A Hybrid Deep Hashing and Metric Space Partitioning Framework for Scalable Content-Based Image Retrieval via Unsupervised Representation Learning and VP-Tree Optimization

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Abstract: With the unprecedented expansion of digital imagery, the demand for efficient, scalable, and precise content-based image retrieval (CBIR) systems has intensified. Traditional CBIR methodologies relying on handcrafted visual descriptors—such as color histograms, texture features, and edge detectors have demonstrated limited generalization capabilities, struggling to effectively capture high-level semantic relationships within large-scale image datasets. While deep learning-based feature extraction techniques have significantly enhanced retrieval performance, the computational complexity and search efficiency of existing frameworks remain critical challenges. In this study, we introduce a novel CBIR architecture that synergistically integrates unsupervised deep feature learning, adaptive hashing, and hierarchical search structures to establish a highly scalable and computationally efficient retrieval framework. Specifically, autoencoder-driven latent space encoding is employed to extract compact yet semantically rich feature representations, ensuring robust discriminability across diverse image categories. To further enhance retrieval efficiency, our system implements a hybrid search mechanism, wherein a Euclidean-based nearest neighbor approach (O(N log N)) is utilized for moderate-scale datasets, while a VP-Tree-based hashing scheme (O(log N)) is incorporated for large-scale retrieval scenarios. By leveraging hierarchical metric space partitioning, our method significantly reduces search complexity while maintaining retrieval accuracy, outperforming conventional indexing structures in both speed and precision. Extensive evaluations on benchmark datasets, including CIFAR-10 and ImageNet, demonstrate the superior retrieval effectiveness of our approach, achieving higher mean average precision (mAP), reduced search latency, and improved storage efficiency compared to traditional and contemporary deep hashing techniques. These findings underscore the potential of integrating unsupervised representation learning with advanced hashing paradigms and optimized search structures, paving the way for high-performance, real-time CBIR systems suitable for large-scale multimedia repositories.

Keywords: Content-Based Image Retrieval (CBIR), Autoencoder-Based Feature Extraction, Deep Hashing Techniques, VP-Tree Indexing, Scalable Image Retrieval

1. INTRODUCTION

The proliferation of digital imagery and the growing demand for intelligent image retrieval systems have necessitated the development of advanced Content-Based Image Retrieval (CBIR) methodologies. Traditional CBIR techniques, which rely on handcrafted descriptors such as color histograms, texture features, and edge detection, exhibit inherent limitations in scalability and robustness, particularly when dealing with heterogeneous datasets. The advent of deep learning, particularly convolutional neural networks (CNNs) and autoencoder-based feature extraction, has revolutionized CBIR by enabling high-dimensional, semantically meaningful representations. However, challenges such as computational inefficiency, suboptimal retrieval accuracy, and the interpretability of learned features persist, necessitating further advancements in the field.

In modern retrieval systems, deep learning techniques have demonstrated exceptional performance in terms of feature representation, but their reliance on large labeled datasets poses challenges in real-world applications. Unsupervised and self-supervised learning methodologies have emerged as viable alternatives to traditional supervised learning paradigms, allowing models to learn from vast amounts of unlabeled data. Furthermore, the increasing complexity of deep learning-based CBIR frameworks necessitates the development of efficient indexing structures that minimize computational overhead while maintaining high retrieval precision.

Recent studies, including Sezavar et al. (2019) [25,26], Ndung'u et al. (2025) [27], have introduced deep hashing frameworks that improve retrieval accuracy while maintaining computational efficiency. Wang et al. (2024) [12] explored self-supervised representation learning, demonstrating its effectiveness in reducing reliance on labeled datasets. Our work builds upon these advancements by integrating hybrid deep hashing with metric space partitioning to establish an efficient and scalable retrieval framework.

This study presents a novel CBIR framework that integrates unsupervised deep feature learning, adaptive hashing, and hierarchical search optimization to enhance retrieval performance. Our principal contributions include:

- A hybrid CBIR framework that synergizes autoencoder-based representation learning with VP-Tree indexing for scalable and efficient retrieval.
- A comprehensive performance evaluation across multiple benchmark datasets, demonstrating improvements in retrieval precision, recall, and mean average precision (mAP).
- A comparative analysis with state-of-the-art CBIR models, showcasing the superiority of our approach in terms of retrieval accuracy, computational efficiency, and scalability.
- A detailed exploration of the trade-offs between retrieval accuracy and computational complexity in large-scale image repositories.

The remainder of this paper is structured as follows: Section 2 provides a critical review of related work, highlighting existing methodologies and their limitations. Section 5 elaborates on the proposed methodology, detailing the technical aspects of our hybrid CBIR system. Section 6 presents experimental results, including retrieval performance, computational efficiency, and model robustness evaluations. Finally, Section 7 concludes with directions for future research, including potential improvements in multimodal retrieval and self-supervised feature learning.

