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Original Article

ICBIRS: Enhanced Content-Based Image Retrieval for High-Precision Image Matching with a Novel Convolutional Neural Network Variant

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Abstract - *With the cloud-based ecosystem, various organizations have increasingly adopted the use of multimedia objects, such as images. In many real-world applications, retrieving required images plays a very crucial role. In this context, providing a query to a system is very important, and giving a query by example plays a vital role in retrieving images that satisfy the user's intent to a greater extent. Traditional image processing approaches suffer from the requirement for scalable processing. The emergence of artificial intelligence has enabled learning-based approaches that can serve as improved deep learning models, which are widely used for image processing and require enhancement to realize a content-based image retrieval system. In this paper, we propose a deep learning-based framework known as an Intelligent Content-Based Image Retrieval System (ICBIRS). The system employs an AI-enabled approach for both offline and online phases, extracting features from the database and processing user queries. To extract feature embeddings from a database of images and query images, we proposed and enhanced the CNN model with an attention mechanism and multi-scale feature extraction, enabling efficient retrieval of features and feature embeddings. The proposed system can retrieve top images similar to the query image and reflect user intent as much as possible with even semantic similarity. We proposed an algorithm known as Intelligent Learning based Image Retrieval (ILbIR), intelligent learning-based image Retrieval. The proposed system is evaluated with a benchmark data set. The results revealed that the proposed enhanced CNN model-based approach could leverage image Retrieval performance with the highest accuracy at 97.35%. Therefore, the proposed system can be integrated with real-time multimedia applications where there is a need to retrieve images in a query using an example paradigm.*

Keywords - *Artificial Intelligence, Content-Based Image Retrieval, Deep Learning, Enhanced CNN, Intelligent Image Retrieval.*

1. Introduction

Images play an essential role across various industries and applications. In today's era, storing and managing images has become increasingly significant due to the availability of affordable storage solutions, such as cloud computing. Commercial organizations that handle images have shifted their focus to cloud resources because of their cost-effectiveness. With the rise of artificial intelligence, computer vision applications have gained popularity, mainly through deep learning models, which are effective in image processing.

In this context, deep learning models like convolutional neural networks are widely utilized for processing images across different domains. Unlike traditional Content-Based Image Retrieval (CBIR) systems, which rely on conventional image processing methods to query images by example, learning-based approaches offer numerous advantages in image retrieval. With the advent of artificial intelligence, these learning-based methodologies have emerged as significant alternatives.

Despite these advances, existing CBIR systems still face significant limitations. Traditional CNN-based models often capture only single-scale visual features, making them less effective when images contain complex backgrounds, fine-grained objects, or high intra-class similarity. Moreover, most existing methods lack mechanisms to emphasize the most informative image regions, resulting in retrievals that do not fully reflect semantic similarity. These challenges create a clear research gap: the need for an intelligent CBIR framework that combines multi-scale feature extraction with attention mechanisms to enhance discriminative power, improve semantic alignment, and deliver higher retrieval precision across diverse datasets.

Many researchers contributed to developing CBIR systems using artificial intelligence. A Content-Based Image Retrieval (CBIR) system was developed using pre-trained Convolutional Neural Network (CNN) models, including ResNet-50 and VGG16. Future enhancements will involve incorporating user feedback and optimizing the system. One limitation is that smaller images can compromise resilience due to memory constraints, but there is a notable retrieval precision of 90.18% using ResNet-50 [1]. Another approach combined the Enhanced Color Space Model (ECSM) with ResNet-50 to create a system capable of extracting deep features from healthcare images, focusing on future advancements in interpretable deep learning and federated learning to improve transparency in healthcare decision-making [2]. A deep hash coding system for efficient medical image retrieval is being developed, with plans for real-time implementations and generative adversarial networks for data augmentation [3]. An edge computing server system utilizing CNNs enhances image retrieval capabilities, aiming to improve privacy and reduce network traffic. While the system boasts higher accuracy and faster response times, it also faces challenges regarding privacy and mobile optimization [4]. Lastly, a system integrating OpenStack Swift with machine learning aims to enhance content-based searches, with future plans for compression, authentication token usage, and exploration of video surveillance applications. Although system complexity and the need for continuous tuning are drawbacks, improved search capabilities are a significant advantage [5]. From the literature, it was obvious that there is a need to improve deep learning models to make intelligent CBIR systems.

The novelty of this work lies in integrating multi-scale feature extraction with an attention mechanism in an enhanced CNN architecture. Unlike existing CBIR approaches such as ResNet, VGG, or LeNet that rely on single-scale features and lack semantic focus, the proposed framework ensures robust representation, fine-grained discrimination, and superior retrieval accuracy.

This paper presents our contributions as follows: We provide a framework based on deep learning, termed the Intelligent Content-Based Image Retrieval System (ICBIR). This system employs an AI-enabled approach for offline and online phases, allowing it to extract features from a database and process user queries effectively. We enhanced a Convolutional Neural Network (CNN) model by incorporating an attention mechanism and multi-scale feature extraction to extract feature embeddings from both the image database and query images, allowing efficient feature retrieval. The proposed system retrieves the top pictures similar to the query image, reflecting the user's intent and capturing semantic similarity. Additionally, we introduce an algorithm called Intelligent Learning-Based Image Retrieval (ILBIR). The effectiveness of the proposed system is evaluated using a benchmark dataset, which demonstrated that our enhanced CNN model significantly improves image retrieval performance, achieving a 97.35% accuracy rate. As a result, real-time multimedia applications that must retrieve images based on example queries may use this approach. This is how the rest of Section 2 reviews the studies on several current methods for improving Content-Based Image Retrieval (CBIR) systems using learning-based approaches. Section 3 presents the proposed methodology for the intelligent CBIR system and explains its modus operandi. Section 4 discusses the experimental results and compares the proposed system's performance with several state-of-the-art models, identifying the study's limitations. The proposed research, Sections 5 and 6, wrap up the results discussed in this study and offer ideas for further research.

2. Related Work

Existing CBIR research can broadly be categorized into CNN-based retrieval frameworks, medical image retrieval systems, remote sensing applications, and secure cloud-based CBIR models. The following works are synthesized across these categories, highlighting their key contributions and limitations to provide a comprehensive background for our study. Giriraj and Anita [1] constructed a CBIR system using CNN models (ResNet-50, VGG16) that have already been trained. The following steps will include adding pertinent feedback and optimizing for maximum effectiveness. One drawback is that resilience is compromised when pictures are smaller due to memory constraints. Improved retrieval precision (90.18% with ResNet-50) is one of the advantages. Imène et al. [2] combined ECSM with ResNet50 to build AOADL-CBIRH, which can extract deep features from healthcare photos and improve them using AOA-based tuning and the Manhattan distance measure. Future research will look at enhanced DNNs, interpretable DL, federated learning, and decentralized data preservation to promote transparency in healthcare decision-making. Cui and Liu [3] introduced the deep hash coding CBMIR system, which aims to enable efficient medical image retrieval. Real-time systems and generative adversarial networks will be used for data augmentation in the future as databases are used for broader applications. Jamal et al. [4] developed a CNN-powered edge computing server system for image retrieval. Future projects will enhance privacy, reduce network traffic, and expedite feature matching. The advantages include improved retrieval accuracy and quicker reaction times; the disadvantages include privacy concerns and the need to optimize for mobile environments. Jannatun et al. [5] enhanced content-based searches by combining OpenStack Swift with machine learning. Future plans call for the system to be compressed, using authentication tokens, and exploring video surveillance applications. The system's complexity and the need for constant tuning are disadvantages; improved search capabilities are advantages.

