Journal of Information Systems Engineering and Management
2025, 10(38s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

A Comprehensive Analysis of Feature Extraction and Retrieval Techniques used in Content-Based Image Retrieval Systems

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ARTICLE INFO

Received: 27 Dec 2024

Revised: 17 Feb 2025

Accepted: 28 Feb 2025

ABSTRACT

In this paper, the literature review about various feature extraction methods adopted for extracting feature of query image and database images has been discussed. There are main two approaches to implement content based retrieval system. First is the conventional machine learning methods another is deep learning convolution neural network architectures. Efforts are made for detailed survey of both the machine learning and deep learning approaches for the purpose of extraction of most important salient features of images directly affecting the retrieval performance for classifying the images in particular category and finally retrieving most relevant top images.

Keywords: retrieval, performance, implement

1. INTRODUCTION

With the advancements of computing technology and digital devices billions of people are browsing web. There is an exponential growth of digital data in the form of texts, images and videos every day. Taking care of the huge information archives on web is a significant issue. The web repositories for multimedia data are massively used by our daily life applications. Images in web repositories are stored in digital format. Retrieving images from the vast multimedia databases is a big challenge. Image retrieval is the process of searching the digital images from the large scale databases. User retrieves the most similar images from the database according to features of query image. Text Based Image Retrieval (TBIR) (Alkhawlani, Elmogy, & El-Bakry, 2015) and the Content Based Image Retrieval (CBIR) (Smeulders, Worring, Santini, Gupta, & Jain, 2000)(Kokare, Chatterji, & Biswas, 2002) are the two common information retrieval methods. In TBIR, the image search system was based on the information associated with images like image tags or the titles surrounding the image is the. A tag or a particular keyword is labeled to every database image. These assigned labels help in retrieving information from large scale database. There were some major problems associated with TBIR. The textual information may not be consistent with visual contents. Annotation or description of the images is done manually in the database for describing the content of images like size, format, dimensions or other metadata about the image. Assigning a particular tag or keyword to every image in the database is a laborious and monotonous task. Image retrieval depends upon matching a textual query with the annotations of image. Images annotations may vary from personal viewpoints about understanding the image. Along with these stated issues of TBIR the retrieval efficiency of TBIR is very low. The main issue seen in TBIR system is the direct involvement of humans for annotating the

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images throughout the retrieval process. Assigning only a single keyword for describing the entire context of image is not sufficient. To overcome these shortcomings of TBIR another system retrieving images with more efficiency is to be put forward. The text based content retrieving information from large scale multimedia database is to be replaced by CBIR. Content based information retrieval system retrieves relevant images from the large scale archives using visual query information such as color, shape and texture etc. CBIR has another term as QBIC (Query By Image Content) retrieval system. The CBIR system is the image search system that processes the visual query image and retrieves the relevant visual documents or images efficiently from the very large-scale visual corpus based upon similar extracted.

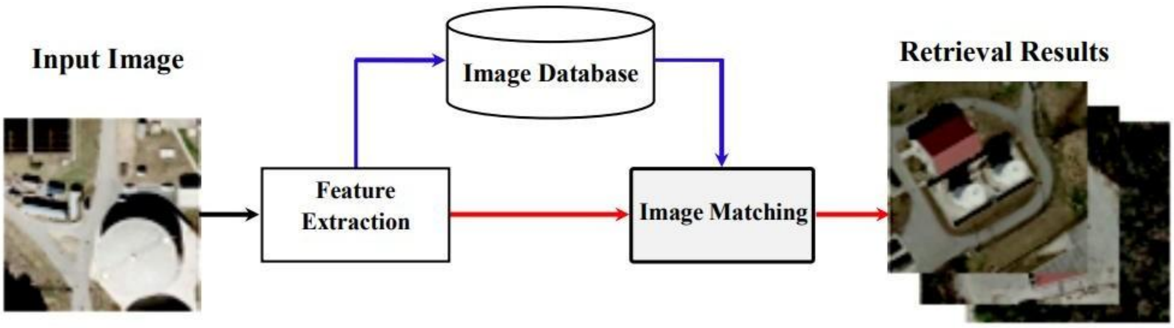

Fig 1. Query image and dataset image matching and result retrieval

2. SALIENT FEATURE EXTRACTION

Extracting candidate features to represent images is the initial and most important step of CBIR for selective representative image features for better design of RSIR system. Salient feature extraction is basically reducing the dimensions of the feature vector. Thus reduced feature vector can efficiently represent only meaningful parts of image as a comparative lower dimensional feature vector. Retrieval performance in terms of storage requirements, computational time, retrieval time, high similarity index of CBIR system is directly affected by quality of extracted features. Several feature extraction feature descriptors are used by researchers to describe the visual features of images. Feature in form of vector is having low dimensions. Well known feature descriptors used by researchers are categorized as:

a. Global features: Global features represent the images as a whole in terms of shape, color and texture. Widely used global feature descriptors are Dominant Color Descriptor (DCD), Gray Level Co-Occurrence Matrix (GLCM), Vector of Locally Aggregated Descriptors (VLAD) etc.
b. Local features: Representing image as significant patches in terms of salient key points in the images. Local Feature descriptors: Scale Invariant Feature Transform (SIFT), Speed Up Robust Factor (SURF), Histogram of Gradients (HoG), Bag of Words (BoW), Local Binary Patterns (LBP) etc.
c. Learned Features: Representation of image using deep learning architectures such as Convolutional Neural Networks (CNN), Artificial Neural Networks (ANN), pre- trained models.

2.1 Feature extraction based on global and local features

The image features are divided into two categories that is global features and local features. Global features represent the whole image. Color, shape, texture and spatial information represent the whole image. Specific areas of a picture, such as borders, blobs and corners represent the local features. (M.Shivakumar, 2021) has discussed the overview of color, shape, texture feature descriptors like LBP etc.

2.2 Feature extraction based on global features descriptors

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The color feature is the basic feature used by researchers for image classification and retrieval. It performs well despite of image size and orientation. (I.M.Hameed, 2021) has presented an overview of the CBIR framework, low-level feature extraction techniques, similarity measurements, machine learning methods and evaluation metrics for content-based image retrieval system.

Color moments, color correlograms, color histograms, and Colour Co-occurrence Matrix (CCM) feature descriptors are the main feature (A. A.Mohamed, 2016; N.Shrivastava & V.Tyagi, 2015) to extract the color features. Color features are computed based on color spaces. Color spaces are of two types: linear color spaces like RGB and non-linear color spaces like HSV. popularly used color spaces used by researchers are RGB, HSV and YCbCr. The color moments, color correlogram (Huang, J., Kumar, S. R., Mitra, M., Zhu, W. J., & Zabih, R., 1997), color histogram (Flickner, 1995), and DCD, CCM (Qiu, 2003) provide the foundation of these color spaces. Color features are robust feature descriptors. They are invariant to translation, rotation, and scale (N.Shrivastava & V.Tyagi, 2015).

Texture feature represents patterns of the image which is not based upon single intensity like color. Wavelet transform, Gabor filter (Manjunath, 2001), Markov random field (Cross, 1983), GLCM (Hawlick, 1979), and Edge Histogram Descriptor (EHD) (Won, 2002) are the popularly used algorithms used for extracting texture features of the image by the researchers. Still computational complexity is the main concerning issue for texture features (Alzu'bi, 2015).

Shape is extracted on the basis of region or boundary of the image (Tian, 2018). Shape extraction is done either within entire region or only. Fourier descriptor (Zhang D. I., 2012) (Zhang D. &. 2004) and moment invariants (Suk, 2011) are popularly used shape extraction methods to extract the shape features of an image. Shape descriptors are variant to translation and scale. Thus it is better to merge shape feature descriptor with other descriptors to excel accuracy. Invariant moments, consecutive boundary segments, aspect ratio, polygonal approximation, fourier descriptors, b-splines etc. are the popular methods used to calculate shape descriptors.

2.2 Feature extraction based on local features descriptors

SIFT identifies the key points of the image (Low, 2004). It is robust against image scale and rotation. Still SIFT image descriptor has two main drawbacks. First, it occupies a large amount of memory. Second computational cost is higher (Montazer, 2015). To overcome these limitations of high memory consumption and computation cost the researchers have

proposed SURF feature descriptor to reduce the feature vector dimensionality (U.Sharif, 2019). SURF has further reduced the feature vector dimensions. Still there is need to further reduce the dimensionality.

