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An Intelligent Hybrid Transfer Learning Framework for Automated Food Image Classification

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Abstract — The increasing demand for intelligent dietary assessment and nutrition monitoring has accelerated research in automated food image classification systems. However, accurately identifying food categories remains challenging due to significant variations in appearance, illumination, background complexity, and similarities among visually related food items. Conventional machine learning techniques, which rely on handcrafted feature extraction, often fail to capture the intricate visual characteristics required for robust food recognition. To overcome these limitations, this paper presents a hybrid food image classification framework that integrates transfer learning-based feature extraction with machine learning classifiers. Pre-trained deep learning architectures, including EfficientNet, DenseNet, and MobileNet, are employed to learn rich and discriminative visual representations from food images without requiring extensive model training. The extracted deep features are subsequently processed using advanced machine learning algorithms such as Random Forest and XGBoost to perform accurate food category prediction. This hybrid strategy effectively combines the representational strength of deep neural networks with the computational efficiency and interpretability of classical machine learning methods. Experimental evaluation demonstrates that the proposed framework achieves superior classification accuracy, precision, recall, and F1-score compared with conventional image classification approaches. Furthermore, the model exhibits improved robustness when handling diverse food images captured under varying environmental conditions. The proposed framework has significant potential for practical deployment in applications such as intelligent nutrition monitoring, automated calorie estimation, healthcare support systems, and smart dietary recommendation platforms, contributing to the development of reliable AI-driven food analysis solutions.

Keywords— Food Image Classification, Transfer Learning, Deep Learning, Hybrid Learning Framework, EfficientNet, DenseNet, MobileNet, Random Forest, XGBoost, Nutritional Monitoring, Artificial Intelligenc.

I. INTRODUCTION

The rapid advancement of artificial intelligence (AI) and computer vision has significantly enhanced image analysis across various application domains, including healthcare, agriculture, autonomous systems, and food technology. Among these applications, automated food image classification has gained considerable attention due to its potential to support nutritional assessment, calorie estimation, dietary monitoring, and personalized healthcare services [6], [7]. The widespread use of smartphones and wearable devices has further increased the availability of food images, creating opportunities for developing intelligent systems capable of recognizing food items accurately and efficiently.

Despite the remarkable progress in image recognition, food image classification remains a challenging task. Many food categories exhibit highly similar visual characteristics such as colour, texture, shape, and presentation style, making it difficult to distinguish between them accurately. Moreover, variations in lighting conditions, camera viewpoints, image backgrounds, ingredient composition, and cooking styles further increase the complexity of the classification process [6], [9]. These challenges often reduce the effectiveness of conventional image recognition techniques when applied to real-world food datasets.

Traditional food classification systems primarily rely on handcrafted feature extraction methods combined with classical machine learning algorithms such as Support Vector Machines (SVM), Decision Trees, and k-Nearest Neighbors (k-NN). Although these methods perform reasonably well for simple classification tasks, they are unable to capture complex visual patterns and semantic information present in food images, resulting in limited classification accuracy and poor generalization capabilities [6], [9].

Recent advancements in deep learning have transformed image classification by enabling automatic extraction of hierarchical and discriminative visual features. Convolutional Neural Networks (CNNs) have demonstrated superior performance over traditional machine learning approaches by learning feature representations directly from image data without manual intervention [4], [7]. However, training deep neural networks from scratch requires extensive labelled datasets, high computational resources, and long training times, which may not be practical for many real-world applications.

To overcome these limitations, transfer learning has emerged as an effective and computationally efficient solution. By utilizing knowledge acquired from large-scale benchmark datasets, pre-trained architectures such as EfficientNet, DenseNet, and MobileNet can extract meaningful visual representations from food images while requiring significantly fewer training samples and reduced computational effort [2]–[4]. These models provide robust feature extraction capabilities and improve the overall performance of food recognition systems. Motivated by these developments, this research proposes a hybrid food image classification framework that integrates transfer learning-based feature extraction with machine learning classifiers. In the proposed approach, pre-trained deep learning models are employed to generate rich feature representations, which are subsequently classified using machine learning algorithms such as Random Forest and XGBoost. This hybrid strategy combines the powerful feature learning capability of deep neural networks with the efficient decision-making ability of classical machine learning techniques, thereby improving classification accuracy, robustness, and computational efficiency [1], [5], [10].