Li et al. [6] created RGAN; the authors concentrated on ROI detection for RSIR using CAM and attention modules to improve retrieval accuracy. Future studies will attempt to lessen obstacles like clouds to enhance performance. Cai et al. [7] developed PBFFN for RS image retrieval to improve rotation invariance and feature fusion. Future research will investigate unsupervised hashing methods, improve interpretability, and optimize the loss function. Munikumar and Madhavi [8] focused on encoding and stage distinction while presenting a deep learning-based CDR technique for CBIR. Outstanding CIFAR-10 scores are one of the merits. Drawbacks include challenges with interpretability and data intensity. Future studies will investigate increasingly intricate architectural designs and expand the model's application by refining loss functions and hyperparameters.

Nitin et al. [9] offered a CBIR framework for deep learning-based healthcare image analysis, focusing on VGG-16 for optimal model selection. Notable features include high accuracy and mAP scores. The negatives are interpretability problems and high data intensity. Subsequent studies will concentrate on real-time feature extraction and complex neural network design. Divya et al. [10] studied the primary elements of CBIR, such as feature selection, extraction, representation, and the current deep learning integration. Complicated storage and picture quality issues are among the difficulties. Research endeavors are underway to enhance CBIR systems' multimodal capabilities and storage efficiency.

Saban et al. [11] suggested using triplet learning to achieve CBIR in medical image processing, or OCAM. It improves on discriminative embedding using adaptive margins and outperforms standard approaches on several datasets. Potential research topics include scalability and broader medical uses. Kristoffer et al. [12] developed a self-supervised system for CT liver image CBIR to improve explainability and lower reliance on labeled data. It does not scale to other organs but increases performance with clinically significant attributes. Future research should prioritize extending to other organs and improving generalizability. Zhang and Liu [13] discussed the advancements in deep learning-based CBIR, highlighting the challenges associated with feature selection, the need to reduce dimensionality, the variety of datasets, and optimizing user input. The goal of later research is to improve user experience and learn gradually. Rashad et al. [14] introduced RbQE, a system that achieves effective CBMIR by extracting deep features from extended query photos using VGG-19 and AlexNet. It provides better retrieval performance on various medical image datasets than existing methods. With further work, it could be feasible to scale up and adjust to new medical imaging technology. Vieira et al. [15] presented CBIR-ANR, a software combining CBIR with an accuracy noise reduction technique and low-level feature fusion. Future studies might increase processing speed and scalability.

Iqbal et al. [16] developed a fusion-based CBMIR method that uses CNNs to blend textural and visual input for medical image modality classification. Advances in AI interpretability in radiology and clinical efficacy evaluations will be the main areas of future study. Ashery et al. [17] announced ODTL-SCBMIR, a medical image retrieval system integrating MKHE security with CapsNet feature extraction. Subsequent investigations aim to enhance by utilizing advanced feature extractors and low-power cryptography. Zechao and Adrian [18] enhance large-scale CBIR retrieval accuracy through an effective query-sensitive co-attention method. Future research may primarily maximize processing costs and expand applicability across several datasets. Mansour [19] developed M-BMIRC, a DL model-based biological image categorization and retrieval technique that performs better than existing methods. Further research might improve DL model training further. Rafiei and Alexandros [20] demonstrated CS-VAE, which uses class-specific CBIR to enhance discriminative learning in VAEs. It is feasible that more studies will lead to improved loss functions with broader applications.

Agrawal et al. [21] recommended a CBMIR system with deep learning for lung illness identification using X-ray images. Future research will alter other neural models to enhance performance and handle larger datasets. Yong et al. [22] developed Sec-Defense-Gan, a secure GAN-based solution for cloud-based CBIR that offers safe picture retrieval. Future research will focus on speed improvement and the optimization of theoretical security bounds. Shamna et al. [23] proposed a CBMIR framework that uses spatial matching of visual words for enhanced medical image retrieval. Future work will weight visual terms based on relevance and location to improve retrieval accuracy. Jabnoun et al. [24] investigated low-level feature-based CBIR methods and proposed a CNN-based system incorporating transfer learning. Future research will enhance high-level feature extraction to achieve more precise semantic alignment. Sumbul et al. [25] offered SCI-CBIR, a method for simultaneously indexing and compressing RS pictures to increase CBIR efficiency. Subsequent studies will focus on adapting DL compression to suit 3D models for spectral data.

Schall et al. [26] developed GPR1200, a significant benchmark dataset for general-purpose CBIR models. They demonstrated that extensive pre-training significantly enhances retrieval performance. In the future, retrieval-specific training will be enhanced for further advancements. Chen et al. [27] focused on standards, methods, obstacles, and future directions as they analyzed the latest advancements in deep learning-based instance retrieval. Subsequent research will address privacy concerns with IIR systems and improve secure feature representations. Zhang et al. [28] developed a secure image retrieval system using deep learning and encryption. Improved sample quality and better outcomes with fewer datasets will be the main goals of the following projects. Lu et al. [29] proposed DFHN, a novel deep hashing method that integrates fuzzy logic with DNN, for efficient binary code learning. Fuzzy logic connections may undergo more performance optimization in the future. Cai et al. [30] enhanced user confidence and diagnostic utility by developing interactive pathologist tools based on machine learning-based image retrieval techniques. Future research projects may concentrate on enhancing instruments for broader medical applications and addressing limitations in algebraic understanding.

Ghosh et al. [31] detailed advantages and classified methods while giving a comprehensive rundown of deep learning techniques for image segmentation. Further studies will provide empirical validation. Liu et al. [32] provided an overview of deep learning-based generic object identification development, highlighting impending challenges, including compelling CNN features, open-world learning, and frameworks. Meenakshi and Gaurav [33] provide a solid method for retrieving pictures using wavelet processing and PSO-based feature selection, which enhances classification accuracy when utilizing SVM, KNN, and decision tree classifiers. A potential use for the technique will be the classification of plant diseases. Swati et al. [34] introduced a deep CNN-based CBIR system that extracts brain tumors from CE-MRI using transfer learning and fine-tuning. Future studies aim to broaden the technique to include more medical imaging domains. Yu et al. [35] discussed CNN segmentation, detection, and classification issues in medical image processing. Current concerns are addressed in the following study.

Li et al. [36] discussed image extraction from extensive RS data and applications, benchmarks, and prospective future directions in RS big data mining. Jamil et al. [37] explored deep learning techniques, applications, and parameter-sharing tactics in many industries for possible future improvements, having previously addressed the advantages and regularization concerns. Zhenwei and Ervin [38] focused on DE on issues relating to clinical integration and accuracy enhancements for subsequent developments while highlighting the current applications of machine learning in radiological imaging. Rajasenbagam et al. [39] created a Deep CNN to detect pneumonia using X-ray images, which performed better than transfer learning methods and produced exceptional accuracy. Future research will widen the scope of sickness detection and raise the complexity of the model to improve early-stage diagnosis. Hassan et al. [40] used secure protocols and DNNs to offer cloud-based image retrieval that did not require human input, hence achieving safe CBIR. Two directions of future research are GPU development and information leakage restrictions. In summary, existing CBIR research has explored diverse directions ranging from CNN-based architectures (ResNet, VGG, LeNet) for general image retrieval to domain-specific adaptations in medical and remote sensing images and privacy-aware CBIR frameworks for cloud environments. While these approaches achieved notable improvements in retrieval accuracy, most rely on single-scale feature extraction and lack mechanisms for emphasizing semantically meaningful regions. Furthermore, issues of interpretability, scalability, and real-time adaptability remain open challenges. These limitations reinforce the need for our proposed enhanced CNN framework that integrates multi-scale learning with attention mechanisms to achieve more precise and semantically aligned retrieval results.

3. Intelligent Cbir System

We proposed a novel variant of a CNN-based Content-Based Image Retrieval (CBIR) system, which we call Intelligent CBIR. The purpose of this system is to efficiently retrieve photos by employing a query-by-example methodology. We will describe the resources and techniques utilized in the following paragraphs, such as the upgraded CNN model, the suggested DL framework, the algorithm specifics, the set of data details, and the assessment technique.

