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ORIGINAL

Brain tumor information retrieval system for brain tumor diagnosis

Sistema de recuperación de información sobre tumores cerebrales para el diagnóstico de tumores cerebrales

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ABSTRACT

Application areas for information retrieval include searching a wide range of information from search engines, identifying defective product parts in industry, extracting valuable knowledge from medical images, quickly identifying criminals in the criminal justice system through facial image and fingerprint analysis, and security biometric applications. For the aforementioned objectives, picture is a necessary component to draw original conclusions. The majority of applications rely heavily on picture retrieval, which is based on two main methods: content-based and text-based methods. One useful method used in image searching applications is Content-Based Image Retrieval (CBIR). Colour, texture, and shape descriptors—low-level traits—are used in CBIR to retrieve images. These descriptions make it simple to determine the image's context. The goal of this work is to identify brain tumour locations in magnetic resonance imaging datasets and to distinguish between normal and defective picture types. Additionally, the suggested approach performs well when it comes to classifying photos for medical applications and identifying specific locations of brain tumours. The importance of this finding prompts the creation of fresh methods for identifying patients' medical problems in real time.

Keywords: Content-Based Image Retrieval; Information Retrieval; Brain Tumor; Magnetic Resonance Imaging.

RESUMEN

Las áreas de aplicación de la recuperación de información incluyen la búsqueda de una amplia gama de información en motores de búsqueda, la identificación de piezas defectuosas de productos en la industria, la extracción de conocimiento valioso de imágenes médicas, la identificación rápida de delincuentes en el sistema de justicia penal mediante el análisis de imágenes faciales y huellas dactilares, y las aplicaciones biométricas de seguridad. Para los objetivos antes mencionados, la imagen es un componente necesario para extraer conclusiones originales. La mayoría de las aplicaciones dependen en gran medida de la recuperación de imágenes, que se basa en dos métodos principales: métodos basados en contenido y métodos basados en texto. Un método útil utilizado en aplicaciones de búsqueda de imágenes es la recuperación de imágenes basada en contenido (CBIR). Los descriptores de color, textura y forma (rasgos de bajo nivel) se utilizan en CBIR para recuperar imágenes. Estas descripciones facilitan la determinación del contexto de la imagen. El objetivo de este trabajo es identificar las ubicaciones de los tumores cerebrales en los conjuntos de datos de imágenes por resonancia magnética y distinguir entre los tipos de imágenes normales y defectuosas. Además, el enfoque sugerido funciona bien cuando se trata de clasificar fotos para aplicaciones médicas e identificar ubicaciones específicas de tumores cerebrales. La importancia de este hallazgo motiva la creación de nuevos métodos para identificar los problemas médicos de los pacientes en tiempo real.

Palabras clave: Recuperación de Imágenes Basada en Contenido; Recuperación de Información; Tumor Cerebral; Imágenes por Resonancia Magnética.

INTRODUCTION

Information retrieval is the process of getting relevant data relevant to a user's request out of a multimedia database. An ocean of data, including documents, photos, audio files, and videos, makes up a multimedia database, where managing images is a significant responsibility.(1) The system's capacity to retrieve comparable photos from the stored images while meeting all the requirements specific to the query image is known as image retrieval. In many real-time domains, including medical diagnosis systems, web search, biometrics, target identification systems, and security systems, searching images from multimedia repositories is a challenging issue.(2) Many applications' functionality processes and performance are directly or indirectly improved by designing an effective retrieval mechanism.(3) Text-based image retrieval system and content-based image retrieval system (CBIR) are the two retrieval strategies available to search the image from the image repository.(4) The annotated keywords that are mapped to each image saved in the database are used in a text-based retrieval system to search for the requested photos. This approach necessitates human annotation for photos that have been stored, and extra functionality is needed to manage newly added images that degrade system performance. Furthermore, when the same keyword is used for various types of photos, which have varied meanings depending on the question, the retrieval system's accuracy is impacted by comprehending the meaning of the user's query.(5)

