Online-Journals.org

iJOE International Journal of Online and Biomedical Engineering

iJOE | eISSN: 2626-8493 | Vol. 22 No. 3 (2026) | OPEN ACCESS

https://doi.org/10.3991/ijoe.v22i03.59271

PAPER

# Towards a Personalized Nutrition Using an Intelligent Dietary Assessment System

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## ABSTRACT

Artificial intelligence (AI) is increasingly impacting the medical field, especially in nutrition, where machine learning algorithms offer new opportunities for personalized dietary assessment. This paper presents a prototype of an AI-based expert system designed to support meal planning and nutrient intake evaluation, addressing individual dietary requirements, preferences, and constraints. The system employs essential image processing steps such as resizing, normalization, and magnification to ensure the accuracy and consistency of food image data. Using advanced image recognition models, the system processes visual food inputs to classify dishes and support nutritional analysis. The FOOD-MOR Dataset, comprising diverse traditional and modern Moroccan dishes, serves as the foundation for training and testing the models. A comparative evaluation of two pre-trained convolutional neural networks, VGG16 and MobileNetV2, was conducted. Using VGG16, the model achieved 81% accuracy with a macro F1-score of 0.80, while MobileNetV2 reached 86% accuracy and a 0.86 macro/weighted F1-score, demonstrating superior performance on the 10-class food classification task. These results indicate that the lighter MobileNetV2 architecture is more suitable for efficient, real-time food recognition. This study highlights the potential of AI-powered food recognition systems to enhance personalized nutrition by accurately identifying meals and facilitating dietary monitoring in diverse culinary contexts and cuisines.

## KEYWORDS

artificial intelligence (AI), machine learning, diet, nutrition, food intake, dietary assessment

## 1 INTRODUCTION

Energy is defined as the capacity to perform work [1]. Through process of digestion, the food we consume is converted into energy, measured in Calories (C), kilocalories (kcal), or Joules (J) [2]. Macronutrients such as carbohydrates, proteins, and fats provide most of this energy and must be consumed in appropriate amounts to maintain health [3], [4]. Additionally, there is growing concern regarding chronic diseases, health issues, and the rapid increase in obesity among young individuals.

Azzimani, K., Haggouni, J., Bihri, H., Khalis, M., Azzouzi, S., Charaf, M. E. H. (2026). Towards a Personalized Nutrition Using an Intelligent Dietary Assessment System. *International Journal of Online and Biomedical Engineering (iJOE)*, 22(3), pp. 149–169. https://doi.org/10.3991/ijoe.v22i03.59271

Article submitted 2025-10-24. Revision uploaded 2025-12-31. Final acceptance 2026-01-02.

Artificial intelligence (AI) is characterized by the ability of computer programs to process and learn from datasets, enabling knowledge extraction, case identification, and decision support [5]. AI technology is rapidly advancing in the medical field, offering innovative solutions for clinical practice. A significant volume of data is being generated by wearable sensors, smartphones, and other mobile devices, which can be utilized by deep learning algorithms across various healthcare domains [6]. Recent advances in computer science have positioned AI as a crucial component of modern healthcare [7].

In particular, AI algorithms are frequently employed to assist and support medical professionals in their work and research [8]. AI has demonstrated its potential in precision medicine, particularly in personalized nutrition, by recommending customized and adapted therapies [9].

Nutritional assessment methods typically gather data on dietary intake, physical activity, family medical history, and other relevant factors [10]. Clinical evidence also shows that inadequate dietary intake contributes to malnutrition, emphasizing the need for tools that enhance the accuracy and consistency of nutritional evaluation [11].

In this study, data is collected from diverse images of Moroccan dishes—both traditional and modern—to develop a culturally contextual dataset.

This diverse dataset enhances the credibility of the study by incorporating a wide range of food types. Deep learning techniques are then applied to build a predictive model capable of estimating nutrient intake based on food recognition. Using the updated Moroccan Food Composition Table (MFCT) [12], the system provides nutritional insights that assist dietitians in monitoring patients' diets and recommending suitable meal plans. To our knowledge, this is the first system to combine food image recognition with personalized dietary analysis specifically designed for North African cuisine.

The remainder of this paper is organized as follows: Section 2 presents the problem statement and related work. Section 3 describes the materials and methodology. Section 4 presents the main results, followed by improvement recommendations in discussion in Section 5. Section 6 concludes the paper and outlines future research directions.

## 2 BACKGROUND THEORY AND LITERATURE REVIEW

### 2.1 Problem statement

The nutritional assessment of patients is conducted using general and specific assessment tools and methods. These methods predominantly rely on the patient's memory, which introduces significant limitations. Additionally, they are time-consuming and require trained professionals to interview patients and collect relevant data [13].

Previous studies have highlighted concerns regarding the reliability of data obtained through traditional methods, as self-reported food intake is often prone to errors and misestimation, leading to potential biases [14].

Moreover, the accuracy of self-reported dietary data is not guaranteed, particularly in individuals with memory impairments due to conditions such as dementia and Alzheimer's disease [15]. In such cases, ensuring adequate nutrition and accurately assessing dietary intake becomes particularly challenging. Proper nutritional assessment is crucial, as it safeguards overall well-being and helps prevent functional decline associated with aging and disease conditions [16]. Therefore, obtaining accurate and reliable nutrient intake data is essential for designing and evaluating therapeutic diets for patients under medical care.

To address these challenges, the proposed system employs advanced methodologies for preprocessing food images, integrating deep learning and computer vision techniques to accurately recognize and classify modern and traditional Moroccan dishes. By automating portion size estimation and nutrient analysis, the system mitigates human error and bias inherent in conventional self-reporting methods. The AI-driven approach enhances accuracy, particularly for individuals with memory-related conditions, by providing an objective and reliable dietary assessment.

Additionally, the system personalizes nutrition recommendations by analyzing dietary patterns and health conditions. Unlike conventional approaches, it facilitates real-time, objective data collection, improving the reliability of dietary assessments. This expert system supports precise and individualized nutritional planning, ultimately enhancing dietary management and health outcomes.

This study aims to contribute to the growing intersection of AI and personalized nutrition by demonstrating how convolutional neural networks (CNNs) can revolutionize dietary assessment and nutritional planning. We seek to deepen the understanding of their role in shaping the future of nutrition and overall well-being.

