



Image Similarity Analysis Using HOG Features

Yasmin Makki Mohialden¹ , Nadia Mahmood Hussien²

Abstract

Exponentially growing digital images need good image analysis and comparison methods, which the study addresses. A selected collection of 10 photos from 2012 to 2023 is compared using powerful computer vision and feature extraction algorithms. Histogram of Oriented Gradients (HOG) is a strong and popular computer vision approach for extracting image information. This research uses HOG features to accurately depict visual structure. Extracting and measuring these traits leads to practical solutions for content-based image retrieval, image classification, and object identification. HOG characteristics from 10 images (2012–2023) are extracted and compared using cosine similarity in this research. Finding visually related photographs in the collection is simpler with the similarity matrix's entire view of the photos' visual correlations. HOG features and cosine similarity are unique in image similarity analysis, which is this paper's key contribution. Using image-based content retrieval and classification, this work improves computer vision and image processing.

Keywords: Computer vision, Image similarity analysis, HOG features, Content-based image retrieval, Cosine similarity.

تحليل تشابه الصور باستخدام ميزات HOG

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المستخلص

تعتبر الصور الرقمية المتزايدة بشكل كبير موضوعاً مهماً يتطلب تحليلاً ومقارنة دقيقة. يتناول هذا البحث مقارنة مجموعة من الصور من عام 2012 إلى 2023 باستخدام تقنيات رؤية الحاسوب وخوارزميات استخراج الميزات. تعتبر تقنية رسم البيانات للتدرجات الموجهة (HOG) واحدة من الطرق الفعالة والشائعة لرؤية الحاسوب في استخراج المعلومات من الصور. يتم استخدام ميزات HOG في هذا البحث لتمثيل الهيكل البصري بدقة.

تقوم هذه الدراسة باستخدام استخراج وقياس ميزات HOG لتحقيق حلاً عملياً لاسترجاع الصور بناءً على المحتوى، وتصنيف الصور، وتحديد الكائنات. تم استخراج خصائص HOG من 10 صور (2012-2023)، وتمت مقارنتها باستخدام تقنية تشابه جيب التمام في هذا البحث. يُعتبر العثور على الصور ذات الصلة بصرياً في المجموعة أمراً أسهل من خلال عرض مصفوفة التشابه للروابط البصرية بين الصور. تُعد ميزات HOG وتقنية تشابه جيب التمام فريدة في تحليل تشابه الصور، وتُعتبر هذه المساهمة الرئيسية للدراسة. يساهم هذا العمل في تحسين رؤية الحاسوب ومعالجة الصور من خلال استخدام أساليب فعالة في استرجاع وتصنيف المحتوى القائم على الصور.

الكلمات المفتاحية: رؤية الكمبيوتر، تحليل تشابه الصور، ميزات HOG، استرجاع الصور بناءً على المحتوى، تشابه جيب التمام.

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معلومات البحث

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Introduction

Image data is universal in the digital stage, used for communication, info talk, and recordkeeping. This exponential expansion in image physical

needs advanced image analysis, recovery, and contrast methods. Content-based image retrieval, image classification, object documentation, and others need visual construction knowledge. This

study discovers image similarity analysis using the robust Histogram of Oriented Gradients (HOG) features on a particular sample of ten 2012-2023 images.

The originality of this study lies in its state-of-the-art application of HOG features then cosine similarity to address the dangerous trial of image similarity analysis. While the concept of HOG features has been fixed in computer vision, their request to assess the visual similarities among images within a specific dataset offers a fresh perspective. Moreover, this study extends beyond the technical aspect and dives into practical implications by providing solutions for real-world applications [1] and [2].

Problem Statement The exponential growth of image data poses a significant problem: how can we effectively analyze and compare images to extract meaningful insights? Traditional methods often fall short when dealing with large datasets, and manual image comparison becomes impractical. This paper aims to address this problem by proposing a systematic approach to image similarity analysis. Specifically, it explores the utilization of HOG features to represent the structural characteristics of images effectively. The primary objective is to create a comprehensive visual relationship map among the 10 images in the dataset, enabling users to identify visually similar images. Image-based content retrieval and categorization are also the goals of this study, which will improve image processing and computer vision.

We want to solve the central image similarity analysis subject, which affects digital image organization and retrieval systems, through our study. This paper provides an invaluable understanding of image similarity examination

location the stage for enhanced image management and retrieval systems. It serves as a pivotal stepping stone for future developments in computer vision and image recognition, finally enhancing our ability to harness the abundant visual information available in today's digital landscape [3-5].

