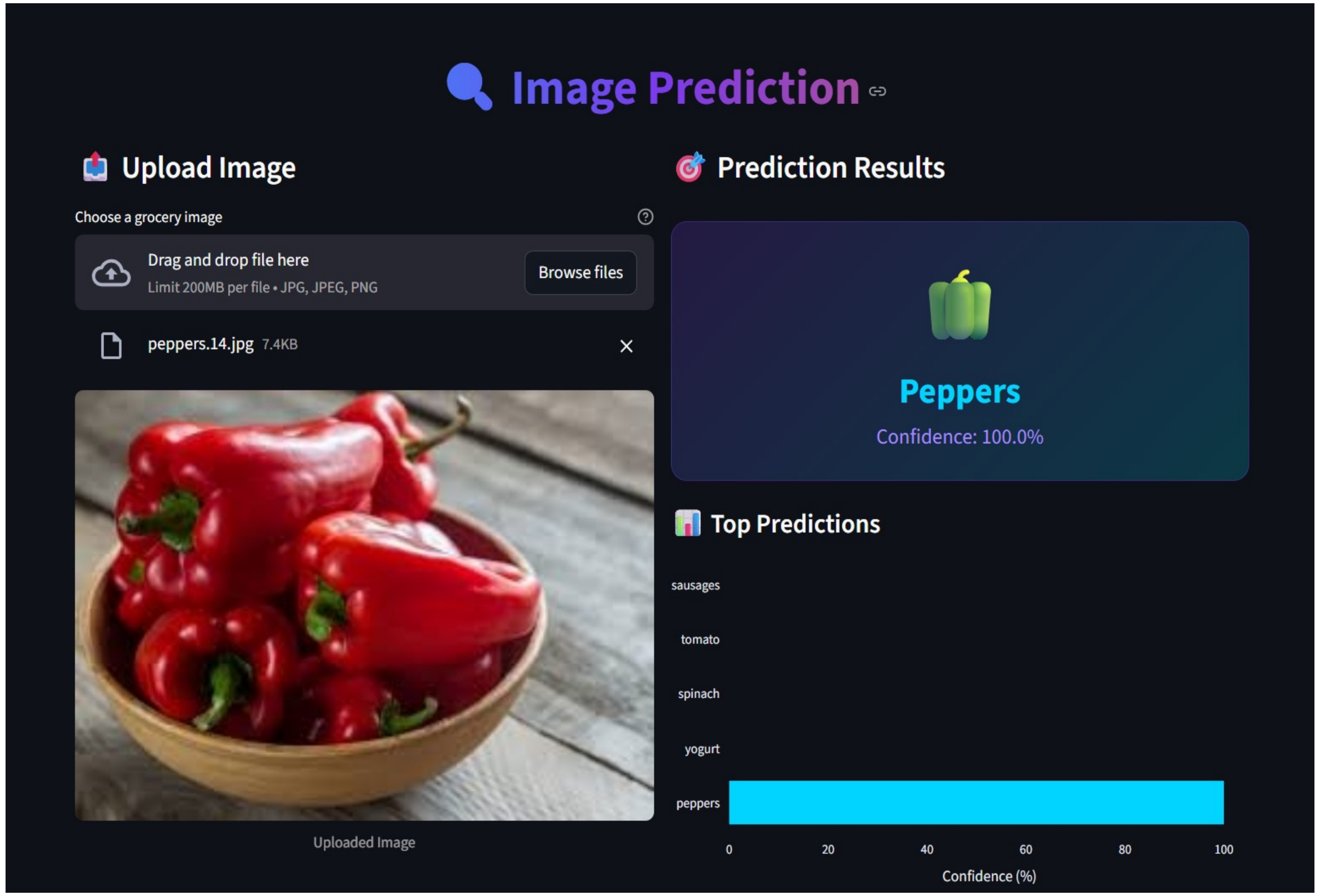
