Journal of Data Acquisition and Processing
ISSN: 1004-9037
https://sjcjycl.cn/
DOI: 10.5281/zenodo.777333

CONTENT BASED MEDICAL IMAGE RETRIEVAL USING DEEP LEARNING ALGORITHMS

Dr.K.Saminathan
Assistant Professor, PG & Research Department of Computer Science, A.V.V.M Sri Pushpam College (Affiliated to Bharathidasan University), Poondi, Thanjavur, Tamil Nadu, India, arksami@avvmspc.ac.in

Mrs.Amsavalli.S
Research Scholar, PG & Research Department of Computer Science, A.V.V.M Sri Pushpam College (Affiliated to Bharathidasan University), Poondi, Thanjavur, Tamil Nadu, India.
amsareseacher@gmail.com

Dr. Chitra Devi.M
Principal, Queens College of Arts & Science for Women (Affiliated to Bharathidasan University), Pudukkottai, India, m.chithradevi@gmail.com

Abstract
Content Based Medical Image Retrieval (CBMIR) is a technique that search relevant images in large repositories according to the content of the query image which is based on selected features such as color, texture, shape or any other features that can be derived from images. The feature extraction and similarity measurement are two vital steps in image retrieval process. The most difficult issue is the semantic gap which the information in the image is lost due to the representation of image in terms of its features. The semantic gap is a significant gap between the representation of image features and visual understanding. Deep learning algorithms produces better results for various machine learning and computer vision. The Deep Learning (DL) possesses various machine learning algorithms. DL methods have been used in many applications areas and these approaches can also be applied in CBMIR. Machine learning techniques can be explored to address the problem of semantic gap that exists. Here we try to reduce the semantic gap by learning discriminative features directly from images by using machine learning techniques and thereby we classify the images. However, deep learning lack generalization and suffer from over fitting whenever trained on small datasets. In order to the obtain better results, these algorithms need larger dataset for the training of the model.

Keywords: Content Based Medical Image Retrieval (CBIR), Artificial Intelligence (AI), Machine Learning (ML) algorithm, query image.

1. INTRODUCTION

The use of digital cameras, smartphones, and the internet has increased as a result of recent technological advancements. As a result, the amount of image collections has exploded, incorporating digital libraries, medical images, and so on. Besides, Forensic Medical Image Matching (FMIM) is one of the content based image retrieval that might be impacted by progressive degenerative disorders and aging [1]. The amount of shared and retained multimedia data has increased and made it difficult to find or recover an appropriate image from an archive. To keep up with this rapid increase, large-scale picture recovery methods are essential. The most basic requirement of any image retrieval model is to find and categorize photos that have visual-spatial relationships with the research problem. Digital photographs have been increasingly popular in recent years in a variety of fields, including medicine, scientific research, and education. Digital images are produced in large quantities by hospitals and medical institutions. The various digital images are being utilized in different applications such as education, healthcare, defence, etc to get back relevant images with their contents such colour, texture and shape in large scale database [2] To enhance the performance of CBMIR new model is proposed in the large medical datasets. The input image data are taken from a new Pap smear dataset that consists of 917 cell images. These images are modified by using two global descriptors such as MLBP and HOG to extract the feature vectors [3].

Radiological images are used in health care, for medical practitioner to analyse a Radiological image's primitive visual features efficiently [4]. The main goal is to construct a solid system that accurately produces, maintains, and queries picture collections [5]. The feature extraction is the significant aims of the every CBIR systems. Feature extraction is the most important goal of every CBIR system. Low-level properties like as texture, colour, and shape are used to characterize an item in this type of system [6]. In this area, as a result, photographs that are identical to the query image are those that are similar to it and they're found. The majority of Internet web page extract photos using text-based algorithms that involve descriptions as input. The CBMIR has three modules such as administrator, information processing and retrieval and users [7].

The server receives a query by typing in certain content or concepts that correspond to the terms in the archive. The output is obtained based on similarity detection, and this method can return photos that aren't relevant. Although much investigation is being done to improve the performance of automated picture classification, differences in human vision can cause the retrieval technique to be deceive. Because it is focused on the image examination of features that are a portion of the query image, content-based image retrieval (CBIR) is a framework that can solve the key challenges.

CBIR's core principle is to evaluate image information using low-level properties of an image, and to use feature vectors as an image's index. Similar retrieval is the subject of retrieval methods, which are mostly based on an image's multi-dimensional properties [8]. The fundamental need of the CBIR is to supply an input query image and it compares the visual features of the query image with image in the archive, as well as visual similarity in terms of image quality.

New machine learning approaches have made significant advances in recent years. Deep learning, a family of machine learning algorithms that attempt to model high-level abstractions in data by employing deep architectures composed of multiple non-linear transformations, is one important breakthrough technique [9]. Deep Learning is a collection of tactics in which Artificial Intelligence (AI) algorithms or methods are employed to display substantial level impressions of data using deeper models. There are numerous current studies in the subject of learning information and complicated capabilities without the need of human-crafted knowledge.

The CBIR problem is solved by using a deep learning algorithm for photographs that have been annotated by humans. The module on the architecture approach for CBIR uses a deep learning framework and applies it to a state-of-art deep learning approach.

The Fig. 1depicts that the fundamental principles and mechanisms of image retrieval. To acquire more accurate findings, a computational complexity cost is required to create the attribute more robust and distinctive in regards to representing the integration of low-level texture information. Nevertheless, if the characteristics are chosen incorrectly, the image retrieval model's performance is poor. The retrieval time and proposing a pre-clustering of the database based on different features produce good results in a much shorter time in all method [10]. Even though utilizing deep learning for image segmentation and retrieval in computer vision has received a lot of research interest, there is still a lot more emphasis on CBIR applications. Modern CBMIR uses four essential sets namely pre-processing, similarity measures, feature extraction, and semantic gap minimization approach. In feature extraction, low-level features of images e.g. intensity-based, texture-based, wavelet-based and shape-based features are computed to form feature vector [11]. This paper gives the reviews on existing deep learning methods for the content based medical image retrieval methods.

