Research Article

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Estimating glycemic index in a specific dataset: The case of Moroccan cuisine

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Abstract: A healthy lifestyle encompasses physical, mental, and emotional well-being, with healthcare and nutrition as central components. For those with chronic diseases such as diabetes, effective self-management involves continuous monitoring and dietary adjustments. Understanding the glycemic index (GI) is vital, as it indicates how carbohydrates affect blood sugar levels. Advancements in artificial intelligence have enhanced diabetes management through food image recognition systems, which identify food items and provide nutritional information, helping individuals track their dietary intake and GI consumption effectively. Despite their high performance, existing systems often lack inclusivity for diverse cuisines, such as Moroccan cuisine, which is known for its unique dishes of spices and health benefits. This study addresses these gaps by proposing the first comprehensive Moroccan food dataset, comprising 8,300 images across 70 food categories. The research subsequently proposes an advanced model to enhance food image recognition accuracy using convolutional neural network and attention mechanisms achieving more than 90% accuracy. In addition, estimating the GI values of Moroccan foods will help to raise public awareness of their health implications and facilitate decision-making on dietary self-management. The results demonstrate state-of-the-art performance, indicating promising potential for the first GI estimation of Moroccan food images.

Keywords: food image dataset, food image recognition, deep learning, glycemic index, image processing

1 Introduction

In today's fast-paced world, the importance of a healthy lifestyle is more crucial than ever, particularly in the context of rising rates of chronic diseases such as diabetes, heart disease, and obesity. A significant challenge faced by individuals, especially those managing chronic illnesses, is the effective integration of nutritious food choices and proactive healthcare practices into their daily routines. Diabetes, in particular, requires constant monitoring of blood sugar levels, adherence to medication regimens, and lifestyle modifications such as

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dietary changes and regular exercise. Self-management empowers individuals to make informed decisions about their health and take proactive steps to manage their condition effectively and reduce the risk of complications. One important aspect of diabetes self-management is understanding the glycemic index (GI), which measures how carbohydrates in foods affect blood sugar levels. Foods with a low GI are digested and absorbed more slowly, leading to gradual increases in blood sugar levels, while high-GI foods cause rapid spikes [1]. Despite the recognized importance of healthy eating, many people lack the tools and knowledge necessary to make informed dietary decisions, leading to poor health outcomes. Motivated by the need for improved self-management strategies among individuals with chronic conditions, this research aims to address the gap in dietary monitoring systems, particularly regarding the GI and its impact on blood sugar control. Understanding the GI of foods is essential for diabetes management, as it guides individuals in selecting foods that promote stable blood sugar levels. While artificial intelligence (AI) and deep learning technologies have advanced dietary monitoring, existing food image recognition systems often overlook specific cultural cuisines, including Moroccan cuisine that has lately increased in popularity and has become known around the world. Due to its distinctive cuisine, Morocco has also become one of the most popular travel destinations [2]. Additionally, Moroccan food is renowned for vegetables, fruits, and monounsaturated fats like olive oil, all of which are beneficial for people with chronic conditions who need to check their diets daily [3]. According to Chauveau et al. [3], Mediterranean diets are advised to slow the evolution of kidney disease and prevent complications, and Moroccan cuisine is one of the cuisines that have common food habits with Mediterranean countries due to their geographical proximity. This study proposes to create the first comprehensive Moroccan food dataset, focusing on traditional and commonly consumed dishes, to enhance dietary assessment for diabetes self-management. An innovative food image recognition approach is developed utilizing DenseNet combined with an attention mechanism to improve classification accuracy for Moroccan foods. Additionally, an estimation of GI values for these dishes is presented, categorizing them into low-, medium-, and high-GI groups, thereby empowering Moroccan consumers to make informed dietary choices. The specific contributions of this work include:

- Moroccan food dataset development: Collecting and preprocessing a robust dataset of Moroccan dishes resulting in 70 categories and 8,300 images and enabling tailored research in food image recognition and dietary assessments.
- Novel methodology proposal: Developing a food image recognition system using DenseNet model and attention mechanism technique to enhance classification accuracy for Moroccan cuisine.
- GI estimation: Estimating and categorizing GI values for Moroccan foods, providing essential insights for diabetes self-management.

The structure of this article is organized into four sections. Section 1 investigates the state-of-the-art in food computing, highlighting the limitations faced in these fields. Section 2 presents the development of the Moroccan food dataset, the proposed food image recognition methodology and the estimation of GI values for Moroccan foods. Section 3 details the experiment steps and the obtained results; finally, the article concludes with insights and recommendations for future research directions.

2 Literature review

2.1 Food image recognition systems

Food image recognition is the most important task in various food applications, whether it is a health application such as dietary assessment or otherwise. Several approaches have been proposed to classify food images: most of them are applying deep learning models for their efficiency in food image classification [4]. One of the common methods used by multiple approaches for food recognition is convolutional neural network (CNN) models [5]. Jiang et al. [6], Ye and Zou [7], and Deng et al. [8] used different versions of region-based convolutional neural network (RCNN) for food image classification and nutrition analysis. Ran et al. [9]

and Ambadkar et al. [10] used the concept of transfer learning and applied several CNN pretrained models such as DenseNet-169 and Inception, while Latif et al. [11] proposed three types of CNNs with a different number of layers to recognize fruits and vegetables. Various authors choose to concatenate certain deep learning methods, for example, Şengür et al. [12] fused the extracted features from VGG16 and AlexNet models and then classified them using an SVM classifier. Likewise, Zhang et al. [13] proposed a combination of features extracted from DenseNet, AlexNet, and Inception and classified with subnetwork-based neural network classifier. Some authors proposed hybrid systems that combine supervised and unsupervised deep learning methods. Xue et al. [14] pretrained the images with the unsupervised method autoencoder and then extracted and classified features using DenseNet. Similarly, Mandal et al. [15] performed semi-supervised food recognition using generative adversarial networks and CNN.