Background of the study

Applications of object detection are important in many fields, such as biometrics, industrial inspection, web searching, historical research, medical diagnostics, and satellite systems for geographical information.(6) It is a difficult challenge in the medical diagnosis system to identify and name the precise region of interest and classify disorders in Computer Tomography (CT) and Magnetic Resonance Imaging (MRI) scans.(7) Finding the size and position of tumour or cancerous cell in a picture is a crucial application as well. Finding similar things to retrieve can be highly helpful in security systems, architectural designs, and more.(8) It can be used to extract objects with similar traits or patterns. Content-based retrieval of remote sensing images for analysis works well in geographic information satellite systems. It is a difficult challenge for robots in robotics to execute automation and to make pertinent decisions and actions for identifying the geometry, forms, and sizes of household items.(9) The size of medical pictures, such as CT and MRI scans, is constantly growing in the medical setting. Applications that use images have additional difficulties and important issues like content interpretation, knowledge management, indexing, and storage management.(10) To process and learn the region of interest from a distinct database, an effective recognition mechanism is needed.(11) Target object detection approaches have been created in an effort to address such issues and retrieve a set of objects from the database based on similarity attributes such as colour, form, and texture shown in figure 1.

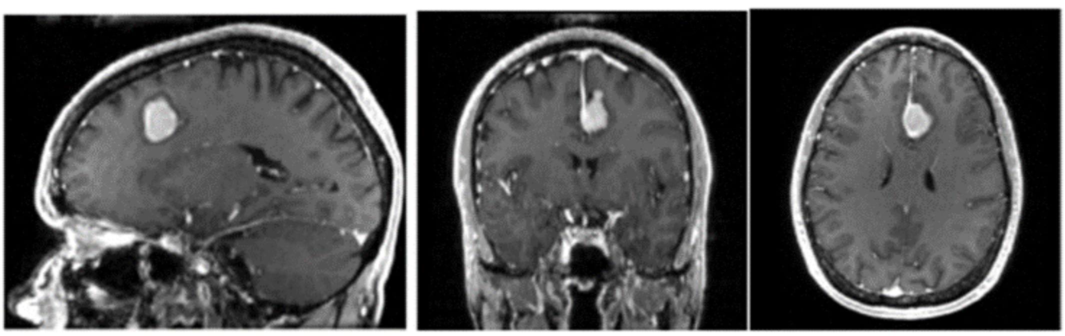

Figure 1. Slices of MRI brain image in three various dimensions

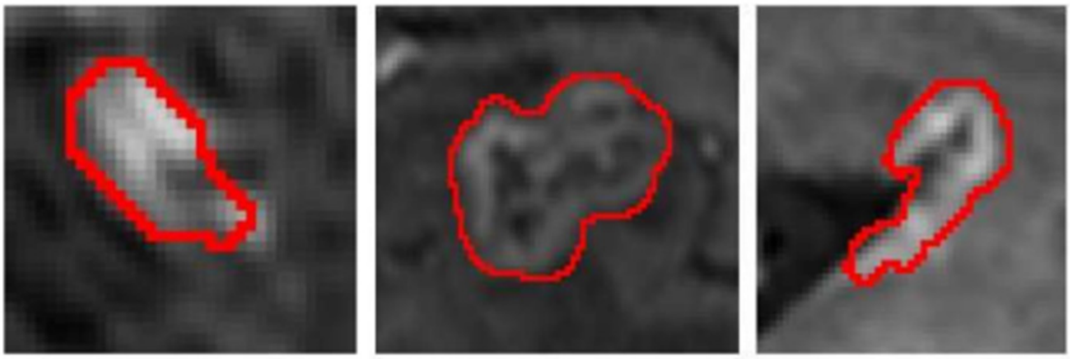

Figure 2. Examples of brain tumors in various structures

Researchers have used data from the GLOBOCAN 2023 International Agency for Research on Cancer to provide statistics about the worldwide cancer burden with a focus on 20 global areas. Since the early identification, treatment, and prevention of cancer have advanced, the number of cancer deaths has decreased by 23 %, from 215,1 (per 100 000 inhabitants) to 166,4.[12] Effective image processing algorithms that are applied to different image modalities like CT and MRI are necessary for early medical diagnosis in figure 2. The most difficult research gaps in the field of medical diagnostics are being addressed by this effort, which includes identifying brain tumours in medical imaging and locating related images or regions in databases. Finding the region of interest is a key step in extracting sufficient and pertinent features in these applications.[13] With the extracted features development of efficient algorithms for the detection of region of interest (ROI) and the learning algorithms also necessary to categorise the fresh images for the existing features.[14] The invention of an automated system for identifying tumour cells in brain imaging and classifying normal and abnormal brain images is the main feature of the proposed study.

