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Research Article

Improved Support Vector Machine Kernel Utilising Hybrid Evolutionary Techniques for Medical Image Classification

Dr J. Anvar Shathik[1], Krovvidi S B Ambika[2], Dr Kavita Tukaram Patil[3], Dr G Madhu Sudan[4], Roopa U[5], S. Harish[6]

[1]Professor, Department of Computer Science & Engineering, Anjuman Institute of Technology and Management, Belalkanda, Bhatkal, Karnataka, 581320 Email: anvarshathik@gmail.com

[2]Assistant Professor, Department of CSE, Aditya University, Surampalem, Andhra Pradesh

[3]Assistant Professor, SVKM's Institute of Technology, Dhule-424001

Email: meetpatilkavita@gmail.com

[4]Assistant Professor, Department of Statistics, Faculty of Science, Central University of Allahabad, Prayagraj, Uttar Pradesh. Email: gmadhusudan7@gmail.com

[5]Assistant Professor, Department of Management Studies, Dayananda Sagar College of Engineering, Bangalore, Karnataka

[6]Assistant Professor, Department of Mechanical Engineering, Cambridge Institute of Technology, Bengaluru, Karnataka Email: harishs.mech@cambridge.edu.in

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ABSTRACT

Digital imaging advancements have led to the creation and storage of massive medical picture archives. Images captured by X-ray, CT, MRI, PET, and ultrasound machines provide crucial anatomical and functional data for use in diagnosis, research, and education. Digital medical photos provide a large and diverse medical database. Good image retrieval systems are essential for the effective search of large data sets. Image Searching Based on Content CBIR is currently often used in the medical imaging retrieval industry to find pictures in the database that are comparable to the query image. Feature extraction and matching are the two main components of CBIR. Extracting characteristics from a picture in order to create a unique representation is known as "feature extraction." Extend Feature vectors are a kind of visual data that includes information like colour, texture, and shape. Both query pictures and stored images in databases go through this procedure. In order to find a suitable match, Feature Matching compares certain characteristics of each picture in the database. The most challenging aspect of CBIR systems is the incorporation of flexible methods for processing pictures with a wide range of attributes and classifications. This study investigates the challenge of extracting medical photos from a large and diverse collection. The primary goal of this study is to compare and contrast existing content-based image retrieval classification techniques, and to propose a new classification methodology.

Keywords: *(Computed Tomography), Feature Matching, Feature Extraction, Content Based Image Retrieval, Magnetic resonance imaging.*

Introduction

Increases in the accessibility of high-resolution medical imaging modalities including X-rays, MRIs, CT scans, and histopathological pictures have led to amazing developments in the area of medical image analysis in recent years. These imaging methods are now crucial to medical diagnosis, therapy planning, and follow-up. The intricacy of these pictures and the urgency with which diagnoses must be made make good interpretation and categorization difficult[1-3].

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The automatic categorization of medical images is a growing field, and machine learning algorithms have emerged as strong tools in this arena. Support Vector Machines (SVMs) are one kind of algorithm that has shown itself adept at tackling classification problems like these. SVMs are well-suited for complex image analysis applications because to their proficiency in locating optimum decision boundaries, especially in high-dimensional feature fields[4].

While SVMs are useful, they are very sensitive to the kernel function and model parameters that are used. Choosing an appropriate kernel and tweaking its settings may be difficult and time-consuming. In addition, conventional approaches to parameter tuning often include heuristic algorithms or grid searches, neither of which guarantees an optimum result. As a result, we need cutting-edge methods that can improve the SVM's performance in medical picture categorization[5].

Exploring novel approaches that may considerably boost the performance of SVMs in medical picture categorization is the driving force behind this study. By combining genetic algorithms with particle swarm optimisation, we hope to speed up and improve the process of selecting and optimising SVM parameters automatically. We anticipate that this will lead to improved medical picture categorization and a lighter workload for doctors and researchers.[6]

Clinical and scientific communities rely heavily on medical image analysis to help with illness diagnosis and treatment planning in the current healthcare system. Medical imaging modalities such as X-rays, MRIs, CT scans, and histopathological pictures have grown crucial due to the increased information they provide in conducting thorough diagnoses as technology has advanced. However, accurate categorization and analysis, which often involves complex, multidimensional data, is necessary to fully use these pictures.[7]

Machine learning algorithms have established themselves as a cornerstone of medical research and clinical applications in the quest to automate and improve the accuracy of medical picture categorization. Medical image analysis is only one of many categorization jobs where Support Vector Machines (SVMs) have shown their worth. They shine in this field thanks to their capacity for pinpointing appropriate decision limits in high-dimensional feature fields. Selecting an appropriate kernel function and setting appropriate hyper parameters are crucial to the success of SVMs.

