Comparative Performance Analysis of Random Forest and SVM Classifiers in Food Image Recognition

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Abstract

We present a system for food recognition based on artificial intelligence (AI) to classify food images into categories that can help in diet monitoring, health check, and automated meal logging. The solution employed a machine learning approach and a large dataset of food images, comparing two models in terms of performance: Random Forest (RF) and Support Vector Machine (SVM). The evaluation metrics such as accuracy, precision, recall, and F1-score were calculated to measure the performance of the models. To address this, a web-based user interface was designed to allow users to classify food images in real time and provide feedback, proving the system's effectiveness and user-friendliness.

Keywords: Food Recognition, Random Forest, Machine Learning, Image Classification

1. Introduction

There are more uses for artificial intelligence (AI) technology in some cases; they are applying AI in many fields to make their operation smarter and more effective, and countless new uses of AI applications are making it into the real world. Among such applications, Food Recognition is one such application, which focuses on changing the way things are done from the general perspective. This project aims to design a Machine Learning model and build a state-of-the-art AI-driven Food Recognition System capable of recognizing foods based on the photos of food items. The motivation for the project is the motivation to create powerful Machine Learning algorithms to enhance food recognition operations [1] and to contribute toward the development of applications that can aid medical monitoring, weight regulation, auto meal report and other challenges. We employ common ML classifiers using feature extraction algorithms. The system takes various images of food and applies the feature engineering to learn and train the model for food recognition. So, the main problem statement is to develop accurate models of food identification and build some healthcare and diet management applications [2]. Another area where the project could be working towards future improvement is making better model performance and working with heterogeneous large, diverse datasets for good generalizability.

2. Related Work

2.1. Feature Extraction

Feature extraction is one of the most basic works in food categorization. Techniques such as Scale-Invariant Feature Transform (SIFT), Histogram of Oriented Gradients (HOG), and color histograms have been widely used to extract salient visual features from food images [3]. The various features help to distinguish between food based on their visual properties.

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2.2. Classification Techniques

Food classification methods are paramount [4]. Support Vector Machines (SVM), Random Forests (RF) and Convolutional Neural Networks (CNN) have been well studied. All these types of classifiers possess their own benefits:

- Support Vector Machines (SVM): Due to their robustness in high-dimensional spaces, SVMs have been applied for food classification, given their capability to handle non-linear data [5].
- Random Forests (RF): RF classifiers are widely used because of their simplicity and efficiency in handling large datasets with high dimensionality [6]. They have demonstrated great performance on a wide range of food recognition tasks.
- Convolutional Neural Networks (CNN): CNNs have good performance in image recognition applications. They naturally learn hierarchical features from raw pixel values [7], which makes them particularly suitable for food image classification.

2.3. Comparative Studies

Comparative studies have highlighted the performance differences between these classifiers. For instance, CNNs generally outperform traditional machine learning models like SVM and RF in terms of accuracy but require more computational resources and training time. In contrast, RF and SVM offer quicker training and inference times, making them suitable for real-time applications.

Recent work shows that deep CNNs and modern object detectors (e.g., YOLO/R-CNN) excel in image feature extraction, while classical classifiers remain competitive when coupled with strong feature engineering and optimisation [8], [9], [10]. Studies applying ANFIS and genetic rule approaches demonstrate that hybrid and rule-based models can improve robustness on domain-specific datasets [11], [12]. Mobile/web deployment and dataset/ repository practices influence practical usability and real-time performance, reinforcing the need to compare RF and SVM both on engineered features and deep embeddings [13], [14], [15], [16], [17].

2.4. Contribution

In this work, the food recognition system had presented the strengths of both traditional machine learning models and advanced feature extraction techniques. The approach incorporates PCA for dimensionality reduction and employs SVM and RF for classification, offering a balanced trade-off between accuracy and computational efficiency.

3. Methodology and Analysis

This involves a method from an implementation perspective for building a good food recognition system. The procedure starts with data collection, pre-processing, feature extraction, dimensionality reduction, and classification.