SURF solves the high dimensionality constraint of SIFT and was introduced by (Bay, 2008).

LBP extracts the texture of the image and computationally simpler to implement and.

HoG represents the shape of the image objects and initially implemented by (Dalal, 2005). HoG depicts the distribution of local intensity gradients and the orientations of an object's edge.

Feature extraction based on CNN (Convolution Neural Networks)

Convolution neural networks learn image features through its layered architecture. CNN's have the multiple layers. CNN's has fully connected, pooling, and convolutional layers. Filters are applied to input images using a convolutional layer to learn features. The first convolution layers learn features like texture and edges. Complex features are learned by later layers. Pooling layer is responsible for down sampling the incoming inputs. Finally fully connected layer makes predictions about the input image's class or label. Last layers learn features like objects. Last layers learn to connect higher features to individual classes. CNN's are invariant towards translation, scaling, and rotation (Voulodimos, 2018).

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2.3 Feature extraction based on Transfer Learning (TL)

A neural network trained on large dataset gains knowledge from this data and this acquired knowledge termed as weights of the network. Only the learned features in the form of weights can be extracted and then transferred to any other neural network instead of training that neural network from the initial stage. Instead of building a model from scratch pre- trained models are trained on large dataset are used as a feature extractor by removing the output layer and using the entire network as a fixed feature extractor by freezing the weights of initial layers while retraining only higher layers for new problem specific dataset. Correct weights for the network are identified for the network by multiple forward and backward iterations. The weights and architecture acquired by pre-trained models previously trained on huge datasets may be used directly and apply the learned weights on our target problem known as transfer learning. ImageNet dataset is a rich source of millions of labelled images across thousands of classes that enables the ImageNet dataset a valuable source of training deep learning pre-trained models .Knowledge is acquired by pre-trained model on ImageNet dataset that helps to acquire a rich (Huang, J., Kumar, S. R., Mitra, M., Zhu, W. J., & Zabih, R., 1997) set of learned features and weights helps in adapting the model to specific target task and enhances accuracy. Transfer learning can be employed between entirely different but relevant source domain and target domain samples. Pre-trained models are trained on source domain and then learning can produce much higher accuracy results on the target task.

Fine tuning is the most important phase of transfer learning as the experimental dataset is small and the selected images are different from various images in the source domain. The model is fine-tuned by freezing the model.

(G.Huang, 2017) produced the Dense Convolutional Network (DenseNet) which links each and every layer to the other layers in a feed-forward fashion. L layers have connections with one between in each layer and its successive layers in the traditional convolutional networks.

Table 1: Recognition results for various feature extraction methods used by researchers

Authors	Feature Extraction Technique	Dataset	Observations
(N.Shrivastava & V.Tyagi, 2015)	1) Corel 2) CIFAR	Color (HSV) Texture (Gabor Filter) Shape (Fourier Descriptor)	1) Corel: 0.7690 2) CIFAR: 0.859
(A.ponomarev,2015)	1) Corel 2) CIFAR	Color (DCT) Texture(DWT) Shape (K-means)	1) Corel: 0.83 2) Caltech: 0.7
(P.shrivastava,2017)	1) Corel 1k 2) Corel 5k 3) Corel 10k 4) Olivia 2688 5) GHIM10k	Texture (LBP) Shape(Legendre Moments)	1) Corel 1k: 0.9995 2) Corel 5k: 0.5676 3) Corel 10k: 0.3537 4) Olivia 2688:0.9999 5) GHIM10k: 0.9172
(M.Sajjad, 2018)	Corel 1k	Color (CH) Texture (RLBP)	0.8777
(Pavithra, 2018)	1) WANG 2) Corel-10k 3) OxfordFlower	Color (DCD)	1) WANG: 0.735 2) Corel-10k: 0.4136 3) OxfordFlower: 0.3186
(N.Tadi Bani,2019)	Simplicity	Color	0.8284

