



Contents lists available at [JESA](https://jesa.aks.or.id/index.php/jesa/index)

Journal of Engineering and Science Application

journal homepage: <https://jesa.aks.or.id/index.php/jesa/index>



Implementation of a Food Image Retrieval System Based on Color Feature Extraction Using Color Moments (CIELab) and Texture Feature Using Local Binary Pattern (LBP)

Nurdian Kasim^a, Adha Mashur Sajiah^b, L.M. Fid Aksara^c

^{a,b,c}Department of Informatics, Faculty of Engineering, Halu Oleo University, Kendari, Indonesia

Article Info

Keywords:

Content Based Image Retrieval
CIELab
Color Moments
Local Binary Pattern
Image Retrieval

ABSTRACT

The rapid growth of digital image content on social media has positioned food as one of the most frequently shared visual objects. Text-based search is often inadequate for retrieving food images due to their high visual complexity in color, shape, and texture, as variations in ingredients, lighting, and camera angle can produce highly diverse images even within the same food category. This study implements a Content-Based Image Retrieval (CBIR) system for food images by combining Grid Color Moments in the CIELab color space for color feature extraction and Multi-Scale Local Binary Pattern (LBP) for texture feature extraction. The CIELab color space was chosen for its stability under varying lighting conditions, while the multi-scale LBP approach captures texture patterns at several levels of observation. The system processes 3,600 food images across nine classes (Burger, Donut, Ice Cream, French Fries, Klepon, Fried Noodles, Fried Rice, Pizza, Rendang), using an 80:20 stratified split for database and query images. The retrieval process involves image preprocessing, feature extraction, feature vector normalization, similarity computation, and ranking of the most visually similar images. Similarity is computed using Euclidean Distance and Chi-Square Distance, evaluated with Precision@10 and Recall@10 on a Top-10 retrieval scheme. Results show the proposed feature combination improves performance over a baseline method that does not use grid-based and multi-scale feature extraction, with the best result achieved using Chi-Square Distance: Mean Precision@10 of 0.7133 and Mean Recall@10 of 0.0223. These findings confirm that combining color and texture features effectively represents food image characteristics and improves retrieval accuracy, offering a practical alternative to text-based food image search systems.

This is an open access article under the [CC BY-SA](https://creativecommons.org/licenses/by-sa/4.0/) license.



Corresponding Author:

Nurdian Kasim
Department of Informatics
University Halu Oleo
Kendari, Indonesia

1. INTRODUCTION

Food is a fundamental human necessity that serves not only as a source of energy but also as an integral part of culture and daily life. In the digital era, food has evolved into a popular visual subject on social media platforms such as Instagram, TikTok, and Pinterest. According to a report by Visual Capitalist (2024), over 30% of image-based content on social media relates to food, demonstrating that food has now also become a representation of social expression and modern lifestyle trends[1].

However, identifying and retrieving information about food based on digital images remains a significant challenge [2]. Food images possess high visual complexity due to variations in color, shape, and texture, compounded by factors such as ingredients, ripeness, camera angles, and lighting, which can result in vastly different images even for the same type of food [3]. Therefore, a system capable of automatically and objectively analyzing the visual content of food images is required [4].

Content-Based Image Retrieval (CBIR) offers a solution for searching images based on visual content rather than text or filenames by extracting visual features such as color, shape, and texture [5]. Text-based approaches are inadequate for food images because textual descriptions are subjective and difficult to generate automatically for thousands of images. CBIR has proven more efficient as it can identify visual similarities between images without relying on manual descriptions [6], although its application to food imagery is challenging; the diversity of colors and textures makes consistent feature extraction difficult [7].

Color features are commonly used to represent material types and food ripeness levels; one such method employs Color Moments, which calculate the mean, variance, and skewness of the color distribution [8]. The CIELab color space was selected because it separates luminance (L^*) and chromaticity (a^* , b^*) components, making it more stable against lighting variations compared to RGB or HSV [9]. Regarding texture features, Local Binary Patterns (LBP) are widely used due to their ability to detect subtle surface variations with low computational complexity and their robustness against lighting changes [10].

Previous research indicates that the combination of CIELab Color Moments and LBP holds promise for food image classification [11]; however, most studies have focused on classification tasks rather than retrieval a scheme in which a user submits an image as a query and the system returns similar images. Furthermore, some studies utilize small datasets with limited categories, failing to adequately reflect the diversity of food images found in the real world. Few studies have explored this color-texture feature combination within a Content-Based Image Retrieval (CBIR) framework using retrieval metrics for evaluation, particularly regarding the specific combination of CIELab and LBP.