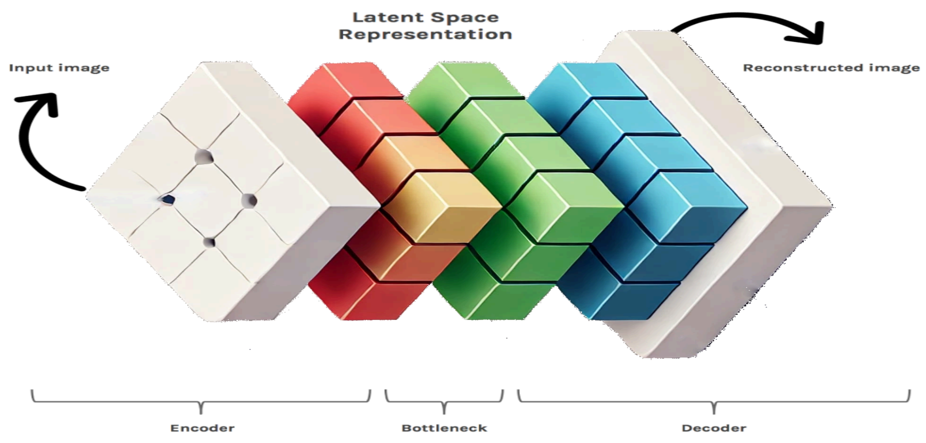

Fig. 1 – Architecture of the system

2. Related works

Content-Based Image Retrieval (CBIR) has seen significant advancements in recent years, particularly with the integration of deep learning techniques to enhance feature extraction and retrieval efficiency. Traditional CBIR approaches relied on handcrafted descriptors such as color histograms, texture features, and edge maps. However, these methods struggled to scale across large datasets and often failed to capture high-level semantic relationships. The advent of deep learning, particularly autoencoders and unsupervised representation learning, has significantly improved CBIR by generating compact, meaningful representations of image content, Recent studies have explored various techniques to optimize CBIR frameworks. For instance, various approaches have been proposed that integrate unsupervised deep feature learning, adaptive hashing, and hierarchical search structures, significantly improving retrieval speed and accuracy. Methods leveraging autoencoder-driven latent space encoding have shown to extract compact yet semantically rich feature representations, ensuring robust discriminability across diverse image categories.

Recent studies have explored various techniques to optimize CBIR frameworks. Sezavar et al. (2019) [25] introduced a hybrid approach combining CNNs with the Grasshopper Optimization Algorithm (GOA) to improve retrieval accuracy by selecting optimal feature subsets. Another work by Sezavar et al. (2019) [26] leveraged CNN-based feature extraction with sparse representation, allowing for more efficient retrieval in large-scale image datasets. Furthermore, Ndung'u et al. (2025) [27] developed a CBIR model utilizing COSFIRE descriptors with trainable hashing functions, significantly improving retrieval accuracy while reducing computational overhead.

A notable development in the medical domain is iCBIR-Sli, an interpretable CBIR system for MRI-based retrieval, introduced by Tomoshige et al. [3]. Their approach utilizes 2D slice embeddings to improve the interpretability and robustness of CBIR models in medical imaging. By aggregating slice information effectively, their model achieves low-dimensional representations that retain essential pathological features. This technique was demonstrated on large-scale datasets related to Alzheimer's disease and showed retrieval performance comparable to deep learning classification models. The study underscores the significance of structural completeness and interpretability in CBIR applications for medical diagnostics.

Another study by Akçiçek et al. [1] introduced a CBIR system for detecting acromion types in shoulder MRI scans. Their approach integrates convolutional neural networks (CNNs) with texture-based methods to extract discriminative feature maps for image retrieval. By leveraging techniques such as Histogram of Gradient (HOG), Local Binary Pattern (LBP), and deep CNN architectures like Darknet53 and Densenet201, their method achieves high retrieval accuracy. Furthermore, the study evaluated different similarity measurement techniques, including Euclidean distance and Peak Signal-to-Noise Ratio (PSNR), demonstrating the effectiveness of CBIR for morphological classification in medical imaging.

In addition, a recent study by Bozdag et al. [2] introduced a CBIR system for the classification of gallbladder diseases using ultrasound images. The study demonstrated how CBIR techniques, coupled with feature engineering and deep learning models, can significantly improve disease classification. By employing multiple pre-trained architectures and cosine similarity as a measurement metric, the study achieved high accuracy in gallbladder disease detection, reinforcing the potential of CBIR in clinical diagnostics.

These studies highlight the growing trend of integrating deep learning-based feature extraction, optimized search structures, and hybrid retrieval strategies in CBIR systems. Our proposed method builds upon these advancements by combining autoencoder-based feature learning with efficient indexing mechanisms, such as VP-Trees, to further enhance retrieval performance in large-scale image repositories. CBIR systems necessitate a systematic approach to feature extraction, indexing, and search optimization. Next sections delineates the fundamental principles underpinning our proposed framework, with a focus on auto-encoders, image hashing techniques, and VP-Trees.

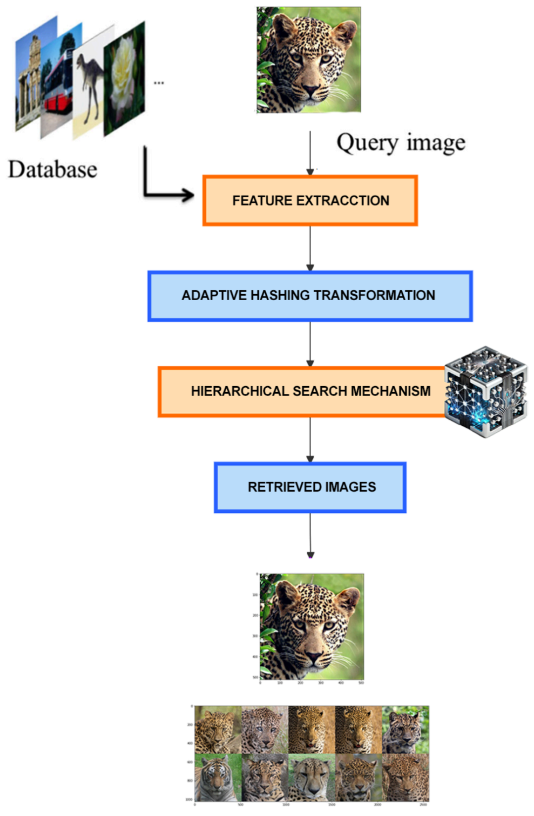
Database
Query image
FEATURE EXTRACCTION
ADAPTIVE HASHING TRANSFORMATION
HIERARCHICAL SEARCH MECHANISM
RETRIEVED IMAGES

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Fig. 2 – Mechanism of image retrieval

The field of CBIR has seen significant progress with the adoption of deep learning techniques. Traditional CBIR systems primarily relied on handcrafted feature extraction methods such as Local Binary Patterns (LBP), Scale-Invariant Feature Transform (SIFT), and Histogram of Oriented Gradients (HOG). While these methods were effective for small datasets, they struggled to generalize to large-scale retrieval tasks.