## 2.2 Related works

Recent research has explored various approaches to enhancing personalized nutrition and food menu planning through advanced technologies. Several studies have introduced AI-driven methodologies to improve food recognition, dietary assessment, and nutritional recommendations.

The remote food photography method (RFPM) is a semi-automated imaging application designed to estimate food intake based on images captured by participants. Initial validation studies have demonstrated the reliability and validity of RFPM; however, its effectiveness is constrained by its reliance on human raters for food intake estimation, which introduces potential biases and inconsistencies [14].

Moreover, optical character recognition (OCR) has been integrated into numerous applications, enabling users to extract nutritional information from menu descriptions or food labels by simply capturing a photo. In this context, a recent study [17] explored multimodal machine learning models to identify food items, estimate portion sizes, and infer detailed nutrient profiles from captured images, these vision-based approaches significantly improve the accuracy and scalability of dietary assessment compared to manual self-reporting methods.

One notable approach involves smartphone-enabled, real-time remote nutritional assessment, allowing practical monitoring of dietary habits in free-living individuals [18]. This method demonstrated how mobile technologies can help accurate food measuring without requiring manual data entry. Initially, face recognition technology was implemented in mobile user interfaces and was later adapted for food recognition and portion estimation [19].

Recent study in interactive mobile technologies [20] shows the value of intuitive design in health promotion apps that can influence dietary behaviors and self-efficacy, highlighting the potential of modern tools in personalized nutrition systems. Personalized nutrition has emerged as a key area in modern nutritional science, emphasizing diet customization based on individual dietary patterns to optimize health and prevent disease. Several mobile health applications now use artificial intelligence and image recognition to simplify nutritional tracking. For example, validation research on a smartphone app demonstrated that automatic food image recognition can estimate nutrient and food group contents with reasonable accuracy [21]. Additionally, GoCARB [22], a funded project aimed at assisting diabetes patients, helps users count carbohydrates and estimate the required prandial insulin dose.

In the domain of food recommendation systems, a research [23] explored AI-driven approaches for personalized dietary support. The study presents a user-aware food recommendation framework that integrates individual preferences, nutritional requirements, and contextual information to generate personalized food suggestions.

Another study [24] proposes a hybrid decision-making approach for nutrition management, incorporating both knowledge-based recommendations and data-driven techniques. This approach enables users to make informed dietary choices based on a comprehensive health platform that considers both physical and mental health factors.

Such comprehensive platforms may complement the use of mobile health applications to further enhance nutrition-related outcomes. Additionally, recent findings indicate that more intensive use of mobile health applications is associated with higher nutrition knowledge, improved healthy eating self-efficacy, and more positive body image [25].

Contemporary research has emphasized the growing role of image-based food monitoring systems in diabetes management, highlighting advances in food image segmentation, classification, and calorie estimation [26]. These improvements enable more reliable identification of food items and portion sizes from images, supporting automated dietary assessment while reducing the need for manual food logging.

The significance of meal planning and carbohydrate counting has been widely documented in diabetes management research [27]. However, even well-trained diabetic patients face difficulties in accurately estimating their carbohydrate intake, which may negatively impact glycemic control and daily insulin dosing accuracy. Recent research highlights not only the central role of carbohydrate intake in managing glucose levels but also the persistent challenges patients encounter in estimating carbohydrate amounts and adhering to precise carbohydrate and other nutrient counting in real-world settings.

To address this challenge, researchers have focused on developing AI-based systems capable of automatically recognizing food items and estimating their carbohydrate content, thereby improving the accuracy of prandial insulin dose calculations.

Despite these advancements, existing food recognition and dietary assessment systems often lack adaptability to culturally specific diets and fail to offer fully automated nutritional analysis. Many systems rely on generic food composition databases, which limits their accuracy for region-specific cuisines such as Moroccan dishes. To address these limitations, our previous work [28] introduced a prototype for estimating food intake by comparing images of dishes before and after meals and linking them with the Moroccan Food Composition Table (MFCT) to calculate caloric intake. Building upon this foundation, the present study extends that approach by recognizing a wider range of food items from the FOOD-MOR dataset and estimating detailed nutrient intake, thereby improving both the generalizability and the depth of dietary assessment.

## 3 MATERIALS AND METHODS

### 3.1 Dataset

The FOOD-MOR database, developed in collaboration with OFPPT Guelmim, comprises a set of 2,000 images, evenly distributed across 10 distinct categories of Moroccan traditional and modern dishes, with 200 images per category.

This dataset includes emblematic Moroccan dishes such as 'Beghrir,' 'Couscous,' Cake, 'M'laoui,' Whole Bread, Pizza 4 Seasons, Pizza Seafood, Rice, 'Seffa,' and 'Tajine PT.' Designed to facilitate advanced research in food recognition, it also serves as an educational tool for culinary professionals and researchers exploring Moroccan gastronomy.

Moreover, the FOOD-MOR database contributes to nutritional disease prevention in Morocco. Its diverse content enables public awareness campaigns, enhances the knowledge of healthcare professionals, fosters research and innovation, and promotes the production and consumption of healthier foods.

We used a sample of food images from different categories, representing a subset of the 200 images allocated to each class. These images are part of the dataset used for training and evaluating the model. The images are distributed across various food categories within the dataset. Each food category is represented by a number of images available for a specific class, such as 'Seffa,' 'Beghrir,' and 'Rice,' among others. The dataset includes up to 200 images per category.

For the recipe-based classification, datasets of food ingredient images were selected built on predefined criteria. In the subsequent step, images of Moroccan cuisine were incorporated alongside other widely consumed foods to enhance diversity and improve the reliability of the classification results.

These reliable data serve as a foundation for the development and implementation of food-based dietary guidelines and the recommendation of appropriate therapeutic diets [29].

Morocco, a country with a rich and diverse gastronomic heritage, has undergone a nutritional transition influenced by urbanization, increased consumption of commercially prepared foods, dining out, and changes in household meal patterns. This transition is further shaped by evolving social dynamics, particularly the increasing contribution of Moroccan mothers in the workforce. The demanding work schedules of both parents, combined with children's school routines, have contributed to a growing reliance on fast, processed foods and restaurant meals. Consequently, the frequency of traditional home-cooked meals has declined, affecting dietary habits and overall nutritional balance [30].