Addressing this gap, this study develops a Content-Based Image Retrieval (CBIR) system for food images that combines color feature extraction using Color Moments in the CIELab color space with texture feature extraction using Local Binary Pattern (LBP). The system is designed to extract and identify food image similarities based on representative visual characteristics regarding color and texture, thereby improving the accuracy of retrieving similar food images.

2. RESEARCH METHOD

2.1 Data Collection

The dataset used consists of 3,600 food images distributed across nine classes with 400 images per class namely Burger, Donut, Ice Cream, French Fries, Klepon, Fried Noodles, Fried Rice, Pizza, and Rendang. The images were obtained through internet searches and manual photography, then selected based on visual quality, the clarity of the food object, and variations in color and texture.

2.2 Metode Analysis

Food images first undergo a preprocessing stage involving size adjustment (256×256 pixels) and food object segmentation using the GrabCut method, with Otsu Thresholding serving as an alternative if GrabCut segmentation proves suboptimal. Subsequently, color feature extraction is performed using Grid Color Moments in the CIELab color space by calculating the mean, standard deviation, and skewness for each grid (3×3) and color channel (L, a, b). Texture feature extraction is carried out using Multi-Scale Local Binary Patterns (with radii of 1, 2, and 3) to capture texture patterns across various scales. Both types of features are then combined into a single feature vector and normalized using a Min-Max Scaler. The similarity between the query image and database images is calculated using Euclidean Distance and Chi-Square Distance, followed by ranking to produce the top 10 most relevant images.

2.3 System Developments

The system was developed using the Rational Unified Process (RUP), comprising four phases:

a. Inception

Identification of system requirements and scope, along with a literature review covering CBIR methods, CIELab Color Moments, LBP, and image similarity measurement techniques.

b. Elaboration

System architecture design using Unified Modeling Language (UML) including Use Case, Activity, and Class diagrams as well as the design of feature extraction workflows, feature fusion, and the user interface.

c. Construction

Implementation of image processing modules, color and texture feature extraction, and modules for image searching and ranking based on similarity.

d. Transition

System testing and evaluation using Precision and Recall metrics, followed by system refinements based on the test results.

2.4 Testing

Testing was conducted to evaluate the capability of the method and system in retrieving food images. The dataset was partitioned using an 80:20 stratified split (80% for the database and 20% for query test data) to prevent data leakage. Evaluation was performed using Precision@10 and Recall@10 metrics within a Top-10 retrieval scheme, comparing two distance measurement methods Euclidean Distance and Chi-Square Distance and assessing the performance of the proposed method (Grid Color Moments + Multi-Scale LBP) against a baseline method.

3. RESULTS AND DISCUSSION

3.1. System Implementation

System design was carried out using the Unified Modeling Language (UML) to describe the system's structure and behavior in a structured manner [12].

3.1.1 Use Case Diagram

A use case diagram illustrates the interaction between the user and a CBIR-based food image retrieval system. The user acts as the primary actor, uploading a food image as a query and initiating the function to search for similar images [13]. Internally, the system performs color and texture feature extraction, similarity calculation, and ranking before displaying the Top-K retrieval results to the user.

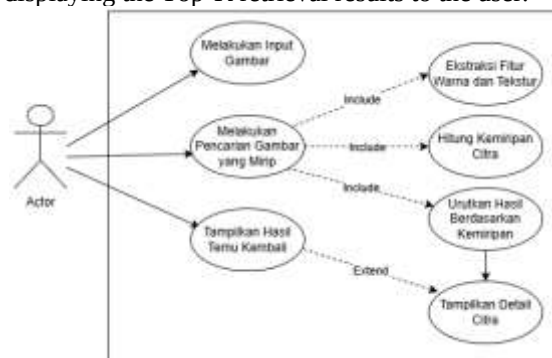


Figure 1. Use Case Diagram

3.1.2 Activity Diagram

The activity diagram illustrates the system's workflow, spanning from the user opening the system and uploading a query image to the system displaying the most similar image results [14]. The system extracts color features (CIELab Color Moments) and texture features (LBP), combines these features, calculates similarity using a matching method, and performs ranking before presenting the results to the user.



Figure 2. Activity Diagram

3.1.3 Class Diagram

The class diagram illustrates the system structure, which comprises several key classes: ImageInput for the image upload process; ImagePreprocessing for resizing and normalization; FeatureExtraction for color and texture feature extraction; FeatureVector and FeatureDatabase for feature storage; Similarity for similarity calculation; Ranking for result ordering; and RetrievalResult for displaying search results to the user [15].