Gao et al. [16] proposed a high-accuracy food image classification with data augmentation and feature enhancement through vision transformer; the method includes Augmentplus, LayerScale, and multi-layer perception mechanism of feature local enhancement, referred to as AlsmViT. Nguyen et al. [17] addressed the segmentation, recognition and counting of food instance in real time by a multi-task neural network with three branches dedicated to counting, semantic segmentation, and contour map generation. Liu et al. [18] presented a fruit identification system for estimating the glycemic load value. The authors prepared a fruit dataset and proposed a Faster RCNN deep learning model for image identification, then obtained the pre-calculated GI from different online sources to calculate the glycemic load based on the GL formula, the identified fruit, and the predicted volume. Khan et al. [19] investigated a method for estimating the GI of foods by applying machine learning to food images from the foodpics extended database, which aligns with international GI tables for low-, medium-, and high-GI categories. The study involves capturing food images, processing them with various image analysis techniques, and using machine learning models to predict the GI category with five different classifiers: AdaBoost with random forest, J48 decision tree, k-nearest-neighbor, Naive Bayes, and sequential minimal optimization-based SVM.

2.2 Food image datasets

A well-annotated dataset with a large amount and varied images is an essential task for a powerful food recognition system. The food dataset is classified by the number of images and classes, the type of food, and the source of images. Some datasets are publicly available for use, while others are privately constructed for a specific approach. Certain datasets are specialized in fruit and vegetables, such as VegFru [20], and it contains 292 categories and 160,000 images gathered from the Web. Fruits 360 [21] was made up of 131 categories of fruits and vegetables and 90,000 images captured using a camera in a laboratory. The two mentioned datasets are publicly available, while Latif et al. [11] proposed a private fruit dataset to evaluate their contribution containing 40 classes and 41,509 images captured with a camera. The second type of dataset presented in this study is the specific cuisine dataset. In terms of datasets for Japanese food, UEC Food100 [22] and UEC Food256 [23] are both well-liked. UEC Food256 has 256 dishes with 25,000 images including the bounding box. Vireo Food-172 [30] and Chinese FoodNet [31] are two Chinese datasets containing 110,000 images of 172 category and 180,000 images of 208 categories, respectively. Other cuisines are presented such as a Kenyan food dataset [32] with 8,174 images and 13 dishes, a Brazilian food dataset [36] composed of 1,250 images of 9 classes, and a Thai food dataset [35] with 15,770 images and 50 categories, and the images are collected from the web. All the previous mentioned datasets are publicly available, while a private Turkish food dataset [45] and Asian food dataset [40] are proposed containing 7,500 images and 15 classes collected from the web, and 35,842 images of 16 classes gathered from restaurants, respectively. The last type is the miscellaneous dataset. As a result of the need for a benchmark food recognition system, several authors took the initiative to create benchmark datasets that included a variety of food categories. Among benchmark datasets, Food524DB [28] and ISIA Food-500 [29] are the largest. ISIA Food-500 was made up of 500 categories and about 399,000 images that were obtained from the Web, whereas the Food524DB dataset contained 247,000 images of 524 dishes collected from four existing datasets. Another large dataset, Food2k [38], has 1 million images and 2,000 categories. However, the dataset is still not publicly available. Table 1 presents the existing food datasets.

Table 1: List of food image datasets

Ref	Years	Dataset	Type	Image	Class	Performance	Source	Availability
[20]	2017	VegFru	Fruits and vegetables	160k	292	83.51%	Web	Public
[21]	2017	Fruits-360	Fruits and vegetables	90k	131	96%	Camera	Public
[22]	2012	UEC Food100	Japanese	14k	100	68.9%	Web	Public
[23]	2014	UEC Food256	Japanese	25k	256	63.2%	Web	Public
[24]	2014	ETHZ Food 101	Miscellaneous	101k	101	69%	Web	Public
[25]	2014	UNICT FD889	Miscellaneous	3,583	889	75%	Camera	Public
[26]	2015	FooDD	Miscellaneous	3,000	23	88%	Camera	Public
[27]	2019	FoodX-251	Miscellaneous	158k	251	97%	Web	Public
[28]	2017	Food524DB	Miscellaneous	247k	524	90%	Existed datasets	Public
[29]	2020	ISIA Food-500	Miscellaneous	399k	500	94%	Web	Public
[30]	2016	Vireo Food-172	Chinese	110k	172	86%	Web	Public
[31]	2017	Chinese FoodNet	Chinese	180k	208	92%	Web camera	Public
[32]	2019	Kenyan Food13	Kenyan	8,174	13	90.6%	Web	Public
[33]	2009	PFID	Fast food	4,545	101	90%	Restaurant camera	Public
[34]	2017	UNIMIB2016	Italian	1,027	73	97%	Camera	Public
[35]	2017	THFOOD-50	Thai	15,770	50	98%	Web	Public
[36]	2020	MyFood	Brazilian	1,250	9	89%	Web	Public
[37]	2019	SUEC Food	Segmented Asian food	31,995	—	87%	Existed dataset	Public
[38]	2021	Food2K	Miscellaneous	1M	2,000	97.33%	Web	Private
[11]	2020	Self-made dataset	Fruits	41,509	40	98%	Camera	Private
[39]	2020	Self-made dataset	Pastry	1,289	16	95%	Camera	Private
[40]	2019	Ville Cafe	Asian food	35,842	16	94.67%	Restaurant	Private
[41]	2020	Self-made dataset	3D models of miscellaneous categories	4k	10	91%	AutoCad	Private
[42]	2019	BTBUFood-60	Miscellaneous	60k	60	96.19%	Web	Private
[43]	2019	Self-made dataset	Segmented Asian food	14k	100	97.22%	Existed datasets	Private
[44]	2019	AIFood	Miscellaneous(with ingredient labeling)	3,72,095	24	96.12%	Web/existed datasets	Private
[45]	2017	TurkishFoods-15	Turkish food	7,500	15	83.75%	Web	Private

3 Proposed approach

3.1 Moroccan food dataset

The presented dataset is the first Moroccan food dataset to construct a food recognition system suitable for consumers of Moroccan food and address various applications of food computing, such as dietary monitoring. Creating the Moroccan food dataset involves several systematic steps to ensure the accuracy and reliability of the data. The following section presents the general outline of these steps:

Determine the dataset scope: The scope of the Moroccan food image dataset is defined to ensure that the collected data are relevant to the research objectives and can provide meaningful insights when used. It includes the following:

- Image dimension: The chosen images are two-dimensional array images with a color palette described by three vectors that contain the Red, Green, and Blue values in which each image pixel is represented by the RGB triplet.
- Categories: Based on the objectives of the presented approach, the categories of the dataset are chosen carefully based on the published studies of the traditional Moroccan dishes that are consumed by the Moroccan population [46–48], and the common non-traditional dishes that are consumed all over the world including Moroccan consumers.
- Exclusion and inclusion of the content: The Moroccan dataset presented includes 2D RGB images of traditional and common dishes consumed by the Moroccan population. The image content must contain the food

as the main object and a single food item, not multi-element food objects. Excluded images are those with different objectives in terms of content and type.
- Geographical coverage: First, the geographical coverage of the Moroccan food dataset is mainly the Moroccan country and then Mediterranean countries such as Italy with their traditional dishes consumed by the Moroccan population due to geographical proximity. Other countries such as France have an impact on the daily diet of the Moroccan population as a result of colonial history.