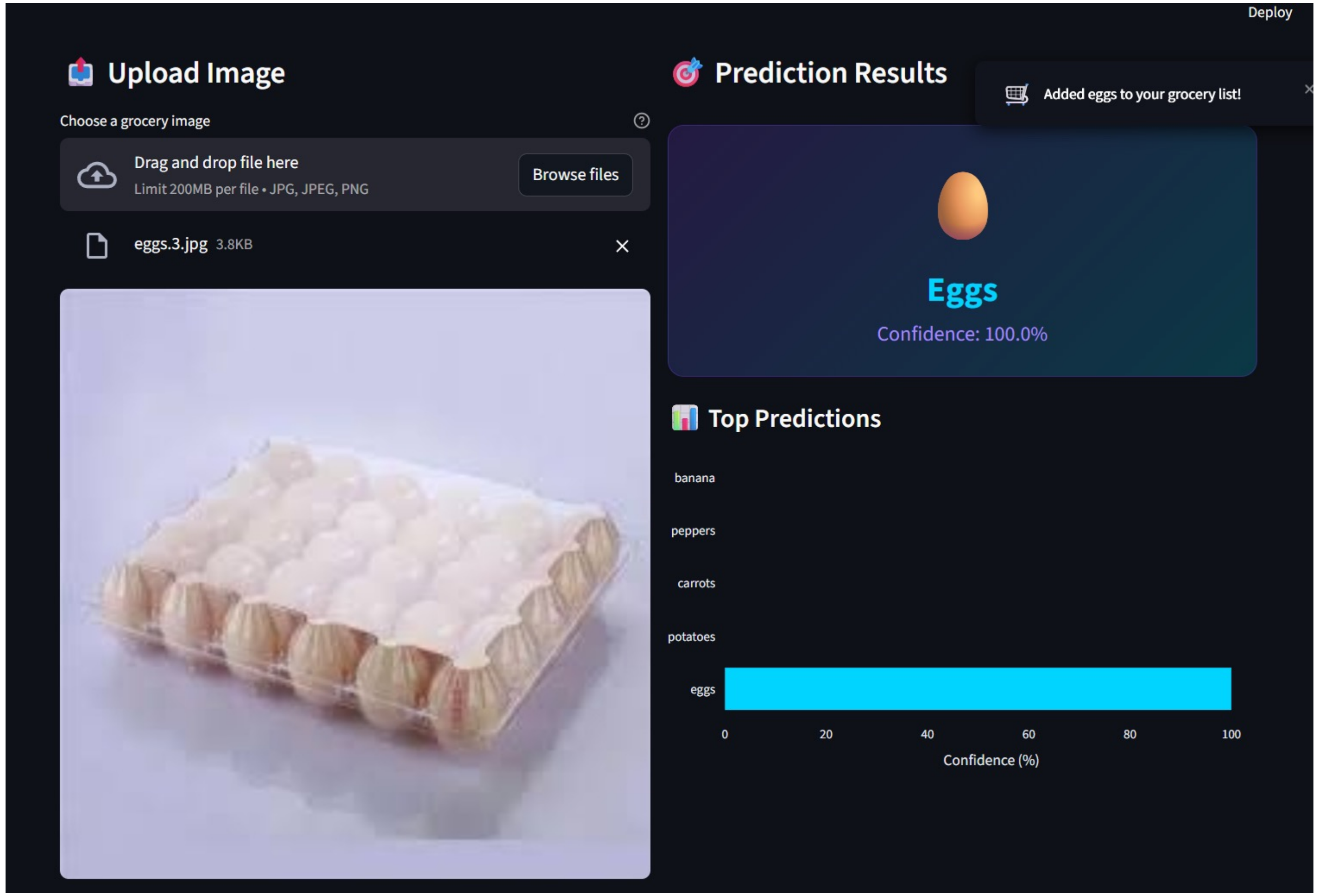