The creation and curation of a comprehensive dataset focusing on Moroccan cuisine play a crucial role in ensuring accurate dietary assessment. This process involves systematically capturing images of plated meals containing a diverse range of food items to ensure a representative sample of various cuisines and dietary patterns. Additionally, the dataset includes a mix of foods that people typically eat in Moroccan cuisine. To enrich its comprehensiveness, the dataset integrates both locally captured images and those sourced online, ensuring a robust and culturally relevant food recognition model.

## 3.2 Pre-processing

The Figure 1 presents a sample of food images from different categories, representing a subset of the 200 images allocated to each class. These images are part of the dataset used for training and evaluating the model.


**Fig. 1.** Sample of food images by category

To prepare the dataset for our convolutional neural network (CNN) and deep neural network (DNN) models, several essential preprocessing steps were applied to ensure compatibility and optimize model performance. The initial step involved resizing all images to a standardized resolution of 50×50 pixels. This dimension was selected to ensure efficient computation without losing important visual information required for classification [31]. This resizing not only promoted uniformity across the dataset but also reduced training complexity, thereby accelerating processing without compromising the integrity of image content.

Moreover, this step addressed the variation in original image dimensions, which could otherwise hinder the model's generalization capabilities. Following resizing, image color formats were standardized. Since OpenCV reads images in the BGR (Blue-Green-Red) format, a conversion to the RGB (Red-Green-Blue) format was performed. This adjustment aligns the input data with the expectations of most deep learning frameworks and enhances the extraction of color-related features, improving the model's learning ability.

As part of the transfer learning process, images were subsequently upscaled to 256×256 pixels to meet the input size requirements of pre-trained models such as MobileNetV2 and VGG16. This resizing allowed the models to leverage more detailed spatial information and extract finer patterns, which in turn improved predictive performance.

To further enrich the training data and enhance the model's generalization, data augmentation techniques were applied. These included random rotations, horizontal and vertical flips, zooming, and shifts. Such transformations introduced variability similar to real-world conditions and reduced the risk of overfitting. Overall, the combination of resizing, color correction, and augmentation significantly improved the quality and consistency of the dataset, contributing to robust model performance.

## 3.3 Model architecture

Figure 2 illustrates the workflow of our proposed model. The implementation is carried out in Python v3.10, utilizing transfer learning models to enhance food classification accuracy. The models were trained on a dataset comprising 2,000 images across 10 different categories of food and subsequently deployed to predict the category of an input food item.

When a new image is introduced into the system, it undergoes several preprocessing steps, including resizing, normalization, and data augmentation, to enhance model robustness and generalization. The preprocessed image is then fed into the trained model, which analyzes its features and compares them to the characteristics of the pre-learned classes to determine the most probable food category. The ultimate objective of this study is to accurately identify consumed foods and correlate them with a food composition database. This integration allows for precise nutritional intake assessment and facilitates the development of personalized nutrition strategies tailored to individual dietary needs.

Two pre-trained convolutional neural network architectures, VGG16 and MobileNetV2, were fine-tuned for the food classification task. VGG16 was chosen for its depth and strong representational capacity, while MobileNetV2 was selected as a lightweight alternative designed for computational efficiency, allowing for a clear comparison between model performance and resource requirements.

In this research we highlight how AI can make nutrition easier to understand and manage. By turning simple food images into meaningful dietary insights, these technologies have the potential to reduce the effort of tracking what we eat and give people clearer guidance toward healthier choices.

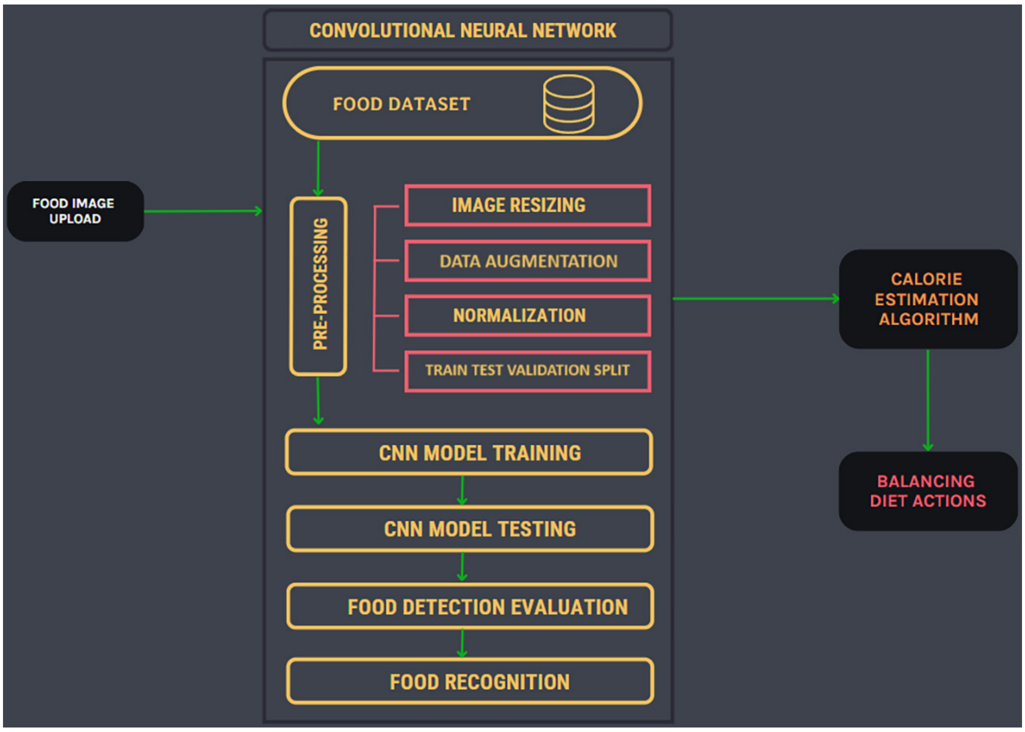


**Fig. 2.** Workflow of our model

## 3.4 Training details

For model training and evaluation, the dataset was partitioned using the train_test_split function. Specifically, 80% of the images were allocated for training and 20% for testing. From the training subset, 25% was further reserved for validation, resulting in three disjoint sets: training, validation, and testing. This validation set was used to monitor model performance during training and to support early stopping, helping to reduce overfitting. In total, 1,600 images were used for training and validation, while 400 images were retained exclusively for testing, ensuring an unbiased final evaluation.

