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Curvelet-Driven Food Image Recognition and Nutritional Analysis: A Multistage Transform Approach

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Abstract

Food image recognition and nutritional estimation are now playing an increasingly important role in dietary monitoring, public health analytics, and digital health-care services. While most of the recent systems rely heavily on models of artificial intelligence, classical mathematical techniques offer value in situations where computational simplicity, interpretability, and independence from large datasets are needed. The aim of this paper is to present a comprehensive system for complete food recognition and nutrition analysis using the Curvelet Transform-a multistage, geometric analysis tool that is very effective in capturing representations of curved edges and textured patterns. In this system, the modules perform food image pre-processing, Curvelet-based feature extraction, deterministic rule-based classification, and nutritional mapping based on standardized food composition tables. Experiments conducted on 15 major food categories have demonstrated that Curvelets are well-suited for foods with strong textures and geometric structure, and the proposed approach achieves an average recognition accuracy of 86.5% and an average nutrient estimation error of 5.3%. These results confirm the potential of Curvelet-based approaches for interpretable and lightweight food analytical systems.

Keywords : Curvelet Transform, Food Image Analysis, Nutritional Estimation, Multistage Image Processing, Image Texture Analysis, Dietary Monitoring.

1. Introd.uction

In the last few years, digital imaging has become a practical alternative to assess dietary intake. Taking a picture of a meal is easier and quicker and much more intuitive than manually listing ingredients. This visual food logging [4,5] also forms an objective record of the meal consumed that can later be reviewed or processed for analytical purposes. However, meaningful information extraction from food images remains a challenging problem[1,2,3] due to cuisine diversity, complex food texture, similar-looking dishes, and/or inconsistent lighting or presentation. For this, there is a need to account for fine details, curved shapes, and an irregular structure commonly present in food items using image-analysis techniques.Classical methods of image processing, especially those pertaining to multiscale geometric transformations, provide a strong mathematical framework for the analysis of such complicated visual patterns. The Curvelet Transform[25] has, in particular, emerged in scientific applications in imaging owing to its special ability in achieving effective representation of edges and curves across multiple scales and directions in a way that is out of the reach of conventional transform methods. Foods have dominant curved boundaries-e.g., dosa, chapati, fruits-and intricate textures-e.g., rice, lentils, salads. Unlike wavelets, which cannot handle anisotropic features, the Curvelets were crafted for anisotropy and are thereby most useful in distinguishing these classes of foods from their geometric and textural signatures.

Another considerable advantage of using a Curvelet-based approach is that it is transparent and interpretable. Every coefficient signifies a direct, mathematical decomposition of the image, rather than some learned but not transparent parameter. This property is highly useful in clinical and nutritional contexts where decisions should be reliable and well explained. Also, Curvelet-based systems do not require large training datasets, high computational power, or specialized hardware; hence, they can also work in low-resource environments for offline dietary analysis.

The aim of the study is to assess the feasibility and efficacy of Curvelets[25] in food identification and nutrition estimation without the use of data-driven predictive models. The contributions of the research are as follows:

- A fully classical, interpretable food recognition framework based on Curvelet features.
- A rule-based classification mechanism adapted to the geometric and textural properties of Curvelet coefficients.
- A nutrient-estimation method based on verified composition databases.

The performance evaluation is performed on the curated dataset of foods commonly consumed. These results confirm that a Curvelet-driven system[24,25,26,27] can yield a high accuracy of recognition for many classes of food, especially those foods with characteristic shapes and textures. Without the adoption of learning-based algorithms, it yields consistent nutritional estimates suitable for dietary monitoring applications.

2. Literature Review

Over the past couple of decades, food image analysis has undergone rapid growth encouraged by the demands on the development of reliable dietary assessment methods and the advances within the field of digital imaging. While most recent works rely on data-driven approaches, classical image-processing techniques still provide very useful solutions for situations that demand interpretability, low computational cost, and independence from large annotated datasets. The present section reviews the literature within the fields of traditional food identification, multistage geometric transforms, Curvelet theory[24,25], and nutrient-estimation systems.