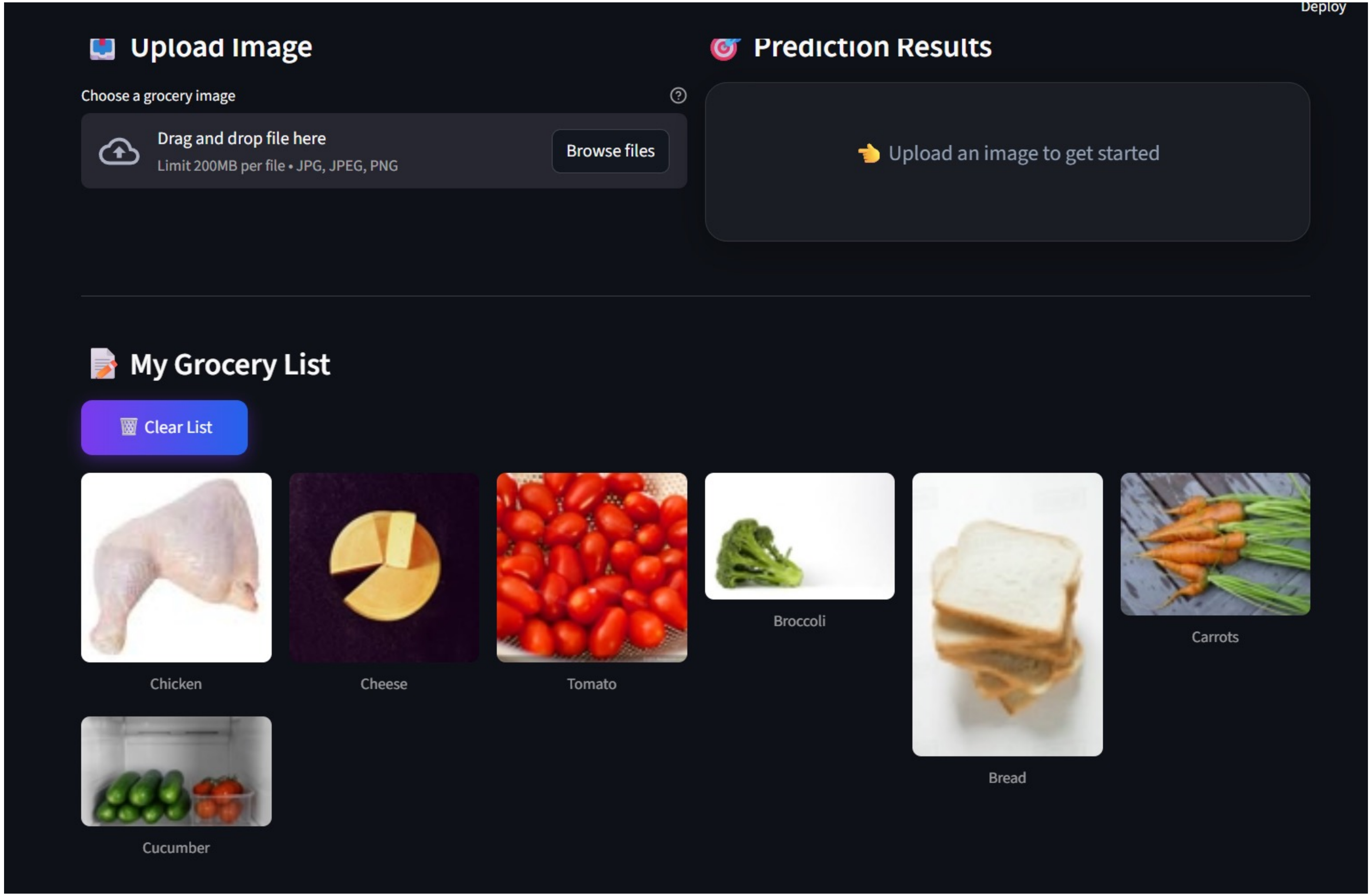