Depth of data information: Each image is labeled with the food category it belongs to, and the estimated nutritional information of the GI is added. Search engines and existing datasets were employed to gather the images. Three techniques were used for web scraping: the Google Image Download Library extension, the Microsoft Bing Image Downloader Library, and the extension of Google Download All Images, each of which is written in Python. We collected several categories using UECFOOD256, Food-101, and fruits-356. UEC Food256 has 256 dishes with 25,000 images including the bounding box from Japanese cuisine, Fruits-360 composed of 131 categories of fruits and vegetables and 90,000 images captured using a camera in a laboratory, and Food101 that has Miscellaneous food types containing 101,000 images and 101 category.

These techniques have led to the creation of 70 classes as a starting point and a total of 8,300 images, representing the most popular and eaten foods in Morocco. A total of 51 categories are purely traditional dishes from the Moroccan culture, such as harira soup, rfissa, couscous, and bastille. However, 19 classes are common dishes consumed all over the world including Moroccan people such as pasta, pizza, and chocolate cake.

Images that are duplicated and undesirable are produced when data are acquired through search engines. Data preparation starts with editing and deleting duplicate images. Then, the size of images in each class is uniformed across the dataset. To start, we split the dataset into two folders, the training set and the testing set; training set contains 6,668 images, while the testing set contains 1,632 images, all of which have been scaled to 150 × 150. To improve the efficiency of the food recognition system by concentrating on the food item and disregarding the background and other items in the image, the principal food is extracted from the background using a semi-automatic segmentation technique called GrabCut [49]. GrabCut method extracts automatically the foreground as a first step; then, a user interaction step is proposed for segmentation improvement by drawing a line around the food item. Figure 1 represents an example of an image before and after applying GrabCut segmentation. Figure 2 presents the samples of the dataset images.

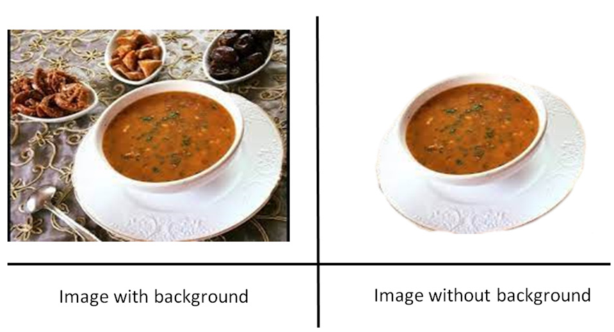

Figure 1: Example of GrabCut extraction. Source: Created by the authors.

3.2 Food image classification

Potent kind of deep learning method known as the CNN has demonstrated outstanding results in a variety of areas, including the recognition of food images [50]. Different works have proved that CNN outperforms other sort of deep learning networks and classical machine learning. In recent years, several CNN models have been used, each with unique layers and parameters. The majority of CNN models use a pooling layer to create feature maps and backpropagation to improve the learning phase. Transfer learning is a technique that

Figure 2: The 70 categories of Moroccan food dataset. Source: Created by the authors.

leverages knowledge gained from one task and applies it to another, related task: in this case, the principal task is object recognition and the related task is food image recognition. By utilizing pretrained models on the large dataset ImageNet [51], transfer learning helps overcome the limitation of scarce data in food recognition. Instead of starting from scratch, the pretrained model's knowledge is fine-tuned and adapted, making the learning process more efficient and effective. In this article, the DenseNet pretrained CNN model has been chosen for food image classification; DenseNet addresses the vanishing gradient problem and encourages feature reuse by densely connecting each layer to every other layer in a feedforward manner. This connectivity pattern results in a dense and highly interconnected network, promoting better gradient flow, enhanced information flow, and increased parameter efficiency. The skip connections in DenseNet facilitate effective feature propagation across different layers, allowing the network to capture intricate patterns and context from images [52]. In this article, we propose the combination of the attention mechanism technique and DenseNet for food image classification; the attention mechanism goes beyond simple weightings of input features and incorporates more complex interactions among them. It utilizes additional mechanisms, such as gating or memory components, to better capture long-range dependencies and context in the data. By doing so, the attention mechanism technique can effectively focus on the most relevant parts of the input and selectively combine information from different sources. As described in Figure 3, we used DenseNet model as the backbone network, and then, the attention mechanism module is defined by applying a convolutional operation followed by a sigmoid activation to calculate the attention weights. The attention weights are then multiplied element-wise with the input feature maps resulting from DenseNet to highlight important regions. Finally, a pooling layer is applied to reduce spatial dimensions, and fully connected layer with softmax activation function is added to output the predicted classes.

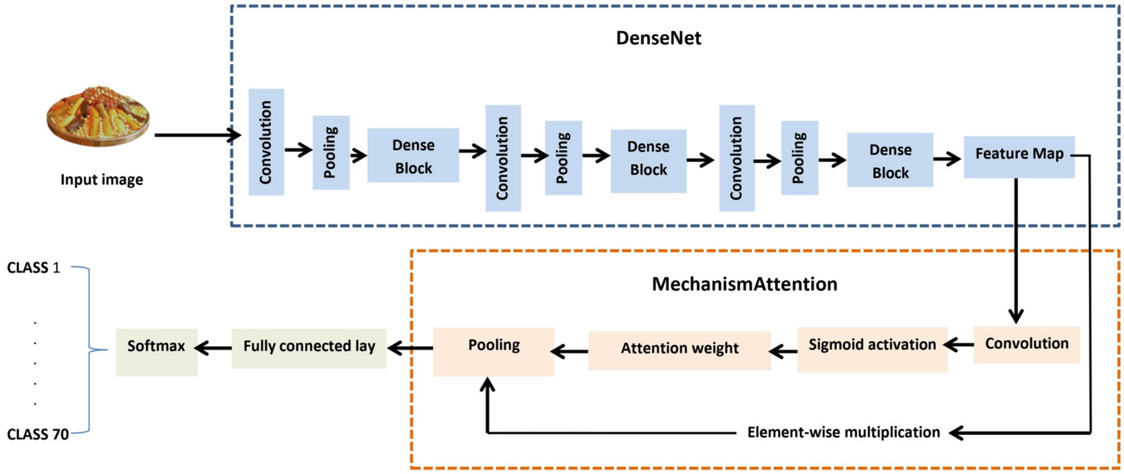

Figure 3: Architecture of the food image classification approach. Source: Created by the authors.