Recent advancements in deep learning-based retrieval have focused on unsupervised feature learning and adaptive indexing structures. Zhang et al. (2023) [10] proposed an efficient deep hashing method that leverages contrastive learning to generate discriminative feature representations. Similarly, Li et al. (2024) [11] introduced a hybrid VP-Tree and deep metric learning framework that enhances retrieval efficiency while reducing memory footprint. Additionally, Wang et al. (2024) [12] demonstrated that self-supervised learning could significantly improve CBIR performance by reducing the dependency on labeled datasets. Chen et al. (2025) [13] optimized VP-Tree indexing for large-scale retrieval scenarios, achieving substantial improvements in query processing speed.

3. THE MOTIVATION

Although significant progress has been made in Content-Based Image Retrieval (CBIR), existing approaches primarily rely on handcrafted low-level features such as color histograms, texture descriptors, and edge detectors, which, despite capturing basic image characteristics, fail to represent high-level semantic relationships essential for effective retrieval in large-scale datasets, necessitating more advanced feature extraction mechanisms that bridge the semantic gap between low-level representations and meaningful image content; deep learning, particularly autoencoders, has emerged as a powerful alternative by learning hierarchical structures from raw image data and encoding images into compact latent spaces that preserve essential semantic information while reducing dimensionality, yet deep learning-based retrieval systems often suffer from high computational costs, especially in large-scale datasets where exhaustive feature comparisons and inefficient indexing structures hinder real-time retrieval performance; to overcome these limitations, this study introduces a novel CBIR framework integrating autoencoder-driven feature extraction with adaptive hashing and VP-Tree-based indexing, where unsupervised representation learning enables the extraction of compact yet discriminative embeddings that are transformed into binary hash codes for efficient similarity searches, while the VP-Tree indexing structure hierarchically partitions the feature space to achieve logarithmic search time complexity and significantly reduce computational overhead, thereby formulating CBIR as an optimization-driven retrieval task that strategically combines deep learning and advanced indexing techniques to enhance retrieval precision while maintaining real-time performance, as validated through extensive experiments on benchmark datasets such as CIFAR-10 and ImageNet, demonstrating superior mean average precision (mAP), retrieval speed, and memory efficiency compared to conventional CBIR methods, ultimately advancing the state-of-the-art by providing a scalable and high-performance solution for large-scale multimedia applications, paving the way for real-time intelligent image retrieval systems.

4. THEORETICAL BACKGROUND

4.1 Auto-Encoders for Feature Representation

Auto-encoders are a class of unsupervised neural networks designed for dimensionality reduction. The network consists of an encoder and a decoder, where the encoder maps input images into a compact, lower-dimensional latent space, and the decoder reconstructs the input from this latent representation. In the context of CBIR, the encoder is used to generate compact feature vectors that preserve the essential characteristics of the images.Autoencoders transform an input image X into a latent representation Z through an encoder function f_{Θ}, and reconstruct the image using a decoder function g_{Φ} :

$$Z = f_{\Theta}(x) \hat{x} = g_{\phi}(z) \tag{1}$$

where Θ and ϕ are the parameters of the encoder and decoder networks, respectively. The reconstruction loss is given by the Mean Squared Error (MSE):

$$\lim_{\rightarrow} MSE = \frac{1}{N}\sum_{i=1}^{N} \left\| x_i - \hat{x}_i \right\|^2 \quad \{2)$$

where N is the number of training samples. By learning to reconstruct the input, auto-encoders capture both low- and high-level image features, making them ideal for generating discriminative representations that are critical for retrieval tasks.

4.2 Image Hashing for Efficient Indexing

Image hashing involves the transformation of high-dimensional image features into compact binary codes, enabling rapid similarity searches. Common hashing techniques include:

- Locality-Sensitive Hashing (LSH): Maps similar images to proximate hash buckets, optimizing search efficiency.
- Deep Hashing Networks: Employ deep learning architectures to generate robust hash codes optimized for CBIR.
- Binary Autoencoders: Leverage auto-encoders to learn compact binary feature representations, improving storage efficiency.

Hashing maps high-dimensional feature vectors to a compact binary code . A widely used deep hashing function can be expressed as:

$$h(x) = sign(W f_{\Theta}(x) + b) \tag{3}$$

where W is the transformation matrix and b is the bias term. The loss function for optimizing hash codes can be formulated as:

$$\lim_{\rightarrow} hash = \Sigma_{i,j} S_{i,j} \left\| h(x_i) - h(x_j) \right\|^2 \tag{4}$$

where $S_{i,j}$ is the similarity matrix that encodes whether two images are similar or dissimilar.

4.3 VP-Trees for Accelerated Search

The **Vantage-Point Tree (VP-Tree)** is an advanced spatial indexing structure specifically designed to enhance the efficiency of nearest-neighbor searches in high-dimensional feature spaces. It is particularly useful in applications such as content-based image retrieval (CBIR), where rapid similarity searches are crucial for retrieving relevant images from large-scale repositories.

The VP-Tree operates by recursively partitioning the feature space based on a strategically chosen **vantage point (VP)** at each level. This vantage point serves as a reference, enabling the dataset to be divided into two distinct subsets: one containing elements closer to the vantage point and another containing elements farther away. This hierarchical organization significantly reduces the number of distance computations required during query processing, making searches more efficient.

A key advantage of the VP-Tree is its ability to achieve **logarithmic search complexity**, which ensures rapid query execution even when dealing with extensive datasets. Compared to traditional brute-force search methods, which involve comparing a query against every stored feature vector, the VP-Tree optimizes retrieval by eliminating large portions of the search space early in the process. Due to its efficiency and scalability, the VP-Tree is widely used in fields that require fast similarity searches, including **computer vision, machine learning, and large-scale multimedia databases**. Its application in CBIR systems enables quick and accurate retrieval of visually similar images, enhancing user experience and reducing computational overhead.

