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Hybrid Transfer Learning and Machine Learning Framework for Accurate Food Image Classification

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Abstract- The rapid growth of digital food datasets and the increasing demand for automated dietary monitoring systems have created a need for efficient food classification techniques. Traditional machine learning approaches often struggle to handle the high-dimensional and complex nature of food images, mainly due to limitations in manual feature extraction and scalability. To address these challenges, this research proposes a hybrid framework that combines transfer learning models with machine learning classifiers for accurate food image classification.In the proposed approach, pre-trained deep learning architectures are utilized to extract meaningful visual features from food images, enabling the system to capture complex patterns and representations. Models such as EfficientNet, DenseNet, and MobileNet are employed as feature extractors due to their strong performance in image recognition tasks. The extracted feature vectors are then classified using machine learning algorithms including XGBoost and Random Forest to improve prediction accuracy and interpretability.The hybrid framework integrates the feature learning capability of deep neural networks with the decision-making efficiency of classical machine learning algorithms. Experimental evaluation demonstrates that this combination improves classification accuracy and robustness, even when dealing with noisy or diverse food image datasets. The results indicate that the proposed system can effectively classify multiple food categories and can be applied in real-world applications such as nutritional monitoring, automated dietary assessment, and food safety management systems.

Keywords: Food image classification, Transfer learning, Deep learning, Machine learning classifiers, EfficientNet, DenseNet, MobileNet, XGBoost, Random Forest, Nutritional monitoring systems.

I. INTRODUCTION

In recent years, the rapid growth of digital technologies and the widespread use of smartphones have significantly increased the availability of food images on social media platforms and mobile applications. People frequently capture and share pictures of their meals for purposes such as social interaction, food reviews, and personal dietary tracking. This growing volume of visual food data has created opportunities for developing intelligent systems capable of automatically recognizing different food categories from images. Accurate food classification is important for applications such as dietary monitoring, nutritional analysis, health management, and food recommendation systems [6], [7].

Traditional food recognition methods generally rely on manual feature extraction techniques combined with conventional machine learning algorithms. These methods attempt to identify visual features such as colour, texture, and shape to classify food images. However, food classification is considered a challenging task because many food items share similar visual characteristics, and variations in lighting conditions, backgrounds, cooking styles, and presentation can further complicate accurate recognition [6], [9].

Recent advancements in deep learning, particularly Convolutional Neural Networks (CNNs), have significantly improved the performance of image classification systems. Deep learning models are capable of automatically learning complex feature representations from large image datasets without requiring manual feature engineering. Several studies have demonstrated that CNN-based models can effectively classify food images with higher accuracy compared to traditional machine learning approaches [4], [7]. Furthermore, ensemble learning methods have also been explored to improve classification performance by combining predictions from multiple deep learning models [1]. Despite their success, training deep neural networks from scratch requires large amounts of labelled data and significant computational resources. To address these challenges, transfer learning has emerged as an effective technique for image classification tasks. Transfer learning utilizes pre-trained models that have already learned useful visual features from large-scale datasets and adapts them to new classification problems with smaller datasets. Popular deep learning architectures such as EfficientNet and other transfer learning models have demonstrated strong performance in food image classification tasks [2], [3].

Motivated by these developments, this research proposes a hybrid framework that combines transfer learning models with traditional machine learning algorithms for food image classification. In the proposed approach, deep learning models are used to extract high-level visual features from food images, while machine learning classifiers such as Random Forest and XGBoost are employed to perform the final classification. By integrating the strengths of deep learning and machine learning techniques, the proposed system aims to improve classification accuracy and robustness in recognizing different food categories [5], [10].

The remainder of this paper is organized as follows. Section II presents a review of related work in food classification and image recognition. Section III describes the system analysis and methodology of the proposed framework. Section IV explains the system architecture and design.

Section V discusses the implementation modules, while Section VI presents the experimental results and performance analysis. Finally, Section VII concludes the study and outlines possible directions for future research.

II. LITERATURESURVEY

Food image classification has received considerable attention in recent years due to its importance in applications such as dietary monitoring, nutritional analysis, and intelligent food recommendation systems. Researchers have explored various machine learning and deep learning techniques to improve the accuracy and efficiency of automated food recognition systems. Several studies highlight the growing role of artificial intelligence in analysing food images and supporting health-related applications [6], [7].