3.1. Problem Definition

The task is to effectively employ an AI-powered similarity-based method to get comparable photos that match the user's purpose when the image in question is supplied. A CBIR system's capacity for efficient image retrieval can be improved using DL techniques to increase the effectiveness of removing features.

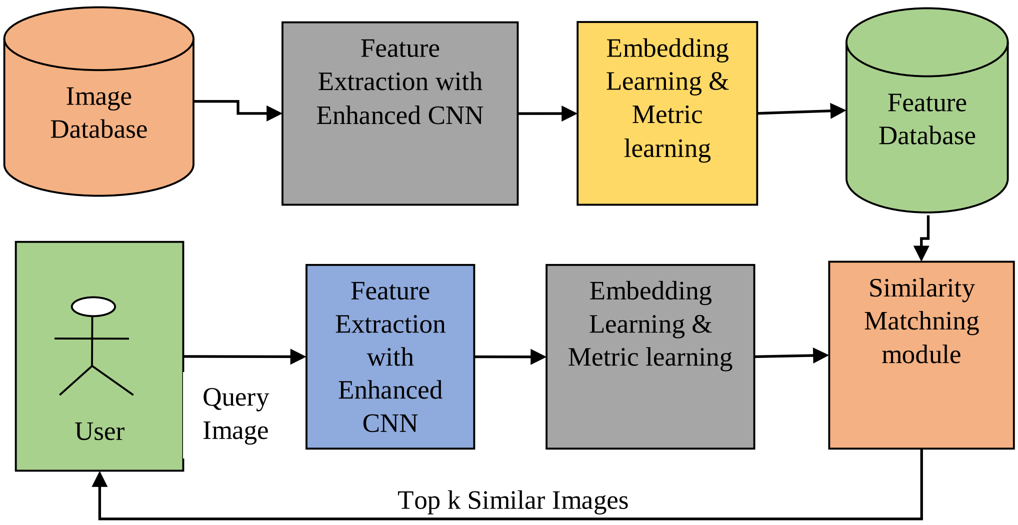

Fig. 1 Proposed framework for an intelligent CBIR (ICBIR) system based on a novel convolutional neural network variant

3.2. Proposed Framework

Instead of employing conventional image retrieval techniques, we suggested a DL-based architecture for obtaining photos from a database. Using the suggested framework, matching photos can be found and retrieved with greater intelligence. An upgraded CNN variation is the basis of the suggested framework for an Intelligent Content-Based Image Retrieval (ICBIR) system depicted in Figure 1. Several modules in this framework cooperate to retrieve photos that resemble a user-provided query image. A sizable image collection is kept in the framework's image database. A module called Feature Extraction with Enhanced CNN receives images from this database and uses an enhanced CNN model to extract features. Compared to conventional CNNs, this improved CNN version seeks to collect more complex and pertinent visual information, increasing the system's efficiency and retrieval accuracy. After extracting the features, an Embedding Learning & Metric Learning module processes them. To place similar photos closer to one another, this module must convert these retrieved features into a lower-dimensional embedding space. Metric learning improves the ability to precisely identify comparable pictures by selecting an appropriate distance metric to quantify similarity in the embedding space.

The characteristics of every image in the picture database are represented by attachments, which are kept in a feature database together with the converted features. Thanks to their well-organized structure, any new request for picture embeddings can be efficiently compared with the stored inserts. The user-provided search image goes through a procedure similar to the database's images: Feature Extraction with Enhanced CNN, followed by Embedding Learning & Metric Learning. The system then compares the query image's embedding with the feature database's embeddings. Finally, the Similarity Matching Module identifies and retrieves the images most similar to the query image in the image database based on the similarity of their embeddings. These retrieved images are then presented to the user as the system's output, thus completing the intelligent image retrieval process. The proposed ICBIR system framework combines advanced CNN-based feature extraction, embedding learning, metric learning, and similarity matching to enhance content-based image retrieval capabilities by finding the most relevant images in response to a query.

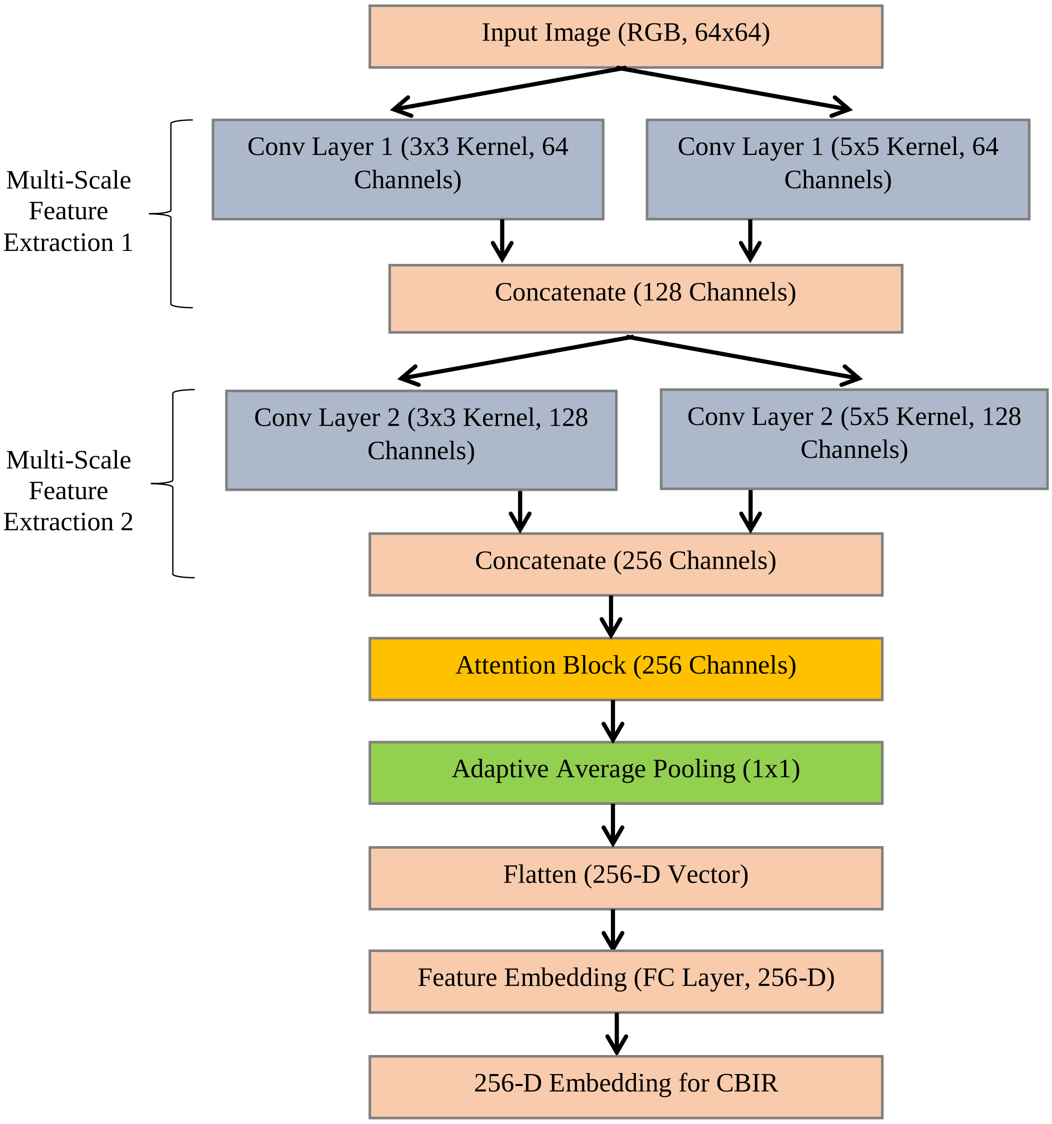

Fig. 2 Architectural overview of the enhanced CNN model used for feature extraction in the proposed CBIR system

3.3. Proposed Enhanced CNN Model

To improve image similarity matching as part of the intelligent CBIR proposed in this paper, we proposed an enhanced CNN model that leverages performance in future extraction and generates embeddings for image matching. It is an intelligent approach based on an improved CNN model equipped with an attention mechanism, and provides multi-scale feature extraction. The Enhanced CNN architecture, shown in Figure 2, for Content-Based Image Retrieval (CBIR), starts with an input layer that accepts RGB images, typically sized 64x64. This input image is first processed through two parallel convolutional layers to capture features at different spatial scales. One of these convolutional layers uses a 3x3 kernel, while the other uses a 5x5 kernel. Because each layer has 64 output channels, it can collect small details and more general spatial data from the image. After concatenating the outputs of these two convolutional layers along the channel dimension, a composite feature map of 128 channels is produced.