3.3 GI estimation

3.3.1 General context

GI is a numerical scale that quantifies the postprandial blood glucose response to a specific amount of carbohydrates in a test food relative to the response induced by the same amount of carbohydrates in a reference food, usually glucose or white bread. It was developed to aid individuals, especially those with diabetes, in making food choices that help regulate blood sugar levels [53]. Foods with a higher GI are digested and absorbed more rapidly, resulting in a quicker and more substantial increase in blood glucose levels; low-GI foods, characterized by slow starch digestion, offer benefits in managing diabetes, aiding weight control, enhancing satiety, and preventing cardiovascular disease. In a medical context, the GI serves as a tool to guide dietary choices, particularly for individuals managing diabetes or seeking to control blood sugar levels. Moreover, clinical studies have shown that low-GI diets reduce risk factors cardiovascular diseases, improve glycemic control, reduce blood lipids, lower blood pressure, and are associated with reduced body weight [54]. The GI categorizes foods into high (GI ≥ 70), moderate (GI 56–69), or low GI (GI ≤ 55) [54]. With the global escalation of type 2 diabetes and obesity rates, there is a growing interest in the GI of foods worldwide [55]. The GI is used to understand the carbohydrates quality, while the concept of the GL is related to the quantity of carbohydrates consumed during a meal. GL provides insights into the combined impact of the quantity and quality of carbohydrates on blood glucose levels. Assessing GL aids in understanding how various-sized portions of these foods compare in terms of their impact on blood glucose levels. Foods are categorized as low (GL < 10), medium (10 < GL < 20), or high (GL > 20) based on their GL values [54].

3.3.2 GI methodology

Various researchers have presented the scientific and medical methods to determine GI. Wolever et al. [53] introduced the physiological basis of the GI determination; they involve both normal and diabetic participants consuming portions of test foods and white bread, each having 50 g of available carbohydrates (ACs). To determine accuracy, the white bread is used multiple times per participant. Capillary blood samples are taken from the participants at various intervals, varying for normal and diabetic people. For normal people, the times are fasting and 15, 30, 45, 60, 90, and 120 min after the meal. For diabetics, it is fasting and 30 min intervals for 3 h. If insulin or an oral hypoglycemic agent is taken, it is administered after the fasting blood sample and 5–10 min before the meal. The glycemic response for each food is calculated as a percentage of the mean response to the white bread. As shown in equation (1) and Figure 4, the GI is determined as the incremental area under the blood glucose response curve (AUC). This response is triggered by a 50 g portion of available carbohydrates (AC) from a test food, expressed as a percentage of the response caused by the same amount of AC from a standard food (such as white bread or glucose). Finally, equation (2) calculates the GL by multiplying the carbohydrate content and GI of food [54]:

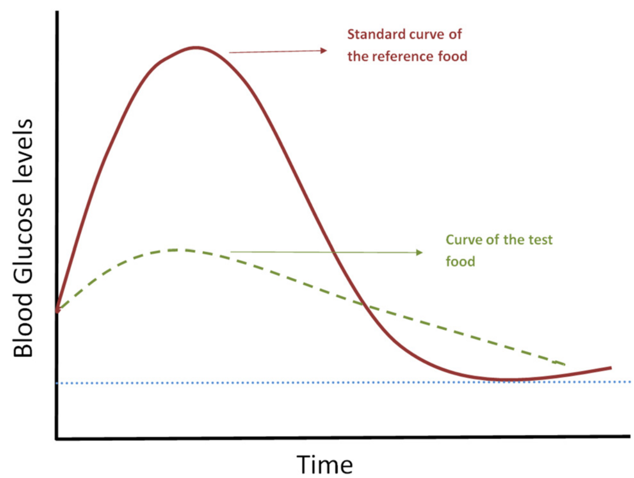

Figure 4: GI determination using the incremental AUC. Source: Created by the authors.

$$GI_{food} = AUC_{food/mean}AUC_{reference} \times 100, \quad (1)$$

$$GL_{food} = GI_{food} \times AC_{perserving}/100. \quad (2)$$

Variables such as food portion size, choice of standard food, repeated testing of the standard food, frequency and timing of blood sampling, and the method of area calculation can affect the GI value. Other factors include the method of blood sampling, participant characteristics, dose and timing of insulin, and degree of diabetes control. These variables can affect the absolute glycemic response; standardizing them seems to have only slight effects on the resulting GI value. For mixed ingredient meals and when several carbohydrate items are included, the weighted mean of their respective GI values is used to calculate the GI of the meal. As shown in equation (3), the weighting is determined by the percentage of total meal carbs that each food contributes [53]:

$$GI_{meal} = \frac{\sum_{i=1}^{n}\left(GI_i \times \frac{Carbs_{food_i}}{Total\ Carbs_{meal}}\right)}{n}. \quad (3)$$

Several reviews have discussed the GI methodology, covering the development of the concept and the various methods used to determine GI values [56]. The comprehensive review emphasizes methodological considerations, including recommendations for the number of subjects, sex, subject status, pretest conditions, carbohydrate test dose, blood sampling procedures, sampling times, test randomization, and calculation of glycemic response AUC. These technical recommendations aim to enhance the implementation and quality of GI measurements in laboratories.