The organization of the remaining sections is as follows: Section 2 presents a background of the CBIR and explains the tumours; The operations, performance and methodology are discussed in in Section 3; Section 4 compares and lists the results of proposed model with existing state of art techniques., and Section 5 concludes the research work with future directions.

Proposed Framework

The goal of this research project is to provide an algorithm that will enable the efficient extraction of relevant and precise data for the purpose of identifying tumour cells in a brain imaging. The suggested work's architecture diagram is shown in figure 3. The mean filter is first applied to the MRI images from the database before they are sent to the classification system in order to further improve the image by removing streak artefacts.

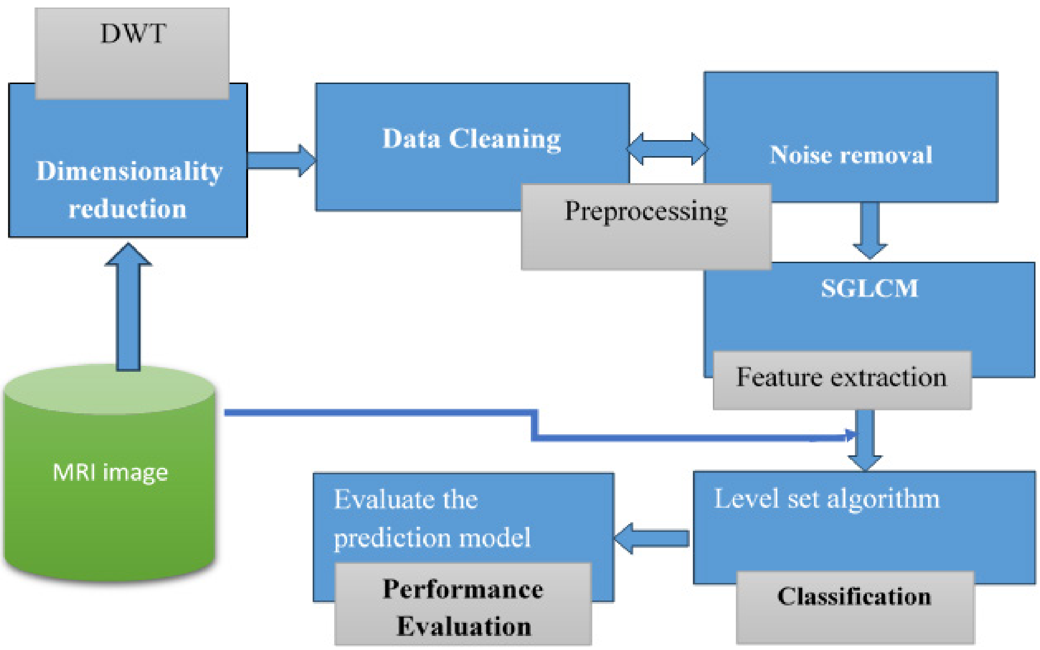

Figure 3. Overall architecture

Removal of Noise

The quality of MRI pictures can be affected by Gaussian noise and salt and pepper noise, which are common in acquired images. The performance of any work, including feature extraction, reduction, and classification of the processed MRI pictures, is generally deteriorated by poor quality MRI images.(15) High performance in eliminating background noise and streak artefacts is offered by the combination of Gaussian smoothing, median filter, and template matching. The median filter is a form of order-statistic filter that uses a non-linear filtering technique to remove noise from an input. The computational efficiency of the impulse noise allows for its identification. Maintaining the edges during the noise reduction procedure is the primary goal.

Dimensionality Reduction using DWT

The image is subjected to two-dimensional Discrete Wavelet Transform (DWT) in order to reduce storage requirements and enhance computational complexity.(16) It breaks down the image into wavelet basis functions that are mutually orthogonal. The mother wavelet φ is translated, scaled, and dilated in these wavelet functions. Approximation coefficients and detail coefficients are the two types of coefficients produced by DWT. Low pass and high pass filters are used to create them. When these coefficients are applied column-wise, four subbands, such as LL, LH, HL, and HH, are produced.