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		Texture	
(M.k.Alsmadi,2020)	Corel	Color (YCbCr) Texture (Gray level co-occurrence matrix) Shape (Canny edge detector)	0.9015
(S.Jabeen, 2018)	SURF	1) Corel 1k 2) Corel 1.5k 3) Caltech 256	1) Accuracy: 0.86 2) Accuracy: 0.832 3) Accuracy: 0.3898
(U.Sharif, 2019)	SIFT	1) Corel 1k 2) Corel 1.5k 3) Corel 5k	1) Accuracy: 0.8439 2) Accuracy: 0.7814 3) Accuracy: 0.5737
(A.sarwar, 2019)	LBP	1) Wang 1k 2) Wang 1.5k 3) Holiday	1) Accuracy: 0.8958 2) Accuracy: 0.7602 3) Accuracy: 0.6923
Baig (2020) [49]	HoG SURF	1) Corel 1k 2) Corel 5k 3) Caltech 256	1) Accuracy: 0.8641 2) Accuracy: 0.8123 3) Accuracy: 0.6839
(T.Ojala, 2002)	LBP16 riu$_2$	ImageNet	Average Error Rate: 8.40%
(S.S. Hussain,2016)	1) SIFT based RVD 2) CNN based RVD	INRIA Holidays Oxford	1) mAP: 45.1% 35.1% 2) mAP: 63.5% 44.5%
(A.Chadha, 2017)	1) Fast-VLAD 2) Multi VLAD 3) CNN 4) Fast-VDCNN	1) Caltech and Stanford dataset 2) Holidays Holidays dataset	1) mAP: 72.8% 76.1% 2) mAP: 73.2% 73.7% 3) Matching Complexity: 4 4) Matching Complexity: 14
(Yang, Jiang, Li,Tian, & Lv, 2017),	GLCM+HOG +LBP	1) WANG 2) Oxford Flowers dataset 3) CIFAR-10	Average Precision: 0.766 Recall: 0.164 Retrieval time: 0.42sec Average Precision: 0.596 Recall: 0.146 Retrieval time: 0.83sec Retrieval time: 19.4 sec
(Do & Cheung, 2017)		1) CIFAR 10	1) MAP: Supervised: 53.17% 1) MAP: Unsupervised 77.22%

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	SASH	2) MNIST 3) NUS-WIDE	2) MAP: Supervised 75.48% 2) MAP: Unsupervised 63.31% 3) MAP: Supervised 64.01% 3) MAP: Unsupervised 45.05%
(Bosch, 2007)	PHOG	ImageNet Caltech-101 TRECVID 2006	Average Precision Average Precision :66.50% (Classification) Average Precision: 77.80% (Retrieval)
(J.Li, 2017)	DMINTIR	Oxford 5k Paris 6k	Mean Average Precision: 85.34% Mean Average Precision: 81.75%
(He, 2016)	Landmark Image Retrieval by Jointing Feature Refinement and Multimodal ClassifierLearning	1) MediaEval 2012 2) NUS-WIDE	1) Mean Average Precision: 68.32% 2) mAP: 60%
(B.Chaudhuri B. L., 2016)	Archive of 2100 images from 21 different categories selected from aerial orthoimagery	ARGMM	63.56%(accuracy) 72.34%(Precision) 69.87%(Recall)
(B.Chaudhuri B. S., 2017)	UC-MERCED dataset	MLIRM	74.29 (Accuracy) 85.68(Precision) 80.25(Recall)
(G.Huang, 2017)	1) AID 2) UCM 3) Optimal 4) NWPU	DenseNet	1) 97.44% 2) 99.50% 3) 95.89% 4) 94.98%
(J.Zhang, 2019)	1) UCM 2) AID 3) Optimal-31 4) NWPU-RESISC45	DenseNet	1) 98.67(50% traing ratio) 99.50% (80% training ratio) 2) 95.37(20% traing ratio) 97.19% (50% traing ratio) 3) 95.41 (80% training ratio) 4) 92.90% (10%