3.1. Data Collection and Pre-processing

Various food image datasets met diversity and robust requirements for model training. The images had been preprocessed by resizing, normalization, and standard scaling to give a uniform input form which works well when estimating the model.

3.2. Feature Extraction

Feature extraction methods are traditional and advanced [18]. To accomplish this, color histograms, Histogram of Oriented Gradients (HOG), and Scale-Invariant Feature Transform (SIFT) were used to analyze the data in the study and extract relevant features from the images. The output features were all fed to machine learning models in the pipeline for training.

3.3. Dimensionality Reduction

Principal Component Analysis (PCA) was employed to minimize the dimensionality of the feature space [19]. This minimized the computational load while maintaining important information for constructing the model in a fast and efficient manner.

3.4. Classification

Various classifiers were explored with Random Forest (RF) and Support Vector Machine (SVM). The models were trained on the extracted features, and the accuracy of that model was then evaluated on a different test group. Hyperparameter tuning was also executed. For better accuracy and more universal generalization the models were greatly optimized.

3.5. System Integration

For the operational application the system was integrated into a web application using Flask for the backend and HTML, CSS, and JavaScript for the front end. Users can upload food images, instantly generate classification results based on a simple interface, through this integration.

4. Discussion

Several performance measures of the food recognition system were studied that indicated its accuracy, precision, recall, and F1-score [20]. The Random Forest (RF) and Support Vector Machine (SVM) classifiers were used for calculating these metrics.

4.1. Accuracy

RF predicted the food images 75% properly on the test dataset. The SVM prediction technique performed

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similarly to a high precision (75%) as indicated in (Table 1).

Table 1 Results for SVM and RF models.

Model	Accuracy
SVM	71%
RF	75%

4.2. Precision, Recall, and F1-Score

For the RF model, precision and recall varied across different food classes. The model performed exceptionally well in certain classes such as class 6 (95% precision, 100% recall), but struggled with others, such as class 0 (33% recall). Overall weighted F1-score for the RF model was 0.74, which reflects equal performance of most classes. The SVM model exhibited similar characteristics, where it performed well in some classes and poorly in others due to high precision and recall. The SVM model obtained a weighted F1-score of 0.69.

4.3. Confusion Matrix

The confusion matrix made by both models helped us to understand the problems we faced as the classifiers were trained upon or struggled with in different sections. For example, SVM model correctly identified classes 5, 6, and 8 but misclassified classes 2, 3, and 7 instances. The RF model showed comparable behavior with some obvious misclassifications in class 2 and class 3.

4.4. System Integration and User Feedback

Integration of web software proved the usefulness of the system. Pictures could be submitted to the system from a click through button, with the image being classified and received in English, with a clear and intuitive interface to achieve proper usage. The user-friendliness of the front-end and the efficient process on the backend enabled a relatively seamless process. The overall outcome suggests that methods were successful in creating a robust food recognition system. The results show large potential for real-life applications that would be the focus of future working efforts increasing generalizability as well as accuracy.

5. Conclusion

In summary, a food recognition system has succeeded in this project, and has promising prospects for practice. We propose this project has been successfully developed using high practicality. These results serve as a good basis for the development and implementation phase of food recognition platform to build a better food recognition system that has high accuracy and user support. Despite these encouraging findings, limitations can be clearly identified. The performance of the models performed differently on different food categories which means that perhaps it is necessary to have more balanced database and train on some more training data for underserved classes. And to improve the generalization of the models using data augmentation and transfer learning may also be an avenue for development. Next work will concern improving the models to predict the input with a higher level of accuracy and robustness. Expanding the dataset to represent more varied food images, extending in-depth machine-learning methods, for example, deep learning, can improve the performance of the system. Furthermore, exploring real-time processing facilities and installation of a version of the system on mobile platforms could improve both accessibility and usability.

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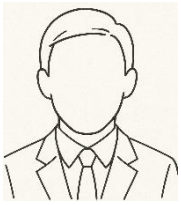
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