MRI Bias Correction

Because bias fields have uncertain or incomplete properties, correcting the bias in brain MRI pictures is a very difficult undertaking. Intensity inhomogeneities have a significant impact on segmentation quality since the bias fields directly affect intensity values. The bias fields, which are known to intrinsically affect the segmentation quality, particularly in brain tumour segmentation, are a major cause of intra-volume intensity inhomogeneities.(17) Since the segmentation accuracy depends on the intensity values, the entire procedure may be relied upon for efficient reduction or elimination of bias fields. To handle the bias fields and intensity inhomogeneities, the model must be trained appropriately, which results in a notable increase in computation time and dependence on extra measures.(18) In order to solve these problems, the suggested research study has included a training mechanism that, in contrast to existing supervised learning algorithms, pre-trains the model without requiring ground truth. The quality of input images is significantly impacted by motion, field bias, artefacts, intensity inhomogeneities, and other factors. MRI device images are typically subjected to numerous modalities. In the prediction and segmentation stages, either the noise levels or the artefacts cause false positives, which cause unwanted and needless confusion. Field bias correction techniques help address such artefacts in different ways. As a N3 algorithm, the suggested model applies a normalisation algorithm based on non-parametric and non-uniform-based methods.(19,20) The process of removing the unsettling artefacts also normalises the intensity of the input medical images. To find the artefacts and remove them from the calculations, the N3 algorithm is modified into an N41TK bias correction method.

Spatial Gray-Level Dependence Matrices

Field bias correction techniques help address such artefacts in different ways. As a N3 algorithm, the suggested model applies a normalisation algorithm based on non-parametric and non-uniform-based methods.(21) The process of removing the unsettling artefacts also normalises the intensity of the input medical images. To find the artefacts and remove them from the calculations, the N3 algorithm is modified into an N41TK bias correction method. The Spatial Gray-Level Dependence Matrix (SGLDM) is a spatial matrix that is created by grouping all of these values, which reflect the pixels and their spatial properties. The textural analysis's output provides just the spatial features, not the shape of the tumor-affected cells.(22)

Deep Learning Architecture based on Level Based Learning

The deep learning framework in the suggested model has little to no variation between the layers, which are typically referred to as shallow and deep layers with distinct functions. The architecture's layers are intricately interconnected, enabling efficient communication via a knowledge or information bridge that operates on the local and global characteristics found in the input images.(23) The architecture of the suggested model is shown in figure 3, and when 128x128 images are fed into it, correct segmentation results are produced. The segmentation results are generated in the same dimensions after the photos are analysed.(24) To ensure promising reconstruction outcomes, the features are further refined and classified using a multi-level learning technique once the down sampling procedure is completed. Multi-level learning architectures are frequently employed in the context of image processing for tasks like object detection, picture segmentation, and image recognition, where the input images may contain characteristics or objects of different sizes or scales.(25) By including many levels of processing, these architectures may capture features at varying spatial resolutions and capture both local details and global context, resulting to increased performance in handling objects or features of varied sizes or scales. An image or a set of brain tumour images is the typical input to the proposed architecture.[26] Apart from the input images, some image segmentation deep learning architectures may also accept additional information as input to help direct the segmentation process or enhance the segmentation accuracy. The architecture that is presented here consists of an encoder, a decoder, and a few layers for padding.[27] The encoder's convolutional layers are in charge of achieving maximum pooling results, and the dropout layers guarantee the same goal. At the moment, the encoder uses two convolutional layers, which feeds the output to the following layers for a Conv2D Transpose operation. All these processes are finished prior to the processing of the decoder.[28,29]

RESULTS AND DISCUSSION

Forty photos have been selected from the datasets for analysis, with the normal and diseased brain tissues properly segmented. The model was trained using photos from 28 patients, of which 15 were declared normal and the rest images to be aberrant. Twelve patient images—ten normal and five abnormal—were taken into consideration for the testing dataset. To achieve optimal accuracy and performance of the prediction model, the training and testing data were divided into appropriate categories based on the number of photos in figure 4.