The primary challenge in CBIR systems is the incorporation of flexible methods for processing pictures of varying features and classifications. Medical picture retrieval from a large and diverse database is the topic of this study. This study's overarching goal is to examine the performance of existing content-based image retrieval classification algorithms and to suggest a unique classification method based on their findings. The primary challenge in CBIR systems is the incorporation of flexible methods for processing pictures of varying features and classifications. Medical picture retrieval from a large and diverse database is the topic of this study.

This study's overarching goal is to examine the performance of existing content-based image retrieval classification algorithms and to suggest a unique classification method based on their findings. How well an image classification system works is contingent on three factors: feature extraction method, feature selection method, and classification algorithm. The feature extraction method must be able to retrieve features in which the classification process remains unaffected by changes in the feature's scale or rotation in the spatial domain. Because of the nature of pictures, this is challenging to do in the spatial realm. Different areas of the body produce medical pictures with varying forms and properties[8].

The term "Content Based Image Retrieval" (or "CBIR" for short) refers to a method of searching for photos in a big image database based on a user's query using visual cues. Industrial, forensic, remote sensing and instructional uses are just some of the places where CBIR has been put to use. It's proof that the medical research and system development fields are making great strides forward. As a diagnostic tool, Content-Based Medical Image Retrieval (CBMIR) is optimised for a variety of medical tasks, including classification, data mining, and the retrieval of problematic areas that are visually comparable. In several medical specialties, including dermatology, cytology, histology, cardiology, and radiology, CBMIR plays a crucial role in reducing diagnostic turnaround times.

Content-Based Image Retrieval

Today, more and more pictures are taken and kept digitally thanks to the proliferation of the internet and other information technologies. Because of this, there is a pressing need for efficient methods of managing massive collections of images and retrieving relevant images. As a result, solving the retrieval issue requires the creation of an automated picture retrieval system.

With the proliferation of online picture archives over the last several decades, content-based image retrieval has emerged as a vibrant field of study. Recent years have seen a shift away from text-based picture retrieval and towards the use of Content-Based picture Retrieval techniques instead. This not only helps with the problems of manual annotation taking too long, having too much human involvement, and lacking unity and impartiality, but it also allows for the input of pictures' numerous visual information into retrieval systems.[9]

Many academics are drawn to CBIR because the methods, tools, and algorithms utilised in it draw from a wide range of disciplines, including pattern recognition, statistics, and computer vision. It's a very new field of study; therefore there are still many questions to be answered. CBIR offers a wide variety of potential uses, from museums and medical studies to foretelling the weather and designing new fabrics.

The CBIR system excels when traditional keyword searches fail because of its emphasis on automated retrieval. CBIR use visual qualities including gloss, texture, and form to store, identify, and search for photos based on the premise that semantically important images have comparable visual properties. Images may be retrieved from a database using content-based image retrieval (CBIR), as opposed to utilising just text indices. The basic objective of CBIR is to train a computer to recognise high-level concepts like sunsets, people, and mountains in digital photographs[10]. This raises the issue of how a computer translates between the numerical arrays that make up digital pictures and the meanings of the words that describe them. These days, content-based picture retrieval is used by a few online businesses. Perhaps the most well-known is tiny eye, a search engine for finding comparable photographs on the Internet. However, other picture search engines like Google Images have yet to incorporate similar improvements.

Information retrieval attempts to answer questions posed by users by locating records in a database that contain answers to those questions. Computer-based image retrieval (CBIR) relies on area segmentation methods that have been widely studied in computer vision, and the determination of relevance is the most difficult part of CBIR[11]. Complete object segmentation is a more involved method of picture division that yields semantically significant things (such a ball, a vehicle, or a horse).. Primitive aspects, such as colour, shape, and texture, and even spatial connections between objects, are automatically retrieved and used as the basis for content-based picture retrieval. Well-known examples of commercial solutions based on CBIR technology include Query-based image content (QBIC). There have been several investigations into and methods developed for representing visual features. To scientists in the field of computer vision, "bridging the semantic gap" is one of the most formidable tasks. Humans have the ability to discriminate between things thanks to their years of life experience; they look at an image from several angles before deciding what it is.