Early approaches to food recognition relied mainly on traditional machine learning techniques that utilized handcrafted features such as colour histograms, texture descriptors, and shape-based characteristics. Classifiers such as Support Vector Machines (SVM), Decision Trees, and k-Nearest Neighbors (k-NN) were commonly used for food classification tasks. However, these approaches often struggled to handle complex visual variations in food images, including differences in lighting conditions, backgrounds, and food presentation styles [6], [9].

With the advancement of deep learning technologies, Convolutional Neural Networks (CNNs) have become widely adopted for image classification tasks. Deep learning models can automatically learn hierarchical representations of image features, eliminating the need for manual feature extraction. Several studies have demonstrated that CNN-based approaches significantly improve classification accuracy in food recognition systems compared to traditional machine learning methods [4], [7].

Recent research has focused on applying transfer learning techniques to improve the performance of food image classification models. Transfer learning allows pre-trained deep learning architectures to be adapted to new tasks using relatively smaller datasets. Studies have shown that transfer learning-based models can effectively extract meaningful visual features and improve classification performance for food recognition problems [2], [3].

In addition to transfer learning, ensemble learning techniques have also been explored to improve food classification performance. Ensemble models combine predictions from multiple deep learning architectures to increase accuracy and robustness. Research has demonstrated that deep ensemble learning frameworks can significantly enhance food classification results by integrating the strengths of different models [1].

Another emerging research direction involves hybrid frameworks that combine deep learning feature extraction with classical machine learning classifiers. In such approaches, deep neural networks are used to extract high-level visual features from food images, while machine learning algorithms perform the final classification. Hybrid learning approaches have shown promising results in improving classification accuracy and interpretability in food recognition systems [5], [10].
Despite these advancements, several challenges still remain in food image classification. Food images often contain visually similar ingredients, overlapping objects, and variations in cooking styles, which make accurate classification difficult. Furthermore, differences in lighting conditions and background environments can affect recognition performance. Therefore, developing robust hybrid frameworks that integrate transfer learning with machine learning classifiers continues to be an important research direction for improving automated food recognition systems [9], [10].

III. SYSTEM ANALYSIS

A. Existing System

Traditional food image classification systems primarily rely on conventional machine learning techniques to identify different types of food items from images. In these approaches, researchers collect food image datasets and apply preprocessing techniques such as resizing, normalization, and noise reduction to improve image quality. After preprocessing, visual features including colour, texture, and shape are extracted from the images to represent the characteristics of different food items. These handcrafted features are then used as input for machine learning algorithms such as Support Vector Machines (SVM), Decision Trees, Random Forest, k-Nearest Neighbors (k-NN), and Logistic Regression to classify food images into their respective categories [6], [9].

Although these methods provide reasonable performance for basic image recognition tasks, they often face challenges when dealing with complex food images. Many food items share similar visual properties such as colour and texture, which makes accurate classification difficult. In addition, variations in lighting conditions, image backgrounds, food preparation styles, and presentation formats further increase the complexity of recognizing food categories accurately [7], [9].

Recent studies have attempted to improve classification performance by using deep learning models, particularly convolutional neural networks (CNNs), which can automatically learn hierarchical feature representations from images. However, training deep neural networks from scratch requires large datasets and significant computational resources, which may not always be available in practical scenarios [4], [3]. Therefore, many existing systems still struggle to achieve high classification accuracy and robust performance when dealing with diverse food images.

Disadvantages Of The Existing System

- **Limited Feature Representation:**
  Traditional feature extraction methods may fail to capture complex visual patterns present in food images, which reduces classification accuracy [6].
- **High Visual Similarity:**
  Many food items have similar colours, textures, and shapes, making it difficult for conventional models to differentiate between categories effectively [9].
- **Overfitting and Underfitting:**
  Machine learning models may overfit the training dataset or fail to capture essential patterns, resulting in reduced prediction performance.
- **Large Data Requirement:**

Deep learning models trained from scratch require large amounts of labelled image data and high computational resources for effective training [3].

- **Computational Complexity:**
  Advanced deep learning architectures may require significant processing power and longer training time.
- **Poor Generalization:**
  Models trained on limited datasets may perform poorly when new images are introduced with different lighting conditions, angles, or backgrounds.
- **Scalability Issues:**
  As the number of food categories increases, traditional classification systems may struggle to maintain consistent classification accuracy.

