*International Journal of Computational and Experimental Science and ENgineering*
***(IJCESEN)***
*Vol. 11-No.2 (2025) pp. 1673-1682*
*http://www.ijcesen.com*



***ISSN: 2149-9144***

**Research Article**

# Enhanced Convolutional Neural Network for Efficient Content-Based Image Retrieval

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**Article Info:**

**DOI:** 10.22399/ijcesen.937
**Received :** 30 November 2024
**Accepted :** 28 January 2025

**Keywords :**

Artificial Intelligence,
Deep Learning,
Convolutional Neural Network,
Content-Based Image Retrieval.

**Abstract:**

The use of picture objects in various real-world applications has increased dramatically with the rise of cloud-based ecosystems for managing, analyzing, and storing multimedia material. CBIR is a method for obtaining photos from the cloud and other storage infrastructures. It involves using an image input to look for images that match the database. Because of its methodology, this phenomenon is deemed preferable to text-based search. However, conventional CBIR techniques rely on similarity and feature comparison metrics. As AI grows, learning-based approaches are also shown to be beneficial for matching semantic material. Therefore, we presented a deep learning architecture to achieve an effective learning-based CBIR system in this research. To improve the matching experience in image retrieval, we suggested a modified CNN model for feature extraction from images. We proposed the Intelligent Content-Based Image Retrieval (ICBIR) algorithm. For our tests, we used the ImageNet micro dataset. The suggested modified CNN model-based CBIR system performs better than current techniques in picture retrieval that as closely resembles user intent as feasible, according to experimental data.

## 1. Introduction

CBIR is a well-established and effective image retrieval technique that uses the query by example phenomena. Irrelevant images may be obtained when a text-based search is conducted on them. Using CBIR, the query image may yield very relevant imagery. This method is generally recognized for picture retrieval on the cloud and other platforms. However, the literature indicates that CBIR needs to be improved using AI-enabled techniques. The lack of matching pictures reflecting semantic qualities is problematic with the current CBIR systems. Our goal in this study is to improve the CBIR system by utilizing learning-based methodologies. Numerous learning-based contributions have already been made to CBIR [1-3]. Plaza et al. [4] demonstrate how deep learning excels in remote sensing applications using large satellite datasets. The ease of use, cost, and effectiveness of cloud computing enhance data processing. It was offered a method for progressive image retrieval that uses quality grading, contour matching, and textual comparison to guarantee quality [5-18]. According to Ma et al. [11], the CBIR in AI has evolved as more people utilize digital gadgets and the internet. This analysis looks at theory, approaches, applications, and future challenges. Ozturk et al. investigated the application of CNN features to improve dictionary learning for CBIR, showed promising results, and suggested further integration for efficacy [15]. Using a 187-dimensional feature vector generated from low-level data, Soares et al. [19] improved picture retrieval and ensured efficiency by combining CBIR and ANR in the CBIR-ANR method. According to the research, learning-based techniques are needed to enhance the representation of semantic characteristics. The following are the contributions we make in this study to this goal.

1. We suggested a deep learning architecture to achieve an effective learning-based CBIR system and a modified CNN model for feature extraction from images to improve image retrieval matching.
2. we proposed an algorithm called LbM-CBIR to implement the suggested architecture.
3. We created an application to implement the framework and algorithm. According to experimental data, the suggested modified CNN model-based CBIR system performs better than current techniques in picture retrieval that closely resemble user intent.

This is the format for the rest of the paper. In Section 2, previous research on newly specified CBIR techniques is reviewed. In Section 3, the method based on learning-based phenomena is presented. Experiments are shown and discussed in Section 4. Section 5 wraps up the learning-based CBIR system and suggests its future development.