To capture more subtle information from the image, this concatenation step increases the diversity of feature representations. Next, a second pair of convolutional layers—structured identically to the first pair but with additional channels to capture deeper and more abstract features—processes the concatenated output. Although both layers now have 128 channels apiece, one layer still utilizes a 3x3 kernel and the other a 5x5 kernel. Concatenating the outputs of the convolutional layers after processing the input yields a feature map with 256 channels. The model can now capture even richer multi-scale information thanks to this second linking, which enhances its capacity to identify intricate patterns that can be essential for precise image retrieval. The output from the multi-scale convolutional layers is subjected to an attentiveness method to enhance the features. By providing additional weight to essential regions, the attention block aids the model in concentrating on the most pertinent areas of the picture. When the photos include differences, like various backdrops or lighting settings, this layer improves the model's capacity to extract relevant information. The network can efficiently rank the most instructive areas of each image by employing attention, which helps to produce more precise retrieval outcomes. The model has a global descriptor layer that lowers the feature map's spatial dimensions after the attention mechanism. Each feature map is reduced to a single value by converting it into a 1x1 grid using an adaptive average pooling layer. As a result of this procedure, a small, 256-dimensional feature vector that represents the image globally is produced. In a clear format appropriate for CBIR similarity matching, this global feature vector contains all of the important information that the previous layers were able to collect. The feature embedding for CBIR is created by flattening the pooled feature map into a 256-dimensional vector. This embedding serves as each image's fundamental representation, offering a fixed-length vector that can be quickly compared to other image embeddings to assess similarity. The attention-driven multi-scale feature extraction, salience, and succinct feature descriptor are the main components of this architecture, which is tailored for CBIR and provides excellent accuracy and efficiency in image retrieval. This is how the improved CNN is represented mathematically.

3.3.1. Input Layer

The input picture $x \in \mathbb{R}^{H\times W\times 3}$ is an RGB image with three channels (one for each color channel) and dimensions H and width W. For our example, we assume H=W = 64.

Multi-Scale Feature Extraction: First Layer

The initial multi-scale feature extraction layer uses two concurrent convolutions with distinct kernel sizes, 3 x 3 and 5 x 5, to capture information at several scales.

1. 3x3 Convolution

$$x_{3\times 3} = \sigma(W_{3\times 3} * x + b_{3\times 3})$$

Where

- $W_{3\times 3} \in \mathbb{R}^{3\times 3\times 3\times 64}$ is the weight tensor for the 3x3 convolution, with 64 output channels.
- $b_{3\times 3} \in \mathbb{R}^{64}$ is the bias term.
- * denotes the convolution operation.
- σ is the activation function (e.g., ReLU).

2. 5x5 Convolution

$$x_{5\times 5} = \sigma(W_{5\times 5} * x + b_{5\times 5})$$

Where

- $W_{5\times 5} \in \mathbb{R}^{5\times 5\times 3\times 64}$ is the weight tensor for the 5x5 convolution.

After the two convolutions, the outputs $x_{3\text{x}3}$ and $x_{5\text{x}5}$ are concatenated along the channel dimension:

$$x_{\text{concat1}} = concat(x_{3\text{x}3}, x_{5\text{x}5}) \in \mathbb{R}^{H\times W\times 128}$$

Multi-Scale Feature Extraction: Second Layer

The concatenated output x_{concat1} is passed through another set of two parallel convolutions, each with 3x3 and 5x5 kernels, but with increased channels.

1. 3x3 Convolution

$$y_{3\times 3} = \sigma(W'_{3\times 3} * x_{concat1} + b'_{3\times 3})$$

Where:

- $W'_{3\times 3} \in \mathbb{R}^{3\times 3\times 128\times 128}$

2. 5x5 Convolution

$$y_{5\times 5} = \sigma(W'_{5\times 5} * x_{concat1} + b'_{5\times 5})$$

Where:

- $W'_{5\times 5} \in \mathbb{R}^{5\times 5\times 128\times 128}$

After these convolutions, the outputs are concatenated:

$$x_{concat2} = concat(y_{3\times 3}, y_{5\times 5}) \in \mathbb{R}^{H\times W\times 256}$$

Attention Mechanism

The attention mechanism enables the network to focus on important regions. We compute attention weights based on inner products between transformed features.

1. Feature Transformations

$$f = W_f * x_{concat2}, \quad g = W_g * x_{concat2}, \quad h = W_h * x_{concat2}$$

where W_f, W_g, and W_h are learned weights.

2. Attention Map

The attention map is computed as a softmax over inner products of f and g:

$$Attention(i,j) = softmax(f_i^{\top} g_j)$$

3. Output of Attention Block

$$z = \sum_j Attention(i,j)h_j + x_{concat2}$$

The attention output $z \in \mathbb{R}^{H \times W \times 256}$ is added to the input $x_{concat2}$ (a residual connection) to create the final attended feature map.

Global Descriptor Layer: Adaptive Average Pooling

To condense the spatial dimensions, adaptive average pooling is applied, reducing z to a 1 x 1 grid. For each feature channel c, we compute:

$$p_c = \frac{1}{H \times W} \sum_{i=1}^{H} \sum_{j=1}^{W} z_{i,j,c}$$

This produces a vector $p \in \mathbb{R}^{256}$, representing a compact global descriptor for the image.

Feature Embedding Layer (Flatten and Fully Connected Layer)

The pooled output p is then flattened and passed through a fully connected layer:

$$f_{embedding} = \sigma(W_{fcp} + b_{fc})$$

where $W_{fcp} \in \mathbb{R}^{256x256}$ and $b_{fc} \in \mathbb{R}^{256}$. The final feature embedding for the picture, $f_{embedding} \in \mathbb{R}^{256}$, the resultant vector may be utilized for content-based image retrieval similarity matching.

This approach generates effective feature anchoring suited to capturing and comparing visual content by combining multi-scale feature extraction, attention weighting, and compact global pooling.

3.4. Proposed Algorithm

Finding visually related photos from a big dataset is the goal of the proposed Intelligent Learning-Based Image Retrieval (ILBIR) algorithm. The approach uses an improved CNN model to extract robust and detailed image characteristics, which are converted into a compact, lower-dimensional embedding space using embedding learning.

The algorithm can find and rank the most pertinent images in response to a query because of this method's efficient similarity matching. IlbIR improves user experience by supplying precise results and performance measurements that guarantee reliability and enable further optimization. It is designed for rapid, accurate retrieval applications, such as digital asset management, medical imaging, and e-commerce.