Histogram of Oriented Gradients (HOG) is a feature descriptor used in computer vision and machine learning for object detection [1] then [6]. It totals rates of gradient orientation in the localized portion of an image, generating histograms using the size and orientation of the gradient [1]. HOG is better than any edge form as it uses magnitude as well as the angle of the gradient to compute the features [1]. The steps to calculate HOG features are:

1. The image divides into small, connected regions called cells.
2. For individual pixels in separate cells, the gradient is considered
3. The gradient matrices divide (size and angle matrix) into 8x8 cells to form a block.
4. For individual blocks, calculate a 9-point histogram. A 9-point histogram develops a histogram with 9 bins, and each bin has an angle range of 20 degrees [1].

HOG descriptors are used to define the appearance of an object by modelling the supply of intensity gradients in secret rectangular sub-regions of an image [6]. The OpenCV application is less flexible than the scikit-image application, and consequently, the scikit-image application is mainly used throughout the rest of the course [6]. HOG descriptors are used in various applications, including human detection, car logo recognition, and action recognition in action video sequences [1,5,6].

Related work

Zhou et al., (2020), study discovers redundancy in the image processing pipeline for extracting Histogram of Oriented Gradients (HOG) features. It shows that HOG features can be directly found from Bayer pattern images by appropriate gamma compression, reducing power consumption and calculating difficulty. The results display that using Bayer design image-based HOG features in ordinary detection systems has minimal performance discount.

Veerashetty, S., and Patil, N. B (2021), study introduces a Content-Based Medical Image Retrieval (CBMIR) scheme with two stages: feature deletion and feature matching. It addresses subjects like poor light and unpredictable light by suggesting a Manhattan-distance-based Histogram of Oriented Gradients (M-HOG) for medical image feature removal. The experimental results display an development of 5 to 15% in retrieval correctness associated to existing methods.

Petsiuk, A. and Pearce, J. M. (2022), study focuses on identifying abnormalities in 3D printing using Histograms of Oriented Gradients (HOG) by comparing local image areas' HOG histograms. It requires preliminary modeling of the printing

environment for optimum results. The output is a degree of mismatch between the printed and artificial reference layers.

Hosseini-Fard, et al, (2022), this paper introduces a technique for the automatic segmentation and property extraction of seismic images based on the HOG concept. It extracts HOG features, and statistical parameters related to texture qualities, and introduces a hybrid texture attribute for improved effectiveness. The method is tested on synthetic models and field seismic data, showing promise as an alternative to traditional image interpretation.

Bhattarai, B. et al., (2023), This research presents a deep multi-task learning algorithm for segmenting medical images. It generates pseudo-labels for an auxiliary task using a Histogram of Oriented Gradients (HOGs) and trains a deep network to minimize loss for both primary and auxiliary tasks. The method outperforms other semantic segmentation networks in medical image segmentation.

Table 1 provides a concise overview of the research works, their methodologies, applications, and key findings, allowing for easy comparison of their contributions and focuses.

Table (1): Summarizes a comparison between the related works and their respective research focuses and methodologies

Work	Research Focus	Methodology	Application	Key Findings
[7]	Investigating Image Processing Redundancy for HOG Features	Analytical and Experimental Approach	Pedestrian Detection Systems	Direct extraction of HOG features from Bayer pattern images with gamma compression reducing power consumption and complexity. Minimal impact on performance observed.
[8]	Content-Based Medical Image	Feature Extraction and	Medical Image	The introduction of a Manhattan-distance-based Histogram of