A variety of general-purpose image retrieval engines have been built, however there is still a lack of understanding on how to choose and use basic characteristics to identify pictures. Large picture databases have expanded quickly in recent years. Images captured by satellites are sent to NASA every day, totalling 1.5 terabytes. Every day, thousands upon thousands of photographs are taken for various purposes and saved digitally all over the globe. There are now a few of content-based picture retrieval systems out there, but many of them are either too niche or fall short of customers' needs.

Numerous academic and commercial content retrieval applications have been developed. Over the last decade, CBIR has emerged as a thriving sector of image retrieval research. The rapid development of new technologies has made CBIR for medical pictures an absolute need[12]. For simple retrieval, it is necessary to thoroughly extract and categorise an image's information using effective methods.

Typically, medical pictures are a composite, highly inconsistent, and diverse collection of very small structures. Then, feature extraction and picture classification are required to facilitate straightforward restoration. One of the most active areas of study in the computer vision community is content based visual information retrieval (CBIR). In terms of image retrieval, CBIR is more reliable and convenient. The CBIR system analyses user-defined criteria to obtain the best possible photos.

Input photos are obtained, features are extracted, images are classified, and ultimately, the classified images are stored in a database of image features that may be accessed via web-based services in order to get images with comparable content. Colour, texture, and form are only some of the low-level properties that may be extracted using the MUVISX technology. It compares the query image to the user-defined database and returns the photos that are the most like the query image. Comparable systems and software to MUVISX include QBIC Visual SEEK, SQUID, and Photo book. CBIR drastically reduces the time it takes to recover lost data compared to traditional methods of retrieval.

Content Based Image Retrieval in Medical Domain

There has been a meteoric rise in the volume and complexity of digital data created, stored, communicated, analysed, and accessible in hospitals as a result of the proliferation of computer technology in the medical arena. A system that can automatically archive and retrieve the vast quantities of digital photographs produced by healthcare facilities is essential. More and more digital photographs are being gathered and utilised in the medical field, necessitating the development of new methods for managing visual data. To retrieve a picture, most existing medical image archives need either the patient's identity or a set of textual key words contained in the patient's record.[13]

CBIR has been widely discussed in the imaging community and used in the medical imaging industry during the last several years. Visual resemblance is, of course, more trustworthy than text-based similarity, and thus makes picture retrieval based on image content more useful in many contexts. The visual qualities of medical pictures have been found to have a significant impact on diagnosis, according to clinical data. With the advent of PACS, there has been a growing need to centrally store and organise all patient-related data, including but not limited to text, photos, charts, temporal data, etc. For PACS to effectively enhance care quality and efficiency, it must have methods that enable rapid retrieval of medical images. The retrieval should also deliver photographs that satisfy the criteria supplied by the professionals in order to help the doctor efficiently analyse and diagnose the problem. The diagnostic utility of PACS is enhanced by the incorporation of CBIR features that make it simpler and more efficient for medical staff to work with stored pictures.

Proposed CBIR Framework

In Figure 1.we see the basic layout of a CBIR that may be used with query pictures. Image databases, queries, pre-processing, segmentation, feature extraction, a feature database, similarity measurements, and an image ranking scheme are all part of the system.

Enrollment and inquiry are the two primary subsystems involved in the realisation of CBIR for query pictures. Data is gathered by the enrolment system via the query image database. From both public query databases and hospital picture archives, we collect and preserve a wide variety of original normal and pathological query photographs. These photographs undergo preliminary processing[14].

After that, features are taken from the ROI's segmented pictures and saved to the feature database. Using the user's query, the query subsystem will search the picture database for matching images. Pre-processing and segmentation are applied to this picture as well. Next, features are taken from the region of interest. Using a distance metric, we compare the features of the images in our database with

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the characteristics in our query and choose the ones that are most similar. The best possible matches are ranked and retrieved for diagnostic analysis.

