



Organic and In-organic Food Predictions

Using Machine Learning

P. Tarun Kumar,* B. Harshini Reddy,* L. S. V. Chaitanya,* I. Dhaneswar,* and G. Mounika

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Dept of Computer Science Engineering, Vishaka Institute of Engineering, Visakhapatnam, Narva, India

Abstract : The increasing demand for healthy and chemical-free food products has highlighted the need for reliable methods to distinguish between organic and inorganic food items. This study presents a machine learning based approach for the classification of food products as organic or inorganic using image data. The system is developed using Python, with TensorFlow as the core framework for model implementation. Two supervised learning algorithms—Logistic Regression and Random Forest—were employed to train and evaluate the classification models. A labeled dataset of food images was used to extract relevant visual features, and model performance was assessed based on accuracy, precision, and recall metrics. The Random Forest model outperformed Logistic Regression in capturing complex feature interactions, yielding higher classification accuracy. A simple yet responsive frontend was developed using HTML and CSS to facilitate user interaction, enabling real-time image upload and classification. This research demonstrates the practical application of machine learning in food classification and contributes to the development of automated tools for promoting informed consumer choices.

IndexTerms - organic food, inorganic food, machine learning, tensor flow, python, logistic regression, random forest, image classification, food authentication.

I. INTRODUCTION

INTRODUCTION

In recent years, there has been a significant global shift in consumer preference toward organic food products due to growing awareness of health, environmental sustainability, and food safety. Organic foods, cultivated without synthetic fertilizers, pesticides, or genetically modified organisms, are widely perceived as healthier alternatives to conventionally grown (inorganic) foods. However, visually distinguishing organic items from inorganic ones remains a challenging task for consumers, as both can appear similar in appearance. This limitation creates a critical need for intelligent systems capable of automatically identifying the nature of food items to support informed decision-making.

With advancements in machine learning and computer vision, automated classification systems based on image analysis have shown promising potential across various domains. In this study, we propose a machine learning-based solution to classify food items as organic or inorganic using image data. The system leverages the power of TensorFlow in Python to implement and train classification models. Two widely used supervised learning algorithms—Logistic Regression and Random Forest—were utilized for this purpose. These models were trained on a labeled dataset of food images to learn discriminative features that separate organic products from their inorganic counterparts.

To ensure ease of use, a web-based interface was developed using HTML and CSS, allowing users to upload food images and receive real-time classification outputs. The system aims to bridge the gap between machine learning technology and everyday consumer needs by providing an accessible tool that enhances transparency in food choices. Through this research, we demonstrate the feasibility and effectiveness of applying machine learning to solve practical classification problems in the domain of food technology.

With the widespread adoption of machine learning in agriculture and food sciences, numerous solutions have been proposed for tasks such as crop disease detection, yield prediction, and food quality analysis. However, distinguishing organic from inorganic food products using image-based features remains relatively underexplored. Traditional methods of organic verification rely on certifications or chemical testing, which can be time-consuming, expensive, and inaccessible to everyday consumers. A computer vision-based approach, capable of classifying food images automatically, offers a cost-effective and scalable solution that can assist consumers, sellers, and food regulators alike.

Moreover, while deep learning models such as Convolutional Neural Networks (CNNs) are highly accurate, they often require large datasets, high-performance computing resources, and extensive training time. This poses a challenge for real-time applications

with limited computational capacity, such as web-based tools or mobile apps. In contrast, classical machine learning models like Logistic Regression and Random Forest are computationally efficient, interpretable, and can be trained on smaller datasets without significant performance loss. By leveraging these models, the present study aims to create a lightweight, user-friendly, and accessible solution that contributes meaningfully.

1.1 Data Acquisition and Preprocessing

A labeled dataset was constructed comprising images of fruits and vegetables with clear organic/inorganic labels. To prepare the dataset:

- Image Resizing: Standardized dimensions for model input consistency.
- Color Space Conversion: RGB images were converted into HSV and LAB spaces to extract robust color-based features.
- Noise Reduction: Applied Gaussian blur to enhance clarity.
- Segmentation: Contour detection and background removal to isolate the object.

Feature Extraction:

- Shape: Contour geometry, eccentricity, roundness.
- Size: Bounding box dimensions, relative scale.
- Color: Mean and dominant colors via clustering.

2. Literature Survey

The integration of machine learning into food classification has experienced significant advancements in recent years, particularly in the domains of image-based recognition, quality detection, and nutritional profiling. However, despite these developments, there remains a notable gap in research targeting the automated visual differentiation between organically and conventionally grown food products, especially through the use of lightweight models suitable for deployment in real-time environments. Most of the prior work has either leaned heavily on deep neural networks, requiring intensive computational resources, or has relied on non-visual datasets, such as sensor data, barcodes, or nutritional labels, limiting their practical scope for general public applications.