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			training ratio) 94.95% 20% training ratio)
(Li Y. M., 2021)	1) CIFAR-10 2) CIFAR-100 3) ImageNet	(1) DenseDsc (2) Dense2Net	Accuracy 1) 94.05% (CIFAR-10) 74.24 % (CIFAR-100) 76.3%(ImageNet) 2) 94.19(CIFAR-10) 73.68% (CIFAR-100) 77% (top-1 accuracy ImageNet)
(S.Thirumaladevi, 2023)	1) UCM, 2) SIRI-WHU	AlexNet, VGG16, VGG19	1) UCM dataset: 93.57%(AlexNet) 94.08%(VGG-16) 95%(VGG-19) 2) SIRI-WHU 91.34%(AlexNet) 92.78%(VGG-16) 93.4%(VGG-19)
(P.S.Tan, 2023)	Soundscapes1 Soundscapes2 Urban Sound 8k	DenseNet-121	F1-score : 80.70% F1-score: 87.30% F1 score: 69.60%
(F.Salim, 2023)	1) Fruit-360 2) Fruit Recognition	DenseNet-201 Xception MobileNetV3-small ResNet-50	1) Test Accuracy: 97.33 (DenseNet-201) 84.34 (Xception) 95.65 (MobileNetV3-small) 98.36 (ResNet-50) 2) Test Accuracy: 99.13 (DenseNet-201) 97.73 (Xception) 62.73 (MobileNetV3-small) 76.47 (ResNet-50)
(T.Chauhan,2021)	X-Ray image	1) Adam optimizer and crossentropy loss function 2) LR-Scheduler-StepLR	1) 98.45% (Accuracy) 1) 96.63% (Precision) 1) 100% (Recall) 1) 98.27% (F1-Score) 2) 63.15% (Accuracy) 2) 64.29% (Precision) 2) 32.09% (Recall) 2) 43.22% (F1 Score)

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(Aziz, 2021)	BraTs2019	1) ResNet-50 2) DenseNet-201 Cubic-SVM	1) 84.4% accuracy (LGG) 1) 86.7% accuracy (HGG) 2) 83.8 % accuracy (LGG) 2) 87.4% accuracy (HGG)
(S.Dong, 2019)	1) GID 2) ISPRS	ResNet-101	1) 77.74% accuracy 2) 86.67% accuracy
(Li J. W., 2018)	JSRT (Japanese Society of Radiological Technology)	Inception-V3 Using 1) Softmax 2) Logistic 3) SVM	Accuracy: 1) 86.40% 2) 85.10% 3) 85.70%
(J.Xin, 2023)	UCMD	1) YOLO-ResNet-50 2) YOLO-ResNet-50-PCA 3) YOLO-ResNet-50-PCA-W	1) mAP: 94.03% ANMR: 0.0448 2) mAP: 95.17% ANMR: 0.0345 3) mAP: 95.94 ANMR: 0.0325
(V.Risojević,2021)	1) RESISC-45 2) AID 3) UCM	Fine tuning on target dataset ImageNet (SWAV) àMLRSNet (Single Label)	ClassificationAccuracy: Domain adaptive 1) 95.24 2) 93.92 3) 96.89 Fine Tuning: 1) 95.89 2) 96.09 3) 97.14
(Z.Zhang, 2022)	1) RSSCN7 2) OPTIMAL-31	1) MKANetClass 2) MobileNetV3	MKANetClass: RSSCN7 1) Precision: 0.8963 mAP: 0.9167 MobileNetV3: RSSCN7 1) Precision: 0.8573 mAP: 0.8586 MKANetClass: OPTIMAL-31 2) Precision: 0.7447 mAP: 0.7399
(Y.Chen, 2023)	Drone Action	Deep saliency smoothing hashing (DSSH)	Precision: 60.09%

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(G.Cheng, 2017)	NWPU- RESISC45	CH,LBP,GIST,BOVW, BOVW+SPM,LLC,AlexNet,VGG-16 GoogleNet	Overall Accuracy: CH: 24.84% LBP: 19.20% GIST: 15.90% BOVW: 41.72% BOVW+SPM:27.83% LLC: 38.8% AlexNet: 76.69% VGG-Net16: 76.47% GoogleNet:76.19%
(G.Sumbul, 2021)	1) UC-Merced 2) IRS- BigEarthNet	DAS-RHDIS	Accuracy: 56.8% Precision: 65.3% Recall: 70% F1-Score: 67.5%
(B.Demir, 2022)	DLRSD 2) BigEarthNet-S2	PLASMA-MTL	mAP: 1) 97.5% 2) 97.7%

3. CONTRIBUTION OF THE WORK TO BE PROPOSED

The content based remote sensing information retrieval system may be useful in various fields like agriculture and forestry. Content based image retrieval system may prove to be boon in agricultural fields to detect the diseased crops just by aerial view. Deforestation may be monitored by remotely sensing the affected area. Other applications of remote sensing image retrieval system are geosciences where satellites may take pictures to know about earth geological conditions at a particular time and space. Astrologers may take information about the movements of planets by remotely sensing the positions of planets. Scientists may capture information about the minerals available on planets. Weather forecasting department may use remote sensing for predicting the weather conditions. Military department may collect data about dangerous border areas by remotely sensing the border area. Other application areas of content based remote sensing image retrieval are oceanography, geology, archeology and astrology.