## 2. Related Work

Wiggers et al. [1] presented a high-accuracy Siamese Neural Network for pattern recognition and document picture retrieval; next research will examine other designs and datasets. Kumar et al. [2] suggested a hierarchical CBIR architecture that prioritizes color, texture, and form characteristics and demonstrates superior retrieval; machine learning integration is planned for future work to increase efficiency. Hasoon and Hassan [3] provided a face image retrieval system that enhances retrieval efficiency by utilizing object identification, LBP, K-means, and the Firework algorithm; more work may improve indexing and clustering. Ahmed et al. [4] presented a feature detection and PCA-based image retrieval system that outperforms many approaches; CNN integration is planned for future development to improve performance further. Kruthika et al. [5] suggested a CBIR system that achieves 98.42% accuracy in early Alzheimer's diagnosis by merging 3D Capsule Networks, CNNs, and autoencoders; future studies will focus on improving CapsNet designs.

Hatibaruah et al. [6] enhanced the CT image retrieval process by presenting the 3D-LOZFP descriptor; further research might improve feature reduction and testing. Celebi et al. [7] examined developments in dermoscopy image analysis, emphasized the significance of combining visual elements and clinical information, and made recommendations for future advancements. Gupta et al. [8] suggested a 99.7% accurate face recognition technique that combines decision trees and random forests with SURF and SIFT characteristics. Allegretti et al. [9] presented a ResNet-50-based skin image retrieval system that improves dermatologist diagnosis accuracy but is not very interpretable. Yan et al. [10] presented D-MVE-Hash, which integrates deep learning with multiple views to enhance hash-based retrieval but still needs optimization.

Schall et al. [11] improved performance and shortened training time by introducing a supervised aggregation technique for dl image retrieval. Majhi and Pal [12] presented a block-level technique for image retrieval that combines SVD and DCT characteristics. Though useful, further feature extraction methods and improved weighting schemes might be investigated in later research. Dhingra and Bansal [13] examined five techniques for extracting CBIR texture features and concluded that DWT, GLCM, and LBP are the best. Integrating deep learning and fusing techniques are future projects. Ahmed et al. [14] suggested a CBIR technique that combines texture, color, and shape characteristics with GoogLeNet and VGG-19 for precise picture retrieval. For larger datasets, future research may improve efficiency and scalability. Daniela et al. [15] suggested a hybrid approach that achieves over 80% accuracy in comparable image retrieval when used to retrieve low-quality legal document pictures.

Yang et al. [16] examined 90 papers on deep learning for sketch-based image retrieval (SBIR), emphasizing patterns, hypotheses, and lines of further inquiry. Danapur et al. [17] suggested a CBIR technique that improves retrieval accuracy by integrating PCA and AdaBoost with CENTRIST, RLBP, and HSV characteristics. Das and Neelima [18] presented a biological image retrieval system that outperforms current techniques in terms of accuracy by utilizing Zernike moments, curvelets, and HOG features. Sudha and Aji [19] examined remote sensing image retrieval (RSIR) methods, emphasizing difficulties and offering suggestions for improving retrieval efficiency and accuracy. Zhan et al. [20] displayed an image retrieval hierarchy. technique for photogrammetry that combines global and local information for precise, efficient matching.

Dubey et al. [21] examined advances in content-based picture retrieval using DL, evaluated the effectiveness of various approaches, and pinpointed patterns and potential future paths. Swati et al. [22] demonstrated a deep learning-based CBIR system that achieves 96.13% mAP for brain tumor MR images using VGG19 and CFML. Li et al. [23] examined CBIR developments between 2009 and 2019, highlighting developments in image representation and search and upcoming difficulties with deep learning and huge data. Shamna et al.

[24] presented a Topic and Location Model-based automated medical picture retrieval system that improves accuracy and efficiency. Passalis et al. [25] suggested a regularized deep metric learning technique that encodes generative elements and class variance to enhance picture retrieval.