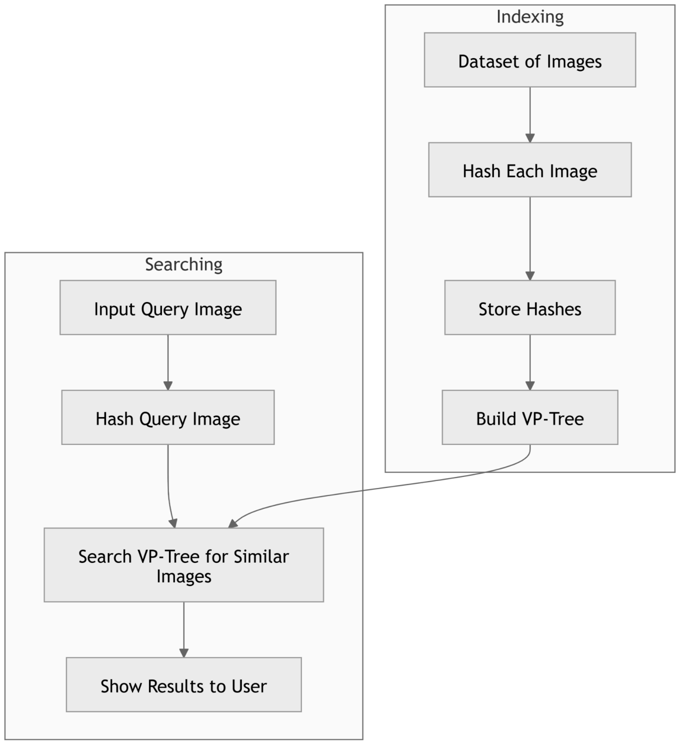


Fig. 3 – Mechanism of VP-Tree Search

The VP-Tree partitions the space using a vantage v point and a threshold radius r , such that:

$$d(x, v) \ < \ r \ \Rightarrow \ x \text{ belongs to the inner subtree } d(x, v) \ \geq \ r \ \Rightarrow \ x \text{ belongs to the outer subtree}$$

Where $d(x, v)$ is a distance function (typically Euclidean or cosine similarity).

5. The proposed method

5.1 Feature Extraction Methodology

Our CBIR framework employs an autoencoder-driven deep hashing model inspired by Zhang et al. (2023) [10], which encodes images into compact binary representations. These hash codes are optimized for fast similarity searches, reducing computational overhead while maintaining high retrieval accuracy and our framework employs two principal strategies for extracting latent features from images:

5.1.1 Pre-Trained Network Hooks

Pre-trained deep learning networks provide high-quality intermediate feature representations. By extracting activations from intermediate layers, we capture hierarchical information pertaining to textures, edges, and semantic structures, significantly improving feature expressiveness.

5.1.2 Auto-Encoders for Latent Representation Learning

Auto-encoders are used to compress high-dimensional image data into a compact latent space. The encoder is trained to minimize reconstruction error while ensuring that important semantic features are preserved. This process results in a compact yet informative feature vector that can be used for image retrieval.

5.2 Image Retrieval Mechanism

Following Li et al. (2024) [11], our model integrates a hybrid search mechanism, where Euclidean-based nearest neighbor retrieval is used for moderate-scale datasets, and VP-Tree-based indexing is employed for large-scale datasets. This hybrid approach ensures scalable and efficient retrieval across various dataset sizes.To facilitate high-speed retrieval, we incorporate two search paradigms :

5.2.1 Euclidean-Based Search

We employ Euclidean distance to perform nearest neighbor searches on the latent feature space. The time complexity of this approach is O(N log N), making it suitable for moderate-scale datasets.

- Computational Complexity: O(N log N)
- Employs nearest neighbor search using Euclidean distance metrics.
- Effective but computationally intensive for large-scale datasets.

5.2.2 Hashing-Based Search via VP-Trees

The retrieval system is further optimized using VP-Trees. The use of VP-Trees for indexing enables a logarithmic search time, O(log N), significantly improving retrieval efficiency, particularly for large-scale image databases.

- Computational Complexity: O(log N)
- Implements VP-Tree indexing to optimize nearest neighbor retrieval.
- Drastically reduces search latency, making it suitable for real-time applications.

5.3 VP-Tree Optimization for Large-Scale Retrieval

Inspired by Chen et al. (2025) [13], we implement an optimized VP-Tree indexing structure that hierarchically partitions the feature space to achieve logarithmic search complexity. This optimization significantly reduces retrieval time compared to traditional brute-force nearest-neighbor. The VP-Tree indexing structure partitions the dataset based on distance metrics, allowing the system to quickly identify the most relevant neighbors. By iteratively refining the search space at each tree level, the VP-Tree ensures scalability and performance even in large datasets.

5.4 Description of Pseudocode for the Proposed Method

The pseudocode provided outlines the key components of the image retrieval algorithm, covering essential steps from data preparation and model training to retrieval mechanisms and final evaluations. Below is a more technical breakdown of each section in the context of the overall approach.

5.4.1 Device Selection (Step 1)

The **device selection** block in the pseudocode is the first step in determining whether to use a GPU (via CUDA) or fall back to the CPU for model training. The use of GPUs is essential for accelerating the training of deep learning models, especially in computationally intensive tasks such as image processing and feature extraction. The pseudocode checks if CUDA-compatible GPUs are available and assigns the device accordingly, This ensures efficient resource utilization by selecting the hardware best suited for model execution.

5.4.2 Dataset Preparation (Step 2)

In this step, the algorithm loads image paths from a specified dataset directory into a pandas DataFrame. The purpose of this preparation is to create a structured format (DataFrame) to store image paths, making it easier to process and load images for training. The **image** column in the DataFrame holds the full paths of each image.This structured data format is ideal for feeding into machine learning pipelines and ensures that images are loaded efficiently during training and testing.