3.3.3 GI challenges

Several evaluations of the published data discuss the variation in GI values among certain foods, attributable to factors such as botanical distinctions, compositional and processing differences, and potential variations in the methods used to determine GI values. The majority of GI values are derived from commercially processed foods, and alterations in ingredients or processing methods by manufacturers can influence these values. The type and structure of starch, particularly the content of amylose and amylopectin, play a role in determining the GI of foods such as rice and potatoes. Other factors such as moisture, storage conditions, and processing influence starch characteristics, consequently affecting GI [57,58]. The ripening process in fruits and vegetables can elevate their GI [54]. Cooking techniques such as boiling, frying, steaming, microwaving, and roasting globally influence the GI. In previous studies [59,60], cooking processes lead to physical changes in the starch microstructure of potatoes, affecting the overall GI. In Table 2, mashed and boiled potatoes typically have higher GI than fried, microwaved, or baked ones. Ultimately, the choice of cooking method can impact the glycemic response, taking into consideration a favorable option for lower GI.

Table 2: Example of potato GI with different cooking methods [60]

Reference	Boiled	Baked	Roasted	Mashed	French fries	Microwave
Method 1	64	53	55	74	38	—
Method 2	71	48	53 (crisped)	77	40	—
Method 3	—	72	73	88	64	—
Method 4	74 ± 28 (fresh)	68 ± 21 (fresh)		76 ± 30 (fresh)	—	—
Method 5	59–64	—	—	88	76	—
Method 6	88 ± 9	93 ± 11		91 ± 9		79 ± 9
Method 7	—	—	—	74–97	—	—

The individual characteristic has an impact factor on the GI determination, and GI values can vary between individuals and even within the same individual on different occasions. Factors such as individual metabolism, health status, and the presence of other foods in the digestive system can contribute to this variability [56]. GI values are typically determined under controlled conditions with fasting individuals. However, real-world eating often involves consuming foods in combination. The glycemic response to a mixed meal may differ from the response to individual foods. Several approaches have determined GI using clinical trials [61–63], while others rely on intelligent systems to estimate GI and GL values. Liu et al. [18] presented a fruit identification system for estimating the GL value. The authors prepared a fruit dataset and proposed a Faster R-CNN deep learning model for image identification, then obtained the precalculated GI from different online sources to calculate the GL based on the GL formula, the identified fruit, and the predicted volume. Bas [64] used a three-step methodology to integrate the GI and GL values of foods with various decision-making approaches. Step 1 is to assign foods with measured GI values to GI classes and determine the membership values of the foods in each GI class using Fuzzy c-means classification. In Step 2, the data from Step 1 are used to assign foods with no measured GI values to GI classes using the fuzzy pattern recognition technique and estimate GL. In Step 3, a linear programming-based diet model is proposed for glycemic control. Estimating the GI of food outside the clinical trials faces challenges stemming from individual variability, as factors such as age, genetics, and overall health contribute to diverse responses. The impact of food preparation and processing is significant, with cooking methods and ingredient combinations influencing GI, posing a challenge for accurate estimation solely through image recognition. The complexity intensifies when dealing with mixed meals, as the interaction between diverse components complicates the estimation of the overall GI. Temporal effects further add to the complexity, as variations in the rate of carbohydrate digestion and absorption over time, influenced by factors such as meal timing and metabolic state, make precise predictions challenging. Figure 5 resumes the mentioned factors affecting GI determination.

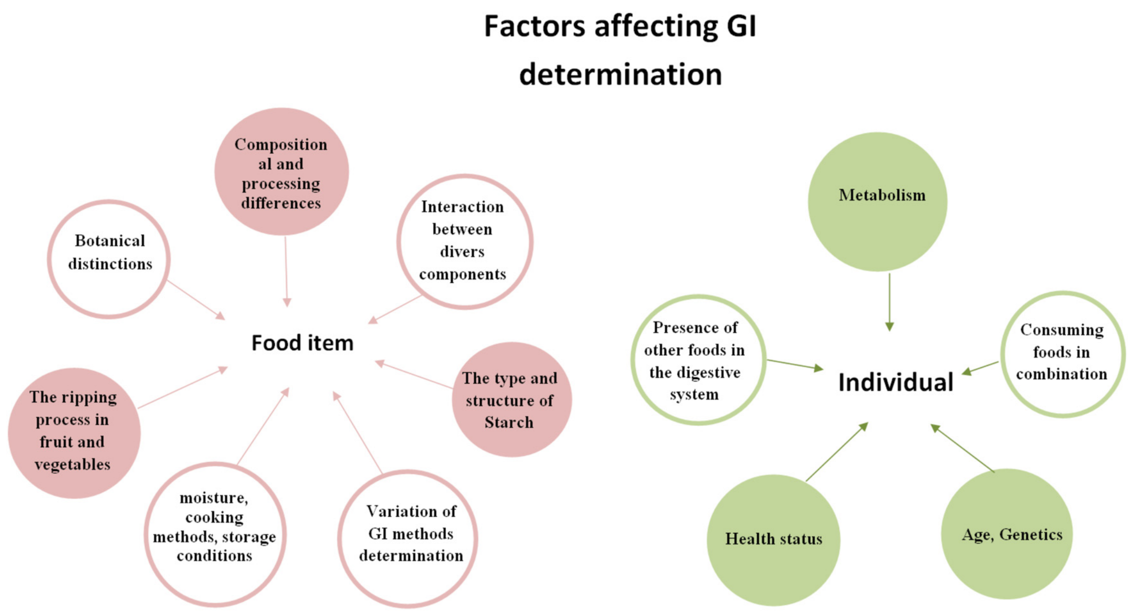

Figure 5: Factors impacting GI determination. Source: Created by the authors.

3.3.4 GI estimation of Moroccan food

The GI is important to Moroccan citizens as it provides a valuable tool for making informed dietary choices, promoting health, preventing chronic diseases, and aligning traditional dietary practices with modern health considerations. Consuming low-GI foods may contribute to better blood sugar management, which is important for preventing and managing conditions like diabetes. This knowledge is particularly crucial given the rising rates of diabetes globally, including in Morocco. As there is no public dataset or recognition system providing GI values for Moroccan food, raising awareness about the GI and its implications for health is the main objective of this article, it aims to sensitize Moroccan citizens to the impact of knowing the GI on dietary self-management decisions. Morocco has a rich culinary tradition with a diverse range of foods. Understanding the GI can help individuals tailor their traditional meals to be more health-conscious. For instance, incorporating a mix of low-GI foods, such as legumes and whole grains, into traditional Moroccan dishes can have positive health implications. Given the challenges outlined in assessing the GI and the absence of precalculated GI values for Moroccan cuisine, our study offers estimated GI values and classifies Moroccan foods into low-, medium-, and high-GI categories. This classification aims to assist Moroccan consumers in making informed dietary choices for effective self-management. The proposed method for estimating the GI involves the following steps:
- Categorize food items into simple and multiple components.
- For simple food items, provide the corresponding GI values using public sources [57,58].
- For multiple food items (meals), assess the carbohydrate content of each item based on a standard adult portion size.
- Calculate the GL for each food item in the meal using the formula: GL = (GI of the food) × (amount of carbohydrates in the food in grams)/100.
- Determine the total GL of the meal by summing up the GL values for all food items, thereby obtaining the GL of the entire meal.
- Estimate the overall GI of the meal using the GL formula, providing approximate intervals.

