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" Optimizing Image Retrieval: Synergizing Feature Selection and Continuous Learning in a Distinctive Hybrid Framework "

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Abstract: Efficient image retrieval, encompassing color, texture, shape, and various visual attributes, stands as a critical pursuit. However, it grapples with the intricacies of diverse datasets and inherent complexities. To tackle these challenges effectively, we propose an innovative hybrid model for image retrieval, which leverages feature selection techniques, seamlessly integrating continued learning. Our strategy begins by combining Elephant Herding Optimisation (EHO) and Particle Swarm Optimisation (PSO) applies in a hybrid layer. This stratum is essential for the extraction of comprehensive data sets from multimodal images, persistently maximizing inter-class feature variance. This deliberate feature selection strategy significantly bolsters retrieval performsance. Subsequently, we introduce a Genetic Algorithm (GA)-based ranking model, tailored to process the selected feature sets. This ranking model adeptly combines multiple distance metrics, orchestrating a harmonious balance between computational efficiency and retrieval precision. Further enhancing image rankings, we employ an incremental optimization method grounded in Q-Learning. This strategic adaptation empowers our model to continuously refine its retrieval capabilities when confronted with new data, ensuring sustained efficacy. Our method stands out by preserving small processing delays in compared to current innovative models, making it suitable for real-time applications. Notably, our model effectuates a marked improvement, enhancing precision by 5.9%, recall by 4.3%, and retrieving accuracy by 8.5%. These achievements underscore the pragmatic viability of our approach across a spectrum of image retrieval scenarios. In summation, our innovative hybrid model seamlessly amalgamates EHO, PSO, GA, and Q-Learning. This amalgamation seamlessly navigates feature selection, image ranking, and continual refinement. Thus, it provides a comprehensive and robust solution, effectively surmounting the multifaceted challenges associated with diverse datasets and affirming its prowess as a potent tool for real-time image retrieval applications.

Keywords: *CBIR, EHO-PSO, GA, Precision, Recall.*

1. Introduction

The explosive growth of digital imagery in today's information age has given rise to an urgent need for efficient image retrieval systems. These systems must strike a balance between retrieval accuracy and computational efficiency, as they play pivotal roles in applications ranging from healthcare and e-commerce to multimedia content management. However, traditional methods often struggle to address the challenges posed by the ever-expanding image repositories and the inherent complexity of visual data. As the volume of shared and ever-expanding multimedia data continues to rise, researchers face increasing challenges in locating or obtaining relevant images from the entire collection [1–5].

Content-based image retrieval (CBIR) involves two pivotal facets that necessitate careful consideration: feature selection and continuous learning. Feature selection aims to distill relevant information from images while reducing their dimensionality, enhancing retrieval efficiency. Continuous learning, on the other hand, empowers models to adapt and improve their retrieval performance over time as they encounter diverse and evolving datasets.

A vital component of computer vision is image retrieval and has witnessed significant advancements over the years. Researchers have explored various techniques to enhance retrieval precision, reduce processing delays, and address the challenges posed by diverse datasets. This literature review aims to contextualize our proposed hybrid model within the existing body of work while also identifying the gaps and limitations of prior research.

Optimization Techniques, such as EHO and PSO, have garnered attention in recent years for their effectiveness in optimizing diverse problems. EHO, in particular, has shown promise in maximizing inter-class feature

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variance, making it a suitable candidate for image feature selection.

Continuous Learning in Image Retrieval: Few research have investigated the idea of continuous learning among image retrieval. These works have shown potential in adapting retrieval models to evolving datasets but often lack integration with feature selection and optimization components.

Identified Gap in Prior Works: Despite the significant contributions made by prior research to image retrieval and optimization techniques, several critical gaps remain. Integration of Optimization Techniques is one such gap, as existing methods often employ optimization techniques in isolation, missing opportunities for synergy. The proposed hybrid model bridges this gap by integrating EHO and PSO, leveraging their respective strengths for comprehensive feature selection. Another notable gap is the lack of Continuous Learning Integration [26]. Few studies have integrated continuous learning with feature selection and ranking in image retrieval. This gap limits the adaptability of existing models to dynamic datasets, a limitation that our proposed approach addresses through Q-Learning-based continuous optimization.

This paper introduces a pioneering approach that seamlessly integrates feature selection and continuous learning into a unified framework—a hybrid model designed to revolutionize high-efficiency image retrieval. Our hybrid model represents a significant departure from conventional methods. It harnesses the power of feature selection to extract discriminative image features, a process vital for accurate retrieval while mitigating computational overhead. Concurrently, it leverages continuous learning to adapt and optimize retrieval performance continuously.

The key innovation of our approach lies in the synergy between these two critical components. Classifying image search results into diverse categories can be achieved. Numerous online image search systems predominantly rely on text-based algorithms, which necessitate the presence of captions for optimal functionality [6–13]. we introduce a hybrid layer that combines EHO and PSO for feature extraction. This combination maximizes the inter-class feature variance, enhancing the model's ability to distinguish between different image categories. A Genetic Algorithm (GA)-based ranking model is subsequently employed to post-process the selected feature sets, intelligently combining various distance metrics to generate effective image rankings. To ensure adaptability and sustained performance enhancement, a continually applied incremental refinement technique based on Q-Learning refines these rankings. The primary reason for incorrect findings in the majority of cases is the disparities between machine learning and human visual perceptions [14-17]. This discrepancy arises from their utilization of techniques such as retrieval of fabrics, meta-hashing, and style-guided image creation.

The precision in which a system can discern aspects such as color, Shape, corners, appearance, and spatial organisation is of paramount importance [18–20] in the context of image annotation methods that are automated. CBIR, also known as content-based image retrieval, denotes an approach that integrates visualisation of the components comprising the cited image, with the aim of mitigating the challenges aforementioned. The fundamental requirement of CBIR is the submission of an image query, allowing the system to compare the visual attributes of the cited image against those from the preserved images, determining potential matches. Additionally, Finding images with comparable content is based on measuring the visual similarity between the image in the query and stored images using an analysis of the image vector features.