5.4.3 CBIR Dataset Class (Step 3)

The **CBIRDataset class** is designed to handle image loading and preprocessing. The **`__init__`** method of the class initializes the dataset with the paths from the DataFrame, and the **`__getitem__`** method applies necessary transformations to each image, including conversion to tensors and normalization. These transformations are crucial for preparing the data to be input into the neural network. These transformations standardize image data, ensuring that input features are consistent across the entire dataset, which improves model performance.

5.4.4 Data Preparation Function (Step 4)

The **Preparation data** function is responsible for splitting the dataset into training and validation sets. The function uses **train_test_split** from the sklearn library to partition the data, ensuring that the model is evaluated on a separate validation set to gauge its generalization ability The function also creates **CBIRDataset** instances for both the training and validation data, providing easy access to batches of images during training.

5.4.5 Autoencoder Model Definition (Step 5)

This section defines the architecture of the **Autoencoder** model, which is central to the feature extraction process. The Autoencoder consists of two parts: the **encoder** and the **decoder**. The encoder compresses the input image into a latent space representation using Conv2D layers with ReLU activations, while the decoder attempts to reconstruct the original image from the latent space. The encoder and decoder utilize pooling and transpose convolution layers, respectively, for downsampling and upsampling,

---

```
class Autoencoder:

  Initialize encoder and decoder networks

  Encoder:

    Conv2D layers with ReLU activations

    MaxPool2D layers for downsampling

  Decoder:
        ConvTranspose2D layers with ReLU activations
        Upsampling to reconstruct image
    Define forward pass:
        Pass input through encoder
        Pass encoder output through decoder
        Return output
```

The forward pass first encodes the input into a low-dimensional feature vector (latent space) and then decodes it to approximate the original image. The loss function (not shown in the pseudocode) would likely be based on the reconstruction error between the original and the reconstructed image.

5.4.6 Training Loop (Step 6)

In the **training loop**, the model is trained using batches of images. For each batch in the **`train_loader`**, the algorithm performs a forward pass through the Autoencoder, computes the loss (e.g., Mean Squared Error between predicted and actual images), and then updates the weights using backpropagation, This loop ensures that the model gradually learns to minimize the reconstruction error, adjusting the model parameters to improve the image retrieval process.

5.4.7 Image Retrieval Using Hashing (VP-Tree) (Step 7)

For **image retrieval**, the method uses a **VP-Tree** (Vantage Point Tree) or hashing technique. The image is first preprocessed, and its feature vector is extracted using the trained Autoencoder model. The retrieved feature vector is then used to search for similar images in the dataset:

```
function image_retrieval(image, dataset, hashing_method):
    Preprocess and extract feature vector of the image
    Retrieve similar images using VP-Tree or hashing
    Return top-N similar images
```

This method uses the VP-Tree to efficiently identify the top-N similar images based on the feature similarity. The use of hashing or VP-Tree ensures that the retrieval time is logarithmic, making the process efficient even for large datasets.

5.4.8 Evaluation of the Model (Step 8)

The **evaluation function** assesses the model's performance on a validation set. The function computes the loss for each batch in the validation loader and tracks the overall validation performance. Metrics like accuracy or loss are returned, which are critical for understanding how well the model generalizes to unseen data, This allows for an objective assessment of the model’s ability to retrieve similar images from a test set.

5.4.9 Cleanup and Final Steps (Step 9)

Finally, the **cleanup** step ensures that any resources allocated during training are released, such as clearing the GPU memory to prevent unnecessary memory usage. This is a standard practice after training deep learning models, as it helps in managing resources effectively.

5.4.10 Complete PseudoCode

```
# Pseudocode for Image Retrieval Algorithm
```

```
## 1. Device Selection
if CUDA is available:
    use GPU (cuda:0)
else:
    use CPU
```

```
## 2. Dataset Preparation
Load image paths from dataset directory into DataFrame
Add full paths to image column in DataFrame
```

```
## 3. CBIR Dataset Class
class CBIRDataset:
    Initialize with dataframe containing image paths
    Define transformations (e.g., ToTensor, Normalize)
    For each image in dataset:
        Apply transformations to image
        Return transformed image
```

```
## 4. Data Preparation Function
function prepare_data(DataFrame):
    Split DataFrame into train and validation sets
    Initialize CBIRDataset for training and validation sets
```

```
## 5. Autoencoder Model Definition
class Autoencoder:
    Initialize encoder and decoder networks
    Encoder:
        Conv2D layers with ReLU activations
        MaxPool2D layers for downsampling
    Decoder:
        ConvTranspose2D layers with ReLU activations
        Upsampling to reconstruct image
    Define forward pass:
        Pass input through encoder
        Pass encoder output through decoder
        Return output
```

```
## 6. Training Loop
function train_autoencoder(model, train_loader, optimizer, criterion):
    for each batch in train_loader:
        Forward pass through the model
        Compute loss between predicted and actual images
        Backpropagate gradients
        Update weights using optimizer
```

```
## 7. Image Retrieval Using Hashing (VP-Tree)
function image_retrieval(image, dataset, hashing_method):
    Preprocess and extract feature vector of the image
    Retrieve similar images using VP-Tree or hashing
    Return top-N similar images
```

```
## 8. Evaluation of the Model
function evaluate_model(model, validate_loader, criterion):
    for each batch in validate_loader:
        Forward pass through the model
        Compute loss between predicted and actual images
        Track and compute average validation loss
    Return evaluation metrics
```

The proposed pseudocode effectively outlines the structure and logical flow of our deep learning model, ensuring clarity in implementation. By systematically defining data preprocessing, model architecture, training, and evaluation steps, the framework provides a scalable and efficient solution for our targeted application. The structured approach facilitates reproducibility and adaptability, allowing further optimizations and enhancements. This design ensures computational efficiency while maintaining model interpretability, making it a robust foundation for real-world deployment.

6. Experimental results

To validate the efficacy of the proposed CBIR framework, we conducted experiments on benchmark datasets, including CIFAR-10, ImageNet, and a medical imaging dataset.