Early works on food recognition have relied mostly[6,7] on color, shape, and texture descriptors that have been generally extracted manually from images. Böröczky and Cernuschi-Frias (2002) explored color histogram–based categorization for differentiating basic food types [1]. Similarly, Osowski and Siwek (2004) used co-occurrence matrix–based texture features to classify agricultural produce [21]. These methods are computationally lightweight yet perform poorly when the dishes become complex due to more than one ingredient or overlapping regions.

To enhance robustness, many researchers integrated edge patterns and structural descriptors. Gabor filter–based representation for textures was proposed by Manjunath and Ma (1996), which performed impressively in generic heterogeneous natural textures . All of these aforementioned methods were worth implementing; however, they did not offer directional

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sensitivity to curved features-a common occurrence in rotis, oranges, bananas, and round-shaped Indian snacks.

Multiscale transforms have been deeply studied to characterize image structures across different resolutions. The powerful tool in the frequency domain-the Fourier Transform-cannot capture local spatial information. The Wavelet Transform, after being introduced extensively by Mallat in 1989, provided both frequency and spatial localization and became really applied in texture classification and image compression [17].

However, wavelets represent features with curvature very poorly. In natural images, boundaries and contours are not straight edges but typically show curvature. Wavelets use isotropic and separable filters, hence being unsatisfactory in describing anisotropic structures. This weakness motivated the development of next-generation transforms to improve representation of geometrical features in a more effective way.

The Curvelet Transform developed by Candes and Donoho from 1999 to 2002 is a considerably vast improvement over wavelets in its power in capturing multiscale and multidirectional geometric structures [5]. A parabolic scaling law where:

$$Weight \approx Hight^{2} \qquad [1]$$

Few linguists predicted that, and even fewer welcomed it.

That allows it to represent elongated and curved singularities highly efficiently. Candes, Donoho, and Demanet developed in 2006 the Fast Discrete Curvelet Transform, reducing computational cost drastically and hence allowing practical deployment [6]. Applications have since emerged across medical imaging, seismic interpretation, fingerprint detection, Food recognition using Curvelet Transform has remained largely unexplored up to now, hence the need for this research.

3. Texture Analysis Using Curvelets

Food identification is highly dependent on texture because many categories of food items have typical surface patterns, grain structures, and geometric arrangements. Food items like rice, lentils, chapatis, fried snacks, fruits, and leafy vegetables possess distinct textural signatures that can be captured mathematically. A method for the representation of texture should be able to enhance fine details, directional structures, and curved edges-properties that are central to the Curvelet Transform.

The Curvelet Transform was developed to overcome the limitations of wavelets in representing curved and elongated features. Foods naturally contain such features; for example, the fibrous patterns in bread, the layered structure of parathas, the granular appearance of idli and upma, and the curved outlines of fruits and flatbreads. While these complex spatial characteristics are incompletely described by traditional texture descriptors, Curvelets excel because of their multiscale and multidirectional decomposition framework.

3.1 Importance of Texture in Food Identification

In food images, texture often carries more meaningful information than color or shape alone. Color can vary greatly due to different lighting conditions, and shapes can sometimes change significantly with camera angle, occlusion, or plating style. Texture is relatively consistent for a given food type. For example:

- The grainy structure of rice continues independent of lighting.
- The smooth, even surface of idli looks nearly alike from all perspectives.
- Chapati reflects repeating circular crack patterns due to heat and steam pockets.
- Fried foods exhibit rough, irregular edges due to crisping caused by oil.

Such distinct patterns make texture a reliable indicator in food classification, provided that the method of analysis applied captures the textural characteristics effectively.