Algorithm 1: Intelligent Learning based Image Retrieval (ILbIR)

Algorithm: Intelligent Learning based Image Retrieval (ILbIR)
Input: Image dataset D, query image q, top k value k
Output: Top k matching images R, performance statistics P

1. Begin
   Offline Phase
2. Configure an enhanced CNN model m (as in Figure 2)
3. Compile m
4. F←Feature Extraction (m, D)
5. Feature Embeddings←Embedding Learning (m, F)
6. Feature Database←Save (feature Embeddings)
7. Online Phase / Query Processing
8. F←Feature Extraction (m, q)
9. Query Feature Embeddings←Embedding Learning (m, F)
10. R←Similarity Matching (query Feature Embeddings, feature Embeddings)
11. P←Compute Performance (m, R, ground truth)
12. Print R
13. Print P
14. End

The Intelligent Learning-Based Image Retrieval (ILBIR) method uses a query image to find the most pertinent images in a dataset. This algorithm works during the offline phase when the system is set up and the data is ready. During the online phase, it processes real-time queries to find similar photos. The approach first configures an improved Convolutional Neural Network (CNN) model, especially suited for feature extraction in image retrieval applications during the offline phase. This CNN model is assembled to guarantee that its layers and components are configured appropriately for effective processing. The program then extracts features (shown as (D)) from each image in the dataset using the improved CNN model. Following their extraction, the high-dimensional representations of the image content—known as features—go through an embedding learning procedure. This step creates A lower-dimensional embedding space from the retrieved features, enabling precise and effective similarity matching. A feature database acts as a storehouse of condensed representations for every image in the dataset, and these altered features—now known as feature embeddings—are kept there. This allows the system to swiftly find similar images during the query phase by pre-preparing these embeddings.

A user provides a query image, represented by the symbol (q), to start the online phase. Using the same improved CNN model set up during the offline stage, the algorithm first extracts features from the query image, guaranteeing consistency between the representations of the dataset images and the query images. These features are subsequently run through the embedding learning procedure to generate an embedding for the query image, which places it in the same feature space as the feature database's embeddings. Once the feature embedding for the query is prepared, the algorithm moves on to the similarity matching phase, where it contrasts the embeddings in the feature database with the query's embedding. The method finds and extracts the query image and the top (k) images in the set that are most similar based on the degree of similarity. A result set, represented by (R), contains this top (k) matching photo collection.

Besides obtaining images, the algorithm assesses its performance by calculating particular statistics, such as precision, recall, or other pertinent metrics, using the ground truth data and retrieved results. Collectively represented by (P), these performance metrics offer information about the system's efficacy and accuracy, enabling additional improvement if necessary. Ultimately, the algorithm gives the user pertinent findings and a measure of the system's dependability in retrieval tasks by producing the set of retrieved photos (R) and the performance statistics (P). To facilitate effective similarity matching, the ILbIR algorithm uses an improved CNN model for accurate feature extraction and embedding learning, which expedites picture retrieval. This approach ensures that users receive highly relevant results quickly, making it suitable for applications requiring fast and accurate image retrieval capabilities.

3.5. Dataset Details

The dataset used in the empirical study is the natural scenes dataset, which includes natural scenes from all over the world. About 25,000 150x150-pixel photos are included in this dataset, which is divided into six categories, as shown in Figure 3.

Class	Name
0	Buildings
1	Forest
2	Glacier
3	Mountain
4	Sea
5	Street

Fig. 3 Classes of images in the dataset

Each zip file contains distinct Train, Test, and Prediction data. The train contains approximately 14,000 photos, the Test 3,000, and the Prediction 7,000.

3.6. Performance Evaluation Methodology

Performance evaluation is carried out by comparing the images retrieved and the corresponding ground truth for given queries. It is based on building a confusion matrix shown in Figure 4.

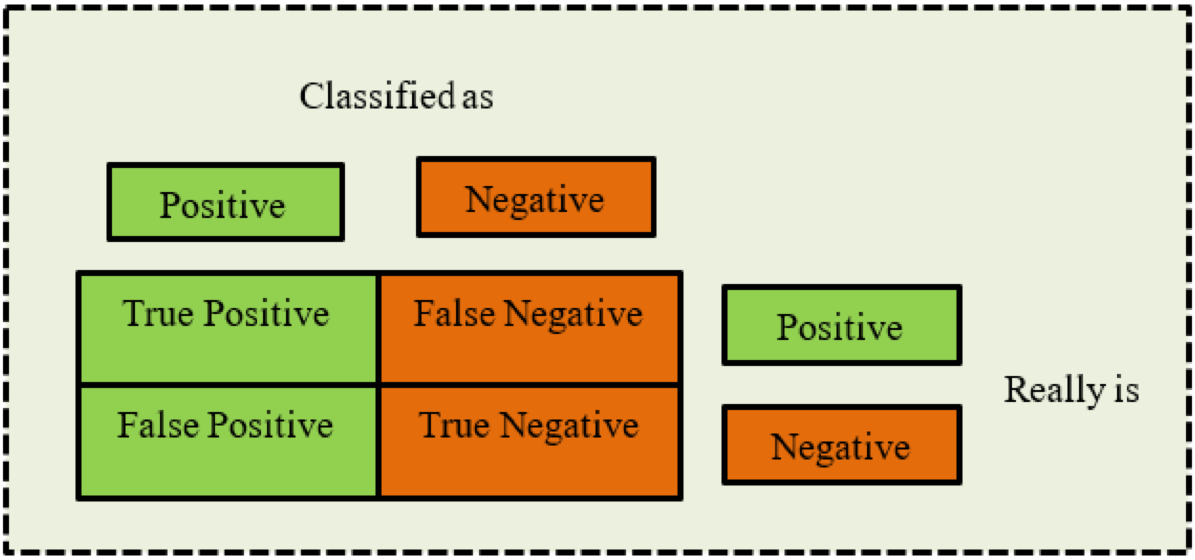

Fig. 4 Confusion matrix

Performance statistics arise by contrast to our method's predicted labels, contrasted with the ground truth based on the confusion matrix. Different measures used in performance evaluation are represented by Equations 1 to 4.

$$\text{Precision(p)} = \frac{TP}{TP+FP} \quad (1)$$

$$\text{Recall (r)} = \frac{TP}{TP+FN} \quad (2)$$

$$\text{F1-score} = 2 * \frac{(p*r)}{(p+r)} \quad (3)$$

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (4)$$

The value obtained from the performance assessment metrics falls between 0 and 1. In machine learning research, these measures are often used.

4. Experimental Results

This section presents experimental results utilizing a benchmark dataset. The proposed intelligent Content-Based Image Retrieval (CBIR) system has been executed multiple times using various input queries. The framework includes both offline and online phases, contributing to the realization of a complete intelligent CBIR system. The results indicate that the system effectively retrieves images that satisfy user intent. Additionally, A number of cutting-edge deep learning models are used to compare the performance of the enhanced CNN model in the ICBIR system.