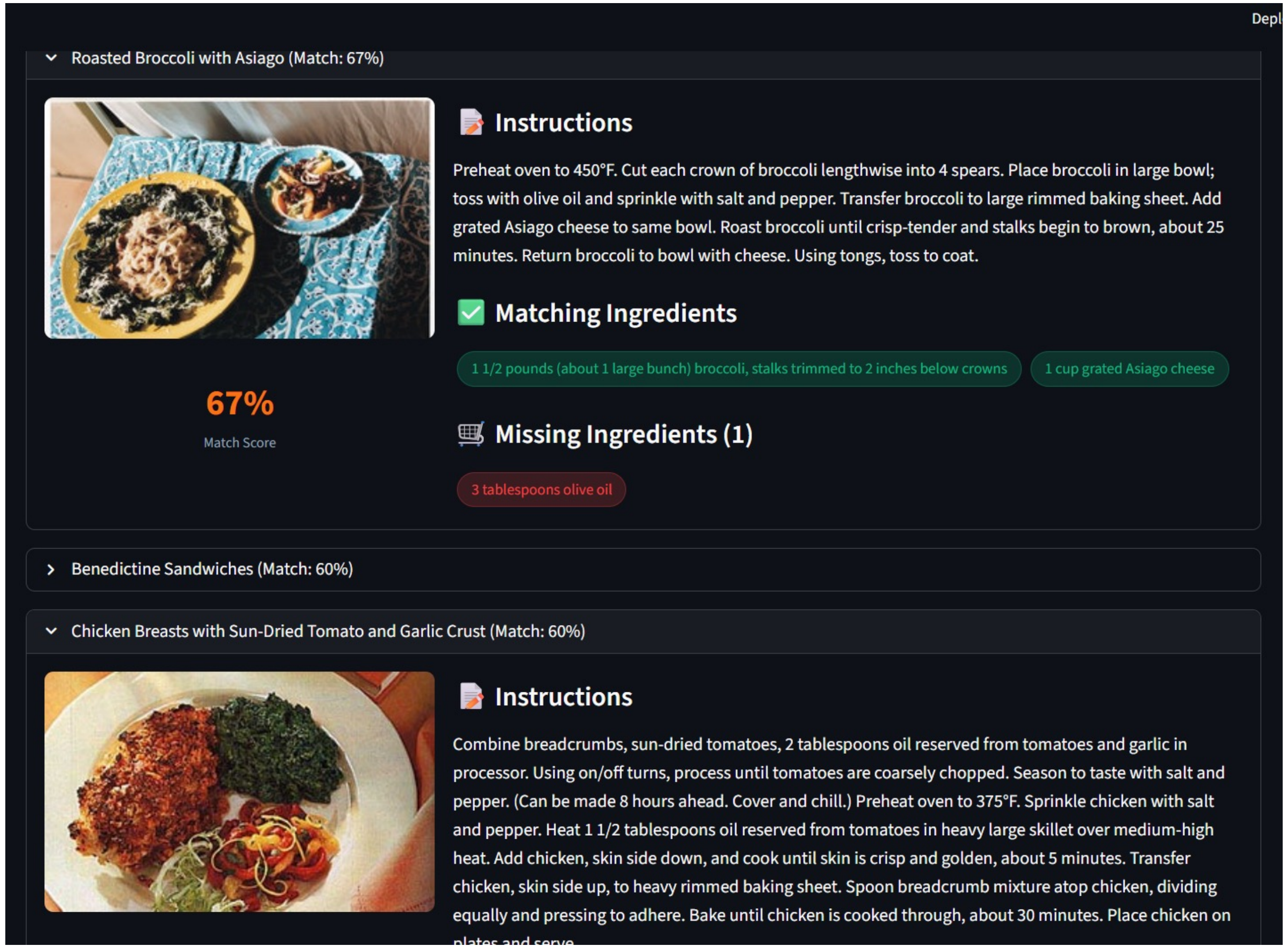
Image Prediction
Upload Image
Choose a grocery image
Drag and drop file here
Limit 200MB per file • JPG, JPEG, PNG
Browse files
peppers.14.jpg 7.4KB
Uploaded Image
Prediction Results
Peppers
Confidence: 100.0%
Top Predictions
sausages
tomato
spinach
yogurt
peppers
0
20
40
60
80
100
Confidence (%)