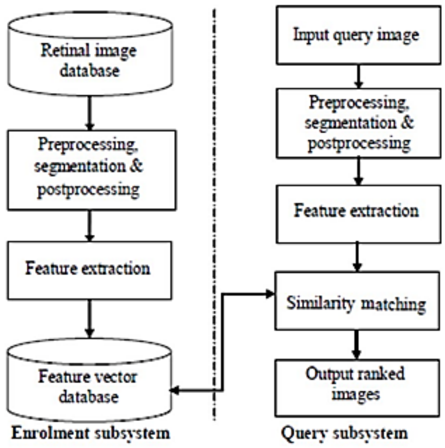

Figure 1. CBIR framework

CT scan pictures are used as input in the proposed medical image retrieval system. The suggested CBIR system is shown in block form in Figure 2. An HSV picture is created that combines the results of the query with the database.

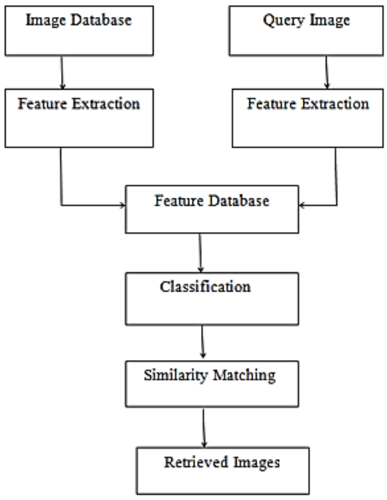

Figure 2. Block diagram of proposed CBIR

Feature Extraction

Multimedia data mining serves a crucial purpose in the study of medical image retrieval and categorization. Feature extraction is crucial for effective image retrieval. However, it is exceedingly challenging to extract information from medical images owing to the variety of image feature extraction, the diverse assessment methodologies, and the clinical criteria. Semantic feature extraction may vary greatly amongst mining techniques. Global image properties-based, neighborhood-level features-based, relevance feedback-based, and semantic-based research have all made significant strides in CBIR.

In the beginning, algorithms were created to assist recover photos based on their low-level properties, such as colour, texture, and form. They work well for simple photos or those with little semantic meaning and are straightforward to implement. However, these algorithms have significant restrictions when working with vast content picture databases, and it is difficult for the semantics of an image to be exposed by the visual characteristics. Therefore, region-based image retrieval techniques based on picture segmentation were developed to boost the CBIR systems' retrieval accuracy. By portraying pictures at the object level, which is meant to be nearer to the perception of the human visual system, these techniques hope to address the shortcomings of global features. Segmentation outcomes are crucial to the success of such approaches. Segmenting pictures into regions and then using this segmentation to obtain two-dimensional visual characteristics for region-based queries is a common practise in traditional CBIR systems for medical imaging. Multidimensional feature extraction may present fresh possibilities for visual feature extraction and retrieval, but such methods have the advantage of including only relevant regions in the formulation of a query. This is especially true for medical images, which are inherently multidimensional. The suggested technique employs the Fuzzy C-means clustering algorithm to extract features based on segmentation.

The two main components of any content-based retrieval strategy are feature extraction performed offline and picture retrieval performed in real-time. The system uses efficient content based image retrieval, in which visual properties (colour, shape, texture, and spatial information) are extracted automatically from each picture in the database based on its pixel values and stored in a separate database inside the system. However, a much more compelling case for using the signature is to infer a stronger link between picture representation and visual semantics. Using an online image retrieval system, a user may submit a query example in order to locate certain pictures.

One of the crucial jobs in CBIR is the extraction of excellent features that compactly describe a query picture. Both the query and the database pictures are analysed for their distinguishing properties. A feature vector is used by the system to represent this specific case. Although the CBIR function may be fully implemented with only a single feature, the resulting performance is less than ideal. For instance, colour histograms might provide unexpected results in terms of retrieval since they ignore spatial information. Texture and form both have their own restrictions, much as the colour histogram does.

You can't boil down an image's worth of aesthetic qualities into a single characteristic. The most accurate response is to integrate numerous characteristics by automatically assigning weights to each feature component in accordance with the needs of a given application. The pictures that were retrieved are reorganised in accordance with the global similarity measure after being sorted by similarity using the CBIR algorithm with a single feature. Delivering the 'n' most comparable photos to the user. Since the ranked pictures produced by various single features have varying similarity weight when fused, normalisation within a feature is required prior to the construction of the comprehensive similarity measure.