Tuyet et al. [26] suggested a two-step process that improves precision and recall using DL for content-based medical picture retrieval. The goal of future research is to improve feature context comprehension. Punithavathi et al. [27] suggested SIRS-IR, which uses encrypted sharing and feature extraction to provide safe cloud image retrieval. Future research will focus on improving tuning methods and retrieval performance. Vieira et al. [28], with noise reduction and effective feature vectors, the CBIR-ANR program improves picture retrieval; nonetheless, its execution duration varies. Upcoming research may optimize processing stages. Arai et al. [29] presented DI-PSS, a framework to improve the accuracy of illness categorization by harmonizing brain MRI data. More extensive validation will be provided later. Arora et al. [30] optimized CBIR for healthcare using deep learning models, finding VGG-16 most effective. Future work will explore rotational invariance further. Agrawal et al. [31] created a deep learning-based CBMIR system for lung illness diagnosis, increasing AUPRC by 26.55% and precision by 49.71%. Shamna et al. [32] demonstrated a CBMIR system that enhances retrieval accuracy by employing spatial matching of visual words. Additional testing and optimization are tasks for the future. Wang et al. [33] suggested Sec-Defense-Gan, a GAN-based secure CBIR solution that safeguards model and picture data. The work on efficiency and theoretical bounds will come later. Kumar and Madhavi [34] presented a deep learning-based multi-stage CBIR system, although it has poor interpretability and needs a large amount of labeled data. Future research entails tweaking and investigating sophisticated designs. Ozturk et al. [35] offered a novel triplet-learning method for CBIR called OCAM, which adjusts margin values to increase accuracy. Additional testing and optimization will be part of future development.Rohrich et al. [36] demonstrated that CBIRS can increase diagnostic accuracy and save the time needed to interpret a chest CT scan by 31%. It is necessary to conduct more clinical studies. Xing et al. [37] improved the accuracy and interpretability of medical picture retrieval using a multi-label proxy metric learning technique. More validation will be a part of future development. Gautam and Khanna [38] designed a CBIR system with ResNet-50 and VGG16 for increased retrieval accuracy. Upcoming projects will focus on managing larger picture sizes, extending datasets, and enhancing feedback. Li et al. [39] developed a 3D visualization technique for CBIR systems to lessen dependency on 2D views and improve feature visibility. Subsequent research ought to improve 3D rendering and validate other datasets. Issaoui et al. [40] created the AOADL-CBIRH technique, which combines deep learning with sophisticated image processing to enhance the retrieval of medical images. Future research should concentrate on testing with various datasets and optimizing hyperparameters.

## 3. Proposed System

We suggested a learning-based architecture to achieve an effective CBIR. For feature extraction, it is predicated on a modified CNN model. The following subsections give additional information about our process.

### 3.1 Problem Definition

The challenge is creating a CBIR system based on a learning-based methodology for effectively retrieving pictures representing the user's intent and perceptual semantic attributes.

### 3.2 Our Framework

We proposed implementing an effective learning-based CBIR system using a DL architecture. To improve the matching experience in image retrieval, we suggested a modified CNN model for feature extraction from images. The suggested structure is displayed in Figure 1. The framework learned from the training dataset and acquired the necessary information to provide improved feature representation by using a modified CNN model. Because it may reflect semantic properties, the learning-based feature extraction approach offers benefits over the conventional approach. Results are generated by comparing the characteristics of the query picture with the training image. Elasticsearch is integrated with the obtained results to improve future picture retrieval's scalability and efficiency. For image processing, CNN has proven to be highly helpful. This explains why the CBIR architecture uses an improved CNN. CNN has more robust features for picture feature extraction that even mirror users' semantic views, according to research conducted in [22] and [23].

### 3.3 Modified CNN

The CNN model's performance is subpar when utilized for CBIR since it must be modified to fit