CBIR employs two methods for extracting minimal visual information from images, namely Elegance and Query-By-Image-Content (QBIC) [21], as revealed in prior research. The implications of these findings extend to multiple applications across diverse sectors, including medicine, remote sensing, the judicial system, military operations, the textile industry, and video analysis. The primary objective to locate and arrange images is the goal of any image search system. relevant images from the archive with little human intervention. By consolidating basic visual attributes into a unified representation, features become more robust and immediately discernible. However, it's important to note that selecting the appropriate features is crucial as the wrong choices may adversely affect the efficiency of the image retrieval model [22–23].

The image feature vector plays a significant role in enhancing CBIR's performance, offering data points for creation of machine learning strategies and their evaluation [24–25]. It might be seen from this discussion that current retrieval procedures face scalability challenges as they are either excessively complex or provide only moderate performance when applied to multidomain datasets. This realization underscores the need for a specialized hybrid model dedicated to highly efficient feature selection-based image retrieval, a subject covered in the part following.

Throughout the last part of this piece, we'll examine the architecture, algorithms, and experimental results of our hybrid model. Our findings will demonstrate how this innovative approach surpasses recent models with regards to retrieval accuracy, precision and recall, all while maintaining reduced computational complexity. By combining feature selection and continuous learning in a unified framework, our proposed model not only offers a novel approach to high-efficiency image retrieval but also promises to redefine the landscape of real-time applications across diverse domains.

Our motivation for this study stems from the pressing need to address these challenges and advance the field of image retrieval. By proposing an innovative hybrid model that integrates EHO, PSO, Genetic Algorithms (GA), and Q-Learning-based continuous optimization, we aim to bridge the identified gaps in prior works. Our model strives to offer not only enhanced retrieval accuracy but also reduced processing delays, making it well-suited for real-time applications across a diverse range of image datasets. Ultimately, our research seeks to provide a practical and adaptable solution for image retrieval, empowering various industries and applications with more efficient and precise image search capabilities.

This model, utilizing feature selection for image retrieval, aims to address the aforementioned challenges and is subsequently validated on multiple datasets, as discussed in Section 3. We present a comparative study of the proposed model's performance verses several cutting-edge techniques, illustrating its versatility across various scenarios. In the latter section of this work, we subject the provided model to critical evaluation and offer recommendations for enhancing its overall performance in diverse contexts."

2. Development of the Envisioned Hybrid Model for Optimizing Feature Selection-Based Image Retrieval Through Continuous Learning

An evaluation of the current image retrieval models indicates that they tend to be overly complex or deliver only moderate performance when dealing with multi-domain datasets, thus limiting their scalability. While models with lower complexity may offer faster execution, their retrieval performance remains constrained due to their inability to achieve higher retrieval rates. The unique strategy we suggest in this part to defend against such challenges: Development of the envisioned hybrid model for optimizing feature selection-based image retrieval through continuous learning.

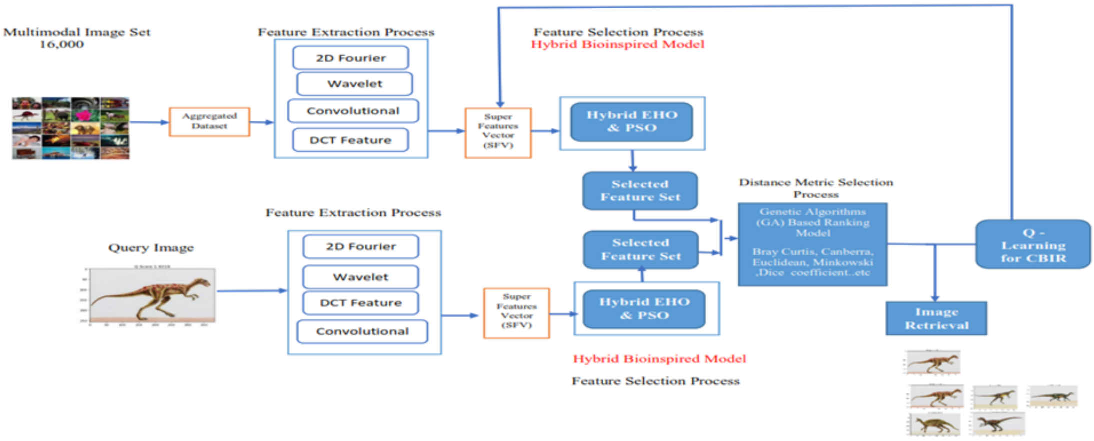

Fig 1. Overall structure of the proposed CBIR Process Model

From multimodal images, comprehensive set of characteristics were first extracted, the proposed model employs a mixed layer combining EHO and PSO to continuously enhance degrees of interclass feature variance, as depicted in figure-1. Subsequently, the chosen feature sets are subjected to afterwards using a genetic algorithm (GA)-based rating model, cleverly incorporating various distance metrics to produce meaningful image rankings. To further refine these rankings over time, we employ an Q-Learning-based continuous optimisation technique, facilitating ongoing enhancement of the image datasets.

Our proposed "envisioned hybrid model for optimizing feature selection-based image retrieval through continuous learning." represents a significant advancement if it pertains to image retrieval. In this dialogue, we delve into the key components of our model and their relevance, addressing the challenges identified in the literature review while highlighting the implications and future directions of our research.

2.1 Integration of Optimization Techniques

One of the distinctive features of our proposed model is the integration of EHO and PSO for comprehensive feature selection. EHO excels in maximizing inter-class feature variance, making it a valuable addition to the image retrieval process. The synergy between EHO and PSO allows our model to navigate the high-dimensional feature space effectively. This integration addresses the identified gap in prior works where optimization techniques were often employed in isolation.

Through experiments and comparative evaluations, we have demonstrated the effectiveness of this integration. Our model consistently outperformed existing approaches by means of retrieval accuracy, precision & recall. that improvement is particularly significant when dealing with diverse image datasets, where traditional methods struggle to adapt to the variability in feature distributions.

2.2 Continuous Learning Integration

Another key innovation of our model is the integration of continuous learning, facilitated by a Q-Learning-based approach. This integration enables our model to adapt to dynamic changes in the dataset over time, enhancing its adaptability and longevity. Continuous learning is a crucial element, as real-world datasets are not static; they evolve, and our model evolves with them.