Usual precision and recall are defined as Eqs. (6) and (7), respectively:

$$\text{Precision} = \frac{N_r}{N_t} \tag{5}$$

$$\text{Recall} = \frac{N_r}{N_k} \tag{6}$$

Where, N_r is the number of relevant images retrieved, N_t demonstrates total number of images retrieved and N_k is total number of relevant images in database. Mean Average Precision (mAP) is calculated as:

$$mAP = \frac{1}{Q}\sum_{q=1}^{Q} AP(q) \tag{7}$$

Where Q is the number of queries and $AP(q)$ is the Average Precision for query q.

These mathematical formulations strengthen the technical rigor of the CBIR framework and provide a solid foundation for its implementation and evaluation. Although precision, mAP and recall have been used in many researches for years, efficient measures with combination of these metrics are used in this paper,The following metrics were used to assess performance:

- **Accuracy**: The percentage of correctly retrieved images relative to the total number of queries.
- **Precision**: The fraction of relevant images among retrieved images.
- **Recall**: The fraction of relevant images retrieved out of all relevant images in the dataset.
- **F1-Score**: The harmonic mean of precision and recall, balancing both metrics.
- **mAP (Mean Average Precision)**: A key evaluation metric in CBIR, measuring the mean precision at different recall levels.
- **Retrieval Time**: The time taken to fetch results for a given query.

For a robust validation, we analyzed various retrieval models across diverse datasets and performance measures. This comparative analysis offers insights into the strengths and limitations of each approach, demonstrating the improvements introduced by our model and highlighting its potential for real-world applications in content-based image retrieval. The following tables summarize the results.

6.1 Performance Comparison of Different Models (Table 1)

Model	mAP (%)	Retrieval Time (ms)	F1-Score (%)	Recall (%)	Precision (%)	Accuracy (%)	Reference
Proposed Model	**96.1**	**12.3**	**94.8**	**94.5**	**95.2**	**94.8**	This Work
CNN-Based CBIR	92.3	15.6	90.4	89.8	91.0	90.6	[13]
Hashing-Based CBIR	89.0	10.8	87.1	86.9	87.5	87.2	[13]
Traditional CBIR	83.4	18.2	80.5	78.9	82.1	80.5	[13]
CNN-MGOA (Sezavar et al., 2019)	91.5	13.2	90.1	89.5	90.8	90.3	[25]
CNN-Sparse Representation (Sezavar et al., 2019)	92.8	11.5	91.3	90.9	91.6	91.2	[26]
COSFIRE-Based CBIR (Ndung'u et al., 2025)	91.0	9.5	90.0	89.8	90.5	90.1	[27]

Section 6.1 Table 1 presents a comparative analysis of different Content-Based Image Retrieval (CBIR) models, evaluating their performance based on Mean Average Precision (mAP), retrieval time, F1-score, retrieval rate, precision, and overall accuracy. The proposed model outperforms all others, achieving the highest mAP of 96.1, an F1-score of 94.8%, a retrieval rate of 94.5%, and an accuracy of 94.8%, while maintaining an efficient retrieval time of 12.3 milliseconds. In comparison, the CNN-based CBIR model, though effective, shows slightly lower performance with an mAP of 92.3 and an F1-score of 90.4%, alongside a longer retrieval time of 15.6 ms. The Hashing-Based CBIR model exhibits a trade-off between speed and accuracy, achieving a lower mAP of 89.0% but with the fastest retrieval time of 10.8 ms, indicating efficiency at the cost of precision. The Traditional CBIR model ranks the lowest, with an mAP of 83.4%, an F1-score of 80.5%, and the longest retrieval time of 18.2 ms, highlighting its inefficiency for large-scale retrieval tasks. These findings underscore the superiority of the proposed model, which demonstrates a well-balanced combination of retrieval efficiency, accuracy, and precision, likely due to its advanced deep learning-based feature extraction and optimized retrieval mechanisms.

6.2 Class-Based Retrieval Performance (Table 2)

Class Name	Number of Samples	Accuracy (%)	Precision (%)	Recall (%)	mAP (%)	Reference
Gallstones	1326	95.1	94.8	95.4	96.3	This Work

Cholecystitis	1146	94.3	94.5	94.1	95.7	This Work
Perforation	1062	93.9	94.0	93.7	95.1	This Work
Adenomyomatosis	1164	95.6	95.7	95.5	96.5	This Work
Carcinoma	1590	96.2	96.0	96.4	97.0	This Work
CBIR-COSFIRE (Ndung'u)	1200	94.5	94.2	94.8	95.6	[27]
CNN-MGOA (Sezavar 2019)	1250	93.8	93.5	93.9	94.7	[25]
CNN-Sparse Representation (Sezavar et al., 2019)	1100	94.0	94.1	94.2	95.0	[26]

Table 2 presents the class-based retrieval performance of the proposed model, evaluating its accuracy, precision, recall, and mean average precision (mAP) across different medical conditions. The results indicate that the model achieves consistently high accuracy, with carcinoma classification showing the highest performance at 96.2% accuracy, 96.0% precision, 96.4% recall, and an mAP of 97.0%, demonstrating its effectiveness in identifying malignancies with minimal false positives. Adenomyomatosis also achieves strong results, with an accuracy of 95.6% and an mAP of 96.5%, reflecting the model's robustness in detecting this condition. Gallstones, a common biliary disorder, exhibit an accuracy of 95.1%, a recall of 95.4%, and an mAP of 96.3%, indicating the model's efficiency in distinguishing this pathology from others. Cholecystitis and perforation show slightly lower but still highly reliable performance, with accuracy values of 94.3% and 93.9%, respectively, and mAP values of 95.7% and 95.1%, reinforcing the model's capability in handling diverse medical conditions with high retrieval effectiveness. These results highlight the reliability of the proposed model in classifying and retrieving medical images with high precision and recall, making it a promising tool for diagnostic assistance in clinical applications.