**Loss Function and Optimizer:** During training, the models use the categorical cross-entropy loss function, which measures how close the predicted class probabilities are to the true class labels in a multi-class classification setting. For each training image the loss is computed as:

$$J_{i(w,b)} = L(y^{\{(i)\}}, \{\hat{y}\}^{\{(i)\}}) = -\left( y^{\{(i)\} \backslash log\left(\{\hat{y}\}^{\{(i)\}}\right)} + (1 - y^{\{(i)\}}) \backslash log(1 - \{\hat{y}\}^{\{(i)\}}) \right) \quad (1)$$

where $y^{(i)}$ represents the true class label, $\hat{y}^{(i)}$ is the predicted probability for each food class. The Adam optimizer is used to update the model weights because it is efficient and adapts the learning rate during training.

## 3.5 Definition of metrics

To objectively evaluate the performance of the proposed food classification models, several standard evaluation metrics are used. These metrics are computed using the predictions generated by the trained models and the corresponding ground-truth labels. In addition to accuracy, class-wise precision, recall, and F1-score are reported using the *classification_report()* function from the Scikit-learn library.

**Accuracy:** Measures the overall correctness of the classification model and is defined as the ratio of correctly predicted samples to the total number of samples:

$$Accuracy = \left( \frac{Correctly\ Predicted\ Class}{Total\ Testing\ Class} \right) \times 100 \quad (2)$$

**Precision:** Indicates the proportion of correctly predicted positive samples among all samples predicted as positive:

$$Precision = \frac{TP}{TP + FP} \quad (3)$$

**Recall:** Measures the ability of the model to correctly identify all relevant samples of a given class:

$$Recall = \frac{TP}{TP + FN} \quad (4)$$

**F1-score:** Combines precision and recall into a single value, providing a balanced evaluation of the model's performance.

$$F1 - score = \frac{2 \times TP}{2 \times TP + FP + FN} \quad (5)$$

**True Positive (TP):** The number of food images correctly classified as a specific food category.

**True Negative (TN):** The number of food images correctly identified as not belonging to a given food category.

**False Positive (FP):** The number of food images incorrectly classified as a specific food category.

**False Negative (FN):** The number of food images belonging to a specific food category that are incorrectly classified as another category.

# 4 RESULTS

## 4.1 Results using VGG16

To load the pre-trained VGG16 model with ImageNet weights while excluding the fully connected (top) layers, we employ the Keras library. When utilizing a pre-trained model for image classification tasks, it is often necessary to adapt the architecture to suit the specific problem at hand. In our case, we append a new fully connected Dense layer at the end of the modified network to perform classification on our custom dataset. This final layer is specifically designed to classify images of dishes into 10 categories defined in the FOOD-MOR database.

Figure 3 illustrates the architecture of the modified VGG16 model. The network starts with an input layer that accepts RGB images of size 256×256. These inputs are processed through several convolutional layers utilizing 3×3 filters and ReLU activation functions to extract hierarchical image features. Max-pooling layers with 2×2 filters are employed to reduce spatial dimensions. The final Dense layer, equipped with a Softmax activation function, performs the classification task by outputting probabilities across the 10 food categories, facilitating accurate food recognition.

The model is compiled by specifying the following components:

- Loss function: Categorical_crossentropy, which computes the cross-entropy loss between the true labels and the predicted probabilities for multi-class classification.
- Optimizer: Adam, chosen for its efficient gradient descent optimization and adaptive learning rate.
- Metrics: Multiple evaluation metrics, detailed in Section 3.5.

To evaluate the performance of the classifier, we utilize the classification_report() function from the Scikit-learn library. This function provides essential metrics such as precision, recall, and F1-score for each class individually, along with macro and weighted averages. Figure 4 shows the classification report of the VGG16 model, highlighting performance across different food categories such as Gateau, Pain complet, etc. Key metrics such as F1-score, precision, and recall are presented for each class.

The training history of the VGG16 model, summarizes accuracy and validation accuracy at various training epochs. At epoch 20, the model achieves 65.13% training accuracy and 76.25% validation accuracy. By epoch 30, training accuracy improves to 81.00% with a slight increase in validation accuracy to 77.25%. At epoch 80, both training and validation accuracies stabilize around 81.00%, indicating convergence.

The VGG16 model's classification performance across 10 food classes shows mostly accurate predictions. For example, the model correctly identified 36 instances of Gateau and 33 of Couscous. While most classes were well classified, some confusion occurred—such as Pizza Fruit de Mer being sometimes mistaken for Pizza 4 saisons, and Tajine PT occasionally misclassified as beghrir.

Figure 5 presents the training and validation accuracy trajectories of the VGG16 model across 30 epochs. At the beginning of training, the accuracy for both datasets is relatively low, but the model quickly improves within the first few epochs. The validation accuracy consistently remains higher than the training accuracy, indicating that the pre-trained VGG16 features generalize well to the FOOD-MOR dataset. The validation curve shows small ups and downs, but overall, it keeps improving and becomes more stable toward the later epochs. In contrast, the training accuracy increases more gradually and reaches around 0.65 by the final epoch. This difference between the two curves suggests that the model is not overfitting heavily, but still benefits from regularization and data variability. Overall, the figure demonstrates a stable learning process and confirms that VGG16 adapts effectively to the task of meal recognition.

Figure 6 displays the confusion matrix of the VGG16 model, detailing its performance across the 10 food classes. The matrix reveals the number of correctly and incorrectly classified instances for each class. For instance, Gateau was correctly predicted 36 times, and Couscous was correctly predicted 33 times.