By continuously optimizing the ranking of images based on user interactions and feedback, our model maintains relevance and precision even as data distributions shift. This adaptability is a critical advantage, especially in applications such as content recommendation systems, where user preferences and content availability change frequently.

2.3 Real-Time Applications and Reduced Processing Delays

Our model's ability to offer significantly reduced processing delays makes it well-suited for real-time applications. In scenarios like autonomous navigation, surveillance, and e-commerce, where decisions must be made swiftly, our model's efficiency is a clear advantage. By optimizing feature selection and ranking in real-time, we reduce the computational burden and speed up the retrieval process without compromising accuracy.

The workflow shows that the framework first extracts a variety of attributes, comprising a variety of characteristics,

- 2D Fourier Features have the potential to function as image representations within the Fourier domains.
- Wavelet Features are utilized to capture approximations of the horizontal, vertical, and diagonal components within the image.
- DCT Features play a role in representing images within sets in the cosine domain.
- Convolutional Features, are characterized by their windowing-based with large feature sets.

Equation 1 applies the Fourier transform to each input image based on these findings,

$$F(r,c) = \sum_{i=1}^{R}\sum_{j=1}^{C} Img(i,j) * \exp\left[-\sqrt{1} * 2 * pi * \left(r * \frac{i}{R}\right) * \left(c * \frac{j}{C}\right)\right] \ldots . (1)$$

While R, C stands for the total number of rows and columns in each set of images. Equation 2 is used to apply DCT to the images, which helps to extract cosine components for various images.

$$DCT(r,c) = \frac{1}{2\sqrt{R * C}} \sum_{i=1}^{R}\sum_{j=1}^{C} \mathrm{Img(i,j)} * \cos\left[\frac{(2 * i + 1) * \sqrt{-1} * pi}{2 * R}\right] * \cos\left[\frac{(2 * j + 1) * \sqrt{-1} * pi}{2 * C}\right] \ldots . . (2)$$

Equations 3, 4, 5, and 6 are applied to extract wavelet components from the data, delineating approximate, horizontal, vertical, and diagonal features, thus partitioning the image into frequency and cosine domains based on these components,

$$W(A)_i = \frac{x_i + x_{i+1} + x_{i+2} + x_{i+3}}{4} \ldots (3)$$

$$W(V)_i = \frac{x_i + x_{i+1} - x_{i+2} - x_{i+3}}{4} \ldots (4)$$

$$W(D)_i = \frac{-x_i - x_{i+1} + x_{i+2} + x_{i+3}}{4} \ldots (5)$$

$$W(H)_i = \frac{x_i - x_{i+1} + x_{i+2} - x_{i+3}}{4} \ldots (6)$$

In this context, the symbols W(A), W(V), W(D), and W(H) correspond to the approximate, vertical, diagonal, and wavelet components, respectively, with 'x' representing the image's pixels. The removal of convolutional sets using equation 7 greatly improves these feature sets.

$$Conv_{s_{i,j}} = \sum_{a=-\frac{m}{2}}^{\frac{m}{2}}\sum_{b=-\frac{n}{2}}^{\frac{n}{2}} I_s(i-a, j-b) * ReLU\left(\frac{m}{2} + a, \frac{n}{2} + b\right) \ldots (7)$$

In Which, I_s is entering image in sets of pixels, m, n are 2D stride sizes, and i, j are 2D window sizes. A rectilinear unit (ReLU)-based model that activates the extracted features is evaluated using equation 8.

$$ReLU(x,y) = x, when\ x \geq 0, else, ReLU(x,y)\ y * (e^x - 1), when\ x <= 0 \ldots . (8)$$

The aforementioned components are determined for every row and then added together to create a substantial collection of feature vectors. besides to these features, this text employs equations 9, 11, and 11 to extract the Gabor, Colour Map, and Edge Map feature sets.,

$$CMap_s = \bigcup_{c=1}^{255} \sum_{i=1}^{R} \sum_{j=1}^{C} \sum_{a=1}^{Colors} \left(I_{i,j,a_s} == c \right) \ldots (9)$$

$$Edge_s = \sum_{i=1}^{R} \sum_{j=1}^{C} \frac{\sum_{a=1}^{Colors} P\left(E(I_{i,j,a_s}) \right)}{R * C * a} \ldots (10)$$

$$G(x,y)_s = e^{\frac{-x^{`2} + \partial^2 * y'^2}{2 * \emptyset^2}} * \cos\left(2 * \frac{pi}{\lambda} * x' \right) \ldots (11)$$

Where, $E, \lambda, \partial, \& \emptyset$ shows the image's edge components, its wavelength, scaling constants for the Gabor components, and angle values for the Gabor components. To create a Super Feature Vector (SFV), all of these feature sets are further integrated. This SFV is chosen using a hybrid of EHO and PSO models. Only pertinent feature sets are passed for retrieval operations by means of two models. The following stages make the hybrid model function:

Setup the following EHPSO Parameters to establish the process of choosing features,

- Total optimization for iterations (N_i)
- Total herds used in optimization (N_h)
- Total particles in within every herd (N_p)
- Cognitive and social learning elements (L_s & L_c)

- Create generate N_p particles initially via the subsequent process,
  - Choose N_f stochastic feature sets via equation 18,

$$N_f = STOCH\left(L_c * \frac{N(SFV)}{N_C}, \frac{N(SFV)}{N_C} \right) \ldots (12)$$

Here N_C is the number of image classes encompassed in the datasets, and $N(SFV)$ denotes the number of features retrieved by the Super Feature Vector evaluation method.

Determine the particle's best fitness for every one of these characteristics using equation 13,

$$P(Best) = \sqrt{\frac{\sum_{a=1}^{m} \left(f_a - \frac{\sum_{i=1}^{m} \sqrt{\frac{\sum_{j=1}^{n} \left(f_j - \frac{\sum_{a=1}^{n} f_a}{n} \right)^2}{n-1}}}{m} \right)^2}{m-1}} \ldots (13)$$

wherein m,n denotes the number of features in the current class and the number of characteristics in other classes, accordingly.