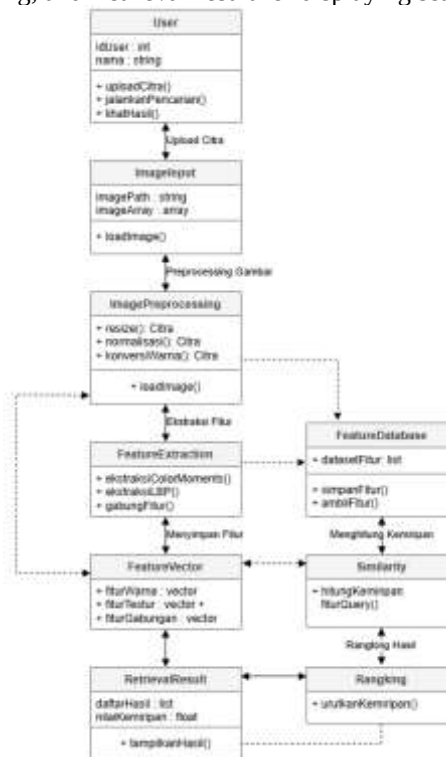


Figure 3. Class Diagram

3.1.4 System Interface

The system is implemented as a web application using the Flask framework to support the process of uploading query images and displaying retrieval results.



Figure 4. System main page layout

The main page provides an image upload component and a "Search for Similar Images" button to initiate the search process.



Figure 5. Image retrieval result display

The results page displays the query image alongside the top 10 retrieved images, complete with rankings, image classes, and distance values—where a lower distance value indicates a higher degree of similarity.

3.2. Image Retrieval Results

Testing was conducted by comparing a query image against all images in the database. For instance, in a test using a query image from the "Rendang" class, the Euclidean Distance method successfully retrieved 9 out of the top 10 images from the same class with one image from the "Donut" class appearing at the fourth rank yielding distance values ranging from a minimum of 0.7295 to a maximum of 0.8408. Meanwhile, the Chi-Square Distance method yielded similar results, with the majority of retrieved images also belonging to the "Rendang" class, indicating that this method is capable of effectively measuring feature vector similarity.

Table 1. Retrieval Results (Chi-square Distance)

Peringkat	Nama Citra	Output Gambar	Kelas	Nilai Distance	Relevan
1	Rendang_025.jpg		Rendang	0,4137	Ya
2	Rendang_004.jpg		Rendang	0,4701	Ya

3	Rendang_310.jpg		Rendang	0,4868	Ya
4	Rendang_445.jpg		Rendang	0,5127	Ya
5	Donat_020.jpg		Donat	0,5173	Tidak
6	Rendang_179.jpg		Rendang	0,5425	Ya
7	Rendang_101.jpg		Rendang	0,5443	Ya
8	Rendang_310.jpg		Rendang	0,5456	Ya
9	Rendang_001.jpg		Rendang	0,5528	Ya

3.3. Precision dan Recall Evaluation

Table 2. Summary of Mean Precision@10 and Mean Recall@10

Metrik Jarak	Mean Precision@10	Mean Recall@10
Euclidean	0,7079	0,0221
Chi-Square	0,7133	0,0223

Based on Table 2, the Chi-Square Distance method yields slightly higher Mean Precision@10 and Mean Recall@10 values compared to Euclidean Distance, indicating a superior ability to measure the similarity of color and texture feature vector distributions.

3.4. Comparative Analysis of Test Results

Table 3. Comparative Analysis of Test Results

Skenario	Mean Precision@10	Mean Recall@10
Baseline + Euclidean Distance	0,6324	0,0198
Baseline + Chi-Square Distance	0,6297	0,0197
Grid Color Moments + Multi-Scale LBP + Euclidean Distance	0,7079	0,0221

<i>Grid Color Moments + Multi-Scale LBP + Chi-Square Distance</i>	0,7133	0,0223
---	--------	--------

Based on Table 3, the application of Grid Color Moments and Multi-Scale LBP consistently improved performance compared to the baseline method across both distance metrics. Dividing the image into a grid yielded a more detailed color feature representation, while Multi-Scale LBP captured texture patterns at multiple scales, resulting in richer texture information. The combination of Grid Color Moments, Multi-Scale LBP, and Chi-Square Distance delivered the best overall performance.