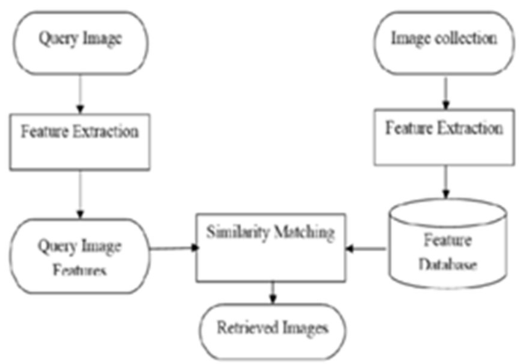

Fig. 1 Image retrieval concept

1.1 Image Segmentation

The objective of image segmentation is to group sections of a picture that belong to the same object class together. Pixel-level classification is another name for this approach. To put it another way, it entails dividing pictures (or video frames) into several segments or objects.

Colour: Due of their resistance to rotation, translation, and scale changes, colour characteristics are said to be particularly stable and robust. Except for colour photographs used for diagnosis in ophthalmology, pathology, and dermatology, most medical images are grayscale. The rank matrix learning vector quantization (LiRaMLVQ) technique is used to represent colour features. They compared the recovery rates attained using extracted and original features for eight different standard colour spaces, and found that each colour space had a significant outcome.

Shape: Color and texture features pale in comparison to shape features. Shape features are the greatest descriptors for diagnosing disease, lesion, or bulk in medical imaging. The results demonstrated that retrieving round shaped or circumscribed margin masses, the system offers high precision to all lesion types.

Texture: Textures are multi-dimensional visual patterns made up of entities or sub-patterns with attributes like brightness, colour, slope, and size. In image texture analysis, feature extraction is a technique for computing a characteristic of a digital image that may be numerically expressed.

1.2 Feature Selection

A feature vector is processed and saved in a visual feature database for each image in CBIR systems. When a user submits a query, the feature vector for that query is computed first. All the vectors in the visual feature database are compared to this query vector using a similarity criterion. The user is shown the photographs that are most similar to the query image. It goes without saying that the CBIR systems rely heavily on the image properties. Feature vectors are used to represent features taken from photos. The CBIR system will then index and discover the most similar and relevant images using these features.

1.3 Classification

DL technique is used to classify the image retrieval. The Deep Convolutional Neural Network (DCNN) is trained to detect the medical images utilizing a supervised learning approach. Medical photos are classified into multiple classifications based on body component or organ information for this purpose; more information on the dataset may be found here. Image classification methods typically contain two modules: feature extraction and classification. In an end-to-end learning system, DCNN learns both the hierarchy of deep convolutional features and the classifier from the training picture data. Instead of making domain-specific assumptions, as is the case with handmade features, the deep learning algorithm learns low-level, mid-level, and abstract features directly from the photos. As a result, it can more successfully identify the class of a query image, and the learnt characteristics can be used for image retrieval.

2. LITERATURE REVIEW

The literature review section of the paper includes the works proposed previously image retrieved based on content using various techniques.

CBIR (content-based image retrieval) is a scientific research challenging issue that has been investigated in the interactive media community for a long time. For image description, a number of image retrieval algorithms based on low-level statistical features have been developed. For visual representations, a number of low-level statistical features have also been grown over the years [12].

Latif et al. [13] examined supervised approach for selecting continuous features. To close the scalability issue in content based image retrieval systems, the suggested solution uses statistical association rules. This method can also be used to reduce dimensionality, so alleviating the "computational complexity curse." The proposed strategy enhances the accuracy of the query result, according to the results of the experiments. The Object recognition is one of the task to recognise the object and labelling it to fit in a predefined class and its location [14]. A Neural network (NN) architecture is proposed for decomposing the medical images which are semantic to the latent codes such as abnormal and normal anatomy code. The normal anatomy code denotes normal anatomies which represents that the samples are healthy, whereas the abnormal anatomy code denotes abnormal changes. The algorithm retrieves the images by calculating the two codes based on the selected sematic element from the image dataset and can utilize it [15].

2.1 Convolution neural network (CNN) based method

An image annotation system based on multi-module deep transfer learning was suggested by Yin & Bi [16] with the goal of using deep convolution neural network technology to optimize neural network configurations and enhance labelling efficiency. Convolution Neural Network was trained using Image Net pictures to accomplish image identification for the kidney classification problems in ultrasound images. It looked at how the amount of transfer affects detection performance. This implies that a transferred and modified CNN might exceed a state-of-the-art functionality. Nowadays, CNN based CBMIR is used to detect and classify the disease specific features of the standard COVID-19 using the chest X-ray dataset by utilizing transfer learning approach [17]. Venketbabu et al. (2020) used sparse representation for improving the retrieval accuracy of the CNN, which gives the average efficiency of 98.7% [18]. Qayyum et al. (2017) developed a DL based CBMIR utilizing DCNN. The developed model was trained with intermodal dataset which contains 5 modalities and 24 classes. The accuracy of 99.77% and average prediction of 0.69 was accomplished for the retrieval tasks. It was concluded that the proposed model is suitable for retrieving the multimodal medical images of various organs [19].