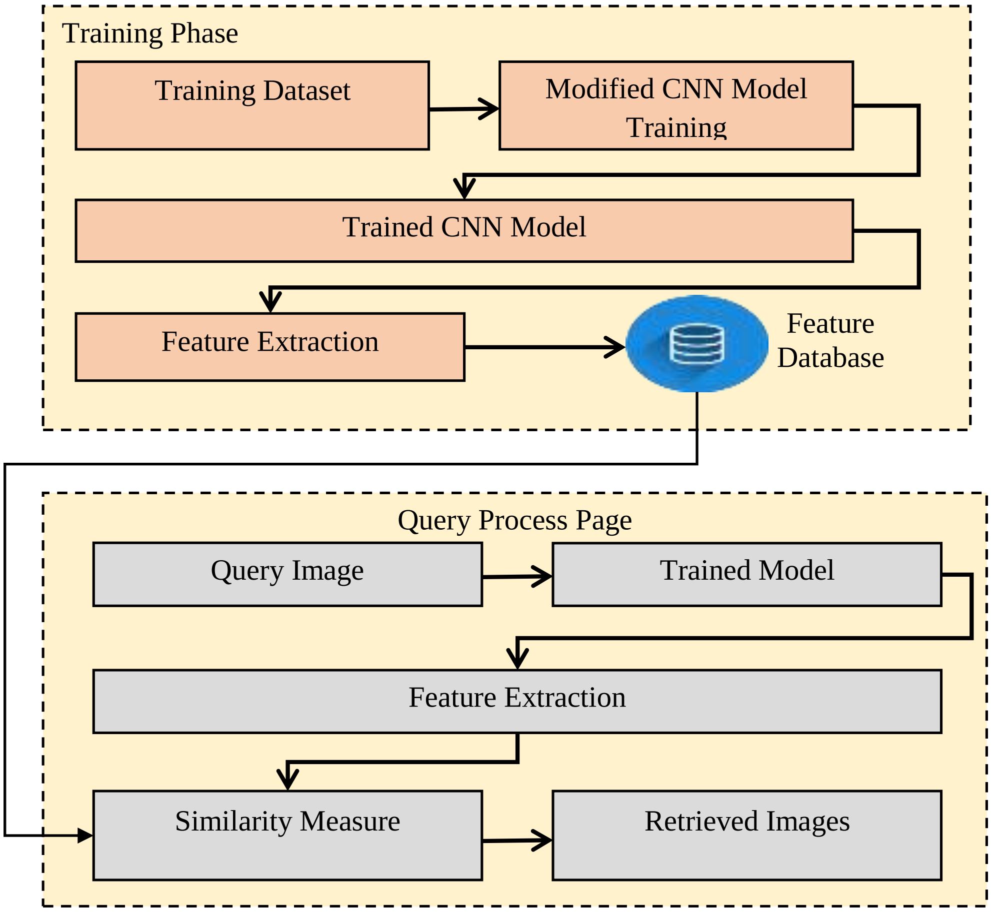



***Figure 1.*** *The framework for effective learning-based CBIR*

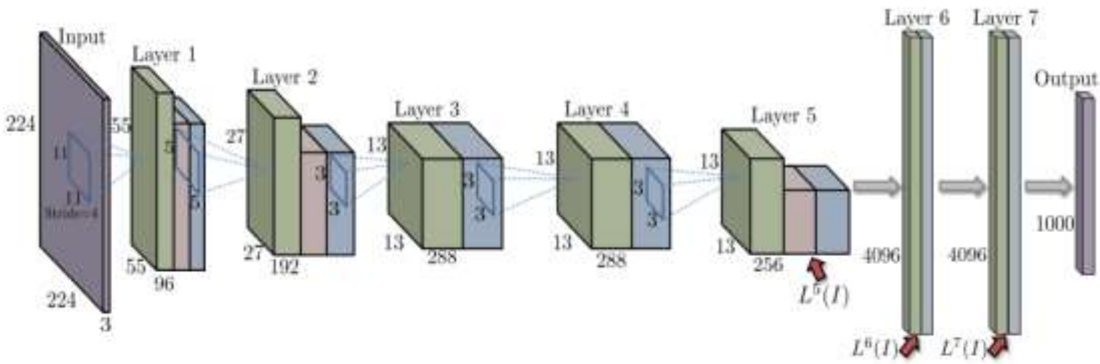



***Figure 2.*** *Modified CNN architecture*

the specific situation. Consequently, we conducted an empirical investigation and updated CNN; Figure 2 depicts the architecture. Through experimentation, CNN layers are set up, and the optimal arrangement is identified. Users' semantic judgments and purposes are reflected in the pictures that the modified CNN can retrieve. The architecture's layers can extract features from photos and refine them for better image matching in CBIR. Experiments are conducted using the ImageNet dataset. Actual research is conducted using the small ImageNet database. Convolutional layers collect features from the input picture, while max pooling layers optimize it. The size of the input or query picture is 224x224. The green units in the architecture represent convolutional layers, whereas the red units represent max pooling layers. The blue units show transformation using ReLU. Output generation is handled by the final three levels, which are fully linked. Whereas the stride is set to 1 in other convolutional layers, it is set to 4 in the first one