4 CONCLUSION

This study successfully designed and implemented a food image retrieval system based on Content-Based Image Retrieval (CBIR), utilizing a combination of Grid Color Moments (in the CIELab color space) and Multi-Scale Local Binary Pattern (LBP) texture features. The system enables image retrieval based on visual similarity independent of textual information through stages comprising preprocessing, feature extraction, similarity calculation, and result ranking. Evaluation results demonstrate that the proposed feature combination improves performance relative to the baseline; Mean Precision@10 increased from 0.6324 to 0.7079 using Euclidean distance and from 0.6297 to 0.7133 using Chi-Square distance. Optimal performance was achieved using the combination of Grid Color Moments, Multi-Scale LBP, and Chi-Square distance, yielding a Mean Precision@10 of 0.7133 and a Mean Recall@10 of 0.0223. Future research could further develop the system by diversifying the dataset, testing alternative similarity methods, and integrating deep learning approaches such as Convolutional Neural Networks (CNN) for automated feature extraction.

REFERENCES

- [1] M. D. Agaputra, K. R. R. Wardani, and E. Siswanto, "Pencarian Citra Digital Berbasis Konten dengan Ekstraksi Fitur HSV, ACD, dan GLCM," *Jurnal Telematika*, vol. 8, no. 2, 2020, [Online]. Available: <http://wang.ist.psu.edu/docs/related/>.
- [2] P. Serianti, R. Muharar, M. Oktiana, N. Aulia, and T, "Sistem Temu Kembali Citra Termal Kanker Payudara Pada Citra Rekam Medis," vol. VIII, no. 4, pp. 6958–6967, 2023.
- [3] D. Agna Fauzan and Y. Arum Sari, "Algoritme Information Gain Feature Selection pada Sistem Temu Kembali Citra Makanan Menggunakan Ekstraksi Fitur Warna dan Tekstur," 2019. [Online]. Available: <http://j-ptiik.ub.ac.id>
- [4] N. Syachdini, L. Anjelir, H. Manik, P. Studi Sistem Informasi, and S. Kaputama Binjai, "Penerapan Metode VSM Sistem Temu Balik pada Ulasan Google Maps Kafe di Kota Binjai," 2025, doi: 10.8734/Kohesi.v1i2.365.
- [5] C. Putri Beauty and Y. Arum Sari, "Temu Kembali Citra Makanan Menggunakan Color Histogram Dan Local Binary Pattern," 2020. [Online]. Available: <http://j-ptiik.ub.ac.id>
- [6] A. F. Ahsani, Y. A. Sari, and P. P. Adikara, "Temu Kembali Citra Makanan Menggunakan Ekstraksi Fitur Gray Level Co-occurrence Matrix dan CIE L*a*b* Color Moments Untuk Pencarian Resep Masakan," 2019. [Online]. Available: <http://j-ptiik.ub.ac.id>
- [7] E. P. Purwandari, D. Andreswari, and U. Faraditha, "Ekstraksi Fitur Warna dan Tekstur untuk Temu Kembali Citra Batik Besurek," 2020. [Online]. Available: www.ejournal.unib.ac.id/index.php/pseudocode
- [8] A. S. Sinaga, "Segmentasi Ruang Warna L*a*b*," *Jurnal Mantik Penusa*, vol. 3, no. 1, pp. 43–46, 2019.
- [9] A. Zakaria and R. Munir, "Steganografi Citra Digital Menggunakan Teknik Discrete Wavelet Transform pada Ruang Warna CIELab," 2021.
- [10] M. A. Siregar, "Ekstraksi Local Binary Pattern Terhadap Klasifikasi Kopi Menggunakan Modular Neural Network (MNN),"
- [11] G. B. Waluyo, Y. A. Sari, and B. Rahayudi, "Pengenalan Citra Makanan Kue Tradisional menggunakan Ekstraksi Fitur HSV Color Moment dan Local Binary Pattern dengan K-Nearest Neighbour," 2021. [Online]. Available: <http://j-ptiik.ub.ac.id>
- [12] D.: Yudhi and F. Saputra, "Modul UML (Unified Modelling Language)," 2023.
- [13] Siska Narulita, Ahmad Nugroho, and M. Zakki Abdillah, "Diagram Unified Modelling Language (UML) untuk Perancangan Sistem Informasi Manajemen Penelitian dan Pengabdian Masyarakat (SIMLITABMAS)," *Bridge: Jurnal publikasi Sistem Informasi dan Telekomunikasi*, vol. 2, no. 3, pp. 244–256, Aug. 2024, doi: 10.62951/bridgev2i3.174.
- [14] Haviluddin, "Memahami Penggunaan UML (Unified Modelling Language)," 2019.
- [15] Y. Septiana, Y. H. Agustin, and A. R. Jungjunan, "Sistem Informasi Geografis Perumahan Menggunakan Metode Rational Unified Process," *Jurnal Algoritma*, vol. 21, no. 1, pp. 131–140, May 2024, doi: 10.33364/algoritma/v.21-1.1463.