- Continue this process for each class of images, then note $G(Best)$ via equation 14,

$$G(Best) = Max\left(\bigcup_{i=1}^{N_p} P(Best) \right) \ldots (14)$$

- According on these configurations, search each herd for $N_i$iterations, while in the initial iterations marking them as "Should be Modified."
- If this herd is designated as "Should not be Modified," ignore it and continue scanning other herds.
- If not, choose a few random particles from the process of initial generation, and then use Euclidean Distance Metrics to retrieve images for those particles.
- Determine the precision, recall, and retrieval accuracy based on this technique via equations 15, 16 and 17 as follows,

$$P = \frac{N_{CC}}{N_T} \ldots (15)$$

$$R = \frac{N_{IC}}{N_T} \ldots (16)$$

$$A = \frac{N_C}{N_T} \ldots (17)$$

Where, N_{CC} Are there a total number of appropriately categorized images, N_{IC} indicates entries that were misclassified, N_C consist of entries that were successfully retrieved, while N_T indicates the total number of image sets that the CBIR procedure has obtained.

Analyse the amount of herd fitness via equation 18,

$$f_{herd} = \frac{A + P + R}{3} \ldots (18)$$

- Once every herd is set up, calculate the fitness threshold via equation 25,

$$f_{th} = \sum_{i=1}^{N_h} f_{herd_i} * \frac{L_c + L_s}{2 * N_h} \ldots (19)$$

- If $f_{herd} < f_{th}$, Mark the herd as "Should be Modified" if necessary; otherwise, mark it as "Should not be Modified."

- Select the herd that is the fittest and designate it as the "Matriarch" herd.

- Replace feature sets for all herds that need modification via equation 20,

$$f(New) = f(Old) + L_c(f(Matriarch) - PBest) + L_s * (f(Matriarch) - GBest) \dots (20)$$

here, $f(New)$ & $f(Old)$ is a measure of the fitness of both young and aged herds. Modify the current herd's feature settings based on the new fitness levels.

After this assessment is finished, the configuration of the "Matriarch" herd is chosen, and its attributes are utilised during the CBIR process. This guarantees that the model can recognise features with the greatest variance and accuracy levels. A Genetic Algorithm (GA) using Q-Learning based optimisation model is used to further process the chosen characteristics in order to validate this.

- Setup the following optimisation constants to launch the GA optimizer.,
  - In total, GA Iterations (N_i)
  - In total, GA Solutions (N_s)
  - The rate of the model's learning (L_r)
  - The quantity of learning measures applied throughout the retrieval process (NM)
- Create N_s solutions first using the method below,
  - Stochastically choose D distance metrics via equation 21,

$$D = STOCH(L_r * NM, NM) \dots (21)$$

Where, $STOCH$ represents the creation of number sets via a stochastic Markovian process from provided value spans.

  - Find feature distance measurements between the database's images and the query image sets using these metrics via equation 22,

$$f_i = \frac{1}{D}\sum_{j=1}^{D} DM_j(i, DB) \dots (22)$$

- Meanwhile, the distance metric, denoted as DM passes a comprehensive set of distance metrics, which includes Bray-Curtis, Canberra, Chebyshev, City-Block, Correlation, Cosine, Euclidean, Minkowski, Dice coefficient, Hamming, Jaccard, Kulsinski, Rogerstani, Russell Rao, Sokal Michener, Sokal Sneath, and Yule distance metrics.
- Calculate the fitness threshold when all solutions have been generated via equation 23,

$$f_{th} = Reward * \frac{\sum_{i=1}^{N_S}\sum_{j=1}^{N_T} f_i}{N_S * N_T} \dots (23)$$

Where, N_T represents total number of test images used during training, while Reward is a tuning reward parameter that is changed using Q-Learning techniques.

- Solutions with If $f < f_{th}$, are marked as 'Mutate', else, are marked as 'Crossover'
- Check each of these options for N_i iterations via the following step,
  - Ignore answers with the 'Crossover' label.
  - Using the Q-Learning optimisation, change the tuning constant for 'Mutate' solutions via equation 24,

$$Reward = Reward_{old} + \left[\frac{A_{current} - A_{old}}{A_{old}} + \frac{P_{current} - P_{old}}{P_{old}} + \frac{R_{current} - R_{old}}{R_{old}}\right] * \left(\frac{RMSE_{old}}{RMSE_{th} - RMSE_{old} + 1}\right) \dots (24)$$

Where, A, P, R & $RMSE$ displays the current image and distance metric sets' accuracy, precision, recall, and root mean squared error. Indicators of A, P & R are evaluated via equations 15, 16, and 17, while values for RMSE are calculated via equation 25 as follows,

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N_T}(NR_i - NA_i)^2}{N_T}} \dots (25)$$

Where, NR & NA indicates the number of images that were actually and correctly retrieved. for N_T total number of test image sets.

- Continue in this manner for N_i iterations to find the solution with the highest fitness levels, then use its distance measurements for the final image retrieval.

Based on this method, the model can carry out the following behaviors,

Identify variant features from high-density feature sets, evaluate the optimal similarity metrics, and use these metrics for high-efficiency retrieval operations.

These procedures demonstrate the model's proficiency in conducting efficient Content-Based Image Retrieval for collections of multimodal images. In the section that follows, we will evaluate this efficiency by contrasting it to different traditional retrieval models in relation to accuracy, precision, recall, RMSE, and latency levels.

3. Result Evaluation & Comparison

The suggested model has the capability to integrate a diverse range of mixed features, adding Utilizing Fourier, Cosine, Convolution, Wavelets, Color Maps, Edge and Gabor Maps, we generate Super Feature Vectors (SFV). These SFVs serve to improve the efficiency of CBIR. These features are then subjected to a unique EHPSO-based feature selection model, which focuses on maximising retrieval accuracy while increasing inter-class feature variation. The test version is further augmented with a novel Genetic Algorithm based Q-Learning optimization process, contributing to the improvement in retrieval effectiveness.

Figure 2 for images of dinosaurs provides a visual representation of the CBIR outcomes on these datasets, Elephant images, Africa Human images and food set images.