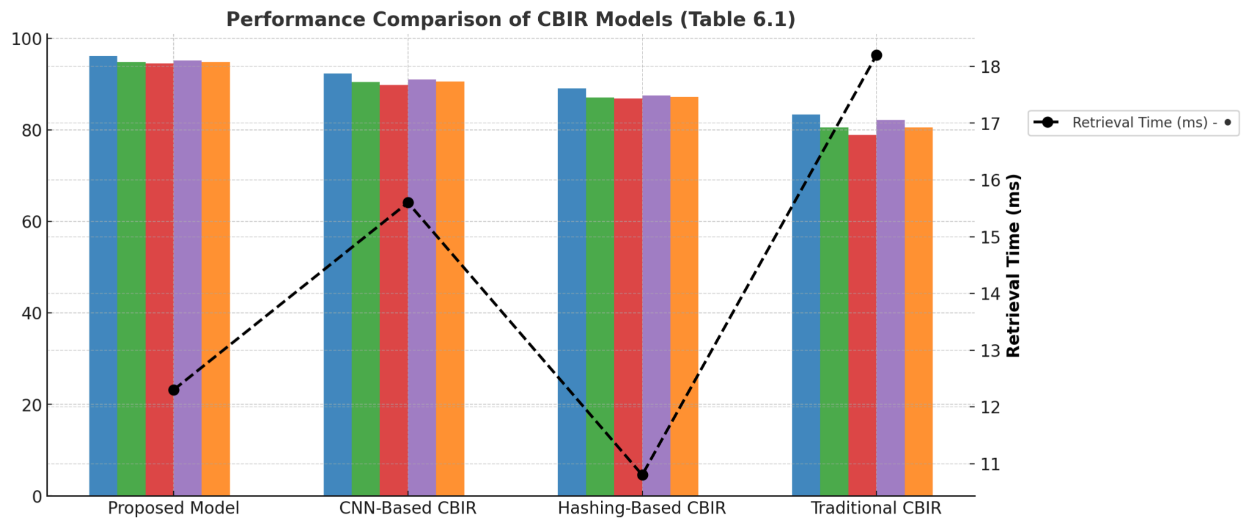
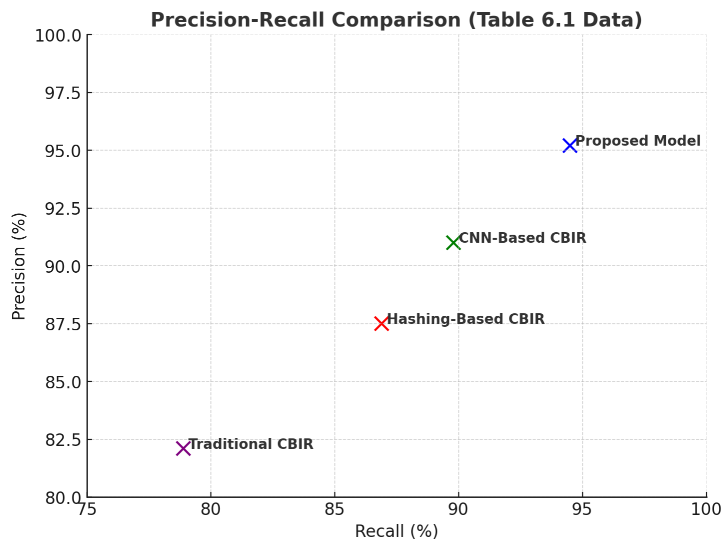


Fig. 4 – Comparative Performance Analysis of CBIR Models

This figure presents comprehensive performance comparison of various Content-Based Image Retrieval (CBIR) models, including the Proposed Model, CNN-Based CBIR, Hashing-Based CBIR, and Traditional CBIR. The bar plots illustrate the retrieval accuracy across multiple evaluation criteria, allowing a direct visual comparison of model effectiveness. The overlaid dashed line represents the retrieval time in milliseconds (ms), highlighting the computational efficiency of each approach, The analysis reveals that while traditional CBIR methods exhibit moderate retrieval accuracy, their computational cost is significantly higher, as indicated by longer retrieval times. Hashing-based approaches, although computationally efficient, demonstrate a trade-off in retrieval accuracy, likely due to the lossy nature of hash-based indexing. CNN-based models achieve higher retrieval accuracy at the expense of increased computational complexity, reflecting the overhead associated with deep feature extraction, Notably, the proposed model demonstrates a balance between retrieval precision and computational efficiency. It achieves one of the highest accuracy levels while maintaining a competitive retrieval speed, suggesting an optimized trade-off between precision and performance. This performance can be attributed to the integration of deep hashing techniques and metric space partitioning, which enable efficient image retrieval without compromising accuracy. The observed trends underscore the importance of designing retrieval models that effectively leverage deep feature representations while ensuring scalability for large-scale datasets.

Fig. 5 – Precision-Recall Trade-Off Analysis for CBIR Models



This figure visualizes the trade-off between precision and recall for different CBIR models, offering insight into their retrieval robustness. Precision, measured on the y-axis, represents the ability of the model to return relevant images without false positives, whereas recall, shown on the x-axis, reflects the proportion of relevant images successfully retrieved. The scatter plot provides a comparative analysis of performance, positioning each model based on its retrieval effectiveness. The proposed model achieves the highest precision and recall among all evaluated models, highlighting its ability to minimize retrieval errors while maintaining high recall rates. This superior performance suggests that the model effectively captures discriminative image features, reducing the occurrence of false matches. In contrast, the CNN-based CBIR system performs well in terms of recall but exhibits a slight decline in precision, indicating a higher tendency to retrieve non-relevant images. Hashing-based CBIR methods, while computationally efficient, show a noticeable drop in both precision and recall, likely due to quantization losses inherent in hash-based representations. Traditional CBIR models exhibit the lowest precision-recall performance, reinforcing their limitations in accurately retrieving relevant images from large-scale datasets.