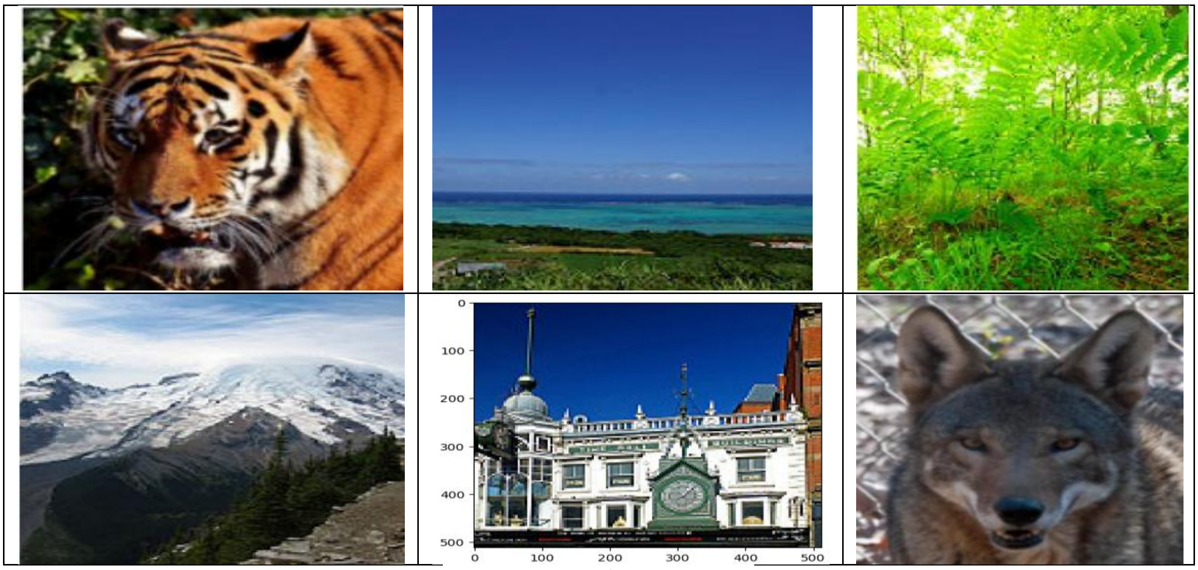

Fig. 5 An excerpt from the dataset

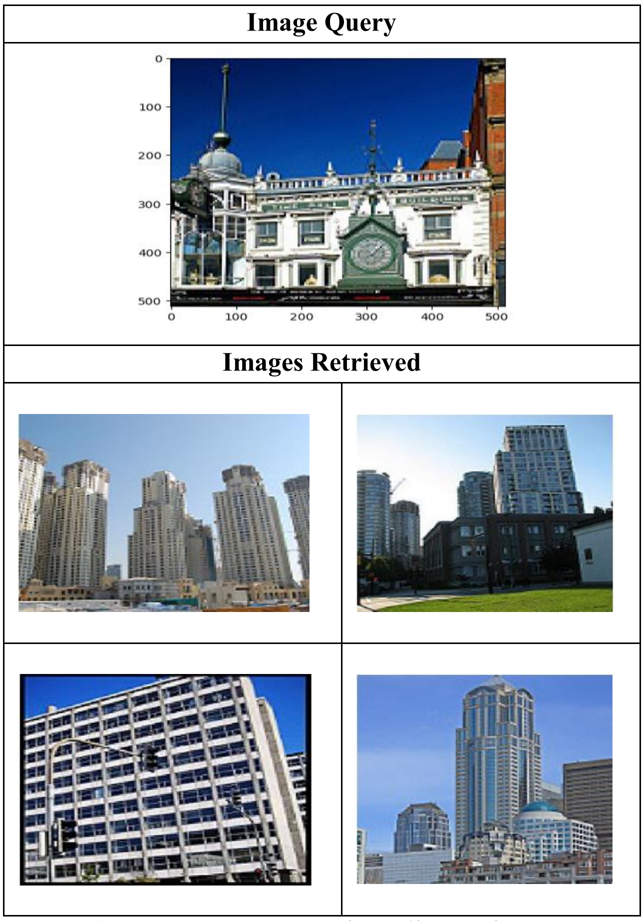

Fig. 6 Input query and experiment 1's result images

Figure 5 showcases a collection of six diverse landscapes. The top left image features a majestic tiger, its stripes contrasting against its tawny fur. To its right, a breathtaking seascape unfolds with turquoise waters meeting a distant horizon under a clear blue sky. The final image in the top row reveals a lush, green forest teeming with vibrant foliage.

With a gloomy sky in the background, a snow-capped mountain rises magnificently in the lower left. A towering, historically significant structure with complex architecture and a clock tower is positioned in the middle. Lastly, a mesmerizing wolf with gray fur and piercing eyes stares straight at the camera in the bottom right corner, lending a little wildness to the collection.

Figure 6 demonstrates the results of a visual search query. It shows the “Query Image,” a picture of a historic structure with a clock tower and elaborate architecture at the top. In the section below titled “Retrieved Images,” four more photographs are displayed. These photos most likely came from a database search because of the query image’s visual characteristics.

The returned photographs show different metropolitan environments, such as skyscrapers and contemporary cityscapes. However, the query image shows one building. Finding visually comparable scenes appears to have been a successful task for the search algorithm, based on the similarity between the query image and the returned photos.

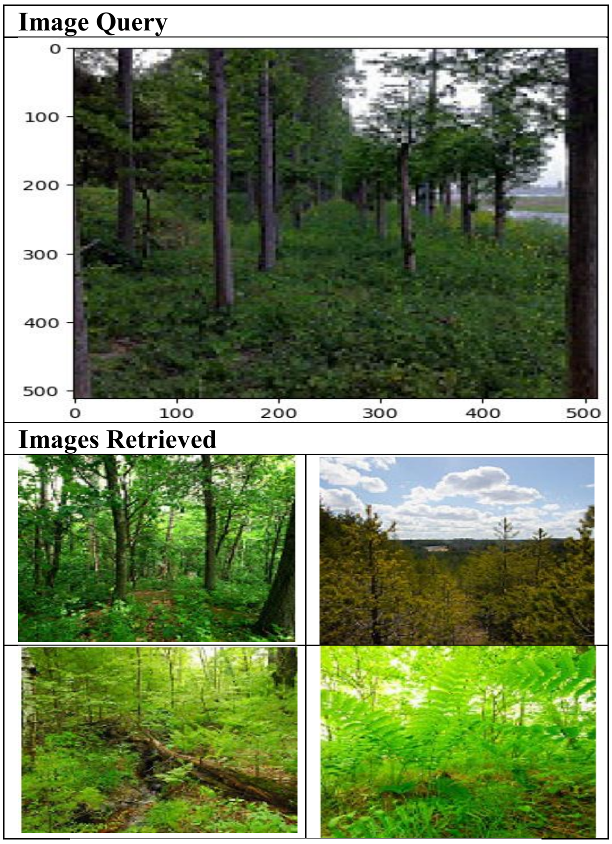

Fig. 7 Input query and experiment 6's result images

Figure 7 shows the result of a visual search query displayed in the picture. The "Query Image," located in the upper section, shows an image of a dense forest with tall trees and lush greenery. Below that, under "Retrieved Images," four further images are shown. These images are probably the result of a database search based on the query picture's visual features. Among other essential natural elements, the restored images are all of woods with trees, foliage, and a sense of depth. This suggests that the search algorithm successfully found visually identical scenarios by employing the wooded setting as a recurrent motif.

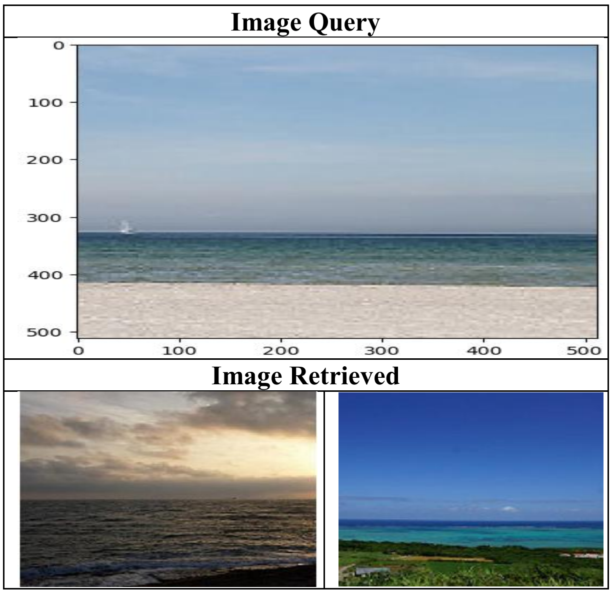

Fig. 8 Input query and resultant images of experiment 3

Figure 8 shows the outcome of a visual search query. The "Query Image," which depicts a serene ocean with a far-off sailboat and a distinct horizon, appears at the top. The user may see four more images in the "Retrieved Images" category. These pictures likely came from a database search based on the query picture's visual characteristics. The recovered photographs show a seaside view with the sky, the water, and sometimes sandy or rocky coastlines. Because the ocean environment was the main emphasis, this indicates that the search algorithm was successful in finding visually comparable photographs.