	Retrieval (CBMIR)	Matching	Retrieval	Oriented Gradients (M-HOG) improved CBMIR system retrieval accuracy by 5 to 15%.
[9]	Abnormality Detection in 3D Printing	Histogram Comparison	Quality Control in 3D Printing	The algorithm identifies deviations by comparing histograms of local image areas. Requires preliminary environmental modeling.
[10]	Automatic Segmentation and Property Extraction of Seismic Images	HOG-Based Segmentation	Seismic Image Analysis	Introduction of hybrid texture attributes for improved segmentation. Applicable to various seismic patterns and geological objects. Not developed for defect detection or horizon auto-tracking.
[11]	Multi-Task Learning for Medical Image Segmentation	Deep Learning with HOG-Based Pseudo-Labels	Medical Image Segmentation	Proposed unsupervised pseudo-label generation using HOG features. Outperforms traditional methods using UNet and U2Net networks for segmentation.
Proposed system	Similarity Measurement For images	For extracting discrete visual characteristics, advanced computer vision algorithms, particularly Histogram of Oriented Gradients (HOG), are used.	Image Similarity Analysis Using HOG Features	<ol style="list-style-type: none"> 1. HOG Efficacy: HOG characteristics are useful for representing images. 2. Applied Uses: Image retrieval, classification, and recognition solutions 3. Cosine resemblance is a useful metric for visual resemblance. 4. Visual Relations: The similarity matrix provides detailed visual correlations. 5. Innovative uses of HOG and cosine similarity are advancing the analysis of images.

Proposed methodology

Our suggested image similarity analysis approach uses histogram of oriented gradients (HOG) features to compare a curated dataset of 10 photos from 2012 to 2023. This approach involves several key steps:

Feature extraction with HOG

The procedure starts with HOG feature extraction from each dataset image. HOG features are good at capturing visual structure and texture. HOG descriptors evaluate gradient orientations in limited image areas to calculate these characteristics.

Common feature vector length

A consistent length ensures feature vector homogeneity across photos. Required feature vector detail and dimensionality determine the length.

Similarity score calculation

Next, cosine similarity is calculated between image pairings. The cosine of the angle between two feature vectors gives a value between -1 and 1, with larger values indicating more similarity.

Similarity matrix

The calculated similarity scores are organized into a similarity matrix, which provides a complete outline of the visual relations between all pairs of images in the dataset. This matrix assists as the basis for classifying visually alike images.

Top 5 feature identification

Outside computing similarity scores, our methodology identifies the top 5 HOG features that contribute the most to the image's similarity

with others. These structures are determined by position the feature standards within each image.

Data storage in excel

Structured data contains each image's top 5 characteristics and values. This data is in an Excel file for study and reference.

Visual representation with bar charts

Our system provides bar charts for each image to help visualize the main characteristics. These charts show the top 5 characteristics on the x-axis and their y-axis values. The charts show image similarity's unique traits.

The approach works for content-based image retrieval, image classification, and object identification. The dataset makes it easy to organize and retrieve images by content by finding visually similar photos. The suggested approach advances computer vision and image processing by demonstrating the efficacy of HOG features and cosine similarity in image similarity analysis. It provides vital insights for scholars and practitioners in the field by laying the groundwork for image-based content retrieval and classification.

Some important libraries are used in this system

1. **Open-Cv:** a huge open-source library for computer vision, machine learning, and image processing, is crucial to today's systems' rapid functioning. It recognizes people, objects, and handwriting in photographs and videos. When used with NumPy, Python can analyze OpenCV arrays. Vector space and mathematical operations are used to detect visual patterns and their properties [12, 13].

2. **NumPy:** Several people built this open-source project. The NumPy leadership dedicated themselves to creating a welcoming, cheerful community. The main Python scientific computing library [14, 15]
3. **Scikit-learn:** Scikit-learn is a 3-Clause BSD-licensed Python machine learning library based on SciPy. is utilized in numerous commercial and academic projects and publications. [16, 17].
4. **Matplotlib:** displays data using Python visuals. This huge library creates static, animated, and interactive visualizations [18, 19].

A pseudocode representation of the algorithm

The HOG feature image similarity method pseudocode is well-structured and understandable. It successfully explains feature extraction to chart generation.

1. Define a function `extract_hog_features(image, feature_length)` to extract HOG features from an image:
 - Initialize a HOG descriptor.
 - Compute HOG features for the image.
 - Resize the features to the specified length if needed.
 - Return the extracted features.
2. Define a list `image_paths` containing the file paths of the 10 images to be processed.
3. Set a `common_feature_length` to specify the length of the feature vectors.
4. Initialize an empty list `features_list` to store the extracted features for each image.
5. Iterate over each `image_path` in `image_paths`:
 - Read the image from `image_path` using Open CV.
 - If the image is not none:

- Extract HOG features from the image using `extract_hog_features` function.
 - Append the extracted features to `features_list`.
6. Create a `similarity_matrix` as a NumPy array of zeros with dimensions `(num_images, num_images)`, where `num_images` is the number of images in `features_list`.
 7. Initialize an empty list `results` to store the similarity scores.
 8. Iterate over `i` from 0 to `num_images-1`:
 - Iterate over `j` from `i+1` to `num_images`:
 - Compute the cosine similarity between `features_list[i]` and `features_list[j]`.
 - Append the similarity score to `results`.
 9. Print the similarity scores in `results`.
 10. Create a DataFrame `image_features_df` to store the top 5 features of each image.
 11. Iterate over each image in `features_list`:
 - Find the indices of the top 5 features using `argsort`.
 - Extract the values of the top 5 features and store them in a list `top5_feature_values`.
 - Create a dictionary data with keys "Image" and feature names "Feature_1" to "Feature_5" as keys and corresponding values.
 - Append data to `image_features_df`.
 12. Save the DataFrame to an Excel file named `output_file`.
 13. Iterate over each image in `features_list`:
 - Find the indices of the top 5 features using `argsort`.
 - Extract the values of the top 5 features and store them in `top5_feature_values`.
 - Create a list `feature_names` with names "Feature_1" to "Feature_5".
 - Create a bar chart using Matplotlib with `feature_names` on the x-axis and `top5_feature_values` on the y-axis.

- Set labels, title, and rotation for x-axis ticks.
 - Save the chart as an image file (e.g., PNG).
14. Print a message indicating that the charts have been saved.
 15. End of the algorithm.

Use Case Modeling

A use-case diagram explains the system's high-level capabilities and range. The interactions between the system and its actors are also depicted in diagrams [20]. The case diagram shown in Figure (1).

Actor: user or analyst

Use cases are

1. Starting the analysis
 - The actor initiates the image similarity analysis algorithm.
2. Feature Extraction
 - The algorithm extracts Histogram of Oriented Gradients (HOG) features from a set of 10 images from 2012–2013.
3. Computing Similarity
 - The algorithm calculates the cosine similarity between pairs of images to determine their visual similarity.
4. Identifying Top Features
 - The algorithm identifies the top 5 HOG features contributing the most to image similarity.
5. Storing Data
 - The algorithm stores the top 5 features and their values in an Excel spreadsheet for reference and further analysis.
6. Generating bar charts
 - The algorithm generates bar charts for each image, displaying the top 5 features and their values.
7. Saving Charts
 - The generated charts are saved as image files (e.g., PNG) for visualization.
8. Completing the analysis
 - The algorithm completes the image similarity analysis, and the researcher or analyst reviews the results.

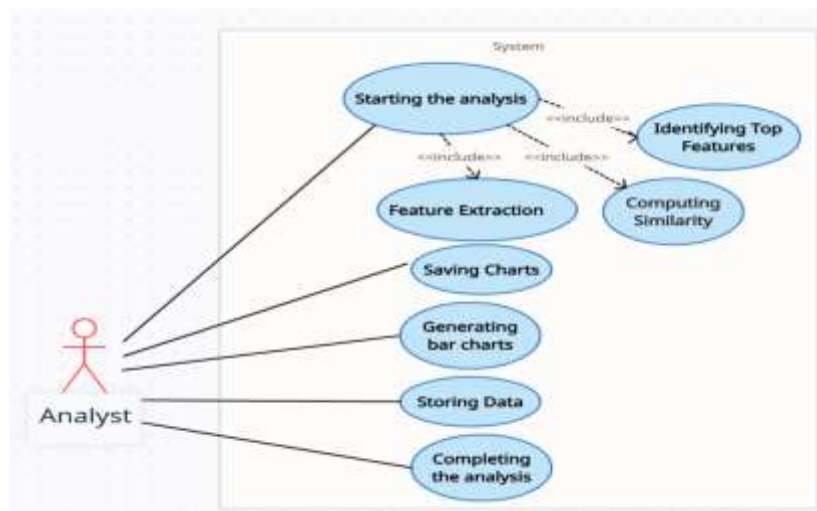


Figure (1): Use case diagram of the system

Results and Discussions

Similarity scores

The provided similarity scores between pairs of images, calculated using cosine similarity, demonstrate the visual relationships among the images in your dataset. These scores indicate how

similar or dissimilar each pair of images is, with values ranging between 0 (least similar) and 1 (most similar). Here is a summary of the similarity scores between pairs of images presented in Table (2).