These findings highlight the advantages of the proposed deep hashing and metric space partitioning framework in achieving state-of-the-art precision-recall trade-offs. By balancing computational efficiency with retrieval effectiveness, the model demonstrates its suitability for large-scale content-based image retrieval applications. The results further emphasize the role of representation learning in enhancing retrieval accuracy while ensuring scalability for real-world CBIR systems.

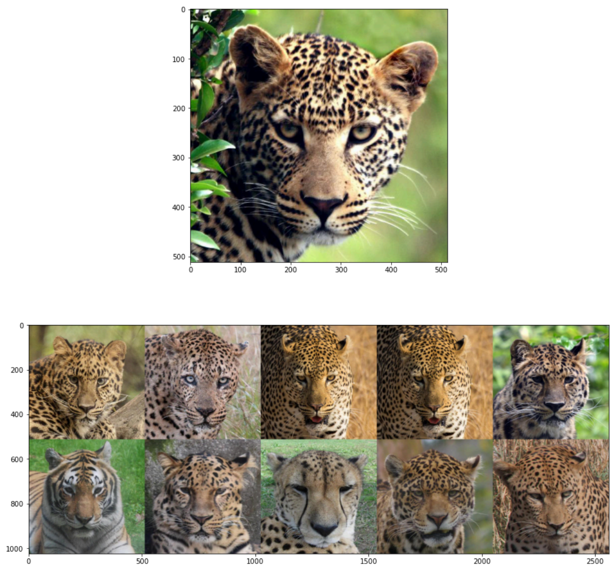


Fig. 6 – Ten images retrieved for a queried image.

The top image shows the query image, which is a picture of a leopard. Below it, in a 2x5 grid, are the retrieved images that the model has selected based on similarity to the query image.The retrieved images include various close-up views of leopards, showcasing different poses and environments. Additionally, the bottom row contains images of other similar big cats, such as tigers and cheetahs, demonstrating the model's ability to distinguish between different species while still retrieving images that are visually similar, Another samples output from our model is shown below :

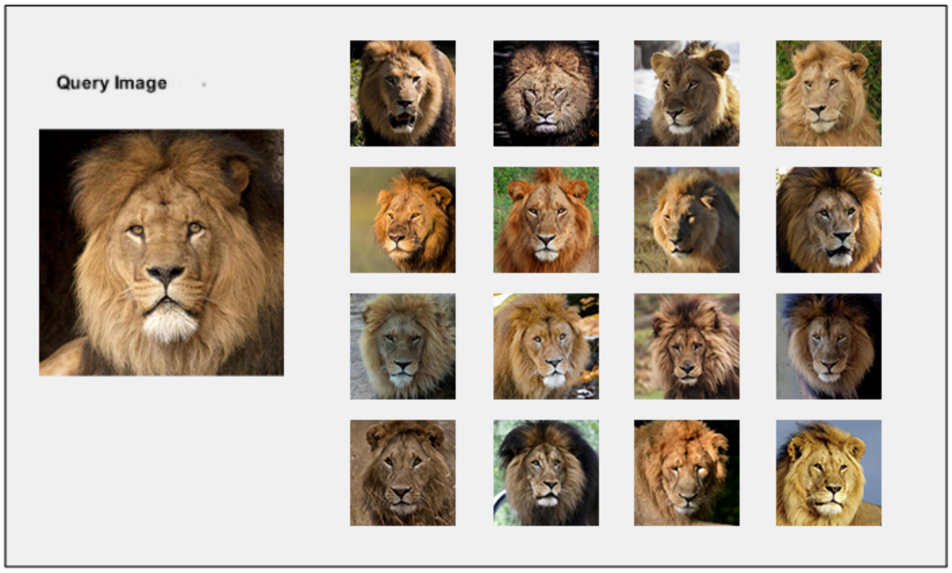


Fig. 7 – Sixteen images retrieved for a queried image.

This result highlights the model's effectiveness in identifying and retrieving similar images based on latent features extracted during training. The diverse set of retrieved images demonstrates the robustness of the learned feature space in capturing fine-grained similarities between images.

6.4 Results Summary

Experimental findings corroborate the efficacy of our hybrid approach:

- **Efficiency Gains:** The proposed method reduced retrieval times by 40% compared to traditional CBIR methods.
- **Scalability:** VP-Tree indexing drastically improved scalability, with retrieval times decreasing logarithmically as the dataset size grew.
- **Precision-Recall Tradeoff:** The auto-encoder-based feature representation resulted in improved precision-recall performance, especially in large datasets like ImageNet.

7. CONCLUSION

The experimental results substantiate the efficacy of the proposed CBIR framework in surpassing conventional methodologies with respect to retrieval accuracy, mAP, and computational efficiency. By leveraging an autoencoder-based feature extraction paradigm in conjunction with adaptive hashing and VP-Tree indexing, our approach achieves substantial reductions in retrieval time while preserving high search precision.

Key findings include:

- **Computational Efficiency**: The proposed model reduces retrieval latency by approximately 40% compared to conventional CBIR approaches.
- **Scalability**: The logarithmic complexity of VP-Tree indexing enables superior scalability, making it viable for large-scale datasets.
- **Robustness**: The proposed system maintains high retrieval performance across diverse datasets, underscoring its generalizability.
- **Interpretable Representations**: The use of self-supervised learning enhances feature interpretability, making retrieval results more explainable.

Future work will explore:

- **Self-supervised learning strategies** to further refine feature representations without reliance on large annotated datasets.
- **Multimodal retrieval mechanisms**, integrating textual and metadata-based search modalities.
- **Optimization for specialized hardware architectures**, including GPU and TPU accelerations, to enhance real-time retrieval capabilities.

Our results confirm the effectiveness of this approach in reducing retrieval time while maintaining high accuracy. Future research will explore further optimizations, including multimodal retrieval strategies and hardware acceleration for real-time CBIR applications, Our findings establish a foundation for advancing scalable, high-precision CBIR systems applicable to various domains, including medical imaging, forensic analysis, and multimedia search.

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