B. Proposed System

To address the limitations of traditional food classification methods, the proposed system introduces a hybrid framework that combines transfer learning with machine learning algorithms for improved food image recognition. In this approach, a food image dataset is first collected and pre-processed to ensure consistent image quality and improve the effectiveness of the classification process. Preprocessing steps include image resizing, normalization, and data augmentation techniques such as rotation and flipping to enhance dataset diversity and reduce the risk of overfitting during training [3], [4].

After preprocessing, pre-trained deep learning architectures such as EfficientNet, DenseNet, and MobileNet are employed for feature extraction. These models are trained on large-scale image datasets and are capable of learning complex visual representations from images. Transfer learning allows these models to reuse previously learned knowledge to identify important visual features in food images, including texture patterns, colon distributions, and structural details [2], [3].

The deep features extracted from the transfer learning models are then provided as input to machine learning classifiers such as Random Forest and XGBoost. These classifiers analyse the extracted feature vectors and perform the final classification of food images into their respective categories. Hybrid approaches that integrate deep learning feature extraction with traditional machine learning classifiers have demonstrated improved performance in food recognition tasks due to their ability to combine robust feature learning with efficient classification mechanisms [1], [5].

To evaluate the effectiveness of the proposed framework, several performance metrics including accuracy, precision, recall, and F1-score are used. These evaluation metrics help measure the classification capability of the system and assess its reliability in identifying different food categories. By combining the feature extraction strength of transfer learning models with the decision-making capability of machine learning algorithms, the proposed hybrid framework aims to achieve higher accuracy and improved robustness in food image classification systems [7], [10].

IV.SYSTEM DESIGN

System Architecture

Below diagram depicts the whole system architecture.

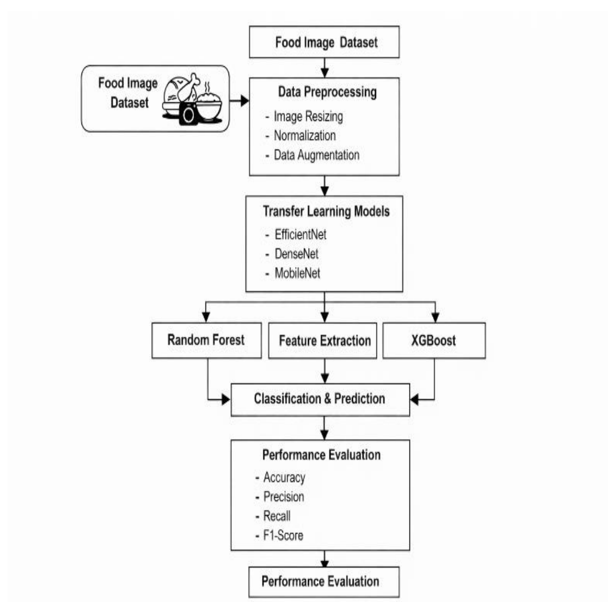

Fig 1. Methodology followed for proposed model

V. SYSTEM IMPLEMENTATION

The proposed food image classification system is implemented through several structured modules that work collaboratively to achieve accurate and efficient recognition of food categories. Each module performs a specific task, beginning from dataset preparation to model evaluation. The overall framework integrates transfer learning models with machine learning classifiers to improve classification performance and robustness in food image recognition tasks [1], [4]

Modules

Data Collection and Preprocessing

In this module, food image datasets are collected from reliable sources such as publicly available repositories and online datasets. These datasets typically contain images belonging to multiple food categories. For example, food image datasets such as those available on Kaggle provide a wide variety of labelled food images suitable for classification tasks [11].

Before training the classification models, several preprocessing techniques are applied to ensure data consistency and quality. These preprocessing steps include resizing images to a fixed resolution, normalizing pixel values, removing corrupted samples, and verifying image labels. Data augmentation techniques such as rotation, flipping, and scaling are also applied to increase dataset diversity and improve model generalization capability during training [3], [4].