4. CONCLUSION

CBIR system processes the query images thus the performance of CBIR solely depends upon the visual features. The accuracy results for retrieval system are directly reflected by the efficiency of feature extraction methods. To find more discriminating features or the combination of features capable of discriminating image features is still an issue. (Tong, Xia, Hu, Zhong, Datcu, & Zhang, 2019; Shao, Zhou, Deng, Zhang, & Cheng, 2020).This paper has discussed the literature review related to the recognition of various feature extraction techniques based on local, global, feature fusion based feature descriptors toextract the features of images. The summary of recognition results obtained for various feature extraction approaches has been demonstrated. In the end, the research gaps have been analyzed based on the literature review.
(n.d.).

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ABBREVIATIONS

CBIR	Content Based Image Retrieval
ANN	Artificial Neural Networks
ANMR	Average Modified Retrieval Rank
BoW	Bag of Words
CNN	Convolutional Neural Networks
DCD	Dominant Color Descriptor
GLCM	Gray Level Co-Occurrence Matrix
HoG	Histogram of Gradients
LBP	Local Binary Patterns
QBIC	Query By Image Content
RSIR	Remote Sensing Image Retrieval
SIFT	Scale Invariant Feature Transform
SURF	Speed Up Robust Factor
SVM	Support Vector Machine
TBIR	Text Based Information Retrieval
VLAD	Vector of Locally Aggregated Descriptors
CCM	Colour Co-occurrence Matrix
EHD	Edge Histogram Descriptor
CH	Color Histogram
HSV-CH	High Saturation Value - Color Histogram
CM	Color Moment
DWT	Discrete Wavelet Transform
RLBP	Rotated Local Binary Patterns
MRF	Markov Random Field
RVD	Robust Visual Descriptor
FV	Fisher Vectors
MAP	Mean Average Precision
VDCNN	Voronoi based Deep Convolutional Neural Network
VLAT	Vector of Locally Aggregated Tensor
DBPSP	Difference Between Pixels of Scan Pattern
FREAK	Fast Retinal Key points
BRISK	Binary Robust Invariant Scalable Key Points
BoVW	Bag of Visual Words
LIOP	Local Intensity Order Pattern
LBPV	Local Binary Patterns Variance
CoHOG	Co-occurrence Histograms of Oriented Gradients
ROI	Region of Interest

Journal of Information Systems Engineering and Management
2025, 10(38s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

KULSH	Kernel Based Unsupervised Locality Sensitivity Hashing
DBQ-IH	Double Bit Quantization and Index Hashing
RBA	Relaxed Binary Autoencoder
SFH	Simultaneous Feature Hashing
HCR	Hash Code Reconstruction
UDPHA	Unsupervised Deep Hashing
JPEG	Joint Photographic Expert Group

OSA-HSR	Object Scale Adaptive High Spatial Resolution
DMINTIR	Discriminative Multi-View Interactive Image Re-Ranking
ARG	Attributed Relational Graph
MLIRM	Multilabel Image Retrieval Method
SBS-CNN	Similarity Based Supervised Learning Using Convolution Neural Network
ReLU	Rectified Linear Unit
CNN-FE	CNN Feature Extractor
LCLU	Land Cover and Land Use
VGG	Visual Geometry Group
BN	Batch Normalization
CIFAR	Canadian Institute For Advanced Research
HGG	High-Grade Glioma
LGG	Low-Grade Glioma
JSRT	Japanese Society of Radiological Technology
RED	Reciprocal Exponential Distance
DSSH	Deep Saliency Smoothing Hashing
NWPH	North Western Polytechnical University
DAS-RHDIS	Diverse Anchor Selection-Relevant, Hard, Diverse positive and negative Image Selection