### 3.4 Proposed Algorithm

As seen in Algorithm 1, it provides CBIR findings and performance statistics after receiving a dataset and query picture as input. Picture preprocessing is possible by enhancing their quality and separating data into T1 and T2 sets. T1 is used to configure

***Algorithm 1.*** *Intelligent Content-Based Image Retrieval (ICBIR)*

**Algorithm:** Intelligent Content-Based Image Retrieval (ICBIR)
**Inputs**
Dataset D (CIFAR-10)
Query image q
**Output**
Image retrieval results R, Performance P

1. Begin
2. D'←DataPreprocess(D)
3. (T1, T2)←PrepareData(D')
4. Build enhanced CNN model m
5. Compile m
6. m'←TrainModel(m, T1)
7. Persist m'
8. Load m'
9. F←FeatureExtraction(random sample from T2 or q)
10. R←RetrieveMatchingImagery(Features of T1, F)
11. P←FindPerformance(ground truth, R)
12. Display R
13. Display P
14. End

and train the modified CNN. Following feature extraction from the query picture using the trained model, image retrieval is accomplished by matching.

### 3.5 Dataset Details

The dataset was obtained from [21]. It's referred to as a little ImageNet dataset for testing. Figures 3 and 4 show that training and test samples are included.
The photos in the small ImageNet dataset are employed to evaluate the suggested framework. In Section 4, the experimental findings are displayed.

## 4. Experimental Results

Using TensorFlow and Python 3, we created an application to test the framework. The framework incorporates the improved CNN model. Learning-based feature extraction is superior to older methods because it can capture semantic characteristics. The findings are generated by comparing the characteristics of the training photos with the query image. Integrating the obtained results with Elasticsearch will make future image retrieval more scalable and practical.


***Figure 3.*** *A selection from the Mini-ImageNet dataset's training samples*

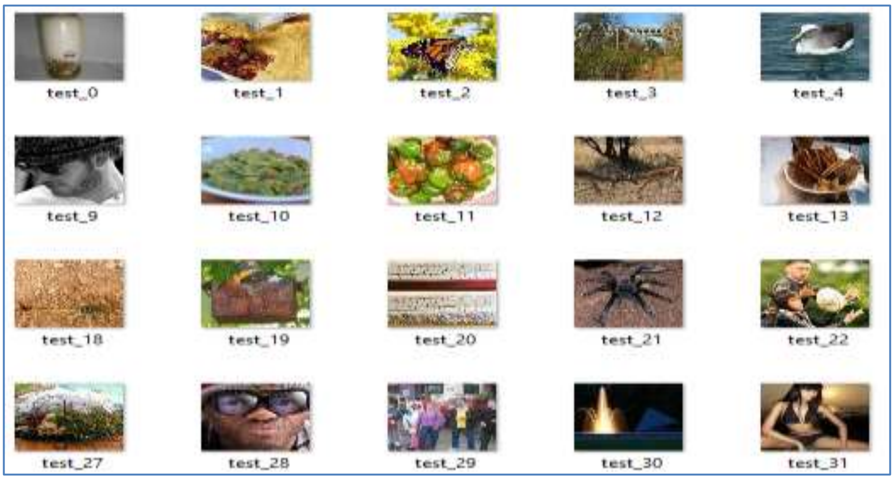
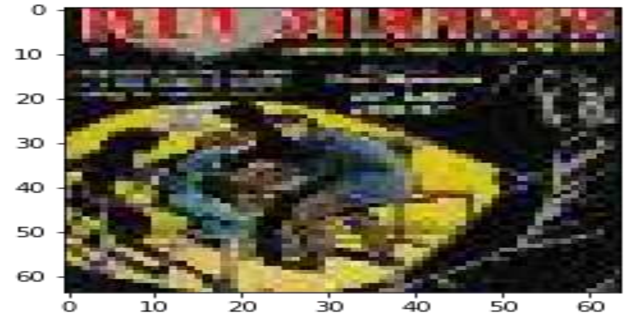
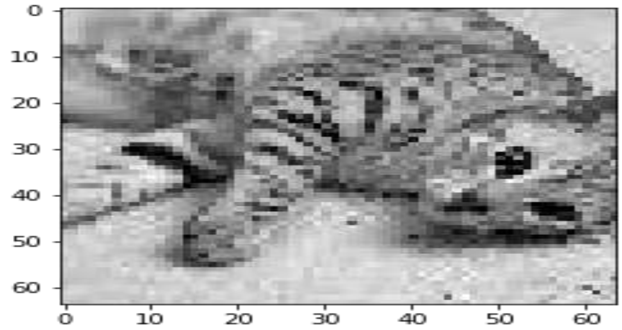