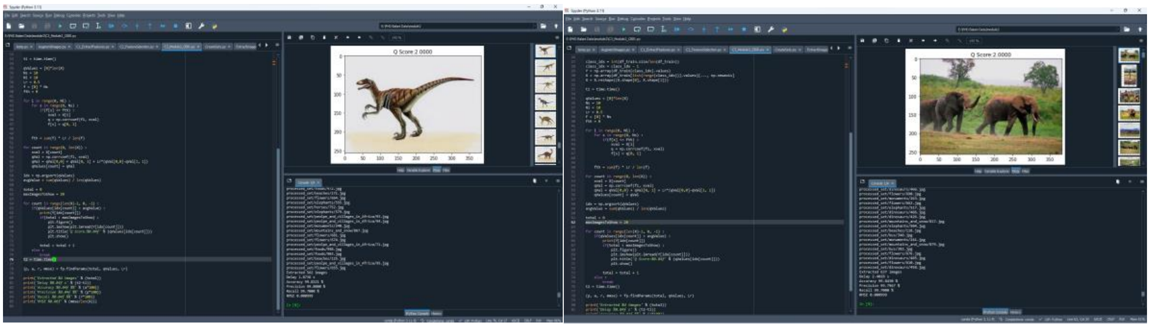

Fig 2(a) Result for images of elephants and dinosaurs

Fig 2(b)COREL Dataset for CBIR Dinosaur, Elephant, Africa Human and Food Image Set.

These datasets were combined Corel-1K,5K and 10K for training and validation purposes, records were used. The merged dataset was divided into ratios of 75:15:15, wherein 75% of the photos were utilized for training, 15% were used for testing & the remaining 15% were used for validation. With the help of this method, CBIR results were computed for various Number of Test Images (NTI) and compared with the suggested model. Table 1 shows these results in terms of accuracy according to:

Table 1. The retrieval accuracy varies when applied to different images within the Corel 1K DB.

Input Image Serial No	**PROPOSED MODEL**	**Features Extraction Fourier & Wavelet**	**Features Extracted Fourier, Wavelet, DCT& Convolution**
	Accuracy		
Beaches	99.85%	99.74%	99.80%
Buses	99.84%	99.77%	99.79%
Dianosures	99.84%	99.60%	99.59%

Elephant	99.85%	99.79%	99.80%
Flowers	99.85%	99.76%	99.76%
Foods	99.85%	99.78%	99.78%
Horses	99.84%	99.79%	99.80%
Mouments	99.83%	99.79%	99.81%
mountains_and_snow	99.86%	99.79%	99.82%
peolpe_and_villages_in_Africa	99.86%	99.81%	99.81%

The analysis output, results shown in Table 1 and demonstrate that the proposed model performs better across a range of CBIR applications compared to DCT Convolution features by a margin of 0.01% and Fourier wavelet features by 0.07%. This advantage stems from the amalgamation of high-density features with retrieval similarity metrics characterized by exceptional efficiency.

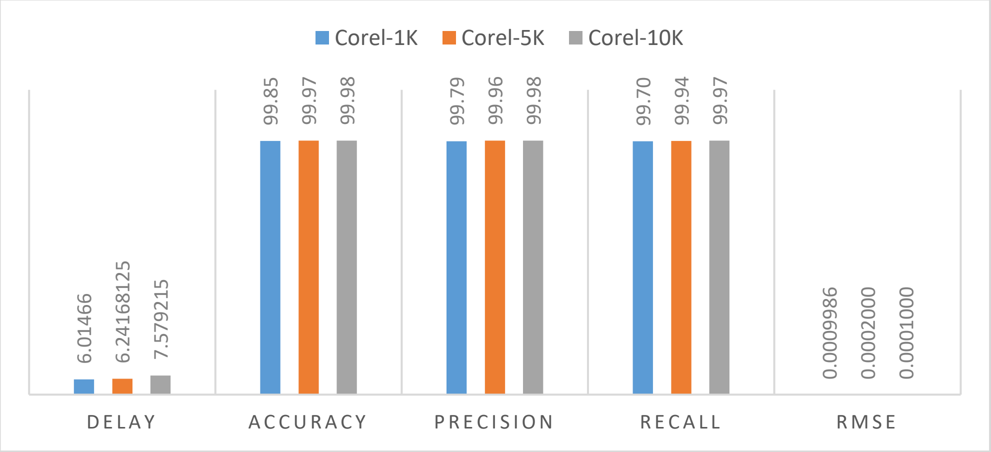

Fig 3. Comparison of accuracy, precision, recall and RMSE.

In Proposed Model Comparison of accuracy, precision, recall and RMSE are evaluating on Corel 1K, 5K, and 10K, various datasets.

A review of retrieval precision involved the utilization of closely aligned training and testing sets. The detailed outcomes from this assessment are presented in table 2, it also contains a comparative analysis in precision achieved for these proposed model in contrast to contemporary retrieval models.

Table 2. Retrieval Precision for Corel-1K DB

Corel-1K classes	EODH-SIFT (Tian et al. 2014)	CMLBPCED (Pavithra and Sharmila 2018)	CD-CW (Ashraf et al 2018)	CHLDP-DSIFT (Zhou et al.)2018a	CH-LDP (Zhou et al.)2018b	DGHM-SURF (Ruqia Bibi.)2020	Proposed Models
Africa	14.92	81	75	82.6	77.9	79.89	98.48
Beaches	37.8	66	60	56.8	60.1	68.31	98.64
Buildings	53.9	78.75	50	77.1	69.1	93.81	97.97
Buses	96.7	96.25	90	98.9	87.6	97.53	99.78
Dinosaurs	99	100	100	100	99.4	97.56	100
Elephants	65.9	70.75	80	75.5	59.25	90.02	97.95
Flowers	91.2	95.75	85	97.3	95.8	96.52	98

Horses	86.9	98.75	70	95.9	91.85	93.81	98.3
Mountains	58.5	67.75	55	77.8	64	79.21	98.48
Foods	62.2	77.25	70	89.5	78.1	88.76	98.87

This advantage arises from the integration of metric for retrieval similarity, high-density feature sets characterized by exceptional effectiveness and the incorporation of bio-inspired framework aimed at enhancing precision levels.