Figure 6 illustrates the overarching architecture of the proposed approach. The output of the food image classification model includes the food class label and its associated category level. According to Foster-Powell et al. [58], GI values are not specified for foods such as meat, poultry, fish, salad vegetables, cheese, or eggs due

Figure 6: Global architecture of the proposed approach. Source: Created by the authors.

to their minimal carbohydrate content. Even in substantial quantities, these foods are unlikely to significantly raise blood glucose levels. Table 3 outlines the approximate GI intervals for the classes in the Moroccan dataset and the corresponding category for each food item.

Table 3: GI estimation of the Moroccan food dataset

Type	Label	Estimated GI	Category
Simple food item	Apple	39–44	Low
	Banana	47–62	Medium
	Dates	69–100	High
	French fries	54–76	High
	Lentils	29–37	Low
	Orange	33–53	Low
	Pears	25–43	Low
	Zitoun	0–15	Low
Multiple food item	Bahla	67–71	High
	Basbousa	58–69	Medium
	Batbout	75–95	High
	Baghrir	75–95	High
	Amlou	60–78	High
	Bissara	56–69	Medium
	Briouat with almonds	70–88	High
	Caesar salad	50–68	Medium
	Chebakia	76–90	High
	Chicken basstila	70–80	High
	Chicken nuggets	55–62	Medium
	Chicken with potatoes and olives	62–95	High
	Chocolate cake	54–70	High
	Couscous	59–68	Medium
	Crackers with almonds	78–86	High
	Croissant	70–78	High
	Feet of beef	0–28	Low
	Fekkas	79–86	High
	Feves with sauce	46–55	Low
	Fish and vegetables	54–59	Medium
	Fish bastilla	49–65	Medium
	Fried calamari	0–36	Low
	Gazelle horn	76–84	High
	Hamburger	66–76	High
	Harcha	60–69	Medium
	Harira	64–69	Medium
	Jam	61–79	High
	Kaak	74–80	High
	Lasagna	54–63	Medium
	Liver with sauce	15–45	Low
	Maakouda	77–83	High

(Continued)

Table 3: *Continued*

Type	Label	Estimated GI	Category
	Meatball with tomato sauce	15–45	Low
	M'hancha	78–86	High
	Msamen	72–90	High
	Nougat	65–70	High
	Paella	66–70	High
	Pizza	60–80	High
	Rfissa	62–78	High
	Rghayf	76–82	High
	Seffa	55–65	Medium
	Seffa with rice	69–79	High
	Sellout	79–88	High
	Sfenje	72–90	High
	Snowballs	70–78	High
	Spaghetti	51–69	Medium
	Sweet bread	72–75	High
	Tagine with artichokes and peas	22–25	Low
	Tagine with beef	29–33	Low
	Tagine with quince	25–35	Low
	Tagine with vegetables	55–69	Medium
	Taktouka	29–35	Low
	Tkalya	33–45	Low
	Tomatoes and onion salad	0–15	Low
	Traditional bread	56–66	Medium
	Traditional macaroon	69–80	High
	White beans with tomatoes	45–55	Low
	Zaalouk	15–25	Low

4 Experiment and results

4.1 Dataset evaluation

Evaluating an image dataset is an essential phase to ensure the quality and suitability of the data for training and testing a food image recognition model. Several steps were taken into consideration for evaluating the Moroccan food dataset. Diverse data were collected to help the model generalize better in real-world scenarios. The data were manually preprocessed to detect and remove duplicate or near-duplicate images and to examine resolution, clarity, and noise to preserve high-quality aspects. Data balance has also an impact on model performance, as imbalanced data across different classes can lead to biased results. Figure 7 displays the initial distribution of the dataset categories, while data augmentation techniques were used on training, testing, and validation sets, each configured with parameters to randomly rotate images by up to 2 degrees, flip them horizontally, and zoom in by up to 10%, and oversampling the minority class until it reaches the desired balance with the majority class, to enhance the data's balance and increase model robustness.

The dataset was divided into training, test, and validation sets. The training set consists of 6,668 images for training the model, while the test set comprises 1,632 images to evaluate the model's performance after training. Additionally, 30% of the training set was allocated to the validation set to assess the model's effectiveness during the training phase.

Three baseline models, MobileNet, DenseNet, and EfficientNet, were trained on the training set and evaluated on the validation and test sets. MobileNet, a CNN model with 28 layers and 4.2 million parameters, is well suited for mobile applications due to its use of depth separable convolution techniques to minimize parameter count. On the other hand, EfficientNet, with 201 layers and a total of 15 million parameters, scales