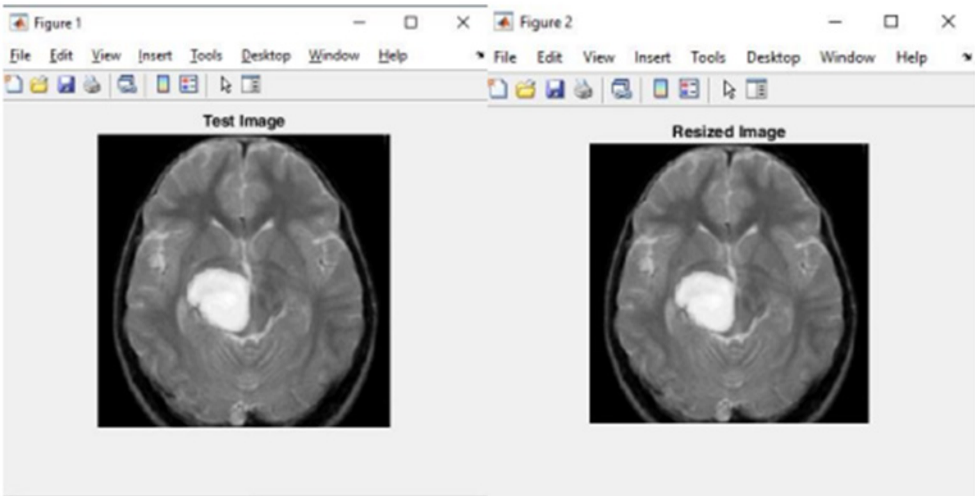

Figure 4. (a) Input Medical Image, (b) Resized Image

The basic goal of any prediction modelling constructed using machine learning and deep learning algorithms is to achieve accuracy in segmentation and classification in below Figure 5. The precision with which the tumorous cells are extracted from the input medical images determines the segmentation quality. The deep learning system needs to recognise and retrieve all of these locations while excluding any healthy cells.

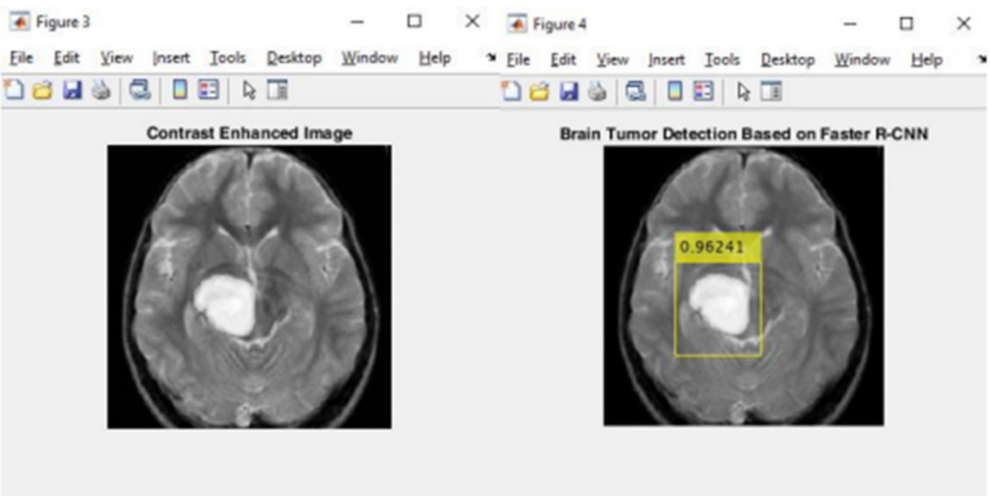

Figure 5. (a) Contrast Enhanced Image, (b) Segmented Brain Tumour

Higher percentages of healthier cells are typically present, and input images are typically contaminated with noise and disruptions that could be interpreted as areas affected by tumours in figure 6. The accuracy of the suggested model in quickly and accurately identifying every location impacted by a tumour and separating it from surrounding areas is assessed. The performance of the suggested model is shown in the accompanying figure, along with comparisons with alternative methods.