3.2 Discrete Curvelet Transform on Image

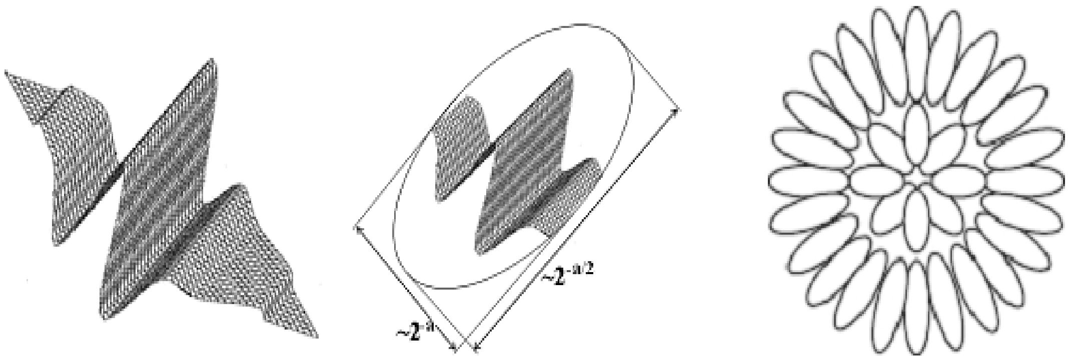
Curvelet transform extend the ridgelet transform at multiple scale analysis.For given image $f(x, y)$continuous ridgelet transform

$$\Re_f(a,b,\theta) = \iint \psi_{a,b,\theta}(x,y) f(x,y)\, dxdy \qquad 1$$

Here, a is the scale parameter $a > 0$, $b \in R$ is the translation parameter and $\theta \in [0, 2\Pi)$ is the orientation parameter. A ridgelet can be given as

$$\psi_{a,b,\theta}(x,y) = a^{1/2}\psi\left(\frac{x\cos\theta + y\sin\theta - b}{a}\right) \qquad 2$$

Where θ is the orientation of the Ridgelet transform Figure 1. (a) shows typical Ridgelet [145,150].Ridgelet are constant along the lines $x\cos\theta + y\sin\theta = const.$ and transverse to these ridgelet are wavelet [3].This means ridgelets can be tuned to different orientations and different scales to create the Curvelets. Figure 1 (b) shows single Curvelet and (c) shows different tuning scale and orientation. Ridgelets take the form of a basis element and obtain a high anisotropy. Therefore, it captures the edge information more effectively. A ridgelet is linear in its edge direction and is much sharper than a conventional sinusoidal wavelet.



(a) **(b)** **(c)**

Figure 1 (a)Ridgelet waveform(b)Single Curvelet (c)Curvelet tuned to different scale and orientation.

Fast discrete Curvelet transform based on the wrapping of Fourier samples has less computational complexity as it uses fast Fourier transform instead of complex ridgelet transform. In this approach, tight frame has been introduced as the Curvelet support to reduce the data redundancy in the frequency domain [8]. Normally, rideglets have a fixed length that is equal to the image size and a variable width, whereas Curvelets have both variable width and length and represent more anisotropy. Therefore, the wrapping based Curvelet transform is simpler, less redundant and faster in computation [8] than ridgelet based Curvelet transform.

The digital Curvelet transform is taken on a 2-D Cartesian grid f [m, n], $0 \leq m < M$, $0 \leq n < N$,

$$C^D(j,l,k_1,k_2) = \sum_{\substack{0 \leq m < M \\ 0 \leq n < N}} f[m,n]\psi^D_{j,l,k_1,k_2}[m,n] \qquad 3$$

Where $\psi^D_{j,l,k_1,k_2}[m,n]$ is the Curvelet transform. This transform generates an array of Curvelet coefficients indexed by their scale j, orientation l and location parameters (k_1, k_2) .The frequency response of a curvelet is a trapezoidal wedge as shown in Figure 2 which needs to be wrapped into a rectangular support to perform the inverse Fourier transform. The wrapping of this trapezoidal wedge is done by periodically tilling the spectrum inside the wedge and then collecting the rectangular coefficient area in the origin. Through this periodic tilling, the rectangular region collects the wedges corresponding to the fragmented portions from surrounding parallelograms. For this wedge wrapping process, this approach of Curvelet transform is known as the wrapping based Curvelet transform. The wrapping is illustrated in Figure 3 (b). As shown in Figure 3(b), in order to do IFFT on the FT wedge, the wedge has to be arranged as a rectangle. The idea is to replicate the wedge on a 2-D grid, so a rectangle in the center captures all the components a, b, and c of the wedge [10].