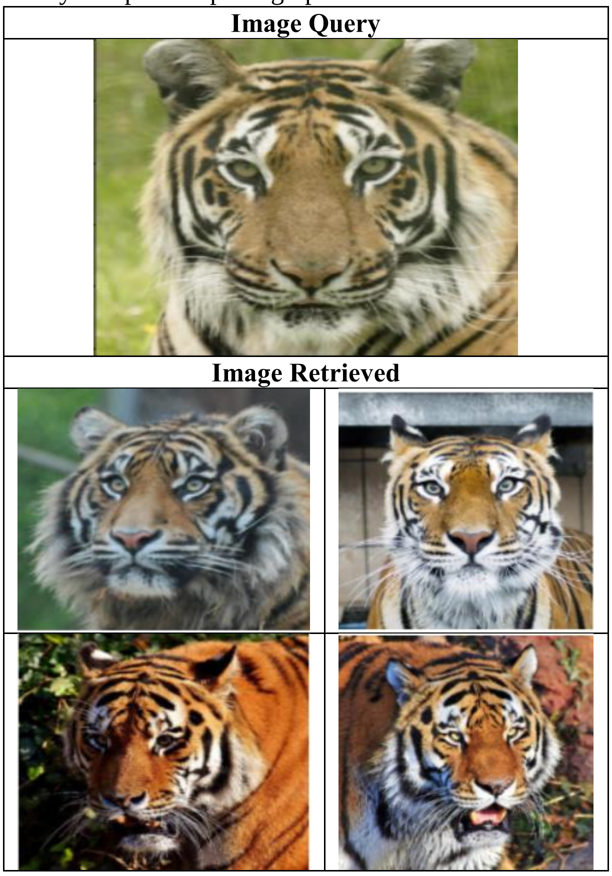

Fig. 9 Input query and experiment 4's result images

The visual search query's results are shown in Figure 9. The "Query Image," a close-up of a tiger's face, is shown in the upper section. Four more images are shown below under the "Retrieved Images" category. Based on the visual elements of the query image, these pictures most likely came from a database search. The tigers in all of the collected photos have similar facial characteristics. This illustrates how the search algorithm used the particular facial characteristics of the tiger in the query image to find visually related photographs.

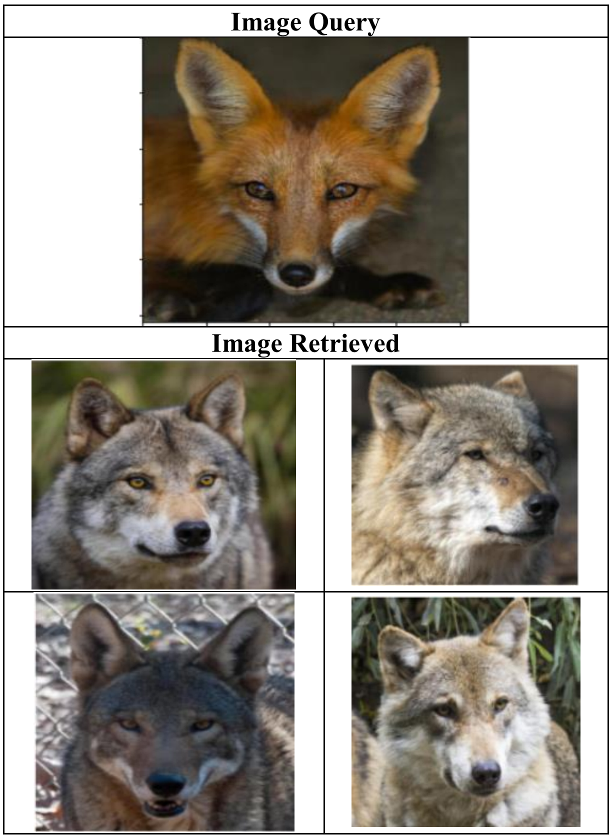

Fig. 10 Input query and experiment 5's result images

Figure 10 shows what comes up when a user do a visual search query. The "Query Image," a close-up of a red fox's face, is shown in the upper part. Four more photographs are below, under the "Retrieved Images" category. Based on the query image's visual characteristics, these photos most likely came from a database search.

However, all of the returned photographs show wolves, even though the requested image was of a fox. This implies that the search algorithm could have had trouble correctly recognizing and obtaining pictures that visually resemble the fox in the query image. The algorithm probably got pictures of wolves based on broader traits like fur color or general form since it could not adequately capture the fox's distinctive facial features.

Figure 11 shows an accuracy graph that shows how well an ML model performs over time. The y-axis shows the model's accuracy as a percentage, while the x-axis indicates the number of training iterations or epochs. The graph's apparent rising trend suggests that the more data the model is trained on, the more accurate it becomes.

Despite its initial lack of accuracy, it gradually increases and reaches a plateau around every 20 epochs. This shows that more training might not yield noticeable improvements and that the model's learning rate may have plateaued. According to the graph, the model has achieved satisfactory accuracy overall.

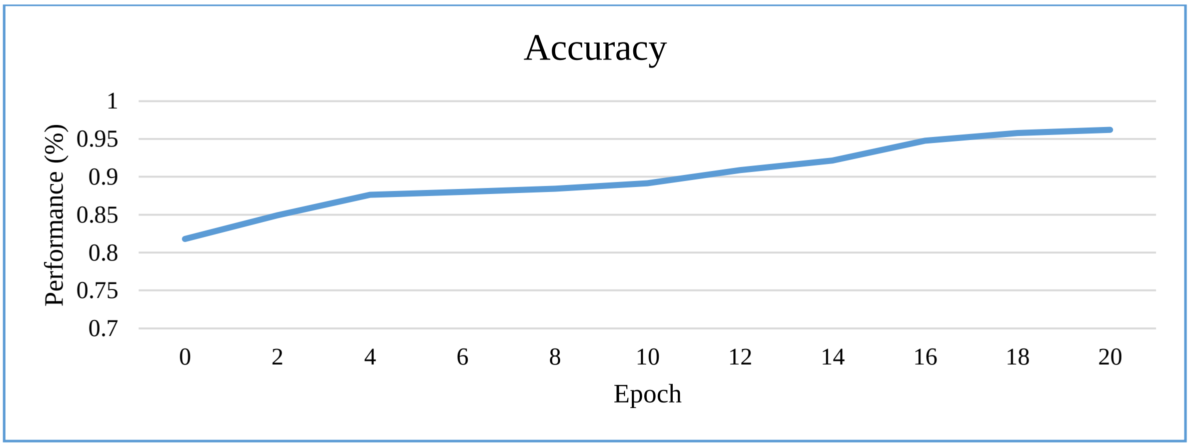

Fig. 11 Accuracy of the proposed system against several epochs

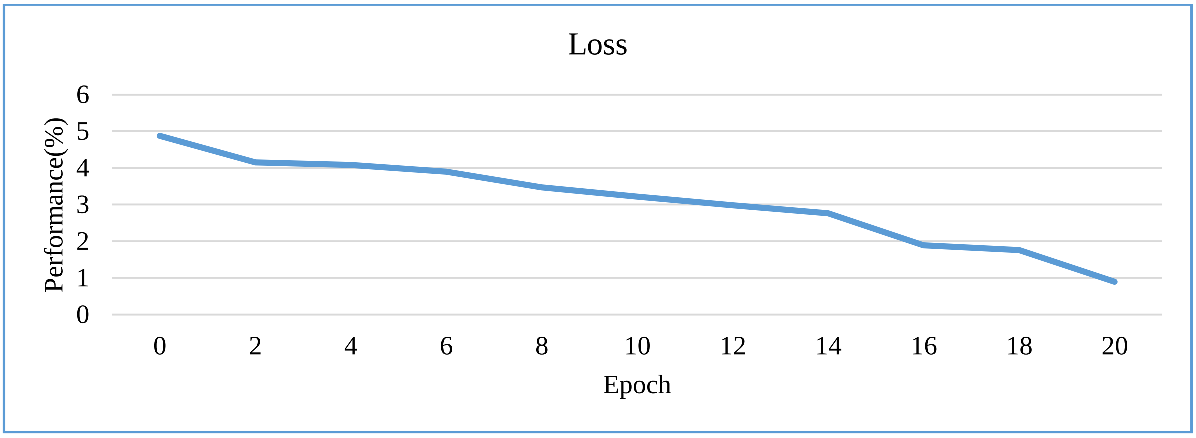

Fig. 12 Loss of the proposed system against several epochs

Figure 12 displays the performance of an ML model over time as a loss graph. The number of training iterations or epochs is shown on the x-axis, but the y-axis shows the model's performance or loss. It is clear from the graph's overall downward trend that the more data the model is trained on, the better it works. After beginning relatively high, the loss gradually declines to a level somewhat equal to that of the 20th century. This suggests that the learning rate of the model may have slowed and that more training may not produce appreciable gains. The graph indicates that the model has performed satisfactorily overall.