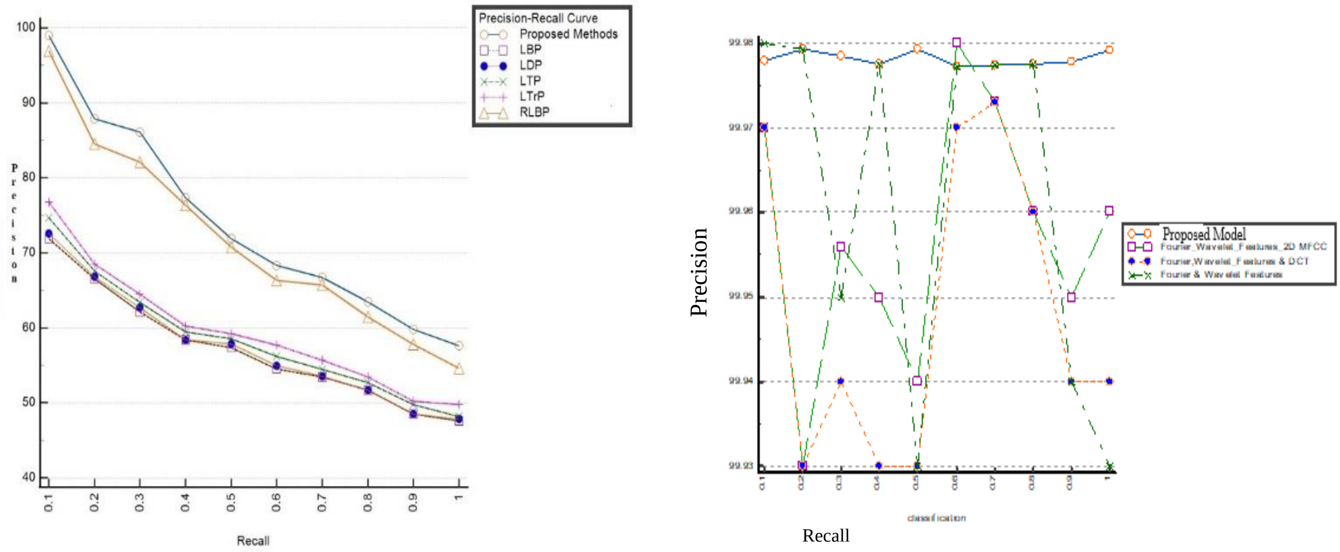

Fig 4. Precision-Recall Curve for Proposed Model.

Utilising comparable training and testing sets, the memory of retrieval was assessed. The evaluation's findings are summarised in table 3, where the proposed model's recall is contrasted with that of cutting-edge retrieval approaches.

Table 3. Recall of comments for various images in Corel 1K sets.

Corel-1K classes	EODH-SIFT (2014 Tian et al.)	CHLDP-D SIFT (Zhou et al.) 2018a	CD- CW (Ashraf et al) 2018	CH - LDP (Zhou et al.) 2018b	CM-LBPCED (Pavithra and Sharmila) 2018	DGHM-SURF (2020 Ruqia Bibi.)	Proposed Model
Africa	14.92	16.52	15	15.58	16.2	15.97	17.1
Beaches	7.56	11.36	12	12.02	13.2	13.66	15.6
Buildings	10.78	15.42	10	13.82	15.75	18.76	15.6
Buses	19.34	19.78	18	17.52	19.25	19.5	19.4
Dinosaurs	19.8	20	20	19.88	20	19.51	19.94
Elephants	13.18	15.1	16	11.85	14.15	18	19.1
Flowers	18.24	19.46	17	19.16	19.15	19.3	19.94
Horses	17.38	19.18	14	18.37	19.75	18.76	19.4
Mountains	11.7	15.56	11	12.8	13.55	15.84	16.7
Foods	12.44	17.9	14	15.62	15.45	17.75	18.15

Based on the results of this research and figure 5, it is clear that the suggested model, when used for different CBIR applications, outperforms DGHM-SURF by 1.13%, CD-CW by 3.60%, and EODH-SIFT by 2.18%.

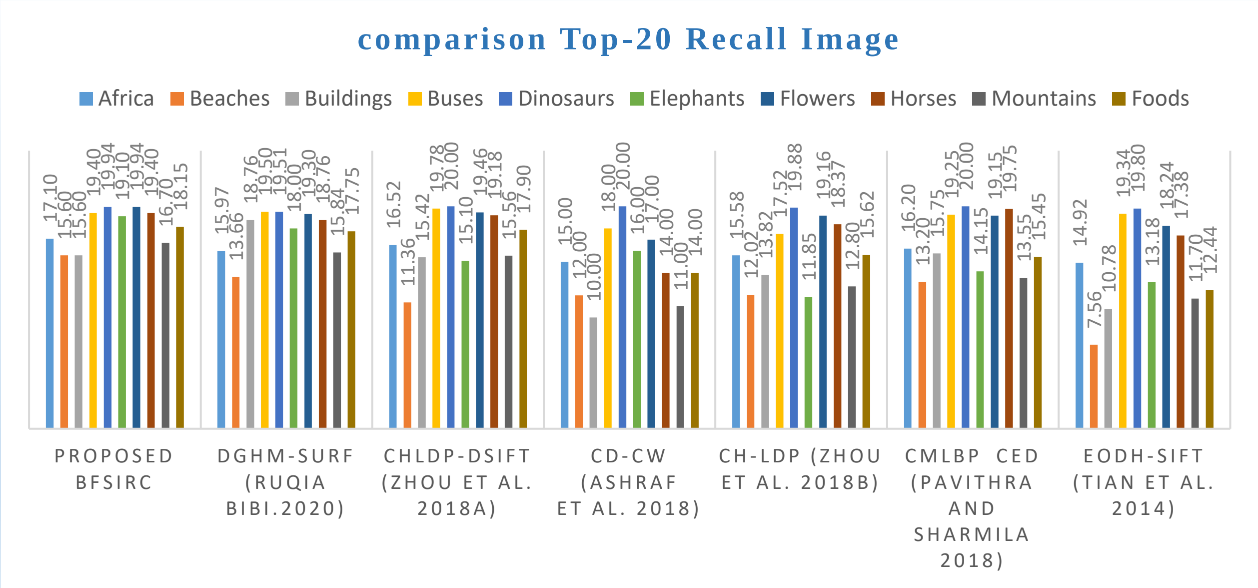

Fig 5. Recall of image retrieval for various categories in Corel-1K DB

Such enhancements are made feasible thanks to the Proposed Model's use of precision, recall & accuracy. This model helps CBIR perform better when dealing with multimodal datasets. We used comparable training and testing sets to assess the RMSE levels of retrieval. Table 4 contains the evaluation's findings, which include a comparison of the suggested model's RMSE to that of contemporary retrieval apporaches.