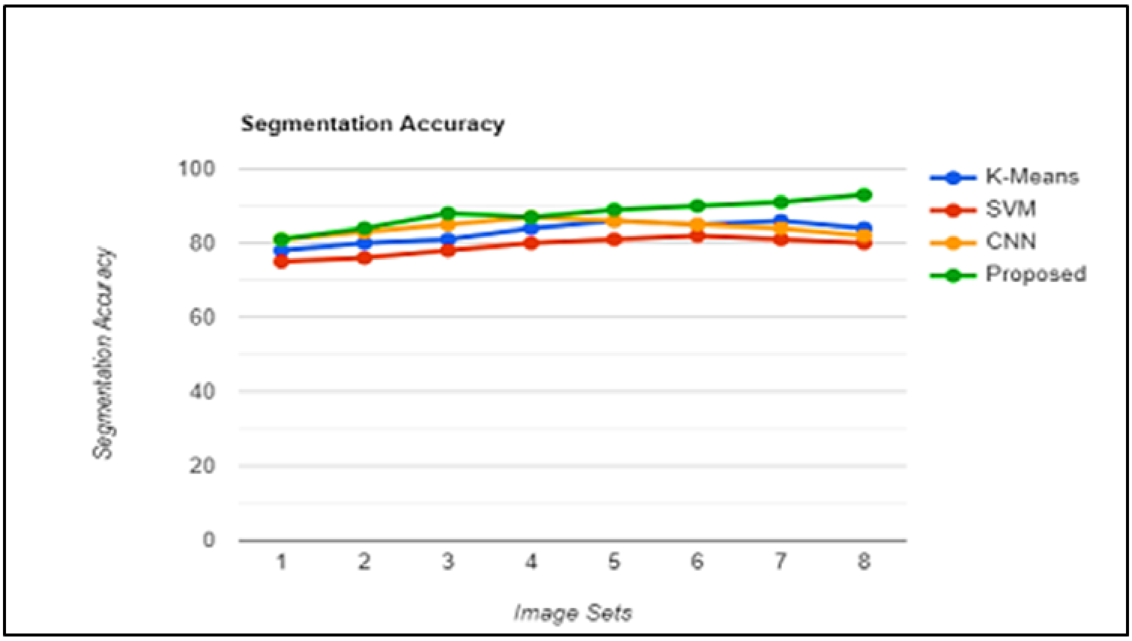

Figure 6. Segmentation Accuracy of proposed model Vs other models

One crucial parameter for illustrating the prediction model's performance is the amount of time required for segmentation and classification. The program or algorithm that takes the least amount of time to derive the results will be given preference. The segmentation process will take milliseconds for every machine learning or deep learning framework, and this section discusses how long the suggested model takes to complete compared to the other models. The time used by the suggested deep learning framework is shown in figure 7, and it is clear that it takes less time than other state-of-the-art methods. Therefore, the suggested approach has done better for segmentation than the other CNN, SVM, and K-Means methodologies.

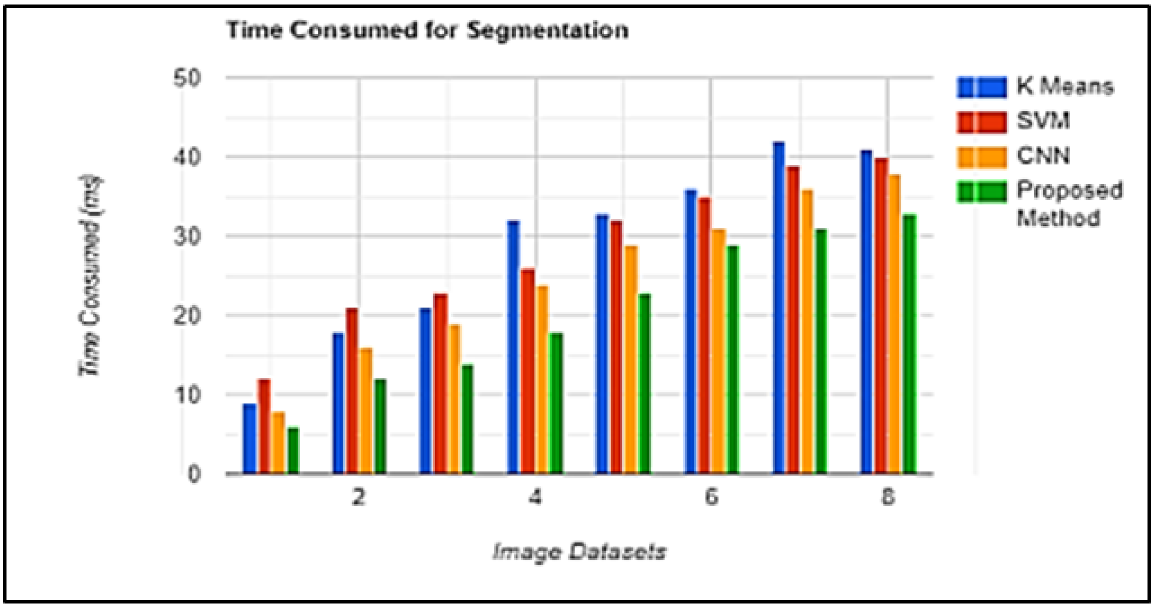

Figure 7. Time Consumed for Segmentation by the proposed model Vs other models

The unequal quantity of pixels formed against the total data elements contained in each input medical image usually results in a number of errors or improper segmentation. Errors may occur when the input photos are multimodal and come from different datasets. The current model is designed to process many modalities in order to lower error rates because it is usually trained on a single modality. The error rate of the suggested model in comparison to the other models for the mistakes during segmentation findings is shown in figure 8 below. Error rates increase whenever tumor-affected cells are overlooked during identification or when healthy cells are mistakenly recognised as tumor-affected cells. It is clear from the comparison data that the suggested methodology produced fewer segmentation errors.