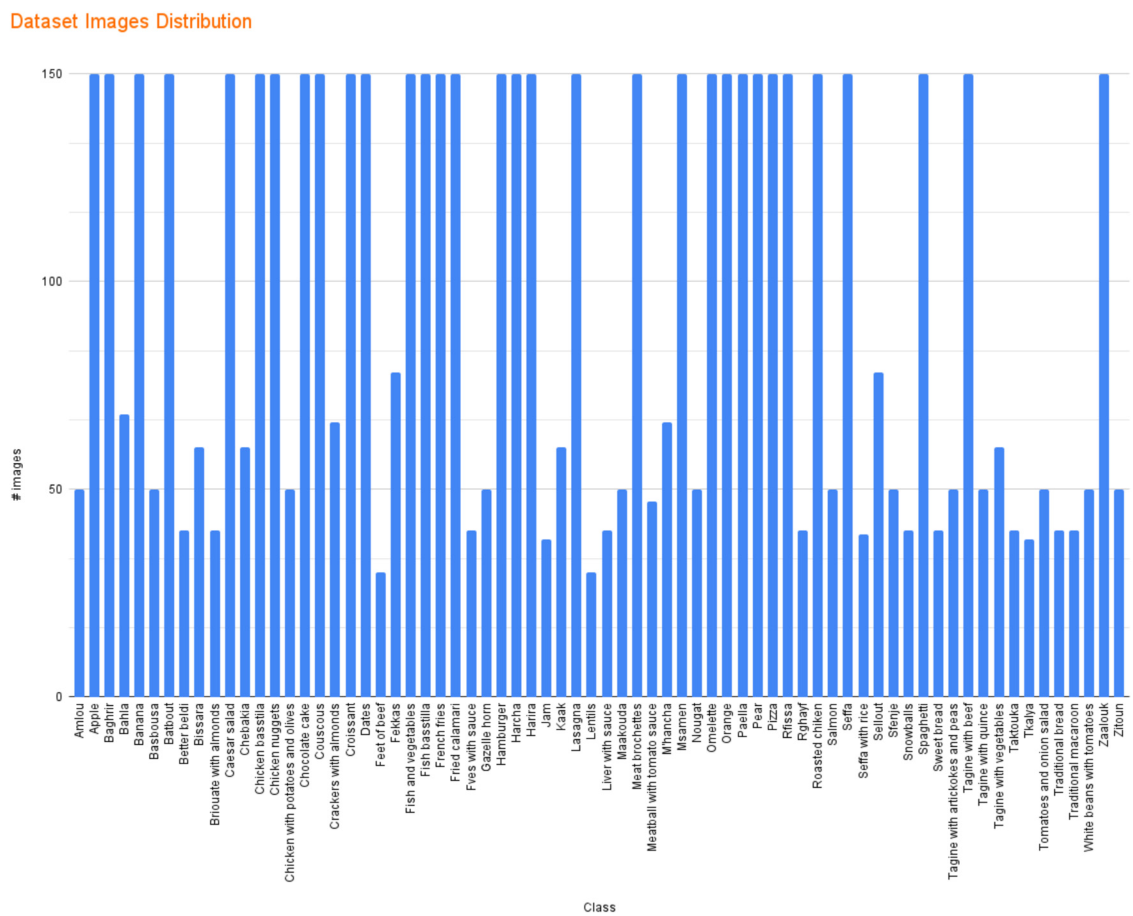

Figure 7: Dataset image distribution. Source: Created by the authors.

the depth, width, and resolution of the CNN architecture to improve accuracy. The authors initially created a fundamental model, B0, and then scaled it to produce models B1 through B7. All of these models employ the transfer learning concept by using weights pretrained on the large-scale ImageNet dataset and fine-tuning them on the specific sub-dataset. While all images start as 150 × 150 pixels, they are resized to fit the model's required input size. MobileNet supports input sizes greater than 32 × 32, while DenseNet and EfficientNet accept an input shape of 224 × 224.

For training phase, the batch size chosen was 16, the learning rate is 0.001, and the number of training epochs was set to 50. Table 4 provides accuracy results for MobileNet-V3, DenseNet169, and EfficientNet B0, B1, and B5. Furthermore, Table 5 presents additional assessment metrics, including precision score, recall score, and $F1$ score, used to compare the performance of the three models. The precision score measures a classifier's capacity to avoid classifying negative (FP) samples as positive (TP):

Table 4: Training, validation, and testing accuracy of food dataset evaluation

Model/performance	Training accuracy	Validation accuracy	Testing accuracy
MobileNet-V2	0.917	0.772	0.945
DenseNet169	0.918	**0.903**	**0.908**
EfficientNetB0	0.917	0.7471	0.84
EfficientNetB1	0.918	0.756	0.857
EfficientNetB5	0.79	0.821	0.837

Table 5: Results of the evaluation metrics of food dataset

Model/performance	Precision score	Recall score	$F1$ score
MobileNet-V2	0.873	0.872	0.872
DenseNet169	**0.909**	**0.908**	**0.908**
EfficientNetB	0.876	0.875	0.875

$$\frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}}. \tag{4}$$

The recall score looks for all the positive samples:

$$\frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}}. \tag{5}$$

The mean of the precision score and the recall score is the $f1$ score:

$$\frac{\text{precision*recall}}{\text{precision + recall}}*2. \tag{6}$$

The evaluation of the dataset has shown a state-of-the-art performance, which proved that the dataset is well prepared considering the variety, quality, and quantity of the images. Based on the experiment results, the pretrained model Dense-Net169 has achieved the highest score up to 90%.

4.2 Food image classification

In this experiment, the aim is to enhance food image classification using a combined approach of the attention mechanism technique and DenseNet architecture. The Moroccan food dataset is used for training, validation, and testing the model. Initial preprocessing involves resizing images to 224 × 224. Data augmentation techniques (rotation, horizontal flipping, and zooming) are applied to the training data. The architecture consists of a DenseNet-169 backbone, initialized with pretrained weights from ImageNet, integrated with the multi-head

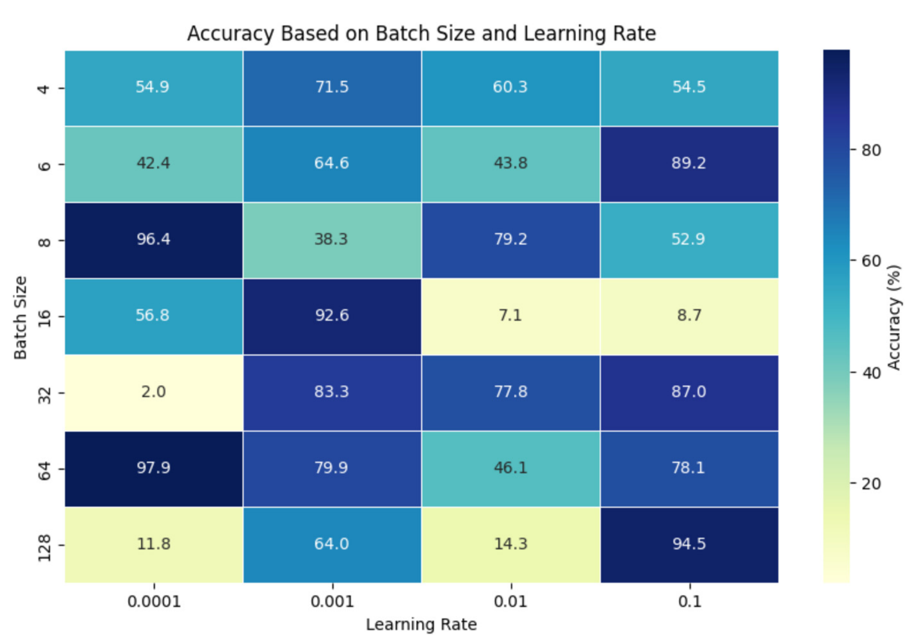

Figure 8: Accuracy based on batch size and learning rate. Source: Created by the authors.