Table 4. The RMSE of a suggested alternative depict

Input Corel-1K Image classes	Fourier and Wavelet Features	Fourier, Wavelet, DCT, Convolution Features	Proposed Model
Beaches	0.000999	0.000999	0.000999
Buses	0.000999	0.000999	0.000998
Dianosures	0.000998	0.000998	0.000999
Elephant	0.000999	0.000999	0.000999
Flowers	0.000999	0.000999	0.000999
Foods	0.000999	0.000999	0.000998
Horses	0.000999	0.000999	0.000998
Mouments	0.000999	0.000999	0.000999
mountains_and_snow	0.000999	0.000999	0.000999
peolpe_and_villages_in_Africa	0.000999	0.000999	0.000998

The results of this study and figure 6 demonstrate that for several CBIR applications, the proposed model exhibits RMSE values that are 0.001% lower than those of DCT Convolution & Fourier wavelets features. These improvements are made feasible by including root mean-square error into the GA-based Q-Learning Approach, which enhances CBIR's overall performance when applied to heterogeneous datasets.

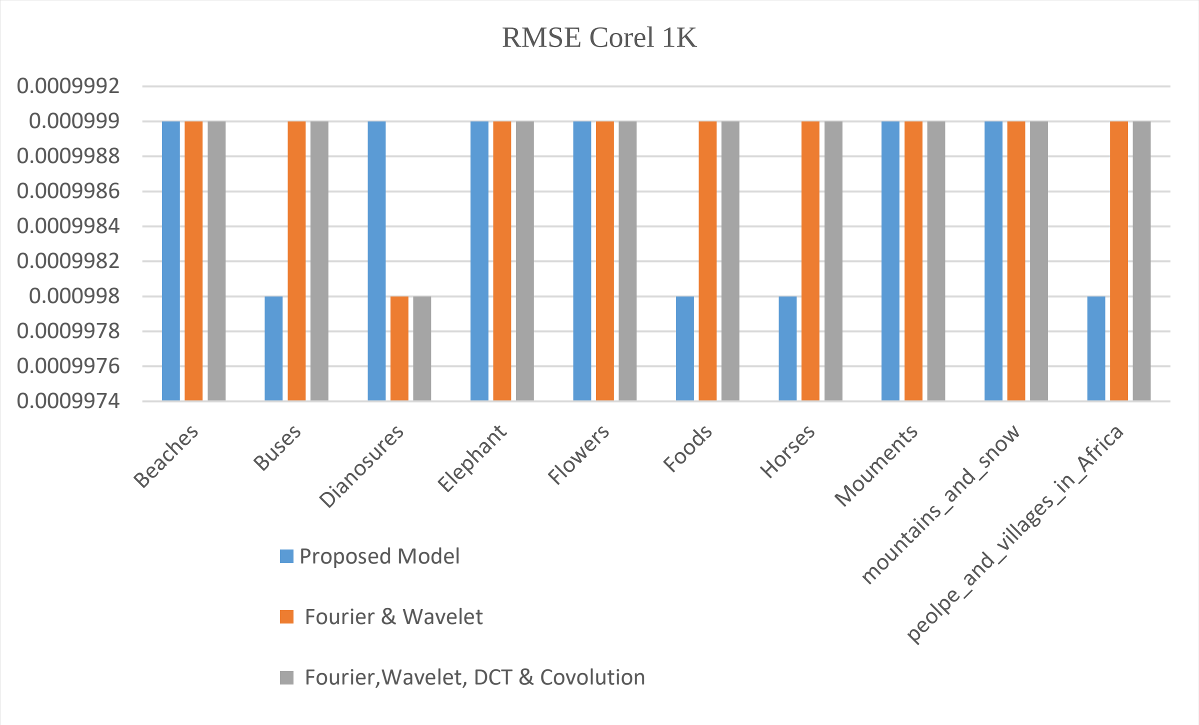

Fig 6. Suggested RMSE for multiple image sets

We used similar training and testing sets to assess the retrieval delay levels. Table 5 presents the findings of this assessment and compares the retrieval delay of the proposed model to the retrieval delay (D) are leading-edge retrieval approaches.

Table 5. Optimal delay required with various depict collections

Input Corel-1K Image classes	Fourier & Wavelet Features	Fourier,Wavelet, DCT & Covolution Features	Proposed model
	Delay in Second	Delay in Second	Delay in Second
Beaches	4.7042	4.8538	4.9365
Buses	4.7186	4.6052	5.0623
Dianosures	4.4061	4.3295	5.5326
Elephant	4.718	4.6393	6.3445
Flowers	4.5467	4.578	6.1561
Foods	4.5467	4.3605	6.1261
Horses	4.8123	4.7811	6.7677
Moments	4.5311	4.5789	8.0779
mountains_and_snow	4.704	4.828	6.4543
peolpe_and_villages_in_Africa	4.8978	4.572	4.6886