Deploy
Upload Image
Choose a grocery image
Drag and drop file here
Limit 200MB per file • JPG, JPEG, PNG
Browse files
eggs.3.jpg 3.8KB
Prediction Results
Added eggs to your grocery list!
Eggs
Confidence: 100.0%
Top Predictions
banana
peppers
carrots
potatoes
eggs
0
20
40
60
80
100
Confidence (%)

Output :


Deploy
Upload Image
Choose a grocery image
Drag and drop file here
Limit 200MB per file • JPG, JPEG, PNG
Browse files
Prediction Results
Upload an image to get started
My Grocery List
Clear List
Chicken
Cheese
Tomato
Broccoli
Bread
Carrots
Cucumber

Output :



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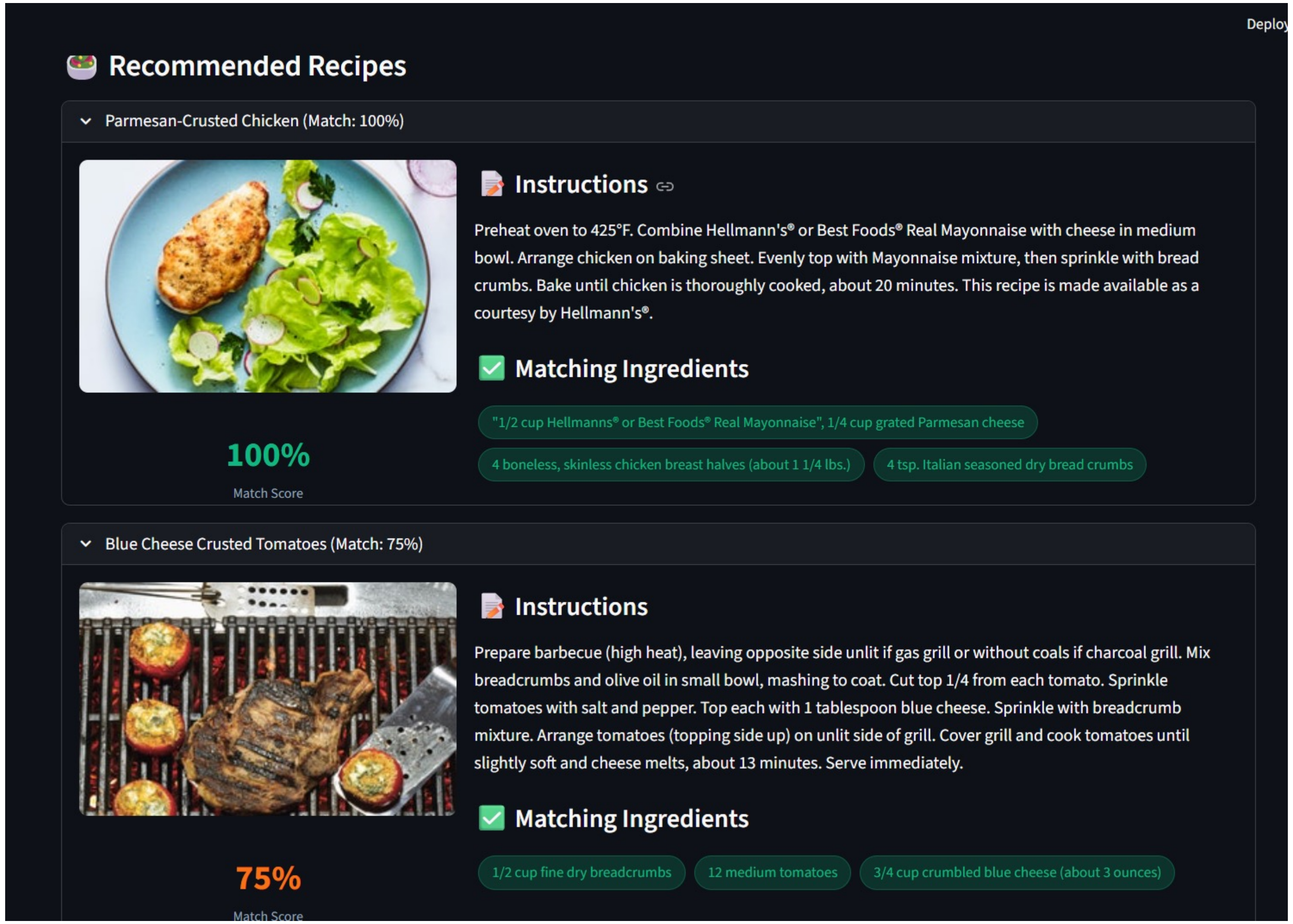
Roasted Broccoli with Asiago (Match: 67%)
Instructions
Preheat oven to 450°F. Cut each crown of broccoli lengthwise into 4 spears. Place broccoli in large bowl; toss with olive oil and sprinkle with salt and pepper. Transfer broccoli to large rimmed baking sheet. Add grated Asiago cheese to same bowl. Roast broccoli until crisp-tender and stalks begin to brown, about 25 minutes. Return broccoli to bowl with cheese. Using tongs, toss to coat.
Matching Ingredients
1 1/2 pounds (about 1 large bunch) broccoli, stalks trimmed to 2 inches below crowns
1 cup grated Asiago cheese
67%
Match Score
Missing Ingredients (1)
3 tablespoons olive oil
Benedictine Sandwiches (Match: 60%)
Chicken Breasts with Sun-Dried Tomato and Garlic Crust (Match: 60%)
Instructions
Combine breadcrumbs, sun-dried tomatoes, 2 tablespoons oil reserved from tomatoes and garlic in processor. Using on/off turns, process until tomatoes are coarsely chopped. Season to taste with salt and pepper. (Can be made 8 hours ahead. Cover and chill.) Preheat oven to 375°F. Sprinkle chicken with salt and pepper. Heat 1 1/2 tablespoons oil reserved from tomatoes in heavy large skillet over medium-high heat. Add chicken, skin side down, and cook until skin is crisp and golden, about 5 minutes. Transfer chicken, skin side up, to heavy rimmed baking sheet. Spoon breadcrumb mixture atop chicken, dividing equally and pressing to adhere. Bake until chicken is cooked through, about 30 minutes. Place chicken on plates and serve.