***Figure 4.*** *A snippet from the Mini-ImageNet dataset's training samples*

30860 train: comic book



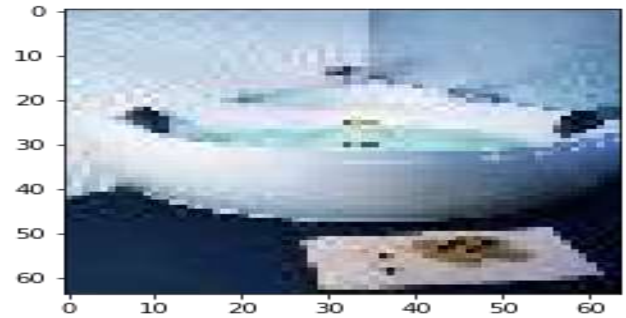
Test 7810: Cat from Egypt



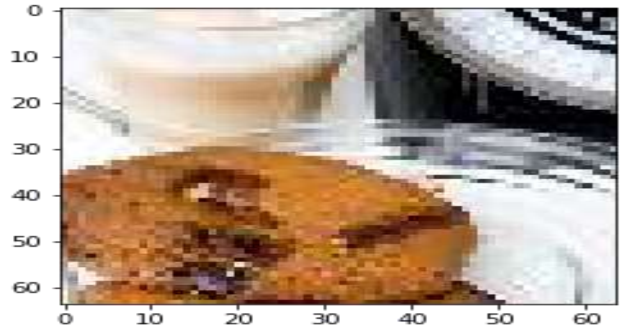
Train 21145: The teapot

Test 5597: snail

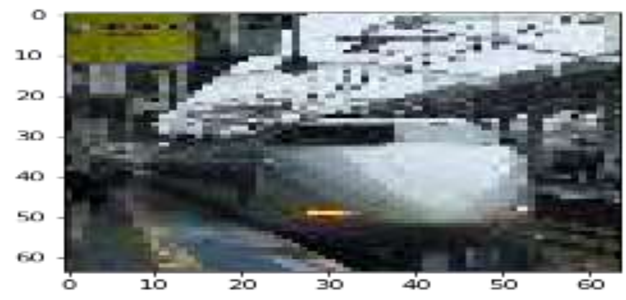
bathtub, bathtubing tub, bathtub, tub : train 37042