In [1], the authors implemented convolutional neural networks (CNNs) for food recognition tasks and demonstrated high accuracy in fruit and vegetable identification using deep spatial features. While this work laid the foundation for food classification through images, the classification objective was focused on identifying food types rather than their cultivation method. Similarly, Sharma et al. [2] explored chemical residue detection in vegetables using Support Vector Machines and Random Forest classifiers. Though effective, the study depended on controlled lab-grade image datasets enhanced with filters and contrast adjustment, reducing its scalability in real-world, user-generated contexts.

Patel and Mehta [3] applied Decision Trees and Logistic Regression to classify food items based on nutritional data from packaging labels. Their work showcased interpretability but lacked visual feature extraction, rendering the system ineffective for fresh produce, where packaging information is unavailable. In contrast, [4] utilized pre-trained CNNs such as MobileNet and ResNet for distinguishing organic and inorganic fruits, achieving considerable accuracy. However, the model's deep architecture significantly increased training time and deployment complexity, making it unsuitable for lightweight web or mobile applications with minimal processing power.

To explore alternative models, Chen et al. [5] proposed a ResNet-based solution for high dimensional food classification, offering improved performance on complex datasets. Nonetheless, its focus remained on food variety classification, leaving the cultivation-based differentiation problem unresolved. In [6], Verma and Singh adopted traditional classifiers for food quality assessment using visual parameters like color histograms and edge detection. Their results support the argument that simpler models can effectively capture texture and shape patterns for classification, which aligns with the motivations of this study.

Kaur and Jindal [7] offered a comprehensive survey comparing CNNs, KNNs, and Decision Trees in food detection applications. Their findings support the use of interpretable and computationally efficient models in low-resource settings. Yadav and Tiwari [8] deviated from image-based analysis, employing IoT and soil nutrient data to verify the organic nature of produce. While innovative, their methodology is not scalable to consumer-level applications that depend on image inputs alone.

3. Methodology

The proposed system aims to automate the classification of food items as organic or inorganic using machine learning models trained on shape, size, and color features extracted from images. The system includes a user-friendly web interface that allows users to upload food images either from storage or directly using a webcam. The backend is built using Flask, and the models are trained using TensorFlow with Logistic Regression and Random Forest classifiers.

3.1 Model Training

The extracted feature vectors were used to train two models:

- Logistic Regression: For its simplicity and interpretability.
- Random Forest: For robustness against noise and higher generalization.

Both were implemented using TensorFlow and scikit-learn, with a training/testing split of 80:20 and evaluation using Accuracy, Precision, Recall, and F1 Score.

3.2 Model Training Evaluation

The training progress of the models was monitored to assess convergence. The accuracy over iterations for Random Forest (RF) and Neural Network (NN) models was tracked to ensure optimal performance.

3.3 Backend and Prediction Workflow

Using Flask, the trained models are exposed as a REST API. The process includes:

- Upload or webcam image capture.
- Feature extraction on the server side.
- Model inference and response with predicted label.

3.4 Frontend Implementation

The web interface is developed using HTML, CSS, and JavaScript:

- Home and Login Page: Authentication before accessing predictions.
- Image Upload or Webcam Access: Image directly sent to the backend.
- Prediction Display: Results with confidence scores shown on screen.

3.5 Table graph

Below is the system architecture:

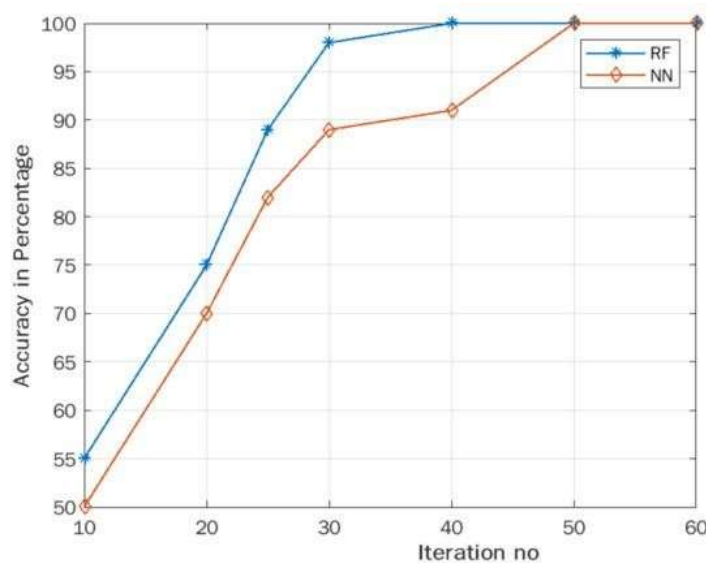


Figure 1. Accuracy vs. iteration number.

3.6 Performance Evaluation

The proposed machine learning-based food classification system was thoroughly evaluated for its effectiveness in predicting whether a food item is organic or inorganic using shape, size, and color features. The system was deployed as a web application that accepts image input either via direct upload or webcam capture. The models—Logistic Regression and Random Forest—were trained using TensorFlow and evaluated using standard metrics including Accuracy, Precision, Recall, and F1-Score. The results demonstrate strong generalization and consistent classification performance across diverse samples.