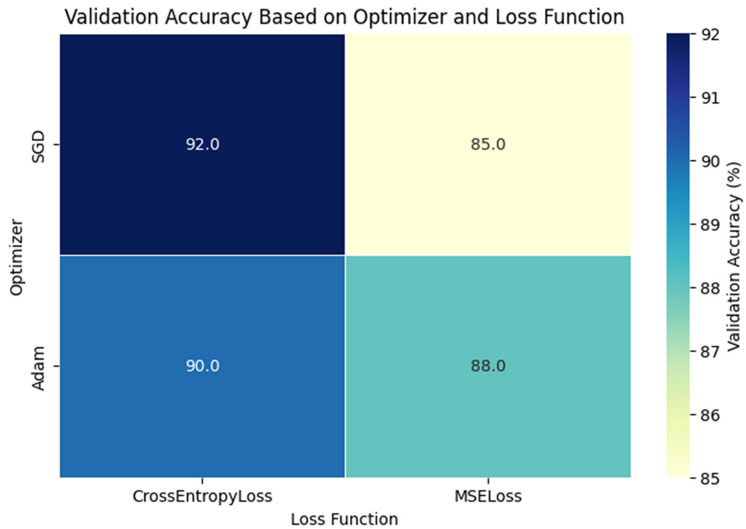

Figure 9: Validation accuracy based on optimizer and loss function. Source: Created by the authors.

attention mechanism. During training, the model is fine-tuned using softmax activation function, and an early stopping approach is implemented; this regularization technique early stops the model if it performs poorly on the validation set to avoid the overfitting and helps to choose the adapted number of epochs. For hyperparameters, the learning rate used is 0.001, and the optimum value for the batch size is fixed in 16 after training the model on different values as presented in Figures 8 and 9. A multi-heads attention mechanism is added on top of the DenseNet-169 model with eight attention heads to capture different relationships within the image; this will provide more flexibility in capturing both global and local features. Evaluation metrics encompass accuracy, $F1$-score, and confusion matrices. The model is trained on the training set, validated on the validation set for hyperparameter tuning, and finally assessed on the testing set. The expected results are improved accuracy and $F1$ score compared with stand-alone DenseNet. The approach's efficacy is anticipated in intricate food categories benefiting from attention mechanisms. As described in Table 6, a DenseNet model on its own without attention has achieved reasonably good performance on the Moroccan food dataset. Adding the attention mechanism improved the classification performance due to how effectively the attention mechanism can highlight relevant features in the dataset. Table 7 presents a comparison of the obtained results with the state-of-the-art studies.

Table 6: Results of the evaluation metrics of food image classification

Model/performance	Precision score	Recall score	$F1$ score
MobileNet-V2	0.873	0.872	0.872
DenseNet169	0.909	0.908	0.908
EfficientNetB	0.876	0.875	0.875
Proposed approach	**0.925**	**0.921**	**0.921**

Table 7: Comparison of the obtained results with the state-of-the-art studies

Ref	Method	Dataset	Performance (accuracy)
[6]	Faster RCNN VGG-16	UEC-FOOD100 UEC-FOOD256, FOOD20-with bbx	71.7%
[9]	Attention Mechanism DenseNet	VIREO Food 172	87.6%
[10]	Inception V3, Inception V4, ResNet, andnception ResNetV2	Food-101.	92%
Proposed approach	DenseNet-169+Multi-head attention mechanism	Self-made dataset: First Moroccan food dataset	92.5%

5 Conclusion and future works

This article introduces the first Moroccan food image dataset and an innovative food classification approach, coupled with the estimation of GI. The creation of a new food image dataset addresses a crucial need for improved resources in the domain of dietary assessment for Moroccan food consumers, enabling the first accurate and efficient food recognition from images. A food classification approach is proposed offering a promising solution for automating the categorization of various food items based on the state-of-the-art results. Additionally, the GI estimation are directly connects dietary patterns to their glycemic impact, facilitating personalized nutrition recommendations and aiding individuals in making informed dietary choices.

Regarding the high performance of the new Moroccan food dataset and the proposed approach for food recognition and GI estimation, Moroccan food image recognition presents unique challenges that make achieving optimal performance more difficult compared to recognizing other types of objects. While some food items, such as fruits, vegetables, pizza, and French fries, typically have regular shapes, traditional Moroccan dishes may vary significantly in appearance due to factors such as cooking methods and mixing. Additionally, the ingredients of the same dish can be changed, which impacts the nutritional information provided. To enhance the robustness and versatility of the dataset, future work could involve expanding the dataset by collecting more images with different appearances and including a version with three-dimensional images to address volume estimation tasks. Additionally, incorporating images with "reference objects" would further support volume estimation efforts.

Given the increasing openness to international cuisine, the dataset could be extended to include miscellaneous categories, thereby improving its utility as a benchmark for food recognition systems. Furthermore, to facilitate comprehensive food analysis, future versions of the dataset could include detailed information on macronutrients, micronutrients, and ingredients.

For GI estimation, one notable challenge highlighted in this study is the variability in GI values influenced by factors such as food processing, cooking methods, and ingredient combinations. These variables pose difficulties in accurate estimation solely through image recognition. Nonetheless, the methodology we propose offers an approximate results, since our aim is to raise awareness among Moroccans, which gives ranges of estimated GI values for complex meals. Collaborating with clinical research institutions will enable clinical studies to validate the estimated GI values, increasing the reliability and scientific rigor of the findings. Additionally, partnerships with biochemistry departments can lead to in-depth analyses of how specific dishes affect metabolic responses, paving the way for tailored dietary recommendations

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