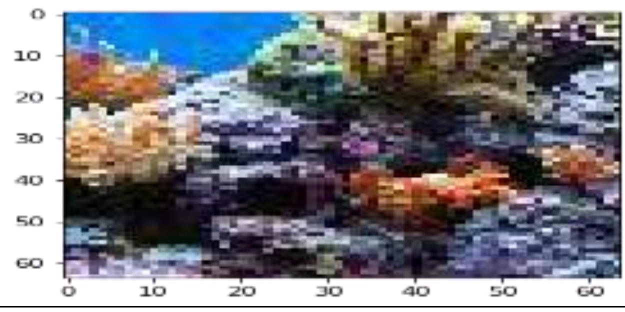
Test 5693: plate



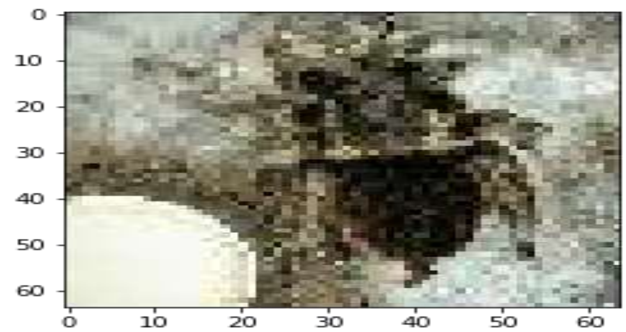
3224 validation: bullet train, bullet



Coral reef : out of domain 737.



7735 validation: tarantula



Out of domain 4062: drop, drop-off, and cliff

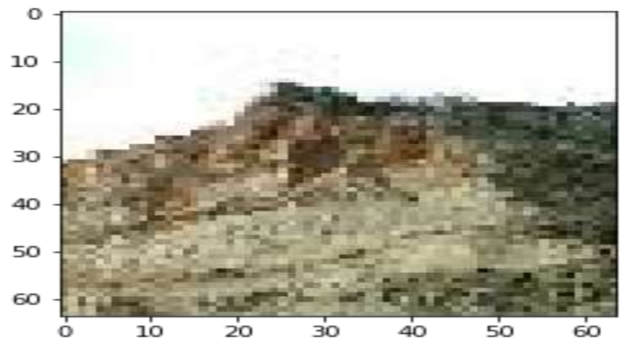


***Figure 5.*** *Labeled training and test images*

***Figure 6.*** *Results of five input query images (leftmost) and the top five output images*

***Figure 7.*** *Results of five additional input query images (leftmost) and the top five resulting images*

Figure 5 visualizes randomly chosen training and test pictures. Every sample has labels attached to it. Figure 6 shows the CBIR findings against five input questions. Five photographs are the top five outcomes of the suggested CBIR system, with the query image being the least. Figure 7 displays the outcomes of CBIR in terms of about five more input inquiries. Five photographs are the top five outcomes of the suggested CBIR system, with the query image being the least amount. In Figure 8, the model's accuracy is displayed. Taking note of the top five category outcomes yields the most accuracy. Figure 9 shows a visualization of the model loss. In general, the model loss decreases as the number of epochs increases.