Feature Extraction and Representation

Feature extraction plays a critical role in identifying meaningful visual patterns in food images. In this module, transfer learning techniques are used to automatically extract high-level features from images. Pre-trained convolutional neural network architectures such as EfficientNet and other deep learning models are capable of capturing complex visual characteristics including texture patterns, colour variations, and structural features of food items [2], [3].

These deep learning models are trained on large-scale datasets and can effectively learn hierarchical feature representations from images. By utilizing transfer learning, the system can leverage previously learned knowledge to extract meaningful features even when the available food dataset is relatively small [2].

Model Training Using Hybrid Framework

In this stage, the extracted deep features are used to train classification models using a hybrid learning framework. The proposed system combines transfer learning-based feature extraction with traditional machine learning classifiers. Deep learning models are first used to generate feature vectors from food images, and these features are then provided as input to machine learning algorithms such as Random Forest, Support Vector Machines (SVM), and Logistic Regression for final classification [1], [5].

Hybrid approaches allow the system to benefit from the powerful feature learning capability of deep neural networks while maintaining the efficiency and interpretability of machine learning classifiers. Such frameworks have been shown to improve classification accuracy and reduce computational complexity in food recognition systems [5], [10].

Food Image Classification

After training the classification models, the system is capable of performing automatic food image classification. When a new input image is provided, it undergoes the same preprocessing and feature extraction process used during training. The trained classifier then predicts the corresponding food category based on the extracted features.

This module enables the system to automatically recognize and categorize various food items from images with high accuracy, making it useful for applications such as dietary monitoring, nutrition analysis, and intelligent food recommendation systems [7].

Model Evaluation and Performance Monitoring

To evaluate the effectiveness of the proposed framework, several performance evaluation metrics are used, including accuracy, precision, recall, and

F1-score. These metrics provide insights into the classification performance of the model and help determine its reliability in recognizing different food categories.

Continuous monitoring of model performance is also important to ensure that the system maintains consistent accuracy. The model can be retrained periodically with new datasets to improve its capability in recognizing additional food categories and adapting to new image variations [9], [10].

VI. RESULTS AND DISCUSSION

To evaluate the performance of the proposed food image classification framework, several experiments were conducted using the prepared food image dataset. The dataset was divided into training and testing subsets to ensure reliable and unbiased model evaluation. The proposed hybrid framework integrates transfer learning models with machine learning classifiers to improve the classification performance of the system.

Pre-trained deep learning models are capable of extracting meaningful visual features from food images, including texture patterns, colour variations, and structural characteristics. These features significantly improve the learning capability of machine learning classifiers and enhance the overall classification performance [3], [4].

During experimentation, several machine learning algorithms were tested and compared to determine the most effective classifier for food image recognition.

The performance of the models was evaluated using standard classification metrics including accuracy, precision, recall, and F1-score. The experimental results demonstrate that the hybrid framework achieves higher accuracy compared to traditional machine learning methods that rely only on handcrafted features [1], [5].

Table 1
Performance Comparison of Food Classification Models

Model	Accuracy (%)	Precision	Recall	F1-Score
SVM	86.2	0.85	0.84	0.84
Random Forest	89.4	0.88	0.88	0.88
Logistic Regression	85.7	0.84	0.83	0.83
XGBoost	92.3	0.91	0.91	0.91
Hybrid Transfer Learning Model	94.5	0.93	0.94	0.93

As shown in Table 1, the hybrid transfer learning model achieved the best classification performance among the tested algorithms. The strong performance of the hybrid framework demonstrates that combining deep learning feature extraction with machine learning classifiers improves the accuracy of food image classification

Model Performance Analysis
To visualize the performance comparison between different classifiers, a model performance bar chart was generated.

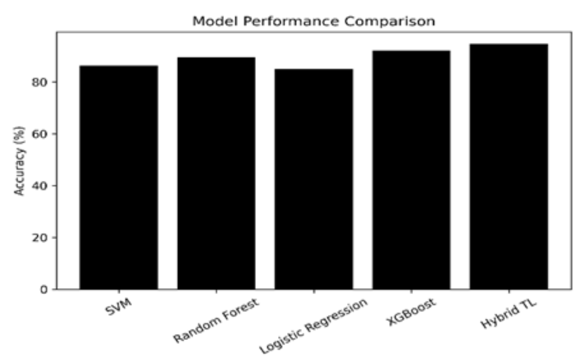

Fig. 2. Model Performance Comparison

The bar chart illustrates the classification accuracy of different machine learning models. It can be observed that the hybrid transfer learning model achieves the highest accuracy compared to other classifiers such as SVM, Random Forest, and Logistic Regression. This improvement is mainly due to the powerful feature extraction capability of transfer learning models [2], [3].