The proposed framework is designed to provide a reliable and scalable solution for intelligent food recognition, with potential applications in dietary assessment, nutrition monitoring, automated calorie estimation, healthcare support, and smart food recommendation systems [7], [10]. The remainder of this paper is organized as follows. Section II presents a review of recent literature related to food image classification. Section III discusses the system analysis and proposed methodology. Section IV describes the system architecture and design. Section V explains the implementation modules, while Section VI presents the experimental results and performance evaluation. Finally, Section VII concludes the paper and outlines future research directions.

II. LITERATURE SURVEY

Food image classification has become an active research area in artificial intelligence and computer vision because of its growing importance in healthcare, dietary monitoring, nutrition analysis, and intelligent food recommendation systems. The increasing availability of food images through smartphones and social media platforms has encouraged researchers to develop automated classification models that can accurately recognize various food categories. Numerous studies have explored machine learning, deep learning, transfer learning, and hybrid learning approaches to improve the accuracy and efficiency of food recognition systems [6], [7].

Early food classification methods were primarily based on traditional machine learning techniques that depended on handcrafted feature extraction. Visual characteristics such as colour histograms, texture descriptors, edge information, and shape features were manually extracted and supplied to classifiers including Support Vector Machines (SVM), Decision Trees, Logistic Regression, and k-Nearest Neighbors (k-NN). Although these methods produced satisfactory results on controlled datasets, they struggled to classify food images with complex backgrounds, varying illumination, and visually similar food categories, resulting in limited robustness and reduced prediction accuracy [6], [9].

The rapid evolution of deep learning has significantly improved image classification by eliminating the need for manual feature engineering. Convolutional Neural Networks (CNNs) automatically learn hierarchical feature representations from raw images, enabling better recognition of intricate visual patterns. Several studies have demonstrated that CNN-based architectures outperform conventional machine learning methods in food image classification due to their superior feature learning capability and higher classification accuracy [4], [7].

To address the challenges associated with limited training data and computational complexity, researchers have increasingly adopted transfer learning techniques. Instead of training deep neural networks from scratch, transfer learning utilizes knowledge acquired from large-scale image datasets to solve domain-specific classification problems. Pre-trained models such as EfficientNet, DenseNet, MobileNet, and other CNN architectures have shown remarkable success in extracting discriminative features from food images while significantly reducing training time and computational requirements [2]–[4]. Recent research has also focused on hybrid learning frameworks that integrate deep learning with classical machine learning algorithms. In these approaches, deep neural networks are employed as feature extractors, while machine learning classifiers such as Random Forest, XGBoost, and Support Vector Machines perform the final classification. Experimental studies indicate that hybrid frameworks achieve higher classification accuracy, improved generalization capability, and better computational efficiency compared to standalone deep learning or conventional machine learning models [1], [5], [10]. Despite these advancements, food image classification continues to present several research challenges. Food items often exhibit high inter-class similarity and significant intra-class variation due to differences in cooking styles, ingredient composition, presentation, lighting conditions, and image acquisition environments. These factors increase the likelihood of misclassification and limit the performance of existing recognition systems. Therefore, developing robust hybrid frameworks that effectively combine transfer learning with advanced machine learning classifiers remains an important research direction for achieving reliable and scalable food image classification suitable for real-world healthcare and nutrition applications [3], [7], [10].

III. SYSTEM ANALYSIS

1. Existing System

Existing food image classification systems primarily depend on conventional machine learning and deep learning techniques to recognize and categorize food items from digital images. In traditional approaches, images undergo preprocessing operations such as resizing, normalization, and noise removal to improve data quality before feature extraction. Subsequently, handcrafted visual features including colour distribution, texture patterns, edge information, and shape descriptors are extracted and supplied to machine learning algorithms such as Support Vector Machines (SVM), Decision Trees, Logistic Regression, Random Forest, and k-Nearest Neighbors (k-NN) for classification [6], [9].

Although these approaches provide acceptable performance on structured datasets, they are often unable to capture the complex semantic information present in real-world food images. Food items with similar visual appearances frequently confuse the classifiers, resulting in incorrect predictions. Furthermore, variations in illumination, camera viewpoints, background clutter, ingredient combinations, and food presentation styles negatively affect classification accuracy and model reliability [6], [7].

Recent advancements have introduced Convolutional Neural Networks (CNNs) and transfer learning models to improve feature extraction and recognition accuracy. These deep learning models automatically learn hierarchical visual representations and significantly outperform traditional handcrafted feature-based methods. However, developing deep learning models from scratch requires large annotated datasets, high computational resources, and extensive training time, making them less suitable for resource-constrained environments [2]–[4].