Haripriya & Porkodi (2021) also used the deep Convolutional Neural Network (CNN) for the classification of DICOM image. The developed network model was trained with 22 classes of medical images and average accuracy of 84% was achieved. It was concluded that by increasing the number of layer, which results in higher accuracy [20]. Zhang et al. (2020) also used the DCNN to retrieve the medical images. The Empirical Mode Decomposition (EMD) method was utilized to decompose the medical images into five components. The developed model was validated with IRMA dataset containing 11000 X-ray images, 116 classes. The IRMA error of 43.21 and average precision of 86% was achieved [21]. Cai et al. (2019) developed a novel CBMIR framework utilizing hash code and CNN. The proposed framework takes on a Siamese network in which pair of images are utilized as inputs. The proposed model was validated with the TCIA database and found that the proposed model has 34.07% to 157.92% less time delay compared to existing methods [22]. Sundararajan et al. (2019) introduced a DBCNN model for feature representation of the image and demonstrated that proposed DBCNN shows predominant performance as compared to an existing method [23].

Jiang, et al. [24] described that ML is a class of ANN that has more layers and allows for higher levels of attribute extraction and better data interpretations. Particularly, the CNN has demonstrated to be an effective approach for various computer vision applications, including image detection and segmentation. Mostayed et al. [25] provided a segmentation method for medical images based on a version of the classic U-net artificial neural design. The suggested design uses content-adaptive convolution to replace the combination techniques in typical U-Net back propagation, resulting in a considerable reduction in performance metrics. Also, it didn't try to reach state-of-the-art accuracy for either task; instead, it aimed to promote on the U-Net design and architecture norm. Recently, pre-trained CNN, the new age of DL could be utilized to extract expressive and accurate features [26].

Table. 1 Observation of CNN from various papers

CNN	ACCURACY	MODEL TIME	TRAINING TIME
AlexNet	0.894	271 MB	1140.15 s

GoogleNet	0.898	471 MB	332.28 s
VGG-16	0.901	537.4 MB	1960.2 s
VGG-19	0.904	558.2 MB	5411.31s
ResNet-50	0.907	94.3 MB	2101.9 s

Abdelhalim et al. [27] described the Data enhancement for skin lesions that used a sequential deep convolution networks based on individual. CNN classifier is proposed for overcoming the lack of labeled data. SPGGAN-TTUR is utilized to gain sufficient artificial training dataset for feature extraction in order to enhance the effectiveness of the CNN-based automated skin lesion identification system. The lack of labelled skin lesion images is the limitation of CNN-based automatic skin lesion classification in feature extraction images.

For retinal vascular classification, Noh et al. [28] described a unique and efficient multi-scale CNN framework. It begins with a signal processing-based theoretical examination of organizations member's architectures. Diabetic retinopathy images are commonly used to identify retinal illnesses and could be utilized to diagnose and treat chronic vascular disorders and diabetes in the future. The suggested optical scale-space estimated CNN (SSANet) delivers state-of-the-art performance over four databases, according to proposed technique. Also use neural network to solve further medical image analysis difficulties in the future.

Fundus imaging is a reflection of the pattern formed on the eye's lens and it is used to diagnose optic disease all over the world. The optical disc, the retina, and the system of arteries are the three primary structures in the retinal fundus image. Because retinal problems are blood vessel illness are crucial for detecting Diabetic Retinopathy (DR) [29].

In addition to this, the studies related on medical imaging, image-to-image translation for unsupervised domain adaptation [30], and the disease decomposition that can indicate underlying abnormal regions [31] have been exploited. The training of feature extractor might be considered so that the proximity in the latent space will be equivalent to the semantics in the digital images [32].

2.2 Fuzzy Logic based method

Hong et al. [33] examined the contour detection based image processing system for formation of blood channels based on fuzzy logic in diabetic retinopathy data. Although fuzzy logic-based approaches do not necessarily produce better performance than deep learning-based methods, they do not necessitate vast image collections, vast computing services, or period for classification process. To enhance the speed and user's interaction with the image retrieval systems, the images to be gotten to from the web sources and the CBIR framework can be executed over World wide web (WWW) and Samraj (2015) reported that the proposed fuzzy C-means algorithm offers efficient outcomes [34].

Darwish et al. (2015) presented Type-2 Fuzzy Logic (T2GFL) to overcome the two significant problems in conventional CBIR system, such as sematic gap and perception subjectivity [35]. Sriramakrishnan & Shanmugam (2012) introduced a novel image segmentation algorithm named as Fuzzy Edge Detection and Segmentation (FEDS) [36]. Wasinphongwanit & Phokharatkul (2010) proposed a conventional rough set theory for the image retrieval [37].

Lotfabadi et al. 920130 [38] developed fuzzy feature section technique. However, it utilized a single feature selection method "from a fuzzy-rough domain which utilizes fuzzy-rough dependency function". It uses the fuzzy-rough lower approximation on the basis of fuzzy-equivalent class. For this reason, Jensen & Shen (2008) recommended the fuzzy indiscernibility relations rather than fuzzy equivalence classes and features are extracted based on fuzzy boundary region [39]. However, the fuzzy rough model sensitive to the minor variation in numerical data. So, the feature extraction utilized by Zhao et al. (2009) which is an enhanced model of fuzzy-rough set [40]. Muller et al. (2004) proposed a CBIR framework through relating the features of texture analysis and colour quantization [41]. Chinnasamy (2014) presented a method based on transformation domain, segmentation and fuzzy logic for the retrieval of medical images [42].

The Type-2 Fuzzy Logic (T2FL) method was proposed to improve and solve the problems in the conventional CBIR which includes semantic gap. By employing T2FL, it has the prospective to prevail over the limitations of type-1 fuzzy logic and produce a new generation of fuzzy controllers with superior for various CBIR application to handle high level of insecurity [43].

Systems used by Fuzzy C-means Clustering algorithm provide CBIR retrieve images based on visual features such as texture, colour and shape, depending on image descriptions or textual indexing to retrieve the images from database in a fast and an efficient manner [44].