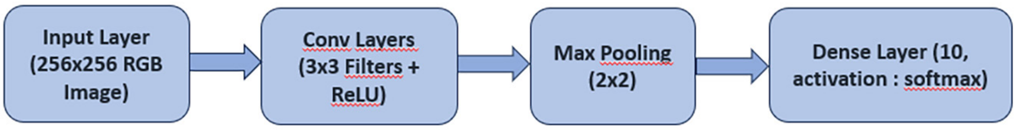


**Fig. 3.** Model generated after VGG16 adjustments

Classification Report

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| Gateau | 0.95 | 1.00 | 0.97 | 36 |
| Pain complet | 0.90 | 0.91 | 0.91 | 47 |
| Pizza 4 saisons | 0.57 | 0.87 | 0.69 | 46 |
| Pizza fruit de Mer | 0.80 | 0.11 | 0.20 | 36 |
| Tajine PT | 1.00 | 0.82 | 0.90 | 34 |
| beghrir | 0.97 | 0.91 | 0.94 | 34 |
| couscous | 0.79 | 1.00 | 0.88 | 33 |
| lmlaaoui | 1.00 | 0.82 | 0.90 | 44 |
| rice | 0.90 | 0.75 | 0.82 | 48 |
| seffa | 0.64 | 0.93 | 0.76 | 42 |
| accuracy | | | 0.81 | 400 |
| macro avg | 0.85 | 0.81 | 0.80 | 400 |
| weighted avg | 0.85 | 0.81 | 0.80 | 400 |

**Fig. 4.** Results of the VGG16 pre-trained model


**Fig. 5.** Training and validation accuracy graph for VGG16 model

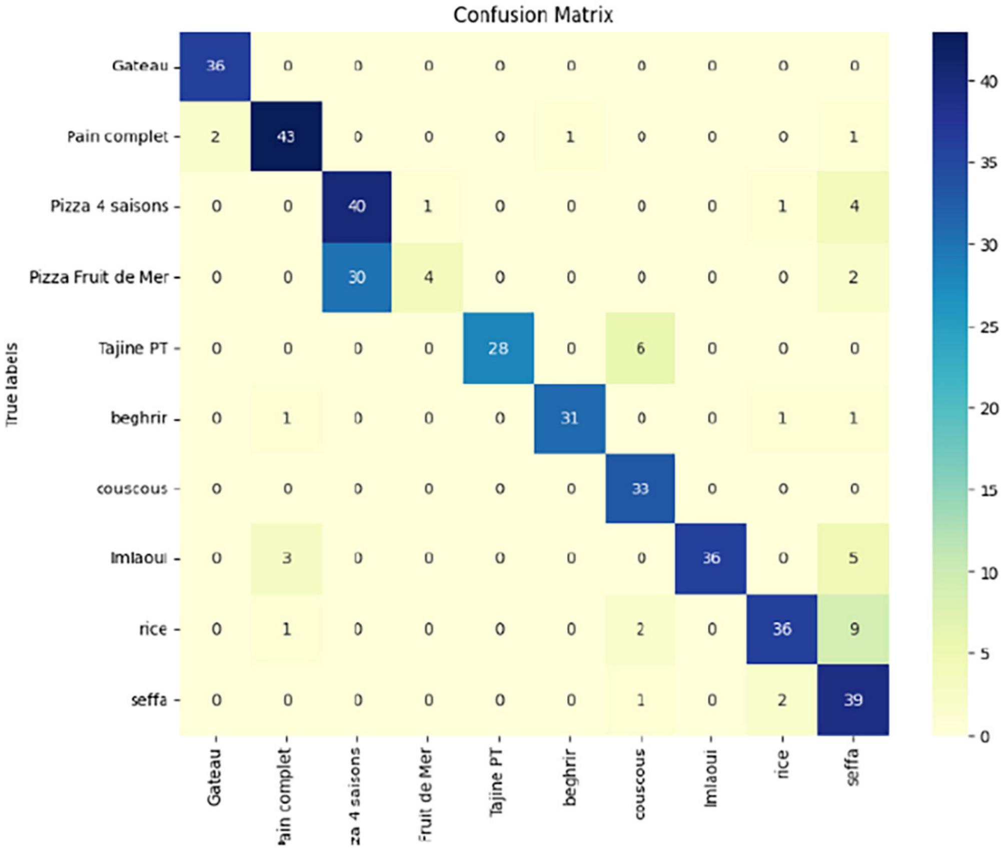


**Fig. 6.** Confusion matrix of VGG16 model

To evaluate the stability of the model, VGG16 was trained across multiple independent runs with different epoch settings (30 and 80 epochs). At 30 epochs, the first run achieved an overall accuracy of 75.81% with a macro F1-score of 0.758, while the second run reached an accuracy of 75.45% and a macro F1-score of 0.755. The difference in accuracy between the two runs is less than 0.4 percentage points, indicating consistent performance across independent trainings.

At 80 epochs, performance improved for both runs. The first run achieved an accuracy of 82.50% with a macro F1-score of 0.821, while the second run reached 82.25% accuracy and a macro F1-score of 0.804. These results show a performance variation of less than 0.3 percentage points in accuracy between runs. Overall, the close agreement in accuracy and F1-score values across runs suggests that the VGG16 model exhibits stable behavior and that the reported performance is not dependent on a single training instance.

The observed accuracy and F1-score variations across runs remained limited, indicating stable performance. Formal significance testing will be considered in future work.

## 4.2 Results using MobileNetV2

The pre-trained MobileNetV2 model is adapted for a classification task involving seven specific food classes by extending its architecture with additional layers. To extract higher-level feature representations, a GlobalAveragePooling2D layer is applied to the output of the convolutional base. The resulting features are then concatenated and further processed to create a more expressive feature vector tailored to the classification task.

To improve generalization and model performance, several layers are added after the pooling stage. These include a Dense layer with 512 units and a ReLU activation function to introduce non-linearity, followed by a Dropout layer with a rate of 0.5 to reduce the risk of overfitting. Finally, a Dense output layer with a Softmax activation function is employed to assign each input image to one of the seven target categories.

Figure 7 illustrates the architecture of the adapted MobileNetV2 model. It begins with an input layer that accepts 256×256 RGB images, which are passed through convolutional layers for feature extraction. A GlobalAveragePooling layer reduces the spatial dimensions, followed by a Dense layer with 512 neurons and ReLU activation. A Dropout layer (rate = 0.5) is then applied. The final classification is performed by a Dense Softmax layer, enabling accurate categorization of the input images into seven food classes.