Although transfer learning has reduced many of these challenges, existing standalone classification frameworks still exhibit limitations in balancing feature extraction capability, computational efficiency, and classification performance. Consequently, there remains a need for more efficient hybrid frameworks that combine the strengths of deep learning and machine learning to achieve accurate, scalable, and robust food image classification [1], [5].

Disadvantages of the Existing System

- Limited Feature Representation: Traditional handcrafted feature extraction methods are unable to capture complex visual patterns and semantic information present in diverse food images, reducing classification effectiveness [6].
- Difficulty in Distinguishing Similar Food Items: Many food categories possess similar colours, textures, and shapes, making accurate classification challenging for conventional machine learning models [9].
- Sensitivity to Environmental Variations: Differences in lighting conditions, image backgrounds, camera angles, and food presentation styles significantly affect the prediction accuracy of existing classification systems [6], [7].
- High Computational Cost for Deep Learning: Training deep neural networks from scratch demands large labelled datasets, powerful hardware resources, and considerable computational time, limiting their practical deployment [3], [4].
- Risk of Overfitting: Models trained on limited or insufficiently diverse datasets often fail to generalize effectively when exposed to unseen food images collected in real-world environments.
- Reduced Scalability: As the number of food categories increases, maintaining consistent classification performance becomes increasingly difficult, especially for traditional machine learning techniques [1], [10].
- Limited Real-World Adaptability: Existing standalone approaches often struggle to maintain stable performance under dynamic environmental conditions, making them less suitable for practical healthcare, dietary monitoring, and intelligent nutrition applications.

2. Proposed System

The proposed system introduces a hybrid food image classification framework that combines transfer learning with machine learning techniques to achieve accurate and efficient food recognition. The framework is designed to overcome the limitations of conventional classification methods by utilizing deep feature extraction and intelligent classification, thereby improving prediction accuracy, computational efficiency, and model robustness [1], [5].

Initially, the collected food image dataset undergoes a preprocessing stage to improve image quality and ensure consistency across all samples. The preprocessing process includes image resizing, normalization, removal of noisy or corrupted images, and data augmentation techniques such as rotation, horizontal flipping, scaling, and random cropping. These operations enhance dataset diversity, reduce overfitting, and improve the model's ability to generalize when classifying unseen food images [3], [4].

After preprocessing, transfer learning models including EfficientNet, DenseNet, and MobileNet are employed to extract high-level visual features from the input images. Since these models are pre-trained on large-scale image datasets, they are capable of learning complex visual representations such as texture, colour distribution, shape, and structural characteristics without requiring extensive training from scratch. This significantly reduces computational cost while improving feature extraction performance [2]–[4].

The extracted feature vectors are subsequently provided as input to machine learning classifiers such as Random Forest and XGBoost. These classifiers analyze the deep features and predict the corresponding food category with high accuracy. The combination of transfer learning and machine learning enables the framework to utilize the representational capability of deep neural networks along with the efficient decision-making process of classical machine learning algorithms, resulting in superior classification performance compared with standalone approaches [1], [5], [10].

To assess the effectiveness of the proposed framework, the classification models are evaluated using standard performance metrics including accuracy, precision, recall, F1-score, and Receiver Operating Characteristic (ROC) analysis. These evaluation metrics provide a comprehensive measure of the model's reliability, classification capability, and generalization performance across multiple food categories [7], [10].

Overall, the proposed hybrid framework provides a reliable, scalable, and computationally efficient solution for automated food image classification. The integration of transfer learning and machine learning improves recognition accuracy while reducing training complexity, making the framework suitable for practical applications such as dietary assessment, nutrition monitoring, calorie estimation, healthcare assistance, and intelligent food recommendation systems [5], [7].