2.3 Generative Adversarial model (GAN) based method

Gupta et al. [45] proposed the Generative Adversarial model so that the scan resolution should be improved. Various forms of Generative Adversarialmodels and their implementations are generated in imaging techniques with enhanced corners and patterns for lower quality images.During training, the limited dataset and hardware limits were encountered, however these could be overcome as computing power improves. Park et al [46] adopts a strategy called generative adversarial network that uses multilayered deep fully convolutional networks to balance deficits and perform accurate and exact optic disc segmentation.It also enhanced the effectiveness of the suggested methodology by using computer vision techniques for pre- and post-processing both during M-GAN.On the majority of metrics, the proposed M-GAN outperformed than other approaches.

Iqbal & Ali [47] proposed the medical generative adversarial network that creates simulated medical information and differentiated masks, which could then be utilized for automated object recognition. Also, M-GAN synthesize the retinal images in general. The methodology aids image classification results when employed as an intensive training dataset. In comparison to previous approaches, the technique exhibited a lower proportion of false positives at nodal vessels and produced clearer lines.

Using unsupervised domain modification and synthetic aggressive networks, Mahapatra & Ge [48] suggested a novel deep learning framework for regulating various sorts of medical images. The suggested method accomplishes the dataset impartial by training on a single type of image and achieving state-of-the-art performance in registering various kinds of image.

3. CBIR based on medical images

(i) Lung cancer

The classification approach (support vector machine) is used in [49] to determine whether there is cancer in the lungs or not. This procedure demonstrates the system's ability to identify lung cancer. As a result, we can differentiate between the data and aid in diagnosis. It is estimated that the efficiency is greater than 80%. An approach based on Fourier descriptors with luminance is presented [50].

(ii) Diabetic Retinopathy

Fourier descriptor is proposed in [51] on the basis of eye tracker gaze measurements, a model for recognizing essential portions or images is provided, and the conclusions of its comparative analysis are outlined and analyzed. The software application will be integrated with technologies that will extract the feature and categorize scholarly publications linked to the ailment shown by the medical imaging. Chbeir et al. [52] proposed a hyper data model. It combines and projections a variety of visual properties to a collection of areas. Affordable option tools for diverse groups of participants: we developed a Medical Image Management System (MIMS) that has been validated in collaboration. With a group of doctors and individuals in order assess its usability and efficiency.

Bugatti et al. [53] proposed KNN classifier for CBIR systems, a new strategy to reducing the semantic gap and the "dimensionality curse" problem has been developed. The suggested methodology collects visual patterns used by physicians to detect anomalies in images and applies them not just to the data preprocessing, but also to the development of different classifiers based on these visual patterns, which combine features with various image functions in overcoming the conceptual divide embedded in CBIR systems, as well as increasing precision of the searches that are focused on content. Zhang et al. [54] introduced a novel texture generation approach extract with a distinct flavor the procedure necessitates the use of all available resources. Textural information from the spatial domain has an advantage as well as the frequency domain. The collection of dominating axes is calculated using the frequency domain.

For identifying fundus disorders, retinal vascular segmentation is critical. Furthermore, existing retinopathy segmentation approaches have flaws, such as low micro vascular segmentation and incorrect pathological data extraction. iuqin et al. [55] created a fundus retinal vascular simulation analysis on the enhanced deep learning U-Net framework to address these issues.

Deformable U-Net (DUNet) is an earlier part retinal vascular segmentation system that uses a U-shape structure to leverage the local properties of the skin lesion. Also, incorporate deformation inversion into the network model, which was influenced by the recently developed deformed convolutional networks. The proposed method segments the pathological retinal vessels, which is an early stage of diagnosing some severe disease. The DUNet provides a general, high-performance computing framework for retinal vessel segmentation. In future, more retinal vessel data will be consolidated to validate the proposed model and efficient implementation is required to decrease the computation time.

(iii) Blood cells

The creation of an approach that includes the CBIR model with another module that examines the semantics of medical diagnoses and descriptions provided to a radiology specialist. Texture and intensity extractors are four aspects were assessed by Chuctaya et al. [56]. Various trials were carried out using the large amount of data. Based on the results, the Gabor transform produces the greatest results in this case.

The technique compares a contour fingerprint from a shape's pixel intensities using the centroid distance matrix. Seng et al. [57] comes up with wavelet analysis in content based image retrieval to locate the images that are the most similar to the query image for scanned blood cells. This system's capability can be enhanced by using multi-level search, which combines two or more indexing algorithms to limit down retrieval results.

Willy& Kufer [58] presented experimental design of CBMIR, an intelligent retrieval system for processing large amounts of data. There are several organs of importance. Also demonstrated that when the suggested CBMIR was paired with a multicriteria optimization methodology, the retrieved images were more realistic than when only one optimization was used. Dong et al. [59] proposed an intelligent retrieval system for processing large amounts of data. To obtain edge detection, a grey co-occurrence matrix is used in keeping with the set. The approach is employed in content-based applications. Innovation demonstrates that the article's method can be improved retrieval effectiveness of a directional medical clustering algorithm images.

(iv) Skin Lesion

Melanoma and other fungal infections can be detected via dermoscopy, which is a common diagnostic procedure [60]. Furthermore, due to a lack of labeled data and a class-imbalanced database, skin lesion identification using computer-aided diagnostic approaches is a difficult endeavor. To conduct comparison searches, content-based image retrieval techniques rely on automated features taken from images. The main disadvantage is that such functions frequently fail to adequately express how consumers perceive and demand from them. The suggested skin lesion style-based GANs can efficiently create high-quality edge detection images, improving the detection quality of the results.