Experimental Results

It is not recommended to directly handle raw pictures from MRI scanners or query MRI databases due to the presence of artefacts. The presence of extraneous tissues, blurring from vibration, and background noise are just a few examples. The only way to get very precise outcomes is to get rid of these undesirable characteristics. Researchers and programmers often have strong preferences when it comes to the pre-processing stage of image analysis utilising a CAD system. The programmer decides the intended procedure and the order of operations. Data collecting technique and scanner characteristics will determine the next steps. For accurate tumour analysis, it is essential to employ the optimal number of MRI slices. To improve the quality of the MR image for further analysis is the primary goal of pre-processing. Noise, background, and pixel intensity range will all vary depending on the equipment and subjects used to create the MR picture. Noise analysis is hindered by poor

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picture quality and distracting areas. Segmentation algorithms can only perform as well as the pre-processing of the pictures they are fed into them.

Extracting features from a picture condenses it down to just the essentials, revealing the image's pixel structure in the process. The recovered features vectors inform the classifier about the GLCM qualities of the input picture, which helps the classifier better understand the image. The primary objective of the features extraction procedure is to reduce the time, effort, and information needed to describe a huge dataset of pictures. When processing MR pictures, GLCM is utilised to remove unnecessary details. The suggested features extraction method is the quickest, easiest, and most effective option. The effectiveness and precision of a classification algorithm are dependent on the quality of the retrieved features.

Database

All the image segments available in the database are in the pivotal perspective, with a pixel size of either 256 or 512 and a bit depth of 16. The McConnell Brain Imaging Centre at the Montreal Neurological Institute at McGill University is the source of these images, which may be accessed via the Brain Web Database. The need for certification of such systems is rising in tandem with rising interest in computer-aided quantitative analysis of medical image data. Unfortunately, there is no 'ground truth' or highest quality level for assessing the study of collected data. As a Simulated Brain Database (SBD), these pages provide a solution to the endorsement problem. The SBD stores a collection of manageable MRI data volumes generated by an MRI diagnostics device. The neuroimaging community may use these measurements to evaluate the efficacy of different image analysis techniques in a controlled environment. The SBD now stores simulated MRI data from the perspectives of both normal and multiple sclerosis (MS) brains. Full three-dimensional information volumes have been re-enacted for each of these, with a variety of cut thicknesses, noise levels, and power inconsistencies, across three different arrangements (T1-, T2-, and Proton-Density (PD-) weighted). You may download and examine these data from three different orthogonal views (the sagittal, coronal, and transverse planes).

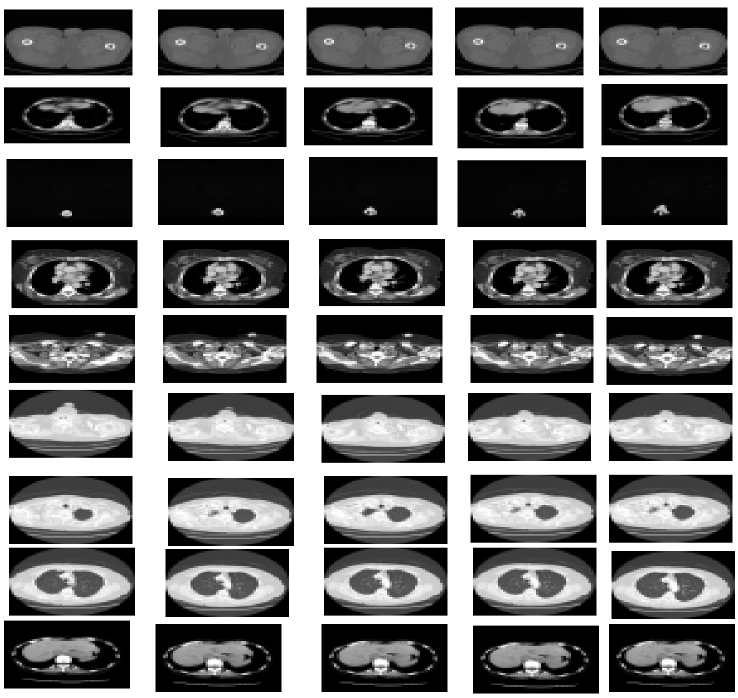

Figure 3. Sample 10 classes if CBIR images

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The classification accuracy, specificity, and sensitivity of the suggested technique are determined as evaluation metrics for the proposed classification methodology. The following are the indicators of performance:-