**Fig. 7.** Model generated after MobileNetV2 adjustments

Finally, a Dense output layer is added to classify the images into 10 distinct food categories. This modification enables the pre-trained MobileNetV2 model to be fine-tuned for a specific classification task while maintaining high computational efficiency. By leveraging the model's capability to extract relevant features from input images and adapting them to the targeted classes, the overall classification performance is significantly improved. Figure 8 displays the classification report for the fine-tuned MobileNetV2 model, highlighting its performance across various food categories. For instance, classes such as "Gâteau" and "Lmlaoui" demonstrate high precision and recall. The model achieves an overall classification accuracy of 86%, indicating robust and reliable performance for the given task.

Classification Report

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| Gateau | 0.92 | 0.97 | 0.95 | 36 |
| Pain complet | 0.86 | 0.94 | 0.90 | 47 |
| Pizza 4 saisons | 0.71 | 0.54 | 0.62 | 46 |
| Pizza fruit de Mer | 0.56 | 0.69 | 0.62 | 36 |
| Tajine PT | 0.87 | 1.00 | 0.93 | 34 |
| beghrir | 1.00 | 0.82 | 0.90 | 34 |
| couscous | 0.97 | 0.88 | 0.92 | 33 |
| lmlaaoui | 0.93 | 0.98 | 0.96 | 44 |
| rice | 0.97 | 0.81 | 0.89 | 48 |
| seffa | 0.85 | 0.98 | 0.91 | 42 |
| accuracy | | | 0.86 | 400 |
| macro avg | 0.87 | 0.86 | 0.86 | 400 |
| weighted avg | 0.86 | 0.86 | 0.86 | 400 |

**Fig. 8.** Results of the MobileNetV2 pre-trained model

Figure 9 shows the training history of the MobileNetV2 model, including the accuracy and loss curves for both training and validation sets over 30 epochs.

The validation accuracy increases quickly during the first few epochs and then stabilizes around 0.86–0.88, showing that the model performs well on unseen data. The training accuracy also increases regularly, reaching about 0.82 by the end of training. The loss curves decrease throughout the training process, with the validation loss generally staying lower than the training loss. This pattern suggests that the model learns effectively and does not show strong signs of overfitting, since the difference between training and validation performance remains small. Overall, the curves demonstrate stable learning and confirm that MobileNetV2 adapts well to the FOOD-MOR dataset.

Figure 10 displays the confusion matrix for the MobileNetV2 model, illustrating classification performance across the ten food categories. It shows the number of correct and incorrect predictions for each class. For example, the model correctly classified 39 instances of "Rice" and 43 of "Lmlaoui," highlighting its performance in distinguishing between different food items.

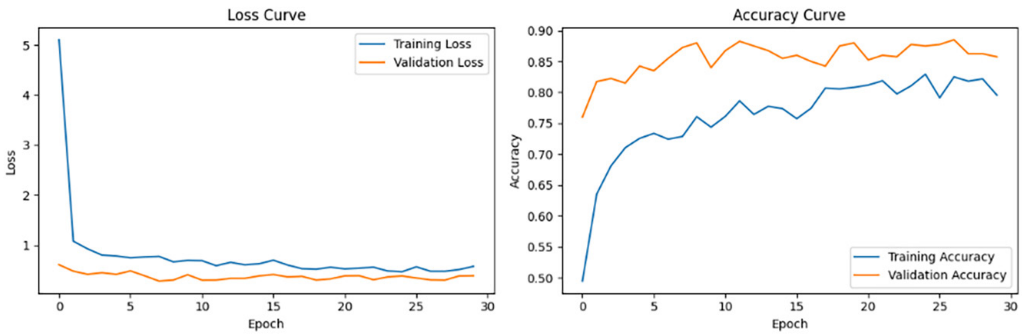


**Fig. 9.** Training and validation accuracy graph for MobileNetV2 model

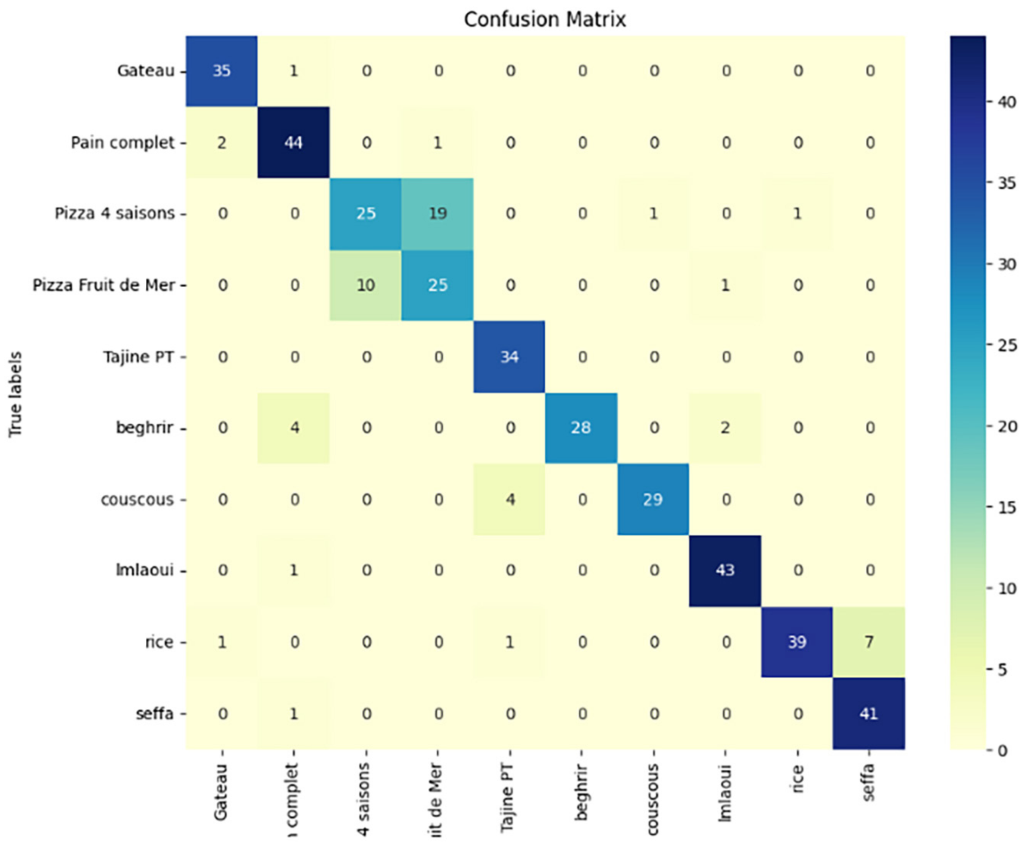


**Fig. 10.** Confusion matrix of MobileNetV2 model

The results indicate that:

- The model exhibits strong performance, with training and validation accuracies of 83% and 87%, respectively. This close alignment suggests effective learning of the training data without signs of overfitting.
- Performance Metrics: The training accuracy stabilizes around 83%, while validation accuracy settles around 87%. This slight discrepancy indicates good generalization capability.
- The training and validation accuracy curves closely follow each other throughout training, confirming the absence of overfitting. The accuracy increases rapidly during the initial epochs, particularly up to epoch 8, then progresses more slowly until epoch 30 before stabilizing. This pattern suggests that the model first captures the primary patterns and then gradually refines its understanding.
- Both training loss and validation loss decrease sharply within the first few epochs, indicating that the model quickly learns the fundamental structure of the data. The subsequent flattening of the loss curves suggests a convergence toward optimal performance.
- The error rates (training and validation) consistently decrease with increasing epochs, demonstrating effective learning. Notably, performance stabilizes around epoch 60, with only marginal improvements observed up to epoch 80.
- However, these results do not guarantee the model's suitability for all scenarios. A comprehensive evaluation including additional performance metrics—such as precision, recall, F1-score, and confusion matrix analysis—is necessary to better understand the model's strengths and limitations.
- Error Analysis: A detailed analysis of misclassifications is crucial. This includes examining the confusion matrix to identify classes with high error rates and investigating the nature and causes of these errors.

The MobileNetV2 model demonstrated strong performance across the ten food categories. For example, it correctly classified 43 instances of *Lmlaoui* and 39 of *Rice*. However, some confusion occurred between similar classes such as *Pizza 4 saisons* and *Pizza Fruit de Mer*, indicating areas where the model could be improved.

To assess the robustness and reproducibility of the MobileNetV2 model, additional experiments were conducted using multiple independent training runs. Two runs were performed with 30 epochs and two additional runs with 80 epochs, using the same dataset split and training configuration.

For the 30-epoch runs, overall classification accuracy ranged between 85.5% and 87.0%, with macro F1-scores from 0.855 to 0.870. The first run achieved 85.5% accuracy and a 0.855 macro F1-score, while the second run reached 87.0% accuracy with a 0.870 macro F1-score, indicating limited run-to-run variability.

At 80 epochs, the model showed slightly improved performance, with accuracies between 88.0% and 88.3% and macro F1-scores ranging from 0.882 to 0.888. The first run achieved 88.25% accuracy, while the second reached 88.0%, confirming stable convergence with longer training.

At the class level, frequently consumed dishes such as Lmlaoui, Couscous, Beghrir, and Tajine PT consistently achieved high precision and recall, often exceeding 95% across runs. Most misclassifications occurred between visually similar classes, particularly Pizza 4 saisons and Pizza Fruit de Mer, across all experiments.

Overall, the small variation in accuracy (within approximately ±1.5%) and macro F1-score across multiple runs demonstrates that MobileNetV2 delivers stable and reproducible performance on the FOOD-MOR dataset.

## 5 DISCUSSION

In recent years, photos of food are everywhere—on social media, blogs, and countless online platforms. This growing wave of food imagery shows just how much we enjoy capturing and sharing our everyday culinary moments in a visual, engaging way. Importantly, this phenomenon presents a unique opportunity to push the power of visual data to advance the field of personalized nutrition.

By leveraging state-of-the-art image recognition technologies and machine learning algorithms, nutritionists and healthcare professionals can exploit this wealth of food-related content to gain deeper insights into individual dietary behaviors and preferences. This user-generated imagery not only serves as a rich data source but also enhances the accuracy and adaptability of AI-based nutritional systems, enabling the delivery of personalized dietary recommendations that align with users' lifestyles and culinary habits.

Several studies have explored the use of image-based food recognition systems for dietary assessment and personalized nutrition. The proposed CALO mama system by Sasaki *et al.* [21], which relies on deep learning–based image recognition within a smartphone application to automatically identify food items and estimate nutrient intake, showing reliable performance while highlighting challenges in distinguishing visually similar food categories. Likewise, the goFOOD™ system introduced by Lu *et al.* [22] integrates CNNs with image preprocessing and food segmentation to support automated dietary assessment, reporting strong recognition results, mainly on controlled datasets. Earlier work by Reddy et al. [31] applied convolutional neural networks for food recognition and calorie estimation, demonstrating the suitability of CNN architectures for this task. In comparison, the proposed approach employs transfer learning with pre-trained VGG16 and MobileNetV2 models, enabling efficient feature extraction from food images while reducing training complexity. The use of lightweight and deep CNN architectures allows the proposed system to balance recognition performance and computational efficiency, making it suitable for personalized nutrition applications across diverse food categories.

Based on the results obtained from our pre-trained models, VGG16 and MobileNetV2, as presented in the confusion matrix, the following key observations can be made regarding classification performance:

**Class-Specific Performance:**

- "**Gateau":** This class shows a high true positive rate (35 correct predictions in MobileNetV2 and 36 in VGG16) with almost no confusion across both models, demonstrating consistent performance and strong feature discrimination for this item.
- **"Pain complet":** With 44 correct predictions in MobileNetV2 and 43 in VGG16, this class is well recognized by both models, though minor misclassifications occur toward visually related items such as "Pizza 4 saisons" and "Pizza Fruit de Mer," indicating partial overlap in texture and color cues.
- **"Imlaoui":** Both models achieve solid classification for this class, with MobileNetV2 performing better (43 correct predictions vs. 36 for VGG16), though small confusions with "Pain complet" and "Pizza 4 saisons" remain due to subtle shared visual structures.