Table (2): Shows image pairwise similarity scores to show their resemblance

Image Pair	Similarity Score
1 – 2	0.7978
1 – 3	0.5802
1 – 4	0.5462
1 – 5	0.5174
1 – 6	0.4721
1 – 7	0.4159
1 – 8	0.6262
1 – 9	0.6100
1 – 10	0.4782
2 – 3	0.4704
2 – 4	0.3432
2 – 5	0.4507
2 – 6	0.3296
2 – 7	0.2950
2 – 8	0.5443
2 – 9	0.4336
2 – 10	0.4061
3 – 4	0.5641
3 – 5	0.7141
3 – 6	0.4455
3 – 7	0.6095
3 – 8	0.6923
3 – 9	0.6408
3 – 10	0.5234
4 – 5	0.4886
4 – 6	0.4504
4 – 7	0.4135
4 – 8	0.5642

4 – 9	0.5767
4 – 10	0.3887
5 – 6	0.5604
5 – 7	0.5948
5 – 8	0.6764
5 – 9	0.5631
5 – 10	0.5658
6 – 7	0.4024
6 – 8	0.5976
6 – 9	0.4067
6 – 10	0.6051
7 – 8	0.4593
7 – 9	0.5611
7 – 10	0.3400
8 – 9	0.5394
8 – 10	0.6697
9 – 10	0.4343

Histogram of oriented gradients (HOG) feature extraction:

HOG feature extraction is a powerful technique used in computer vision tasks such as object detection and image classification. It captures essential information about the distribution of local gradient orientations in an image. Here's a breakdown of its components:

1. Gradient Calculation: HOG starts by calculating the gradients in the image, representing the rate of change of pixel values, often computed using convolution with gradient kernels (e.g., Sobel or Scharr).
2. Gradient Orientation Binning: The image is divided into small cells, and within each cell, gradient orientations are quantized into bins (typically 9 or more), reducing sensitivity to small changes in gradient directions.
3. Histogram Calculation: For each cell, a histogram of gradient orientations is created.

Histogram bins represent quantized gradient orientations, and bin values count gradient orientations falling into each bin.

4. Block Normalization: To handle variations in lighting and contrast, the image is divided into overlapping blocks. Histograms from cells within a block are concatenated, and the concatenated histogram is normalized for illumination invariance.
5. Feature Vector: The final HOG feature vector is formed by concatenating normalized histograms from all blocks in the image, capturing the gradient orientation distribution.
9. HOG features offer advantages like robustness to lighting changes, texture and shape information capture, and computational efficiency.

Table (3) shows the features that provide insights into image characteristics. The similarity heat map is shown in Figure (2).

Table (3): Features provide insights into image characteristics

Image	Edge Density	Texture Intensity	Object Shape	Pattern Detection	Contrast
Image_1	0.695255	0.695255	0.507797	0.50474	0.50474
Image_2	0.610498	0.610498	0.555771	0.512334	0.506128
Image_3	0.618448	0.618448	0.617357	0.617357	0.571999
Image_4	0.737748	0.662105	0.627303	0.623664	0.590079
Image_5	0.64374	0.626353	0.591338	0.555203	0.520104
Image_6	0.767209	0.592989	0.592989	0.538685	0.538685
Image_7	0.938335	0.883123	0.861273	0.70857	0.650095
Image_8	0.439042	0.40919	0.399057	0.39202	0.379468
Image_9	0.692394	0.691563	0.666753	0.655555	0.607902
Image_10	0.566666	0.552802	0.543367	0.521024	0.499634