Skin lesion fragmentation is critical for computer methodologies of recognition and characterization. Clinical selected features, on the other hand, are influenced by a margin of error when accomplished by specialists. These constraints are addressed in this study, which allows for a detailed investigation of lesions' morphology as well as the retrieval of non-linear properties of province border lines. Both dermologists and computerized optimization algorithms will benefit from automated melanoma detection. Appropriate skin lesion analysis can help computer vision algorithms deliver insights on how to improve individual user's abilities by improving the initial evaluation [61].

Table. 2comparison of different images

Medical images	CT image	MRI image	Fused image
Lungs	56561	1712	5982
Blood cell	56432	1298	10938
Eye	41178	1054	6532
Skin	3987	1953	2614

An image retrieval system called Simplicity (Semantics-sensitive Integrate Matching for Picture Libraries) is proposed by Wang et al. [62]. This retrieval system uses a wavelet-based feature selection approach and the kmeans statistical clustering technique to split image regions. The results of the trials suggest that this extraction system can be effectively used for medical image retrieval. Bugatti et al. [63] provided the approach is appropriate in real-world medical settings and outperforms the well-known Rocchio methodology. To conduct similarity queries, content-based image retrieval techniques rely on automated features taken from images. The main disadvantage is that such features frequently fail to adequately represent what consumers perceive and expect from them.

Atnafuetal. [64] proposed a new image features framework that provides either metadata- and content-based image descriptions and uses also for optimal feature extraction in an image database. Multi-criteria approaches can be formulated by using this technique. The images are collected from microscopy database. MedGAN in [65] is a brand-new end-to-end solution for medical image translation. It incorporates the dependent and the imperative adversarial framework with new features that represent conjunction to improve global sustainability and environmental frequency precision of results, and a CasNET generator framework. The above method is used for CBIR image classification which provides Higher accuracy and mAP compare with other works; high dimension descriptors such as HOG; Sensitivity to intra-class as well as inter-class variety; High performance on imbalanced databases. Due to the high use of digital images in hospitals and clinics, there is an increase in the size of medical images' databases [66].

The above table shows the comparative study of various papers and their advantages. Comparing this our paper provides better efficiency.

Table. 3 Comparative study of existing methods

Ref	Diseases referred	Proposed Method	Advantages
[24]	ophthalmological and cardiovascular disease	CNN(Transfer learning)	Transfer learning does requires lot of data, improves baseline performance, decrease training time
[25]	cell nuclei and thorax	U-Net Architecture	high accuracy
[28]	chronic vascular diseases and diabetes	scale-space approximation	Retinal scale-space approximated CNN (SSANet) achieves state-of-the-art accuracy across four publicly available datasets
[45]	diabetic retinopathy and vascular occlusion	M-GAN with two stacked FCN(Multi kernel pooling b/w FCN)	Accurate and precise segmentation was confirmed by deriving the best performance from all four datasets,
[59]	melanoma	transfer learning	leading to the performance improvement of the classification model
[60]	skin lesion variations.	clustering algorithm	Efficiency is high when compared to the others used in the study.

[67]	General	Multi-module fine Tuning	Learning and optimizing node weight under all kinds of Single-models circumstance
[68]	diabetic retinopathy, Age-related Macular Degeneration (AMD)	STEAR algorithm	do not require having large image datasets
[69]	glaucoma, diabetic retina, RVO and RAO, Diabetes Retinopathy	Fuzzy kohonen clustering network(GIFKCN)	The proposed method is more effective based on the sensitivity, FPF and accuracy as compared to the other methods.
[70]	glaucoma	Sequential Minimal Optimization (SMO), and Random Forest	capable of distinguishing and classifying abnormalities in retina
[71]	Fundus disease	Residual learning along with Nesterov Adaptive Moment Estimation (Nadam)	proposed algorithm reduced network complexity and improved segmentation accuracy
[72]	Diabetic Retinopathy (DR)	deformable convolution	It provides high-performance computing framework for retinal vessel segmentation.
[73]	hypertension, diabetes, arteriosclerosis, cardiovascular disease, and stroke	GMM classifier	Efficiently extracts main blood vessels but also segments small blood vessels

4.CONCLUSION

A strategy for retrieving more relevant images is content-based image retrieval. A long-standing issue in digital image processing is retrieving just comparable images. CBMIR is an excellent solution for better managing this problem because it assists in locating relevant images from vast medical collections. To address the problem of the semantic gap, machine learning techniques can be investigated. Using machine learning approaches, we narrowed the semantic gap by learning discriminative features directly from images and therefore classifying the images. This paper presents a thorough overview of Deep Learning (DL) methods for the content based medical image retrieval. A performance examination of the existing DL based picture recovery strategies is likewise directed as far as the mean normal accuracy for various no. of recovered pictures. The examination pattern in image retrieval proposes that the DL based models are driving the advancement. A recently developed models like auto encoder networks, generative adversarial networks and reinforcement learning have demonstrated the superior performance for image retrieval. The revelation of better objective function has been additionally the pattern to oblige the learning of the hash code for discriminative, vigorous and effective image retrieval. The semantic preserving class-specific feature learning utilizing various networks and quantitation methods is also the new pattern for the image retrieval. Other trends include utilization of attention module, transfer learning, etc. The utilization of multi-layer CNN of the CBRI performs better than the single layer features and offers competitive performance on different famous CBIR benchmarks. The hashing based CBIR method with DCNN is utilized to generate the hash codes and predicts the labels of image. The DCNN based CBIR system effectively performs the image retrieval. The CBIR system in fusion with DL and compressed feature also provides the better performance. The integration of DL with CBIR application can be experimented and tested as a future research direction.

CONFLICT OF INTEREST

Concerning the writing, and publishing of this manuscript, the authors reported no conflicts.

ACKNOWLEDGEMENT

The author’s expresses the sincere thanks toA.V.V.M Sri Pushpam College(Autonomous), for their support in the completion of this manuscript.