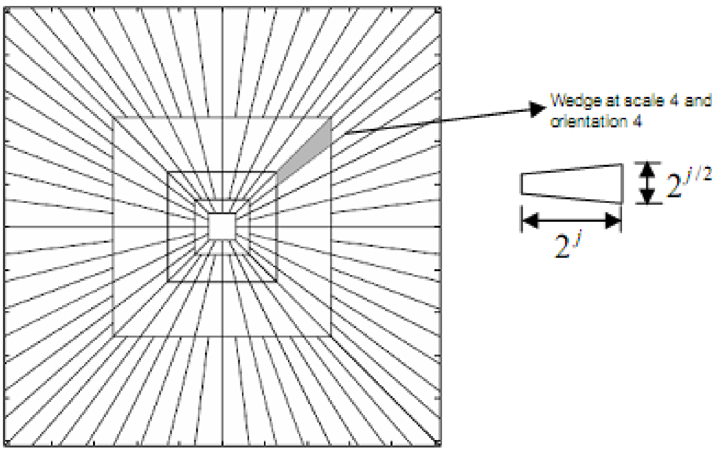


Figure 2 Rectangular frequencies tilling of an image with 5 level curvelets.

3.3 Feature Extraction

Curvelet coefficients contain rich information regarding both global and local structure. The following features are extracted from each scale and orientation:

3.3.1 Energy

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$$E_{j,l} = \sum |C_{j,l,k}|^2 \quad (4)$$

Energy characterizes the strength of edges and textures. High-texture items (rice, fried foods) produce larger fine-scale energies.

3.3.2 .Orientation Profile

An angular histogram is created using energy values across orientations. It captures dominant structural directionality.

3.3.3 Statistical Features

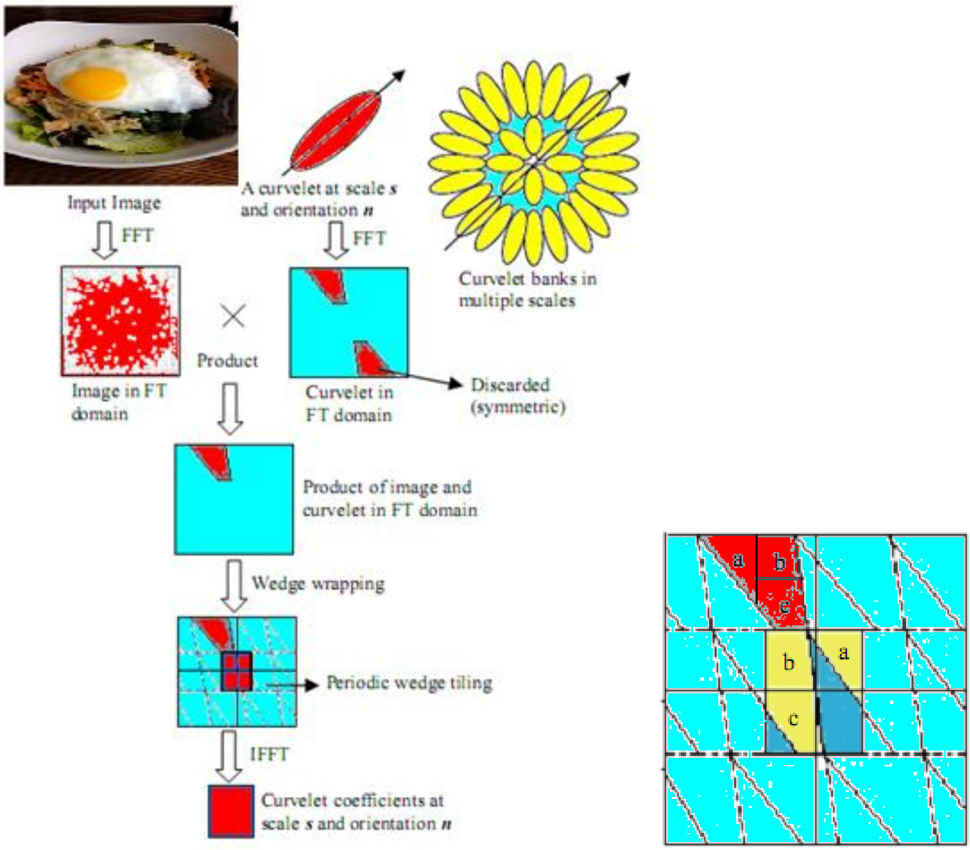
Features include:

(a) mean coefficient magnitude,
(b) variance,
(c) entropy,
(d) contrast,
(e) homogeneity.