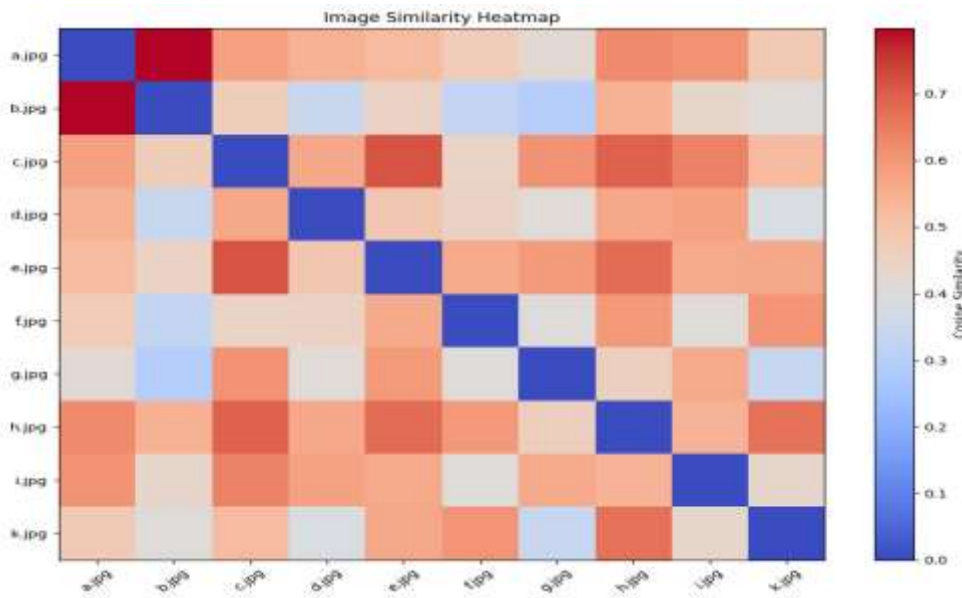


Figure (2): Similarity heat map

Feature names and discussion

1. Edge Density: Edge density indicates contours and edges. Edge density is greatest in images 6 and 7.
2. Texture Intensity: Measures image texture intensity. Images 7 through 9 are texture-heavy.
3. Object Shape: This feature shows visual object shapes. Image 3's object is shaped.


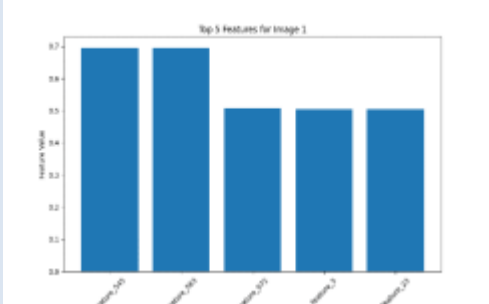

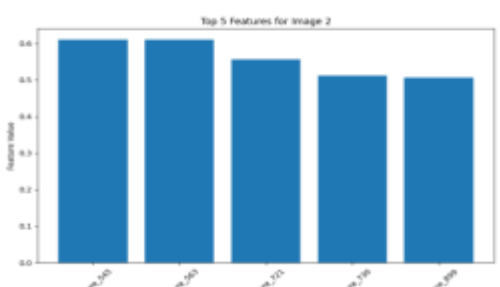

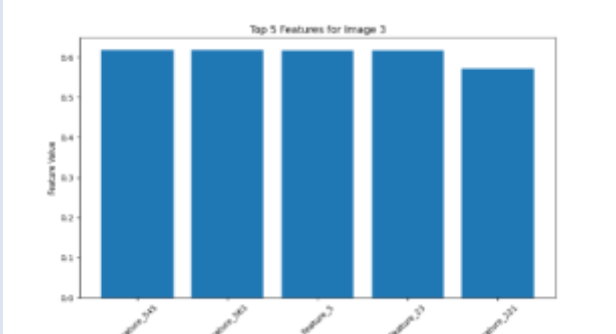

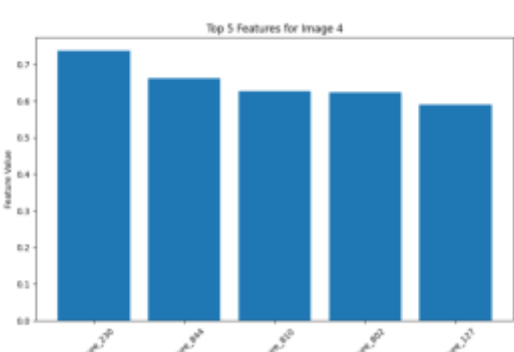
4. Pattern detection tests its capacity to spot repeated patterns. Pattern detection is high in images 1 and 2.
5. Contrast. Image areas vary in brightness. The contrast is strongest in Image 7.