REFERENCES:

[1] Nguyen, K., Nguyen, H.H., Tiulpin, A. AdaTriplet: Adaptive Gradient Triplet Loss with Automatic Margin Learning for Forensic Medical Image Matching. In: Wang, L., Dou, Q., Fletcher, P.T., Speidel, S., Li, S. (eds) Medical Image Computing and Computer Assisted Intervention – MICCAI 2022. Lecture Notes in Computer Science, vol 13438.

[2] A Arun and P Nirmaladevi, A Survey on Current Semantic level Algorithms for improving Performance in CBIR 2021 IOP Conf. Ser.: Mater. Sci. Eng. 1055 012118.

[3] Hirald Dwaraka Praveena, Nirmala S. Guptha, Afsaneh Kazemzadeh, B. D. Parameshachari, and K. L. Hemalatha, Effective CBMIR System Using Hybrid Features-Based Independent Condensed Nearest neighbor Model, Hindawi, Journal of Healthcare Engineering, 2022, 9 pages.

[4] Kumar, S., Pradhan, J., Pal, A.K. et al. Radiological image retrieval technique using multi-resolution texture and shape features. Multimed Tools Appl., 81, 13633–13660 (2022)

[5] Dash, S., Shakyawar, S. K., Sharma, M., & Kaushik, S. 2019. Big data in healthcare: management, analysis and future prospects. Journal of Big Data, 6(1), 1-25.

[6] Bhamare, D. P., & Abhang, S. A. 2015. Content based image retrieval: A review. International Journal Of Computer Science And Applications, 8(2).

[7] Dargan, S., Kumar, M., Ayyagari, M. R., & Kumar, G. 2020. A survey of deep learning and its applications: a new paradigm to machine learning. Archives of Computational Methods in Engineering, 27(4), 1071-1092.

[8] Subhadip Maji, Smarajit Bose, CBIR Using Features Derived by Deep Learning, ACM/IMS Transactions on Data ScienceVolume 2Issue 3August 2021 Article No.: 26pp 1–24.

[9] Rashmi Vishraj, Savita Gupta, Sukhwinder Singh,A comprehensive review of content-based image retrieval systems using deep learning and hand-crafted features in medical imaging: Research challenges and future directions,Computers and Electrical Engineering,Volume 104, Part A,2022,108450.

[10] Kabir, M. A. 2020. Retinal Blood Vessel Extraction Based on Adaptive Segmentation Algorithm. In 2020 IEEE Region 10 Symposium (TENSYMP) (pp. 1576-1579). IEEE.

[11] Latif, A., Rasheed, A., Sajid, U., Ahmed, J., Ali, N., Ratyal, N. I., & Khalil, T., 2019. Content-based image retrieval and feature extraction: a comprehensive review. Mathematical Problems in Engineering, 2019.

[12] Bansal, M., Kumar, M., & Kumar, M. (2020, February). 2D object recognition techniques: State-of-the-art work. Archives of Computational Methods in Engineering, 28(3), 1147-1161.

[13] Kazuma Kobayashi, Ryuichiro Hataya, Yusuke Kurose, Mototaka Miyake, Masamichi Takahashi, Akiko Nakagawa, Tatsuya Harada, Ryuji Hamamoto, Decomposing normal and abnormal features of medical images for content-based image retrieval of glioma imaging,Medical Image Analysis,Volume 74,2021,102227,ISSN 1361-8415.

[14] Yin, S., & Bi, J., 2018, July. Medical image annotation based on deep transfer learning. In 2018 IEEE International Conference on Internet of Things (iThings) and IEEE Green Computing and Communications (GreenCom) and IEEE Cyber, Physical and Social Computing (CPSCom) and IEEE Smart Data (SmartData) (pp. 47-49).

[15] Agrawal, S., Chowdhary, A., Agarwala, S. et al. Content-based medical image retrieval system for lung diseases using deep CNNs. Int. j. inf. tecnol. 14, 3619–3627 (2022).

[16] Venketbabu, T., Arunkumar, R., & Balasubramanian, M. (2020). Improved Convolutional Neural Networks in Content Based Image Retrieval System for Medical Image Analysis. Solid State Technology, 63(6), 9194-9208.(18)

[17] Qayyum, A., Anwar, S. M., Awais, M., & Majid, M. (2017). Medical image retrieval using deep convolutional neural network. Neurocomputing, 266, 8-20. (19)

[18] Haripriya, P., & Porkodi, R. (2021). Parallel deep convolutional neural network for content based medical image retrieval. Journal of Ambient Intelligence and Humanized Computing, 12(1), 781-795. (20)

[19] Zhang, S., Zhi, L., & Zhou, T. (2020). Medical image retrieval using empirical mode decomposition with deep convolutional neural network. BioMed Research International, 2020. (21)

[20] Cai, Y., Li, Y., Qiu, C., Ma, J., & Gao, X. (2019). Medical image retrieval based on convolutional neural network and supervised hashing. IEEE access, 7, 51877-51885. (22)

[21] Sundararajan, S. K., Sankaragomathi, B., & Priya, D. S. (2019). Deep belief CNN feature representation basedcontent based image retrieval for medical images. Journal of medical systems, 43(6), 1-9.

[22] Jiang, Z., Zhang, H., Wang, Y., & Ko, S. B. 2018. Retinal blood vessel segmentation using fully convolutional network with transfer learning. Computerized Medical Imaging and Graphics, 68, 1-15.

[23] Mostayed, A., Wee, W. G., & Zhou, X. 2019, December). Content-Adaptive U-Net Architecture for Medical Image Segmentation. In 2019 International Conference on Computational Science and Computational Intelligence (CSCI) (pp. 698-702).