**Misclassification Patterns:**

- **“Pizza 4 saisons”:** This class displays notable confusion with “Pizza Fruit de Mer,” especially in MobileNetV2 (19 and 10 misclassifications respectively), while VGG16 shows a very different pattern, with 1 misclassification of “Pizza 4 saisons” → “Pizza Fruit de Mer” and 30 misclassifications of “Pizza Fruit de Mer” → “Pizza 4 saisons,” highlighting a model-specific bias in handling these visually similar pizza classes.
- **“Couscous”:** With only 4 correct predictions in MobileNetV2 and 33 in VGG16, this class shows moderate confusion with “Tajine PT” and “Baghrir,” likely due to overlapping color–texture profiles and insufficient distinctive cues in certain samples.
- **“Rice”:** Both models classify rice well overall (MobileNetV2: 39 correct, VGG16: 36 correct), though slight confusion appears with “Gateau” and “Seffa,” potentially caused by similar granular textures or light-colored visual patterns.

**Minority Class Performance and Confusion:**

- **“Pizza 4 saisons”:** This class exhibits the lowest performance in MobileNetV2 (25 correct predictions) and a much higher score in VGG16 (40 correct), confirming a large performance gap and indicating that finer discriminative features or higher-resolution cues are needed to separate similar pizza types.
- **“Pain complet & Imlaoui”:** Despite strong accuracy in both models, small misclassifications in these classes mainly toward “Pizza” categories suggest exact feature overlap; MobileNetV2 performs slightly better for “Imlaoui,” while VGG16 shows more consistent results across bread-like items.
- **Visually similar dishes:** Classes with strong structural resemblance (especially pizza varieties) show systematically higher misclassification in MobileNetV2, indicating that VGG16 is better at detailed distinctions, while MobileNetV2 benefits more from augmentation in simpler, texture-dominant classes.

## 6 RECOMMENDATIONS FOR IMPROVEMENT

**Increase Data for Minority Classes:** To address the class imbalance observed in the dataset, it is recommended to collect additional training samples for under-represented classes such as “Pizza 4 saisons.” Expanding the dataset for these minority classes will help the model learn more distinctive features and reduce misclassification rates, particularly among visually similar food categories.

**Implement Data Augmentation Techniques:** Applying advanced data augmentation strategies (e.g., rotation, zoom, flipping, and brightness adjustment) can significantly increase the diversity of training examples, especially for classes that exhibit high confusion rates. This approach enhances the model’s robustness and generalization ability by exposing it to varied representations of the same class during training. In our experiments, the impact of augmentation is evident in the differences between MobileNetV2 and VGG16: MobileNetV2 shows improved performance in classes with simpler or more uniform structures (e.g., Imlaoui and Rice), suggesting that augmentation helped it learn more stable low-level patterns. In contrast, VGG16 benefits more in visually complex categories such as pizza types, where augmented variations appear to strengthen its ability to recognize nuanced visual distinctions.

**Model Fine-Tuning:** To improve the model's generalization capability, it is advisable to consider fine-tuning the pre-trained VGG16 model on a larger and more diverse dataset, particularly one that better captures the visual similarities and subtle distinctions between certain dishes. By incorporating more representative samples, the model could learn to differentiate between classes with overlapping visual features, ultimately reducing misclassifications and enhancing performance on complex categories.

In contrast, the MobileNetV2 pre-trained model demonstrated greater effectiveness in recognizing food dishes in our experiments. When applied to the test dataset, MobileNetV2 achieved an overall classification accuracy of 86%, indicating its robustness and suitability for this specific food recognition task. This result comparison in Table 1 suggests that MobileNetV2 may be better optimized for feature extraction in food imagery, possibly due to its lightweight architecture combined with depth wise separable convolutions that allow it to capture discriminative features more efficiently.

**Table 1.** Accuracy comparison of the two models

| Model | Epochs | Train Accuracy | Test Accuracy |
|---|---|---|---|
| VGG16 | 30 | 0.81 | 0.8149 |
| MobileNetV2 | 30 | 0.86 | 0.8575 |

## 7 CONCLUSION

This study focused on the development and evaluation of food recognition models using the VGG16 and MobileNetV2 architectures to classify a variety of traditional Moroccan dishes alongside modern foods. The results demonstrate that both models are capable of effectively identifying food items, with the MobileNetV2 model slightly outperforming VGG16 in terms of overall classification accuracy. Specifically, classes such as "Imlaoui" and "Gateau" were accurately identified, while some confusion remained between visually similar dishes, notably "Pizza 4 saisons" and "Pizza Fruit de Mer."

The integration of these deep learning models with a Moroccan food composition table presents a valuable step toward personalized nutrition. By accurately identifying food items from images, the system allows for the estimation of caloric and nutritional content. This enables healthcare professionals and nutritionists to generate personalized dietary plans based on both traditional and modern food consumption patterns. Such an approach ensures dietary assessment that aligns closely with cultural eating habits and modern culinary trends, thereby enhancing the applicability and effectiveness of personalized nutrition recommendations.

To further improve model performance, several strategies are recommended:

- Increase Data for Minority Classes: Addressing class imbalance by collecting more samples for underrepresented categories (e.g., "Pizza 4 saisons") will enhance the model's ability to learn distinguishing features and improve classification performance.
- Data Augmentation: Introducing a broader range of training samples through augmentation techniques such as rotation, scaling, and brightness adjustment can increase model robustness and reduce overfitting, particularly for classes with high visual similarity.

- Model Fine-Tuning: Fine-tuning the VGG16 and MobileNetV2 models on larger and more diverse datasets, particularly those containing similar food classes, can enhance their generalization ability and reduce misclassification rates.
- Hyperparameter Tuning and Feature Engineering: Exploring advanced optimization techniques and incorporating domain-specific features could further enhance classification accuracy, especially for complex and ambiguous food classes.

The successful implementation of this recognition system not only underscores the effectiveness of pre-trained deep learning architectures in food classification tasks but also highlights the promising role of machine learning in dietary monitoring and management. With continued refinement, such models can be instrumental in developing intelligent systems for real-time nutritional assessment, and personalized healthcare solutions.

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