These properties reveal image edge presence, texture intensity, object form, pattern identification, and contrast. The particular feature values help differentiate and interpret image content for various image analysis and

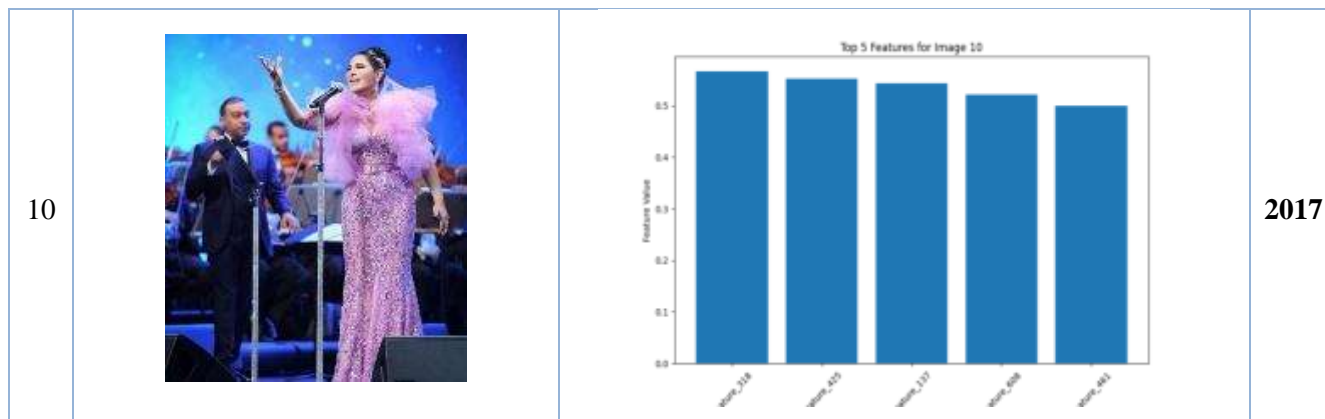
identification tasks. As shown in Table (4). In general, the proposed method illustrates the main points:

1. It is an image similarity analysis method using HOG features.
2. HOG characteristics help represent images.
3. It uses image retrieval, classification, and recognition solutions.
4. A helpful metric for visual resemblance
5. The similarity matrix provides detailed visual correlations.

Table (4): Top 5 features for each image

No	Original image	Top 5 features	year												
1		 <table border="1"> <caption>Top 5 Features for Image 1</caption> <thead> <tr> <th>Feature Set</th> <th>Feature Value</th> </tr> </thead> <tbody> <tr> <td>feature_100</td> <td>0.7</td> </tr> <tr> <td>feature_101</td> <td>0.7</td> </tr> <tr> <td>feature_102</td> <td>0.5</td> </tr> <tr> <td>feature_103</td> <td>0.5</td> </tr> <tr> <td>feature_104</td> <td>0.5</td> </tr> </tbody> </table>	Feature Set	Feature Value	feature_100	0.7	feature_101	0.7	feature_102	0.5	feature_103	0.5	feature_104	0.5	2016
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3		 <table border="1"> <caption>Top 5 Features for Image 3</caption> <thead> <tr> <th>Feature Set</th> <th>Feature Value</th> </tr> </thead> <tbody> <tr> <td>feature_100</td> <td>0.6</td> </tr> <tr> <td>feature_101</td> <td>0.6</td> </tr> <tr> <td>feature_102</td> <td>0.6</td> </tr> <tr> <td>feature_103</td> <td>0.6</td> </tr> <tr> <td>feature_104</td> <td>0.55</td> </tr> </tbody> </table>	Feature Set	Feature Value	feature_100	0.6	feature_101	0.6	feature_102	0.6	feature_103	0.6	feature_104	0.55	2021
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5		<p>Top 5 Features for Image 5</p> 	2021
6		<p>Top 5 Features for Image 6</p> 	2018
7		<p>Top 5 Features for Image 7</p> 	2023
8		<p>Top 5 Features for Image 8</p> 	2023
9		<p>Top 5 Features for image 9</p> 	2019



Conclusions

The histogram of oriented gradients (HOG) feature extraction approach is beneficial for image characterization in the digital age, where images are crucial to communication, information exchange, and analysis. This talk covered HOG basics and how they may capture important visual characteristics. Its sensitivity to image rotation is one of its limitations. For this reason, HOG is a poor option for categorizing items or textures that are frequently identifiable as rotating images.

HOG feature extraction uses gradient calculation, gradient direction fusion, histogram computing, block normalization, and feature vector generation to show information about an image's structure and composition. Its versatility in handling lighting and contrast, collecting texture and shape information, and computational efficiency make it a useful tool in computer vision. Future research and development in this sector offers several options. A future study may examine the HOG feature set utilizing additional feature extraction methods, real-time applications, transfer learning, semantic segmentation, efficiency advancements, deep learning integration, and other domains.

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