[24] Ali Ahmed, Alaa Omran Almagrabi, Ahmed Hamza Osman, Pre-trained convolution neural networks models for content-based medical image retrieval, International Journal of Advanced and Applied Sciences, 9(12) 2022, Pages: 11-24.

[25] Abdelhalim, I. S. A., Mohamed, M. F., &Mahdy, Y. B. 2021. Data augmentation for skin lesion using self-attention based progressive generative adversarial network. Expert Systems With Applications, 165, 113922.

[26] Noh, K. J., Park, S. J., & Lee, S. 2019. Scale-space approximated convolutional neural networks for retinal vessel segmentation. Computer methods and programs in biomedicine, 178, 237-246.

[27] Zheng, K. 2015. Content-based image retrieval for medical image. In 2015 11th International Conference on Computational Intelligence and Security (CIS) (pp. 219-222). IEEE.

[28] Pei, Wu, Huang, Zhuang, 2021C. Pei, F. Wu, L. Huang, X. Zhuang, Disentangle domain features for cross-modality cardiac image segmentation, Med. Image Anal., 71 (2021), p. 102078.

[29] Y. Tang, Y. Tang, Y. Zhu, J. Xiao, R.M. Summers, A disentangled generative model for disease decomposition in chest X-rays via normal image synthesis, Med. Image Anal., 67 (2021).

[30] Hong, S., Wen-Cheng, C., & Li, T.2006, Medical image description in content-based image retrieval. In 2005 IEEE Engineering in Medicine and Biology 27th Annual Conference (pp. 6336-6339).

[31] Saad M. Darwish and Raad A. Ali, Observations on Using Type-2 Fuzzy Logic for Reducing Semantic Gap in Content–Based Image Retrieval System, IJCTE 2015 Vol.7(1): 1-8 ISSN: 1793-8201.

[32] Samraj, J. (2015). NazreenBee. M," Content Based Medical Image Retrieval Using Fuzzy C-Means Clustering With RF ". International Journal of Innovative Science, Engineering & Technology, 2(1).

[33] Darwish, S. M., & Ali, R. A. (2015). Observations on using type-2 fuzzy logic for reducing semantic gap in content–based image retrieval system. International Journal of Computer Theory and Engineering, 7(1), 1.

[34] Sriramakrishnan, C., & Shanmugam, A. (2012). An fuzzy neural approach for medical image retrieval. Journal of Computer Science 2012, 8 (11), 1809-1813.

[35] Wasinphongwanit, P., & Phokharatkul, P. (2010, August). Image retrieval using contour feature with rough set method. In 2010 International Conference on Computer, Mechatronics, Control and Electronic Engineering (Vol. 6, pp. 349-352). IEEE.

[36] Lotfabadi, M. S., Shiratuddin, M. F., & Wong, K. W. (2013, April). Using fuzzy rough feature selection for image retrieval system. In 2013 IEEE Symposium on Computational Intelligence for Multimedia, Signal and Vision Processing (CIMSIVP) (pp. 42-48). IEEE.

[37] Jensen, R., & Shen, Q. (2008). New approaches to fuzzy-rough feature selection. IEEE Transactions on fuzzy systems, 17(4), 824-838.

[38] Zhao, S., Tsang, E. C., & Chen, D. (2009). The model of fuzzy variable precision rough sets. IEEE transactions on Fuzzy Systems, 17(2), 451-467.

[39] Muller, H., Rosset, A., Vallee, J. P., & Geissbuhler, A. (2004, April). Comparing features sets for content-based image retrieval in a medical-case database. In Medical Imaging 2004: PACS and Imaging Informatics (Vol. 5371, pp. 99-109). SPIE.

[40] Chinnasamy, S. (2014). Performance improvement of fuzzy-based algorithms for medical image retrieval. IET Image Processing, 8(6), 319-326

[41] Umar Bashir and Preeti Sondhi, FUZZY C-MEANS BASED IMAGE RETRIEVAL SYSTEM, International Journal of Multidisciplinary Education Research, 2021, 10

[42] Gupta, R., Sharma, A., & Kumar, A., 2020. Super-resolution using GANs for medical imaging. Procedia Computer Science, 173, 28-35.

[43] Park, K. B., Choi, S. H., & Lee, J. Y., 2020. M-gan: Retinal blood vessel segmentation by balancing losses through stacked deep fully convolutional networks. IEEE Access, 8, 146308-146322.

[44] Iqbal, T., & Ali, H., 2018, Generative adversarial network for medical images (MI-GAN). Journal of medical systems, 42(11), 1-11.

[45] Mahapatra, D., & Ge, Z., 2020. Training data independent image registration using generative adversarial networks and domain adaptation. Pattern Recognition, 100, 107109.

[46] Agarwal, R., Shankhadhar, A., & Sagar, R. K., 2015, Detection of lung cancer using content based medical image retrieval. In 2015 Fifth International Conference on Advanced Computing & Communication Technologies (pp. 48-52).

[47] Zhang, G., Ma, Z. M., He, Y., & Zhao, T. N., 2008. Texture characteristic extraction for dominant directions in content-based medical image retrieval. In 2008 International Conference on BioMedical Engineering and Informatics (Vol. 2, pp. 253-257).

[48] Maiorana, F. 2013. A medical content based image retrieval system with eye tracking relevance feedback. In Proceedings of the 26th IEEE International Symposium on Computer-Based Medical Systems, 297-302. IEEE.

[49] Chbeir, R., Amghar, Y., Flory, A., &Brunie, L, 2001, A hyper-spaced data model for content and semantic-based medical image retrieval. In Proceedings ACS/IEEE International Conference on Computer Systems and Applications, 161-167, IEEE.