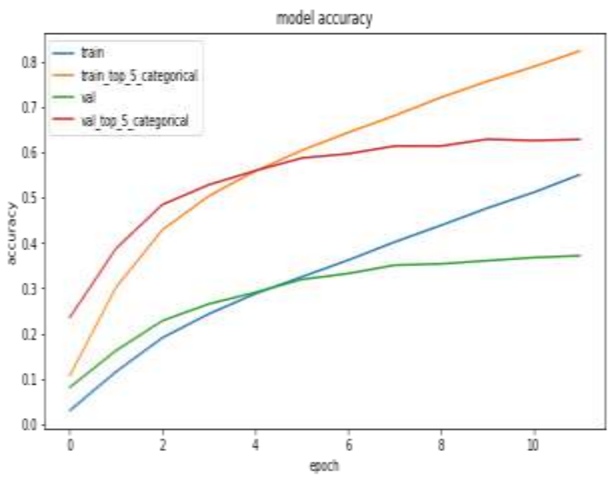



***Figure 8.*** *Accuracy performance of the model throughout epochs*

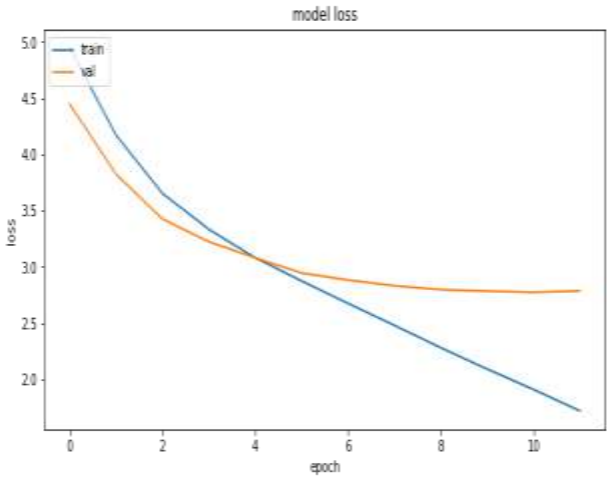



***Figure 9.*** *Loss performance of the model against epochs*

***Table 1.*** *Comparison of Performance*

| Model | Precision | Recall | F1-Score | Accuracy |
|---|---|---|---|---|
| MLP | 90.89 | 71.54 | 81.21 | 78.48 |
| CNN | 94.56 | 82.56 | 88.56 | 89.75 |
| Proposed Model | 97.98 | 93.86 | 95.92 | 94.69 |

Table 1 shows the accuracy of the proposed CBIR system compared to existing methods. Accuracy increases indicate improved CBIR performance.
Figure 10 compares the proposed CBIR system to the most sophisticated models, MLP, and baseline. CNN. When evaluating performance, accuracy is the statistic employed. With 78.80% accuracy, the MLP model performs the worst. CNN's baseline model outperformed MLP with an accuracy of 89.75%. At 94.69% accuracy, the suggested CBIR system, based on a modified CNN, performed best. According to the findings, the suggested learning-based strategy performs better than the current models. Similar works have been reported in the literature [41-45].

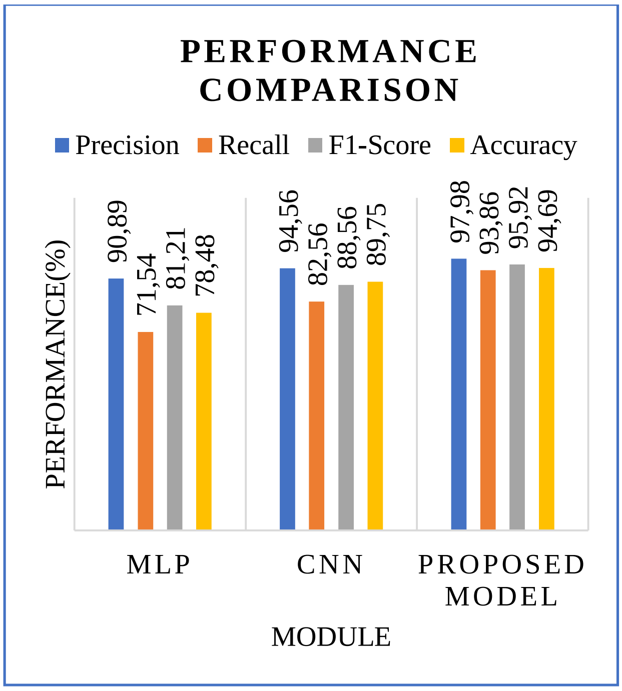



***Figure 10.*** *Comparison of the suggested CBIR system's performance with current models*

## 5. Conclusion and Future Work

We proposed implementing an effective learning-based CBIR system using a DL architecture. To improve the matching experience in image retrieval, we suggested a modified CNN model for feature extraction from images. We suggested an algorithm for implementing the suggested framework called LbM-CBIR. For our tests, we used the ImageNet micro dataset. The suggested modified CNN model-based CBIR system performs better than current techniques in picture retrieval that as closely resembles user intent as feasible, according to experimental data. The accuracy of the proposed CBIR system was 94.69%. To create a more effective CBIR system, we want to enhance our approach in the future by utilizing hash codes based on online learning.

## Author Statements:


- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper
- **Acknowledgement:** The authors declare that they have nobody or no-company to acknowledge.
- **Author contributions:** The authors declare that they have equal right on this paper.
- **Funding information:** The authors declare that there is no funding to be acknowledged.
- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.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