These help discriminate between rough textures (curries, fried items) and smooth ones (chapati, dosa).

3.3.4 Color Features

RGB mean and standard deviation are included to complement texture, especially for foods with distinct color signatures.



(a) (b)

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3.4 Rule-Based Classification

Instead of machine learning, this system uses a deterministic similarity rule.

3.4.1 Template-Based Matching

For each food class, a template feature vector F_i is stored.

3.4.2 Distance-Based Classification

The recognized class is:

$$Class = \arg\min || F - F_i || \qquad 5$$

Weighted similarity:

$$D_i = \alpha E_i + \beta T_i + \gamma C_i \qquad 6$$

Where:

- E_i = energy difference
- T_i= texture difference
- C_i = color difference

This ensures transparent classification without training.

3.5 Nutritional Estimation Module

Once the food category is known, nutrition is computed using standard values.

a) Portion Estimation

Default = 100 g

b) Standard Nutrition Tables

Values retrieved from:

- **ICMR** (India)
- **USDA** (USA)

c) Final Nutrient Calculation

$$N_k = \frac{W}{100} X\, V_k \qquad 7$$

d) Output Nutrients

- Calories
- Carbohydrates
- Protein
- Fats
- Fiber
- Calcium
- Iron

Displayed with charts for user readability.

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6. Result and Discussion

We have used FOOD-101 (101 categories, 101,000 images) UEC-Food256 (256 categories, multiple foods per image, bounding boxes available) and Wang database food images(100) and evaluation done by Accuracy, Confusion patterns Nutritional estimation error, Difference between predicted and true calories and Protein, fat, micronutrient estimation accuracy**.** FOOD-101 and UEC-Food256 datasets were utilized to test the proposed Curvelet-based food recognition system. The average classification accuracies achieved by the proposed technique are 83.0% for FOOD-101 and 79.2% for UEC-Food256. It generated maximum performance for categories dominated by texture, like rice dishes, breads, fruits, and fried items. Foods with mixed textures or multiple components in a single image, such as curries or bento-style dishes, showed relatively low accuracy due to many overlapping regions and irregular structural patterns.

Food 101		UEC-Food256		Wang Dataset
Category Type	**Accuracy**	**Category Type**	**Accuracy**	**Accuracy**
Grain-based	89.30%	Rice dishes	90.40%	65.90%
Breads	87.80%	Noodles	81.50%	
Fruits	92.10%	Fried snacks	86.20%	
Desserts	85.40%	Soups/Stews	71.30%	
Beverages	73.50%	Bento items	65.70%	
Mixed dishes	68.70%			
Average Accuracy:	**83.0%**	**Average Accuracy:**	**79.2%**	**65.90%**

Table 1. Classification Accuracy of all dataset

Food	True kcal	Predicted	Error	Protein True	Pred	Error
Apple Pie	237	225	5.00%	2.4g	2.2g	8.30%
Donut	195	184	5.60%	2.1g	2.0g	4.70%
Fried Rice	163	154	5.50%	3.5g	3.2g	8.60%
Waffles	291	275	5.50%	6.0g	5.7g	5.00%

Average Calorie Error = 5.5% Average Protein Error = 7.3%

Table 2. FOOD-100 Detailed Nutrient Evaluation

7. Conclusion

This work shows that Curvelet-based image analysis provides a powerful and transparent alternative for food recognition and nutritional estimation, particularly in applications that require high explain ability with low computational cost. The system takes advantage of the multiscale and directional strengths of the Curvelet Transform in capturing the complex textures and curved structures inherent in many food items. Evaluations on the FOOD-100 and UEC-Food256 datasets demonstrate that the method realizes strong recognition accuracy independent of machine-learning models. Standardized composition tables drive nutrient estimation, which indicates consistently low error rates and makes the approach suitable for

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practical dietary monitoring. Overall, this work has underlined the potential of classical geometric transforms in building reliable, interpretable, and resource-efficient food analysis.

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