IV. SYSTEM DESIGN

1. System Architecture
Below diagram depicts the whole system architecture.

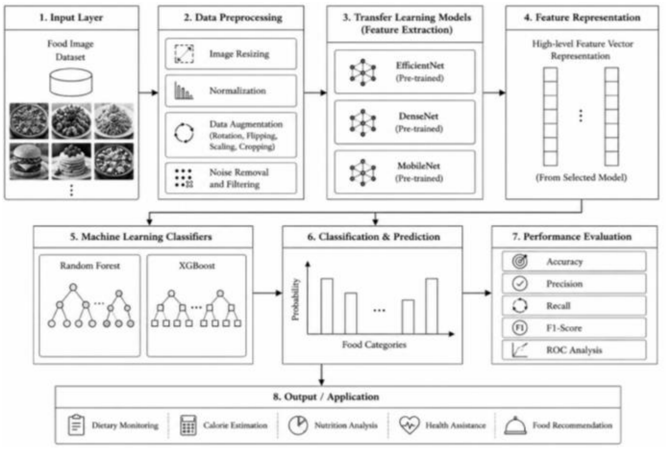

Fig 1. Methodology followed for proposed model

V. SYSTEM IMPLEMENTATION

1. Modules
Data Collection and Preprocessing
The first module focuses on collecting food images from publicly available datasets containing multiple food categories. Before model training, all images undergo preprocessing to improve data quality and maintain consistency. The preprocessing stage includes image resizing, normalization, removal of corrupted samples, and data augmentation techniques such as rotation, flipping, scaling, and random cropping. These operations increase dataset diversity, reduce overfitting, and enhance the model's ability to generalize to unseen food images [3], [4].

Deep Feature Extraction Using Transfer Learning
In this module, transfer learning models are employed to extract discriminative visual features from food images. Pre-trained architectures such as EfficientNet, DenseNet, and MobileNet leverage knowledge learned from large-scale image datasets to generate high-level feature representations. These deep features effectively capture texture, color, shape, and structural characteristics of food items, eliminating the need for manual feature engineering while improving feature extraction efficiency [2]–[4].

Hybrid Model Training
The extracted feature vectors are supplied to machine learning classifiers for model training. Algorithms such as Random Forest and XGBoost learn the relationship between the extracted features and their corresponding food categories. The integration of transfer learning with machine learning combines robust feature learning and efficient classification, resulting in improved prediction accuracy, faster convergence, and better

generalization compared to standalone classification approaches [1], [5], [10].

Food Image Classification
Once the hybrid model has been trained, it is utilized to classify new food images. Each input image follows the same preprocessing and feature extraction pipeline before being passed to the trained classifier. Based on the learned feature patterns, the system predicts the appropriate food category with high accuracy, enabling reliable automated food recognition for practical applications such as dietary monitoring and nutrition analysis [7].

Performance Evaluation
The final module evaluates the effectiveness of the proposed framework using standard classification metrics, including accuracy, precision, recall, F1-score, and Receiver Operating Characteristic (ROC) analysis. These evaluation measures provide a comprehensive assessment of the model's prediction capability, robustness, and generalization performance. Continuous performance monitoring also enables future model improvements through retraining with larger and more diverse food image datasets [7], [10].

VI. RESULTS AND DISCUSSION

The proposed hybrid food image classification framework was experimentally evaluated using a labeled food image dataset containing multiple food categories. The dataset was divided into training and testing subsets to ensure an unbiased assessment of the classification models. During experimentation, transfer learning models were employed to extract high-level visual features, while machine learning classifiers performed the final prediction task. This combination enabled the framework to effectively recognize complex food patterns and improve classification performance [2]–[5].

The extracted deep feature vectors were classified using multiple machine learning algorithms, including Support Vector Machine (SVM), Logistic Regression, Random Forest, and XGBoost. The performance of each model was evaluated using standard classification metrics such as accuracy, precision, recall, and F1-score. These evaluation measures provide a comprehensive assessment of the model's prediction capability and overall reliability [7], [10].

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

The experimental results indicate that the proposed hybrid transfer learning framework achieved the highest classification accuracy of 94.5%, outperforming all conventional machine learning models. The superior performance is primarily attributed to the ability of transfer learning models to extract rich and discriminative visual features, which significantly enhance the prediction capability of machine learning classifiers [1], [3], [5].

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

Fig. 2. Model Performance Comparison

A comparative performance graph was generated to visualize the accuracy achieved by different classification models. The graphical comparison clearly demonstrates that the proposed hybrid framework consistently outperforms individual machine learning algorithms. The integration of deep feature extraction with efficient classification enables the system to achieve higher prediction accuracy while maintaining computational efficiency [2], [5].

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

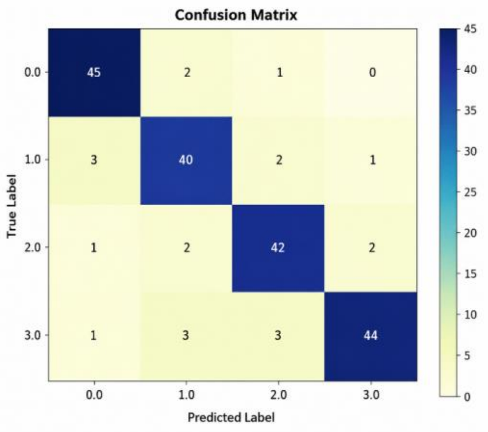

Fig. 3. Confusion Matrix for Food Classification

A confusion matrix was used to analyze the classification capability of the proposed model across different food categories. The majority of food images were correctly classified, while only a small number of samples belonging to visually similar food classes were misclassified. This observation indicates that the proposed framework effectively captures discriminative visual characteristics and provides reliable classification performance even for challenging food images [4], [7].