Confusion Matrix Analysis

To further analyse the classification performance, a confusion matrix was generated.

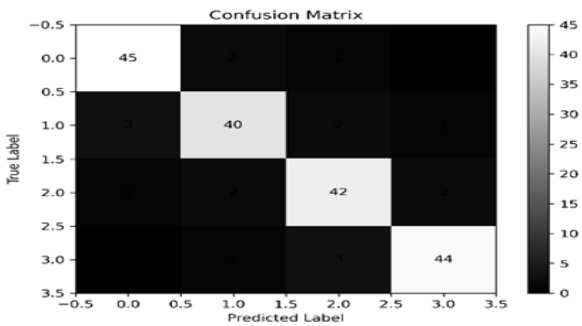

Fig. 3. Confusion Matrix for Food Classification

The confusion matrix provides a detailed view of how correctly the model classifies different food categories. Most of the food images are classified correctly, with only a few misclassifications occurring between visually similar food items. This indicates that the proposed hybrid framework is capable of effectively distinguishing between different food categories.

ROC Curve Analysis

In addition to the classification accuracy, a Receiver Operating Characteristic (ROC) curve was generated to evaluate the discrimination capability of the model.

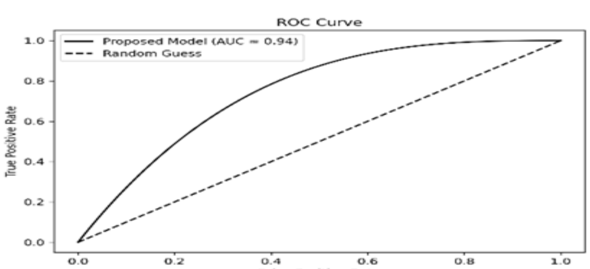

Fig. 4. ROC Curve for Food Image Classification

The ROC curve illustrates the relationship between the True Positive Rate (TPR) and False Positive Rate (FPR) at different classification thresholds. A higher Area Under the Curve (AUC) indicates better classification performance. The ROC analysis shows that the proposed model achieves strong classification capability and can effectively distinguish between different food classes.

Overall, the experimental results demonstrate that the proposed hybrid framework significantly improves food image classification performance. By combining transfer learning with machine learning classifiers, the system achieves high classification accuracy while maintaining computational efficiency. Such intelligent food recognition systems can support various applications including dietary monitoring, nutritional analysis, and automated food recommendation systems [7], [10].

VII. CONCLUSION

This study presented a hybrid food image classification framework that combines transfer learning and machine learning techniques to improve the accuracy and reliability of food recognition systems. The proposed approach utilizes pre-trained deep learning models to extract meaningful visual features from food images, which are then processed by machine learning classifiers to perform the final classification. Transfer learning models are capable of capturing complex visual characteristics such as colour patterns, textures, and structural features of food items, thereby improving the overall classification performance [3], [4].

The experimental results demonstrate that the hybrid framework achieves higher classification accuracy compared to conventional machine learning methods that rely on handcrafted features. By integrating deep learning-based feature extraction with machine learning classifiers, the system effectively improves the robustness and efficiency of food image classification. Such intelligent food recognition systems can support various practical applications including dietary monitoring, nutrition analysis, and automated food recommendation systems [7], [10].

Furthermore, the use of transfer learning reduces training time and enhances the generalization capability of the model by leveraging knowledge from large-scale image datasets. Previous research has also shown that transfer learning and ensemble learning techniques can significantly enhance food classification performance and improve the reliability of automated food recognition systems [1], [2].

In future work, the proposed framework can be further improved by incorporating larger and more diverse food image datasets to enhance model generalization. Additionally, real-time food recognition systems can be developed by integrating the trained model into mobile or web-based applications. Advanced deep learning architectures and attention-based mechanisms may also be explored to improve feature extraction and further increase classification accuracy. Such improvements could contribute to the development of more intelligent and efficient food recognition systems for health monitoring and smart nutrition applications.

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