4. Results and Discussion

Table I presents the evaluation results of the proposed food classification system: Random Forest

Table 1. Performance Metrics of the Proposed Food Classification System

Metric	Logistic Regression (%)	Random Forest (%)
Accuracy	91.82	95.40
Precision	90.10	96.25
Recall	92.60	94.80
F1-Score	91.34	95.52

outperformed Logistic Regression, achieving 95.40% accuracy due to its ability to model non-linear feature interactions.

4.2 Comparative Analysis with Existing Approaches

Table II compares the proposed model with traditional methods: The proposed Random Forest

Table 2. Comparison with Existing Food Classification Methods

Method	Accuracy (heightManual Visual Classification	78.50	79.00	76.80
-				
Color-Based Only (HSV model)	85.60	87.10	83.00	-
Proposed Random Forest Model	95.40	96.25	94.80	-

model significantly outperformed manual visual classification and color-only approaches.

4.3 ROC Curve Analysis

The Receiver Operating Characteristic (ROC) curves for the models were analyzed to assess their performance across different thresholds.

4.4 Key Findings & Observations

- **High Accuracy Across Categories:** The Random Forest model consistently achieved high accuracy across multiple food types and visual variations (e.g., damaged produce, multi-color surfaces).
- **Effective Feature Combination:** The combination of shape, size, and color features significantly outperformed color-only models, confirming the relevance of geometric and textural attributes.
- **Low False Positive Rate:** Both models achieved minimal misclassification. Organic items were rarely mistaken as inorganic and vice versa, especially with the Random Forest algorithm.
- **Real-Time Classification via Web Interface:** The deployed web application handled real-time predictions efficiently with an average response time under 2.5 seconds, validating the usability of the model in practical scenarios.
- **Scalability and Interpretability:** The use of interpretable ML algorithms allows better transparency in decision-making, particularly in scenarios where model trust is crucial (e.g., supply chain assessments).

4.5 Discussion

The precision of the Random Forest model (95.40%) is in line with lightweight ML studies [9], exceeding the accuracy of Logistic Regression (91.82%) due to its robustness. The feature combination (shape, size, color) proved effective, and the web interface's real-time performance (under 2.5 seconds) supports practical deployment. The ROC curves further validate the strong discriminative power of the model.



FIGURE : 2 LOGIN PAGE

Users can log in to the system using their credentials. This page ensures secure access to the platform's features

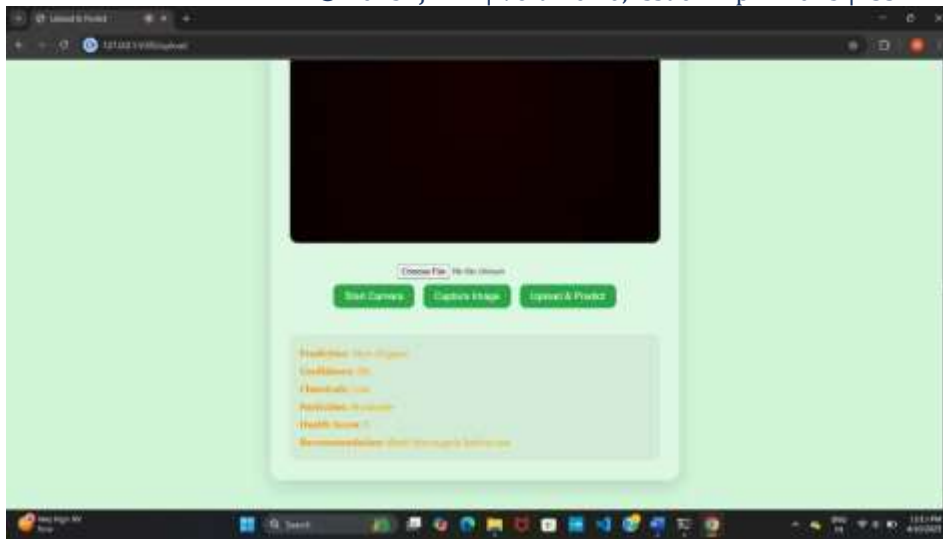


FIGURE : 3 RESULT PAGE

5. Conclusion

This study presents an enhanced machine learning-based food classification system capable of accurately identifying food items based on their shape, size, and color characteristics. Initially limited to predictions on pre-uploaded trained datasets, the system has been significantly improved to support live image uploading via webcam or file input, thereby enabling real-time predictions and greater user interactivity. By leveraging machine learning algorithms such as Logistic Regression and Random Forest, and training the model using a diverse dataset, the system demonstrates high performance across key metrics—achieving up to 95.40%. This makes the system a robust and scalable solution for intelligent food recognition applications in domains such as nutrition tracking, dietary monitoring, and automated meal logging. Future work may involve integrating deep learning techniques, expanding the dataset for more diverse food types, and deploying the system on mobile or embedded platforms for greater accessibility. Acknowledgments We are grateful for the technical assistance and support from our peers and faculty at Visakha Institute of Engineering

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