[50] Bugatti, P. H., Ribeiro, M. X., Traina, A. J. M., & Junior, C. T., 2008, Content-based retrieval of medical images by continuous feature selection. In 2008 21st IEEE International Symposium on Computer-Based Medical Systems, 272-277, IEEE.

[51] Zhang, G., Ma, Z. M., Tong, Q., He, Y., & Zhao, T. 2008, Shape feature extraction using Fourier descriptors with brightness in content-based medical image retrieval. In 2008 International Conference on Intelligent Information Hiding and Multimedia Signal Processing (pp. 71-74).

[52] Xiuqin, P., Zhang, Q., Zhang, H., & Li, S. 2019. A fundus retinal vessels segmentation scheme based on the improved deep learning U-Net model. IEEE Access, 7, 122634-122643.

[53] Chuctaya, H., Portugal, C., Beltrán, C., Gutiérrez, J., López, C., &Túpac, Y. 2011, M-CBIR: A medical content-based image retrieval system using metric data-structures. In 2011 30th International Conference of the Chilean Computer Science Society (pp. 135-141). IEEE.

[54] Seng, W. C., &Mirisaee, S. H., 2009, A content-based retrieval system for blood cells images. In 2009 International Conference on Future Computer and Communication (pp. 412-415). IEEE.

[55] Willy, P. M., &Kufer, K. H., 2004. Content-based medical image retrieval (CBMIR): an intelligent retrieval system for handling multiple organs of interest. In Proceedings. 17th IEEE Symposium on Computer-Based Medical Systems (pp. 103-108). IEEE.

[56] Dong, S., Dong, K., & Yin, L., 2013, The application of local structure classification in content-based 3d medical image retrieval. In 2013 Seventh International Conference on Image and Graphics (pp. 639-642). IEEE.

[57] Qin, Z., Liu, Z., Zhu, P., & Xue, Y., 2020. A GAN-based image synthesis method for skin lesion classification. Computer Methods and Programs in Biomedicine, 195, 105568.

[58] Pereira, P. M., Fonseca-Pinto, R., Paiva, R. P., Assuncao, P. A., Tavora, L. M., Thomaz, L. A., &Faria, S. M., 2020. Dermoscopic skin lesion image segmentation based on local binary pattern clustering: comparative study. Biomedical Signal Processing and Control, 59, 101924.

[59] Wang, J. Z., Li, J., & Wiederholdy, G., 2000, November). Simplicity: Semantics-sensitive integrated matching for picture libraries. In International Conference on Advances in Visual Information Systems, 360-371. Springer, Berlin, Heidelberg.

[60] Bugatti, P. H., Ponciano-Silva, M., Traina, A. J., Traina, C., & Marques, P. M., 2009, Content-based retrieval of medical images: from context to perception. In 2009 22nd IEEE International Symposium on Computer-Based Medical Systems (pp. 1-8). IEEE.

[61] Atnafu, S., Chbeir, R., &Brunie, L., 2002, June). Content-based and metadata retrieval in medical image database. In Proceedings of 15th IEEE Symposium on Computer-Based Medical Systems (CBMS 2002) (pp. 327-332). IEEE

[62] Armanious, K., Jiang, C., Fischer, M., Küstner, T., Hepp, T., Nikolaou, K., & Yang, B. 2020. MedGAN: Medical image translation using GANs. Computerized Medical Imaging and Graphics, 79, 101684.

[63] Shakarami A, Tarrah H. An efficient image descriptor for image classification and CBIR. Optik (Stuttg). 2020 Jul;214:164833.

[64] (a) Dureja, A., Pahwa, P. (2022). Medical Diagnosis Using Image-Based Deep Learning and Supervised Hashing Approach. In: Unhelker, B., Pandey, H.M., Raj, G. (eds) Applications of Artificial Intelligence and Machine Learning. Lecture Notes in Electrical Engineering, vol 925.(b) Rout, N.K., Ahirwal, M.K. & Atulkar, M. Content-Based Medical Image Retrieval System for Skin Melanoma Diagnosis Based on Optimized Pair-Wise Comparison Approach. J Digit Imaging (2022)

[65] Yin, S., & Bi, J., 2018, Medical image annotation based on deep transfer learning. In 2018 IEEE International Conference on Internet of Things (iThings) and IEEE Green Computing and Communications (GreenCom) and IEEE Cyber, Physical and Social Computing (CPSCom) and IEEE Smart Data (SmartData) 47-49. IEEE.

[66] Orujov, F., Maskeliūnas, R., Damaševičius, R., & Wei, W., 2020. Fuzzy based image edge detection algorithm for blood vessel detection in retinal images. Applied Soft Computing, 94, 106452.

[67] Mondal, S. S., Mandal, N., Singh, A., & Singh, K. K., 2020. Blood vessel detection from Retinal fundas images using GIFKCN classifier. Procedia Computer Science, 167, 2060-2069.

[68] Bisneto, T. R. V., de Carvalho Filho, A. O., & Magalhães, D. M. V., 2020. Generative adversarial network and texture features applied to automatic glaucoma detection. Applied Soft Computing, 90, 106165.

[69] Xiuqin, P., Zhang, Q., Zhang, H., & Li, S., 2019. A fundus retinal vessels segmentation scheme based on the improved deep learning U-Net model. IEEE Access, 7, 122634-122643.

[70] Jin, Q., Meng, Z., Pham, T. D., Chen, Q., Wei, L., &Su, R., 2019. DUNet: A deformable network for retinal vessel segmentation. Knowledge-Based Systems, 178, 149-162.

[71] Zhao, J., Gong, W., Huang, J., Jiang, S., Huang, Z., & Tu, Y., 2019. A New Method for Retinal Vascular Segmentation based on the GMM Algorithm. In 2019 IEEE 8th Joint International Information Technology and Artificial Intelligence Conference (ITAIC) (pp. 1875-1878). IEEE.