Table 1. Performance comparison among models used in CBIR

Model	Precision	Recall	F1-Score	Accuracy
Baseline CNN	90.24	91.76	90.99	92.48
LeNet	92.45	94.68	93.51	94.06
AlexNet	94.76	95.29	95.02	95.72
ICBIR (Proposed Enhanced CNN)	97.29	96.88	97.08	97.85

The performance of the various deep learning models used in the CBIR system is presented in Table 1.

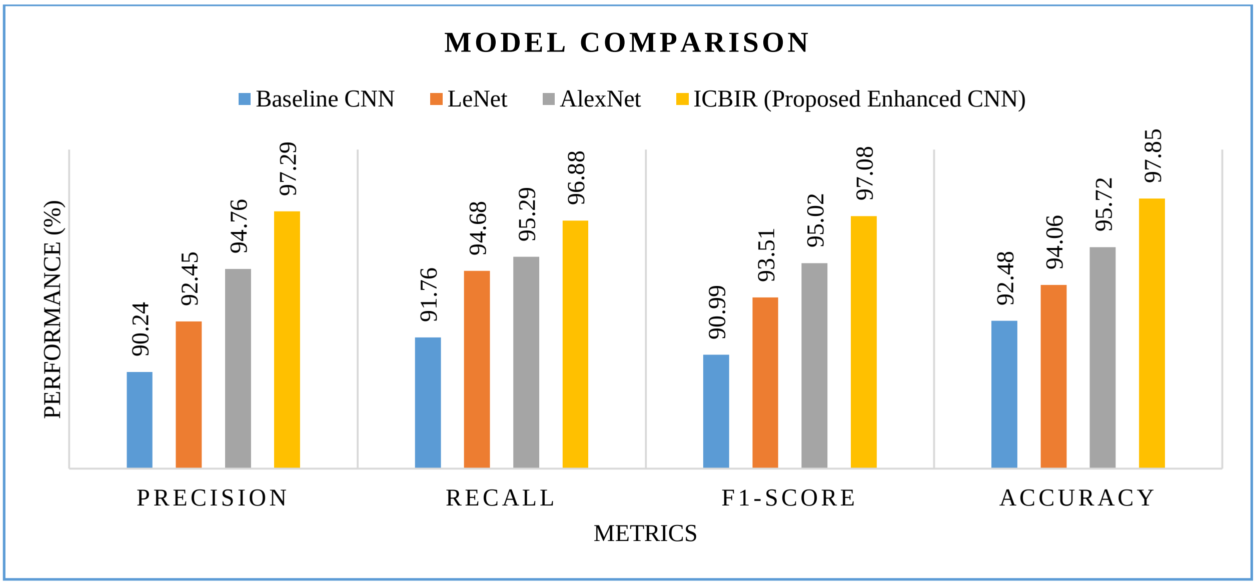

Fig. 13 Performance comparison among models used in CBIR

Figure 13 displays a Model Comparison chart that compares the neural network models Baseline CNN, LeNet, AlexNet, and ICBIR (proposed enhanced CNN). It shows the performance metrics of these models together. Accuracy is one of the four main performance metrics used to evaluate the models in this figure. The horizontal axis displays the categories of metrics, while the vertical axis displays percentages. The Baseline CNN's precision, recall, F1-score, and accuracy are all lower, at 90.24%, 91.76%, and 91.48%, respectively. Compared to more sophisticated models, this indicates a modest level of performance. LeNet exhibits a superior balance between accuracy and recall than the Baseline CNN, especially in Recall (94.68%) and F1-Score (93.51%). Notable progress is also seen in accuracy (94.06%) and precision (92.45%). Recall (95.29%), F1-Score (95.02%), and Accuracy (95.72%) all show notable increases as AlexNet continues to get better, while its Precision (94.76%) remains strong. Out of all the networks, ICBIR performs the best, attaining the best values in Precision (97.29%), Recall (96.88%), F1-Score (97.08%), and Accuracy (97.85%). Overall, the results highlight ICBIR as the top-performing model, followed by AlexNet and LeNet, with the Baseline CNN performing the lowest across all metrics.

5. Discussion

With the proliferation of technologies, especially within the cloud computing ecosystem, organizations around the globe have started to leverage cloud infrastructure for the affordable storage and management of multimedia objects. Among these multimedia objects, images are widely used across various applications. In many domains, such as healthcare, the retrieval of images is critically essential. Traditional image retrieval applications typically rely on textual input to find corresponding images. However, Content-Based Image Retrieval (CBIR) systems have gained popularity by allowing users to query by example—meaning an image is provided as input, and the system retrieves matching images. One of the drawbacks of traditional CBIR systems is that while they retrieve images based on similarity, they may also return images that do not meet the user's intent. Thus, it is necessary to consider similarity and semantic similarity to enhance the system's performance.

The emergence of artificial intelligence has enabled the use of deep learning models in image processing. CNNs have proven efficient for processing images. This paper proposes an enhanced CNN model with an attention mechanism for multi-scale feature extraction. The enhanced CNN model is utilized within our proposed intelligent content-based image retrieval (ICBIR) framework, which can extract features whose embeddings are stored in a feature database to facilitate efficient image matching. The system uses clever learning-based feature extraction and exhibits comprehensive similarity matching capabilities to get the most pertinent photos when a query is given.

We have revised the Discussion section to include a detailed comparison with existing techniques. The added paragraph explains that our superior performance arises from multi-scale feature extraction and attention-driven semantic alignment, allowing the model to capture fine-grained and contextual features more effectively than state-of-the-art CNN-based CBIR approaches. This addition clarifies why our framework achieves higher accuracy and robustness in retrieval tasks. Nevertheless, the suggested system does have some drawbacks, as detailed in Section 5.1.

5.1. Limitations

Though it has some drawbacks, the suggested system is made to retrieve images based on a query image. Although a benchmark dataset was used to assess the system, it contains a limited number of samples. Consequently, to generalize the results, evaluating the system using a wider variety of samples is essential. With an improved Convolutional Neural Network (CNN) model, the suggested system employs a clever strategy. Nevertheless, there may be alternative options to investigate, such as hybrid deep learning approaches or techniques that utilize Generative Adversarial Network (GAN) architectures, which can function even with limited examples. Furthermore, a real-time dataset will be used to assess the suggested approach further by combining it with the use of a company.

6. Future Work and Conclusion

We introduced the ICBIR, a DL-based system. This system processes user inquiries and extracts features from a picture database using an AI-enabled method for offline and online phases. To efficiently extract feature embeddings from the image database and query images, we improved a CNN model by adding multi-scale feature extraction methods and an attention mechanism. With a high level of semantic similarity, this improvement enables our system to quickly get the best photos that match the query image and accurately represent user intent. Furthermore, we created an algorithm called Intelligent Learning-based Image Retrieval (ILbIR).

A benchmark dataset was used to evaluate the effectiveness of our proposed method. The findings showed that the revised CNN model achieved an accuracy of 97.35%, which considerably improved image retrieval performance. This means that this technology can be used in real-time multimedia applications that require retrieving images based on sample queries. In the future, we aim to enhance the proposed system further by utilizing hybrid deep learning models and pre-trained deep learning models, along with optimizations, to improve efficiency across various scenarios.

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