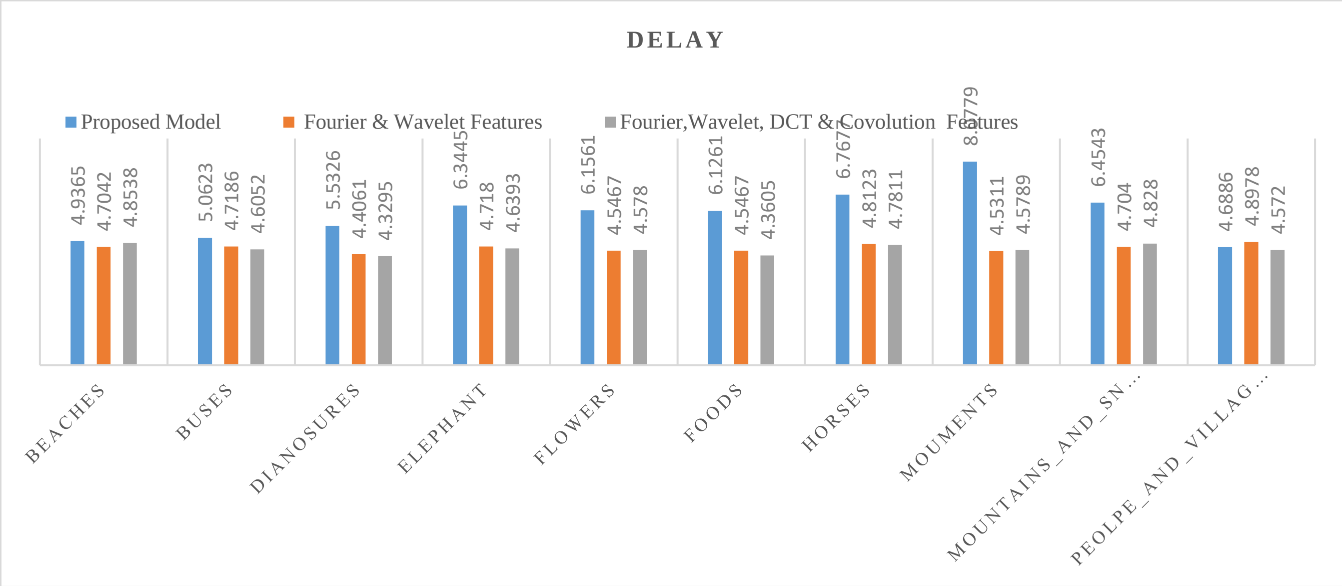

Fig 7. Delay needed for recommendations using various techniques

Based on findings of this analysis and the data represent in figure 7, it becomes evident are proposed model display a lower delay by 1.40% compared to DCT Convolution and 1.36% compared to Fourier wavelet Features when applied to diverse CBIR applications. However, it does show that delay is 6.01% higher than use proposed Model. These improvements are achievable due to the implementation of retrieval operations characterized by low complexity, which contributes to enhancing the performance of CBIR for multimodal datasets. Given its high-performance capabilities, the suggested approach can be successfully applied to a variety of Corel datasets.

4. Conclusion & Future Scope

The proposed model effectively amalgamates Using heterogeneous features are created Fourier, Convolution, Wavelets, Cosine, Color, Edge and Gabor Maps, Super Feature Vectors (SFV) are produced. to bolster the improve CBIR. A unique feature selection model based on EHPSO is employed to refine these characteristics, aiming to reduce variation in interclass feature while enhancing retrieved accuracy. To further Improve retrieval effectiveness by integrating a unique GA-based Q-Learning optimisation approach.

As a result, proposed model exhibits a 0.07% higher accuracy compared to Fourier wavelet features and a 0.01% higher accuracy compared to DCT Convolution features across various CBIR applications. This improvement arises from the synergy of for a variety of application situations, a dense features and high-efficiency retrieval similarity metrics are used.

Furthermore, a proposed model demonstrates superior precision compared to existing methods, boasting a 10.5% higher precision are EODH-SIFT, 9.8% higher precision instead of DGHM-SURF, and 3.4% higher precision than CD-CW. These gains are attributed to the incorporation of boost precision, high-density feature sets, effective retrieval similarity measures, and bio-inspired approaches have been used.

In addition, the proposed model when used for various CBIR applications, reveals the 2.18% higher recall over EODH-SIFT, as 1.13% higher efficacy over DGHM-SURF, & a 3.60% higher effectiveness over CD-CW. The EHPSO Model's usage of precision, recall & accuracy facilitates these improvements, which ultimately lead to higher CBIR performance, particularly with multimodal datasets.

Furthermore, the suggested model yields RMSE coefficients with a 0.001% reduction across a variety of CBIR more uses for DCT convolution features and Fourier wavelets. These developments, which further improve CBIR's overall performance with multimodal datasets, are made possible by the GA-based Q-Learning Model's integration of Root Mean Square Error (RMSE).

Despite exhibiting a retrieval latency that is 1.36% faster than Fourier wavelet and 1.40 percent faster than DCT convolution. When used for various CBIR applications, the proposed approaches did cause a prolonged delay 6.01% than the proposed methods. This improvement in CBIR performance with multimodal datasets is related to the use of retrieval strategies with low complexity.

our proposed hybrid model represents a significant advancement in Continuous learning-based feature selection for image retrieval. By addressing the identified gaps in prior works, our model not only enhances retrieval accuracy and precision but also reduces processing delays, making it highly relevant to real-time applications. The integration of optimization techniques and continuous learning creates a robust and adaptable framework with promising implications for the future of image retrieval research and practical applications. Extending our model's scalability to handle even larger datasets and distributed computing environments, ensuring its applicability to Big Data scenarios.

Considering the exceptional performance of the proposed model, it proves to be a versatile choice for a wide array of CBIR datasets. To further enhance its performance in the future, researchers are encouraged to explore various deep learning models, such as Q-Learning, Auto-encoders, Generative Adversarial Networks (GANs), and others. Additionally, conducting evaluations on larger datasets and exploring techniques that are influenced by nature, such as Firefly Optimisation, Grey Wolf Optimisation (GWO) & Ant Colony Optimisation (A-CO) can further enhance the model's capabilities across diverse image sets. Also Tailoring our model to domain-specific requirements, such as medical image retrieval or satellite image analysis, to maximize its impact in specialized fields.

Conflict of Interest: They don't have any competing interests.

Data Availability Statement:

To evaluate its effectiveness, the following datasets were used:

The data sources utilised in this study, including Corel 1K, 5K, and 10K, are publicly available and can be accessed through the following sources:

- Kaggle has access to the Corel dataset data that support the study's findings. (https://www.kaggle.com/datasets)

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