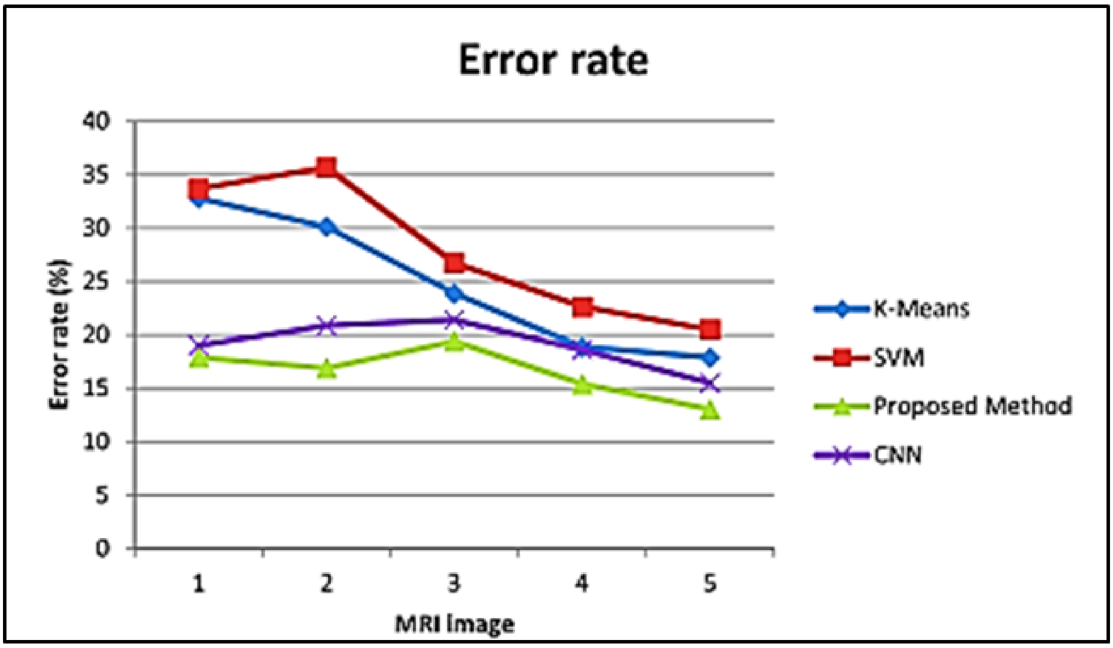

Figure 8. Error Rate of proposed segmentation Vs other models

Five algorithms were suggested by the research effort to obtain the pertinent photos. The computational complexity and system performance are enhanced by the suggested picture retrieval algorithms. By using a huge database with many image categories and taking into account various backgrounds in real-time applications, this work can be expanded. By developing a productive method for indexing and rating the photos, this endeavour can gain further credit.

CONCLUSIONS

Higher percentages of healthier cells are typically present, and input images are typically contaminated with noise and disruptions that could be interpreted as areas affected by tumours. The accuracy of the suggested model in quickly and accurately identifying every location impacted by a tumour and separating it from surrounding areas is assessed. The table 6.5 below contains the rate of error. Applications for information retrieval include multimedia retrieval, semantic matching, integrated solutions, health care systems, digital repositories, search engines, and more. It is an emerging field of technology. Information retrieval's primary features are comparison, indexing, feature extraction, model representation, and performance measurement. The majority of applications in the field of information retrieval work by focussing on images. Image retrieval is a fundamental functional component in many multimedia applications, especially in search engines and medical diagnostic systems. The search engine is designed to successfully handle a wide range of user queries under various limitations. It also creates medical diagnosis systems that can solve a wide range of medical problems by successfully scanning the photos. A thorough examination of the image is required in order to respond to this kind of request from the user. CBIR is a technology that researchers have created to search photos in numerous automated applications. The literature study revealed that handling backgrounds, feature extraction techniques, feature representation, storage used by the images during intermediate level processing, computational complexity, and query retrieval time were some of the research issues that content-based image retrieval (CBIR) sustained.

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CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

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