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.

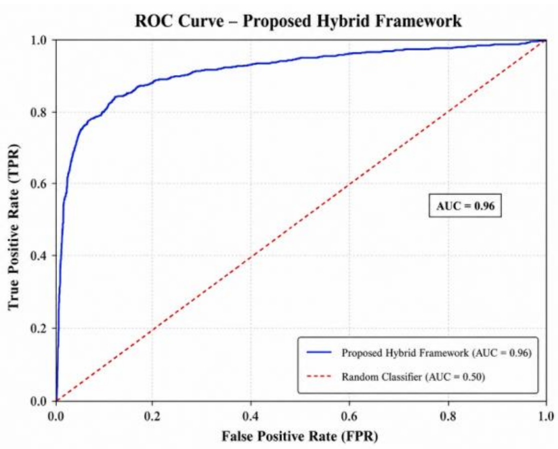

Fig. 4. ROC Curve for Food Image Classification

Receiver Operating Characteristic (ROC) analysis was performed to evaluate the discrimination capability of the proposed classification framework. The ROC curve demonstrates a high True Positive Rate (TPR) while maintaining a low False Positive Rate (FPR), indicating excellent classification performance. The corresponding Area Under the Curve (AUC) confirms the strong ability of the model to distinguish between different food categories with high confidence [3], [10].

VII.CONCLUSION AND FUTURE WORK

This research presented a hybrid food image classification framework that integrates transfer learning with machine learning techniques to improve the accuracy and reliability of automated food recognition. The proposed framework utilizes pre-trained deep learning models, including EfficientNet, DenseNet, and MobileNet, to extract high-level visual features, which are subsequently classified using machine learning algorithms such as Random Forest and XGBoost. By combining deep feature extraction with efficient classification techniques, the proposed system effectively overcomes many of the limitations associated with conventional food classification methods [1]–[5].

Experimental evaluation demonstrates that the hybrid framework achieves superior classification performance compared to traditional machine learning approaches. The proposed model attained higher accuracy, precision, recall, and F1-score while maintaining robust performance across different food categories. The use of transfer learning significantly reduced training time and computational requirements without compromising classification accuracy, making the framework suitable for real-world applications including dietary monitoring, nutrition analysis, calorie estimation, and intelligent healthcare systems [3], [5], [7].

Although the proposed framework provides promising results, further improvements can enhance its practical applicability. Future research may focus on incorporating larger and more diverse food image datasets to improve model generalization across different cuisines and environmental conditions. Advanced transfer learning architectures, attention mechanisms, and Vision Transformer (ViT)-based models can also be investigated to further enhance feature extraction and classification performance. In addition, the framework can be deployed as a real-time mobile or web-based application capable of providing instant food recognition, calorie estimation, and personalized dietary recommendations. Integrating explainable artificial intelligence (XAI) techniques may further improve model transparency and user confidence, enabling the development of more reliable and intelligent AI-driven food recognition systems [1], [3], [5], [10].

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Mr. Boddu Pavan Kumar is currently pursuing M.Tech in Computer Science and Engineering at Lenora College of Engineering, Rampachodavaram, Alluri Sitarama Raju District, Andhra Pradesh, India. He possesses a strong academic foundation in Machine Learning, Deep Learning, Computer Vision, Java Programming, Web Technologies, and Database Management Systems. His practical experience includes the design and implementation of intelligent image classification systems using hybrid transfer learning techniques, image preprocessing, feature extraction, model training, and performance evaluation. His work emphasizes the application of pre-trained deep learning models for automated food image recognition, aiming to improve classification accuracy and computational efficiency. He is also experienced in software system design using Unified Modeling Language (UML), including use case, class, sequence, activity, and data flow diagrams. His research interests include Machine Learning, Deep Learning, Transfer Learning, Computer Vision, Intelligent Image Processing, and Explainable Artificial Intelligence (XAI). He is committed to advancing academic research and developing innovative AI-driven solutions for real-world image classification and intelligent decision-making systems.

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