Deploy
Recommended Recipes
Parmesan-Crusted Chicken (Match: 100%)
Instructions
Preheat oven to 425°F. Combine Hellmann's® or Best Foods® Real Mayonnaise with cheese in medium bowl. Arrange chicken on baking sheet. Evenly top with Mayonnaise mixture, then sprinkle with bread crumbs. Bake until chicken is thoroughly cooked, about 20 minutes. This recipe is made available as a courtesy by Hellmann's®.
Matching Ingredients
"1/2 cup Hellmanns® or Best Foods® Real Mayonnaise", 1/4 cup grated Parmesan cheese
4 boneless, skinless chicken breast halves (about 1 1/4 lbs.)
4 tsp. Italian seasoned dry bread crumbs
100%
Match Score
Blue Cheese Crusted Tomatoes (Match: 75%)
Instructions
Prepare barbecue (high heat), leaving opposite side unlit if gas grill or without coals if charcoal grill. Mix breadcrumbs and olive oil in small bowl, mashing to coat. Cut top 1/4 from each tomato. Sprinkle tomatoes with salt and pepper. Top each with 1 tablespoon blue cheese. Sprinkle with breadcrumb mixture. Arrange tomatoes (topping side up) on unlit side of grill. Cover grill and cook tomatoes until slightly soft and cheese melts, about 13 minutes. Serve immediately.
Matching Ingredients
1/2 cup fine dry breadcrumbs
12 medium tomatoes
3/4 cup crumbled blue cheese (about 3 ounces)
75%
Match Score

Measuring Success: Evaluation Metrics

For our project, we selected ResNet18, a renowned Convolutional Neural Network architecture, for its balance of depth and computational efficiency.

	Label Propagation	**Label Spreading**	**Self-Training (Pseudo-Labeling)**
Train accurancy	95.04%	96.54&	100%
Test accurency	77.36%	77.53%	77.94%
F1 Score	0.77	0.77	0.78
Recall	0.77	0.78	0.78
Precision	0.78	0.78	0.78

Results and Observations

The experimental results show that **Self-Training** is the most effective semi-supervised method for this task.

- **Best overall performance** – Self-Training outperforms Label Propagation and Label Spreading
- **Scalability** – Handles large unlabeled datasets efficiently
- **Stable learning** – High-confidence pseudo-labels improve accuracy
- **Practical suitability** – Well adapted to real-world grocery image classification

Thank You !

We appreciate your attention and welcome any questions.