Accuracy = (TP/TN)/ (TP+TN+FP+FN)*100%

Specificity =TN/ (TN+FP)*100%

Sensitivity =TP/(TP+FN)*100% where True positive (TP):

True negative (TN): False positive (FN): False negative (FN):

In this work of applied research, we employed a CBIR medical picture database including eighty individual images. In this section, we determine all of the variables: Precision = 95%, Sensitivity = 90% and Positive Predictive Value = 100%

The picture dataset is classified using four different classifiers, including KNN, SVM, PSO-based SVM, and GWO-based SVM. The dataset is divided into two groups using the KNN and SVM classifiers. To divide the data into three groups, a support vector machine classifier (SVM) is used. In order to categorise the images, a classifier called Bag of Visual Words is utilised. Finally, we compare the classifiers' performance in terms of accuracy and error. Table 1 displays the results of a comparison of the accuracy and error of several classifiers. It is clear from this table that the GWO-based SVM classifier produces the highest quality classifications.

Table 1 Comparisons of classifier accuracy and error values

Classifier	**KNN**	**SVM**	**PSO based SVM**	**GWO based SVM**
Accuracy (%)	87	92	94	98.3
Error (%)	14	12	9	3.2

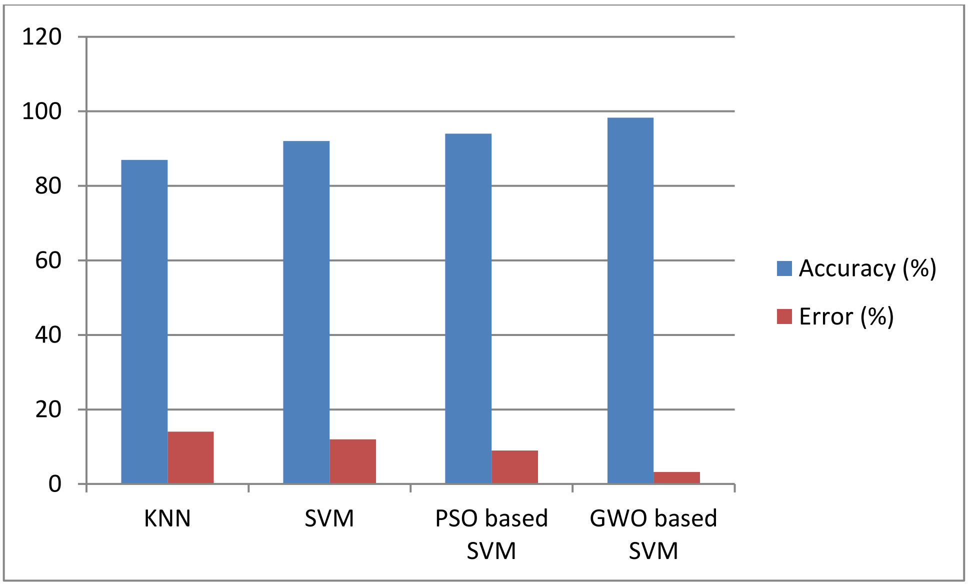

Figure 4. Classifiers accuracy and error comparisons

Figure 4 shows that both the ANN and Bag of Visual Words classifiers perform quite well in terms of accuracy. There will be a 97.3% accuracy using an SVM classifier based on GWO. Accuracy suffers as error increases.

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Conclusion

One of the current areas of study is the development of a content-based picture retrieval system. Accessing medical photos based on their content aids in the making of clinical decisions. Clinical data administration may be simplified by the use of image archive and communication systems that use content-based retrieval techniques. Several methods for retrieving medical images have been studied in this paper, and four revised methods have been offered. The feasibility of using two common conventional contour based shape approaches and seven popular conventional area based techniques in an image retrieval system was thoroughly explored and executed. The study found that improving Precision and Recall in picture retrieval using textual information alone is challenging. Low-level traits including colour, texture, and form are often used by researchers. A content-based image retrieval method is described here using geometric attributes of objects contained in the photos to train a support vector machine classifier.

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